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Is bank risk appetite relevant to bank default in times of Covid-19?

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Is bank risk appetite relevant to bank default in times of Covid-19?

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ABSTRACT

The paper aims to analyze the effect of bank risk appetite on banks' default probabilities during the year of COVID-19 in 12 countries while controlling for bank-specific and country-specific effects over time. A System Generalized Methods of Moments (GMM) model of default probabilities is estimated over the periods 2010—2021. This study confirms the 'risk-mitigation view', in which banks with higher ESG scores are more prudent in lending and have better relationship management, reducing the probability of bank default. Underperforming banks tend to have a higher portion of risky loans in their credit portfolio and therefore demonstrating a higher default propensity. Bank risk appetite, ESG, asset quality, economic growth, and currency depreciation appear to be material drivers for bank risk. We find that a lower risk appetite ratio (corresponding to higher risk appetite) is associated with higher estimated default probability during the COVID-19 outbreak, identified through interaction with a single time dummy for 2020 (the break-out year of the pandemic).

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1. Introduction

Financial institutions adjust their portfolios based on changing risk appetite in response to macroeconomic swings. Bank risk appetite has garnered more attention during crises. According to Kerma (2016), risk appetite is defined as the types and total risks accepted by a bank to meet its strategic and corporate strategies while satisfying capital adequacy requirements and credit needs. Setting risk appetite can be referred to as establishing boundaries for credit risks stemming from a bank's business divisions, product lines, customers, regions, and industries. Appropriate risk appetite helps to maximize shareholder wealth by balancing risk and reward.

Under Basel II, Central Bank should make sure banks have a risk management framework to define and communicate risk appetite. Risk appetite figures and limits are often unclear in banks' annual reports. Research is thus warranted to quantify risk appetite, considering the expected and unexpected components of credit loss of an institution. The objective of the study is to investigate the effect of risk appetite on credit default probabilities of banks in emerging ASEAN countries and their partners which signed the Regional Comprehensive Economic Partnership (RCEP) that is effective on January 1, 2022. RCEP is the world largest trade bloc that creates free trade zone among the member countries. Increased trade flows from the RCEP accelerate bank growth opportunities in financing. An investigation into credit risk appetite and bank stability may shed light on the sustainability of growth in emerging ASEAN and its partners. This study employs a sample of 202 publicly traded banks in Malaysia, Indonesia, Singapore, South Korea, China, Australia, Japan, New Zealand, Thailand, Vietnam, the Philippines, and Laos.

The remainder paper proceeds as follows. Section 2 provides a background of risk appetite. Section 3 reviews related literature. Section 4 describes data gathering processes, sample selection, and empirical strategy. This is followed by a discussion of results in Section 5. The last section concludes the research.

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2. Risk appetite statement

Although the banking industry needs to maintain sufficient capitalization and is closely supervised by regulators, banks differ substantially in their risk appetites. There are three generations of a risk appetite statement (RAS), with the first generation focusing on qualitative disclosure, while second-generation combines both qualitative and quantitative disclosure in financial reports. The third generation of RAS focuses on developing forward-looking risk appetite measures. Developed markets such as Singapore and Hong Kong are in the second or third generation, while most of the emerging ASEAN members including China, Indonesia, Malaysia, and Thailand are still in the first stage of RAS (Wyman, 2015).

RCEP members have varied risk appetite ratios for credit losses with several economies having gone further in risk appetite monitoring and reporting. For instance, based on the calculation of this study, there is a substantial discrepancy in risk appetite ratios within and across countries in the sample. The computation of the risk appetite ratio is explained in detail in Section 4.2.2. Thailand has the lowest average risk appetite ratio (-13.4%) over 11 years (2010-2021) while, Australia and South Korea recorded positive and high risk appetite ratios of 11.5% and 7.4%, respectively. Japanese banks have slightly negative risk appetite ratio of -2.3%. Further, the average risk appetite for Malaysia, Singapore, Indonesia, the Philippines, and China ranges between 1% and 5%. Nonetheless, the dispersion around the mean for Indonesia (11.1%) and Thailand (12.1%) is higher compared to the other countries. reflecting the risk appetite of domestic banks within the same country varies greatly.

Figs. 1 and 2 depict the average risk appetite ratio for each sample country for the period of 2010—2021. Risk appetite ratio is computed as revenue minus operating expenses, excluding expected loss (the numerator) divided by unexpected losses of a bank (the denominator). The country risk appetite ratio is calculated as the equal-weighted average of the sum of risk appetite ratios for all the public listed banks for a particular country in a year. Risk appetite is more volatile in Indonesia, and all countries experienced a decline in risk appetite ratios when the coronavirus outbreak took place in 2020.

Based on Fig. 2, it can be observed that the risk profile of developed markets are quite different from developing countries, with almost all countries having positive risk appetite ratios, except Japanese banks. Identically, all major listed banks observed a decrease in risk appetite ratios when Coronavirus affected the whole world economy in 2020.

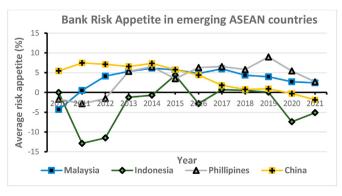


Fig. 1. Average bank risk appetite of emerging ASEAN countries.

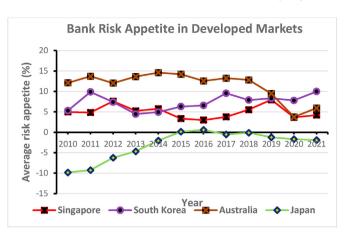


Fig. 2. Average bank risk appetite in advanced markets.

3. Literature and hypothesis development

3.1. Bank default likelihood

Default risk is commonly measured using CDS spread, Merton's standard option pricing model, and accounting-based models, including Altman z-score and other accounting-based z-scores for example, the sum of the ROA and the equity-to-total asset ratio scaled by the return volatility. Higher z-scores imply higher bank stability or lower insolvency risk. It is used extensively in measuring bank default, for instance in Ghenimi et al. (2017), Salami (2018), Di Tommaso and Thornton (2020), Oino (2021), among others.

A ratio between equity and total assets is used as a proxy variable of bank solvency in Vodová (2019), as he advocates higher capital buffer is associated with lower insolvency rates. De Mendonça and de Moraes (2018) calculate credit risk based on two measures: expected bank losses measured by a loan loss provision-to-gross loan ratio and delayed expected loan losses gauged by non-performing loan ratios. In the latest research conducted using a sample of South Korean banks, Aldasoro et al. (2022) employ regulatory capital as the proxy variable for insolvency risk.

To summarize, extant studies investigate bank risk-taking behavior, but the proxy variables used differ largely. Existing research use proxies such as volatility of ROA (García-Kuhnert et al., 2015; Mourouzidou-Damtsa et al., 2019), risk assets-to-total assets ratio (Delis and Kouretas, 2011), regulatory capital measured by core capital ratios, total risk-based capital ratios, and equity-to-total asset ratios (Vodová, 2019; Aldasoro et al., 2022), credit risk measures such as impaired loan ratios, non-performing loan-to-total asset ratios, and loan loss reserve ratios (see Mio et al., 2022), insolvency risk measured by z-scores (Aljughaiman and Salama, 2019; Teixeira et al., 2020; Mio et al., 2022), the CDS spread (Drago et al., 2019; Di Tommaso and Thornton, 2020), and Merton's distance-to-default (DD) (Chiaramonte et al., 2021; García et al., 2022; Jo et al., 2022).

Even though z-scores are the common financial metric for insolvency risk, book value rather than market value information is used in calculating z-scores. To complement, the Merton model relies on a market-based approach and is one of the key models to evaluate default risk (Chiaramonte et al., 2021).

Merton's distance-to-default (DD) is a complete measurement of bank fragility, as it includes three main factors, namely market value of assets, asset volatility, and debt in constructing DD. Increased DD decreases the default probability of a bank. To compute the probability of default, the market value and volatility

of the bank assets are estimated. Then, the distance-to-default for each bank is computed. Lastly, the distance-to-default is scaled to determine the expected default probabilities of a bank. One-year-ahead default probabilities data is readily available from the Bloomberg database and is used in a recent study (see Chiaramonte et al., 2021).

Consistent with García et al. (2022), default probabilities over the next year sourced from Bloomberg are employed as the dependent variable to measure a bank's insolvency risk.

3.2. Risk appetite and bank default likelihood

Financial institutions vary in their business models and assume risks in granting loans, advances, and financing to consumers and businesses, trading, processing, and managing wealth. A bettergoverned bank undertakes risks within its risk capacity and risk limit. Risk appetite refers to the amount of risk that a company is willing to take on in pursuit of earnings growth and business objectives. Having a risk appetite statement and framework allows regulators, stakeholders, and rating agencies to articulate a bank's risk profile (Gontarek, 2016).

Typical RAS encompasses three risk areas, namely operational, market, and credit risk. The risks can be measured qualitatively or quantitatively by various ratios and through stress testing. Risk appetite is relevant to many corporate decisions, including mergers and acquisitions, compensation plans, product development, and capital planning. Banks revise their risk appetite regularly to reflect changes in share prices, regulation and credit policies (Gontarek, 2016).

Banks with lower risk appetite ratios which generate insufficient earnings to cover potential losses, seek to expand their lending activities more rapidly and may experience larger risk exposure. On the contrary, banks with a positive risk appetite ratio, are more conservative and cautious in granting loans, advances, and financing to customers. A lower risk appetite ratio may infer banks engaging in risky lending practices, such as having lax lending criteria and procedures to approve loans more rapidly than other competing banks.

Following this line of reasoning, riskier lending leads to large risk exposure and thus results in a higher bank default likelihood. Also, bank risk appetite is interacted with the Covid-19 year dummy to test the differential impacts of time effect and risk appetite on default risk. It is hypothesized that a lower risk appetite ratio contributes to a higher default probability.

H1. Bank risk appetite is negatively associated with default likelihood

3.3. Environmental, social, and governance (ESG)

There are two competing views of ESG. Under the 'risk mitigation view', corporate social responsibility (CSR) that is captured by ESG scores is viewed positively as it creates moral capital and goodwill among company stakeholders. In contrast, the overinvestment theory views CSR negatively as more CSR activities imply managerial entrenchment or agency problems. Managers over-invest in CSR for their benefits and reputation, rather than for stakeholder interest (Chiaramonte et al., 2021).

In analysing default risk, Switzer et al. (2018) focus on the internal corporate governance mechanism and document a significant positive relation between governance and solvency. Using a sample of European banks, high ESG performance is found to significantly explain bank risk proxied by z-scores, CDS spread, and non-performing loan ratios (Di Tommaso and Thornton, 2020). Di Tommaso and Thornton (2020) advance the statistical

significance of the ESG variable indicating that ESG governance is effective in curbing excessive risk-taking by banks. In addition to that, Tobin's Q ratios, and capital and share price all decline with banks' ESG scores. Several empirical research link bank profitability with ESG (Gangi et al., 2019; Nizam et al., 2019).

Many empirics, however, focus only one aspect of ESG on bank risks, such as environmental friendliness (Gang et al., 2019) and shareholder friendliness (Anginer et al., 2018). But, Chiaramonte et al. (2021) examine the effect of ESG composite scores, its pillars, and sub-components on bank stability. ESG is only significant in affecting bank stability when the variable interacted with the financial crisis dummy (Chiaramonte et al., 2021).

Consistent with the 'risk mitigation view' (Bouslah et al., 2018; Chiaramonte et al., 2021), we conjecture a negative relationship between ESG scores and the default likelihood as higher ESG is associated with greater market trust towards banks. Banks with higher ESG scores tend to have lower overall risk, due to more prudent lending and investment and sustainable business practices. In this paper, the composite ESG scores retrieved from the Bloomberg database are based on a wide array of sustainability topics, which include a diversity of the workforce, consumption of resources, and governance structure.

H2. ESG scores are negatively associated with default likelihood

3.4. Profitability and bank default likelihood

A bank with lower earnings tends to provide advances and financing to riskier borrowers to raise the profit margin. Prior research agrees on a negative relationship between banks' earnings and credit risk (Swamy, 2012; Kjosevski et al., 2019).

According to the mismanagement theory, loan quality reflects management quality. When a bank is poorly managed and inefficient, they tend to have poorer profitability and is more likely to have higher default risk. The mismanagement theory was confirmed in Vithessonthi (2016). Schulte and Winckler (2019), using a large dataset of banks and microfinance institutions (MFIs), report a negative ROA-NPL ratio nexus for both banks and MFIs. By employing the ARDL model on non-performing loans, the coefficient on ROA on NPLs is two-fold larger for NPLs to corporations than for households (Kjosevski et al., 2019). Results in Kjosevski et al. (2019) lend support to Louzis et al. (2010) that profitable banks tend to exclude risky loans in their loan portfolios. A lossmaking bank is inclined to be more aggressive in risk-taking to compensate for the bank's underperformance.

Profit level has a positive and significant influence on bank risk-taking when the latter is measured by the risk assets-to-total assets ratio, but the relationship turned negative when bank risk is measured by non-performing loans ratios in Delis and Kouretas (2011). Likewise, in a recent study, ROE is reported as positive in impacting bank insolvency (Oino, 2021).

We predict an unprofitable bank proxied by a lower ROE reacts more to moral hazard incentives by providing risky loan advances, deteriorating bank solvency consequently.

H3. ROE is negatively associated with default likelihood

3.5. Impairment charges and bank default likelihood

High uncollectible and problematic loans raise the probability of default among banks. Based on extant literature, this paper expects a negative connection between impairment loss and default likelihood. Higher loan impairment charges infer the loan quality has deteriorated. Banks increase their impairment losses in anticipation of a greater amount of non-performing loans in the future. This reduces current profit and drives bank default. Loan impairment

serves as a proxy for loan quality and poorer loan quality is found to link with greater bank default risk (Teixeira et al., 2020). Consistent with previous studies (Lee et al., 2014; Teixeira et al., 2020), a positive relationship is expected between poor asset quality and default likelihood. The quality of credit portfolios is gauged by the ratio between impaired loan charges and net revenue in this paper.

H4. Loan impairment charges-to-net revenue ratio is positively associated with default likelihood

3.6. Economic growth and bank default likelihood

A country with better economic performance measured in GDP growth is associated with lower insolvency risks in prior works (Kjosevski et al., 2019; Baselga-Pascual et al., 2015; Köhler, 2015). Sluggish country growth is associated with higher bank risk captured by higher non-performing loan ratios and lower average z-scores¹ for banks (Schulte and Winkler, 2019). In a recent study, GDP growth turned insignificant in modelling insolvency when the latter is captured by NPL for the sample of microfinance institutions (MFIs) (Schulte and Winckler, 2019).

Higher GDP growth is statistically significant in reducing bank distress levels measured by the capital-to-total assets ratio among Romanian banks (Vodová, 2019). Recent literature confirms the inverse relationship between growth rate and bank risk (Teixeira et al., 2020).

Different from most studies, Ashraf et al. (2017) explains a positive coefficient on GDP growth because countries experiencing rapid growth and high inflation engage in a high level of speculative lending funded by short-term debt, triggering higher chances of bank default. Similarly, Delis and Kouretas (2011) show economic growth has positive and significant explanatory power in bank risk-taking. This study expects a negative correlation between real GDP growth and a bank's default likelihood.

H5. Economic growth is negatively associated with default likelihood.

3.7. Exchange rates and bank default likelihood

A decrease in real effective exchange rate infers a decline in domestic currency. Currency depreciation reduces the net value of imported-oriented corporations. These corporate borrowers may borrow more to finance larger liabilities denominated in foreign currencies. If the corporate borrowers fail to reconcile their debt obligations to lenders, banks will face higher default risk due to the high amount of bad debt written off. Higher exchange rate risk is found to increase non-performing loans for sample banks and MFIs in 106 countries (Kjosevski et al., 2019).

This study hypothesizes a negative change in nominal effective exchange rate (NEER) raises bank distress. Due to domestic currency depreciation relative to foreign currencies, banks with higher external debt that is not perfectly hedged experience a decline in its net worth, leading to a higher default probability. Negative change in NEER diminishes firm-level investment (see Garralda and Sousa, 2017). Non-repayment of corporate borrowers further curtail the equity position of a bank.

H6. A negative change in nominal effective exchange rate is associated with a higher default likelihood

3.8. Inflation and bank default likelihood

Kjosevski et al. (2019) find a positive and significant nexus between changes in consumer prices and financial distress for banks in 106 countries, but the relationship turned negative for sample MFIs. Inflation is significantly and positively correlated to nonperforming loans level in Serbian Banks (Otaševic, 2013), but the coefficient of inflation is negatively correlated to NPLs in Macedonian banks (Kjosevski et al., 2019). Negatively significant inflation on NPLs on household borrowers is shown in Kjosevski et al. (2019). In examining 567 public banks across the US and Europe, inflation is statistically significant in raising bank default risk measured in asset prices (Texeira et al., 2020). Nonetheless, when bank default is gauged by an alternative proxy -z scores, the coefficient sign of inflation turned negative and significant.

Prolonged inflation is bad for bank stability in the long run. We conjecture a positive correlation between inflation rate and credit risk. The hypothesis can be specified as follows:

H7. Inflation is positively associated with default likelihood

3.9. Dividend policy

There are two opposing views of dividend policy on financial distress. While the signalling role of dividend suggests a stronger dividend payment reflects a lower bank risk, wealth distribution indicates higher dividend pay-out is linked to greater default risk.

Under the information content or signalling hypothesis, managers send signals about the firm's quality and earnings growth through increased dividends. There is an opposite relation between dividend pay-out ratios and default risk. Banks tend to smooth dividend payments and only resort to dividend reduction as a last resort (Haq and Heaney, 2012). Tripathy et al. (2021) lend support to the information content hypothesis by proving dividend pay-out has a positive influence on future financial health. Likewise, Pathan et al. (2021) affirm that banks with a greater proportion of long-term shareholdings use dividend payments to curb managerial entrenchment.

Different from the information content hypothesis, the proponents of the wealth redistribution view advocate that dividend payment reduces retained profits and increase a company's reliance on external financing, placing a greater risk on existing debtholders. Onali (2009) supports the wealth redistribution hypothesis. They find banks with larger pay-outs are incentivized to take more risk, and thus face escalated default risk.

Kroen (2022), in analysing dividend pay-out restrictions imposed in the COVID-19 period, advance that higher dividend payouts are associated with more aggressive and risky lending. Moreover, Chen et al. (2019) state that firms with worsening credit health tend to pay a dividend from unrealized earnings because once financial distress is made known to the public, dividend declaration is prohibited. By employing propensity score matching, Chen et al. (2019) infer wealth is transferred from debtholders to equity-holders by showing a linkage between larger dividend payouts and higher subsequent default likelihood. Firms entering the debt restructuring process following dividend declaration are evidenced in Chen et al. (2019).

During the global financial crisis of 2007–2009, banks and finance companies continue to pay dividends despite suffering high net losses. Excessive dividends are associated with greater default likelihood. Dividend payment increases bank fragility as evidenced in Acharya et al. (2017). Dividends make it harder for firms to build up a capital buffer, leading to greater credit risk (Acharya et al., 2011; Kanas, 2013).

In line with the information content hypothesis, this study

 $^{^1}$ A higher z score indicates a lower insolvency risk and a higher bank stability. It is computed as: [ROA+(Equity/Total assets)/ σ (ROA)]. It is commonly used for unlisted banks when market valuation is unavailable.

posits banks with higher dividend pay-out have higher earnings growth and are thus less likely to default.

H8. Dividend pay-out is negatively associated with default likelihood.

4. Sample, variable measurement, and methodology

This section briefly explains the measurement of variables of interest, describes the data and sample selection process and elaborates the empirical strategy.

4.1. Sample description and selection

This research intends to include all publicly traded banks in 15 RCEP members, but public banks' data are not available for three countries, namely Brunei Darussalam, Myanmar, and Cambodia, since banks in Brunei and Myanmar are privately owned. Apart from that, the sole publicly traded bank in Cambodia, Acleda Bank has no data on one-year default probabilities, and hence was excluded. Major Vietnamese banks reported their Tier 1 and Tier 2 capital from 2019 onwards, and hence risk appetite ratios are unavailable for earlier years.

After all, the final sample consists of 202 domestic listed banks in the remaining 12 RCEP countries including Malaysia (10), Indonesia (16), Singapore (3), South Korea (8), China (37), Australia (6), Japan (84), New Zealand (1), Thailand (8), Vietnam (18), the Philippines (10), Laos (1). Data employed are annual observations over 11 years, ranging from 2010 to 2021.

The list of banks was identified from AsianBanks.net and Bloomberg. All data on the dependent variable, 1-year default probabilities, and independent variables were retrieved from the Bloomberg database.

Nonetheless, the total risk-based capital that is needed to compute the focal variable, risk appetite ratio was missing for most of the Japanese banks in the Bloomberg. Therefore, we hand-collected capital adequacy information from the 'disclosure items regarding the composition of equity capital' on the individual Japanese banks' websites. Many Japanese banks keep regulatory capital data up to 10 years on the web.

4.2. Variable measurement

4.2.1. Dependent variable: default probabilities

Bloomberg's one-year-ahead probability of bank defaulting is employed as dependent variable consistent with Dunham and Garcia (2021) and Sclip et al. (2021). The Bloomberg's DRSK module uses historical default rates to forecast real-world default likelihood. Additionally, Merton's methodology is used to derive distance-to-default measure.

4.2.2. Focal independent variable: risk appetite

Risk appetite is commonly expressed in value-at-risk (the sum of expected loss and unexpected loss), amount of debt outstanding, and capital amount. A bank's loan loss distribution can be split into expected loss and unexpected loss. While expected losses refer to average losses resulting from operation covered by loan loss reserves, unexpected losses is above-average losses that should be covered by total risk-based capital determined by Basel.

Following the Basel II Pillar 3 report of Deutsche Bank (Malaysia) Berhad (2019), this study uses expected losses resulting from credit risk and operational risk within a year estimated by banks based on their loss history and external benchmarks. Expected loss calculations are incorporated in the allowance for credit losses which can be found in the explanatory notes of financial statements.

Following Citigroup (2017), the risk appetite ratio for each bank over the years is measured based on the following formula:

Risk appetite ratio= (Revenue-operating expenses-expected loss)/ unexpected loss x 100 (1)

Although both expected losses (covered by loan loss reserves) and unexpected losses (covered by regulatory capital) are commonly used (see FASB, 2016; BCBS, 2017), risk appetite ratio is biased if the unexpected loss is calculated imprecisely. Baviera (2022) finds the regulatory capital calculated using the internal-ratings based (IRB) approach is under-estimated and suggests an incremental capital charge to be added to the regulatory capital amount.

In this study, loan loss reserves and regulatory capital (total risk-based capital) are used as proxies for expected losses and unexpected losses, respectively. A higher unexpected loss indicates a lower risk appetite ratio since more risk-weighted capital need to set aside by the bank to cover riskier loans or larger credit exposure. A higher risk appetite ratio exceeding one is desirable.

Put differently, a positive and higher risk appetite ratio means the net core earnings including reserve for loan losses (the numerator) exceed the regulatory capital (the denominator) of a bank. A higher risk appetite ratio implies lower risk-taking with greater revenue generating ability to cover potential losses. When a bank's reserve for loan losses and operating expenses are more than its net revenue, it results in a negative risk appetite ratio. This also implies a higher bank risk-taking behaviour due to higher provisioning and worsen asset quality.

4.3. Research method

4.3.1. Dynamic panel data model

To determine the factors affecting bank default probability, the system Generalized Method of Moments (GMM) approach (Arellano and Bover, 1995; Blundell and Bond, 1998) is employed to control for the country's unobserved heterogeneity and simultaneity bias. Country dummies cannot be used due to the dynamic nature of the data. By employing System GMM, the regressions in levels are estimated together with the regressions in differences. Specifically, in system GMM, variables in levels are instrumented with lags of their differences, and differenced variables are instrumented with lags in levels.

This paper uses Stata software to estimate the xtabond2 written by Roodman (2009). Standard errors for the two-step system GMM are corrected by implementing Windmeijer's procedure using the xtabond2 program. Aside from that, orthogonal deviation rather than first-differencing is specified in system GMM to preserve the sample size. Different from first-differencing, the orthogonal deviation method deducts the mean of all the available future observations from the current observation (Roodman, 2009).

To ensure the consistency of GMM estimates, two specification tests are used to examine the over-identification of all the instruments, which are the Sargan test and the Hansen test. Although the Xtabond2 program reports both Sargan and Hansen test statistics, the former is non-robust to serial correlation and heteroskedasticity. Therefore, for the two-step variant, the Hansen-J statistic is reported. The failure to reject the null hypothesis of the Hansen test suggests the instruments are jointly valid. For the Arellano-Bond serial correlation test, one should fail to reject the null of no first-order serial correlation (AR1) but should not reject the null of zero second-order autocorrelation in the error term of the difference (AR2). The differenced residuals should be serially independent.

4.3.2. Model specification

To investigate the factors of default probability, the dynamic Generalized Method of Moments (GMM) approach is adopted to control for the unobserved heterogeneity and simultaneity bias. System GMM will be used to estimate the regressions in levels together with the regressions in differences. Specifically, in system GMM, variables in levels are instrumented with lags of their differences, and differenced variables are instrumented with lags in levels. A COVID-19 time dummy is added to account for the COVID-19 outbreak in 2020. Further, risk appetite is interacted with the time dummy to test the effect of risk appetite on bank risk during the COVID-19 period. The regressand and time dummy are treated as endogenous, while the remaining regressors are treated as weakly exogenous. Specifically, to model bank default likelihood (P_{ijt}), the empirical specification in dynamic GMM can be written as:

$$\begin{split} P_{i,j,t} &= \beta_0 + \beta_1 \ P_{i,j,t-1} + \ \beta_2 RISKAPP_{i,j,t} + \beta_3 LIC_{i,j,t} + \beta_4 ESG_{i,j,t} \\ &+ \beta_5 ROE_{i,j,t} + \beta_6 DIV_{i,j,t} + \beta_7 RGDPGR_{i,t} + \beta_8 CPI_{i,t} + \beta_9 NEER_{i,t} \\ &+ \beta_{10} COVID19_t + \beta_{11} COVID - 19_t \times RISKAPP_{i,j,t} + \varepsilon_{i,j,t} + \mu_i \end{split}$$

where subscripts of i, j, and t denote the country, banking firm, and year respectively; $\mu_i =$ unobserved fixed effect that does not change over time for individual banking firms; $\epsilon_{it} =$ error term that is assumed to be normally distributed with mean 0 and variance σ^2 ; P = default probabilities (%); RISKAPP = risk appetite ratio (%); LIC = loan impairment charges-to-net revenue ratio (%); ESG = Environment, Social and Governance scores; ROE = returnon-equity ratio (%); DIV = dividend pay-out ratio (%); RGDPGR = growth rate in real gross domestic product (%); CPI = consumer price index (%), NEER = change in nominal effective exchange rate (%) (see Table 1).

5. Discussion of results

Table 2 summarizes descriptive statistics for all the variables. The average default probability of the sample banks is 0.10%.

The range of risk appetite ratio is large, with the minimum and maximum values equal to -121 and 111%, respectively. A negative and lower risk appetite ratio implies more bank risk taking behaviour. When a bank has higher provisioning due to riskier lending, it will reduce the bank's earnings power (the numerator) and result in a negative risk appetite ratio. The overall variance of risk appetite is 131%, of which the between variance accounts for 71% ($9.6551^2/11.4687^2$) of the variation in risk appetite for 12 sample countries. The degree of bank risk appetite within a country and across countries is large.

The variances for risk appetite and ESG dominate the total variance. The discrepancies in ESG between countries are large, ranging from 4.85 to 62.64 points out of 100 points. It shows that compliance with the ESG standards is large among the sample countries including developed equity markets and emerging and frontier markets in our sample.

Besides, the range of loan impairment charges (LIC) is large, with maximum value 174.95% and minimum value of -45.09%. A positive impairment loan charges indicate banks put aside more money for impaired loans to cover the expected losses. A negative impairment loan charges indicates a reversal of loan write-off.

It is interesting to note that the dividend pay-out in banks within countries is so huge, with a minimum percentage of 0% to a maximum pay-out of 2950%. It is also noteworthy to mention that the within variance outweighs the between variance for indicating a fluctuation in local currency values against a basket of major currencies over time is more than changes in the nominal effective exchange rate between the sample economies. The ranges of time series variable such as CPI, NEER, and RGDPGR is big due to the sample countries encompassing developed, developing, and frontier markets.

Table 3 presents the pairwise correlation between variables. All regressors have a pairwise correlation of less than 0.5. Also, the variance inflation factor is well below 5 and tolerance values more than 0.1, rejecting high multicollinearity between independent variables. As expected, lower economic performance and change in the nominal effective exchange rate are associated with higher bank default chances..

In addition to that, a higher ratio of loan impairment charges to net revenue worsens the credit health of a bank. Confirming our expectation, banks with higher earnings and performing better in ESG have lower credit risk. The pairwise corelation between risk appetite and default probability is negative, suggesting waning risk appetite (thus lower earnings before tax relative to potential losses) is associated with a higher bank default likelihood. A bank's distress level increases when it does not pass the risk appetite ratio test (with risk appetite ratio lower than 1).

Table 4 shows the estimated parameters of interest on bank default. Models 1 and 2 show the estimated coefficients produced by a two-step System GMM estimator without and with Windmeijer bias-corrected standard errors. The lagged default probability ($P_{i,j,t-1}$) is significant, implying dynamic GMM estimator is appropriate to be used. Besides that, autoregressive coefficient is below 1, showing the absence of the weak instrument problem (Blundell and Bond, 1998).

The negative coefficient on lagged default indicates banks with higher default risk will be forced to undergo debt restructuring or to increase their capital, therefore become more solvent. For instance, many banks in Japan underwent business integration or consolidation to streamline their operations. As a results, their income improved and default risk fell.

Overall, both Sargan and Hansen's tests substantiate the validity of the instruments used in the regression. In addition to that, the

Table 1 Variable definition

Variable	Definition	Source
Default probabilities (P)	One-year default probabilities	Bloomberg
Risk appetite (RISKAPP)	(Revenue-operating expenses-expected loss)/unexpected loss) x 100	Bloomberg
Loan impairment charges (LIC)	Loan impairment charges-to-net revenue (%)	Bloomberg
Environmental, social and governance (ESG)	ESG scores	Bloomberg
Return-on-equity (ROE)	(Net income/ending total equity) x 100	Bloomberg
Dividend pay-out (DIV)	(Dividend per share/earnings available for common stockholders) x 100	Bloomberg
Real gross domestic product growth (RGDPGR)	Real gross domestic product growth (%)	Bloomberg
Consumer price index (CPI)	Consumer price index (%)	Bloomberg
Exchange rate (NEER)	Change in nominal effective exchange rate (%)	Bloomberg
COVID-19	A time dummy variable, coded as 1 for the COVID-19 year and 0 for the remaining periods.	World Health Organisation

Table 2 Descriptive statistics.

Variable	Measurement	Overall	Overall	Between	Within	Min.	Max.	
	Unit	Mean	S.D.	S.D.	S.D.			
P	%	0.0974	0.3042	0.1242	0.2764	0.0000	9.8894	
RISKAPP	%	0.8524	11.4687	9.6551	7.3167	-121.6975	111.6524	
LIC	%	10.1858	12.1077	8.4705	8.6970	-45.0900	174.9500	
ESG	Points	30.4315	11.8777	10.1841	6.1264	4.8500	62.6400	
ROE	%	9.4825	6.9585	5.3775	4.4642	-63.4900	41.3400	
DIV	%	30.2903	66.4786	24.9414	61.9502	0.0000	2950.0000	
RGDPGR	%	3.1960	3.4762	2.5018	2.3453	-9.5000	14.5300	
CPI	%	1.5936	2.0100	1.3770	1.4621	-1.1000	18.6800	
NEER	%	0.7594	7.0209	1.3339	6.9040	-16.3211	22.3150	

Notes: P = default probabilities (%); RISKAPP = risk appetite ratio (%); LIC = loan impairment charges-to-net revenue ratio (%); ESG = Environment, Social and Governance scores; ROE = return-on-equity ratio (%); DIV = dividend pay-out ratio (%); RGDPGR = growth rate in real gross domestic product (%); CPI = consumer price index (%), NEER = change in nominal effective exchange rate (%).

Table 3 Pearson pairwise correlation.

	P	RISK- APP	LIC	ESG	ROE	DIV	RGDPGR	CPI	NEER
P RISKAPP	1.00 -0.08***	1.00							
LIC	0.08***	-0.08***	1.00						
ESG	-0.12***	0.30***	0.31***	1.00	1.00				
ROE DIV	-0.08*** 0.00	0.38*** -0.02	0.00 -0.01	0.26*** 0.23***	1.00 -0.06***	1.00			
RGDPGR	-0.09***	0.19***	0.25***	0.15***	0.55***	-0.04*	1.00		
CPI	-0.01	0.28***	0.20***	0.19***	0.49***	-0.02	0.47***	1.00	
NEER	-0.02	-0.01	-0.09***	-0.06**	-0.06**	0.03	-0.03	0.05**	1.00

Notes: P = default probabilities (%); RISKAPP = risk appetite ratio (%); LIC = loan impairment charges-to-net revenue ratio (%); ESG = Environment, Social and Governance scores; ROE = return-on-equity ratio (%); DIV = dividend pay-out ratio (%); RGDPGR = growth rate in real gross domestic product (%); CPI = consumer price index (%), NEER = change in nominal effective exchange rate (%).

Arellano-Bond serial correlation test suggests no second-order autocorrelation (AR2), suggesting the aptness of the instruments used in the model. Instruments are collapsed to circumvent the instrument proliferation problem.

A higher risk appetite ratio indicates lower bank risk taking, with the bank's pre-tax net earnings (the numerator) more than its potential losses proxied by the bank's regulatory capital (the denominator). We hypothesize a negative relationship between risk appetite ratio and default probability. Nonetheless, risk appetite ratio has an unexpected positive coefficient though it is significant. One possible explanation is, banks are more cautious in lending and have under-utilized risk limits. This can potentially undermine their earning potential.

Further, bank risk appetite is interacted with the COVID-19 time dummy to test the differential impacts of time effect and risk appetite on the probabilities of bank default. In times of Covid-19, banks have higher provisioning due to riskier lending and poor asset quality. Higher reserve for loan losses and operating expenses eat up banks' earnings and result in a negative risk appetite ratio. As predicted, a decline in bank risk appetite ratio amid greater uncertainty and ascending impaired loans during the COVID-19 period eventually leads to higher bank default rates. The COVID-19 year dummy, however loses significance when standard errors are corrected using a robust variance estimator produced by the two-step GMM estimation.

The significant association between poor asset quality proxied by a positive coefficient on impairment losses (LIC) and default likelihood in this study is reconcilable to Lee et al. (2014) and Teixeira et al. (2020). When banks grant credit to riskier sectors, they take greater impairment loss which raises the default probabilities. Increasing loan impairment losses hamper a bank's earnings and worsen its credit health.

Conforming to the risk mitigation hypothesis, financial institutions that performed better in ESG tend to face lower bank risk due to greater market trust and more prudent banking activities. The significant and negative coefficient on ESG is consistent with prior studies (Bouslah et al., 2018; Chiaramonte et al., 2021). The finding implies sustainable practices are paramount for bank stability.

Moreover, banks with poor earnings as measured by a lower ROE are more likely to default. The findings are in congruence with Swamy (2012) and Kjosevski et al. (2019). The findings are consistent with mismanagement theory, banks with poorer earnings may be under greater pressure to achieve desired profitability level, and is more likely to assume a higher risk of loans and investments, negatively affecting the quality of credit portfolios and consequently raising default risk.

Contrary to the hypothesized direction, dividend pay-out is positively significant at a 1% level in impacting bank risk. The results, however, support the wealth redistribution hypothesis. Declaring higher dividend to equity-holders before the announcement of financial distress transfer wealth from debtholders to common stockholders, placing the former at greater risk. The positive coefficient on a dividend may suggest excessive dividend leads to financial distress level. Also, it lends support to Chen et al. (2019) who finds firms in Israeli paid dividends from unrealized earnings before debt restructuring took place.

Bank's default risk will be impacted by business cycles. It can be observed from the negative coefficient of growth rate on real GDP. Sluggish economic growth increase banks' default probabilities at a 5% conventional significance level, corroborating Baselga-Pascual et al. (2015), Köhler (2015), and Kjosevski et al. (2019).

The CPI is significant at 5% but the direction is not of predicted. Nevertheless, the positive and significant coefficient on inflation is

Table 4Determinants of bank default likelihood based on the two-step System GMM estimator.

	(1)	(2)
	Two-step Sys. GMM	Two-step Sys. GMM
	(Standard Errors)	with Robust Standard Error
P _{i,j,t-1}	-0.3296***	-0.3296**
igic- i	(0.1191)	(0.1482)
RISKAPP _{i,j,t}	0.0020***	0.0020***
-01-	(0.0004)	(0.0005)
LIC _{i,j,t}	0.0079***	0.0079***
-01-	(0.0014)	(0.0015)
ESG i,j,t	-0.0049***	-0.0049***
4915	(0.0007)	(0.0007)
ROE i.i.t	-0.0029**	-0.0029**
-0,-	(0.0013)	(0.0014)
Div i.i.t	0.0008***	0.0008***
-0,-	(0.0003)	(0.0003)
RGDPGR i.t	-0.0120**	-0.0120**
1,0	(0.0049)	(0.0056)
CPI i.t	-0.0068**	-0.0068**
1,0	(0.0031)	(0.0034)
NEER i.t	-0.0015***	-0.0015***
	(0.0004)	(0.0004)
COVID-19 t	-0.0850*	-0.0850
	(0.0494)	(0.0567)
$COVID-19_t \times RISKAPP_{i,j,t}$	-0.0052***	-0.0052***
1,,,,	(0.0011)	(0.0013)
Intercept	0.2394***	0.2394***
	(0.0293)	(0.0318)
Sargan test	1.11	1.11
(p-value)	(0.77)	(0.77)
Hansen test	3.08	3.08
(p-value)	(0.38)	(0.38)
AR1	-3.08***	-2.69**
(p-value)	(0.00)	(0.01)
AR2	0.45	0.38
(p-value)	(0.65)	(0.70)
AR3	-0.69	-0.65
(p-value)	(0.49)	(0.52)
F-stat. for a time effect test	14.76***	14.18***
(p-value)	(0.00)	(0.00)
Number of instruments	15	15
Number of observations	1317	1317
Number of groups	155	1557

Notes; subscripts of i, j, and t denote country, banking firm and year respectively. The dependent variable is default probabilities (P). P $_{i,j,t-1}$ = lagged default probabilities; RISKAPP = risk appetite ratio (%); LIC = loan impairment charges-to-net revenue ratio (%); ESG = Environment, Social and Governance scores; ROE = return-on-equity ratio (%); DIV = dividend pay-out ratio (%); RGDPGR = growth rate in real gross domestic product (%); CPI = consumer price index (%), NEER = change in nominal effective exchange rate (%). Standard errors are in the parentheses.

in tandem with Otašević (2013), Kjosevski et al. (2019), and Teixeira et al. (2020). Higher inflation is reported to shrink a bank's default likelihood. It may be attributable to the higher interest rate charged on the lending fund as a result of inflationary pressures. When government revises policy rates, it raises the net interest margin for a bank. Texeira et al. (2020) also confirm a positive association between the consumer price index and bank risk when the latter is gauged by the asset prices.

In line with Kjosevski et al. (2019), an inverse relationship between NEER and default risk affirms that home currency depreciation escalates banks' default risk. Corporate borrowers face greater financial difficulties in meeting loan obligations, increasing bank instability and fragility. Domestic currency depreciation makes corporate investment to shrink when the corporate borrowers have large foreign currency debt (Garralda and Sousa, 2017). Business borrowers which borrow foreign currency are less able to repay bank loan. Moreover, when banks have heavy short-term international borrowing, exchange rate depreciation further reduces their equity position, resulting in greater default likelihood.

6. Conclusion

Amid toughening regulations, a low-interest-rate environment, the challenges brought on by the coronavirus, and intense competition within the finance and services industry, traditional banks engage in more risk-taking activities and investment through partnering or venturing into finance technologies, developing new products and services to meet corporate goals. This research analyses the drivers of bank default likelihood with emphasis on bank risk appetite while controlling for bank-level and macroeconomic indicators in the regressions.

Banks and financial institutions have been developing risk management frameworks accelerated by the global financial crisis in 2007/08. Nonetheless, the embeddedness of risk into business decisions and the maturity of risk development is still debatable, particularly in emerging ASEAN markets. Bank risk appetite is still evolving and remains a sophisticated topic.

This paper employs a credit risk appetite ratio in examining banks' default likelihood and finds that a lower risk appetite ratio (thus more bank risk-taking) is linked with escalated default probabilities of banks and financial institutions in 12 economies in

the year of Covid-19 outbreak. We also find that macroeconomic indicators have significant explanatory power. Banks' default likelihood declines with the rate of economic growth, and depreciation of local currency magnifies credit default. Moreover, the findings affirm the mismanagement theory by suggesting a lower bank's ROE increases the chances of bank default. Unprofitable banks are likely to undertake greater risk in their loan portfolios, leading to higher credit default risk.

These results support the view that regulators should monitor and circumvent aggressive credit policy to ensure financial resilience. Additionally, since sustainable practices revealed through ESG scores are critical for bank stability, regulators should require banks to reveal their sustainable activities more frequently on a semi-annual or quarterly basis together with their financial results. Banks should allocate resources to enhance all ESG dimensions beyond governance constituents, to reduce bank risk while fulfilling the role of a responsible corporate citizen. While better ESG brings non-monetary benefits to the stakeholders, it is also effective in reducing bank default risk for the interest of shareholders.

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