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# How does Non-Interest Income affect Bank Credit Risk? Evidence before and during the COVID-19 Pandemic

--Manuscript Draft--

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|---|---|
| **Manuscript Number:** | FRL-D-22-01560R2 |
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| **Abstract:** | This paper considers the COVID-19 pandemic's role and investigates the impact of non-interest income on bank credit risk. Specifically, it performs a comparative analysis between before and during the pandemic periods. The data of listed banks are extracted from the BankFocus for 14 Asian emerging markets. The regression results indicate the positive influence of non-interest income on bank credit risk. Interestingly, the magnitude of the impact is higher in the pre-pandemic period, and it significantly reduces during the pandemic period. This study provides implications for bank practitioners and regulators. |
| **Response to Reviewers:** | Dear Editor-in-Chief,<br>We appreciate the time and effort that you and the reviewers dedicated to providing feedback on our paper and are grateful for the insightful comments on and valuable improvements to our paper. In this newly revised version, we have incorporated all the suggestions made by the reviewer #3. A detailed response letters to the referee is provided along with the revised manuscript that thoroughly addresses his/her comments and suggestions. The text is in green colour for all the revisions and changes throughout the manuscript. |

December 21, 2022

Prof. Laura Ballester
Editor-in-Chief, *Finance Research Letters (FRL)*

Dear Prof. Laura Ballester,

*Re: Manuscript Number: FRL-D-22-01560R1: How does Non-Interest Income affect Bank Credit Risk? Evidence before and during the COVID-19 Pandemic*

Thank you for giving us the opportunity to submit a newly revised draft of the manuscript to *Finance Research Letters.*

We appreciate the time and effort that you and the reviewers dedicated to providing feedback on our paper and are grateful for the insightful comments on and valuable improvements to our paper. In this revised version, we have incorporated all the suggestions made by the reviewer #3.

We hope that the revised version of the manuscript meets your and the referee's expectations and is acceptable for publication in *Finance Research Letters*.

Accompanying this letter, please find the revised version of our paper along with detailed response letters to the referee that thoroughly address his/her comments and suggestions.

Sincerely,

On behalf of the co-authors,

Asad Mehmood

**Responses to Reviewers' Comments:**

We are grateful to both reviewers as their comments helped us to improve our work. We are thankful to Reviewer #2 for appreciating the efforts we made in addressing the comments. Moreover, we are grateful to Reviewer #3 for highlighting the issues that helped us to further improve our work. Therefore, we have addressed all the comments of Reviewer #3. All the revisions are highlighted in green colour both in this file and in the manuscript. We hope that this revised version of the manuscript meets your expectations.

**REVIEWER #2**

***Comments***
The authors scrupulously followed the indications reported in the review. Although I was quite critical of the first version of the paper, I must admit that significant improvements have been made to the current version of the paper. Good luck!

*Response*
Thank you for your appreciation.

**REVIEWER #3**

***Comments***
1. Table A1 of the Appendix: Matching estimator
You should revise the results of matching estimator and the interpretation.
Matching estimator should show if the MEAN DIFFERENCE for each variable of the table 3 remain significant when you compare banks which are similar for the other control variables

*Response*
Thank you for your comment. As per your suggestions, we have revised the results of matching estimators and their interpretation. We use significant control variables in Table 3 for similar banks. Thus, the banks with similar characteristics are based on capital adequacy ratio, loan growth and bank size. Further, we use the same control variables as the matching variables. The results of matching estimators for similar banks indicate significant mean differences for the main study variables, including non-performing loans ratio and non-interest income. All the revisions are presented below are highlighted in green colour in the manuscript:

**In Empirical Analysis and Discussion:**

We further analyse the statistical differences between before and during the pandemic periods for the main study variables, including non-interest income and non-performing loans ratio, a measure of credit risk by using the simple matching estimator methodology (See Appendix A) (Díaz-Mendoza et al., 2014). We use banks with similar characteristics using the significant control variables in Table 3. Thus, the banks have the same attributes based on their capital adequacy ratio, loan growth and size. In this analysis (See Table A1), we first report the averages for non-performing loans ratio and non-interest income for both periods and mean-comparison tests in Panel A. Moreover, Panel B indicates matching estimator coefficients for before and during the pandemic periods for non-performing loans ratio and non-interest income variables. We use significant control variables in Table 3 as matching variables and are used separately, including capital adequacy ratio, loan growth and bank size. Furthermore, in Panel C, the matching variables are used simultaneously.

The results of Panel A (See Table A1) are in line with the findings in Table 3 as the average value of non-performing loans ratio increases and the mean value of non-interest income decreases in the pandemic period. The differences in the means of both variables are statistically significant. These results indicate that although the banks have the same characteristics based on their capital adequacy ratio, loan growth and size, however, their non-performing loans ratio significantly increased, and non-interest income significantly decreased in the pandemic period.

Panels B and C make a comparison of the non-performing loans ratio and non-interest income with respect to before and during the pandemic periods based on banks with similar characteristics. These similarities are based on capital adequacy ratio, loan growth and bank size, termed as the matching variables. The coefficient is the matching estimator and is the mean difference in non-performing loans ratio and non-interest income between the two periods, such as before the pandemic and during the pandemic. In Panel B, for banks with similar capital adequacy ratio, the matching variable, the coefficient value for the non-performing loans ratio indicates that during the pandemic period, on average, the non-performing loans ratio is 7.53% higher than before the pandemic period (See Table A1). The results for other matching variables, such as loan growth and bank size are the same as the capital adequacy ratio. The banks with the same loan growth and bank size have higher non-performing loans ratio during the pandemic period.

Further, in Panel B, the coefficient value for non-interest income for banks with a similar capital adequacy ratio, the matching variable, represents that during the pandemic period, on average, the non-interest income is -22.36% lower than before the pandemic period (See Table A1). Similarly, the results for matching variables, including loan growth and bank size, are consistent with the capital adequacy ratio. The results indicate that banks with similar loan growth and size have lower non-interest income during the pandemic period.

The results of Panel C support the findings of Panel B. In Panel C, the matching variables are used simultaneously, including capital adequacy ratio, loan growth and bank size. The results indicate that banks with similar capital adequacy ratio, loan growth and bank size, on average have a 2.95% higher non-performing loans ratio in the pandemic period than before the pandemic period. Moreover, the same banks, on average have -15.07% lower non-interest income in the pandemic period (See Table A1). Therefore, we conclude that banks experience higher credit risk and earn lower non-interest income in the pandemic period having similar capital adequacy ratio, loan growth and bank size.

**In APPENDIX A. MATCHING ESTIMATORS:**

**Table A1**
Matching estimators.

| Panel A: Average of the credit risk measure and non-interest income for banks with similar characteristics | | | | |
|---|---|---|---|---|
| | NPLR | | NII | |
| Before the pandemic period | 7.598 | | 35.773 | |
| During the pandemic period | 12.591 | | 17.842 | |
| Total | 9.696 | | 28.240 | |
| difference | 4.993*** | | -17.930*** | |
| t-statistic | 2.680 | | -3.470 | |
| Panel B: Matching estimators with matching variables individually | | | | |
| | NPLR | | NII | |
| Matching variables | Coefficient | t-statistic | Coefficient | t-statistic |
| CAR | 7.526*** | 3.320 | -22.364* | -1.710 |

| | | | | |
|---|---|---|---|---|
| LG | 3.813** | 1.990 | -19.298* | -1.930 |
| SIZE | 2.916* | 1.730 | -13.555* | -1.750 |
| Panel C: Matching estimators with matching variables simultaneously | | | | |
| | NPLR | | NII | |
| Matching variables | Coefficient | t-statistic | Coefficient | t-statistic |
| CAR LG SIZE | 2.955*** | 3.210 | -15.069* | -1.720 |

*Notes*: This table shows the matching estimators for non-performing loans ratio (NPLR), a measure of credit risk, and non-interest income (NII) for similar banks based on capital adequacy ratio, loan growth and size. Panel A indicates the averages for NPLR and NII for before and during the pandemic periods. It further reports mean-comparison test for NPLR and NII for two periods (before the pandemic and during the pandemic). Panel B shows the matching estimator coefficients for before and during the pandemic periods for NPLR and NII. The matching variables include capital adequacy ratio, loan growth and bank size and are used individually. Panel C shows the matching estimator coefficients for before and during the pandemic periods for NPLR and NII and the matching variables are used simultaneously. ***, **, * represent statistically significant difference between before and during the pandemic periods at 1%, 5% and 10% levels, respectively. See Table 2 for the definitions of the variables.

***Comments***
Table 4: correlations
-Why the figures of these new correlations are different to previous version?

*Response*
Thank you for your comment. The figures of correlations in the revised version are based on the full sample, and subsamples, including before the pandemic period and during the pandemic period. In the previous (first) version of the paper, we were examining two relationships. However, we excluded the relationship between credit risk and bank financial performance from the revised version because of the suggestions of another reviewer as FRL has editorial limits linked to the maximum size of the article. Therefore, we only considered the relationship between non-interest income and bank credit risk based on the suggestions of another reviewer. Further, we excluded the financial performance (return on assets) variable from the revised version as it was related to the relationship we excluded from the revised version. However, the results of correlations between the variables are the same in both revised and previous versions with respect to their signs (positive or negative).

***Comments***
Table 4: correlations
-Which is the number of observations?

*Response*
Thank you for your comment. We have included the number of observations for each variable (and for each sample) in the correlations Table. All the revisions are presented below and are highlighted in green colour in the manuscript:

**In Empirical Analysis and Discussion:**

**Table 4**
Correlation matrix and multicollinearity diagnostic test.

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| | | Full Sample (2009-2021) | | | | | | |
| 1 | NPLR | 1 | | | | | | |
| 2 | NII | 0.1231*** | 1 | | | | | |
| 3 | CAR | -0.0372* | 0.0138 | 1 | | | | |
| 4 | LG | -0.2277*** | -0.0349* | 0.0513** | 1 | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 5 | LEV | -0.0246 | -0.1344*** | -0.031 | 0.0122 | 1 | | |
| 6 | SIZE | -0.3115*** | -0.0429** | -0.1535*** | 0.0721*** | -0.0215 | 1 | |
| 7 | AGE | 0.0716*** | 0.0174 | -0.0067 | -0.1656*** | -0.1517*** | 0.1379*** | 1 |
| | VIF | - | 1.02 | 1.03 | 1.04 | 1.04 | 1.06 | 1.08 |
| | N | 2,510 | 2,510 | 2,510 | 2,510 | 2,510 | 2,510 | 2,510 |
| | | Before the Pandemic (2009-2019) | | | | | | |
| 1 | NPLR | 1 | | | | | | |
| 2 | NII | 0.2154*** | 1 | | | | | |
| 3 | CAR | -0.1397*** | -0.0740*** | 1 | | | | |
| 4 | LG | -0.2724*** | -0.0872*** | -0.0127 | 1 | | | |
| 5 | LEV | -0.0145 | -0.2455*** | 0.0419* | 0.0620*** | 1 | | |
| 6 | SIZE | -0.2476*** | -0.1467*** | -0.1516*** | -0.0169 | -0.0277 | 1 | |
| 7 | AGE | 0.0954*** | 0.0245 | 0.0187 | -0.2040*** | -0.1806*** | 0.1560*** | 1 |
| | VIF | - | 1.11 | 1.04 | 1.05 | 1.10 | 1.08 | 1.10 |
| | N | 1,815 | 1,815 | 1,815 | 1,815 | 1,815 | 1,815 | 1,815 |
| | | During the Pandemic (2020-2021) | | | | | | |
| 1 | NPLR | 1 | | | | | | |
| 2 | NII | 0.0484 | 1 | | | | | |
| 3 | CAR | -0.0401 | 0.0629* | 1 | | | | |
| 4 | LG | -0.1796*** | -0.0003 | 0.1116*** | 1 | | | |
| 5 | LEV | -0.0387 | 0.0115 | -0.0808** | -0.0484 | 1 | | |
| 6 | SIZE | -0.3775*** | 0.0694* | -0.1590*** | 0.1491*** | -0.0122 | 1 | |
| 7 | AGE | 0.0392 | 0.0081 | -0.0344 | -0.1388*** | -0.0759** | 0.1098*** | 1 |
| | VIF | - | 1.01 | 1.06 | 1.07 | 1.02 | 1.08 | 1.05 |
| | N | 695 | 695 | 695 | 695 | 695 | 695 | 695 |

*Notes*: VIF is the variance inflation factor. N is the number of observations. ***, **, * indicate the statistical significance at 1%, 5% and 10% level, respectively. See Table 2 for the definitions of the variables.

***Comments***

Table 4: correlations

-Explain in the letter why now the correlation NII-NPLR is positive during the pandemic and in the previous version negative

*Response*

Thank you for this comment. The correlation between NII-NPLR is positive in both revised and previous versions during the pandemic period. In the revised version the correlation is 0.0484 and in the previous version, the correlation is 0.072 during the pandemic period (you can see the correlation table (during the pandemic period results) in the previous version, row numbered 3, and column numbered 2). Hence, in both versions, the correlation between NII-NPLR is positive during the pandemic period. For convenience, please see below the table of correlations of the previous version. The correlations between NII-NPLR are highlighted in green colour for both before and during the pandemic periods:

**Correlation Table of Previous Version**

**Table 4**

Correlation matrix and multicollinearity diagnostic test.

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| | | Before the Pandemic Period | | | | | | | |
| 1 | ROA | 1 | | | | | | | |
| 2 | NPLR | -0.422 | 1 | | | | | | |
| 3 | NII | -0.080 | 0.215 | 1 | | | | | |
| 5 | CAR | 0.097 | -0.140 | -0.074 | 1 | | | | |
| 4 | LG | 0.251 | -0.272 | -0.087 | -0.013 | 1 | | | |
| 6 | LEV | 0.049 | -0.015 | -0.246 | 0.042 | 0.062 | 1 | | |
| 7 | SIZE | 0.063 | -0.248 | -0.147 | -0.152 | -0.017 | -0.028 | 1 | |
| 8 | AGE | 0.027 | 0.095 | 0.025 | 0.019 | -0.204 | -0.181 | 0.156 | 1 |
| | VIF (1) | - | 1.22 | - | 1.07 | 1.13 | 1.04 | 1.16 | 1.11 |
| | VIF (2) | - | - | 1.11 | 1.04 | 1.05 | 1.10 | 1.08 | 1.10 |

| | | During the Pandemic Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | ROA | 1 | | | | | | | |
| 2 | NPLR | -0.340 | 1 | | | | | | |
| 3 | NII | -0.051 | 0.072 | 1 | | | | | |
| 4 | CAR | -0.075 | -0.021 | 0.060 | 1 | | | | |
| 5 | LG | 0.053 | -0.191 | -0.001 | 0.111 | 1 | | | |
| 6 | LEV | 0.049 | 0.019 | 0.001 | -0.093 | -0.052 | 1 | | |
| 7 | SIZE | 0.067 | -0.378 | 0.065 | -0.165 | 0.149 | -0.029 | 1 | |
| 8 | AGE | 0.021 | 0.055 | 0.006 | -0.037 | -0.139 | -0.084 | 0.107 | 1 |
| | VIF (1) | - | 1.22 | - | 1.07 | 1.09 | 1.02 | 1.25 | 1.05 |
| | VIF (2) | - | - | 1.01 | 1.06 | 1.07 | 1.02 | 1.08 | 1.05 |

*Notes*: VIF is the variance inflation factor. The rows VIF (1) and (2) present the VIF values for the impact of credit risk on financial performance, and the influence of non-interest income on credit risk, respectively. See Table 2 for the definitions of the variables.

***Comments***
Please specific the frequency of data (daily, monthly…)

*Response*
Thank you for this comment. We have mentioned the frequency of the data in the manuscript. This incorporation is presented below and highlighted in green colour in the manuscript:

**In Research Methodology:**

We consider yearly data and perform analysis on the full sample and subsamples.

***Comments***
I would put table B1 (GMM) in the supplementary material)

*Response*
Thank you for this comment. We have placed Table B1 (GMM) in the supplementary material. This revision is presented below and highlighted in green colour in the supplementary material file:

**In Supplementary Material File:**

**Supplementary Material**

**APPENDIX B. ROBUSTNESS TEST**

**Table B1**

**Table B1**
The GMM regression results.

| | Full Sample (2009-2021) |
|---|---|
| Variable | NPLR |
| $NPLR_{(t-1)}$ | 0.813*** |
| | (528.770) |
| $NPLR_{(t-2)}$ | -0.043*** |
| | (-36.330) |
| NII | 0.008*** |
| | (23.480) |
| CAR | -0.093*** |
| | (-64.830) |

| | |
|---|---|
| LG | -0.024*** |
| | (-69.370) |
| LEV | -0.173*** |
| | (-34.290) |
| SIZE | -0.372*** |
| | (-16.270) |
| AGE | 1.355*** |
| | (20.390) |
| COVID-19 Dummy | 0.083*** |
| | (3.340) |
| Constant | 9.519*** |
| | (20.860) |
| Country fixed effects | Yes |
| Year fixed effects | Yes |
| N | 1,645 |
| AR (2) p-value | 0.764 |
| Sargan test p-value | 1.000 |

*Notes*: This table presents the GMM regression results for the impact of non-interest income on bank credit risk for the full sample, including COVID-19 Dummy. COVID-19 Dummy, a dummy variable, equals 1 if the years belong to the COVID-19 pandemic (2020-2021) and 0 otherwise (2009-2019). $NPLR_{(t-1)}$ and $NPLR_{(t-2)}$ are the one-year and two-year lagged NPLR, respectively. N is the number of observations. t-statistic values are presented in parentheses. ***, **, * represent significance level at 1%, 5% and 10%, respectively. Country and year effects are included in the regression. See Table 2 for the definitions of the variables.

# How does Non-Interest Income affect Bank Credit Risk? Evidence before and during the COVID-19 Pandemic

## Highlights

1. The COVID-19 pandemic has a positive and significant impact on bank credit risk.
2. Overall, non-interest income positively influences bank credit risk.
3. There is high intensity of the impact of non-interest income on bank credit risk in the pre-pandemic period.
4. During the pandemic period, the magnitude of the impact of non-interest income on bank credit risk significantly decreases.

# How does Non-Interest Income affect Bank Credit Risk? Evidence before and during the COVID-19 Pandemic

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**Abstract**
This paper considers the COVID-19 pandemic's role and investigates the impact of non-interest income on bank credit risk. Specifically, it performs a comparative analysis between before and during the pandemic periods. The data of listed banks are extracted from the BankFocus for 14 Asian emerging markets. The regression results indicate the positive influence of non-interest income on bank credit risk. Interestingly, the magnitude of the impact is higher in the pre-pandemic period, and it significantly reduces during the pandemic period. This study provides implications for bank practitioners and regulators.
**JEL Classification:** G21, G32, L25
**Keywords:** Income diversification; non-interest income; credit risk; COVID-19 pandemic.

**Acknowledgments**
We are very thankful to the Editor-in-Chief of the "Finance Research Letters" for their support and guidance and the two anonymous reviewers for their helpful comments on earlier versions of this paper. We are also thankful to all the participants in the Annual Event of Finance Research Letters, *2022 CEMLA CONFERENCE* on "*New Advances in International Finance*", Center for Latin American Monetary Studies (CEMLA), Mexico City, 21-22 April 2022, for their fruitful comments on previous drafts of this paper.

**Declaration of Conflicting Interests**
All authors have no conflicting interests to declare.

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[*] **Corresponding Author**

 

# How does Non-Interest Income affect Bank Credit Risk? Evidence before and during the COVID-19 Pandemic


## Abstract

This paper considers the COVID-19 pandemic's role and investigates the impact of non-interest income on bank credit risk. Specifically, it performs a comparative analysis between before and during the pandemic periods. The data of listed banks are extracted from the BankFocus for 14 Asian emerging markets. The regression results indicate the positive influence of non-interest income on bank credit risk. Interestingly, the magnitude of the impact is higher in the pre-pandemic period, and it significantly reduces during the pandemic period. This study provides implications for bank practitioners and regulators.



**JEL Classification:** G21, G32, L25

**Keywords:** Income diversification; non-interest income; credit risk; COVID-19 pandemic.

**How does Non-Interest Income affect Bank Credit Risk? Evidence before and during the COVID-19 Pandemic**

## 1. Introduction

The recent global financial crisis has been challenging for firms in several developed countries. However, the current COVID-19 pandemic has an influence at a worldwide level. Arguably, this pandemic has also been influencing financial institutions like other firms (Hassan et al., 2022), which are vital for the economy. Among them, banks have a more crucial role in economic growth (Barth et al., 2004). Nevertheless, banks face credit risk, a major risk (Boubaker et al., 2016; Giesecke, 2004) which plays a crucial role in bank survival and stability (Giesecke, 2004). Therefore, such institutions need to adopt a future repositioning strategy, considering this pandemic's influence (Hassan et al., 2022).

Generally, banks expose to credit risk due to debtors and bank management. In the former case, if the debtors cannot repay the borrowed amount in a timely manner, it increases bank credit risk (van Greuning & Bratanovic, 2003). While in the case of the latter, the bank experiences credit risk if the debtor's creditworthiness is not effectively evaluated (Hunjra et al., 2020). Both cases result in the accumulation of non-performing accounts and thus can affect bank survival and stability. Therefore, recently banks started focusing on income diversification and are performing non-traditional activities (Duho et al., 2020).

The increasing focus on income diversification stems from the global financial crisis because of risk in banks. It has significantly increased bank non-traditional activities (DeYoung & Torna, 2013). Thus, these activities generate non-interest income for banks and can affect credit risk. Nevertheless, there is little and mixed evidence in the earlier literature for the relationship between non-interest income and bank credit risk. For instance, some scholars report a positive relationship (Calmès & Théoret, 2015), others find no adverse impact (Abedifar et al., 2018) and rest reveal that more non-interest income lowers the bank credit risk (Dang & Dang, 2021). Moreover, most of the evidence is from developed economies. Therefore, this relationship requires further investigation for emerging economies and how this relationship changes in a crisis period.

We consider listed banks of 14 Asian emerging markets due to their considerable contribution to global economic growth (Arouri et al., 2013). Moreover, the banking sector is vital for Asian economies (Hunjra et al., 2020). Based on the analysis, we find that non-interest income positively impacts bank credit risk. Interestingly, the magnitude of the impact is higher before the pandemic period, while this magnitude significantly decreases during the pandemic period.

Our study significantly contributes to the literature in two ways. First, according to our knowledge, this is the first study providing evidence considering the role of the COVID-19 pandemic. Specifically, this study performs a comparative analysis between before and during the pandemic periods. Second, this study contributes to the scant literature from emerging economies and overall mixed literature on the relationship between non-interest income and bank credit risk.

The paper structure for the next sections is as follows. Section 2 discusses the literature review and Section 3 explains the research methodology. Empirical analysis and discussion are presented in Section 4, and Section 5 concludes the study.

## 2. Literature review

Scholars in the earlier literature have immensely paid attention to credit risk in the banking sector because of its adverse effects and critical role in bank survival (Gadzo et al., 2019; Hunjra et al., 2020; Saleh & Abu Afifa, 2020). It is argued that the financial crisis of 2007–2008 resulted from a compromise on quality in excess lending and improper credit risk management (Gropp et al., 2011). Mainly, the assets portfolio of a bank comprises illiquid loans; thus, they are one of the primary reasons leading toward bank credit risk (Koch & MacDonald, 2000). Scholars consider asymmetric information theory and argue that good and bad borrowers are challenging to distinguish (Auronen, 2003), which probably leads to adverse selection and moral hazard problems (Richard et al., 2008). They present that these problems have led to the considerable accumulation of bank non-performing accounts (Bester, 1994; Bofondi & Gobbi, 2003). Therefore, banks need to properly manage credit risk by reducing non-performing loans (Boussemart et al., 2019).

The bank's traditional sources of income generation, such as loans, involve credit risk because of non-performing loans (Boussemart et al., 2019), leading banks to consider income diversification. Specifically, they focus on non-traditional sources, such as non-interest income (Duho et al., 2020), where they charge fees and commissions against the services (Abuzayed et al., 2018). Nevertheless, present-day theories have distinguishing views on banks' consideration of income diversification. The first strand of literature argues that fee-based activities have small switching costs due to their short-term nature (Deyoung & Roland, 2001). Further, few regulatory restrictions can lead to economies of scope for banks (Claessens & Klingebiel, 2001). In contrast, the second strand of literature argues that banks' reliance on non-interest activities may raise agency issues (Abedifar et al., 2018; John et al., 1994; Saunders, 1994) and moral hazard problems (Boyd et al., 1998). Similarly, studies provide evidence that agency costs are higher than the benefits of income diversification (Akhigbe & Stevenson, 2010; Berger et al., 2010).

The earlier literature pays little attention to the relationship between non-interest income and bank credit risk, as few studies have been conducted. Among them, a study reports that non-interest income activities in U.S. banks incorporate higher credit risk (Calmès & Théoret, 2015). Contrarily, it is revealed that banks with more non-interest income activities in Vietnam have lower credit risk (Dang & Dang, 2021). Similarly, another study reports no adverse effect of non-interest income on bank credit risk in the U.S. (Abedifar et al., 2018). In line with this, we expect that non-interest income activities could be more beneficial for banks to lower credit risk in the current COVID-19 pandemic. The initial phase of this pandemic was challenging for all nations, resulting in a slowdown in economic activities. Thus, banks also suffered from this pandemic (Hassan et al., 2022) and experienced a decline in their traditional activities. However, non-traditional activities allow banks to generate income even during the pandemic period and, thus, decrease credit risk. Therefore, considering the above, we develop the first hypothesis and its sub-hypothesis.

**$H_1$:** Non-interest income positively and significantly influences bank credit risk.

**$H_{1a}$:** Non-interest income has a positive and significant impact on bank credit risk but with a lower magnitude in the current COVID-19 pandemic.

## 3. Research Methodology

We use panel data for a sample of listed banks from 14 Asian emerging markets (see Table 1) extracted from the BankFocus database. We consider yearly data and perform analysis on the full sample and subsamples. The full sample is based on the years 2009-2021. Moreover, the subsamples include before the pandemic (2009 to 2019) and during the pandemic (2020 to 2021) periods.

**Table 1**
Sampling countries and banks.

| Serial Number | Sampling Countries | Sample of Listed Banks |
|---|---|---|
| 1. | Bangladesh | 42 |
| 2. | China | 59 |
| 3. | India | 56 |
| 4. | Indonesia | 53 |
| 5. | Lebanon | 6 |
| 6. | Malaysia | 12 |
| 7. | Pakistan | 20 |
| 8. | Philippines | 16 |
| 9. | South Korea | 9 |
| 10. | Sri Lanka | 34 |
| 11. | Taiwan | 20 |
| 12. | Thailand | 13 |
| 13. | Turkey | 13 |
| 14. | Vietnam | 19 |
| | Total | 372 |

We present the definitions of the variables in Table 2. The main variables of interest are non-interest income (Gupta & Mahakud, 2020) and credit risk, measured using the non-performing loans ratio (Hunjra et al., 2020; Lu & Boateng, 2018). Moreover, we include a set of control variables (see Table 2).

**Table 2**
Variables definitions.

| Variable and measure | Symbol | Definition/Calculation | Source |
|---|---|---|---|
| *Credit risk* | *CR* | | |
| Non-performing loans ratio | NPLR | Non-performing loans / total loans | (Hunjra et al., 2020; Lu & Boateng, 2018) |
| *Non-interest income* | *NII* | | |
| Non-interest income | NII | Non-interest income / total revenue | (Gupta & Mahakud, 2020) |
| *Control variables* | *CV* | | |
| Capital adequacy ratio | CAR | (Tier 1 capital + tier 2 capital) / risk-weighted assets | (Maji & De, 2015) |
| Loan growth | LG | (Current loans - previous loans) / previous loans | (Kashif et al., 2016) |
| Bank leverage | LEV | Total debt / total equity | (Duho et al., 2020) |
| Bank size | SIZE | Natural logarithm of bank total assets | (Duho et al., 2020) |
| Bank age | AGE | Natural logarithm of bank age since incorporation | (Hunjra et al., 2020) |

We estimate the following regression equation to examine the impact of non-interest income on bank credit risk.

$$(NPLR)_{i,t} = \beta_0 + \beta_1(NII)_{i,t} + \beta_2(CAR)_{i,t} + \beta_3(LG)_{i,t} + \beta_4(LEV)_{i,t} + \beta_5(SIZE)_{i,t} + \beta_6(AGE)_{i,t} + \beta_7\Sigma(CE)_i + \beta_8\Sigma(YE)_t + \varepsilon_{i,t} \quad (1)$$

where, NPLR is a measure of credit risk. CE is country fixed effects, YE is year fixed effects, $\beta_o$ is a constant, $\Sigma$ is the summation, $\varepsilon$ is the error term, $_i$ is the firm, and $_t$ is the year. See Table 2 for the definitions of the variables.

We use ordinary least squares (OLS) as the baseline method to estimate our empirical model, including the country and year fixed effects. In addition, we use fixed effects (FE) and random effects (RE) approaches for the robustness check.

## 4. Empirical Analysis and Discussion

Table 3 presents the descriptive statistics for all the study variables for the full sample and subsamples. It further shows the mean-comparison test between subsamples. Concerning the full sample, the mean values of the non-performing loans ratio and non-interest income are 4.59% and 29.94%, respectively. These values represent that on average, banks have a considerable portion of non-performing loans, and generate significant amount of income through non-traditional activities. Moreover, with respect to subsamples, the average value of the non-performing loans ratio has increased from 4.20% to 5.60% during the pandemic, with a significant difference in the means. The mean value of non-interest income has decreased from 30.45% to 28.62%, with a significant difference in the means. Furthermore, the standard deviation values show no extreme volatility for any variable.

**Table 3**
Descriptive statistics.

| | Full Sample (2009-2021) | | Before the Pandemic (2009-2019) | | During the Pandemic (2020-2021) | | | |
|---|---|---|---|---|---|---|---|---|
| | N = 2,510 | | N = 1,815 | | N = 695 | | | |
| Variable | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean Diff | t-stat |
| NPLR | 4.589 | 6.487 | 4.204 | 5.209 | 5.596 | 8.934 | 1.392*** | 4.830 |
| NII | 29.944 | 20.314 | 30.452 | 16.514 | 28.618 | 27.868 | -1.834** | -2.030 |
| CAR | 17.702 | 16.975 | 15.248 | 6.977 | 24.111 | 29.285 | 8.863*** | 12.040 |
| LG | 11.092 | 23.411 | 12.505 | 17.685 | 7.402 | 33.839 | -5.103*** | -4.910 |
| LEV | 1.224 | 1.557 | 1.228 | 1.503 | 1.212 | 1.691 | -0.017 | -0.240 |
| SIZE | 23.398 | 2.015 | 23.514 | 1.827 | 23.095 | 2.414 | -0.420*** | -4.690 |
| AGE | 3.561 | 0.732 | 3.558 | 0.765 | 3.570 | 0.638 | 0.013 | 0.380 |

*Notes*: The differences in means between the subsamples are presented, including the t-statistics based on the mean-comparison test. N is the number of observations. S.D. is the standard deviation. *** and ** indicate statistical significance at 1% and 5% level, respectively. See Table 2 for the definitions of the variables.

We further analyse the statistical differences between before and during the pandemic periods for the main study variables, including non-interest income and non-performing loans ratio, a measure of credit risk by using the simple matching estimator methodology (See Appendix A) (Díaz-Mendoza et al., 2014). We use banks with similar characteristics using the significant control variables in Table 3. Thus, the banks have the same attributes based on their capital adequacy ratio, loan growth and size. In this analysis (See Table A1), we first report the averages for non-performing loans ratio and non-interest income for both periods and mean-comparison tests in Panel A. Moreover, Panel B indicates matching estimator coefficients for before and during the pandemic periods for non-performing loans ratio and non-interest income variables. We use significant control variables in Table 3 as matching variables and are used separately, including capital adequacy ratio, loan growth and bank size. Furthermore, in Panel C, the matching variables are used simultaneously.

The results of Panel A (See Table A1) are in line with the findings in Table 3 as the average value of non-performing loans ratio increases and the mean value of non-interest income decreases in the pandemic period. The differences in the means of both variables are statistically significant. These results indicate that although the banks have the same characteristics based on their capital adequacy ratio, loan growth and size, however, their non-performing loans ratio significantly increased, and non-interest income significantly decreased in the pandemic period.

Panels B and C make a comparison of the non-performing loans ratio and non-interest income with respect to before and during the pandemic periods based on banks with similar characteristics. These similarities are based on capital adequacy ratio, loan growth and bank size, termed as the matching variables. The coefficient is the matching estimator and is the mean difference in non-performing loans ratio and non-interest income between the two periods, such as before the pandemic and during the pandemic. In Panel B, for banks with similar capital adequacy ratio, the matching variable, the coefficient value for the non-performing loans ratio indicates that during the pandemic period, on average, the non-performing loans ratio is 7.53% higher than before the pandemic period (See Table A1). The results for other matching variables, such as loan growth and bank size are the same as the capital adequacy ratio. The banks with the same loan growth and bank size have higher non-performing loans ratio during the pandemic period.

Further, in Panel B, the coefficient value for non-interest income for banks with a similar capital adequacy ratio, the matching variable, represents that during the pandemic period, on average, the non-interest income is -22.36% lower than before the pandemic period (See Table A1). Similarly, the results for matching variables, including loan growth and bank size, are consistent with the capital adequacy ratio. The results indicate that banks with similar loan growth and size have lower non-interest income during the pandemic period.

The results of Panel C support the findings of Panel B. In Panel C, the matching variables are used simultaneously, including capital adequacy ratio, loan growth and bank size. The results indicate that banks with similar capital adequacy ratio, loan growth and bank size, on average have a 2.95% higher non-performing loans ratio in the pandemic period than before the pandemic period. Moreover, the same banks, on average have -15.07% lower non-interest income in the pandemic period (See Table A1). Therefore, we conclude that banks experience higher credit risk and earn lower non-interest income in the pandemic period having similar capital adequacy ratio, loan growth and bank size.

Table 4 shows the correlation matrix for all the study variables. The results show that non-performing loans ratio is significantly associated with non-interest income and control variables. Further, we test for multicollinearity, and the results indicate that the variance inflation factor (VIF) values are less than 5. Thus, there is no issue of multicollinearity.

**Table 4**
Correlation matrix and multicollinearity diagnostic test.

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| | | Full Sample (2009-2021) | | | | | | |
| 1 | NPLR | 1 | | | | | | |
| 2 | NII | 0.1231*** | 1 | | | | | |
| 3 | CAR | -0.0372* | 0.0138 | 1 | | | | |
| 4 | LG | -0.2277*** | -0.0349* | 0.0513** | 1 | | | |
| 5 | LEV | -0.0246 | -0.1344*** | -0.031 | 0.0122 | 1 | | |
| 6 | SIZE | -0.3115*** | -0.0429** | -0.1535*** | 0.0721*** | -0.0215 | 1 | |
| 7 | AGE | 0.0716*** | 0.0174 | -0.0067 | -0.1656*** | -0.1517*** | 0.1379*** | 1 |
| | VIF | - | 1.02 | 1.03 | 1.04 | 1.04 | 1.06 | 1.08 |
| | N | 2,510 | 2,510 | 2,510 | 2,510 | 2,510 | 2,510 | 2,510 |
| | | Before the Pandemic (2009-2019) | | | | | | |
| 1 | NPLR | 1 | | | | | | |
| 2 | NII | 0.2154*** | 1 | | | | | |
| 3 | CAR | -0.1397*** | -0.0740*** | 1 | | | | |
| 4 | LG | -0.2724*** | -0.0872*** | -0.0127 | 1 | | | |
| 5 | LEV | -0.0145 | -0.2455*** | 0.0419* | 0.0620*** | 1 | | |
| 6 | SIZE | -0.2476*** | -0.1467*** | -0.1516*** | -0.0169 | -0.0277 | 1 | |
| 7 | AGE | 0.0954*** | 0.0245 | 0.0187 | -0.2040*** | -0.1806*** | 0.1560*** | 1 |
| | VIF | - | 1.11 | 1.04 | 1.05 | 1.10 | 1.08 | 1.10 |
| | N | 1,815 | 1,815 | 1,815 | 1,815 | 1,815 | 1,815 | 1,815 |
| | | During the Pandemic (2020-2021) | | | | | | |
| 1 | NPLR | 1 | | | | | | |
| 2 | NII | 0.0484 | 1 | | | | | |
| 3 | CAR | -0.0401 | 0.0629* | 1 | | | | |
| 4 | LG | -0.1796*** | -0.0003 | 0.1116*** | 1 | | | |
| 5 | LEV | -0.0387 | 0.0115 | -0.0808** | -0.0484 | 1 | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 6 | SIZE | -0.3775*** | 0.0694* | -0.1590*** | 0.1491*** | -0.0122 | 1 | |
| 7 | AGE | 0.0392 | 0.0081 | -0.0344 | -0.1388*** | -0.0759** | 0.1098*** | 1 |
| | VIF | - | 1.01 | 1.06 | 1.07 | 1.02 | 1.08 | 1.05 |
| | N | 695 | 695 | 695 | 695 | 695 | 695 | 695 |

*Notes*: VIF is the variance inflation factor. N is the number of observations. ***, **, * indicate the statistical significance at 1%, 5% and 10% level, respectively. See Table 2 for the definitions of the variables.

Table 5 presents the OLS, FE and RE regressions results for the full sample and subsamples. Columns 1-3 show the results for the full sample, including the COVID-19 pandemic dummy. Columns 4-6 refer to before the pandemic period, while columns 7-9 refer to during the pandemic period.

The results for the full sample indicate that non-interest income positively influences bank credit risk (non-performing loans ratio), thus supporting hypothesis $H_1$ of the study. These results show that non-interest income increases bank credit risk. It represents that although banks consider non-traditional activities for income diversification to lower the reliance on traditional activities but at the expense of increased credit risk. These results align with the earlier literature that non-interest income activities involve more credit risk (Calmès & Théoret, 2015).

The results of the COVID-19 pandemic dummy in the full sample show a positive and significant impact on bank credit risk. These results represent that this pandemic has significantly increased bank credit risk. Thus, it indicates a problematic situation for banks to get back loans from debtors during the pandemic, increasing the portion of non-performing loans. This difficulty could result from a decline in economic activities, specifically during the first wave of the COVID-19 pandemic due to complete or partial lockdowns across countries, which affected banks in two ways. Firstly, the banks experienced low loan growth because the businesses did not need to get loans from the banks due to a decline in business activities. Thus, this decrease in loan growth increases the levels of non-performing loans (Dang & Nguyen, 2022). Secondly, businesses struggled to generate income because of decreased business operations; therefore, they could not repay their bank loans during the pandemic. This situation also increases the non-performing loans, leading to higher credit risk. Hence, the COVID-19 pandemic increases bank credit risk.

Table 5 further indicates that the results concerning before and during the pandemic periods are consistent with the full sample, as non-interest income has a positive and significant impact on bank credit risk. However, this impact has a higher magnitude before the pandemic period and thus aligns with the earlier literature (Calmès & Théoret, 2015). Contrarily, the results indicate that the magnitude of the impact of non-interest income on bank credit risk significantly lowers during the pandemic period, supporting hypothesis $H_{1a}$ of the study. Interestingly, these results represent that non-interest income activities are essential for banks as such activities help lower their exposure to credit risk in a crisis period. It could be due to reduced traditional activities during the pandemic, decreasing loan growth, increasing non-performing loans and, thus, credit risk. It further leads to reduce bank profits from traditional sources. However, non-traditional sources, such as non-interest income, allow banks to generate profits even during the crisis period. Thus, it helps banks lower the credit risk, which has been increased due to a decline in traditional activities. These results are consistent with the earlier literature (Abedifar et al., 2018; Dang & Dang, 2021).

**Table 5**
The regression results.

| | Full Sample (2009-2021) | | | Before the Pandemic (2009-2019) | | | During the Pandemic (2020-2021) | | |
|---|---|---|---|---|---|---|---|---|---|
| | OLS (1) | FE (2) | RE (3) | OLS (4) | FE (5) | RE (6) | OLS (7) | FE (8) | RE (9) |
| Variable | NPLR | | | | | | | | |
| NII | 0.041*** | 0.028*** | 0.028*** | 0.065*** | 0.066*** | 0.059*** | 0.037*** | 0.028 | 0.032** |
| | (6.390) | (4.820) | (5.020) | (8.910) | (8.800) | (8.320) | (3.070) | (1.210) | (2.410) |
| CAR | -0.017** | -0.053*** | -0.043*** | -0.124*** | -0.249*** | -0.126*** | -0.005 | -0.030 | -0.019 |
| | (-2.320) | (-5.200) | (-4.740) | (-8.700) | (-9.880) | (-7.850) | (-0.370) | (-1.550) | (-1.410) |
| LG | -0.045*** | -0.026*** | -0.028*** | -0.065*** | -0.041*** | -0.048*** | -0.023** | -0.010 | -0.010 |
| | (-9.020) | (-7.070) | (-7.740) | (-10.980) | (-8.700) | (-10.270) | (-2.490) | (-1.050) | (-1.380) |
| LEV | -0.372*** | -0.312*** | -0.390*** | -0.115 | -0.720*** | -0.542*** | -0.527*** | -0.543 | -0.504** |
| | (-4.660) | (-3.600) | (-4.670) | (-1.600) | (-6.860) | (-6.220) | (-2.620) | (-1.320) | (-2.170) |
| SIZE | -0.776*** | -2.289*** | -1.720*** | -0.501*** | -3.138*** | -0.953*** | -1.205*** | 2.153 | -1.406*** |
| | (-9.000) | (-7.000) | (-8.060) | (-6.240) | (-8.650) | (-6.420) | (-5.720) | (1.040) | (-4.660) |
| AGE | 0.575*** | -1.480** | -0.442 | 0.436*** | -1.824** | 0.098 | 0.582 | -0.484 | 0.663 |
| | (3.100) | (-2.230) | (-0.920) | (2.830) | (-2.340) | (0.320) | (1.040) | (-0.040) | (0.800) |
| COVID-19 Dummy | 2.023*** | 3.682*** | 2.492*** | - | - | - | - | - | - |
| | (2.950) | (6.300) | (5.030) | | | | | | |
| Constant | 22.266*** | 61.721*** | 46.048*** | 14.958*** | 85.009*** | 25.206*** | 32.460*** | -41.533 | 37.778*** |
| | (9.860) | (8.680) | (10.880) | (8.510) | (11.020) | (8.360) | (7.490) | (-0.700) | (6.120) |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,510 | 2,510 | 2,510 | 1,815 | 1,815 | 1,815 | 695 | 695 | 695 |
| R-squared | 0.298 | 0.114 | 0.233 | 0.437 | 0.098 | 0.406 | 0.267 | 0.105 | 0.260 |

*Notes*: This table shows the OLS, FE and RE regressions results for the impact of non-interest income on bank credit risk. Columns 1-3 present the results for the full sample, including COVID-19 Dummy. Columns 4-6 indicate results for before the pandemic period, and columns 7-9 show the results for during the pandemic period. COVID-19 Dummy, a dummy variable, equals 1 if the years belong to the COVID-19 pandemic (2020-2021) and 0 otherwise (2009-2019). N is the number of observations. t-statistic values are presented in parentheses. ***, **, * represent significance level at 1%, 5% and 10%, respectively. Country and year effects are incorporated in all the regressions. See Table 2 for the definitions of the variables.

These findings suggest that banks' consideration of non-interest income activities is a favourable approach as it decreases bank credit risk in a crisis period. Therefore, banks should also consider non-traditional activities for their survival and stability as they become more relevant in a crisis. Moreover, bank management needs to properly implement loan policies, requiring debtors to comply with such policies so that banks can get back the loans (Hunjra et al., 2020), not only in normal working conditions but also during a crisis. Thus, they should prevent asymmetric information issues such as adverse selection and moral hazards by monitoring the debtors to decrease the possibility of credit risk (Bester, 1994; Bofondi & Gobbi, 2003).

To further analyse the robustness of the results and address the potential endogeneity issue between the study variables, we employ a two-step system dynamic panel data technique, the generalised method of moments (GMM) (Arellano & Bond, 1991; Arellano & Bover, 1995). This technique is robust as it can resolve potential endogeneity (Blundell & Bond, 1998; Bond et al., 2001), unobserved country heterogeneity, omitted variable bias, and measurement errors (Bond et al., 2001). Additionally, we use one-year lagged dependent variable as instruments to further diminish the potential endogeneity. Moreover, we perform post-estimation tests, including the Sargan test for over-identifying restrictions and Arellano–Bond test for autocorrelation. Furthermore, we incorporate year and country dummies.

We apply the GMM technique to the full sample, including the COVID-19 pandemic dummy. Consistent with the study's main findings, non-interest income positively influences bank credit risk. Moreover, the COVID-19 pandemic significantly increases bank credit risk, ensuring the robustness of our analysis.

## 5. Conclusion

The COVID-19 pandemic is a global challenge which has affected the functioning and performance of both financial and non-financial institutions. We consider banks' vital role in the economy and report that non-interest income lowers the bank credit risk in the current pandemic. Based on the study findings, our study provides practical implications for bank practitioners and regulators. They should focus on income diversification by considering non-interest income activities as it helps decrease bank credit risk in a crisis, as a decline in traditional activities could be compensated by earning income from non-traditional activities. Moreover, they need to focus on asymmetric information problems of adverse selection and moral hazards and should prevent them by effectively monitoring the borrowers. It is essential and becomes more relevant in a crisis period to avoid unprecedented non-performing accounts.

This study has a few limitations. For instance, it considers data of 2 years for the pandemic period as it is currently available for only two years. Further, it focuses on the listed banks of emerging markets. Hence, future studies could enlarge the pandemic period data by considering both listed and unlisted banks. Moreover, comparative analyses could be made between emerging and developed economies and Islamic and conventional banks.

## APPENDIX A. MATCHING ESTIMATORS

**Table A1**

**Table A1**

Matching estimators.

| Panel A: Average of the credit risk measure and non-interest income for banks with similar characteristics | | | | |
|---|---|---|---|---|
| | NPLR | | NII | |
| Before the pandemic period | 7.598 | | 35.773 | |
| During the pandemic period | 12.591 | | 17.842 | |
| Total | 9.696 | | 28.240 | |
| difference | 4.993*** | | -17.930*** | |
| t-statistic | 2.680 | | -3.470 | |
| **Panel B: Matching estimators with matching variables individually** | | | | |
| | NPLR | | NII | |
| Matching variables | Coefficient | t-statistic | Coefficient | t-statistic |
| CAR | 7.526*** | 3.320 | -22.364* | -1.710 |
| LG | 3.813** | 1.990 | -19.298* | -1.930 |
| SIZE | 2.916* | 1.730 | -13.555* | -1.750 |
| **Panel C: Matching estimators with matching variables simultaneously** | | | | |
| | NPLR | | NII | |

| Matching variables | Coefficient | t-statistic | Coefficient | t-statistic |
|---|---|---|---|---|
| CAR LG SIZE | 2.955*** | 3.210 | -15.069* | -1.720 |

*Notes*: This table shows the matching estimators for non-performing loans ratio (NPLR), a measure of credit risk, and non-interest income (NII) for similar banks based on capital adequacy ratio, loan growth and size. Panel A indicates the averages for NPLR and NII for before and during the pandemic periods. It further reports mean-comparison test for NPLR and NII for two periods (before the pandemic and during the pandemic). Panel B shows the matching estimator coefficients for before and during the pandemic periods for NPLR and NII. The matching variables include capital adequacy ratio, loan growth and bank size and are used individually. Panel C shows the matching estimator coefficients for before and during the pandemic periods for NPLR and NII and the matching variables are used simultaneously. ***, **, * represent statistically significant difference between before and during the pandemic periods at 1%, 5% and 10% levels, respectively. See Table 2 for the definitions of the variables.

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**CRediT authorship contribution statement**

**Asad Mehmood:** Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Writing - original draft; Writing - review & editing.
**Francesco De Luca:** Supervision; Formal analysis; Validation; Writing - review & editing; Funding acquisition.

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