International Review of Financial Analysis 79 (2022) 101992

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Systemic risk contribution of banks and non-bank financial institutions across frequencies: The Australian experience☆

Md Lutfur Rahman [a], Victor Troster [b,*], Gazi Salah Uddin [c], Muhammad Yahya [d]

[a] Newcastle Business School, The University of Newcastle, Newcastle, NSW 2300, Australia
[b] Department of Applied Economics, Universitat de les Illes Balears, Palma de Mallorca 07122, Spain
[c] Department of Management and Engineering, Linköping University, 581 83 Linköping, Sweden
[d] Department of Business Administration, Inland Norway University of Applied Sciences, 2418 Elverum, Lillehammer, Norway

ARTICLE INFO

JEL Classification:
C22
C23
G21
G22
G23
G28

Keywords:
Systemic risk
Australian financial sector
Frequency
Delta conditional value-at-risk
Wavelets
Copulas

ABSTRACT

The Australian financial sector (AFS) is highly concentrated and interconnected. Besides, Australian banks' lending portfolios are dominated by residential mortgage loans, and 70% of insurance companies' revenues arise from non-policyholder sources. The AFS also performed relatively well during the global financial crisis (GFC). Given these distinctive features, in this paper, we examine the systemic risk contribution of Australian banks, insurance companies, and other financial services providers. We use a flexible copula-based delta conditional value-at-risk (ΔCoVaR) method across different frequencies. Further, we study the systemic risk determinants in a panel setting. We find that the major Australian banks are systemically more important than all other financial institutions. Systemic risk is typically higher after the GFC than in the pre-crisis period, despite the introduction of more stringent capital requirements. In addition, the short-term ΔCoVaR is significantly higher than the medium- and long-term ΔCoVaRs. Finally, institution-specific characteristics and market-wide variables explain the cross-sectional and time-series variation in systemic risk, and their explanatory power varies across frequencies.

1. Introduction

The financial sector's risk assessment has historically been carried out based on balance sheet components of individual financial institutions (FI), overlooking their heterogeneity and importance to the overall financial system. Similarly, the traditional risk management approach has focused on individual risk exposures of FIs regardless of the linkages among FIs. Nevertheless, losses of an FI may be spilled over to other FIs due to their interconnectivity. As a result, simultaneous failures of several FIs may negatively affect the entire financial system. This potential risk spillover (the so-called systemic risk) has been a concern in recent years. Shocks of illiquidity, insolvency, and losses of an individual FI quickly proliferated to other FIs during the global financial crisis (GFC). Accordingly, regulators have taken *ad-hoc* measures to control systemic risk.[1] Therefore, it is important to estimate an individual FI's systemic risk contribution from a regulatory and an academic standpoint. This analysis helps regulators impose regulatory safeguards on the overall financial system.

This paper examines the systemic risk in the Australian financial sector (AFS) and explains the degree of systemic risk contribution by institution-specific characteristics and market-wide variables. We analyze the AFS for several reasons. The AFS had a relatively good

☆ Victor Troster acknowledges the financial support provided by the Spain's Ministerio de Ciencia e Innovacion - Agencia Estatal de Investigación [grant number PID2020-114646RB-C43]. Gazi Salah Uddin is thankful for the Visiting Fellow Programme Grant by the University of Jyvaskyla, Finland. The authors are thankful to the University of Jyvaskyla, Finland, for the academic facilities provided to Gazi S. Uddin during his stay at Jyvaskyla, where important parts of this work were completed. An earlier version of this paper was presented at the Linkoping University, Sweden.

* Corresponding author.
E-mail addresses: mdlutfur.rahman@newcastle.edu.au (M.L. Rahman), victor.troster@uib.es (V. Troster), gazi.salah.uddin@liu.se (G.S. Uddin), muhammad.yahya@inn.no (M. Yahya).

[1] For example, a systemically important bank is subject to a “crisis responsibility fee” (The White House Office of the Press, 2010), a systemic risk levy (Claessens, Keen, & Pazarbasioglu, 2010), a capital surcharge (Basel Committee on Banking Supervision (BCBS), 2013), a Pigouvian tax (Acharya et al., 2017; Acharya, Pedersen, Philippon, & Richardson, 2013), and more stringent regulations (Dewatripont, Rochet, & Tirole, 2010) in different countries and contexts.

https://doi.org/10.1016/j.irfa.2021.101992
Received 11 May 2021; Received in revised form 16 September 2021; Accepted 26 November 2021
Available online 1 December 2021
1057-5219/

performance during the GFC, in contrast to most developed countries' financial sectors, due to the Australian Prudential Regulatory Authority's (APRA) proactive measures such as mandatory stress tests and high capital requirements (Reserve Bank of Australia (RBA), 2009). Nevertheless, the aggregate financial system's performance may not necessarily reveal the systemic risk profile of the individual FIs (Pais & Stork, 2011). Thus, it is important to assess the systemic risk of the AFS. Besides, unlike the financial sectors in the US and many European economies, the AFS is highly concentrated and interconnected. The largest four banks and the top five life insurance companies hold about 80% of the total assets in the banking and life insurance sectors, respectively. Further, Australian banks' lending portfolios are dominated by residential mortgage loans (D'Hulster, 2017), while special housing FIs provide real-estate mortgage lending in most developed economies (Berglund & Mäkinen, 2019). As for insurance companies, about 70% of their revenue arises from non-policyholder sources (Lange, Saunders, & Cornett, 2015). Finally, total household debt in Australia is about twice the total disposable income, which is relatively higher than that of many industrialized nations. The Australian FIs are also heavily reliant on offshore sources for wholesale funding (International Monetary Fund (IMF), 2019). These characteristics of the AFS may affect systemic risk (Brunnermeier, 2009).

Given the collapse of the whole financial system in response to the downfalls of several FIs during the GFC, researchers examined the extreme-value relationship between a distressed FI and the overall financial system. For this purpose, certain systemic risk measures have been proposed, such as the distressed insurance premium (Huang, Zhou, & Zhu, 2012), the systemicness (Greenwood, Landier, & Thesmar, 2015), the conditional value-at-risk (CoVaR) (Adrian & Brunnermeier, 2016), the systemic risk index (Brownlees & Engle, 2017), and the systemic expected shortfall (Acharya, Pedersen, Philippon, & Richardson, 2017).

This paper employs and extends the most-used systemic risk measure, the ΔCoVaR of Adrian and Brunnermeier (2016). The CoVaR measures the value-at-risk (VaR) of the overall financial system conditional on the VaR of an individual FI. The ΔCoVaR, a measure of risk contribution of an FI to the overall financial system, is the difference between the CoVaR conditional on an individual FI in distress and the CoVaR conditional on an FI being in the median state. The ΔCoVaR is a complete measure of risk independent of ex-ante modeling of returns' conditional distributions (Adrian & Brunnermeier, 2016).

While the original ΔCoVaR methodology of Adrian and Brunnermeier (2016) is based on a semiparametric quantile regression approach, this paper uses a flexible copula-based ΔCoVaR method. The copula method is reliable because it enables estimating the entire joint distribution of returns even in the presence of fat tails or heteroscedasticity (Adrian & Brunnermeier, 2016). In particular, we use a broad range of copula families that model different forms of dependence and extreme co-movements between an individual FI and the financial system as a whole. Moreover, the copula approach segregates the dependence structure (associated with systemic risk) from marginal distributions (related to tail risk), providing estimation flexibility and mitigating the misspecification bias that stems from measuring systemic risk.

This paper adds to the literature both methodologically and contextually. The first contribution of this paper is to examine systemic risk in different frequencies. Although previous studies mostly focus on estimating systemic risk for a particular data frequency (Bernal, Gnabo, & Guilmin, 2014; Black, Correa, Huang, & Zhou, 2016), it is important to analyze the frequency dynamics of systemic risk. Investors operating in different investment horizons (represented by frequencies) may respond differently to an economic shock. Therefore, the systemic risk may change across frequencies. For instance, Lehmann (1990), Lo and MacKinlay (1990), and Jegadeesh (1990) show that the short-term reversals occur at daily or monthly levels; on the other hand, the momentum effects and the long-term reversals take place at 6–12 months and 3–5 years, respectively (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993). We empirically verify this conjecture. If connectedness in FIs is found in a high frequency, it may indicate that investors react to information rapidly. Therefore, a shock to an FI will only have a short-term impact on the financial system. On the other hand, connectedness in a lower frequency may indicate persistent shock and the potential of its transmission for more extended periods. This analysis, mostly ignored by previous studies, has important policy implications as it helps FI managers develop prudential risk management policies.

This paper also explains the systemic risk of the AFS by institution-specific characteristics and market-wide variables. The works of the Australian Prudential Regulation Authority (2013) and Avkiran (2018) analyze the systemic risk of the Australian banks based on the criteria set by the Basel Committee for Banking Supervision (such as size, non-substitutability, and complexity). Nevertheless, none of the previous studies relate institution-specific characteristics to their systemic risk contribution in the Australian context. Therefore, our analysis is worthwhile given the Australian financial sector's unique features, as indicated previously, such as high concentration, dominance of residential mortgage loans, and high reliance on non-traditional activities.

Further, we explore the determinants of frequency-based systemic risk. While previous studies overlooked this analysis, we provide novel evidence on different sets of systemic risk drivers in the short, medium, and long term. This analysis provides important insights to financial institutions in managing their systemic risk exposure in the short term and for longer periods. In this exercise, we derive a semiannual measure of ΔCoVaR and regress it on institution-specific characteristics (VaR, size, leverage, liquidity, profitability, and intangible assets) and market-wide variables (Gross Domestic Product [GDP] growth, cash rate change, exchange rate change, and housing price growth). We do this in a panel setting.

The last contribution of this paper is to analyze the entire financial sector in Australia. While extensive literature focuses on systemic risk of the US and European banks (see, e.g., López-Espinosa, Moreno, Rubia, & Valderrama, 2015; Black et al., 2016; Acharya et al., 2017; Karimalis & Nomikos, 2018), the systemic importance of non-bank FIs is less explored. Long-Term Capital Management's collapse and the near failure of the global insurance organization American International Group showed that the breakdown of insurance companies and managed funds also critically affects the whole financial system (Bernal et al., 2014). Insurance companies are relatively safer than banks as they do not drive monetary or payment systems, and they typically rely on longer-term liabilities than banks do. The increased participation of insurers in non-traditional activities such as credit default swaps, however, has enhanced the likelihood that shocks to the insurance industry affect the entire financial system (Bernal et al., 2014). Managed funds may affect the whole financial sector by defaulting on their borrowing, counterparty derivative contracts, and security transactions. Thus, it is imperative to explore the systemic risk contribution of all components of the financial system.

We report several key findings. We find that the major Australian banks are systemically more important than the regional banks and other FIs. The latter, however, exhibit higher downside risk (VaR) potentially due to their concentrated and more specialized nature of business. Although the Australian government introduced deposit insurance in early 2008 and increased capital requirements, systemic risk in the post-crisis period is higher than that in the pre-crisis period. This result implies a shift in investors' expectations about overall risk and a reduction in too-big-to-fail subsidies, particularly after the GFC. Moreover, systemic risk in the AFS differs across frequencies. Although the short-term systemic risk is generally higher than that in the medium and long term, this result prevails during the crisis period. This finding suggests that systemic risk created in a crisis period is attributed to investors' rapid processing of fundamental and publicly available information. It mostly affects the short-term cyclical behavior of the financial system. Finally, we find that institution-specific characteristics such as

VaR, size, leverage, liquidity, profitability, and intangible assets explain banks' systemic risk contribution. In contrast, VaR, size, liquidity, and profitability determine the systemic risk contribution of non-bank FIs. Besides, housing price growth and cash rate change affect the systemic risk contribution of both types of FIs, whereas the exchange rate change and economic growth determine the systemic risk of banks. Finally, systemic risk across frequencies depends on different sets of explanatory variables.

The rest of the paper advances as follows. Section 2 revises the related literature. Section 3 highlights the key characteristics of the Australian financial sector. Section 4 outlines the methods used in the paper, and Section 5 presents the data and descriptive statistics. Section 6 discusses the empirical results and policy implications. Finally, Section 7 concludes the paper.

2. Literature review

The literature on systemic risk in the financial sector predominantly focuses on three aspects. First, the channels to which risk spillover takes place from an individual FI to other FIs and the financial system as a whole. For instance, banks' exposure to the interbank markets and the Euromarkets is considered one channel (Allen & Gale, 2000). Since banks use both of these markets to manage their liquidity risk, any bank's failure can negatively affect other banks (Furfine, 2003; Upper & Worms, 2004). As for insurance companies, the default of a large insurer with extensive interconnection may have spillovers to the entire financial system, particularly when insurance companies mostly rely on non-core and non-insurance activities (Geneva Association Systemic Risk Working Group, 2010; IAIS, 2012). Bernal et al. (2014) argue that insurance companies may affect the whole financial system by defaulting on their default swap agreements. Based on these arguments, Harrington (2009), Billio, Getmansky, Lo, and Pelizzon (2012), Weiß and Mühlnickel (2014), and Acharya, Philippon, and Richardson (2016) explore the systemic risk contribution of insurance companies. Weiß and Mühlnickel (2014) show that managed funds influence other FIs and the entire sector through the market channel. Managed funds create exposure to other FIs through their borrowing, roles in counterparty derivative contracts, security transactions, and aggressive investment strategies (Dixon, Clancy, & Kumar, 2012).

Another important aspect covered in the systemic risk literature consists of measures of systemic risk and their applications. For instance, Lehar (2005) and Gray, Merton, and Bodie (2019) compute the systemic risk based on FI assets' contingent claims. Huang, Zhou, and Zhu (2009) propose a method that measures systemic risk by the price of insurance against financial distress. Billio et al. (2012) calculate an individual institution's connectedness with the overall financial system by using unconditional correlation from the Granger-causality network and principal component analysis. Acharya, Engle, and Richardson (2012) and Acharya et al. (2017) develop the expected capital shortfall (ECS) and the systemic expected shortfall (SES), respectively, to measure systemic risk. The ECS depicts an FI's capital requirement in a potential distressing event. The SES illustrates an FI's tendency to be undercapitalized when the entire system is undercapitalized. The authors, in general, provide evidence of an increase in systemic risk for the US banks during the GFC. Acharya et al. (2016) demonstrate that insurance companies are the least systemically risky among four types of FIs in the US. However, security dealers and brokers are the most systemically risky. Adrian and Brunnermeier (2016) propose the delta conditional Value-at-Risk (ΔCoVaR), the difference in the VaR of the financial system conditional on an i-th institution being in distress and the VaR of the financial system conditional on an i-th institution being in the median state.

The third relevant strand of the systemic risk literature deals with institution-specific characteristics as determinants of systemic risk contribution of a FI. In general, bank size and leverage significantly increase banks' contribution to systemic risk (Brunnermeier, Dong, & Palia, 2020; López-Espinosa et al., 2015). Black et al. (2016) show that banks with lending portfolios predominantly financed by non-deposit instruments and banks with higher capital ratios contribute to systemic risk. Nevertheless, Laeven, Ratnovski, and Tong (2016) provide evidence that systemic risk is negatively related to the level of capital of a bank. Varotto and Zhao (2018) find a significant inverse relationship between bank profitability and systemic risk. Karimalis and Nomikos (2018) demonstrate that funding liquidity and market volatility negatively affect systemic risk, particularly in a quarterly horizon. In contrast to these studies, Weiß, Bostandzic, and Neumann (2014) contend that a regulatory regime's characteristics, rather than the bank characteristics (such as size, leverage, and quality of bank credit portfolio), are the main drivers of systemic risk.

With regard to non-bank financial institutions' systemic importance, Weiß and Mühlnickel (2014) and Mühlnickel and Weiß (2015) report that both the size and the degree of reliance on non-policyholder liabilities of insurance companies contribute to systemic risk. Bierth, Irresberger, and Weiß (2015) find no evidence that the insurer's size contributes to systemic risk. They provide evidence that the interconnectedness, leverage ratio, and funding fragility are the most important drivers of insurance industry's systemic risk contribution.

Although a large strand of the literature focuses on systemic risk in the US (Acharya et al., 2017; Adrian & Brunnermeier, 2016; Drakos & Kouretas, 2015; López-Espinosa et al., 2015) and in the European banking sector (Black et al., 2016; Karimalis & Nomikos, 2018), only a handful of studies examine systemic risk in the Australian financial sector. For example, Pais and Stork (2011) report that Australian banks' stocks exhibit a high risk of extreme spillovers and interdependencies. This phenomenon has increased markedly since the advent of the GFC. Akhter and Daly (2017) show that Australian banks are contagious to extreme shocks originating from global systemically important banks in the US, Europe, and Japan. Anufriev and Panchenko (2015) and Dungey, Matei, Luciani, and Veredas (2017) provide evidence of a strong link among the four major Australian banks and their connection with the real economy. Bollen, Skully, Tripe, and Wei (2015) report that Australia's major banks' systemic risk increased initially in response to the GFC and the subsequent stock market downturn, but it decreased after introducing the Deposit and Wholesale Funding Guarantee scheme in October 2008.

We find several gaps in the systemic risk literature. First, empirical studies of systemic risk in the financial sector focus predominantly on banks. Thus, insurance companies and other financial services providers' systemic risk contribution is mostly unknown, particularly in non-US countries. Besides, exploring systemic risk across different frequencies is absent in the previous literature. Finally, the empirical studies on systemic risk in the Australian banking sector are based on networks of partial correlations (Anufriev & Panchenko, 2015; Dungey et al., 2017), an augmented market model (Bollen et al., 2015), and financial statement information (Avkiran, 2018). However, none of these approaches explore tail dependence or extreme co-movements of the distribution of returns, which have become relevant after the GFC. These studies also mostly ignore the effect of institution-specific and market-wide variables on the systemic risk contribution of Australian FIs. Therefore, this paper aims at fulfilling these gaps in the literature.

3. The Australian financial sector

According to the Reserve Bank of Australia,[2] the Australian financial sector (AFS) consists of three main types of FIs: (i) authorized deposit-taking institutions (ADIs), (ii) insurers and fund managers, and (iii) non-ADI institutions. The banking sector is the greatest contributor to the overall assets of the AFS. The four largest banks dominate the

[2] https://www.rba.gov.au/fin-stability/fin-inst/main-types-of-financial-institutions.html.

Australian banking sector, holding about three-quarters of the total assets held by ADIs.

The life insurance industry is also highly concentrated, with the top five companies holding about 80% of the industry assets. However, the general insurance industry shows a relatively lower degree of concentration, with the top ten companies accounting for approximately 60% of the industry assets and revenues. The superannuation fund is an important part of the AFS representing about 20% of the whole sector's assets. Nevertheless, the superannuation sector is more dispersed with small funds owning the largest proportion of superannuation assets. Other managed funds and hedge funds have also become relevant in recent years. Overall, the high level of concentration and the dominance of a few large FIs highlight their potential systemic importance in the AFS.

Table 1 reports certain financial soundness indicators of the AFS in 2007 and in 2019. The indicators illustrate the changes in financial soundness since the advent of the GFC. We collect the data used to calculate ratios in Table 1 from FactSet. We focus on profitability, operating efficiency, liquidity, and leverage. The profitability of the FIs (return on asset [ROA]) declined substantially from 2007 to 2019, which may be due to an increase in the capital of the FIs and a decrease in the exposure to non-traditional activities. ROA was smaller than 1% for all the banks in 2019. Besides, the profitability of the regional banks is lower than that of the major banks. The insurance companies and other financial services providers are more profitable than the banks (with few exceptions).

Table 1 indicates that the operating efficiency (the net income per employee in thousand dollars) has substantially increased from 2007 to 2019 for most of the FIs. This increase may be attributed to the expanded use of information technology and the consolidation of certain small FIs with the large ones. The major banks usually have higher operating efficiency than the regional banks potentially because of economies of scale achieved by larger and diversified operations. The other financial services providers, however, show mixed results.

We assess liquidity through the ratio of cash and short-term investments to short-term liabilities. The Australian banks' liquidity ratio has mostly increased from 2007 to 2019, indicating an improvement in the Australian banks' ability to face unforeseen funding requirements or liquidity shortfalls. The enhancement of the Australian banks' liquidity indicator is also consistent with their safety measures after the GFC.

Finally, we measure capital adequacy using the leverage ratio (book value of the total asset to book value of total equity). Table 1 illustrates that the Australian banks' capital cushion has increased from 2007 to 2019, indicated by a general decline in the leverage ratio. This result is also found for most of the other FIs. The leverage ratio of the insurance companies and other financial services providers is typically lower than that of the banks. This result indicates that non-bank FIs have a stronger capital cushion and a greater ability to withstand a crisis than banking companies. In sum, our findings suggest that operating efficiency, liquidity, and leverage position have improved for most of the Australian FIs from 2007 to 2019. Nevertheless, profitability displays a declining trend.

4. Methodology

This section describes the underlying framework used to analyze the systemic risk in the Australian financial sector. We first evaluate the dynamic dependence between a specific FI and the aggregate financial sector index using time-varying copulas. Next, we employ the ΔCoVaR to quantify the risk-spillover effects in the Australian financial sector. Finally, we compute the wavelet-based ΔCoVaR to examine the changes in spillover effects across different frequencies (short, medium, and long run).

4.1. Marginal distribution model

The estimation of a marginal distribution model is essential for estimating copulas. We apply autoregressive moving-average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH) models for the conditional mean and volatility of the returns, respectively. We estimate different GARCH-type specifications: the ARMA(m,n)-GARCH(p,q) of Bollerslev (1986), the Glosten-Jagannathan-Runkle (GJR) ARMA(m,n)-GJR-GARCH(p,q) of Glosten, Jagannathan, and Runkle (1993), and the Exponential ARMA(m,n)-EGARCH(p,q) of Nelson (1991). The best-fitted model is the one that minimizes the Akaike's information criterion (AIC). Appendix A describes the details of the marginal distribution model.

4.2. Time-varying copula

To assess the time-varying dependence between an individual Australian FI and the aggregate financial sector, we employ different time-varying copula models (Gaussian, Student's t, Clayton, and Symmetric Joe-Clayton copula). They are flexible in capturing and modeling dependence (Bekiros, Nguyen, Sandoval Junior, & Uddin, 2017). An important advantage of copulas is that they separate the selection of univariate marginal distribution models from the multivariate dependence structure, simplifying the choice of marginal models and the identification of appropriate copula functions.

Let X_t and Y_t be the stock returns of an individual Australian FI and of the aggregate financial sector, respectively, with marginal distribution functions $F_X(x)$ and $F_Y(y)$, respectively, and a joint distribution function $F_{XY}(x,y)$, for all $(x,y) \in \mathbb{R}^2$. Then, based on Sklar (1959)'s Theorem, we may estimate $F_{XY}(\cdot,\cdot)$ as a function of $F_X(\cdot)$, $F_Y(\cdot)$, and a copula function as follows:

$$F_{XY}(x,y) = C(F_X(x), F_Y(y)), \text{for all } (x,y) \in \mathbb{R}^2 \tag{1}$$

where $C(\bullet,\bullet)$ is uniquely determined for $F_X(\cdot)$ and $F_Y(\cdot)$ continuous such that $C(u_1,u_2) = F_{XY}(F_X{}^{-1}(u_1), F_Y{}^{-1}(u_2))$ is a bivariate copula function, where $u_1 = F_X(\cdot)$ and $u_2 = F_Y(\cdot)$ are random variables following a uniform distribution on $(0,1)$. Hence, we can estimate the joint density $f_{XY}(x,y)$, for all $(x,y) \in \mathbb{R}^2$, as the product between the copula density $c(u_1,u_2)$, for all $(u_1,u_2) \in [0,1]$, and the univariate marginal distributions of an FI and the aggregate financial sector, $f_X(\cdot)$ and $f_Y(\cdot)$, given as:

$$f_{XY}(x,y) = c(u_1,u_2) f_X(x) f_Y(y), \text{for all } (x,y) \in \mathbb{R}^2 \tag{2}$$

where $c(u_1,u_2) = \partial^2 C(u_1,u_2)/\partial u_1 \partial u_2$ is the dependence structure of the return series. A copula may be defined as a multivariate cumulative distribution function with uniform marginal distributions, representing the dependence structure among two or more continuous random variables. As mentioned previously, we consider different time-varying copula models (Gaussian, Student's t, Clayton, and Symmetric Joe-Clayton copula).

Let $C^{Ga}(u_1,u_2) = \phi_\rho(\phi^{-1}(u_1), \phi^{-1}(u_2))$ be the Gaussian copula, where $\phi_\rho(\cdot,\cdot)$ is the bivariate Gaussian distribution function, ρ is the correlation coefficient, and $\phi^{-1}(\cdot)$ is the inverse of the univariate Gaussian distribution. In addition, let $C^t(u_1,u_2) = t_{\rho,v}(t_v{}^{-1}(u_1), t_v{}^{-1}(u_2))$ be the Student's t copula, where $t_{\rho,v}(\cdot,\cdot)$ is the bivariate Student's t-distribution, ρ is the correlation coefficient, v is the number of degrees of freedom, and $t_v{}^{-1}(\cdot)$ is the inverse of the univariate Student's t-distribution with v degrees of freedom. The Student's t copula captures the variations in the distribution tails, and it accounts for possible joint extreme movements that characterize the financial return series.

To consider time-varying dependence for the Gaussian and Student's t copulas, we replace the static correlation coefficient ρ on these copulas by the time-varying correlation coefficient $-\rho_t-$ estimated by the dynamic conditional correlation (DCC) model of Engle (2002). Thus, we apply a DCC-GARCH-copula approach for the Gaussian and Student's t copulas, in line with Berger (2013) and Berger and Uddin (2016). Hence,

Table 1
Financial soundness indicators.

	Profitability (%)		Oper. efficiency		Liquidity		Leverage	
	2007	2019	2007	2019	2007	2019	2007	2019
Major banks								
ANZ	1.10	0.70	121.68	161.19	0.17	0.41	16.82	16.14
CBA	1.10	0.90	118.03	173.31	0.15	0.16	17.39	13.77
NAB	0.90	0.60	117.92	148.01	0.27	0.26	17.21	15.24
WBC	1.00	0.80	123.17	203.62	0.21	0.23	17.52	13.85
Regional banks								
ABA	1.00	0.50	95.15	105.45	0.06	0.13	28.93	15.59
BEN	0.80	0.50	50.17	82.99	0.11	0.12	16.75	13.35
BOQ	0.70	0.50	126.76	142.04	0.12	0.12	23.72	14.42
Insurance companies								
SUN	1.70	1.10	N/A	81.23	N/A	0.85	6.88	7.48
QBE	5.40	1.40	181.26	70.20	0.65	0.60	5.28	4.99
Other financial service providers								
AMP	0.80	−1.70	221.28	−379.54	0.96	0.81	55.57	29.67
ASX	5.60	3.50	563.25	714.08	0.03	0.75	3.46	4.31
CGF	1.00	1.20	239.89	448.04	0.07	0.03	18.82	7.50
CPU	14.10	9.60	28.46	45.78	0.07	0.12	2.08	3.15
EQT	15.70	7.10	33.32	188.44	0.16	0.22	1.33	1.22
EZL	24.10	−0.10	N/A	N/A	0.48	0.20	2.44	1.13
FGR	4.80	−91.30	19.10	−526.05	0.25	0.50	4.68	1.15
MQG	1.20	1.50	149.06	189.76	0.54	0.46	16.19	11.74
PAC	25.30	9.20	270.22	1979.58	0.51	0.03	1.35	1.07
PPT	10.60	9.70	152.14	120.76	0.08	0.42	6.32	1.82
PMV	60.60	6.10	N/A	11.87	0.92	0.09	1.54	1.53

Note: The banks are the Australia and New Zealand Banking Group (ANZ), Commonwealth Bank of Australia (CBA), National Australia Bank (NAB), Westpac Banking Corporation (WBC), Auswide Bank Limited (ABL), Bendigo and Adelaide Bank (BAB), and Bank of Queensland (BOQ). The insurance companies are the Suncorp Group (SUN) and the QBE Insurance Group (QBE). The non-banking companies are AMP, ASX, Challenger (CGF), Computershare (CPU), EQT Holdings (EQT), Euroz (EZL), First Graphene (FGR), Macquarie Group (MQG), Pacific Current Group (PAC), Perpetual (PPT), and Premier Investment (PMV). Profitability is the return on asset. Oper. Efficiency—operating efficiency—is the net income per employee (in thousand dollars). Liquidity is the loan to deposit ratio (for banks) and cash and short-term investment to short-term liabilities (for non-bank FIs). Leverage is the total debt to total capital ratio. See Table A.1 in the Appendix for details of the financial institutions.

we employ the DCC-Gaussian copula $C_{DCC}{}^{Ga}(u_1,u_2) = \phi_{\rho t}(\phi^{-1}(u_1),\phi^{-1}(u_2))$ and the DCC-Student's t copula $C_{DCC}{}^{t}(u_1,u_2) = t_{\rho t,v}(t_v{}^{-1}(u_1),t_v{}^{-1}(u_2))$.

Let $H_t = E_{t-1}(\boldsymbol{r}_t\boldsymbol{r}_t')$, with $\boldsymbol{r}_t = (r_{1,t}, r_{2,t})'$, be the 2×2 matrix of conditional variance-covariance of returns, which can also be written as:

$$H_t \equiv D_t R_t D_t = \begin{pmatrix} \sqrt{h_{1,t}} & 0 \\ 0 & \sqrt{h_{2,t}} \end{pmatrix} \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix} \begin{pmatrix} \sqrt{h_{1,t}} & 0 \\ 0 & \sqrt{h_{2,t}} \end{pmatrix}$$

where R_t is the 2×2 conditional correlation matrix, $D_t = diag\left[\sqrt{h_{1,t}},\ \sqrt{h_{2,t}}\right]$ with $h_{i,t} = E_{t-1}(r_{i,t}{}^2)$ and $r_{i,t} = \sqrt{h_{i,t}}\varepsilon_{i,t}$, for $i = 1, 2$. Then, $\varepsilon_{i,t}$ is a standardized error with mean zero and variance one. Let $\boldsymbol{\epsilon}_t = (\varepsilon_{1,t}, \varepsilon_{2,t})'$be a vector of standardized disturbances. Therefore, we estimate time-varying linear correlations $\rho_{i,\ j,t}$ by applying the DCC method proposed by Engle (2002) as follows:

$$R_t \equiv diag(Q_t)^{-1} Q_t\ diag(Q_t)^{-1} = E_{t-1}\left(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t^{'}\right)$$

$$Q_t \equiv \left[q_{i,j,t}\right] = \overline{R}(1-a-b) + a\boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}_{t-1}^{'} + bQ_{t-1} \tag{3}$$

where R_t has elements $\rho_{i,j,t} = q_{i,j,t}/\sqrt{q_{i,i,t}q_{j,j,t}}$, $\overline{R} = E(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t')$ is the matrix of unconditional correlation of the returns, and a and b satisfy the restrictions $a, b \in (0,1)$ with $a + b < 1$. Following Joe (1997), we apply the two-step maximum likelihood procedure to estimate the marginal models and the copula density for the DCC Gaussian and Student's t copulas. First, we estimate the univariate GARCH marginal parameters $\widehat{\boldsymbol{\theta}}_1$ by fitting univariate marginal distributions that solve:

$$\widehat{\boldsymbol{\theta}}_1 = \underset{\boldsymbol{\theta}_1}{\operatorname{argmax}} \sum_{t=1}^{T} \sum_{j=1}^{n} lnf_j\left(u_{j,t}; \boldsymbol{\theta}_1\right) \tag{4}$$

where $\ln f_j(u_{j,t}; \boldsymbol{\theta}_1)$ is the log-likelihood of the j-th FI stock return, and $\widehat{\boldsymbol{\theta}}_1$ is a $n \times 1$ vector of maximum likelihood estimates of the GARCH marginal parameters. In the second step, given the vector $\widehat{\boldsymbol{\theta}}_1$ from Eq. (4), we compute the DCC-copula dependence parameter – $\widehat{\theta}_2$ – as follows:

$$\widehat{\theta}_2 = \underset{\theta_2(a,b)}{\operatorname{argmax}} \sum_{t=1}^{T} ln\ c\left(F_1\left(u_{1,t}\right), F_2\left(u_{2,t}\right), \dots, F_n\left(u_{n,t}\right); \theta_2(a,b), \widehat{\boldsymbol{\theta}}_1\right) \tag{5}$$

where the copula dependence parameter $\theta_2 \equiv \theta_2(a,b)$ is driven by the DCC parameters a and b of Eq. (3) (see Manner & Reznikova, 2012). As for the Clayton and Symmetric Joe-Clayton (SJC) copulas, we apply the time-varying versions of these copulas developed by Patton (2006). Thus, we implement the Clayton copula formulated as follows:

$$C_t^C(u_1, u_2; \tau_t) = \left(u_1^{-\tau_t} + u_2{}^{-\tau_t} - 1\right)^{-1/\tau_t}, \tau_t \in (0, \infty) \tag{6}$$

for all $(u_1, u_2) \in [0,1]$, where τ_t is the dependence parameter that follows the process

$$\tau_t = \Lambda\left(\omega + \beta\,\tau_{t-1} + \alpha \bullet \left|\mathrm{u}_{1,t-i} - \mathrm{u}_{2,t-i}\right|\right), \tag{7}$$

where $\Lambda(z) = (1 + e^{-z})^{-1}$ guarantees that $\tau_t \in (0,1)$ for all t. The SJC proposed by Patton (2006) is specified as:

$$C^{SJC}(u_1, u_2|\tau_U, \tau_L) = 0.5\left[C^{JC}(u_1, u_2|\tau_U, \tau_L) + C^{JC}(1-u_1, 1-u_2|\tau_U, \tau_L) + u_1 + u_2 - 1\right] \tag{8}$$

where $C^{JC}(u_1, u_2|\ \tau_U, \tau_L) = 1 - \{1 - [(1-(1-u_1)^{\kappa})^{-\gamma} + (1-(1-u_2)^{\kappa})^{-\gamma} - 1]^{-1/\gamma}\}^{1/k}$ is the Joe-Clayton copula with $\kappa = 1/\log_2(2-\tau_U)$, $\gamma = -1/\log_2(\tau_L)$, $\tau_U \in (0,1)$, and $\tau_L \in (0,1)$. The parameters τ_U and τ_L assess the dependence at the upper and lower tails of the distribution, respectively. For $\tau_U = \tau_L$, the SJC dependence structure is symmetric; otherwise, it is asymmetric. Patton (2006) defined the evolution of dependence parameters of the SJC copula as:

$$\tau_{j,t} = \Lambda\left(\omega_j + \beta_j\,\tau_{j,t-1} + \alpha_j \bullet \frac{1}{10}\sum_{i=1}^{10}\left|u_{1,t-i} - u_{2,t-i}\right|\right) \tag{9}$$

with $j = \{U,L\}$, and $\Lambda(z) = (1 + e^{-z})^{-1}$ is the logistic function that guarantees that $\tau_{j,t} \in (0,1)$ for all t. We also apply a two-step procedure to estimate the Clayton and SJC copulas. In the first step, we also estimate the univariate GARCH marginal parameters $\widehat{\boldsymbol{\theta}}_1$ that maximize the log-likelihood of each j-th FI stock return of Eq. (4). Further, given $\widehat{\boldsymbol{\theta}}_1$ of Eq. (4), we estimate the time-varying dependence parameter $-\widehat{\theta}_2^*-$ that solves:

$$\widehat{\theta}_2^* = \underset{\theta_2^*}{\operatorname{argmax}}\sum_{t=1}^{T} \ln c\left(F_1\left(u_{1,t}\right), F_2\left(u_{2,t}\right), \ldots, F_n\left(u_{n,t}\right); \theta_2^*, \widehat{\boldsymbol{\theta}}_1\right). \tag{10}$$

4.3. Value-at-risk (VaR), CoVaR, and ΔCoVaR

To measure the downside risk and risk spillovers between an individual FI and the aggregate financial sector, following Adrian and Brunnermeier (2016), we estimate the VaR, CoVaR, and ΔCoVaR. The VaR measures the maximum loss of a FI, given a tail probability of α%. The VaR is a broadly used measure to evaluate the downside risk of an underlying asset. We estimate the downside VaRs of the Australian FIs. Let $\{X_{1,t}, X_{2,t}\} : t = 1, 2, \ldots, T$, be the continuously compounded stock returns of FIs 1 and 2, respectively, then the $VaR_{\alpha,t}^{1}$ for FI 1 is calculated as the α-th quantile of the distribution of returns:

$$Pr\left(X_{1,t} \le VaR_{\alpha,t}^{1}\right) = \alpha\% \tag{11}$$

The CoVaR is the VaR of an FI conditional on some event of another FI. The downside CoVaR of FI 1 conditional on the extreme downward movements of FI 2 is expressed as:

$$Pr\left(X_{1,t} \le CoVaR_{\alpha,\beta,t}^{1|2} | X_{2,t} \le VaR_{\beta,t}^{2}\right) = \alpha\% \tag{12}$$

where $\Pr(X_{2,t} \le VaR_{\beta,t}^{2}) = \beta$% for a β-th quantile of $X_{2,t}$.

We also estimate the Delta CoVaR (ΔCoVaR), the difference between the VaR for underlying FI stock returns conditional on the extreme movement of underlying the financial sector index return, and the VaR of the underlying FI stock returns conditional on the normal state (median values) of the respective financial sector index return. We can write the ΔCoVaR as follows:

$$\Delta CoVaR_{\alpha,\beta,t}^{1|2} = \left(CoVaR_{\alpha,\beta,t}^{1|2} - CoVaR_{\alpha,50,t}^{1|2}\right) \tag{13}$$

where $CoVaR_{\alpha,50,t}^{1|2}$ satisfies $\Pr(X_{1,t} \le CoVaR_{\alpha,50,t}^{1|2} | X_{2,t} \le VaR_{50,t}^{2}) = \alpha$%, for the 50%-th quantile (or median) of the distribution of $X_{2,t}$. Adrian and Brunnermeier (2016) estimate the $CoVaR_{\alpha,\beta,t}^{1|2}$ by the quantile regression approach, which does not provide time-varying estimates. Conversely, Girardi and Ergün (2013) employ a multivariate GARCH model to estimate $CoVaR_{\alpha,\beta,t}^{1|2}$ by considering dynamic correlation. Nevertheless, their method depends on the selected bivariate distribution of $X_{1,t}$ and $X_{2,t}$, which can generate misspecification errors in the estimation of $CoVaR_{\alpha,\beta,t}^{1|2}$. Following Mainik and Schaanning (2014) and Karimalis and Nomikos (2018), we use copulas to estimate $CoVaR_{\alpha,\beta,t}^{1|2}$. The copula approach provides time-varying estimates of $CoVaR_{\alpha,\beta,t}^{1|2}$, and it is robust to the specification of the bivariate copula so that it overcomes possible misspecification errors.

4.4. Systemic risk across different frequencies

Previous studies mostly concentrate on estimating systemic risk for a particular data frequency. Nevertheless, it is important to analyze the frequency dynamics of systemic risk. This analysis is economically meaningful because the entire financial system may respond to a shock to an individual FI at different frequencies with varying strengths (Baruník & Křehlík, 2018). Therefore, an approach measuring systemic risk on an aggregate level overlooks certain fundamental properties of systemic risk (rather than at different time frequencies). For this purpose, we employ a novel approach for measuring systemic risk across short-, medium-, and long-term frequencies separately.

The main economic argument behind the notion that systemic risk differs across frequencies is that investors operate in different investment horizons (represented by frequencies), indicating their preferences for a particular frequency. Investors with heterogeneous preferences for investment horizons may respond differently to an economic shock. Additionally, investors with diverse trading horizons may lead to stock market fluctuations and cycles of varying lengths (Teply & Kvapilikova, 2017). Therefore, a shock with a stronger long-term (short-term) effect is likely to have a higher power in low (high) frequency, indicating long-term (short-term) connectedness when it is transmitted to other variables. For instance, a permanent change in the investor's expectation about an individual FI's soundness may be better reflected by long-term connectedness and systemic risk than by short-term ones. In line with this theoretical claim, Baruník and Křehlík (2018) argue that investors' time-preference for consumption and their resulting consumption growth have different cyclical components, which generate shocks with heterogeneous frequency responses. This phenomenon creates short-, medium-, and long-term systemic risk.

We decompose the underlying return series into wavelet components to evaluate the VaR and ΔCoVaR across different investment horizons. The wavelet method is based on a Fourier representation of a series on its frequencies. Since the Fourier transform loses the time information, a Fourier representation can be implemented on a rolling window, a wavelet, to recover both time and scale information (Percival & Walden, 2000). We can write a wavelet transform $\psi_{\tau,s}(\cdot)$ with time translation τ and scale s as:

$$\psi_{\tau,s}(t) = s^{-1/2}\psi\left(\frac{t-\tau}{s}\right) \tag{14}$$

for $s, \tau \in \mathbb{R}$, $s \neq 0$, and a mother wavelet $\psi(\cdot)$ that fulfills $\int_{-\infty}^{\infty}\psi(t)dt = 0$ (zero mean) and $\int_{-\infty}^{\infty}|\psi(t)|^2dt = 1$ (unit variance). Since our return series are discrete, we employ a discrete wavelet transform on the data with length 2^J. Wavelets allow us to decompose a series into its composing multiresolution elements. Let $\phi(\cdot)$ be a father wavelet such that $\int_{-\infty}^{\infty}\phi(t)dt = 1$, which depicts the low-frequency component of a signal; let $\psi(\cdot)$ be a mother wavelet such that $\int_{-\infty}^{\infty}\psi(t)dt = 0$, which depicts the high-frequency component of a signal. We can also represent father and mother wavelets as follows:

$$\phi_{J,k}(t) = \left(2^J\right)^{-1/2}\phi\left(\frac{t-2^Jk}{2^J}\right) \tag{15}$$

$$\psi_{j,k}(t) = \left(2^j\right)^{-1/2}\psi\left(\frac{t-2^jk}{2^j}\right) \tag{16}$$

for $j, k \in \mathbb{Z}$. The returns X_t can be decomposed into a series of projections onto $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$ ordered by k translations and a scale j of the wavelet. Bruce and Gao (1996) demonstrate that the wavelet coefficients are approximated by $s_{J,k} \approx \int X_t\phi_{J,k}(t)dt$ and $d_{j,k} \approx \int X_t\psi_{j,k}(t)dt$, with $j = 1, \ldots, J$, where J is the highest feasible scale of X_t. Then, the returns X_t can be expressed as follows:

$$X_t = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t)$$

$$= S_J + D_J + D_{J-1} + \ldots + D_1$$

where $S_J = \sum_k s_{J,k}\phi_{J,k}(t)$ is the smooth signal, $D_j = \sum_k d_{j,k}\psi_{j,k}(t)$, for $j = 1, \ldots, J$, is the detailed signal, and $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ are orthogonal. The equations above assume a continuous signal, but we need to use a discrete wavelet transform (DWT) since our data are sampled at fixed points in time. Therefore, discrete wavelet filters have the same properties of continuous ones such as zero mean and unit variance.

The discrete wavelet transform (DWT) is a band-pass filter that recovers the frequencies around its main frequency, generating a scaling filter $\phi(\cdot)$. A maximum overlap discrete wavelet transform (MODWT) is an extension of the wavelet transform that is indifferent to the number of observations, and the estimator of the MODWT is asymptotically more efficient than that of the DWT (Percival & Walden, 2000). We describe the details of the MODWT in Appendix C to save space.

The choice of the wavelet filter class in the MODWT is important to determine the frequency variation between scales in the data since wavelet basis functions need to represent the data's stylized features. Gençay, Selçuk, and Whitcher (2001) suggest using a wavelet filter with a balanced length (such as length eight) that recovers financial returns' main characteristics. We employ the Daubechies (1992)'s least-asymmetric wavelet filter with length eight, LA(8), because it counterbalances length, symmetry, and smoothness (Gençay et al., 2001). Besides, the LA(8) wavelet filter of Daubechies (1992) was adopted in many empirical applications in finance and economics (Bekiros & Marcellino, 2013; Gençay, Selçuk, & Whitcher, 2005).

Following Bekiros and Marcellino (2013), we implement a periodic extension pattern of the MODWT to consider boundary estimation problems. We employ the MODWT wavelet approximation on the underlying returns to evaluate the VaR and ΔCoVaR for various investment horizons. More specifically, due to heterogeneous investor's behavior and time-horizon of investment, we transform the return series into the short-, medium-, and long-term horizons that correspond to variations over 2–4 days, 32–64 days, and 256–512 days, respectively. Then, we estimate the VaR and ΔCoVaR for each subsequent wavelet.

5. Data and descriptive statistics of FIs' stock returns

We consider twenty FIs operating in Australia: seven banks (four major banks and three regional banks), two insurance companies, and eleven other financial services providers.[3] Our sample spans from 14 November 1999 to 31 December 2019 (5510 daily observations for each FI). We chose this sample period because daily stock price data for the Australian FIs included in our sample are available for this period. Besides, this period enables us to explore time-varying systemic risk for relevant international events such as the GFC and the European debt crisis. Table A.1 in the Appendix presents the names of the FIs, their acronyms used in this paper, their DataStream industry classification, and their DataStream code.

We use daily data consistent with the systemic risk studies of Weiß et al. (2014), Acharya et al. (2016), and Laeven et al. (2016), among others. The daily stock return is calculated as the logarithmic difference of the subsequent stock price changes between time *t-1* and time *t*. We calculate a value-weighted index for each FI by considering the share price and the number of outstanding shares of the remaining FIs, following the standard index calculation methodology of FTSE Russell (see https://www.ftserussell.com/research-insights/education-center/calculating-index-values for a detailed discussion on the methodology of the calculation of the index).

We use a value-weighted index for each FI because major stock price indices are value-weighted such as the Standard and Poor's Composite Index, CRSP value-weighted indices, and Morgan Stanley Capital Index (Bartholdy & Peare, 2005; Chrétien & Coggins, 2010). Moreover, the underlying theory of Capital Asset Pricing Model (CAPM) specifies the use of a value-weighted index as a benchmark to derive the investors' expected rate of return (Bartholdy & Peare, 2005). In practice, investors track these indices to make their investment decisions. Balatti, Brooks, and Kappou (2017) claim that the highest proportion of the capital invested following passive investment approaches is tied to global value-weighted indices. Therefore, these indices should closely reflect the investors' perception of constituent companies' risk exposure.

The resulting indices represent the Australian financial system, allowing us to examine shock spillovers between a distressed FI and the overall financial system. This approach helps avoid spurious correlations between an individual FI and the financial system when the FI has a large share in the financial system's proxy. For example, the Commonwealth Bank of Australia (CBA) accounted for about 28% of the Australian financial sector's total market capitalization as of 31 December 2019 (using market capitalization data obtained from Thompson Reuters DataStream). Therefore, systemic risk estimates between CBA and a corresponding index that includes CBA may be biased due to the significant contribution of CBA to the index. We collect daily stock prices and market capitalization data from Thompson Reuters DataStream.

Table 2 reports descriptive statistics of stock returns of the FIs included in the sample. The major banks have higher mean annualized returns (except for the NAB) than that of the regional banks. CBA has the highest average return (6.3%) among the major banks, while BEN possesses the highest average return (3.3%) among the regional banks. CBA also has the lowest return volatility (0.209) and the highest Sharpe ratio (0.254) among all the banks. The insurance companies, SUN and QBE, display a mean return (standard deviation) of 2.7% (0.259) and 2.9% (0.333), respectively. Their Sharpe ratios are, however, lower than that of all banks (except for NAB).

As for other financial services providers, their average returns and volatility are higher than that of banks and insurance companies (except AMP, FRG, and PPT). The returns of banks and insurance companies are negatively skewed (except ANZ and BEN). On the other hand, the other financial services providers exhibit positively skewed returns (except AMP, CGF, CPU, and EZL).

All FIs have non-normal returns (at the 1% significance level) and statistics of kurtosis higher than 3, indicating that they are heavy-tailed distributed. Moreover, the returns of all FIs (except AMP and CPU) are autocorrelated and heteroskedastic at the 1% significance level.

6. Empirical results and discussion

In this section, we discuss the results of the estimation of marginal models and copula parameters. Next, we analyze the VaR and ΔCoVaR estimates of the FIs for the whole sample, different sub-periods, and different frequencies. Finally, we explore the cross-sectional determinants of systemic risk in the Australian financial sector.

6.1. Time-varying copula-GARCH model

We first estimate marginal models and then use the filtered generated returns to estimate the copula parameters. Searching for the optimal marginal distribution model, we initially estimate an ARMA(m, n) with GARCH(p,q), EGARCH(p,q), and GJR-GARCH(p,q) specifications. We find that the GJR-GARCH(1,1) model minimizes the AIC. This model also adequately captures the autocorrelation and conditional heteroscedasticity of the FIs' return series. We estimate the marginal model's parameters based on Student's t innovations, which is appropriate for return series that display heavy-tailed distributions. We also consider other alternatives to model the innovations ε_t such as non-Gaussian and skewed-t distributions. Nevertheless, the results of different distributional assumptions are somewhat similar, and the Student's t distribution assumption best captures the dynamics in the return series. For the sake of brevity, we omit the results for alternative distributions (but they are available upon request to the corresponding author).

[3] Although there are twenty five banks, four life-insurance companies, seven non-life insurance companies, and eighty nine financial services (sector) companies in the financial subsectors in DataStream, only twenty FIs that are included in our sample have daily stock price data for a long enough sample period to conduct this study.

Table 2
Descriptive statistics of stock returns.

	Mean	S.D.	S.R.	Max.	Min.	Skew.	Kurtosis	JB	$Q(8)$	$Q^2(8)$	ARCH(10)
Major banks											
ANZ	0.043	0.233	0.143	0.137	−0.116	0.007	10.75	**0.000**	**0.000**	**0.000**	**0.000**
CBA	0.063	0.209	0.254	0.118	−0.095	−0.064	8.80	**0.000**	0.067	**0.000**	**0.000**
NAB	0.005	0.236	−0.020	0.160	−0.145	−0.377	12.85	**0.000**	**0.000**	**0.000**	**0.000**
WBC	0.041	0.226	0.139	0.088	−0.118	−0.106	7.49	**0.000**	**0.002**	**0.000**	**0.000**
Regional banks											
ABA	0.027	0.235	0.072	0.239	−0.215	−0.279	31.07	**0.000**	**0.000**	**0.000**	**0.000**
BEN	0.033	0.264	0.086	0.255	−0.112	0.829	18.74	**0.000**	0.120	**0.000**	**0.000**
BOQ	0.011	0.255	0.003	0.120	−0.103	−0.137	7.15	**0.000**	0.176	**0.000**	**0.000**
Insurance companies											
SUN	0.027	0.259	0.066	0.114	−0.295	−1.315	28.38	**0.000**	**0.000**	**0.000**	**0.000**
QBE	0.029	0.333	0.058	0.419	−0.526	−3.781	154.13	**0.000**	**0.000**	**0.000**	**0.000**
Other financial service providers											
AMP	−0.090	0.301	−0.330	0.209	−0.444	−2.911	72.49	**0.000**	**0.004**	0.141	0.198
ASX	0.123	0.249	0.454	0.187	−0.141	0.737	17.34	**0.000**	0.113	**0.000**	**0.000**
CGF	0.090	0.410	0.195	0.199	−0.310	−0.286	16.75	**0.000**	**0.000**	**0.000**	**0.000**
CPU	0.103	0.336	0.276	0.223	−0.416	−1.152	37.30	**0.000**	0.396	**0.043**	0.064
EQT	0.076	0.292	0.226	0.182	−0.152	0.050	15.20	**0.000**	**0.000**	**0.000**	**0.000**
EZL	0.075	0.519	0.124	0.560	−0.665	−0.525	68.43	**0.000**	**0.002**	**0.000**	**0.000**
FGR	−0.190	1.065	−0.187	0.928	−0.763	0.585	26.11	**0.000**	**0.000**	**0.000**	**0.000**
MQG	0.106	0.323	0.298	0.321	−0.264	0.219	25.31	**0.000**	**0.000**	**0.000**	**0.000**
PAC	0.153	0.489	0.293	0.916	−0.452	6.343	203.17	**0.000**	0.072	**0.000**	**0.000**
PPT	0.047	0.308	0.118	0.199	−0.168	0.107	12.03	**0.000**	**0.005**	**0.000**	**0.000**
PMV	0.102	0.310	0.298	0.375	−0.223	1.194	40.40	**0.000**	**0.009**	**0.000**	**0.000**

Note: The table presents the descriptive statistics of daily stock returns of the Australian financial institutions. The sample period spans November 1999 to December 2019. S. D. is the standard deviation. S.R. is the Sharpe ratio. Skew. is the skewness. JB is the *p*-value of the Jarque-Bera (Jarque & Bera, 1980) test for normality. $Q(8)$ and $Q^2(8)$ are the *p*-values of the Ljung-Box test (Ljung & Box, 1978) for autocorrelation in returns and in standardized squared returns, respectively, with eight lags. ARCH(10) is the *p*-value of the conditional heteroscedasticity test of Engle (1982) with ten lags. Bold values of the test statistics denote the rejection of the null hypothesis at the 5% significance level, for each one of the tests. See Table A.1 in the Appendix for details of the financial institutions.

Table 3 reports the GJR-GARCH(1,1) estimation results for the Australian FIs. The estimated AR(1) coefficient is non-significant for all banks (except for BOQ), implying that past returns do not help predict subsequent returns. This result is, however, mixed for the insurance companies and other financial services providers. For example, the AR (1) coefficients are significantly positive for CGF, CPU, EZL, and PPT, indicating the presence of return momentum. On the other hand, the AR (1) coefficients are significantly negative for QBE, ASX, and FGR, implying return reversals.

The ARCH (α) and the lagged conditional variance (β) parameters of the conditional variance equation are significant at the 1% level for all returns. Thus, the conditional variance is significantly affected by past shocks, and it is persistent for all the return series. The estimated leverage parameter (ξ) is significant for many FIs at the 5% significance level (except ABA, BOQ, SUN, ASX, EQT, EZL, PAC, PPT, and PMV), suggesting an asymmetric effect of negative and positive shocks on the conditional variance. Moreover, the tail-dependence parameter (DoF) is significant at the 1% level for all returns, indicating that they display heavy-tailed distributions with potentially joint extreme movements. This result supports the application of the Student's *t*-distribution to estimate the marginal distribution model for the underlying return series. Finally, the diagnostic tests (Q(8), $Q^2(8)$, and ARCH(10)) fail to find autocorrelation and ARCH effects in the underlying return series at the 5% level. Overall, the results report evidence that a GJR-GARCH(1,1) with errors following the Student's *t*-distribution adequately fits the returns of the Australian FIs.

We estimate the dependence parameters between the returns of the Australian FIs and that of their corresponding indices by using the filtered returns generated from the estimated marginal models. We consider widely-used copulas: the Gaussian copula, Student's *t* copula, Clayton copula, and SJC copula. Different copula specifications capture diverse dependence structures. For instance, the Gaussian copula models the overall dependence by assuming a normal distribution of the returns, while the Student's *t* copula considers extreme joint movements. Similarly, the Clayton copula covers lower-tail dependence, and the SJC copula allows for both lower- and upper-tail dependence. We choose the copula that minimizes the AIC.

Table 4 displays the best-fitted copula (Panel A) parameters and the AICs of the Gaussian, Student's *t*, Clayton, and SJC copulas (Panel B). The time-varying-DCC Student's *t* copula is the best model for the pairwise dependence between the Australian FIs and their corresponding indices (except for EQT and EZL). We estimate the time-varying correlations ρ_t of the Student's *t* by the DCC method of Engle (2002) of Eq. (3), where a and b are the evolution parameters of the DCC matrix of the returns of Eq. (3). The estimated parameter ρ is the mean of ρ_t over the period; we run a regression of ρ_t on a constant so that the standard error of the estimated intercept is the estimated standard error of ρ, and we use this estimate to test the significance of ρ.

Panel A of Table 4 shows that the average connectedness parameters (ρ) between individual FIs and their corresponding indices are significant at the 1% significance level. The major banks' average connectedness parameters are higher than those of the regional banks, insurance companies, and other financial services providers. These findings highlight a potentially high systemic risk of the major banks compared with that of the other FIs. Besides, the tail-dependence parameter (DoF) is statistically significant at the 5% level for most of the FIs (except WBC, EZL, and FGR), indicating a potential joint extreme movement between these FIs and their corresponding indices. The estimated parameter of the lagged conditional variance (b) of Eq. (3) is also significant for most of the return series at the 1% level, implying persistency in conditional volatility of the FIs.

6.2. VaR and ΔCoVaR

In this subsection, we examine the VaR and ΔCoVaR estimates. We use the time-varying Student's *t* copula, the optimal copula model, to estimate the VaR and ΔCoVaR (at the 95%-confidence level) for each of the FIs. We estimate the daily VaRs and ΔCoVaRs separately in the whole sample, pre-crisis, crisis, and post-crisis periods using all observations of each period.

Table 3
GJR-GARCH(1,1) estimated parameters.

	AR(1)	MA(1)	β	α	ξ	DoF(ν)	$Q(8)$	$Q^2(8)$	ARCH(10)
Major banks									
ANZ	0.173	−0.128	0.882***	0.062***	0.069***	5.688***	6.14	3.03	3.27
CBA	−0.174	0.225	0.913***	0.055***	0.039***	7.085***	13.62	8.24	8.71
NAB	0.084	−0.036	0.874***	0.084***	0.055***	5.446***	9.71	4.02	4.21
WBC	−0.109	0.147	0.913***	0.045***	0.055***	8.112***	6.58	6.74	6.70
Regional banks									
ABA	0.045	−0.161	0.553***	0.484***	−0.073	2.370***	7.42	6.78	6.77
BEN	0.199	−0.259	0.904***	0.061***	0.030**	4.559***	4.94	3.16	3.18
BOQ[1]	0.699***	−0.722***	0.176***	0.124***	−0.010	4.971***	9.25	9.83	9.72
Insurance companies									
SUN	−0.572	0.580	0.891***	0.083***	0.019	5.522***	7.75	5.86	5.78
QBE	−0.603**	0.628***	0.822***	0.084***	0.061***	5.130***	10.11	3.36	3.33
Other financial service providers									
AMP	−0.424	0.413	0.870***	0.064***	0.062***	4.652***	7.95	0.54	0.55
ASX	−0.836***	0.852***	0.919***	0.068***	0.005	5.201***	5.30	2.15	4.18
CGF	0.747***	−0.773***	0.900***	0.064***	0.052***	5.257***	14.12	8.04	7.86
CPU	0.734***	−0.769***	0.946***	0.033***	0.023***	4.005***	7.63	0.70	0.69
EQT	0.101	−0.138	0.464***	0.590***	−0.110	2.132***	5.75	8.05	8.82
EZL	0.375***	−0.449***	0.615***	0.393***	−0.019	2.470***	1.75	0.28	0.29
FGR	−0.385***	0.385***	0.054***	1.000***	−0.111**	2.035***	13.09	1.63	1.63
MQG	−0.294	0.359**	0.908***	0.043***	0.073***	5.357***	7.69	4.97	4.93
PAC	0.144	−0.188	0.169***	0.952***	−0.243	2.301***	11.00	0.63	0.67
PPT	0.701***	−0.719***	0.891***	0.073***	0.028*	4.614***	9.44	0.86	3.89
PMV	−0.273	0.247	0.350***	0.536***	0.227	2.194***	5.90	3.82	0.88

Note: Both ARMA(1,1) and GJR-GARCH(1,1) models include constant terms in the conditional mean and variance equations, which are approximately zero for all return series. The GJR-GARCH(1,1) of Glosten et al. (1993) is specified as in Eq. (A.3) in the Appendix, where α and β are the ARCH and GARCH parameters, respectively, and ξ captures the leverage effect in the returns. DoF(ν) is the number of degrees of freedom in Eq. (A.2) in the Appendix. $Q(8)$ and $Q^2(8)$ are the Ljung-Box test statistics (Ljung & Box, 1978) of the autocorrelation in the residuals and in standardized squared residuals, respectively, with eight lags. ARCH(10) is the conditional heteroscedasticity residuals test statistic of Engle (1982) with ten lags. The notation ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. See Table A.1 in the Appendix for details of the financial institutions.

[1] The best model for the marginal distribution of the BOQ returns was a GARCH(2,1) model. The estimated coefficient of the second ARCH term is 0.691***.

Table 5 reports the VaR estimates for the Australian FIs. Columns (1), (2), (3), and (4) of Table 5 display the average values of the estimates for the whole sample, pre-crisis (November 18, 1998 to December 31, 2006), crisis (January 1, 2007 to March 31, 2009), and post-crisis (April 1, 2009 to December 31, 2019) periods, respectively. Columns (5)–(7) show the p-values of the test of difference of the average VaR estimates between the (i) pre-crisis and crisis period, (ii) crisis and post-crisis period, and (iii) pre-crisis and post-crisis period. The p-values are derived from the Student's t-test of difference assuming independent samples and unequal variances.

The mean VaRs of the major banks are lower (in absolute value) than that of the other FIs for the whole period. Thus, the major banks exhibit low downside risk compared with the other FIs. Overall, this difference may be attributed to the operational differences across the groups of FIs. For example, the regional banks mostly perform retail banking, and their operations are typically confined within Australia or a particular state. On the other hand, the major banks operate in both retail and wholesale markets. They offer diverse services (e.g., fiduciary services, investment banking, and risk management) along with conventional deposit-taking and lending services. Furthermore, the major banks have overseas operations with a dominant presence in New Zealand (Bollen et al., 2015). As for the other FIs, they focus on more specialized services such as superannuation and insurance (AMP), wealth management and estate planning (EQT), investment products, and managed funds (PPT). Therefore, the major banks' diversified operations may have contributed to their lower VaR levels than that of regional banks, insurance companies, and other financial services providers.

As for the sub-periods, Table 5 reports that the crisis-period mean VaRs of banks are significantly higher than their mean VaRs in the pre- and post-crisis periods. These findings are similar for all the FIs included in our sample at the 5% significance level. The greater uncertainty resulting from the collapse of big FIs (such as Lehman Brothers) and the distressed condition of other FIs (like Merrill Lynch, AIG, and Royal Bank of Scotland) may have helped increase the VaRs of all FIs during the GFC. Besides, the post-crisis mean VaRs of banks are also significantly higher than their pre-crisis mean VaRs (except ABA). This result, however, is mixed for the non-bank FIs.

Table 6 presents the average values of the ΔCoVaRs estimates for different periods. The mean ΔCoVaRs of the major banks are larger in absolute value than that of the other FIs, implying that the entire financial system is more sensitive to risk shocks in the large banks than in the other FIs. This finding is consistent with our prior expectation that large banks are systemically more important than regional banks and other FIs.

Table 6 further shows that the crisis-period mean ΔCoVaRs are significantly greater than the mean ΔCoVaRs in the pre- and post-crisis periods (consistent with Bollen et al., 2015). This result is intuitive. During the crisis period, borrowers typically find it increasingly difficult to repay their debt; policyholders struggle to pay their policy premiums; underwriters become reluctant to underwrite insurance policies. Hence, stock market investors may react negatively to a crisis, which may have increased connectivity across the Australian FIs during the crisis period. The ΔCoVaRs of all FIs dropped significantly after the crisis period (except for FGR), which may be due to the enactment of the Deposit and Wholesale Funding Guarantee (DWFG) scheme in Australia at the end of 2008. The introduction of the DWFG scheme guaranteed funding in case

Table 4
Copula estimates.

	Panel A: Student's *t* copula estimates				Panel B: AIC of different copulas			
	ρ	DoF(v)	a	b	Student-*t*	Gaussian	Clayton	SJC
Major banks								
ANZ	0.732***	6.638***	0.067***	0.913***	−5173	−4922	−3998	−4798
CBA	0.696***	4.852***	0.022	0.974***	−4761	−4300	−3619	−4460
NAB	0.715***	5.470***	0.041	0.948***	−5037	−4710	−3832	−4679
WBC	0.734***	6.501	0.010	0.990	−5183	−4889	−3918	−4878
Regional banks								
ABA	0.113***	21.700***	0.021	0.480***	−77	−68	−48	−71
BEN	0.504***	7.805***	0.026***	0.970***	−2204	−2096	−1748	−2093
BOQ	0.494***	8.931***	0.030***	0.962***	−2018	−1931	−1612	−1928
Insurance companies								
SUN	0.507***	6.945***	0.023***	0.969***	−2057	−1924	−1603	−1886
QBE	0.435***	7.496***	0.015**	0.980***	−1464	−1351	−1182	−1360
Other financial service providers								
AMP	0.502***	10.013***	0.032***	0.960***	−2143	−2068	−1463	−1984
ASX	0.486***	7.845***	0.020**	0.971***	−1779	−1677	−1385	−1686
CGF	0.393***	11.247***	0.011***	0.988***	−1181	−1137	−1004	−1121
CPU	0.367***	9.244***	0.009**	0.988***	−981	−912	−796	−911
EQT	0.072***	29.372**	0.010	0.871***	−32	−28	5	−21
EZL	0.101***	15.195	0.000	0.150	−68	−54	−69	−53
FGR	0.057***	37.650	0.006	0.002	−16	−14	3	−8
MQG	0.519***	5.620***	0.017**	0.979***	−2344	−2111	−1971	−2204
PAC	0.150***	13.653***	0.036**	0.000	−152	−129	5	−149
PPT	0.433***	9.329***	0.014***	0.983***	−1490	−1419	−1272	−1427
PMV	0.204***	11.648***	0.008	0.990***	−363	−328	−269	−295

Note: We specify an ARMA(1,1)-GJR-GARCH(1,1) model for the returns as in Eqs. (A.1)-(A.3) in the Appendix. We estimate the time-varying correlations ρ_t by the DCC method of Engle (2002) of Eq. (3), where a and b are the evolution parameters of the DCC matrix of the returns of Eq. (3). The estimated parameter ρ is the average of ρ_t over the period; we run a regression of ρ_t on a constant so that the standard error of the estimated intercept is the estimated standard error of ρ, and we use this estimate to test the significance of ρ. DoF(v) is the number of degrees of freedom of Eq. (A.2) in the Appendix. SJC is the Symmetric Joe-Clayton Copula proposed by Patton (2006). The Gaussian and Student's *t* copulas are described in Eqs. (B.1)-(B.2) in the Appendix; the Clayton and SJC copulas are described in Eqs. (6)–(9). The symbols ***, **, and * indicate statistical significance of the coefficient at the 1%, 5%, and 10% levels, respectively. See Table A.1 in the Appendix for details of the financial institutions.

of a bank's insolvency, which ultimately reduced a bank run's probability. The regulatory reforms and greater regulatory oversight[4] may explain the decline in insurance companies' and other financial services providers' systemic risk after the GFC.

Although the results above do not come as a surprise, we further find that the post-crisis mean ΔCoVaRs of banks and insurance companies are also significantly higher than corresponding pre-crisis mean ΔCoVaRs. Thus, risk spillover from individual banks and insurance companies to the entire financial system has increased from the pre-crisis to the post-crisis period. This result may imply a shift in investors' expectations about overall risk and a reduction in too-big-to-fail subsidies, particularly after the GFC.

The lower systemic risk contribution of insurance companies than that of banks is consistent with Drakos and Kouretas (2015) and Acharya et al. (2017). Besides, this result is in line with the theoretical model of Acharya et al. (2016). A distress condition in the financial sector may generate fire-sale externalities (asset liquidations due to runs on short-term liabilities) and going-concern externalities (disruptions of new intermediation activities due to solvency risk). While banks generate both externalities, non-banking FIs (like insurance companies) primarily contribute to systemic risk through the going-concern externality as they have less short-term debt and low withdrawal risk. Nevertheless, our finding of higher systemic risk contribution by banks is in contrast to Bernal et al. (2014) and Acharya et al. (2017).[5]

6.3. VaR and ΔCoVaR at different frequencies

This subsection analyzes the VaR and ΔCoVaR estimates at different frequencies and reports the results in Tables 7 and 8. We employ the MODWT wavelet approximation on the underlying returns to transform the return series into the short-, medium-, and long-term horizons that correspond to variations over 2–4 days, 32–64 days, and 256–512 days, respectively. Then, we estimate the VaR and ΔCoVaR for each subsequent wavelet. In each one of these tables, Columns (1)–(3) present the average values of the estimates for different frequencies, whereas Columns (4)–(6) display the *p*-values of the test of differences between the means.

Table 7 indicates that the short-term mean VaRs of all FIs are significantly higher than the medium-term VaRs and long-term mean VaRs at the 1% significance level. Besides, the medium-term mean VaRs of all FIs are greater than the long-term mean VaRs. These findings may be explained by the complications associated with hedging portfolio positions in the short-run (in a 2-4-day horizon), leading to substantial declines in the assets' value. Nevertheless, hedging portfolio positions of the banks is easier in the medium term (in a 32-64-day horizon) and in

[4] For instance, APRA updated capital standards and reporting requirements for general and life insurance companies in Australia effective from January 2013. Under this reform, the capital adequacy is determined after considering insurance risk, insurance concentration risk, asset risk, asset concentration risk, and operational risk. Further, the insurers are required to have their internal capital adequacy assessment program. APRA also introduced a set of reforms for superannuation funds in 2012 to improve integrity, community confidence, and operational efficiency of the sector (Lange et al., 2015).

[5] This discrepancy may arise because these studies include security and commodity brokers into the other financial providers, while we mostly consider providers of specialized financial services such as asset management and superannuation. These FIs contribute to systemic risk through borrowing activities, being a counterparty in a derivative transaction, or asset intermediation. They are, however, less likely to experience a bank-run scenario because they are not a part of a centralized payment and clearing system.

Table 5
VaR estimates.

	Whole sample	Pre-crisis	Crisis	Post-crisis	Test of difference (*p*-value)		
	(1)	(2)	(3)	(4)	(2)–(3)	(3)–(4)	(2)–(4)
Banks							
ANZ	−0.0219	−0.0196	−0.0352	−0.0208	0.000***	0.000***	0.000***
CBA	−0.0202	−0.0183	−0.0328	−0.0190	0.000***	0.000***	0.000***
NAB	−0.0219	−0.0196	−0.0364	−0.0205	0.000***	0.000***	0.000***
WBC	−0.0220	−0.0195	−0.0340	−0.0214	0.000***	0.000***	0.000***
ABA	−0.0219	−0.0217	−0.0244	−0.0214	0.000***	0.000***	0.194
BEN	−0.0252	−0.0226	−0.0417	−0.0237	0.000***	0.000***	0.000***
BOQ	−0.0238	−0.0205	−0.0366	−0.0236	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***	0.000***			
Insurance companies							
SUN	−0.0231	−0.0201	−0.0410	−0.0216	0.000***	0.000***	0.000***
QBE	−0.0267	−0.0270	−0.0320	−0.0255	0.000***	0.000***	0.004***
F-test	0.000***	0.000***	0.000***	0.000***			
Other financial service providers							
AMP	−0.0262	−0.0259	−0.0330	−0.0250	0.000***	0.000***	0.015**
ASX	−0.0224	−0.0242	−0.0364	−0.0182	0.000***	0.000***	0.000***
CGF	−0.0349	−0.0350	−0.0586	−0.0299	0.000***	0.000***	0.000***
CPU	−0.0299	−0.0356	−0.0363	−0.0242	0.155	0.000***	0.000***
EQT	−0.0282	−0.0272	−0.0348	−0.0275	0.000***	0.000***	0.317
EZL	−0.0409	−0.0453	−0.0537	−0.0348	0.000***	0.000***	0.000***
FGR	−0.4335	−0.2547	−0.4748	−0.5600	0.000***	0.020**	0.000***
MQG	−0.0281	−0.0238	−0.0550	−0.0256	0.000***	0.000***	0.000***
PAC	−0.0344	−0.0360	−0.0358	−0.0329	0.888	0.000***	0.001***
PPT	−0.0289	−0.0256	−0.0421	−0.0287	0.000***	0.000***	0.000***
PMV	−0.0287	−0.0294	−0.0296	−0.0281	0.727	0.008***	0.000***
F-test	0.000***	0.000***	0.000***	0.000***			

Note: We report the average values of the VaR estimates for the whole sample, pre-crisis (November 18, 1998 to December 31, 2006), crisis (January 1, 2007 to March 31, 2009), and post-crisis (April 1, 2009 to December 31, 2019) periods. We estimate the daily VaRs separately in the whole sample, pre-crisis, crisis, and post-crisis periods using all observations of each period. Columns (5)–(7) show the *p*-values of the test of difference of the average VaR estimates between the (i) pre-crisis and crisis period, (ii) crisis and post-crisis period, and (iii) pre-crisis and post-crisis period. The *p*-values are derived from the Student's *t*-test of difference assuming independent samples and unequal variance. The *F*-test is the *p*-value of the test of the null hypothesis of no difference between the mean VaRs of banks, insurance companies, and other financial service providers. The symbols ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. See Table A.1 in the Appendix for details of the financial institutions.

the long term (256–512 days), highlighting a relatively smaller VaR in the medium and long term.

The mean VaRs of the major banks are lower (in absolute value) than that of the other FIs for all frequencies, although these discrepancies decline from short-term to medium- and long-term VaRs. These findings corroborate those of Table 5 for different frequencies, indicating that the VaRs of the Australian FIs are persistent.

Table 8 demonstrates that the mean ΔCoVaRs of all FIs are the highest (in absolute value) in the short term, and they gradually decline in the medium and long term. These results imply that systemic risk spillover is weaker in the medium- and long-term frequencies. Higher systemic risk in the short-term indicates that investors in the Australian financial sector process information rapidly. Therefore, a shock to an FI has a stronger short-term impact on the financial system. Further, the mean ΔCoVaRs of the major banks are significantly higher than that of the other FIs, consistent with the findings presented in Table 6. Thus, the major banks are systemically more important than the other FIs, regardless of the data frequency.

Table 8 further illustrates that the relative systemic risk contribution of the FIs changes over time. The aggregate ΔCoVaR results presented in Table 6 indicate that CBA is the systemically most important bank in the whole sample, pre-crisis, and crisis periods, while WBC generates the greatest systemic risk in the post-crisis period. On the other hand, the disaggregated ΔCoVaR analysis in Table 8 reveals that WBC is the systemically most important bank in the short and long term, and CBA has the greatest systemic importance in the medium term. Since CBA and WBC are the two largest banks in Australia, we provide evidence that the largest banks generate the greatest systemic risk in the frequency-based analysis and in subsample periods.

As for non-banking FIs, MQG has the largest short- and medium-term mean ΔCoVaR. Nevertheless, its systemic importance declines in the long term when PPT becomes the systemically most important non-bank FI. Overall, these findings indicate that systemic risk across frequencies differs from the aggregate systemic risk pattern, indicating the relevance of the frequency-based analysis.

6.4. Systemic risk determinants

In this subsection, we explore the determinants of individual FI's systemic risk contribution. We use a semiannual (two-quarter) average of the ΔCoVaR as the dependent variable, and we consider several institution-specific and market-wide explanatory variables. We use the semiannual frequency of data because quarterly data for some explanatory variables are missing.

We use six variables reflecting the idiosyncratic characteristics of the FIs. The first one is the lagged VaR of the FI. The risk of an FI (VaR) contributes positively to forward systemic risk. The second one is the size of the FI estimated as the log of the book value of the total assets (in Australian dollars). There are two competing arguments regarding the relationship between size and systemic risk exposure. A large FI is more immune to macroeconomic and liquidity shocks for its diversified operations, implying a negative relationship between size and systemic risk (Boyd, De Nicoló, & Smith, 2004). On the other hand, large FIs typically receive too-big-to-fail subsidies under distress conditions (Sarin & Summers, 2016) that may stimulate them to take excessive risk, leading to a positive relationship between size and systemic risk.

The third variable considered is the leverage ratio (total assets to the book value of total equity). A large leverage ratio may indicate a high probability of default as leveraged FIs may need to reduce their leverage level by selling assets at fire-sale prices under financial distress (Acharya

Table 6
ΔCoVaR estimates.

	Whole sample	Pre-crisis	Crisis	Post-crisis	Test of difference (*p*-value)		
	(1)	(2)	(3)	(4)	(2)–(3)	(3)–(4)	(2)–(4)
Banks							
ANZ	−0.0135	−0.0121	−0.0218	−0.0129	0.000***	0.000***	0.000***
CBA	−0.0147	−0.0133	−0.0240	−0.0138	0.000***	0.000***	0.000***
NAB	−0.0134	−0.0120	−0.0222	−0.0126	0.000***	0.000***	0.000***
WBC	−0.0146	−0.0129	−0.0226	−0.0142	0.000***	0.000***	0.000***
ABA	−0.0046	−0.0046	−0.0052	−0.0045	0.000***	0.000***	0.194
BEN	−0.0104	−0.0094	−0.0173	−0.0098	0.000***	0.000***	0.000***
BOQ	−0.0105	−0.0091	−0.0162	−0.0104	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***	0.000***			
Insurance companies							
SUN	−0.0103	−0.0089	−0.0183	−0.0096	0.000***	0.000***	0.000***
QBE	−0.0084	−0.0084	−0.0100	−0.0080	0.000***	0.000***	0.004***
F-test	0.000***	0.000**	0.000***	0.000***			
Other financial service providers							
AMP	−0.0100	−0.0099	−0.0126	−0.0096	0.000***	0.000***	0.015**
ASX	−0.0082	−0.0089	−0.0134	−0.0066	0.000***	0.000***	0.000***
CGF	−0.0059	−0.0060	−0.0100	−0.0051	0.000***	0.000***	0.000***
CPU	−0.0059	−0.0070	−0.0072	−0.0047	0.155	0.000***	0.000***
EQT	−0.0035	−0.0033	−0.0043	−0.0034	0.000***	0.000***	0.317
EZL	−0.0023	−0.0026	−0.0031	−0.0020	0.000***	0.000***	0.000***
FGR	−0.0104	−0.0061	−0.0113	−0.0134	0.000***	0.020**	0.000***
MQG	−0.0098	−0.0083	−0.0193	−0.0089	0.000***	0.000***	0.000***
PAC	−0.0018	−0.0019	−0.0019	−0.0018	0.888	0.000***	0.001***
PPT	−0.0090	−0.0080	−0.0132	−0.0090	0.000***	0.000***	0.000***
PMV	−0.0040	−0.0041	−0.0042	−0.0039	0.727	0.008***	0.000***
F-test	0.000***	0.000***	0.000***	0.000***			

Note: We report the average values of the ΔCoVaR estimates for the whole sample, pre-crisis (November 18, 1998 to December 31, 2006), crisis (January 1, 2007 to March 31, 2009), and post-crisis (April 1, 2009 to December 31, 2019) periods. We estimate the daily ΔCoVaRs separately in the whole sample, pre-crisis, crisis, and post-crisis periods using all observations of each period. Columns (5)–(7) show the *p*-values of the test of difference of the average ΔCoVaR estimates between the (i) pre-crisis and crisis period, (ii) crisis and post-crisis period, and (iii) pre-crisis and post-crisis period. The *p*-values are derived from the Student's *t*-test of difference assuming independent samples and unequal variance. The *F*-test is the *p*-value of the test of the null hypothesis of no difference between the mean ΔCoVaRs of banks, insurance companies, and other financial service providers. The symbols ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. See Table A.1 in the Appendix for details of the financial institutions.

& Viswanathan, 2011; Shleifer & Vishny, 2010). Hence, an increase in short-term leverage positively contributes to systemic risk (Acharya & Thakor, 2016; Adrian & Brunnermeier, 2016; Huang & Ratnovski, 2011). On the other hand, a high level of leverage may reduce systemic risk as highly leveraged banks typically have a great-quality loan portfolio, and they are more liquid (Diamond & Rajan, 2001).

The fourth variable examined is the liquidity calculated as the ratio of cash and short-term investments to short-term liabilities. When depositors or holders of off-balance-sheet loans of an FI demand larger withdrawals than normal, an absence of sufficient cash-asset holdings to meet this demand leads to a liquidity crisis. In such circumstances, an FI may need to sell some of its less liquid assets at a fire-sale price that may turn a liquidity problem into a solvency one, which ultimately can result in a systemic default (Brunnermeier & Pedersen, 2008). Lehar (2005), Vallascas and Keasey (2012), López-Espinosa, Rubia, Valderrama, and Antón (2013), and Kleinow and Moreira (2016), among others, provide evidence of a negative relationship between liquidity and systemic risk contribution.

The fifth variable employed is profitability (net income to total assets). Profitability may exhibit a negative relationship with the systemic risk of an FI because profitability shields an FI from defaulting (Lehar, 2005; Varotto & Zhao, 2018). Nonetheless, suppose a large portion of the profitability of an FI comes from non-interest income. In that case, it may increase its probability of default and its systemic risk contribution since non-interest income is associated with high revenue volatility and tail risk (Acharya et al., 2012; Williams, 2016). A high profitability level may also be due to outstanding commitments in risky operations, which can abruptly increase the FI's systemic risk contribution (Brunnermeier et al., 2020; Kleinow & Moreira, 2016; Weiß et al., 2014). Finally, we apply the ratio of intangible assets to total assets, following Adrian and Brunnermeier (2016). Intangible assets may be negatively related to systemic risk contribution since they serve as a buffer against economic shocks. Nonetheless, a large level of intangible assets may stimulate FIs to take excessive risk, leading to a positive relationship between intangible assets and systemic risk.

We consider four market-wide determinants of systemic risk. The first one is the GDP growth rate. Economic activity and financial stability exhibit a positive relationship (Schleer & Semmler, 2015). Under an economic downturn, borrowers may fail to meet loan obligations that can lead to a systemic failure of the FIs (Hirtle, Kovner, Vickery, & Bhanot, 2016). Moreover, economic growth improves the quality of the loan portfolio of FIs, decreasing the ratio of non-performing loans to total loans, which leads to a lower level of systemic risk (Männasoo & Mayes, 2009; Uhde & Heimeshoff, 2009).

The second market-wide variable considered is the interest rate. We employ the change in the cash reserve rate of the Reserve Bank of Australia (RBA) in this regard. If the assets of FIs are very sensitive to changes in short-term interest rates, a monetary tightening can result in large losses to the FIs, which ultimately generates systemic risk (Ramos-Tallada, 2015).

The third market-wide variable is the change in the exchange rate between the Australian dollar (AUD) and the New Zealand dollar (NZD), given the significant exposure of the Australian FIs to the economy of New Zealand. A large number of foreign currency loans in the balance sheet of FIs can trigger simultaneous failures if borrowers find it difficult to service the loans under a depreciation of the domestic currency (Yeşin, 2013).

We also include the housing price growth (the growth rate in the Australia-DataStream real estate price index) as a market-wide variable. Since real estate mortgage loans dominate Australian banks' loan

Table 7
VaR estimates for different horizons.

	Short term	Medium term	Long term	Test of difference (p-value)		
	(1)	(2)	(3)	(1)–(2)	(2)–(3)	(1)–(3)
Banks						
ANZ	−0.0122	−0.0038	−0.0009	0.000***	0.000***	0.000***
CBA	−0.0112	−0.0033	−0.0010	0.000***	0.000***	0.000***
NAB	−0.0124	−0.0037	−0.0009	0.000***	0.000***	0.000***
WBC	−0.0131	−0.0037	−0.0010	0.000***	0.000***	0.000***
ABA	−0.0134	−0.0030	−0.0009	0.000***	0.000***	0.000***
BEN	−0.0158	−0.0044	−0.0014	0.000***	0.000***	0.000***
BOQ	−0.0160	−0.0043	−0.0013	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***			
Insurance companies						
SUN	−0.0135	−0.0037	−0.0010	0.000***	0.000***	0.000***
QBE	−0.0165	−0.0047	−0.0018	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***			
Other financial service providers						
AMP	−0.0167	−0.0048	−0.0014	0.000***	0.000***	0.000***
ASX	−0.0138	−0.0041	−0.0016	0.000***	0.000***	0.000***
CGF	−0.0210	−0.0062	−0.0023	0.000***	0.000***	0.000***
CPU	−0.0208	−0.0057	−0.0018	0.000***	0.000***	0.000***
EQT	−0.0156	−0.0047	−0.0019	0.000***	0.000***	0.000***
EZL	−0.0248	−0.0065	−0.0031	0.000***	0.000***	0.000***
FGR	−0.0547	−0.0147	−0.0046	0.000***	0.000***	0.000***
MQG	−0.0173	−0.0045	−0.0017	0.000***	0.000***	0.000***
PAC	−0.0202	−0.0069	−0.0032	0.000***	0.000***	0.000***
PPT	−0.0175	−0.0050	−0.0018	0.000***	0.000***	0.000***
PMV	−0.0158	−0.0046	−0.0020	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***			

Note: We report the average values of the VaR estimates across different frequencies. We employ the MODWT wavelet approximation on the underlying returns to transform the return series into the short-, medium-, and long-term horizons that correspond to variations over 2–4 days, 32–64 days, and 256–512 days, respectively. Then, we estimate the VaRs for each subsequent wavelet. Columns (4)–(6) show the p-values of the test of difference of the average VaR estimates across different frequencies. The p-values are derived from the Student's t-test of difference assuming independent samples and unequal variance. The F-test is the p-value of the test of the null hypothesis of no difference between the mean VaRs of banks, insurance companies, and other financial service providers. The symbols ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. See Table A.1 in the Appendix for details of the financial institutions.

portfolios, a downturn in the real estate market may cause a deleveraging pressure that can result in higher systemic risk (Downing, Stanton, & Wallace, 2005; Liu, Ren, & Liu, 2019). Conversely, increases in housing prices lead to disproportionate lending, resulting in a higher level of risky assets by the FIs (Gimeno & Martínez-Carrascal, 2010; von Peter, 2009). Therefore, an increase in housing prices may positively contribute to systemic risk too.

We also use two lagged state variables that determine the time-varying conditional mean and variance of stock returns, as in Adrian and Brunnermeier (2016). Since the FIs can be exposed to these state variables differently, we do not establish any prior relationship between them and the systemic risk measures. These control variables are: (i) the change in the equity volatility, calculated as the monthly standard deviation of the daily S&P/ASX 200 Australian index returns; and (ii) the variation in the term spread, calculated as the difference between the Australian 10-year government bond yield and the Australian 3-month bank bill rate. Adrian and Brunnermeier (2016) have used two additional controls, the variation in the three-month Treasury bill rate and the credit spread change. We, however, overlook the variation in the three-month Treasury bill rate to avoid perfect multicollinearity with the other state variables; we also omit the credit spread change because the Australian corporate bond yield data are not available for the whole sample period used in this paper. We collect the S&P/ASX 200 Australian index values from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/); we gather the Australian 10-year government bond yield and the Australian 3-month bank bill rates from the Reserve Bank of Australia (https://www.rba.gov.au/statistics/).

To explore the contribution of institution-specific and market-wide variables to systemic risk, we estimate the following panel regression model:

$$\overline{\Delta \mathrm{CoVaR}}_{i,t} = \alpha + \boldsymbol{\beta}' \boldsymbol{F}_{i,t-1} + \boldsymbol{\gamma}' \boldsymbol{M}_{t-1} + \epsilon_{i,t} \tag{17}$$

where $\overline{\Delta \mathrm{CoVaR}}_{i,t}$ is the semiannual average of the daily ΔCoVaR for the FI i at time t, $\boldsymbol{F}_{i,t-1}$ is a vector of idiosyncratic lagged characteristics of financial institutions, $\boldsymbol{M}_{t-1}$ is a vector of lagged market-wide and state variables, and $\epsilon_{i,t}$ is a panel-regression error term. We obtain data on institution-specific variables from FactSet and Worldscope, and we gather data on market-wide variables from Refinitiv DataStream. Our data consist of an unbalanced panel of 42 semiannual periods, from the first semester of 1999 to the last semester of 2019.

Tables 9 and 10 report the panel regression estimates of Eq. (17) for banks and non-bank FIs, respectively, with standard errors accounting for within-panel serial correlation and cross-sectional heteroscedasticity in parentheses. Column 1 displays the results of the model in which the $\overline{\Delta \mathrm{CoVaR}}_{i,t}$ is the dependent variable, whereas columns 2–4 shows the results of the model in which the decomposed $\overline{\Delta \mathrm{CoVaR}}_{i,t}$ is the dependent variable.

We first focus on Column 1 of Tables 9 and 10. As expected, the lagged VaR of an FI positively contributes to the systemic risk at the 1% level for all types of FIs. Size does not significantly impact the forward systemic risk of banks. However, it contributes to the systemic risk of insurance companies and other FIs, although its coefficient is only significant at the 10% level. These findings for the non-bank FIs are in line with the notion that large FIs tend to receive too-big-to-fail subsidies in a distress condition, which increases their systemic risk contribution to the financial system (Black et al., 2016; Brunnermeier et al., 2020; Karimalis & Nomikos, 2018; Laeven et al., 2016; López-Espinosa et al., 2015; Sarin & Summers, 2016; Varotto & Zhao, 2018).

We further observe a significant positive relationship between banks' systemic risk contributions and their leverage position. However, we find no effect of leverage on the systemic risk of non-bank FIs. This result for banks is in line with our prior expectation that high leverage is a manifestation of a high probability of default that leads to a higher level

Table 8
ΔCoVaR estimates for different horizons.

	Short term	Medium term	Long term	Test of difference (*p*-value)		
	(1)	(2)	(3)	(1)–(2)	(2)–(3)	(1)–(3)
Banks						
ANZ	−0.0073	−0.0024	−0.0007	0.000***	0.000***	0.000***
CBA	−0.0071	−0.0025	−0.0006	0.000***	0.000***	0.000***
NAB	−0.0071	−0.0022	−0.0007	0.000***	0.000***	0.000***
WBC	−0.0077	−0.0024	−0.0009	0.000***	0.000***	0.000***
ABA	−0.0017	−0.0010	−0.0005	0.000***	0.000***	0.000***
BEN	−0.0060	−0.0016	−0.0004	0.000***	0.000***	0.000***
BOQ	−0.0063	−0.0018	−0.0005	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***			
Insurance companies						
SUN	−0.0054	−0.0014	−0.0004	0.000***	0.000***	0.000***
QBE	−0.0040	−0.0010	−0.0003	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***			
Other financial service providers						
AMP	−0.0057	−0.0010	−0.0003	0.000***	0.000***	0.000***
ASX	−0.0053	−0.0014	−0.0004	0.000***	0.000***	0.000***
CGF	−0.0035	−0.0007	−0.0006	0.000***	0.000***	0.000***
CPU	−0.0040	−0.0013	−0.0003	0.000***	0.000***	0.000***
EQT	−0.0010	−0.0005	−0.0006	0.000***	0.000***	0.000***
EZL	−0.0009	−0.0001	−0.0004	0.000***	0.000***	0.000***
FGR	−0.0001	−0.0005	−0.0002	0.000***	0.000***	0.000***
MQG	−0.0062	−0.0018	−0.0005	0.000***	0.000***	0.000***
PAC	−0.0003	−0.0003	−0.0003	0.000***	0.000***	0.000***
PPT	−0.0051	−0.0017	−0.0009	0.000***	0.000***	0.000***
PMV	−0.0017	−0.0012	−0.0006	0.000***	0.000***	0.000***
F-test	0.000***	0.000***	0.000***			

Note: We report the average values of the ΔCoVaR estimates across different frequencies. We employ the MODWT wavelet approximation on the underlying returns to transform the return series into the short-, medium-, and long-term horizons that correspond to variations over 2–4 days, 32–64 days, and 256–512 days, respectively. Then, we estimate the ΔCoVaRs for each subsequent wavelet. Columns (4)–(6) show the *p*-values of the test of difference of the average ΔCoVaR estimates across different frequencies. The *p*-values are derived from the Student's *t*-test of difference assuming independent samples and unequal variance. The *F*-test is the *p*-value of the test of the null hypothesis of no difference between the mean ΔCoVaRs of banks, insurance companies, and other financial service providers. The symbols ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. See Table A.1 in the Appendix for details of the financial institutions.

of systemic risk. Beltratti and Stulz (2012), López-Espinosa et al. (2015), Karimalis and Nomikos (2018), and Brunnermeier et al. (2020), among others, report a positive impact of leverage on systemic risk.

Tables 9 and 10 show that the systemic risk contribution positively responds to liquidity for all types of FIs. This result is economically meaningful. In the case of insufficient liquidity, FIs may need to engage in the fire sale of less liquid assets that can turn a liquidity crisis into a solvency problem, increasing systemic risk associated with the FIs. In line with our result, Yun and Moon (2014) and Karimalis and Nomikos (2018) also report liquidity as a significant determinant of systemic risk. Our results, however, are at odds with Varotto and Zhao (2018), who demonstrate that the systemic risk of banks is invariant to their liquidity.

Table 9 displays a positive relationship between systemic risk and profitability of banks, consistent with the idea that higher profitability is associated with high revenue volatility and tail risk since non-interest income contributes to a large portion of the operating income of major Australian banks (Acharya et al., 2012; Williams, 2016). Besides, a positive relationship between profitability and systemic risk may arise due to outstanding commitments in risky operations, which may increase the systemic risk contribution of a bank (Brunnermeier et al., 2020; Kleinow & Moreira, 2016; Weiß et al., 2014). Nevertheless, Table 10 exhibits a negative contribution of profitability to the systemic risk of insurance companies and other FIs, in accordance with the notion that profitability shields non-bank FIs from defaulting (Lehar, 2005; Varotto & Zhao, 2018).

Tables 9 and 10 also display a positive relationship between intangible assets and systemic risk of banks but no effect of intangible assets on the systemic risk of non-bank FIs. Therefore, banks with higher intangible assets are more prone to failure under financial distress.

As for the market-wide variables, Tables 9 and 10 report that the cash rate change contributes to the systemic risk of banks and non-bank FIs. Conversely, systemic risk is invariant to economic growth and housing price growth. The economic intuition behind the positive response of systemic risk to the cash rate change is that a high cash rate indicates a restrictive monetary policy. Under such circumstances, the lending decisions of the FIs are scarce and expensive, increasing the overall interest rate and the probability of loan default, which in turn leads to a higher level of systemic risk (Lange et al., 2015).

We further observe that the AUD/NZD exchange rate change reduces the systemic risk of banks. This result, however, does not hold for non-bank financial institutions. The negative effect of the exchange rate change on banks' systemic risk may arise because a large number of foreign currency loans in their balance sheet can trigger simultaneous failures of banks. This phenomenon can occur if borrowers find it difficult to service loans in case of a depreciation of the domestic currency (Yeşin, 2013). Australian non-bank FIs have a small presence in foreign markets compared with the banks, which may explain the insignificant relationship between the AUD/NZD exchange rate change and non-bank FIs' systemic risk exposure.

As we move to columns 2 to 4 of Table 9, we find that our key results remain mostly unchanged for the short- and medium-term ΔCoVaR. The VaR, leverage, profitability, intangible assets, cash rate change, and AUD/NZD exchange rate change are significant for both short-term and medium-term systemic risk of banks. Liquidity becomes insignificant for the short-term ΔCoVaR, but it turns significant for the medium-term systemic risk of banks.

As for insurance companies and other FIs (Table 10), most of our results change for the short- and medium-term ΔCoVaR. The lagged VaR, liquidity, profitability, and economic growth are significant for the short-term and medium-term systemic risk of non-bank FIs. While the size is insignificant for the short-, medium-, and long-term ΔCoVaR, the cash rate change is insignificant for the medium- and long-term ΔCoVaR

Table 9
Determinants of systemic risk: Banks.

Dependent variable	$\Delta CoVaR_{it}$	Short-term $\Delta CoVaR_{it}$	Medium-term $\Delta CoVaR_{it}$	Long-term $\Delta CoVaR_{it}$
$VaR_{i,t-1}$	0.362***	0.368***	1.050***	2.897*
	(0.136)	(0.080)	(0.368)	(1.723)
$Size_{i,t-1}$	−0.151	0.094	0.099	−0.065***
	(0.249)	(0.146)	(0.195)	(0.015)
$Leverage_{i,t-1}$	0.767***	0.401***	0.582***	0.005**
	(0.202)	(0.117)	(0.066)	(0.002)
$Liquidity_{i,t-1}$	29.573*	15.732	18.629*	0.140
	(17.416)	(9.906)	(10.896)	(0.112)
$Profitability_{i,t-1}$	441.555***	219.461***	194.240*	−1.541
	(114.644)	(81.755)	(114.165)	(3.097)
Intangible $assets_{i,t-1}$	264.874**	122.629*	180.264***	2.661
	(121.927)	(73.155)	(63.435)	(2.103)
GDP $growth_{t-1}$	−29.450	−7.605	−14.648	−1.006***
	(26.815)	(14.455)	(17.314)	(0.384)
Cash rate $change_{t-1}$	272.242***	193.573***	100.996***	−1.559**
	(52.941)	(24.621)	(26.824)	(0.698)
Exchange rate $change_{t-1}$	−9.887***	−4.404*	−6.141*	−0.100*
	(3.767)	(2.513)	(3.442)	(0.054)
Housing price $growth_{t-1}$	1.468	0.127	−2.759***	0.110***
	(2.047)	(0.718)	(0.999)	(0.034)
Equity vol. $change_{t-1}$	156.585***	89.662***	252.721***	−2.498***
	(28.795)	(13.914)	(56.492)	(0.833)
Term spread $change_{t-1}$	7.343***	5.201***	5.424***	−0.102***
	(0.959)	(0.736)	(0.953)	(0.032)
Constant	−16.913**	−10.419**	−13.679***	−1.390
	(7.913)	(5.194)	(5.264)	(1.370)
Adjusted R^2	0.520	0.503	0.383	0.769

Note: This table shows the panel regression results of $\Delta CoVaR_{it}$ for banks on lagged bank characteristics and market-wide variables. Robust standard errors are in parentheses, accounting for within-panel serial correlation and cross-sectional heteroscedasticity. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Determinants of systemic risk: Insurance companies and other FIs.

Dependent variable	$\Delta CoVaR_{it}$	Short-term $\Delta CoVaR_{it}$	Medium-term $\Delta CoVaR_{it}$	Long-term $\Delta CoVaR_{it}$
$VaR_{i,t-1}$	0.190***	0.149**	0.983**	−4.069
	(0.053)	(0.063)	(0.481)	(2.927)
$Size_{i,t-1}$	0.367*	0.166	0.175	−0.005
	(0.205)	(0.184)	(0.182)	(0.015)
$Leverage_{i,t-1}$	0.014	0.006	0.009	−0.000
	(0.019)	(0.016)	(0.017)	(0.001)
$Liquidity_{i,t-1}$	5.775***	3.132***	3.254***	0.070
	(1.132)	(1.005)	(0.978)	(0.184)
$Profitability_{i,t-1}$	−2.430***	1.423**	1.505**	0.127**
	(0.845)	(0.619)	(0.610)	(0.050)
Intangible $assets_{i,t-1}$	−0.760	0.186	0.318	0.059
	(1.912)	(1.865)	(1.808)	(0.160)
GDP $growth_{t-1}$	7.070	1.203	−4.014	−0.558
	(14.277)	(12.096)	(12.152)	(0.887)
Cash rate $change_{t-1}$	81.694***	47.632*	4.688	−1.283
	(31.278)	(25.845)	(16.087)	(1.185)
Exchange rate $change_{t-1}$	−5.857	−0.369	−1.714	0.060
	(6.399)	(1.968)	(2.236)	(0.116)
Housing price $growth_{t-1}$	−1.656	−0.574	−1.912**	0.041
	(1.373)	(1.060)	(0.972)	(0.074)
Equity vol. $change_{t-1}$	84.272	69.403***	147.966***	−1.177
	(77.602)	(22.574)	(44.257)	(1.035)
Term spread $change_{t-1}$	2.341	2.312***	2.874***	−0.022
	(1.649)	(0.754)	(0.878)	(0.040)
Constant	−1.415	−0.806	−2.336	3.794
	(1.921)	(1.639)	(2.273)	(2.398)
Adjusted R^2	0.356	0.222	0.188	0.169

Note: This table shows the panel regression results of $\Delta CoVaR_{it}$ for non-bank institutions on lagged institution characteristics and market-wide variables. Robust standard errors are in parentheses, accounting for within-panel serial correlation and cross-sectional heteroscedasticity. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

of non-bank FIs. Further, the systemic risk contribution of profitability becomes positive for the short-, medium, and long-term ΔCoVaR of non-bank FIs, in accordance with Weiß et al. (2014), Kleinow and Moreira (2016), and Brunnermeier et al. (2020).

In addition, the housing price growth comes to be significantly negative for the medium-term ΔCoVaR of both banks and non-bank FIs. This finding may be explained by a deleveraging pressure on Australian FIs' loan portfolios caused by a downturn in housing prices, leading to higher systemic risk in the medium term (Downing et al., 2005; Liu et al., 2019).

Column 4 of Table 9 illustrates that VaR, size, and leverage are the most important idiosyncratic variables for explaining banks' long-term systemic risk. However, the estimated coefficient of the size is negative for long-term systemic risk at the 1% level. These findings support the hypothesis that larger and more profitable banks contribute less to systemic risk due to greater capital reserves (Boyd et al., 2004). As for the market-wide variables, both economic growth and the AUD/NZD exchange rate change negatively contribute to banks' systemic risk in the long term. The negative relationship between economic growth and systemic risk of banks arises as economic growth is typically followed by an improvement of the loan portfolio and by a reduction of non-performing loans, decreasing systemic risk (Festić, Kavkler, & Repina, 2011; Hirtle et al., 2016; Louzis, Vouldis, & Metaxas, 2012; Männasoo & Mayes, 2009; Uhde & Heimeshoff, 2009).

In addition, housing price growth positively contributes to banks' long-term systemic risk, which may be explained by the effect of increase in lending due to higher housing prices (Gimeno & Martínez-Carrascal, 2010; von Peter, 2009). Nevertheless, the cash rate change reduces the long-term systemic risk of banks. This result may arise as an increase in cash rate is an indication of a contractionary monetary policy that reduces overall bank credit to business and household sector, decreasing banks' long-term systemic risk exposure. Finally, Column 4 of Table 10 highlights that profitability is the only important variable for explaining the long-term systemic risk contribution of insurance companies and other FIs.

Overall, our results report that systemic risk across frequencies depends on different sets of idiosyncratic and market-wide variables. These findings are consistent with the conjecture that asymmetric systemic risk across frequencies arises as investors operate in different investment horizons. Therefore, economic shocks exert different impacts on the cyclical nature of the financial system.

7. Conclusion and policy implications

This paper examines the Australian financial sector's systemic risk using the delta conditional value-at-risk (ΔCoVaR) approach. The Australian financial sector is highly concentrated and interconnected with a small number of large FIs. The lending portfolio of Australian banks is dominated by residential mortgage loans (D'Hulster, 2017), while insurance companies' revenue generation relies heavily on non-policyholder sources. Besides, Australian FIs predominantly depend on offshore sources of wholesale funding. These characteristics contribute to a unique pattern of systemic risk of Australian FIs.

Although the systemic risk literature has evolved after the GFC, we extend the literature to several fronts. First, we measure systemic risk (by using a flexible copula-based ΔCoVaR method) across different frequencies, whereas the literature mostly focuses on estimating systemic risk in a particular data frequency. This analysis identifies the short-, medium-, and long-term systemic risk, and it links economic properties of the market to the systemic risk in a particular data frequency. Further, we explore the systemic risk profiles of three types of FIs, in contrast to previous studies that mostly examine banks' systemic risk contribution. Finally, we explain the determinants of cross-sectional and time-series variation in systemic risk using institutional characteristics and market-wide variables.

We show that the major Australian banks are systemically more important than the regional banks and other FIs. The non-bank FIs, however, exhibit a higher downside risk (VaR) than that of the banks. The systemic risk of all FIs is significantly higher in the crisis period than in the pre- and post-crisis periods. Further, the VaRs and systemic risk of all FIs dropped significantly after the crisis period, potentially due to the introduction of the DWFG and strong regulatory oversights. Nevertheless, the level of systemic risk in the post-crisis period is higher than that of the pre-crisis period. Besides, our frequency-based analysis reveals that the systemic risk of all FIs is the highest in the short term, and it gradually weakens in the medium and long term.

We also find that institution-specific characteristics such as VaR, size, leverage, liquidity, profitability, and intangible assets explain banks' systemic risk contribution. In contrast, VaR, size, liquidity, and profitability determine the systemic risk contribution of non-bank FIs. Besides, housing price growth and cash rate change affect the systemic risk contribution of both types of FIs, whereas the AUD/NZD exchange rate change and economic growth determine the systemic risk of banks. Finally, systemic risk across frequencies depends on different sets of explanatory variables.

Our findings have important policy implications. The observed disproportionate contribution of major banks to systemic risk suggests that the Australian regulatory authority should increase capital charges for the major banks. Given a statistically significant positive relationship between size and systemic risk of insurance companies and other FIs, the government may consider imposing limits on expanding size. Moreover, the disentangled (short-, medium-, and long-term) systemic risk's positive relationship with the financial institutions' profitability may signal regulators to impose limits on loan portfolio concentration in the high-risk sector for banks. The regulatory authorities may also need to consider the imposition of similar limits on non-traditional activities by banks and insurance companies. Despite the introduction of the DWFG, the increase in the systemic risk after the GFC calls for an adjustment of too-big-to-fail subsidies by the Australian government. Furthermore, the frequency-based analysis indicates that the nature of a shock, diverse responses of investors operating in different investment horizons, and the market's economic properties generate different systemic risk levels across frequencies. Future research is warranted along this line.

Author statement

Md Lutfur Rahman: Conceptualization, Data curation, Resources, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. Victor Troster: Methodology, Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Software, Validation, Investigation. Gazi Salah Uddin: Conceptualization, Supervision, Project administration, Writing - original draft. Muhammad Yahya: Methodology, Software, Formal analysis, Writing - original draft.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2021.101992.

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