Systemic risk and its determinants: Fresh evidence from the Australian banking sector

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Abstract

This study analyzes systemic risk in the Australian banking sector by applying a delta conditional value-at-risk approach (ΔCoVaR). While the literature mostly applies quantile regression framework to measure ΔCoVaR, we rely on a novel copula-based methodology. Additionally, we examine time-frequency dynamics of ΔCoVaR to explore if systemic connectedness between an individual bank and the entire financial system is asymmetric across frequencies. We also explore the determinants of Australian banks' systemic risk contribution in a panel setting. We find several interesting results. First, despite the introduction of deposit insurance scheme and more stringent capital requirements, systemic risk after the global financial crisis in 2008 is typically higher than in the pre-crisis period. Second, short-term ΔCoVaR is significantly higher than the medium- and long-term ΔCoVaR, particularly during the financial crisis and for major banks. Finally, we find that idiosyncratic bank characteristics and market-wide variables significantly describe the cross-sectional and time-series variation in systemic risk, and their explanatory power varies across frequencies.

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1. Introduction

The risk assessment of banking sector has historically been carried out based on balance sheet components of individual banks, overlooking their heterogeneity and their importance to the overall financial system. That is, the traditional risk management approach has focused on individual bank's exposure irrespective of the linkages between the banks themselves. However, in case a bank fails to pay out its liabilities, losses can be spilled over to other banks due to their interbank exposures to the defaulting bank. Consequently, simultaneous losses of several banks may negatively affect the economy as a whole. This potential spillover from a distressed individual bank to the whole banking system (the so-called systemic risk) has been a concern in the recent years. The global financial crisis (GFC) has established that shocks pertaining to liquidity, insolvency, and losses of an individual bank can quickly proliferate to other banks. Accordingly, regulators have taken several *ad-hoc* steps to control systemic risk.[1] Therefore, from a regulatory and academic standpoint, it is important to estimate the systemic risk contribution of an individual bank to identify its systemic importance. Findings from such analysis can help regulators impose regulatory impediments to safeguard the overall financial system.

This paper examines systemic risk in the Australian banking sector, and it explains the degree of systemic risk contribution in terms of idiosyncratic bank characteristics and market-wide variables. The choice of Australian banking sector is motivated by several reasons. First, as opposed to the majority of leading banks in developed countries, Australian banks had a relative good performance in the GFC, which is attributed to Australian Prudential Regulatory Authority's (APRA) proactive measures such as mandatory stress test on housing portfolio in 2003 and 2004

[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 et al., 2010), a capital surcharge (Basel Committee on Banking Supervision, 2013), a Pigouvian tax (Acharya et al., 2013, 2017), and more stringent regulation (Dewatripont et al., 2010) in different countries and different contexts.

and raising capital requirements on housing loans in 2004 (Reserve Bank of Australia, 2009). Nevertheless, the performance of the aggregate banking system and financial soundness of individual banks may not necessarily reveal the systemic risk profile of the banks (Pais and Stork, 2011). Thus, it is interesting to assess the systemic risk of the well-performed Australian banks. Second, unlike the banking sectors in the US and many European economies, the Australian banking sector is highly concentrated and interconnected by a small number of large banks. The largest four banks hold about 80% of the total banking assets (that are identified later in this Section). Third, while special housing finance institutions typically perform real estate mortgage lending in most of the developed economies (Berglund and Mäkinen, 2019), Australian banks' lending portfolio is dominated by residential mortgage loan (D'Hulster, 2017). Additionally, in Australia, total household debt is about twice of the total disposable income, which is relatively higher than that of many industrialized nations. Fourth, the Australian banks are heavily reliant on off-shore sources for wholesale funding. The second, third, and fourth reasons contribute to the vulnerability of the systemic risk (Brunnermeier, 2009).

Given the significant evidence of collapse of the whole financial system in response to a collapse of several financial institutions (for example, Lehman Brothers) during the GFC, academic researchers examine extreme value dependence between a distressed financial institution and the overall financial system. To this vain, several systemic risk measures have been used, such as the distressed insurance premium (Huang et al., 2012), the systemicness (Greenwood et al., 2015), the conditional value-at-risk (CoVaR) (Adrian and Brunnermeier, 2016), the systemic risk index (Brownlees and Engle, 2016), and the systemic expected shortfall (Acharya et al., 2017),.

Our study builds on the most extensively used measure of systemic risk, the ΔCoVaR (Adrian and Brunnermeier, 2016). The CoVaR measures the value-at-risk (VaR) of the overall financial system, conditional on a VaR of an individual institution. The ΔCoVaR, a measure of risk contribution of a bank to the overall financial system, is the difference between the value of the CoVaR conditional on an individual bank in distress and the value of the CoVaR conditional on a bank being in a median state. The CoVaR is a complete measure of risk (Adrian and Brunnermeier, 2016), and it does not depend on ex ante modelling of conditional distributions of returns.

This paper adds to the literature both methodologically and contextually. While the original CoVaR methodology of Adrian and Brunnermeier (2016) is based on semiparametric quantile regression framework, this paper provides a methodological contribution by using a novel copula-based CoVaR method. In general, copula approach is advantageous as it enables estimation of the entire joint distribution even in the presence of fat tails and heteroskedasticity (Adrian and Brunnermeier, 2016). In particular, we use a broad range of copula families that models different forms of dependence or extreme co-movements between an individual financial institution and the corresponding financial system as a whole. Additionally, our modelling approach allows us to segregate the dependence structure (that is associated with systemic risk) from marginal distributions (which is associated with tail risk). This provides estimation flexibility and contributes to mitigate misspecification bias associated with measuring systemic risk.

The second contribution of this paper is to examine systemic risk in different frequencies. While the previous studies mostly concentrate on estimating systemic risk for a particular data frequency, we argue that it is important to analyze the frequency dynamics of systemic risk. The main economic argument behind the expectation that systemic risk may vary across different frequencies is based on the notion that investors operate in different investment horizons (represented by frequencies), and it is essentially a manifestation of their preferences for a particular frequency. Investors with heterogenous preferences for investment horizons may respond differently to a market/economic shock. This phenomenon may create asymmetric systemic risk in the short, medium, and long run. We empirically verify this conjecture in this paper.

The third contribution is to explain systemic risk with respect to idiosyncratic bank characteristics and market-wide variables. Although Avkiran (2018) and Australian Prudential Regulation Authority (2013) analyze Australian banks' systemic risk based on criteria set by Basel Committee for Banking Supervision (such as size, non-substitutability, and complexity), none of the previous studies relate bank-specific characteristics to their systemic risk contribution in the Australian context. The extant literature on this issue focusing banking sectors of other countries is also inclusive. For instance, although Brunnermeier et al. (2012), Beltratti and Stulz (2012), López-Espinosa et al. (2015), and Karimalis and Nomikos (2018) show that bank size and leverage positively contribute to systemic risk, Weiß et al. (2014) demonstrate that bank characteristics such as size, leverage, and non-interest income are not persistent determinants of systemic risk; yet, characteristics of regulatory regime are the leading drivers of systemic risk. Therefore, we shed new light in this regard. In particular, we derive a semiannual measure of ΔCoVaR and regress it on bank characteristics (size, leverage, liquidity, profitability, capital adequacy, and funding structure) and on market-wide variables (Gross Domestic Product (GDP) growth, cash rate, exchange rate change, and housing price growth) in a panel setting.

The final contribution of this paper is the choice of Australian banking sector. While a large literature focuses on systemic risk of the US and European banks (see e.g., López-Espinosa et al., 2015; Black et al., 2016; Acharya et al., 2017; Karimalis and Nomikos, 2018), the Australian banking sector is less explored. Additionally, only a few studies examine systemic risk contribution of four large Australian banks (Avkiran, 2018). Therefore, systemic risk characteristics of other banks remain mostly unknown, despite their increasing presence in the national market. We contribute by examining systemic risk of four major banks (Australia and New Zealand Banking Group, Commonwealth Bank of Australia, National Australia Bank, and Westpac Banking Corporation), as well as three large regional banks (Auswide Bank Limited, Bendigo and Adelaide Bank, and Bank of Queensland), thereby providing a comprehensive picture of the systemic risk in the Australian banking sector.

We report several key findings in this paper. First, despite increasing presence of the regional banks in the Australian economy, we find that the major Australian banks are still systemically more important than the regional banks. Regional banks, however, exhibit high downside risk (value-at-risk) potentially due to their concentrated nature of business. Second, systemic risk in the crisis period is significantly higher than in the pre-crisis period that may be attributed to investors' underestimation of bank risk and capital mismeasurement in the pre-crisis period, which was later adjusted in the crisis period. Although the Australian government introduced deposit insurance in early 2008 and significantly increased regulatory capital requirement, systemic risk in the post-crisis period is typically higher compared to that in the pre-crisis period. This result implies a shift in the investors' expectation about overall bank risk and reduction in too-big-to-fail subsidy particularly after the GFC. Third, systemic risk in the Australian banking system differs across frequencies. Although short-term systemic risk is generally higher than that in medium and long term, this result is prevailing 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, and it mostly affects short-term cyclical behavior of the financial system. Finally, we find that idiosyncratic bank characteristics such as size, leverage, liquidity, and capital adequacy and market-wide variables like GDP growth and cash rate significantly explain the Australian banks' systemic risk contribution. Nonetheless, systemic risk across frequencies is attributed to a different set of explanatory variables.

The rest of the paper advances as follows. Section 2 presents a related literature review. Section 3 highlights key characteristics of the Australian banking sector related to its vulnerability to systemic risk. Section 4 outlines the methodology used in the paper, and Section 5 describes the data. Section 6 presents the empirical results and policy implications. Finally, Section 7 concludes the paper.

2. Literature review

The literature pertaining to systemic risk in banking sector predominantly focuses on three aspects. First, the channels to which risk spillover takes place from an individual bank to other banks and to the financial system as a whole. For instance, banks' exposure to interbank market and to Euromarket is considered to be one channel (Allen and Gale, 2000). Since banks use both markets to manage their liquidity risk, any bank's failure can negatively affect other banks. Furfine (2003) and Upper and Worms (2004) empirically examine this issue. Risk spillover in banking sector can also be attributed to asymmetric information and economic agents' failure to identify good and bad banks (Pais and Stork, 2011). Then, a shock in a bank helps predict shocks in other banks, inducing risk contagion (since information asymmetry in banking sector is higher than other sectors because (i) banks are specialized in financing illiquid (non-marketable) assets that are associated with information frictions, and (ii) the quality of banks' loan portfolio is not directly observable). Furthermore, banks offer relatively homogenous products; they are collectively sensitive to same type of risk, and they are subject to the same macroeconomic drivers. Therefore, a positive return correlation between banks' loan portfolio induces contagion. Hasman and Samartín (2008) and De Vries (2005) support this conjecture.

The second aspect covered in the relevant literature is approaches that measure systemic risk together with their application to banking sectors across the globe. For instance, Lehar (2005) and Gray et al. (2019) measure systemic risk based on contingent claims of financial institution assets. These papers find that correlation across banks has increased over time. Additionally, banks that are large, more profitable, and complying regulatory capital requirements exhibit less systemic risk. Huang et al. (2009) propose an economic framework that measures systemic risk by the price of insurance against financial distress. Insurance premium is calculated based on *ex ante* individual banks' default probabilities and predicted correlations between asset returns. Billio et al. (2012) measure an individual institution's connectedness with overall financial system, using unconditional correlation from Granger-causality network and principal component analysis. The authors find that among different financial institutions (e.g., hedge funds, banks, and insurance companies), banks play the most important role in propagating shocks. Brownlees and Engle (2016) estimate systemic risk based on individual financial institution's size, leverage, and marginal expected capital shortfall. The authors provide evidence that more volatile and less diversified banks are greater contributors to systemic risk.

Acharya et al. (2012) and Acharya et al. (2017) developed the expected capital shortfall (ECS) and the systemic expected shortfall (SES), respectively, to measure systemic risk. ECS depicts a financial institution's capital requirement in a potential distressed event, and SES illustrates a tendency of a financial institution to be undercapitalized when the entire system is undercapitalized. The authors show an increase in systemic risk for the US banks during the GFC. To measure extreme-tail dependence of return distributions of a financial institution and the whole financial system, Adrian and Brunnermeier (2016) proposed 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 median state. By applying the ΔCoVaR, the authors find that banks' leverage, size, and maturity mismatch help predict future systemic risk of US banks.

The third relevant strand of the literature focuses on idiosyncratic bank characteristics (e.g., bank's size, leverage, loan portfolio, and profitability) as determinants of a financial institution's contribution to systemic risk. As for size, a large bank can increase its profits and diversify its portfolio more efficiently, reducing systemic risk since a more profitable and diversified bank is less sensitive to macroeconomic and liquidity shocks (Boyd et al., 2004). Yet, in line with the "too-big-to-fail" conjecture, large banks may take excessive risk that can increase systemic risk. Regarding the leverage of a bank, a high leverage can reduce default risk by improving liquidity and loan quality (Diamond and Rajan, 2001). However, an increase in short-term leverage can enlarge systemic risk. As for the loan portfolio, a large loan portfolio contributes to the vulnerability of a bank by increasing creditor's default rates. Conversely, a small loan portfolio can be highly exposed to credit spread fluctuations. As regards profitability, a high operating profit margin can reduce systemic risk since it shields banks from defaulting. Nevertheless, a high operating profit margin can also be an indication of banks' high engagement in risky non-lending activities (e.g., investment banking and securities trading), which can increase the probability of default and systemic risk (Weiß et al., 2014). Certain studies in the literature also consider VaR, market-to-book value, beta, and equity return volatility as bank-specific determinants of systemic risk (e.g., Adrian and Brunnermeier, 2016; Teply and Kvapilikova, 2017).

Certain empirical studies explore the validity of the theoretical arguments presented above, and they come up with diverse results. In general, bank size and leverage have a significant positive effect on banks' contribution to systemic risk (Brunnermeier et al., 2012; Beltratti and Stulz, 2012; López-Espinosa et al., 2015; Laeven et al., 2016; Karimalis and Nomikos, 2018; Varotto and Zhao, 2018). Black et al. (2016) show that banks with more liquid assets and traditional lending portfolios do not contribute to systemic risk. The authors, however, find that banks with lending portfolios predominantly financed by non-deposit instruments and banks with higher Basel capital ratio contribute to systemic risk. Nevertheless, Laeven et al. (2016) provide evidence that systemic risk is negatively related to banks' capital. The authors further report that the profitability of a bank does not significantly affect systemic risk. In addition, 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 et al. (2014) contend that the characteristics of regulatory regime rather than the bank characteristics (such as size, leverage, and quality of bank credit portfolio) are the main drivers of systemic risk.

Although a large strand of the literature focuses on systemic risk in the US (Giesecke and Kim, 2011; Girardi and Ergün, 2013; Drakos and Kouretas, 2015; López-Espinosa et al., 2015; Adrian and Brunnermeier, 2016; Acharya et al., 2017) and in the European banking sector (Bernal et al., 2014; Drakos and Kouretas, 2015; Black et al., 2016; Karimalis and Nomikos, 2018), only a handful of studies examine systemic risk in the Australian banking sector. For example, Pais and Stork (2011) report that Australian bank stocks exhibit a high risk of extreme spillovers and interdependencies, and 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 in global systemically important banks in the US, Europe, and Japan. Similarly, Avkiran (2018) shows that the major Australian banks are net liquidity buyers that account for about 80% of the domestic systemic risk in banking sector. Anufriev and Panchenko (2015) and Dungey et al. (2017) provide evidence of a strong link among the major four Australian banks and their connection with the real economy. Bollen et al. (2015) report that systemic risk of the Australia's major banks increased initially in response to the GFC and to subsequent stock market downturn, but it decreased with the introduction of the Deposit and Wholesale Funding Guarantee scheme in October 2008. Apart from the above-mentioned papers, Australian Prudential Regulation Authority (2013), Reserve Bank of Australia (2014), and IMF (2019) identify the four major Australian banks as systemically important ones. They conclude that although Australian banks' capital levels have been enhanced and funding risk has been decreased, these banks are vulnerable to common shocks, particularly with respect to homogenous business models followed by the major banks, to their reliance on offshore sources for wholesale funding, and to exposure to real estate sector.

We find several gaps by reviewing the literature. First, empirical evidence on systemic risk in the Australian banking sector is mostly based on analyses of financial statement information (Avkiran, 2018), on network approach (Anufriev and Panchenko, 2015; Dungey et al., 2017), and on augmented market model (Bollen et al., 2015). None of these approaches explore tail dependence or extreme comovements, which have become relevant after the GFC. Besides, the existing literature predominantly focuses on four major Australian banks. Thus, systemic risk characteristics of other banks, which have an increasing presence in the national market, remain largely unexplored. Further, none of these studies relate the degree of systemic risk to idiosyncratic characteristics of Australian banks. Therefore, this study aims at fulfilling these gaps in the literature.

3. The Australian banking sector

The Australian banking sector (ABS) is the greatest contributor to the financial system of Australia, with several key characteristics. First, the ABS is dominated by a small number of large banks. Although the four major banks constitute just 2.7% of the authorized deposit-taking institutions (ADIs), they hold about three-fourth of the total assets held by ADIs. This statistic highlights the systemic importance of these banks and their potential contribution to the vulnerability of the aggregate financial system. In addition, total assets held by the banks is about two-and-half times the value of the Australian nominal GDP. This fact shows the potential of sovereigns' large contingent liability, and it raises a concern about the Australian government's ability to bailout the banks in a crisis with possible losses to be borne by creditors, depositors, and tax payers (Demirgüç-Kunt and Huizinga, 2013).

Besides, residential mortgage loan constitutes about half of the lending of the Australian commercial banks. This rate is higher compared with that of comparable banks in the US, Canada, and European Union countries (D'Hulster, 2017). Additionally, mortgage loans include a high proportion (about 30%) of potentially high-risk interest-only mortgages, and mortgage loan customers appear to be increasingly levered. Furthermore, total household debt is about 200% of the disposable income in Australia, which is relatively higher compared with other developed economies. These facts also underscore the potential vulnerability of the Australian banking sector. Although household debt is backed by significant physical real estate and pension funds, a decline in real estate price can have a negative impact on the aggregate banking industry due to illiquidity associated with the real estate market. Finally, although wholesale funding has recently declined in Australia, it still remains about 36% of the total (non-equity) liabilities. The banks are highly reliant on off-shore sources (about two-third) for the wholesale funding due to competitive pricing offered by them, making the Australian banks sensitive to vulnerabilities in the global financial system.

Table 1 reports certain financial soundness indicators of the ABS in 2007 and in 2018 that illustrate the changes in financial soundness since the advent of the GFC. We focus on capital adequacy, liquidity, asset quality, and profitability. We measure capital adequacy using total capital adequacy ratio (CAR) and Tier 1 risk-based capital ratio (RCR1). CAR is the ratio of total capital available to risk-weighted credit exposures of banks, and RCR1 is the proportion of Tier 1 capital (equity capital and disclosed reserves) to total risk-weighted assets. Against the threshold of 8% and 4.5% for CAR and RCR1, respectively, Table 1 shows that Australian banks' capital cushion has remained strong, and it has particularly strengthened since 2007 to deal with the financial crisis. For instance, for all the four major banks, CAR (RCR1) was between 9% to 10% (6% to 7%) in 2007, which improved between 14% to 15% (12% to 13%) in 2018. Nonetheless, in general, the regional banks' capital adequacy is relatively lower compared with that of the major banks, since all banks are required to maintain an additional capital conservation buffer of 2.5%, while this requirement is 3.5% for the major banks.

We assess liquidity through loan to deposit ratio (LDR) and savings deposit to total deposit ratio (SDTDR). An LDR greater than 100% for the Australian banks (except for BAB in 2007) indicates that, in addition to their own deposits, they rely on borrowed fund to make loans. LDR has declined substantially from 2007 to 2018 (apart from BAB), indicating that banks' liquidity to face unforeseen funding requirements or financial crisis has improved. This is also consistent with their safely measure taken against the financial crisis. As for ABL, its LDR was substantially higher than that of other banks in 2007, implying ABL's lower ability to cover loan losses and a high probability of default. Nevertheless, this situation improved remarkably in 2018. Since SDTDR reveals the reliance of banks on deposit funding, a significant increase in this ratio for most of the banks from 2007 to 2018 underscores that Australian banks are increasingly relying on savings deposits and their reliance on wholesale funding is gradually declining. This implies a decrease in the exposure of banks to external liquidity crunches. In 2018, ANZ had the lowest LDR and highest SDTDR among the four major banks, showing the bank's financial soundness compared with its competitors.

We evaluate the asset quality of the banks using loan loss provision to total loan (LLP) and the ratio of non-performing loan to total loan (NPL). These ratios are lower than 1% for all the four major banks, indicating that banks' expectation of potential loan losses and actual non-payment of loan on a specific period is extremely low compared with the total lending made by the banks. Although the NPL ratio slightly increased in 2018 compared with that in 2007, this ratio is still less than 0.50% for these four banks, implying their efficiency in judging borrowers' creditworthiness and collection of loan on a timely manner. Overall, the NPL ratio for the regional banks is relatively higher compared with that of the major banks. Finally, the banks' profitability (return on equity [ROE]) declined substantially from 2007 to 2018, which may be attributed to an increase in the capital of the banks and to a decrease in the exposure of banks to non-lending activities. In 2018, ROE ranged between 11% to 14% for the four major banks, which is still higher compared with some of the Australian banks' international counterparts in Canada, Sweden, Switzerland, and the UK (Royal Commission, 2018). This finding suggests that Australian banks have been profitable historically. Nonetheless, profitability of the regional banks is relatively lower in comparison with that of the major banks.

[INSERT TABLE 1 HERE]

4. Methodology

This section describes the underlying framework used to investigate the systemic risk in the Australian banking sector. To do so, we first evaluate the dynamic dependence structure between an individual bank and the aggregate banking index by using different time-varying copulas. Further, we employ CoVaR and ΔCoVaR to quantify the risk spillover effects in the Australian banking industry. Finally, we implement wavelet-based CoVaR and ΔCoVaR measures to examine the variations in spillover effects across different frequencies (short, medium, and long run).

4.1. Marginal distribution model

The estimation of marginal distribution model is fundamental for estimating copulas. We select the best-fitted model among various GARCH-type specifications (ARMA(m,n)-GARCH(p,q), ARMA(m,n)-GJR-GARCH(p,q), and ARMA(m,n)-EGARCH(p,q)). We select the model that minimizes the Akaike criterion (AIC). In addition, the EGARCH captures the asymmetric effects of negative and positive shocks on conditional volatility of the returns (Nelson, 1991). We can specify a marginal distribution model for the bank stock return series X_t as:

$$X_t = \mu + \sum_{i=1}^{m} \phi_i X_{t-i} + \varepsilon_t + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j}, \tag{1}$$

where μ is a vector of constants, and ϕ_i and θ_j are the AR and the MA components with m and n lags, respectively. We assume that the white noise process ε_t has a *t*-Student distribution with v degrees of freedom given as:

$$\sqrt{\frac{v}{\sigma_t^2(v-2)}}\,\varepsilon_t \overset{\text{i.i.d.}}{\sim} t_v, \tag{2}$$

and the EGARCH(p,q) model with conditional variance, σ_t^2, is represented by the following equation:

$$\log \sigma_t^2 = \kappa + \sum_{i=1}^{p} \beta_i \log \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \left(\left|\bar{\omega}_{t-j}\right| - E\left|\bar{\omega}_{t-j}\right|\right) + \sum_{j=1}^{q} \xi_j\left(\bar{\omega}_{t-j}\right), \tag{3}$$

where $\bar{\omega}_{t-j} = \varepsilon_{t-j}\sigma_{t-j}^{-1}$, α_j and β_i are ARCH and GARCH parameters, respectively, κ is the intercept of the conditional variance equation, and ξ_j captures the leverage effect in the underlying series. For $\xi_j < 0$, a negative has a greater impact on the future values of conditional variance than a positive shock of equal absolute magnitude. Therefore, an ARMA(m,n)-EGARCH(p,q) model is appropriate as investors tend to react differently to the positive and negative shocks in stock returns, since the ARMA(m,n)-EGARCH(p,q) framework captures these asymmetric dynamics in the return series.

4.2. Time-varying copula

To assess the time-varying dependence between individual Australian banks and the aggregate banking sector, we employ different time-varying copula models (Gaussian, *t*-Student, Clayton, and SJC copula). They are flexible and effective in capturing and modelling dependence (Bekiros et al., 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 easier.

Let X_t and Y_t be the stock returns of an individual Australia bank and the aggregate banking sector, respectively, with marginal distribution functions $F_X(x)$ and $F_Y(y)$, respectively, and a corresponding joint distribution function $F_{XY}(x,y)$. Then, based on Sklar (1959)'s Theorem, we may estimate $F_{XY}(x,y)$ as a function of $F_X(x)$, $F_Y(y)$, and a copula function as follows:

$$F_{XY}(x,y) = C\big(F_X(x), F_Y(y)\big), \tag{4}$$

where $C(\cdot,\cdot)$ is uniquely determined for $F_X(x)$ and $F_Y(y)$ 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, with $u_1 = F_X(x)$ and $u_2 = F_Y(y)$ are random variables following a uniform distribution on $(0,1)^2$. Then, we can estimate the joint density, $f_{XY}(x,y)$, as the product between copula density, $c(u_1,u_2)$, and the univariate marginal distributions of an individual bank and the aggregate banking sector, $f_X(x)$ and $f_Y(y)$, given as:

$$f_{XY}(x,y) = c(u_1,u_2) f_X(x) f_Y(y), \tag{5}$$

where $c(u_1,u_2) = \frac{\partial^2 C(u_1,u_2)}{\partial u_1 \partial u_2}$ is the dependence structure of the return series. A copula may be defined as a multivariate function with empirical uniform distribution functions, representing the dependence structure among two or more continuous random variables. For *n* bank stock return series, the generalized form of a Gaussian copula is given by:

$$\begin{aligned} C(u_1, \dots, u_n) &= \phi_\rho\big(\phi^{-1}(u_1), \dots, \phi^{-1}(u_n)\big) \\ &= \int_{-\infty}^{\phi^{-1}(u_1)} \dots \int_{-\infty}^{\phi^{-1}(u_n)} \frac{1}{2(\pi)^{n/2} |\rho|^{1/2}} \exp\left(-\frac{1}{2}\, z^T \rho^{-1} z\right) dz_1, \dots, dz_n, \end{aligned} \tag{6}$$

where ϕ_ρ is the multivariate Gaussian distribution function, ρ is the correlation matrix, u_i is the marginal distribution function of stock bank return i, and ϕ^{-1} is the inverse of univariate Gaussian distribution. We also employ the *t*-Student copula as follows:

$$C(u_1, \dots, u_n) = t_{\rho,v}\left(t_v^{-1}(u_1), \dots, t_v^{-1}(u_n)\right)$$
$$= \int_{-\infty}^{t^{-1}(u_1)} \dots \int_{-\infty}^{t^{-1}(u_n)} \frac{1}{\Gamma\left(\frac{v}{2}\right)(v\pi)^{n/2}|\rho|^{1/2}} \left(1 + \frac{1}{v} z^T \rho^{-1} z\right)^{-\frac{v+n}{2}} dz_1, \dots, dz_n, \tag{7}$$

where $t_{\rho,v}$ is the multivariate *t*-Student distribution, ρ is the correlation matrix, and v is the degrees of freedom parameter. the *t*-Student copula captures the variations in the tails of the distribution, and it accounts for possibly joint extreme movements that characterize the financial return series. The *t*-Student distribution converges to a Gaussian distribution as $v \to \infty$.

Following Patton (2006), we implement the Clayton copula, formulated as follows:

$$C_t^C(u_1, u_2;\ \tau_t) = \left(u_1^{-\tau_t} + u_2^{-\tau_t} - 1\right)^{-\frac{1}{\tau_t}},\ \ \tau_t \in (0, \infty), \tag{8}$$

where τ_t follows the process

$$\tau_t = \Lambda\left(\omega + \beta\, \tau_{t-1} + \alpha \cdot \frac{1}{10} \sum_{i=1}^{10} \left|u_{1,t-i} - u_{2,t-i}\right|\right), \tag{9}$$

where $\Lambda(z) = (1 + e^{-z})^{-1}$ is the logistic function that guarantees that $\tau_t \in (0,1)$ for all *t*. To consider asymmetric tail dependence between the underlying return series, we apply the Symmetrized Joe-Clayton (SJC) (Patton, 2006), which is specified as:

$$C^{SJC}(u_1, u_2|\tau_U, \tau_L) = 0.5[C^{JC}(u_1, u_2|\tau_U, \tau_L) + C^{JC}(1-u_1, 1-u_2|\tau_U, \tau_L) + u_1 + u_2 - 1], \qquad (10)$$

where $C^{JC}(u_1, u_2|\tau_U, \tau_L) = 1 - \left\{1 - [\{1-(1-u_1)^{\kappa}\}^{-\gamma} + \{1-(1-u_2)^{\kappa}\}^{-\gamma} - 1]^{-\frac{1}{\gamma}}\right\}^{\frac{1}{\kappa}}$ 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:

$$\tau_{j,t} = \Lambda\left(\omega_j + \beta_j\, \tau_{j,t-1} + \alpha_j \cdot \frac{1}{10}\sum_{i=1}^{10}\left|u_{1,t-i} - u_{2,t-i}\right|\right), \qquad (11)$$

with $j = \{U, L\}$, and $\Lambda(\mathrm{z}) = (1+e^{-z})^{-1}$ is the logistic function that guarantees that $\tau_{j,t} \in (0,1)$ for all t.

We estimate time-varying linear correlations ρ by applying the dynamic conditional correlation (DCC) method proposed by Engle (2002) as follows:

$$R_t \equiv \mathrm{diag}\left(\tilde{Q}_t\right)^{-1} H_t\, \mathrm{diag}\left(\tilde{Q}_t\right)^{-1} = E_{t-1}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'),$$
$$Q_t = \bar{R}(1-\alpha-\beta) + \alpha \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}' + \beta Q_{t-1}, \qquad (12)$$

where $H_t = E_{t-1}(\boldsymbol{u}_t \boldsymbol{u}_t')$ with $\boldsymbol{u}_t = \left(u_{1,t}, u_{2,t}\right)'$ is the matrix of conditional covariance of the stock returns, $\bar{R}$ is the matrix of unconditional correlation of $\boldsymbol{\varepsilon}_t$, and α and β satisfy the restrictions $\alpha, \beta \in (0,1)$ with $\alpha + \beta < 1$. Following Joe (1997), we apply the two-step maximum likelihood procedure to estimate the marginal models and the copula density. First, we estimate the GARCH marginal parameters $\widehat{\boldsymbol{\theta}}_1$ by fitting univariate marginal distributions that solve:

$$\widehat{\boldsymbol{\theta}}_1 = \underset{\boldsymbol{\theta}_1}{\operatorname{argmax}} \sum_{t=1}^{T} \sum_{j=1}^{n} \ln f_j\left(u_{j,t};\ \boldsymbol{\theta}_1\right), \tag{13}$$

where $\ln f_j\left(u_{j,t};\ \boldsymbol{\theta}_1\right)$ is the log-likelihood of the *j*-th bank 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. (13), we compute the DCC copula parameters, $\widehat{\boldsymbol{\theta}}_2$, as follows:

$$\widehat{\boldsymbol{\theta}}_2 = \underset{\boldsymbol{\theta}_2}{\operatorname{argmax}} \sum_{t=1}^{T} \ln c\left(F_1\left(u_{1,t}\right), F_2\left(u_{2,t}\right), \dots, F_n\left(u_{n,t}\right);\ \boldsymbol{\theta}_2, \widehat{\boldsymbol{\theta}}_1\right). \tag{14}$$

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

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

$$\Pr\left(X_{1,t} \leq VaR_{\alpha,t}^{1}\right) = \alpha\%. \tag{15}$$

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

$$\Pr\left(X_{1,t} \leq CoVaR_{\alpha,\beta,t}^{1|2} \middle| X_{2,t} \leq VaR_{\beta,t}^{2}\right) = \alpha\%, \tag{16}$$

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

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

$$\Delta CoVaR_{\alpha,\beta,t}^{1|2} = \left(CoVaR_{\alpha,\beta,t}^{1|2} - CoVaR_{\alpha,50,t}^{1|2}\right), \tag{17}$$

where $CoVaR_{\alpha,50,t}^{1|2}$ satisfies $\Pr\left(X_{1,t} \leq CoVaR_{\alpha,50,t}^{1|2} \middle| X_{2,t} \leq VaR_{50,t}^{2}\right) = \alpha\%$, for the 50%-th quantile (or median) of the return distribution $X_{2,t}$. Adrian and Brunnermeier (2016) estimate $CoVaR_{\alpha,\beta,t}^{1|2}$ by the quantile regression approach, which does not provide time-varying estimates. Conversely, Girardi and Ergün (2013) employs a multivariate GARCH model to estimate $CoVaR_{\alpha,\beta,t}^{1|2}$ that considers dynamic correlation. Nevertheless, their method depends on the selected bivariate distribution of $X_{1,t}$ and $X_{2,t}$, which can generate a misspecification error 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 possibly misspecification errors.

4.4 Systemic risk across different frequencies

While the previous studies mostly concentrate on estimating systemic risk for a particular data frequency, it is important to analyze the frequency dynamics of systemic risk. This analysis is economically meaningful as the entire financial system may respond to a shock to individual financial institution at different frequencies with varying strength (Baruník and 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). To this vein, we employ a novel approach for measuring systemic risk across frequencies; we estimate systemic risk over short, medium, and long term separately.

The main economic argument behind the notion that systemic risk may differ across different frequencies is that investors operate in different investment horizons (represented by frequencies), indicating their preferences for a particular frequency. Investors with heterogenous preferences for investment horizons may respond differently to a market/economic shock. Additionally, investors with diverse trading horizons may lead to stock market fluctuations and cycles with varying lengths (Teply and Kvapilikova, 2017). Therefore, a shock with a relatively stronger long-term (short-term) effect is likely to have higher power in low (high) frequency, and when the shock is transmitted to other variables, it will indicate long-term (short-term) connectedness. For instance, a permanent change in investor expectation about soundness of an individual financial institution may be better reflected by long-term connectedness/systemic risk. In line with this theoretical argument, the studies of Cogley (2001), Bandi and Tamoni (2014), and Baruník and Křehlík (2018), among others, argue that investors time-preference for consumption and resulting consumption growth has different cyclical component which generates shocks with heterogenous frequency response. This phenomenon creates short-, medium-, and long-term systemic risk. We empirically verify this conjecture in this subsection.

We decompose the underlying return series into wavelet components to evaluate the VaR, CoVaR, and ΔCoVaR for various 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 and Walden, 2000). We can write a wavelet transform $\psi_{\tau,s}(t)$ with time translation τ and scale s as:

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

for $s, \tau \in \mathbb{R}$, $s \neq 0$, and a mother wavelet $\psi(t)$. Since our return series are discrete, we employ a discrete wavelet transform on the data with length 2^J. We can represent a discrete wavelet transform with time translation $\tau = 2n$ and scale $s = 2J$ as:

$$\psi_{J,n}(t) = (2^J)^{-1/2}\psi\frac{(t-2^n)}{2^n},$$

for $J, n \in \mathbb{Z}$. The discrete wavelet transform (DWT) is a band-pass filter that recovers the frequencies around its main frequency, generating a scaling filter ϕ. We define the vector of J wavelet filter ψ elements as $(h_0, \dots, h_{J-1})$ such that $(i) \sum_{j=0}^{J-1} h_j = 0$, $(ii) \sum_{j=0}^{J-1} h_j^2 = 1$, and $(iii) \sum_{j=0}^{J-1} h_j h_{j+2k} = 0$, with $k \neq 0$. The properties (i)-(iii) of the wavelet filter elements imply an orthogonal matrix of discrete wavelet transform. The scaling filter ϕ elements $(g_0, \dots, g_{J-1})$ also satisfy the properties (i)-(iii).

For a bank returns series $\mathbf{x} = \{X_t\}_{t=1}^{T}$, we can apply the DWT to obtain the vector of wavelet coefficients as $\mathbf{w} = \mathbf{Wx}$, where $\mathbf{w} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_J, \mathbf{v}_J]'$ is a $(J+1)T \times 1$ vector of wavelet coefficients with $T = 2^J$, and the DWT matrix $\mathbf{W}_{(J+1)T\times T}$ specifies the transform (Gençay et al., 2005). Nevertheless, the DWT is restricted to the number of observations of $\mathbf{x}$ being a multiple of 2^J.

A maximum overlap discrete wavelet transform (MODWT) is an extension of the wavelet transform that is indifferent to the number of observations of $\mathbf{x}$, and the estimator of the MODWT is asymptotically more efficient than that of the DWT (Percival and Walden, 2000). Let $h_{j,k}$ and $g_{j,k}$ be an element of the wavelet filter ψ and scaling filter ϕ, respectively. We can write an element of the vector of K wavelet filter and scaling filter elements of the MODWT as $(\tilde{h}_0, \ldots, \tilde{h}_{J-1})$ and $(\tilde{g}_0, \ldots, \tilde{g}_{J-1})$, with

$$\tilde{h}_{j,k} = \left(2^j\right)^{-1/2} h_{j,k} \quad \text{and} \quad \tilde{g}_{j,k} = \left(2^j\right)^{-1/2} g_{j,k} \tag{18}$$

such that $(i) \sum_{j=0}^{J-1} \tilde{h}_{j,k} = 0$, $(ii) \sum_{j=-\infty}^{J-1} \tilde{h}^2{}_{J,k} = (1/2^J)$, and $(iii) \sum_{j=0}^{J-1} \tilde{h}_{j,k}\tilde{h}_{j,k+2} = 0$. We can apply the MODWT to obtain the vector of wavelet coefficients as $\tilde{\mathbf{w}} = \widetilde{\mathbf{W}}\mathbf{x}$, where $\tilde{\mathbf{w}} = [\tilde{\mathbf{w}}_1, \tilde{\mathbf{w}}_2, \ldots, \tilde{\mathbf{w}}_J, \tilde{\mathbf{v}}_J]'$ is a $(J+1)T \times 1$ vector of wavelet coefficients, $\tilde{\mathbf{w}}_j$ are vectors of wavelet coefficients with length $T/2^j$ of the scale of width $a_j = 2^{j-1}$, $\tilde{\mathbf{v}}_j$ are scaling vectors with length 2^j, and the DWT matrix $\widetilde{\mathbf{W}}_{(J+1)T\times T}$ specifies the transform.

We can apply the MODWT to obtain an additive wavelet approximation of the return series. We define $\widetilde{\mathbf{D}}_j = \widetilde{\mathbf{W}}_j{}'\tilde{\boldsymbol{w}}_j$ as the wavelet detail for the MODWT of variations in the returns $\mathbf{x}$ at the scale a_j with levels $j = 1,2, \ldots, J$. Then, we can write the multiscale decomposition for each return X_t as

$$X_t = \sum_{j=1}^{J+1} \widetilde{\mathrm{D}}_{j,t}\,, t = 1, 2, \dots, T-1,$$

where $\widetilde{\mathrm{D}}_{j,t}$ is the t-th element of $\widetilde{\mathbf{D}}_j$. Let $\widetilde{\mathbf{A}}_j = \sum_{k=j+1}^{J+1} \widetilde{\mathbf{D}}_k$ be the MODWT wavelet approximation for $0 \leq j \leq J$. Then, we can decompose the vector of returns $\mathbf{x}$ into as follows:

$$\mathbf{x} = \widetilde{\mathrm{A}}_j + \sum_{k=1}^{j} \widetilde{\mathbf{D}}_k, \tag{19}$$

where $\widetilde{\mathbf{D}}_k$ are the decomposed signals used for further analysis to evaluate the risk spillover across varying frequencies.

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 stylized features of the data. Gençay et al. (2001) suggests using a wavelet filter with a balanced length (such as length eight) that recovers the main characteristics of financial returns. 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). The LA(8) wavelet filter of Daubechies (1992) has been adopted in many empirical applications in finance and economics (Gençay et al., 2005; Bekiros and Marcellino, 2013; Bekiros et al., 2016).

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, CoVaR, and ΔCoVaR for various investment horizons. More specifically, due to heterogeneous investor behavior and time-horizon of investment, we transform the return series into 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, CoVaR, and ΔCoVaR for each subsequent wavelet.

5. Data and descriptive statistics of stock returns of banks

This study considers seven Australian banks: 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). Among them, the first four banks operate nationally and are the major banks, whereas the remaining three are mostly regional banks. While the extant literature on Australian banks predominantly concentrates on four major banks (CBA, WBC, ANZ, and NAB), including the regional banks in our sample allow us to examine if they have become large enough to be systemically important. As of 31 December 2018, these banks hold 81.77% of the gross loans and advances, 81.01% of the total banking assets, and 80.17% of the total deposits in the Australian banking sector(Australian Prudential Regulation Authority, 2018).

The sample period considered in this study spans September 1994 to December 2018. This sample period is chosen because daily stock price data for Australian banks are available for this period, and this period evaluates time-varying systemic risk with respect to relevant international events such as the GFC and the European debt crisis.

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

The resulting indices represent the Australian financial system, allowing us to examine possible shock spillovers between a distressed financial institution and the overall financial system. This approach is useful as it helps to avoid any spurious correlation between an individual bank and the financial system when the bank has a large share in the proxy of the financial system. For example, CBA accounts for about 25% of the total market capitalization of the Australian banking sector. Therefore, systemic risk estimates between CBA and a corresponding index that includes CBA will be biased due to CBA's significant contribution to the index. All data are collected from Thompson Reuters DataStream.

Table 2 presents descriptive statistics of banks stock returns. The major banks typically have a higher mean annualized return (except for the NAB) compared with the regional banks. For instance, among the major banks, CBA has the highest average return of 9.4%, while BAB possesses the highest average return of 5.4% among the regional banks. CBA also has the lowest return volatility (with a standard deviation of 0.210) among all the banks, whereas BAB exhibits the highest return volatility (with a standard deviation of 0.270). CAB also displays the highest Sharpe ratio among all banks, and BAB has the highest Sharpe ratio among regional banks. All the return series are negatively skewed (except for the BAB). The kurtosis values greater than three indicate that the return series are leptokurtic. The null hypotheses of normality, no-autocorrelation, and homoskedasticity are rejected by the Jarque-Bera test, Ljung-Box test, and ARCH-LM test (with few exceptions), respectively, at the 1% level.

[INSERT TABLE 2 HERE]

6. Empirical results and discussion

This section is divided in to three subsections. In the first subsection, we discuss results pertaining to the estimation of marginal models and copula parameters. The second subsection analyzes VaR, CoVaR, and ΔCoVaR estimates for the banks. These estimates are presented for the whole sample period, for different subperiods, and for different frequencies. In the third subsection, we explore the cross-sectional determinants of systemic risk in the Australian banking sector.

6.1 Time-varying copula-GARCH model

As indicated in Section 4, we first estimate marginal models for each one of the return series of the Australian banks, and then we use the filtered generated returns to estimate the copula parameters. Searching for the best-fitted marginal distribution model, we initially estimate an ARMA(m,n) with GARCH(p,q), EGARH(p,q), and GJR-GARCH(p,q) specifications.

We find that the ARMA (1,0)-EGARCH (1,1) model minimizes the AIC. Given the return series display autocorrelation and conditional heteroskedasticity, the ARMA (1,0)-EGARCH (1,1) specification best captures these stylized facts embedded in the series. The parameters of the marginal model are estimated based on *t*-Student innovations. We also consider other alternatives to model the white noise process, ε_t, for instance, using Gaussian and skewed-*t* distribution. The results are somewhat similar, and the *t*-Student distribution captures better 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 authors).

Table 3 reports the ARMA(1,0)-EGARCH(1,1) estimation results for the Australian banks (we omit the estimated parameters for alternative marginal models, but they are available upon request). The estimated AR(1) coefficient in the conditional mean equation is significant for all the return series, implying that past returns help predict subsequent returns. Besides, the AR(1) coefficients are positive for all the major banks, suggesting the presence of return momentum, but the AR(1) coefficients are negative for all the regional banks, implying the presence of return reversals. The ARCH (α) and the lagged conditional variance (β) parameters are significant at the 1% significance level for all the return series. These findings imply that the current-period conditional volatility is significantly influenced by past shocks on conditional variance, and the conditional volatility is persistent for all the return series.

The estimated leverage parameter (ξ) is significant for most of the banks at the 1% level (except for ABL and BOQ), suggesting an asymmetric effect of bad and good news on conditional volatility. Moreover, the tail-dependence parameter (DoF) is highly significant, indicating that the returns distribution display heavy tails and that there are joint extreme movements. This result supports the application of *t*-Student distribution to estimate the marginal distribution model for the underlying return series. The diagnostic tests indicate that although the estimated residuals exhibit deviation from normality (as the Jarque-Bera statistic is significant for all the return series), there is almost no remaining autocorrelation and ARCH effects in the underlying return series (since Q(10), $Q^2(10)$, and ARCH (10) statistics are statistically insignificant at the 5% level). Overall, the Q(10), $Q^2(10)$, and ARCH (10) statistics report evidence that an ARMA(1,0)-EGARCH(1,1) with errors following a *t*-Student distribution fits well the returns of the Australian banks.

[INSERT TABLE 3 HERE]

Using the filtered returns generated from the estimated marginal models, we estimate the dependence parameters between the returns of Australian banks and that of their corresponding indices. We consider four commonly used copulas: the Gaussian copula, *t*-Student copula, Clayton copula, and SJC copula. Different copula specifications capture diverse dependence structures between an individual bank and its corresponding index. For instance, the Gaussian copula models the overall dependence by assuming normality of distribution of returns, while the *t*-Student copula considers joint extreme movements. Similarly, the Clayton copula captures lower tail dependence, and the SJC copula allows for both lower- and upper-tail dependence. The optimal copula framework is chosen by minimizing the AIC.

Table 4 displays the copula estimates. Panels A, B, C, and D report estimates of the Gaussian copula, *t*-Student copula, Clayton copula, and SJC copula, respectively. According to the AIC, the time-varying *t*-Student copula is the best model for the pairwise dependence between the Australian banks and their corresponding indices. Panel B of Table 4 shows that the connectedness parameter (ρ) between individual banks and their corresponding indices are statistically significant at the 1% significance level. The dependence structure is higher for the major banks compared with that of the regional banks. The dependence parameter varies between 0.673 (CBA) to 0.715 (WBC) for the major banks, while the corresponding parameter ranges between 0.101 (ABL) to 0.420 (BAB) for the regional banks. This result indicates the potential for high systemic risk for the major banks compared with the regional banks. The estimated parameter of degrees of freedom (DoF) is statistically significant at the 1% level for most of the banks (except for WBC and ABL), indicating a strong potential of joint extreme movements between these banks and their corresponding indices. The estimated β parameter is significant for most of the return series at the 1% level, implying persistency in conditional volatility.

[INSERT TABLE 4 HERE]

6.2 VaR, CoVaR, and ΔCoVaR

This subsection presents VaR, CoVaR, and ΔCoVaR estimates. As indicated earlier, based on a *t*-Student distributional assumption, we select the best-fitted copula model for each individual bank and its corresponding index by minimizing the AIC. The optimal copula model is then used to estimate the VaR, CoVaR, and ΔCoVaR. We calculate all these measures using a 95% confidence level.

Table 5 reports the VaR, CoVaR, and ΔCoVaR estimates for the Australian banks. Columns 1, 2, 3, and 4 display the estimates for the whole sample, pre-crisis, crisis, and post-crisis periods, respectively. Panel A displays the VaR estimates. We first focus on the whole sample period. We observe that VaRs for the regional banks are greater in absolute value compared with that of the major banks. For example, VaR ranges between -0.023 to -0.025 for the regional banks, whereas VaRs for the major banks are between -0.020 to -0.022. The difference in VaRs across the banks are statistically significant (the *F*-statistic is 272.54). This result implies that regional banks exhibit high downside risk compared with the major banks, and, in the worst possible case, the asset value of the regional (major) banks will decline by 230 to 250 basis point (200 to 220 basis point) on average with a 5% probability.

Overall, this result may be attributed to the operational difference between the two group of banks. The regional banks mostly perform retail banking function and their operations are typically confined within Australia or within a certain state. On the other hand, the major banks operate in both retail and wholesale markets, and they provide diverse services (e.g., fiduciary services, underwriting, investment banking, insurance, and risk management) along with the conventional deposit taking and lending services. Furthermore, the major banks have overseas operations with a dominant presence in New Zealand (Bollen et al., 2015). Thus, the major banks' diversified operations may have contributed to their lower absolute value of VaRs compared with that of less-diversified and concentratedly-operating regional banks.

Among the major banks, CBA has the lowest downside risk indicated by the lowest VaR, while VaRs for the other three major banks are identical. The difference between the VaRs of CBA and the other three major banks are statistically significant. Conversely, BAB exhibits the highest VaR among the regional banks, whereas VaRs for the other two regional banks are identical. This finding again may be attributed to the degree of diversification in the banking operations. For instance, CBA appears to have the most diversified operations with a non-interest income 20% of its interest income. These rates are 17%, 18%, and 13% for ANZ, NAB, and WBC, respectively. On the other hand, the proportion of non-interest income in relation to total income for the regional banks are lower than that of the major banks. For example, non-interest income as a percentage of interest income (calculated from income statement information obtained from FactSet) is 7%, 10%, and 9% for ABA, BAB, and BOQ, respectively.

As for the sub-periods, Table 5 shows that crisis-period VaRs are significantly higher than the VaRs in the pre- and post-crisis periods. For example, the crisis-period VaR of ANZ is -0.035, while its pre- and post-crisis period VaR are -0.021. We find similar results for all other banks in our sample. The post-crisis VaRs are also significantly higher than that in the pre-crisis period (except for ANZ), indicating that downside risk or has increased substantially for the Australian banks since the global financial crisis in 2008.

Panel B of Table 5 presents the CoVaR estimates. Although the major banks have lower VaRs than that of the regional banks, the CoVaRs of the major banks are relatively larger in absolute value compared with that of the regional banks (for the whole sample period). This result is economically meaningful. The larger CoVaRs for the major banks indicate that the entire financial system is more sensitive to risk shocks in the large banks compared with the regional banks. Besides, there are high risk spillovers from the major banks to the entire financial system compared with that of the regional banks.

The sub-period results indicate that the crisis-period CoVaR is significantly greater than that that of the pre-crisis and post-crisis periods. For example, among the major banks, crisis-period CoVaR ranges between -0.034 to -0.038, while CoVaRs are between -0.025 to -0.028 (-0.026 to -0.029) in the pre-(post-)crisis period. This result is intuitive. During the crisis period, borrowers found it increasingly difficult to repay their debt. As a result, non-performing loans increased for most of the Australian banks, which reduced the stock prices of individual banks that negatively affected the whole financial system.

Panel C of Table 5 shows that cross sectional and time-varying patterns of ΔCoVaR are similar to that of VaR and CoVaR. The ΔCoVaR is significantly higher for the major banks compared with that of the regional banks, for the whole sample period. Since ΔCoVaR indicates the systemic risk contribution of individual banks to the entire financial system, this result is consistent with our a priori expectation that large banks are systemically more important than regional banks. Then, in the event of default of a regional bank, its consequence to the entire financial system is less severe compared with that of a major bank, had it defaulted. The geographically less diversified and more concentrated operations of the regional banks may have contributed to this result.

CBA exhibits the highest ΔCoVaR (-0.016), indicating this bank had the highest systemic risk contribution in our sample. Thus, when CBA is in distress, it leads to a 160-basis-point decline in asset value of the entire financial system of Australia. ANZ, NAB, and WBC contribute to 14, 140-, and 150 basis-point declines, respectively, in asset value of the entire financial system when they are in distress. Among the banks considered in our sample, ABL has the lowest ΔCoVaR of -0.005, whereas BAB and BOQ's ΔCoVaRs are -0.009, suggesting that these banks account for 50 to 90 basis-point declines in asset value of the entire financial system when they are in distress.

The cross-sectional differences in systemic risk may be attributed to the level of non-interest income and size of the Australian banks. Among the banks considered in this paper, CBA generated the highest non-interest income (AUD 7,025 million) in 2018. The non-interest income earned by the regional banks were much lower than that of the major banks. ANZ, NAB, and WBC earned a non-interest income of AUD 5,496 million, AUD 5518 million, AUD 4520 million in 2018, respectively. Theoretically, a higher non-interest income leads to a higher revenue volatility that results in higher systemic risk. Conversely, low non-interest income indicates concentrated revenue and high reliance on traditional banking activities that reduce systemic risk. Brunnermeier et al. (2012) and Williams (2016) report evidence that banks with higher non-interest income exhibit high systemic risk in the context of US and Australian markets. As for size, larger systemic risk for the major banks indicates that the maximum efficient scale in terms of risk have been exceeded for the major banks (Williams, 2016).

Our sub-period analysis reveals that the crisis-period ΔCoVaR is significantly greater than that in the pre-crisis period. Then, when the banks are in distress, their negative externality on the whole financial system increases significantly during a crisis period. This finding is consistent with the results presented in Bollen et al. (2015) for the Australian banks. On average, the crisis-period ΔCoVaR is about 40% higher than the pre-crisis period ΔCoVaR. For instance, when ANZ is in distress, it leads to a 130-basis-point decline in asset value of the whole financial system in a non-crisis period; however, a similar distress condition leads to a 220-basis-point decline in asset value of the entire financial system in a crisis period. Further, in the post-crisis period, systemic risk (ΔCoVaR) has declined substantially compared with that in the crisis period, which may be attributed to the enactment of the Deposit and Wholesale Funding Guarantee (DWFG) scheme in Australia at the end of 2008. There was no deposit insurance in Australia before 2008, and the introduction of DWFG scheme was taken positively by the banking sector since it guaranteed funding in case of insolvency of a bank, which ultimately reduced the possibility of a bank run. The DWFG scheme helped decrease the systemic risk in the post-crisis period. Overall, our results indicate that CBA and ABL are the most and the least systemically relevant banks in the Australian banking sector, respectively, among the banks considered in this paper.

[INSERT TABLE 5 HERE]

Next, we interpret the VaR, CoVaR, and ΔCoVaR estimates for different frequencies. Panel A of Table 6 highlights that short-term VaR is significantly higher than medium-term and long-term VaRs. VaR estimates gradually decrease as we move from short-term to long-term trends. For instance, for ANZ, short-, medium-, and long-term VaRs are -0.0143, -0.0062, and -0.0039, respectively, indicating that (in a worst- possible scenario) the asset value of ANZ will decline by 143, 62, and 39 basis point, respectively, in the short-, medium-, and long-term. These differences in VaR estimates across frequencies are statistically significant at the 1% level. The economic interpretation of this result is that it may be difficult to hedge the trading portfolio positions in the short run (in a 2- 4-day horizon), although banks' trading portfolio positions are assumed to be liquid, which leads to a substantial decline in asset value. Nevertheless, exiting or hedging trading portfolio positions of the banks is easier in the medium run (in a 32-64-day horizon) and long run (256-512 days), highlighting a relatively smaller VaR in the medium and long term compared with the VaR in the short term. This result also makes sense from a perspective of stock market's reaction to an extreme change. An extreme change in market conditions (e.g., asset prices, market volatility, and market liquidity) exerts a pronounced impact on stock prices that is evidenced in the short run. However, as time passes, the information is gradually diffused in stock prices, and the impact of an extreme change on stock prices progressively subsides.

Interestingly, while we previously reported that aggregate VaR of the regional banks are significantly greater than that of the major banks, the segregated VaR across frequencies indicate that this result holds in the short and medium run, but not in the long run. More specifically, the VaRs of the regional banks are significantly lower than that of the major banks in the long term. For example, short-term VaR of the regional and major banks ranges between -0.0144 to -0.0174 and -0.0124 to -0.0143, respectively. Notwithstanding, long-term VaRs for the regional and major banks are between -0.0020 to -0.0027 and -0.0033 to -0.0041, respectively. Then, VaR is more persistent for the major banks compared with that of the regional banks. Therefore, an extreme change in market conditions leads to a decline in asset value of the major banks even in the long term.

Panel B of Table 6 indicates that short-term CoVaR is significantly higher than medium- and long-term CoVaRs, implying that risk spillover from an individual bank to the entire financial system is stronger in the short term, but it gradually weakens in the medium and long term. Although we previously found that the CoVaR of the major banks are significantly higher than that of the regional banks (as presented in Table 6), the disaggregated CoVaR across frequencies indicate that the CoVaR of the regional banks is as high as the CoVaR of the large banks in the short run (except for ABL). For instance, the short-term CoVaR for the major banks lies between -0.0169 to -0.0177, while that of two regional banks (BAB and BOQ) are -0.0178 and -0.0173. Then, risk spillovers from the major and regional banks are similarly strong in the short term.

Nevertheless, in the medium and in the long term, risk spillovers from the major banks are stronger than that from the regional banks.

Panel C of Table 6 illustrates that ΔCoVaRs of the major banks are significantly greater than ΔCoVaRs of the regional banks, in consonance with the aggregate ΔCoVaR results displayed in Table 6. Thus, the large banks are systemically more important than the regional banks, regardless of the data frequency considered. Nonetheless, we find certain interesting results in the frequency dynamics of systemic risk. First, according to aggregate ΔCoVaR results, CBA was the systemically most important bank (Table 6). On the other hand, disaggregated ΔCoVaR reveals that both CBA and WBC exhibit similar systemic importance in the short run. When these banks are in distress, they lead to an 85-basis-point decline in asset value of the entire financial system. This result, however, does not hold in the medium and long term. The systemic risk contribution of WBC is higher compared with that of CBA in the medium and in the long term. Besides, as for the regional banks, while we previously reported that BAB and BOQ's systemic importance is identical (in Table 5), their systemic risk contribution varies across frequencies. For instance, BAB is systemically more important than BOQ in the short term; however, BOQ's systemic risk contribution is higher than that of BAB in the medium and long term. Overall, these findings indicate that systemic risk across frequencies may differ from the aggregate systemic risk pattern of the banks. This highlights the relevance of our frequency-based systemic risk analysis.

[INSERT TABLE 6 HERE]

So far, we have interpreted results pertaining to VaR, CoVaR, and ΔCoVaR in the discrete whole sample period and in subperiods. Now we present a time-varying picture of the VaR, CoVaR, and ΔCoVaR estimates in Figure 1. The blue, red, and green lines represent time-varying

VaR, CoVaR, and ΔCoVaR, respectively. Consistent with our previous results, all three risk measures were relatively lower in the pre-crisis period (from the start of the sample period until 2007) in comparison with their level in the crisis period (since the advent of the GFC in 2007 until the end of 2008). This result holds for all the banks except for ABL. The lower systemic risk in the pre-crisis period may be explained by the market error hypothesis and bank capital mismeasurement hypothesis (Sarin and Summers, 2016).[2] Although the GFC initiated in beginning of 2007, the Australian banks appeared to be protected from the global credit crunch at that time. Accordingly, while many countries were cutting their domestic interest rate, the Reserve Bank of Australia increased the domestic rate. Nevertheless, during early 2008, in response to a collapse of the global financial market, the Australian banking shares also experienced a large fall, which negatively affected the whole financial system. This phenomenon is represented by an increase in VaR, CoVaR, and ΔCoVaR between the 2008-2009 period. Nonetheless, systemic risk declined in the post-crisis period compared with that during the crisis period, which may be attributed to the introduction of DWFG in Australia, to regulatory measures taken to increase capital adequacy, and to more prudential risk taking. In agreement with our findings, Sarin and Summers (2016) demonstrate that regulatory measures together with prudent private sector behavior have significantly reduced run risk of the US banks.

[INSERT FIGURE 1 HERE]

[2] The market error hypothesis states that the markets underestimated the risk associated with the banking sector, and they exhibited excessive optimism about financial stability in the pre-financial-crisis period. These were later adjusted in the crisis period, which is demonstrated by dismal return and high risk in the crisis period. Yellen (2016) supports this hypothesis. Conversely, the bank capital mismeasurement hypothesis asserts that the calculated bank capital was a distorted measure of capital that failed to identify the capital gap. Acharya et al. (2016) report evidence of the deficiencies of regulatory capital measures, and they show that "countries that are considered to have the safest banking sectors according to Basel risk weights (e.g., Belgium, France, and Germany) are considered to be the riskiest according to market risk weights."

We now discuss the results related to time-frequency developments of ΔCoVaR. The blue, red, and green lines plot short-, medium-, and long-term ΔCoVaR, respectively. Consistent with our previous results, short-term ΔCoVaR is generally higher than the medium- and long-term ΔCoVaR. This result is more prominently found during the GFC and for the large banks. Systemic risk created in the high frequency (in the short term) may represent the periods (such as the GFC) when an item of financial market information is rapidly processed by investors and a shock to an individual bank mostly affect short-term cyclical behavior of the financial system (Baruník and Křehlík, 2018). Nonetheless, we find instances when long-term ΔCoVaR is greater than short-term ΔCoVaR (e.g., ΔCoVaR during the period of 2016 for most of the major banks). Systemic risk created in the lower frequency (in the long term) indicates that shocks from an individual bank are transmitted to the financial system for longer periods, which may be attributed to the fundamental changes in investor expectation regarding factors such as regulatory changes. As for the regional banks, long-term ΔCoVaR is mostly close to zero for BAB and BOQ, indicating that the systemic risk contribution of these two banks to the entire financial system occurs predominantly between short to medium term.

[INSERT FIGURE 2 HERE]

6.3 Determinants of systemic risk

In this subsection, we explore the determinants of individual bank's systemic risk contribution. We use a semiannual (two-quarter) average of ΔCoVaR as the dependent variable. We consider several idiosyncratic bank characteristics and market-wide variables as explanatory variables.

As for the variables reflecting idiosyncratic bank characteristics, we consider seven variables. The first one is the lagged VaR of the bank. The intuition is that the risk of a bank (VaR) contributes positively to forward systemic risk. The second one is the bank size that is estimated as the log of the book value of total assets in Australian dollars. There are two competing arguments regarding the relationship between bank size and its systemic risk exposure. A large bank may be more immune to macroeconomic and liquidity shocks due to its diversified banking operations. This argument indicates a negative relationship between bank size and systemic risk (Boyd et al., 2004). However, large banks typically receive too-big-to-fail subsidies in the event they are in a distress condition (Sarin and Summers, 2016). This phenomenon may stimulate large banks to take excessive risk, leading to a positive relationship between banks' size and its contribution to systemic risk.

The third variable considered is the leverage ratio that is estimated as the ratio of total asset to book value of total equity. A high leverage apparently may be taken as an indication of a high probability of default. Nevertheless, high leverage may reduce systemic risk as highly levered banks are typically found to have high quality loan portfolio, and they are highly liquid (Diamond and Rajan, 2001). Yet, an increase in short-term leverage may boost systemic risk. The fourth variable examined is liquidity calculated as the loan to deposit ratio (LTD), which measures the funds converted into loans from the obtained deposits. When depositors or holders of off-balance-sheet loan commitments of a bank demand larger withdrawal than normal, an absence of sufficient cash asset holding to meet this demand leads to a liquidity crisis. In such circumstance, the bank may need to sell some of its less liquid assets even at a lower price (a fire sale) that turns a liquidity problem into a solvency one, which ultimately can result in systemic default (Brunnermeier and Pedersen, 2008; Aldasoro and Faia, 2016). On the other hand, Louzis et al. (2012) and Makri et al. (2014) find that a higher LTD discloses a risk preference for low-quality debt that is expected to increase the level of non-performing loans. As a result, the increased level of non-performing loans decreases the stock prices of individual banks, which negatively affects the whole financial system.

The fifth variable used is the capital adequacy of a bank that is estimated as the tier 1 capital ratio, which is a ratio of tier 1 capital to total risk-weighted assets. A well-capitalized bank is less prone to systemic risk since a large bank finds it costlier to take on risk, and adequate capital obviously reduces the probability of default of a bank (Laeven et al., 2016). The sixth variable employed is profitability (return on asset). Profitability should exhibit a negative relationship with a bank's systemic risk because profitability shields a bank from defaulting. However, if a large portion of bank's profitability comes from non-interest income, it may increase bank's probability of default and systemic risk since non-interest income is typically associated with revenue volatility and tail risk (Acharya et al., 2012; Williams, 2016). Finally, we apply banks' funding structure calculated as the ratio of total deposit to total asset. This variable essentially reflects the reliance of banks on deposit funding. A higher level of deposits decreases the level of systemic risk since deposits serve as buffer against different economic shocks (Mayordomo et al., 2014).

As for the market-wide determinants of systemic risk, we consider four variables. The first one is GDP growth rate. Economic activity and financial stability typically exhibit a positive relationship (Schleer and Semmler, 2015). In the event of an economic downturn, borrowers may fail to meet loan repayment obligation that can ultimately lead to a systemic failure of the banks (Hirtle et al., 2016). Moreover, economic growth improves the quality of the loan portfolio, decreasing the ratio of non-performing loans to total loans, which leads to a lower systemic risk (Babihuga, 2007; Männasoo and Mayes, 2009; Uhde and Heimeshoff, 2009; Ali and Daly, 2010; Festić et al., 2011; Chaibi and Ftiti, 2015). The second market-wide variable considered is monetary policy interest rates. We consider the Reserve Bank of Australia (RBA) cash reserve rate in this regard. If the assets of banks are highly sensitive to changes in short-term interest rates, a monetary tightening can result in large losses to the banks that ultimately generate high systemic risk (Ramos-Tallada, 2015).

The third market variable is the change in exchange rate between the Australian dollar (AUD) and the New Zealand dollar (NZD), given the significant exposure of the Australian banks to the economy of New Zealand. A large amount of foreign currency loans in the balance sheet of banks can trigger simultaneous failures of banks if borrowers find it difficult to service the loan in case of a depreciation of the domestic currency (Yeşin, 2013). Finally, we consider housing price growth as a market-wide variable. Since the loan portfolio of Australian banks is dominated by real estate mortgage loan, a downturn in the real estate market may cause a deleveraging pressure that can result in a negative feedback loop and higher systemic risk in the overall banking sector (Downing et al., 2005; Capozza and Order, 2011; Liu et al., 2019). Conversely, increases in housing prices lead to disproportionate lending, resulting in a higher level of risky assets by the banks that reinforces real economic shocks (von Peter, 2009; Gimeno and Martínez-Carrascal, 2010; Anundsen and Jansen, 2013; Anundsen et al., 2016). Thus, an increase in housing prices may positively contribute to systemic risk.

To explore systemic risk's relationship with bank-specific and market-wide variables, we estimate the following panel regression model:

$$\overline{\Delta\text{CoVaR}}_{i,t} = \alpha + \boldsymbol{\beta} \boldsymbol{F}_{i,t-1} + \boldsymbol{\gamma} \boldsymbol{M}_{t-1} + \epsilon_{i,t}, \tag{20}$$

where $\overline{\Delta\text{CoVaR}}_{i,t}$ is the semiannual average of the daily ΔCoVaR for bank *i* at time *t*, $\boldsymbol{F}_{i,t-1}$ is a vector of bank-specific lagged characteristics, $\boldsymbol{M}_{t-1}$ is a vector of lagged market-wide variables, and $\epsilon_{i,t}$ is a panel regression error term. The vector $\boldsymbol{F}_{i,t-1}$ includes the following bank-specific lagged characteristics: *VaR, Size, Leverage, Capital adequacy ratio, Profitability,* and *Funding structure.* *VaR* is the VaR of the bank, $Size$ is the natural log of the book value of assets, and $Leverage$ is the ratio of total asset to book value of equity. $Liquidity$ is the ratio of total loan to total deposit, and $Capital\,adequacy\,ratio$ is the ratio of tier 1 capital (equity capital and disclosed reserves) to total risk-weighted assets. $Profitability$ is the return on asset, and $Funding\ structure$ is the ratio of total deposit to total asset.

The vector $\boldsymbol{M}_{t-1}$ includes the following lagged market-wide variables: *GDP growth rate, Cash rate, Exchange rate change,* and *Housing price growth.* $GDP\,growth\ rate$ is the growth rate of constant dollar Australian GDP, $Cash\,rate$ is the RBA cash reserve rate, $exchange\,rate\ change$ the change in the exchange rate between the Australian dollar and the New Zealand dollar, and $Housing\ price\ growth$ is the growth rate in Australia-DataStream Real Estate price index. We obtain data on bank-specific variables from FactSet and Worldscope, and we gather data on market-wide variables from DataStream. Our panel data consist of 34 semiannual periods from the first semester of 2002 to the last semester of 2018. We selected this sample period because of data availability of the characteristics of the banks.

Table 7 reports the panel regression estimates of Eq. (20) with Newey-West standard errors with up to five autocorrelation periods in parentheses. Columns 1-2 of Table 7 display the results derived from the model that considers $\overline{\Delta\mathrm{CoVaR}}_{i,t}$ as the dependent variable, and Columns 3-8 of Table 7 present the results for the models that consider decomposed $\overline{\Delta\mathrm{CoVaR}}_{i,t}$ as the dependent variable. Model 1 includes only idiosyncratic bank-specific variables, and Model 2 considers both bank-specific and market-wide variables. We first focus on Columns 1-2 of Table 7. As expected, the lagged VaR of a bank contributes positively to the systemic risk at the 1% level. Besides, we find that size has a significant positive impact on forward systemic risk. The estimated coefficient is significant at the 1% significance level. Consistent with our previous findings of higher systemic risk for major Australian banks, this finding is in line with the notion that large banks tend to receive too-big-to-fail subsidies in a distress condition that increase their systemic risk contribution to the financial system (Sarin and Summers, 2016). Our result also supports the findings of Brunnermeier et al. (2012), López-Espinosa et al. (2015), Black et al. (2016), Laeven et al. (2016), Karimalis and Nomikos (2018), and Varotto and Zhao (2018), among others, who show that larger banks are great contributors to systemic risk.

We further observe a significant positive relationship between banks' systemic risk contributions and their leverage position. This result is in line with our a priori expectation that high leverage indicates a high probability of default, which likely leads to a higher systemic risk. Beltratti and Stulz (2012), Brunnermeier et al. (2012), López-Espinosa et al. (2015), Karimalis and Nomikos (2018), among others, report a positive impact of leverage on systemic risk.

Next, we find that systemic risk is significantly lower for the banks with high capital adequacy ratios. This result supports the hypothesis that a well-capitalized bank finds it costlier to take on high risk, and it underscores that high capital adequacy indicates a capital buffer against the probability of a bank's failure. Acharya et al. (2017) argue that a bank failure in a well-capitalized system does not exert negative externalities in the economy. Although Laeven et al. (2016) and Varotto and Zhao (2018), among others, find low systemic risk for well-capitalized banks, Yun and Moon (2014) provide evidence of an insignificant relationship between systemic risk and capital adequacy ratio.

Although the estimated coefficient of liquidity is slightly significant (at the 10% level), a bank's systemic risk contribution positively responds to its liquidity, measured by its LTD. Then, our finding is consistent with Louzis et al. (2012) and Makri et al. (2014), who find that an increasing LTD leads to a higher level of non-performing loans and an greater systemic risk. This result is economically meaningful as the LTD discloses the quality of loans of banks, which ultimately can increase systemic risk associated with the banks. In line with our result, Yun and Moon (2014) and Karimalis and Nomikos (2018) also provide evidence that liquidity is a significant determinant of banks' systemic risk. Nevertheless, our result is in contrast to Varotto and Zhao (2018), who report that bank's specific systemic risk is invariant to its liquidity. The above-mentioned results are robust for both Models 1 and 2.

We find a positive relationship between systemic risk and the profitability of a bank. This result may come as a surprise because high profitability typically shields banks against the default probability; therefore, a high level of profitability should be associated with low systemic risk. Instead, our result is consistent with the idea that since non-interest income contributes to a large portion of operating income of major Australian banks, their higher profitability is associated with a high revenue volatility and tail risk (Acharya et al., 2012; Williams, 2016). This result also holds for Model 2 at the 5% level. The variable reflecting the reliance of banks on deposit funding (funding structure) is statistically insignificant for Model 1, but it is slightly significant (at the 10% level) for Model 2. This result is in line with Laeven et al. (2016), who find a significant positive relationship between systemic risk and banks' funding structure for a large sample of global banks.

As for the market-wide variables, systemic risk is negatively associated with economic growth, and cash rate contributes to systemic risk. The negative relationship between economic growth and systemic risk arises as economic growth is typically accompanied by greater quality of the loan portfolio and a lower level of non-performing loans, which decreases the systemic risk. A financial crisis may follow an economic downturn, in line with (Männasoo and Mayes, 2009; Uhde and Heimeshoff, 2009; Festić et al., 2011; Louzis et al., 2012; Hirtle et al., 2016). The economic story behind the positive response of systemic risk to cash rate is that a high cash reserve rate is an indication of a restrictive monetary policy. Under such circumstance, the lending decisions of the commercial banks are scarcer and expensive, increasing the overall interest rate and the probability of loan default that generates high systemic risk (Lange et al., 2015).

Systemic risk is invariant to the change in the AUD/NZD exchange rate, but it is positively affected by changes in housing prices at the 10% level. The positive relationship between housing prices and systemic risk may be explained by the effect of increases in lending due to higher housing prices, resulting in a self-reinforcing effect that increases houses prices and amplifies real economic shocks (von Peter, 2009; Gimeno and Martínez-Carrascal, 2010; Anundsen and Jansen, 2013; Anundsen et al., 2016). The incremental explanatory power of the model including the market-wide variables is significant. The adjusted R squared for the Model 1 is 56%; when we augment Model 1 with four market-wide variables, its adjusted R squared increases to 69.6%.

We also estimate Eq. (20) separately for short-, medium-, and long-term systemic risk, and we report the results in Columns 3-8 of Table 7. This analysis reveals whether asymmetric systemic risk across frequencies is attributed to a different set of bank-specific and market-wide variables. Our key results remain mostly unchanged for short-term ΔCoVaR. For instance, VaR, size, leverage, and cash rate have significant explanatory power for short-term systemic risk. Nonetheless, liquidity, funding structure, and housing price growth become insignificant for short-term ΔCoVaR, and size, profitability, and cash rate turn into statistically non-significant for medium-term ΔCoVaR. Finally, regarding long-term systemic risk, VaR and liquidity are the most important bank-specific variables for explaining systemic risk, while cash rate is the only market-wide variable that has a statistically significant influence on systemic risk. Overall, our results illustrate that systemic risk across the frequencies is attributed to a different set of idiosyncratic bank-specific and market-wide variables, consistent with our previous conjecture that asymmetric systemic risk across frequencies arises as investors operate in different investment horizons (frequencies), and investors have different speeds of information processing. Therefore, economic shocks exert different impacts on cyclical nature of the financial system.

[INSERT TABLE 7 HERE]

7. Conclusion

This paper examines systemic risk in the Australian banking sector using the delta conditional value-at-risk (ΔCoVaR) approach. The Australian banking sector is characterized as (i) highly concentrated with small number of large banks, (ii) with a loan portfolio dominated by real estate mortgage loan, and (iii) heavily reliant on off-shore sources of wholesale funding. These characteristics contribute to a unique pattern of systemic risk of well-performing Australian banks compared with their North-American and European counterparts.

Although the systemic risk literature has been expanded after the GFC, we extend the literature to several fronts. First, while the literature mostly applies a quantile regression framework to measure ΔCoVaR, we rely on a novel copula-based methodology. The copula approach enables estimation of the entire joint distribution even in the presence of heavy-tailed distributions and heteroscedasticity. Besides, since the literature mostly focus on estimating systemic risk at a particular data frequency, we measure systemic risk across different frequencies. This analysis enables us to identify 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 explain cross-sectional and time-series variation in systemic risk using idiosyncratic bank characteristics and market-wide variables. This analysis has largely been ignored in the context of the Australian banking sector.

We report several key findings in this paper. First, large banks are systemically more important than regional banks. However, from the frequency-based systemic risk analysis, systemic risk contribution of the regional banks is as high as that of the major banks in the short term. Nonetheless, in the medium and in the long term, regional banks are systemically less important than the major banks. Second, systemic risk in crisis period is significantly higher than that in the pre-crisis period, indicating that negative externalities of a distressed financial institution are higher during a crisis period. Although systemic risk in the post-crisis period is significantly lower compared with the crisis period potentially due to the introduction of deposit insurance, the level of systemic risk in the post-crisis period is significantly higher than that of the pre-crisis period, illustrating that systemic risk in the Australian banking sector has increased substantially after the GFC. Third, frequency-based systemic risk further reveals that short-term systemic risk is higher than medium- and long-term systemic risk, showing that systemic risk gradually weakens in the long-term. Finally, we find that idiosyncratic bank characteristics (such as size, leverage, liquidity, and capital adequacy) and market-wide variables (such as GDP growth rate and cash rate) significantly explain systemic risk in the Australian banking sector. Nevertheless, their explanatory power varies across frequencies.

Our findings have important policy implications. Our result of major banks' disproportionate contribution to systemic risk may allow the Australian regulatory authority to increase capital charge for the major banks. Despite the introduction of deposit insurance, an increase in systemic risk in the post-crisis period suggests that the Australian government need to adjust too-big-to-fail subsidies. Furthermore, the asymmetric systemic risk pattern across frequencies indicates that the nature of a shock, diverse response of investors operating in different investment horizons, and economic properties of market account for disparate levels of systemic risk across frequencies. A future research is warranted along this line.

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Table 1

Main financial soundness indicators of the Australian bank sector (in %)

	Capital adequacy				Liquidity				Asset quality				Profitability	
	Total capital adequacy ratio		Tier I risk-based capital ratio		Loan to deposit ratio		Savings deposit to total deposit ratio		Loan loss provision to total loan		Non-performing loan to total loan		ROE	
	2007	2018	2007	2018	2007	2018	2007	2018	2007	2018	2007	2018	2007	2018
ANZ	10.10	15.20	6.70	13.40	142.71	115.14	79.71	87.36	0.19	0.11	0.23	0.33	19.96	12.00
CBA	9.76	15.00	7.14	12.30	150.91	125.40	25.44	29.85	0.14	0.14	0.14	0.42	19.97	14.37
NAB	10.00	14.12	6.70	12.38	141.44	132.93	31.71	45.73	0.23	0.13	0.31	0.25	15.96	11.43
WBC	9.50	14.74	6.50	12.78	137.49	126.63	64.47	77.06	0.18	0.10	0.15	0.20	21.96	12.86
ABL	N/A	14.89	N/A	12.68	190.42	121.79	60.32	69.23	0.00	0.04	0.54	0.31	17.91	7.52
BAB	10.24	12.85	7.98	10.96	91.39	104.24	76.43	80.2	0.06	0.13	1.30	1.34	12.72	7.87
BOQ	11.50	12.76	8.50	10.99	138.84	119.12	29.41	61.11	0.12	0.09	3.27	2.25	14.68	8.79

Notes: This table reports financial soundness indicators for seven Australian banks: 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). Total capital adequacy ratio is the ratio of total capital available to risk-weighted credit exposures of banks, and Tier 1 risk-based capital ratio is the proportion of tier 1 capital (equity capital and disclosed reserves) to total risk-weighted assets. ROE is the return on equity.

Table 2

Descriptive statistics of stock returns of Australian banks

	Mean (%)	Standard Deviation	Sharpe Ratio	Maximum	Minimum	Skewness	Kurtosis	JB	Q(10)	$Q^2(10)$	ARCH(10)
ANZ	7.682	0.240	0.612	0.137	-0.116	-0.023	9.364	**10356.5**	**59.07**	**1942.10**	**816.63**
CBA	9.377	0.210	0.879	0.118	-0.095	-0.088	8.289	**7158.5**	16.41	**2824.96**	**997.66**
NAB	3.643	0.236	0.247	0.160	-0.145	-0.406	11.890	**20375.2**	**49.93**	**1740.50**	**726.03**
WBC	7.390	0.228	0.616	0.086	-0.118	-0.159	6.623	**3381.2**	**30.06**	**3106.10**	**1146.10**
ABL	3.450	0.238	0.226	0.239	-0.215	-0.248	27.896	**158522.9**	**123.20**	**701.09**	**779.83**
BAB	5.383	0.270	0.358	0.255	-0.112	0.701	16.455	**46785.5**	**42.39**	**188.06**	**130.09**
BOQ	3.611	0.257	0.224	0.165	-0.200	-0.180	12.238	**21852.8**	12.83	**424.55**	**247.53**

Notes: The table presents the descriptive statistics of daily stock returns of Australian banks. The sample period spans 1 October 1994 to 31 December 2018. JB is the Jarque-Bera test for normality. Q(10) and $Q^2(10)$ are the Ljung-Box test statistics of the autocorrelation in returns and in standardized squared returns, respectively, with ten lags. ARCH(10) corresponds to the conditional heteroscedasticity test statistic with ten lags. Bold values of the test statistics denote the rejection of the null hypothesis at the 1% significance level, for each one of the tests.

Table 3
ARMA (1,0)-EGARCH (1,1) estimated parameters

	ANZ	CBA	NAB	WBC	ABL	BAB	BOQ
Const.	0.000	0.000**	0.000***	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	0.062***	0.066***	0.053***	0.053***	-0.077***	-0.058***	-0.051***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.011)	(0.012)	(0.012)
Const.	-0.137***	-0.142***	-0.112***	-0.101***	-0.740***	-0.154***	-0.090***
	(0.025)	(0.027)	(0.023)	(0.021)	(0.147)	(0.031)	(0.021)
β	0.984***	0.984***	0.987***	0.989***	0.880***	0.981***	0.989***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.015)	(0.004)	(0.003)
α	0.166***	0.168***	0.159***	0.137***	1.000**	0.143***	0.126***
	(0.014)	(0.013)	(0.013)	(0.012)	(0.481)	(0.013)	(0.011)
ξ	-0.040***	-0.030***	-0.028***	-0.035***	0.073	-0.024***	-0.006
	(0.009)	(0.008)	(0.008)	(0.008)	(0.061)	(0.008)	(0.008)
DoF	7.701***	7.594***	6.418***	10.419***	2.047***	4.516***	4.569***
	(0.640)	(0.654)	(0.421)	(1.372)	(0.046)	(0.282)	(0.253)
LogL	18015	18783	18283	18110	18555	17188	17576
AIC	-36015	-37551	-36551	-36205	-37096	-34363	-35139
BIC	-35968	-37504	-36504	-36158	-37049	-34316	-35092
Skewness	-0.334	-0.308	-0.823	-0.208	0.191	0.415	-0.711
Kurtosis	5.234	4.771	9.069	3.763	16.536	11.353	30.396
JB	1390***	898***	10109***	193***	46884***	18016***	192401***
Q (10)	8.695	12.961	6.598	10.712	17.005	20.076*	11.122
Q^2(10)	5.046	18.249	2.812	13.484	6.652	7.000	1.453
ARCH(10)	4.933	17.885	2.852	13.688	7.101	6.842	1.461

Notes: JB is the Jarque-Bera test statistic for normality. Q(10) and Q^2(10) are the Ljung-Box test statistics for autocorrelation in residuals and standardized squared residuals, respectively, with 10 lags. ARCH(10) denotes the conditional heteroscedasticity test statistic of the residuals with 10 lags. The notation ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively. The notation ***, **, and * on the diagnostic tests denote the rejection of null hypothesis of normality, no autocorrelation, and conditional homoscedasticity of the residuals at the 1%, 5%, and 10% level, respectively.

Table 4
Copula estimates

	ANZ	CBA	NAB	WBC	ABL	BAB	BOQ
			Panel A: Gaussian copula estimates				
ρ	0.723***	0.696***	0.710***	0.730***	0.101***	0.423***	0.419***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.003)	(0.003)
α	0.060***	0.034	0.044***	0.050***	0.015	0.021**	0.013
	(0.012)	(0.031)	(0.012)	(0.016)	(0.011)	(0.010)	(0.011)
β	0.911***	0.944***	0.939***	0.929***	0.574	0.976***	0.986***
	(0.019)	(0.060)	(0.020)	(0.026)	(0.299)	(0.013)	(0.013)
Log(L)	2508.22	2193.16	2401.67	2560.85	32.66	865.72	829.77
AIC	-5012.43	-4382.32	-4799.34	-5117.70	-61.32	-1727.44	-1655.54
			Panel B: *t*-Student copula estimates				
ρ	0.710***	0.673***	0.694***	0.715***	0.101***	0.420***	0.416***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.003)	(0.003)
DoF	6.325***	5.239***	6.268***	6.471	34.834***	8.818***	11.211***
	(0.474)	(0.372)	(0.460)	-	(8.743)	(1.455)	(1.603)
α	0.044	0.018	0.028**	0.011	0.015	0.013	0.011
	(0.044)	(0.014)	(0.014)	-	(0.012)	(0.019)	(0.009)
β	0.949***	0.981***	0.970***	0.989	0.579	0.987***	0.989***
	(0.060)	(0.018)	(0.018)	-	(0.294)	(0.022)	(0.010)
Log(L)	2677.01	2406.36	2551.16	2713.83	35.04	914.08	859.92
AIC	-5348.02	-4806.72	-5096.32	-5421.67	-64.087	-1822.16	-1713.84
			Panel C: Clayton copula estimates				
ρ	0.441***	0.418***	0.418***	0.434***	0.046***	0.242***	0.237***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
ω	0.240***	0.176***	0.473***	0.643***	-0.109	0.115***	0.082***
	(0.046)	(0.046)	(0.067)	(0.076)	(0.084)	(0.038)	(0.021)
α	-1.264***	-0.942***	-0.046***	-0.059	-0.162	-0.688***	-0.478***
	(0.246)	(0.240)	(0.006)	(0.068)	(0.229)	(0.241)	(0.125)
β	0.880***	0.901***	-1.001***	-0.991***	0.942***	0.941***	0.963***
	(0.028)	(0.032)	(0.000)	(0.023)	(0.016)	(0.022)	(0.010)
Log(L)	2086.28	1839.89	1800.57	1912.63	25.69	723.23	701.07
AIC	-4166.56	-3673.78	-3595.13	-3819.25	-45.40	-1440.45	-1396.14
			Panel D: SJC copula estimates				
ρ_U	0.520***	0.507***	0.503***	0.538***	0.001***	0.237***	0.222***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.003)	(0.002)
ρ_L	0.551***	0.528***	0.539***	0.532***	0.002***	0.279***	0.278***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.002)	(0.002)
ω_U	0.074	2.285	2.019	0.037**	-4.708	0.072***	0.054***
	(0.144)	(18.590)	(1.756)	(0.016)	-	(0.021)	(0.013)
α_U	-0.397	-10.000	-10.000	-0.195**	-1.388	-0.365***	-0.275***
	(0.785)	(79.125)	(8.777)	(0.087)	-	(0.107)	(0.065)
β_U	0.987***	0.178	0.473	0.994***	1.309	0.988***	0.991***
	(0.025)	(7.062)	(0.464)	(0.003)	-	(0.004)	(0.002)
ω_L	2.466	2.723***	2.702	2.205***	-2.139	0.757	0.304***
	(2.656)	(0.624)	(1.740)	(0.817)	-	(0.516)	(0.087)
α_L	-10.00	-10.00***	-10.00	-9.963***	-0.897	-3.917	-1.509**
	(9.790)	(2.895)	(7.377)	(3.485)	-	(2.776)	(0.453)
β_L	0.179	-0.210	-0.146	0.326***	3.304	0.743***	0.916***
	(0.961)	(0.256)	(0.616)	(0.293)	-	(0.191)	(0.025)
Log(L)	2545.53	2260.93	2391.92	2545.98	35.24	890.33	831.04
AIC	-5079.06	-4509.88	-4771.85	-5079.97	-58.48	-1768.66	-1650.08

Notes: Panels A, B, C, and D report the estimates of the time-varying Gaussian copula, *t*-Student-copula, Clayton copula, and SJC copula, respectively, between the underlying banks and their corresponding indices. The standard errors are presented in the parenthesis. The symbols ***, **, and * indicate statistical significance of the coefficient at the 1%, 5%, and 10% level, respectively.

Table 5
VaR, CoVaR, and ΔCoVaR estimates

	Whole sample	Pre-crisis	Crisis	Post-crisis	Test of difference		
	(1)	(2)	(3)	(4)	(2) – (3)	(3) – (4)	(2) – (4)
			Panel A: VaR				
ANZ	-0.022	-0.021	-0.035	-0.021	**19.18**	**-19.02**	0.16
CBA	-0.020	-0.018	-0.031	-0.019	**20.00**	**-18.91**	**4.36**
NAB	-0.022	-0.020	-0.036	-0.021	**22.04**	**-20.27**	**6.66**
WBC	-0.022	-0.020	-0.034	-0.022	**20.40**	**-18.34**	**7.74**
ABL	-0.023	-0.022	-0.026	-0.023	**11.91**	**-8.95**	**5.83**
BAB	-0.025	-0.024	-0.040	-0.024	**32.33**	**-30.29**	**5.29**
BOQ	-0.023	-0.020	-0.036	-0.024	**28.21**	**-20.38**	**25.76**
F-statistic (Major banks)	**133.23**	**156.69**	**10.46**	**87.77**			
F-statistic (Reg. banks)	**192.69**	**234.11**	**231.31**	**25.73**			
F-statistic (All banks)	**272.54**	**258.89**	**54.24**	**240.59**			
			Panel B: CoVaR				
ANZ	-0.027	-0.026	-0.034	-0.026	**19.18**	**-19.02**	0.16
CBA	-0.029	-0.028	-0.038	-0.029	**20.00**	**-18.90**	**4.36**
NAB	-0.027	-0.025	-0.035	-0.026	**22.04**	**-20.27**	**6.66**
WBC	-0.028	-0.027	-0.036	-0.028	**20.40**	**-18.34**	**7.74**
ABL	-0.024	-0.024	-0.025	-0.024	**11.91**	**-8.86**	**5.83**
BAB	-0.026	-0.025	-0.032	-0.026	**32.34**	**-30.25**	**5.29**
BOQ	-0.026	-0.025	-0.031	-0.026	**28.21**	**-20.35**	**25.76**
F-statistic (Major banks)	**306.51**	**344.87**	**12.77**	**221.67**			
F-statistic (Reg. banks)	**924.75**	**398.98**	**461.05**	**616.25**			
F-statistic (All banks)	**687.05**	**582.76**	**142.36**	**363.18**			
			Panel C: ΔCoVaR				
ANZ	-0.014	-0.013	-0.022	-0.013	**19.18**	**-19.02**	0.16
CBA	-0.016	-0.014	-0.024	-0.015	**20.00**	**-18.91**	**4.36**
NAB	-0.014	-0.012	-0.022	-0.013	**22.04**	**-20.27**	**6.66**
WBC	-0.015	-0.014	-0.023	-0.015	**20.40**	**-18.34**	**7.74**
ABL	-0.005	-0.005	-0.005	-0.005	**11.91**	**-8.95**	**5.83**
BAB	-0.009	-0.009	-0.015	-0.009	**32.34**	**-30.29**	**5.29**
BOQ	-0.009	-0.008	-0.014	-0.010	**28.21**	**-20.37**	**25.76**
F-statistic (Major banks)	**183.56**	**209.55**	**6.94**	**143.71**			
F-statistic (Reg. banks)	**5426.91**	**3820.75**	**915.14**	**3409.49**			
F-statistic (All banks)	**4615.20**	**4706.50**	**363.52**	**2741.79**			

Notes: Panels A, B, and C report the VaR, CoVaR, and ΔCoVaR estimates, respectively. Bold values of the test statistics represent statistical significance at the 1% level.

Table 6
VaR, CoVaR, and ΔCoVaR estimates for various frequency horizons

	Short-term	Medium-term	Long-term		Test of difference	
	(1)	(2)	(3)	(1) – (2)	(2) – (3)	(1) – (3)
			Panel A: VaR			
ANZ	-0.0143	-0.0062	-0.0039	**-87.16**	**-35.95**	**-109.46**
CBA	-0.0124	-0.0059	-0.0035	**-74.97**	**-40.31**	**-106.04**
NAB	-0.0136	-0.0058	-0.0033	**-79.57**	**-42.15**	**-106.53**
WBC	-0.0141	-0.0065	-0.0041	**-84.36**	**-36.98**	**-108.53**
ABL	-0.0144	-0.0042	-0.0020	**-84.87**	**-51.71**	**-106.04**
BAB	-0.0174	-0.0069	-0.0027	**-90.22**	**-55.59**	**-137.95**
BOQ	-0.0158	-0.0065	-0.0020	**-84.43**	**-71.42**	**-140.97**
F-statistic (Major banks)	**116.84**	**37.79**	**98.52**			
F-statistic (Reg. banks)	**216.49**	**641.60**	**285.46**			
F-statistic (All banks)	**310.04**	**269.93**	**671.40**			
			Panel B: CoVaR			
ANZ	-0.0175	-0.0062	-0.0031	**-196.46**	**-71.25**	**-245.76**
CBA	-0.0172	-0.0067	-0.0026	**-173.07**	**-98.06**	**-263.48**
NAB	-0.0169	-0.0060	-0.0025	**-184.62**	**-93.04**	**-251.05**
WBC	-0.0177	-0.0072	-0.0043	**-174.47**	**-54.73**	**-210.71**
ABL	-0.0147	-0.0049	-0.0022	**-524.30**	**-138.68**	**-651.96**
BAB	-0.0178	-0.0054	-0.0016	**-297.69**	**-140.48**	**-444.57**
BOQ	-0.0173	-0.0055	-0.0016	**-302.06**	**-150.07**	**-450.39**
F-statistic (Major banks)	**47.83**	**220.77**	**999.89**			
F-statistic (Reg. banks)	**3260.45**	**274.56**	**1701.98**			
F-statistic (All banks)	**617.50**	**670.42**	**1960.71**			
			Panel C: ΔCoVaR			
ANZ	-0.0085	-0.0041	-0.0026	**-76.97**	**-35.58**	**-101.91**
CBA	-0.0085	-0.0044	-0.0020	**-66.42**	**-57.47**	**-116.02**
NAB	-0.0080	-0.0037	-0.0020	**-73.77**	**-45.01**	**-105.47**
WBC	-0.0088	-0.0049	-0.0037	**-63.21**	**-23.60**	**-79.43**
ABL	-0.0017	-0.0015	-0.0013	**-9.02**	**-12.31**	**-21.13**
BAB	-0.0060	-0.0026	-0.0007	**-83.83**	**-68.21**	**-146.59**
BOQ	-0.0056	-0.0027	-0.0008	**-74.21**	**-71.41**	**-136.47**
F-statistic (Major banks)	**35.67**	**227.97**	**910.06**			
F-statistic (Reg. banks)	**6667.21**	**819.45**	**939.42**			
F-statistic (All banks)	**3532.78**	**1561.64**	**2443.83**			

Notes: Panel A, B, and C report the VaR, CoVaR, and ΔCoVaR estimates, respectively. Bold values of the test statistics represent statistical significance at the 1% level.

Table 7

Determinants of systemic risk

Variable	Dependent variable: ΔCoVaR_{it} Model 1	Dependent variable: ΔCoVaR_{it} Model 2	Dependent variable: Short-term ΔCoVaR_{it} Model 1	Dependent variable: Short-term ΔCoVaR_{it} Model 2	Dependent variable: Medium-term ΔCoVaR_{it} Model 1	Dependent variable: Medium-term ΔCoVaR_{it} Model 2	Dependent variable: Long-term ΔCoVaR_{it} Model 1	Dependent variable: Long-term ΔCoVaR_{it} Model 2
Constant	-4.783***	-9.393***	-1.719***	-4.181***	-1.187***	-0.708	-0.614	0.334
	(-4.57)	(-3.91)	(-2.95)	(-3.44)	(-2.83)	(-1.61)	(-0.98)	(0.47)
VaR	0.338***	0.333***	0.318***	0.314***	0.317***	0.349***	0.323***	0.310***
	(6.34)	(7.45)	(6.03)	(6.69)	(3.13)	(4.46)	(6.04)	(5.71)
Size	0.471***	0.925***	0.156*	0.404***	0.067	0.076	0.013	-0.071
	(2.96)	(4.29)	(1.68)	(3.90)	(1.20)	(1.38)	(0.15)	(-0.88)
Leverage	0.094***	0.046*	0.046***	0.019	0.019***	0.010*	-0.007	-0.001
	(4.03)	(1.85)	(3.54)	(1.38)	(3.64)	(1.98)	(-0.72)	(-0.08)
Liquidity	0.007*	0.009**	0.003	0.004*	0.004**	0.002	0.004**	0.004*
	(1.97)	(2.44)	(1.56)	(1.97)	(2.33)	(1.58)	(2.02)	(1.67)
Capital adequacy	-0.065*	0.003	-0.020	0.015	-0.019*	-0.018	0.008	0.001
	(-1.66)	(0.17)	(-0.90)	(1.43)	(-1.89)	(-1.58)	(0.44)	(0.08)
Profitability	0.761***	0.426**	0.324***	0.150	-0.149	-0.002	-0.121	-0.009
	(3.31)	(2.15)	(2.64)	(1.36)	(-1.13)	(-0.03)	(-1.03)	(-0.06)
Funding structure	0.002	0.023*	-0.001	0.010	0.010***	0.006**	0.005	-0.000
	(0.21)	(1.72)	(-0.34)	(1.37)	(2.71)	(2.20)	(1.21)	(-0.04)
GDP growth rate		-0.237***		-0.118***		-0.066***		-0.028
		(-3.08)		(-3.13)		(-3.07)		(-1.26)
Cash rate		0.269***		0.144***		0.001		-0.041***
		(3.48)		(3.68)		(0.10)		(-2.67)
Exchange rate		-0.011		-0.005		-0.004		0.001
		(-1.07)		(-0.90)		(-1.40)		(0.32)
Housing price		0.006*		0.002		-0.006***		-0.000
		(1.92)		(0.98)		(-5.10)		(-0.18)
Adjusted R^2	0.560	0.696	0.534	0.672	0.300	0.479	0.281	0.301

Notes: The dependent variable is the semiannual aggregated ΔCoVaR_{it}. Model 1 includes only idiosyncratic bank-specific lagged variables. Model 2 includes both bank-specific and market-wide lagged variables. VaR is the lagged VaR. Size is the natural log of the book value of assets; Leverage is the ratio of total asset to book value of equity; Liquidity is the ratio of total loan to total deposit; Capital adequacy ratio is the ratio of tier I capital to risk-adjusted assets; Profitability is the return on asset; Funding structure is the ratio of total deposit to total asset; GDP growth is the growth rate of constant dollar GDP; Cash rate is the RBA cash reserve rate; Exchange rate change is the change in exchange rate between the Australian dollar and the New Zealand dollar; and Housing price growth is the growth rate in Australia-DataStream Real Estate price index. Newey-West standard errors with up to 5 periods of autocorrelation are in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Figure 1
Time-trends of VaR, CoVaR, and ΔCoVaR

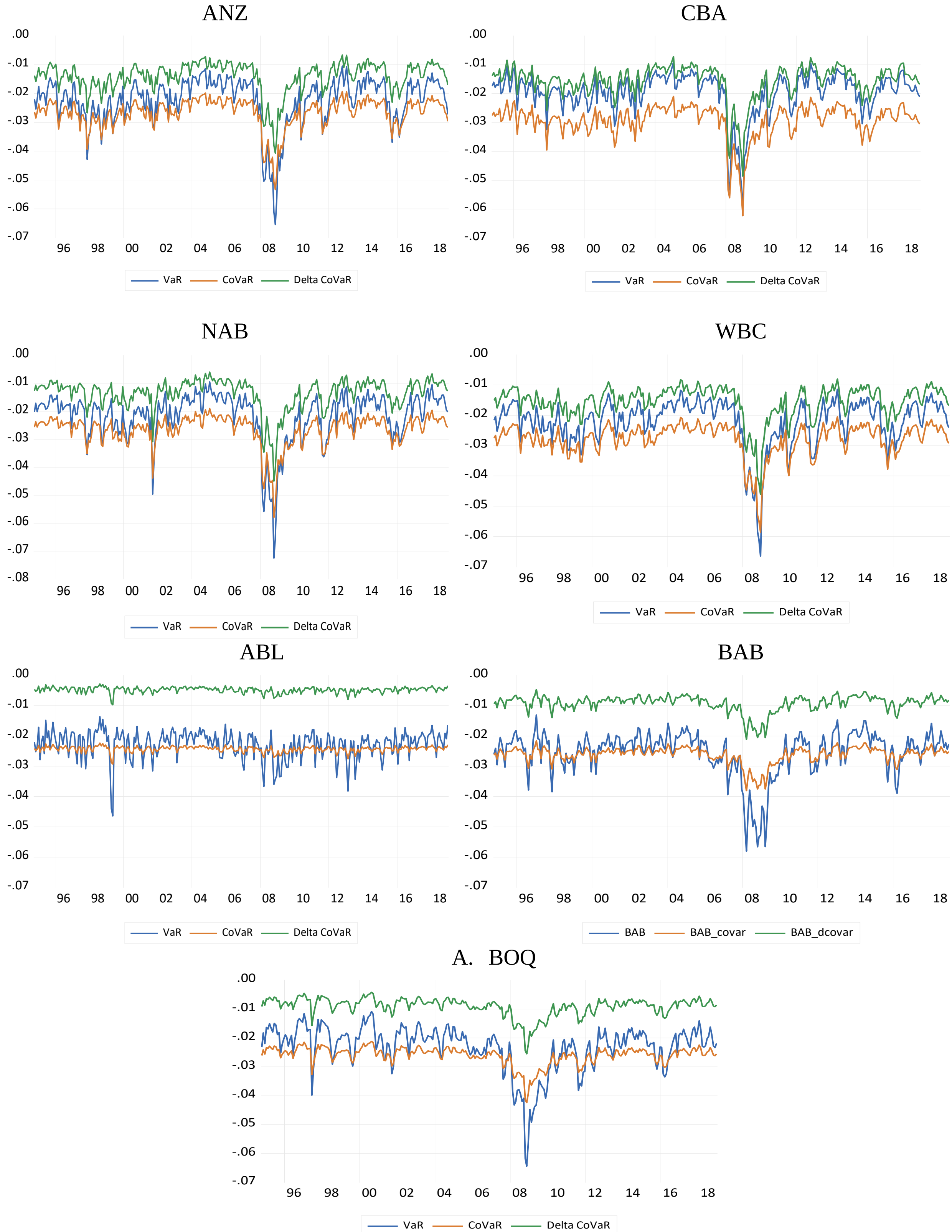

Figure 2

Time-frequency development of ΔCoVaR for different frequencies