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Complementarities and Substitutions between Life Insurance and Banking Industries in Unstable Environments. New Insights using a Quantile Approach

Abstract. *This article investigates the impact of banking characteristics on the life insurance market in 30 OECD countries from 2004 to 2020. By employing the novel unconditional quantile regression approach, we reveal the complementarity effect between banking and insurance industries from countries with less developed life insurance markets through the positive influence of credit expansion and the banking system's size on the life insurance market. Higher banking depth, balanced profitability in the banking sector, and the careful management of liquidity risks associated with larger banks' lending practices can create favourable conditions for the growth of the life insurance sector. As new findings in a turbulent environment, we show that prudent banking behaviour, characterised by a minor pace expansion of the asset size and better control of the liquidity risk, to maintain sound profitability boosts the less developed life insurance industries.*

Keywords: *life insurance density, banking system development indicators, complementarity vs. substitution effect, crises, unconditional quantile regression.*

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1. Introduction

Theoretical and empirical literature substantiate the essential role of insurance companies within the financial system. They are the key to risk management, liquidity provision, savings collection and allocation, and loss mitigation for businesses and individuals (Liu et al., 2014). At the same time, the insurance sector contributes to financial resilience for individuals and firms, mainly through risk management and welfare improvement, while also playing a significant role in

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promoting financial inclusion (Yap et al., 2024). One strand of the economic literature delves into explaining the interplay between the insurance and banking sector stability by identifying several interconnected mechanisms using portfolio theory. Thus, a resilient and well-developed life insurance market will contribute to diversifying the financial market due to the numerous investment opportunities provided by insurers and banks, thus reducing the unsystematic risk to the financial system and enhancing financial stability (Nguyen, 2024).

Sound financial links between the banking and insurance sectors are precursors to financial stability (Bernoth and Pick, 2011). Although the roles played by bank lending and insurance activity are widely acknowledged for economic and financial development, our research thoroughly investigates their complementary or substitutional relationship. Proponents of the substitution effect argue that the insurance and banking sectors compete by providing both funding, positioning life insurance companies as direct competitors that can reduce the market share through intermediated savings (Arena, 2008). Advocates of the complementary relationship between banking and insurance in terms of capital intermediation bring several arguments in this regard: life insurance companies use to provide preponderantly long-term investment opportunities, while in terms of personal savings, the services they offer are distinct and not close substitutes (Webb et al., 2002).

This research expands the existing literature in several novel aspects. First, we will join a few studies that link bank financial depth, the type of bank lending behaviour (aggressive or prudent), and banking performance to the size of the life insurance market. We identify three significant banking determinants for the life insurance sector: size, liquidity risk, and performance. Our analysis reveals that in OECD countries with less developed life insurance markets, the development of this sector can benefit from an expansion in the banking activity in terms of managed assets (mainly loans), reflecting a complementary relationship between the two sectors. In contrast, strong banking performance limits insurance growth, supporting the substitution hypothesis.

Second, we adopt a methodological framework well suited to capture the nuanced relationship between the banking and life insurance sectors. We use unconditional quantile regression, which aligns with our need to examine how banking factors and control variables impact life insurance density at different distribution levels, uncovering asymmetries that linear models overlook. This approach is efficient in heterogeneous settings, providing stable and consistent estimates even in the presence of outliers or heavy-tailed distributions and delivering insights across the full range of life insurance density levels. Unlike traditional VAR/VECM frameworks or Granger causality tests (Liu et al., 2014; Liu and Zhang, 2016; Chang, 2018; Dash et al., 2018), this method allows for a deeper, distribution-wide analysis that better addresses the complexities of sectoral interactions in our context.

Third, we analyse the relationship between the two financial sectors during various turmoil episodes. Specifically, we consider two periods of unstable economic and financial environments, that is, the GFC (started in 2008) (GFC) and the COVID-19 pandemic. Both crises have shaped this relationship, but in different ways and for different quantiles of the life insurance density distribution. Thus, in an unstable environment similar to the GFC, across the inferior quantile of the life insurance density distribution, the banking system's size, performance, and risk indicators show asymmetric dependencies with the size of the life insurance market. The complementarity effect between the size of the insurance sector, on the one hand, and the size and liquidity risk, on the other, turns into a substitution effect between the two industries. We also identify a change in the relationship with banking performance. The two industries become complementary in the relationship between the size of the insurance sector and banking performance.

Furthermore, the findings indicate a distinct pattern in the relationship between the two financial sectors during the COVID-19 pandemic. Even if we also talk about unstable economic and financial environments from countries with less developed life insurance industries, in terms of size, the growth of this sector can occur when the banking system is also developed. Regarding the risks assumed by the banking sector, for countries with the most developed life insurance sectors, the result is similar to that obtained for the GFC. Banking performance becomes irrelevant to the size of the life insurance industry during the pandemic period.

We employ a large panel dataset comprising 30 OECD countries from 2004 to 2020. In the few existing studies on a topic similar to our research, countries are chosen according to their income levels (Liu and Zhang, 2016; Chang, 2018), G-7 membership (Liu et al., 2014), or the euro area affiliation (Dash et al., 2018).

The remainder of the paper is organised as follows. Section 1 reviews previous research on the relationship between the banking and insurance financial sectors. Section 2 describes the data and the methodology. Section 3 presents and discusses the results and robustness checks. Section 4 concludes and provides several policy implications.

2. Literature review

Best practices in prudential supervision support the view that the assessment of financial system resilience should also account for the evolution of interconnectedness between the various segments of the financial system. In this regard, the regular Financial Sector Assessment Programme (IMF) at the country level, which monitors the interconnectedness between sectors as part of the resilience assessment of the broader financial system, can be mentioned. For example, in the UK, there is evidence of steadily increasing interconnectedness between the banking and life insurance sectors. At the same time, in Austria, the insurance sector has historically developed a close relationship with the banking sector, since banks and insurers have entered into joint alliances and partnerships (IMF, 2020). The research of Hodula et al. (2020) confirms the crucial role of the insurance sector in the functioning of the financial system and economic activity. However, there is a trade-off between the benefits of risk sharing and the potential to trigger systemic risk. Consequently, further analysis of the interconnectedness of the insurance sector with other segments of the financial system is strongly encouraged as part of the broader framework for maintaining financial stability.

The European Central Bank is also concerned about the insurance sector from a financial stability point of view, and it regularly monitors and analyses the current developments, prospects, and risks facing the insurance sector of the euro area. Identifying the links between the banking and insurance sectors, the contagion channels through which potential vulnerabilities in one industry could be transmitted to another could be uncovered. The emergence of financial conglomerates and the consolidation of financial services (known as bancassurance) have facilitated the provision of insurance products through the banking business. Although there is a clear competitive advantage with long-term benefits in terms of profitability and risk diversification, this interaction can also be a source of contagion, especially in periods of financial distress (ECB, 2020).

Despite the increasing interest of national and international authorities in this regard, this strand of literature is rarely addressed. Only a few papers have directly investigated the link between the insurance market and banking activities, and the reported findings are mixed. For comparison, there is a growing body of literature that examines the causal links between financial sectors and economic growth (Liu et al., 2014; Sawadogo et al., 2018; Dawd and Benlagha (2023).

In an early study, Beck and Webb (2003) found that the development of the banking sector, measured as the ratio of private credit to GDP, is one of the most critical leading factors for the increase in life insurance demand. The same research direction is followed by Feyen et al. (2011), who approximate the level of financial development by the ratio of total banking assets to GDP, and by Hodula et al. (2020), who use the financial development index. The conclusion points out that life insurance premiums comove with the business cycle and are positively related to a more developed financial system.

Liu and Zhang (2016) offer a nuanced perspective on a country's income level. They discovered a two-way causal relationship between life insurance and banking credit in high-income countries. On the contrary, in low-income countries, the causality is unidirectional, with banking credit influencing life insurance. This highlights a significant divergence in the dynamics between the insurance and banking sectors based on a country's income level. This conclusion is also supported by Chang (2018), who identifies a causal relation that generally runs from banking activities to the insurance sector. When delineating between high-income countries and, respectively, middle- and low-income countries, the results are substantially different in terms of the positive or negative relationship between the two financial sectors.

Liu et al. (2014) argue that the life insurance and banking sectors may impact each other due to their complementary and substitutionary economic roles. They use the bootstrap Granger causality test to investigate the causal relationship between the insurance market and banking activity. The findings reveal a short-term causal relationship between banking credit and the life insurance market in Italy and Germany, but do not identify similar patterns in the UK and the US. The threat of systemic risk that the interconnection between banks and insurers could trigger is an issue that a series of studies have investigated. Gründl (2013) explains that the potential systemic risk in the insurance sector "may become relevant when insurers significantly deviate from the traditional insurance business model and/or become highly interconnected with the banking industry". An in-depth empirical analysis by Chen et al. (2014), based on several linear and nonlinear causality tests, shows significant bidirectional causality between the insurance and banking sectors. However, the impact that banks have on insurers seems to be more substantial and persistent over time than the impact that insurers have on banks. The stress tests performed by the authors confirm that banks can create significant systemic risk for insurers, but the opposite is not applicable.

3. Model specification

3.1 Data Description

Based on a balanced panel with 30 OECD countries, and yearly data from 2004, we used an unconditional quantile model. Due to data availability constraints for key explanatory variables, the period under consideration ends in 2020. Chile, Columbia, Estonia, Latvia, Lithuania, New Zealand, and Slovenia were excluded due to the inaccessibility of the data for some financial indicators. We use the life insurance density (LID) as a proxy for the size of the life insurance market. Because we use cross-country analysis, we choose the LID as the dependent variable, since we do not need to adjust for levels of economic development (Nesterova, 2008). Table 1 provides a detailed description of the variables used in the study.

Table 1. Variable and source of data

Variables	Symbol	Description	Data source
Dependent variable			
LIFE INSURANCE DENSITY	LID	The average annual per capita premium within a country.	OECD Database
Independent variables			
BANK ASSETS TO GDP RATIO	BA_GDP	Bank assets, as a percentage of GDP.	The Global Economy Database
CREDIT TO DEPOSIT RATIO	CDR	Bank credit, as a percentage of bank deposits.	The Global Economy Database
RETURN ON ASSETS	ROA	Banks' pre-tax income to yearly averaged total assets.	The Global Economy Database
CRISIS DUMMY	CD	The dummy variable equals 1 for 2009 and 2010 and 0 otherwise.	Own calculation
COVID DUMMY	COVID	The dummy variable equals 1 for the year 2020 and 0 otherwise.	Own calculation
GDP PER CAPITA	GDPC	The GDP is divided by its total population.	World Bank Database

Variables	Symbol	Description	Data source
INFLATION RATE	INF	The annual percentage change in the Consumer Price Index (CPI).	IMF Database
POLITICAL STABILITY INDEX	PSI	The likelihood that the government will be destabilised or overthrown by unconstitutional or violent means.	World Bank Database
PERCENTAGE OF URBAN POPULATION	PUP	Urban population refers to people living in urban areas.	World Bank Database
AGE DEPENDENCY RATIO, TOTAL	DEP	The number of people under 15 or over 64 in the working age population.	World Bank Database
SCHOOL ENROLMENT, TERTIARY	EDU	The number of students enrolled in tertiary education regardless of age by the population of the age group officially corresponding to higher education and multiplying by 100.	World Bank Database
HOUSEHOLD FINANCIAL ASSETS	HFA	The proportion of currencies and deposits within the total composition of financial assets.	OECD Database
COMMON LAW LEGAL SYSTEM	CMLAW	The dummy variable equals 1 for countries with a common law legal system and zero otherwise.	https://worldpopulationreview.com/country-rankings/common-law-countries

Source: Authors' processing.

We performed a comprehensive causality test to explore the relationship between the banking and life insurance sectors, explicitly targeting the dependent variable, LID, and its connection to the banking sector. Using the Dumitrescu-Hurlin causality analysis, we successfully identified a unidirectional causation from banking factors to LID[1].

3.2 Unconditional Quantile Regression

In this paper, we use unconditional quantile regression (UQR) with fixed effects proposed by Borgen (2016). Unlike Conditional Quantile Regression (CQR), which focusses on quantiles given specific covariates, UQR considers the influence across the entire distribution, providing a broader view. Usually, in a panel data framework, the most common approach for identifying the asymmetric response of LID to different covariates is the conditional quantile regression with fixed effects (Koenker, 2004), which has the following specification:

[1] The results of the Dumitrescu-Hurlin panel causality test can be made available upon request.

$$Q_{y_{i,t}}(\tau|x_{i,t}) = \alpha_i + x_{i,t}^T\beta(\tau). \quad (1)$$

In Eq. (1), $i = \underline{1,N}$ and $t = \underline{1,T}$, represent country and years, respectively, $y_{i,t}$ is the LID in country i and year t, $x_{i,t}$ incorporates the bank-specific and other socioeconomic variables for the country i and year t, $\beta(\tau)$ is the common slope while α_i is a pure location shift indicator in the conditional quantile of the response variable[2]. To capture the unobserved country heterogeneity, Koenker (2004) handles the fixed effects as nuisance parameters by including a penalty factor in the minimisation algorithm:

$$\min_{(\alpha,\beta)} \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{i=1}^{N} w_k\, \rho_{\tau_k}\left(y_{i,t} - \alpha_i - x_{i,t}^T\beta(\tau_k)\right) + \lambda \sum_{i}^{N}|\alpha_i|. \quad (2)$$

In Eq. (2), K denotes the quantiles' index, ρ_{τ_k} represents the quantile loss function; it is a mathematical function used in quantile regression to measure the error or "loss" associated with predictions at a specific quantile. Furthermore, w_k captures the relative impact of the q quantiles $\{\tau_1, \ldots, \tau_q\}$ when estimating the α_i parameters. The penalty term λ has the advantage of decreasing the individual effects to zero, which improves the beta quality, considering the aforementioned estimation approach. In addition, when $\lambda \rightarrow 0$, we deal with a standard fixed effects model and with a panel model without individual effects when $\lambda \rightarrow \infty$.

To provide additional clarity, UQR extends CQR by incorporating Influence Functions (IF) and Recentred Influence Functions (RIF), as introduced by Firpo et al. (2009). According to Firpo et al. (2009) and Dong et al. (2020), in the conditional quantile regression, the distribution of the dependent variable is specified given a particular set of factors, leading to some potential limitations, since it cannot represent the dependence structure among the dependent and the covariates in its entirety. To fix this issue, Firpo et al. (2009) extended this approach to unconditional quantile regression by using the influence function (IF) and the recentred influence function (RIF). The IF measures how individual observations affect a particular statistical estimate, which can be beneficial for understanding distributions with asymmetric characteristics or those affected by extreme values:

$$IF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right) = \left(\frac{v\left[(1-\varepsilon)F_{y_{i,t}} + \varepsilon G_{y_{i,t}}\right] - v\left(F_{y_{i,t}}\right)}{\varepsilon}\right). \quad (3)$$

In Eq. (3), $0 \le \varepsilon \le 1$, $F_{y_{i,t}}$ is the cumulative distribution function of $y_{i,t}$, $G_{y_{i,t}}$ a probability distribution where all the probability is assigned to the point $y_{i,t}$ rather than spread across multiple values, while $v\left(F_{y_{i,t}}\right)$ is the value of the statistic (e.g., median, lower quartile or mean).

[2] The impact of the covariates can be sensitive to the quantile τ of interest but α_i does not. Moreover, the estimation procedure contains an intercept, which captures the common value taken to be the conditional central tendency of the response given a point identified by the centering of the other explanatory variables (Koenker, 2004).

The RIF expands this by providing an adjusted influence measure that allows us to estimate various statistics, such as quantiles, across the distribution. In other words, RIF is an estimator ν with a probability distribution F at point $y_{i,t}$ and is computed by adding this statistic to its IF:

$$RIF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right) = v\left(F_{y_{i,t}}\right) + IF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right). \tag{4}$$

In Eq. (4), $v(F_y)$ is the expected value of the RIF, considering that the expected value of the $IF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right)$ is zero (the expected value of the IF is zero because it measures deviations around the central estimate, so across the entire distribution, these deviations balance out). This indicates that by regressing a particular statistic, the mean, for instance, generates the same coefficients as the OLS estimates. This principle applies to any statistics of interest throughout the LID distribution. Furthermore, the conditional expectation of the $RIF\left(y; v\left(F_y\right)\right)$ can be constructed as a function of the explanatory variables, i.e., $E\left[RIF\left(y_{i,t}; v\left(F_{y_{i,t}}\right)\right) | x_{i,t}\right] = m_v\left(x_{i,t}\right)$. In this case m_v , is a way of modelling how the quantile of interest changes in response to the explanatory variables.

4. Results and discussion

4.1 Baseline Specification

Table 2 and Table 3 show the results of the unconditional quantile regression model for the representative quantiles, i.e., τ = 0.10, 0.25, 0.50, 0.75, 0.90. We introduce each banking factor (i.e., BA_GDP, CDR, and ROA) one by one to control the endogeneity and simultaneity issues.

According to the estimation results, the credit-to-deposit ratio and the size of the banking sector positively impact the life insurance sector, while ROA negatively impacts the development of the life insurance sector. Thus, the liquidity risk and financial depth proxies support a complementary role between the insurance and banking sectors, statistically validated at the inferior quantile. However, the negative relationship between bank performance and life insurance density leans toward supporting the substitution hypothesis rather than the idea of complementarity between these two financial sectors. Therefore, fostering the growth of the life insurance sector involves expanding both the banking sector's scale and the credit expansion rate, coming with the cost of increased exposure to maturity mismatch and liquidity risks. However, when banks experience higher performance, they are expected to harm the development of the life insurance sector. Consequently, our hypothesis is validated and an asymmetric effect of banking variables on life insurance density is found relying on the granular results provided by the unconditional regression approach.

Regarding the control variables, previous studies (see, e.g., Hwang and Gao, 2003; Li et al., 2007) have explicitly focused on financial, sociodemographic, and economic factors that drive the size of the life insurance industry. Zietz (2003) and Outreville (2013) provide a summary of the literature in the field. They emphasise sociodemographic determinants (i.e., education, age dependency ratios, urbanisation), and also economic determinants (i.e. income and inflation), among others, for the development of the life insurance market. Our results are in line with those of the existing literature.

Also, the existing literature suggests that financial literacy may be a more suitable determinant of life insurance demand than education. Thus, Mare et al. (2019) show that not education, but the level of knowledge about insurance, is a statistically significant positive determinant of the development of the life insurance market in Romania. Also, Liebenberg et al. (2012) show that life insurance demand is determined more by the level of financial education than by education.

In this context, we introduce the indicator of household financial assets (HFA) in our regression models as a proxy for the degree of financial sophistication linked to the level of financial education estimated at the national level. For countries with less developed life insurance sectors, we show that the higher the percentage invested in currency and deposits, from total financial assets, the lower the size of the life insurance market. From the 50th quantile and above, this variable becomes statistically insignificant.

By interacting the household financial assets with the tertiary education level, we uncover a positive correlation with the life insurance density, but only for countries from the 10th quantile. A higher level of education can be associated with greater risk aversion because people can better understand the risks and benefits of life insurance policies. However, in countries where the life insurance industry is somewhat more developed (for countries from the 25th quantile), the sign of the interaction variable changes and becomes negative (see also Sen, 2008). Therefore, when highly educated people prefer to invest their financial resources preponderantly in essential financial products rather than diversifying their range of financial investments, the prospects of development of emerging insurance markets are hampered.

The crisis dummy is statistically insignificant and shows that the development of the life insurance sector is not directly affected by the GFC. The result is similar to Dragotă et al. (2022) for 29 OECD countries analysed from 2005 to 2017. However, an indirect impact of this turmoil period can be found when bank-related variables interact with the crisis dummy.

4.2 Robustness checks

We used two approaches to validate the conclusions presented in the previous section. First, we include three interaction variables, combining each bank-related variable with the crisis dummy, the COVID-19 pandemic dummy, and a dummy variable for the legal system. In this way, we check the stability of the results from the baseline model and the persistence of the estimated sign of the statistical relevance of the bank-related variables for the life insurance density during economic, financial, and, as the case may be, sanitary, turbulent periods.

Second, we use the bank credit to the private sector as a percent of GDP for the size of the banking sector (instead of the bank assets to GDP ratio) and the bank liquid assets to deposits and short-term funding indicator (instead of the credit to deposits ratio), and estimate a fixed-effect unconditional quantile regression.

Table 2. The unconditional quantile regression results for the 10th, 25th, and 50th quantiles. Life insurance density is the dependent variable

Variables	**10th quantile**			**25th quantile**			**50th quantile**		
BA_GDP	**0.0107***			0.0010			0.0007		
CDR		**0.0158****			0.0020			-0.0013	
ROA			**-0.0715*****			0.0085			-0.0009
Crisis dummy	-0.1109	-0.0650	-0.0979	-0.0692	-0.0662	-0.0556	-0.0206	-0.0135	-0.0165
COVID dummy	-0.3565	-0.1425	-0.2978	-0.1411	-0,1171	-0.1286	0.0390	0.0348	0.0447
GDPc	**1.6960***	**1.8544****	**1.8509****	**0.6880****	**0.7003****	**0.7123****	**0.8099****	**0.8272****	**0.8226****
INF	**-0.1235****	**-0.1520*****	**-0.1235*****	-0.0215	-0.0259	-0.0174	-0.0052	0.0001	-0.0042
PSI	1.0634	**1.0894***	0.9363	0.0761	0.0847	0.0633	-0.2259	-0.2483	-0.2346
PUP	0.0087	0.0382	0.0133	-0.0381	-0.0349	-0.0356	**-0.0788***	**-0.0792***	**-0.0780***
DEP	-0.0266	-0.0099	-0.0381	-0.0075	-0.0050	-0.0083	-0.0175	-0.0204	-0.0182
HFA	**-0.1481***	**-0.1183***	**-0.1379***	**0.0613***	**0.0650***	**0.0609***	-0.0261	-0.0281	-0.0258
EDU	-0.0455	-0.0349	-0.0483	**0.0200***	**0.0218***	**0.0182***	-0.0124	-0.0148	-0.0130
HFA* EDU	**0.1217***	**0.0866***	**0.1215***	**-0.0508***	**-0.0560***	**-0.0474***	0.0329	0.0383	0.0337
Pseudo R^2	0.2214	0.1855	0.2314	0.0839	0.1135	0.0661	0.0014	0.0062	0.0025
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	510	510	510	510	510	510	510	510	510

Note: **, **, and * indicate significance at the level of 1%, 5%, and 10%, respectively. An intercept was included, but not reported.

Source: Authors' estimation using STATA 14.

Table 3. The unconditional quantile regression results for the 75th and 90th quantiles. Life insurance density is the dependent variable

Variables	**75th quantile**			**90th quantile**		
BA_GDP	0.0017			0.0005		
CDR		-0.0015			0.0001	
ROA			0.0037			-0.0045
Crisis dummy	-0.0951	-0.0811	-0.0806	-0.0954	-0.0923	-0.0959
COVID dummy	**-0.1546***	**-0.1514***	**-0.1382***	-0.0664	-0.0619	-0.0645

Variables	75th quantile			90th quantile		
GDPc	**0.8247***	**0.8611****	**0.8593***	0.6146	0.6233	0.6204
INF	0.0082	0.0157	0.0122	-0.0158	-0.0151	-0.0161
PSI	0.0186	-0.0174	-0.0027	0.0881	0.0829	0.0828
PUP	0.0670	0.0679	0.0698	-0.0081	-0.0074	-0.0081
DEP	0.0040	-0.0001	0.0025	-0.0017	-0.0021	-0.0023
HFA	-0.0358	-0.0376	-0.0355	0.0212	0.0215	0.0218
EDU	-0.0249	-0.0284	-0.0269	0.0137	0.0133	0.0137
HFA* EDU	0.0332	0.0406	0.0366	-0.0259	-0.0254	-0.0263
Pseudo R^2	0.1557	0.1511	0.1494	0.1228	0.1282	0.1278
Country FE	YES	YES	YES	YES	YES	YES
Obs.	510	510	510	510	510	510

Note: **, **, and * indicate significance at the level of 1%, 5%, and 10%, respectively. An intercept was included, but not reported.

Source: Authors' estimation using STATA 14.

4.2.1 The Analysis of the Relationship Banking - Insurance Sectors in Unstable Environments

The robustness checks summarised in Tables 4 and 5 confirm the previous findings reported in Section 3.1, especially for bank-related variables. Therefore, the statistically significant estimates reported in Table 4 and Table 5 remain robust to different specifications, i.e., when including interaction terms between two dummy crises and bank-related factors. The coefficients associated with bank-related variables (BA_GDP, CDR, and ROA) remain stable under the new UQR specification in the 10th quantile.

Additionally, we report regime-shifting behaviour when each variable interacts with the crisis dummy. Therefore, amid financial turmoil, especially in countries from the 10th quantile of life insurance density, banking and life insurance sectors become substitutable in size. At the same time, in times of financial crisis, an increase in banking liquidity contributes to the growth of the life insurance sector. A similar shift in correlation is observed for the relationship between Return on Assets (ROA) and the size of the life insurance sector. The dynamics between the two financial sectors change during periods of instability, such as the GFC. Therefore, a more liquid, moderately sized, and well-performing banking sector can stimulate the growth of the life insurance sector.

A noteworthy finding is that the interaction term between the credit-deposit ratio (CDR) and the crisis dummy is statistically significant across the 90th quantile of the life insurance density distribution. This suggests that in times of financial turmoil and specifically in countries with well-established life insurance markets, an increased appetite for banking risk has a positive impact on the size of the life insurance industry.

The COVID-19 pandemic has influenced the size of the life insurance sector. Still, the impact is sometimes different in terms of signs and statistical significance compared to the reaction of the life insurance market to the GFC. The interactional variable with the size of the banking system reveals that, for the 25th quantile, these two financial sectors remain friends and developed together during the pandemic period. Regarding bank liquidity, the result is similar to that obtained for the interactional term with the previously discussed crisis dummy. In terms of banking performance and the COVID-19 pandemic, these two variables combined have no impact on the development of the life insurance sector.

The legal system (common law versus civil law) influences the ability of financial institutions (such as life insurance companies) to mobilise and allocate their financial resources efficiently. Our results are more nuanced, depending on the bank-related indicator in the regression analysis. Thus, in common law countries, from the 10th quantile for LID, the size of the life insurance sector can be developed when the bank system's liquidity level is high. To our knowledge, this variable was not considered in interaction with different financial indicators to evaluate the impact on the size of the life insurance sector.

Table 4. The UQR results for the 10th, 25th and 50th quantiles, using interactional variables between bank-related variables, crises dummy, and legal system dummy

Variables	**10th quantile**			**25th quantile**			**50th quantile**		
BA_GDP	**0.0139****			0.0013			0.0022		
BA*Crisis	**-0.0068****			-0.0004			0.0029		
BA*COVID	0.0021			**0.0044***			-0.0003		
BA*CMLAW	-0.0087			-0.0022			-0.0061		
CDR		**0.0192*****			0.0026			-0.0017	
CDR*Crisis		**-0.0039***			-0.0006			0.0014	
CDR*COVID		0.0021			0.0022			-0.0002	
CDR*CMLAW		**-0.0143***			-0.0026			0.0009	
ROA			**-0.1184*****			0.0112			0.0041
ROA*Crisis			**0.2477*****			-0.0179			-0.0293
ROA*COVID			0.2047			-0.1104			-0.1351
ROA*CMLAW			0.0044			0.0185			0.0121
Crisis dummy	**0.6871****	**0.4198***	-0.1542	-0.0225	0.0074	-0.0494	-0.3599	-0.1851	-0.0087
COVID dummy	-0.5871	-0.3235	-0.4103	**-0.6352***	**-0.3292***	-0.0702	0.0801)	0.0464	0.1157
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.2098	0.1523	0.2412	0.0385	0.0807	0.0708	0.0040	0.0045	0.0015
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	510	510	510	510	510	510	510	510	510

Note: **, **, and * indicate significance at the level of 1%, 5%, and 10%, respectively. An intercept was included, but not reported.

Source: Authors' estimation using STATA 14.

Table 5. The UQR results for the 75th and 90th quantiles, using interactional variables between bank-related variables, crises dummy, and legal system dummy

Variables	75th quantile			90th quantile		
BA_GDP	0.0014			-0.0012		
BA*Crisis	0.0037			-0.0028		
BA*COVID	-0.0017			-0.0003		
BA*CMLAW	-0.0002			0.0067		
CDR		-0.0013			-0.0003	
CDR*Crisis		0.0001			**0.0015****	
CDR*COVID		0.0020			**0.0076***	
CDR*CMLAW		-0.0009			0.0002	
ROA			0.0085			-0.0025
ROA*Crisis			-0.0322			-0.0118
ROA*COVID			0.2766			0.0132
ROA*CMLAW			0.0613			0.0122
Crisis dummy	-0.5326	-0.0926	-0.0636	0.2321	-0.2794	-0.0915
COVID dummy	0.0434	-0.3566	-0.2750	-0.1050	**-0.8291***	-0.0701
CONTROLS	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.1576	0.1491	0.1525	0.1259	0.1375	0.1288
Country FE	YES	YES	YES	YES	YES	YES
Observations	510	510	510	510	510	510

Note: **, **, and * indicate significance at the level of 1%, 5%, and 10%, respectively. An intercept was included, but not reported.

Source: Authors' estimation using STATA 14.

4.2.2 Additional Measures for the Development of the Banking System

To provide additional robustness to the results, we also used bank credit to the private sector as a percentage of GDP, as an alternative to the bank assets to GDP ratio, to capture the impact of the banking system's size on the life insurance sector. Similarly, we use the indicator bank liquid assets for deposits and short-term funding instead of the credit-to-deposit ratio to capture the liquidity of the banking system.

Due to space constraints, we did not include the table with these results in the article. Estimates linked to banking size and liquidity risk maintain their signs and statistical significance within the new proxy used in the regression models.

5. Conclusions and policy implications

In this paper, we explore the interplay between the banking and insurance markets, using a novel and comprehensive list of indicators for attributes of the banking industry, such as size, liquidity, and performance. The analysis brings key insights into the banking-insurance nexus, particularly in unstable economic and financial contexts. We use the unconditional quantile approach to identify the main drivers of life insurance demand.

We show that the banking and insurance sectors are growing together only in countries where the life insurance sector is less developed. With regard to size and credit expansion, banks and life insurance companies seem to be more friends than foes in a stable economic environment. However, the banking and insurance sectors are more foes than friends with respect to banking performance in stable environments.

Additional findings show that the size of the life insurance market is negatively affected by the onset of the COVID-19 pandemic, but only for countries with values of the life insurance density in the 75th quantile. When banking system indicators for asset size and credit expansion interact with the occurrence of the COVID-19 crisis, they still exhibit a positive relationship with the life insurance market (at the 25th and 90th quantiles).

The GFC started in 2008 appears to put a heterogeneous mark on the relationship between the banking system and life insurance through the positive correlation between credit-to-deposit ratio and the life insurance density exhibited at the 90th quantile (changed from a negative correlation for the 10th quantile of the life insurance density), and also through the positive correlation between banking performance and life insurance, and the negative correlations between bank asset size and life insurance sector, both results being valid only for the 10th quantile of the life insurance density. Policymakers should be aware that in an unstable environment enhanced by a crisis, regardless of its nature, the development path of the life insurance sector should be evaluated in a more granular approach to account for the specificity of the national financial industry.

The granular perspective provided by our findings, in terms of the impact exerted at various quantiles, may serve as a starting point for regulators and European supervisory authorities at micro and macroprudential levels. They can better assess the potential for contagion among the different typologies of financial institutions operating in the banking and insurance sectors, in the context of strengthened supervisory approaches for better management of systemic risk in the financial industry.

The results of this study leave room for future research. An extended analysis period beyond 2020 could shed light on how the evolving of banking financial performance, liquidity risk, and size will affect the development of life insurance markets after the end of the COVID-19 pandemic crisis. It may be interesting for future research to see if the challenges faced during the pandemic may persist in new forms after the major crisis has passed, suggesting a need for continued assessment of the banking-insurance nexus in a post-pandemic environment.

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