Received: 26 June 2020 | Revised: 28 January 2021 | Accepted: 24 December 2021

DOI: 10.1002/ijfe.2600

RESEARCH ARTICLE

WILEY

The effect of Economic Policy Uncertainty on the credit risk of US commercial banks

Carmen Orden-Cruz[1] | **Jessica Paule-Vianez**[1] | **Júlio Lobão**[2]

[1]Facultad de Ciencias Jurídicas y Sociales, Universidad Rey Juan Carlos, Madrid, Spain

[2]Faculdade de Economia, Universidade do Porto, Porto, Portugal

Correspondence
Carmen Orden-Cruz, Facultad de Ciencias Jurídicas y Sociales, Universidad Rey Juan Carlos, Paseo de Artilleros s/n., Madrid 28032, Spain.
Email: carmen.delaorden@urjc.es

Abstract

This article analyses the impact of Economic Policy Uncertainty (EPU) on the credit risk of US commercial banks considering their size, profitability and solvency. To achieve this goal, a sample of 2994 US commercial banks was selected for the period 2017–2019. Using panel data, the results reveal a statistically significant positive relationship between EPU and credit risk of US commercial banks. Banks of less profitability and less solvency were found to be more vulnerable to the effect of EPU on credit risk. No conclusive results were found regarding the impact of bank size on vulnerability to EPU. Overall, our evidence suggests that policy makers and bank managers should consider the effect of EPU on their decisions.

KEYWORDS

commercial banks, credit risk, Economic Policy Uncertainty, profitability and solvency, size

1 | INTRODUCTION

Since Keynes (1936) suggested that uncertainty was a fundamental element in economic decision-making, several economists have focused on the study of Economic Policy Uncertainty (EPU). This interest has increased in recent years, especially since the 2008 global financial crisis. The uncertainty related to fiscal, regulatory and monetary policies delayed the economic recovery by making companies and households reduce or postpone investment, commercial and consumer decisions (Apergis, 2015). The Federal Open Market Committee (2009) and the International Monetary Fund (2013) suggested that these uncertainties contributed to the sharp economic decline during the 2008 global financial crisis, as well as the subsequent slow recovery (Baker et al., 2016). Currently, the reaction of governments to the Covid-19 crisis is highlighting, once again, the importance of considering EPU in economic analysis. In that regard, Baker et al. (2020) show that about half of the forecasted output contraction in the US derives from the negative effect of the uncertainty induced by Covid-19.

A relevant milestone in EPU research has been the development of the news-based EPU index by Baker et al. (2016). Since its inception, many studies have analysed the impact of this uncertainty on the economy, the financial and the commodity markets, as well as on the decision-making and risk management of companies (Al-Thaqeb & Algharabali, 2019). In recent years, one of the areas of special interest is the impact of EPU on the financial sector. Financial risk management is a difficult task at the best times and becomes more complex when uncertainty increases (Hammoudeh & McAleer, 2015).

Research regarding the banking sector is especially necessary given its particular characteristics and the economic impact that a banking crisis may have on the economy. A wide literature confirms that financial institutions, as instruments of monetary policy implementation, are a transmitter of risks and play a key role in macroeconomic dynamics and asset prices (Ciccarelli et al., 2015). There is evidence that financial recessions are worse than normal recessions on average and that the economy seems to recover faster from the first with a

well-capitalized banking sector (Jordà et al., 2017). For this reason, having a healthy banking system is crucial.

The existing literature on the impact of EPU in banking addresses certain aspects such as the pricing of loans (Ashraf & Shen, 2019), the dividend policy of banks (Tran, 2020) and the valuation of banks (He & Niu, 2018). These studies have mainly focused on credit policy (Bordo et al., 2016; Hu & Gong, 2019; Nguyen et al., 2020) because it is the reference indicator of bank lending decisions and have ignored in general the impact of EPU on credit risk.

Our paper aims to close this gap by examining the impact of EPU on bank credit risk, a more complete measure of the "health" of the banking agents and a leading indicator of banking crises (Peltonen et al., 2019). Our study is the first to examine the impact of EPU on the credit risk of commercial banks in the US scrutinizing the influence of banks' characteristics (size, profitability and solvency) on the intensity of that impact. To our knowledge, there is only one similar study, that of Chi and Li (2017), where the authors examine the influence of EPU on the credit risk of Chinese banks. However, these studies did not consider the banks' characteristics on the impact of EPU.

Applying panel data on a sample of 2994 commercial banks in the United States for the period from 2017 to 2019, we found that EPU significantly increases credit risk in commercial banks. Differentiating by bank characteristics, the results show that the credit risk of less profitable and less solvent commercial banks are the most affected by EPU. We did not find conclusive results regarding the impact of bank size on vulnerability to EPU.

After this introduction, Section 2 provides the main strand of the literature on which this paper is based, Section 3 specifies the data and presents the variables selected for the study, Section 4 describes the methodology and econometric models applied in the study, Section 5 shows the results and the robustness checks, Section 6 discusses the results with the previous literature and, finally, Section 7 provides our conclusions.

2 | LITERATURE REVIEW

Credit risk refers to the probability of default by borrowers, but also to the decline in the credit standing of a counterparty or the probability that assets will decline in value (Rose, 1999). For banks, credit risk is one of the most critical factors in risk management and essential for their survival (Basel Committee on Banking Supervision, & Bank for International Settlements, 2000), especially in high risk environments in which the risk of non-payment by debtors increases, generating banking losses (Miller & Noulas, 1997). Bank managers face this complex task while at the same time dealing principally with bank-specific and external factors.

Previous studies have examined the relationship between credit risk and bank-specific factors such as: ownership structure (La Porta et al., 2002), corporate governance (Demirgüç-Kunt & Huizinga, 1999; Laeven & Levine, 2009; Rose, 2017), the efficiency of management (Koju et al., 2018), size (Chaibi & Ftiti, 2015), solvency (Koju et al., 2018; Loaba & Zahonogo, 2019), types of institutional regimes (Salas & Saurina, 2002), and others. Regarding external factors, the banks' credit risk has been found to be correlated with economic and business cycles (Koju et al., 2018), the unemployment rate (Louzis et al., 2012), and inflation rate (Vogiazas & Nikolaidou, 2011).

Another external factor that can influence a bank's credit risk is EPU, defined as the non-zero probability of changes in existing economic policies (Baker et al., 2016). The significance of the consequences of EPU is evident through a wide body of literature that has studied its impact on economic and financial variables such as economic growth (Bachmann et al., 2013), inflation and output (Jones & Olson, 2013) and commercial activity (Bachmann et al., 2013). EPU has also been found to affect currency exchange rate movements and expectations (Beckmann & Czudaj, 2016), financial stress (Sun et al., 2017), stock markets (Adjei & Adjei, 2017; Pastor & Veronesi, 2013; Paule-Vianez et al., 2020a; Ulrich, 2012), commodity markets (Bouoiyour et al., 2018; Shahzad et al., 2017) and even cryptocurrencies (Bouri et al., 2017; Paule-Vianez et al., 2020b), among others.

Moreover, EPU has been researched in banking specific issues such as loan pricing (Ashraf & Shen, 2019), prudential regulation and bank lending (Hu & Gong, 2019) and bank valuations (He & Niu, 2018). Loan growth has attracted special attention as it is the first transmission channel through bank lending decisions and, also, because it can be used as an early banking crisis indicator (Schularick & Taylor, 2012). Studies have shown a negative impact of EPU on the loan growth in commercial banks (Bordo et al., 2016; Caglayan & Xu, 2019; Chi & Li, 2017; Danisman et al., 2020; Hu & Gong, 2019; Jiang et al., 2019; Karadima & Louri, 2020; Nguyen et al., 2020). The studies on credit risk through lending decisions and loan growth usually follow an ex-post approach, and the literature on the ex-ante impact of EPU on bank credit risk is limited. To our knowledge, only Chi and Li (2017) have analysed this issue, in the context of Chinese commercial banks. The authors concluded that bank credit risk increases due to positive connections between EPU and non-performing loan ratios, loan concentrations and the normal loan migration rate.

EPU could be a relevant factor on the bank's credit risk profile but all commercial banks probably are not equally affected by such uncertainty. This paper addresses this issue by considering their size, profitability level, and solvency level, three characteristics that are a prevalent feature in academic research on the banking sector for different reasons.

Bank size is one of the principal concerns of regulators as it relates to the risk associated with "too big to fail" especially true since the global financial crisis of 2008 (Volcker, 2012). Larger banks tend to be riskier, in general, due to moral hazard (Uhde & Heimeshoff, 2009), but also take less risk because of their efficiency and managerial capacity (Salas & Saurina, 2002). Jabra et al. (2017) found an inverse relationship between credit risk and bank size in a study of 280 European banks with panel data for 2003–2013. Specifically, Karadima and Louri (2020), employing a panel dataset of 507 banks from four major euro area countries between 2005 and 2017, demonstrated how a high bank concentration has a significant moderating effect on the positive relationship between EPU and banks' non-performing loans. Using a large sample of US banks during 2000–2017, Tran, et al. (2020), found that banks are more likely to diversify their income stream into new activities generating non-interest income amid high EPU, varying across different classes of bank size. In particular, large banks do not increase their non-interest income activities (NIIA), while small and medium banks do, increasing potentially their risk exposure. When EPU increases, small and medium sized banks increase their NIIA, and potentially increase their exposure to risks, while large banks do not.

Profitability is strongly determined by credit risk (Boahene et al., 2012) but no studies were found that evaluated the role of profitability on bank credit risk. The negative relationship has only been explored with Chinese companies (Guo et al., 2020) and tourism firms (García-Gómez et al., 2021). Recently, Guindos (2019), Vice-President of the European Central Bank, underlined the importance of bank profits, especially in adverse scenarios when healthy banks can sustain the flow of lending to profitable firms. This argument further justifies the need to explore the degree to which EPU impacts credit risk and its dependence on commercial bank profitability.

Finally, the evidence about the relationship between bank solvency and credit risk is mixed. Most of the literature shows that capitalization and bank risk are inversely related (Baselga-Pascual et al., 2015). However, high solvency could also lead banks to lower the quality of their loans to compensate for lower leverage and generating a positive relationship between capitalization and credit risk (Jabra et al., 2017). Exploring the impact of EPU on credit risk considering a bank's solvency as an additional determinant should contribute to shed more light on this controversy.

A better understanding of the potential influence of EPU on banks' credit risk has become even more important as an area of research today. At this critical time, with the Covid-19 pandemic, US EPU levels have risen to historically high levels, almost 60% above 2001 and 2012 highest levels. Economic policy decisions are even more crucial today when they are made under stressful circumstances, generating a Covid-19 induced economic uncertainty (Baker et al., 2020).

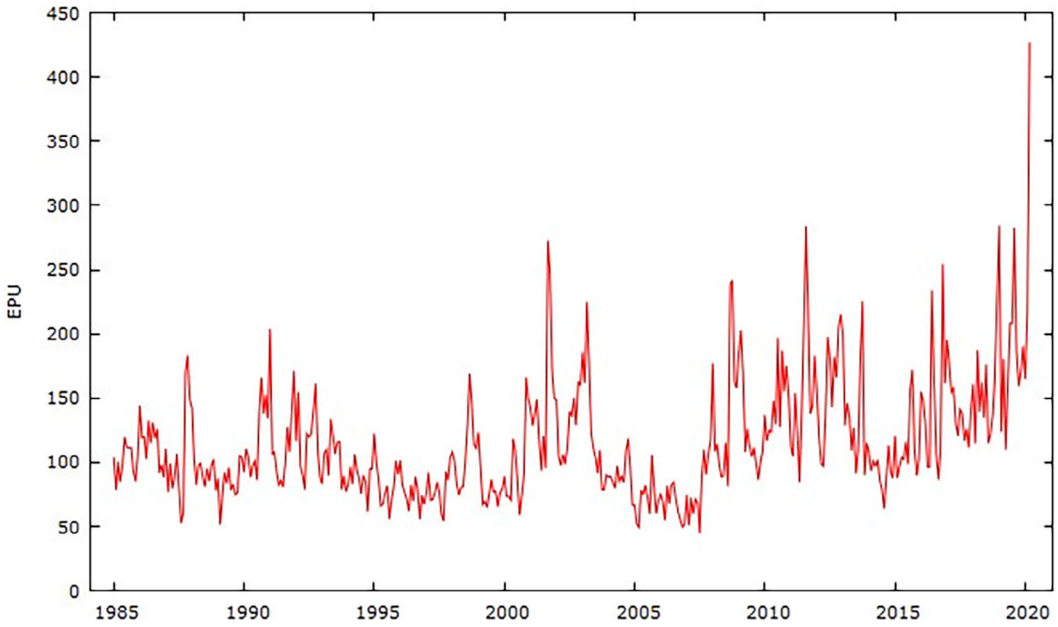

FIGURE 1 Monthly US EPU evolution from January 1985 to March 2020 [Colour figure can be viewed at wileyonlinelibrary.com]

In accordance with the literature, we propose the following hypotheses:

H1. Economic Policy Uncertainty increases commercial banks' credit risk.

H2. Economic Policy Uncertainty has a greater impact on smaller commercial banks' credit risk.

H3. Economic Policy Uncertainty has a greater impact on less profitable commercial banks' credit risk.

H4. Economic Policy Uncertainty has a greater impact on less solvent commercial banks' credit risk.

TABLE 1 Definition and calculation of the variables used

Variable	Definition	Calculation
LLRR	Loan loss reserves ratio	Loan loss reserves to gross loans
NPLR	Non-performing loan ratio	Non-performing loans to gross loans
EPU	Economic Policy Uncertainty	Natural logarithm of Economic Policy Uncertainty index average
Size	Bank size	Natural logarithm of assets
ROA	Return on assets	Net Income to average total assets
Solv	Solvency ratio	Equity to assets
CAR	Capital adequacy ratio	Capital to risk-weighted assets
LDR	Loan to deposit ratio	Total loans to total deposits
GDP	Gross domestic product	Natural logarithm of gross domestic product
FFR	Federal funds rate	Federal funds rate average
Spread	Interest rate spread	3-month commercial paper minus treasury bill rate average

3 | DATA

The sample contains data about 2.994 US commercial banks during the 2017–2019 period. The data was extracted from the Orbis database[1] (Orbis, 2022) and the selection of the commercial banks and the sample period was based on the availability of quarterly data found in the entire sample period in the database.

Regarding the EPU variable, the monthly US EPU[2] (Baker et al., 2016) was selected. This index is based on the frequency of certain keywords including: "economy" or "economics", "uncertain" or "uncertainty" and "legislation", "deficit", "regulation", "Congress", "Federal Reserve" or "White House" that appear in US newspapers. This index reflects the sentiment of economic agents through news related to economic policy, including the fiscal, monetary, commercial and regulatory policy (Baker et al., 2016).

Figure 1 displays how US EPU has evolved from data first recorded in January 1985 to March 2020. It shows how EPU generated by Covid-19 reached historic highs, higher even than the levels reached during the 2008 global financial crisis (US EPU, 2022).

Concerning the variables considered as representatives of commercial bank credit risk, we selected the ratios of (a) loan loss reserves to gross loans and (b) non-performing loans to gross loans, both extracted from the Orbis database. The first ratio represents a measure of a

TABLE 2 Descriptive statistics of variables used

Variable	Mean	Median	Min.	Max.	*SD*	C.V.	Skew.	Kurt.
LLRR	1.340	1.213	0.000	14.437	0.725	0.541	4.692	47.836
NPLR	1.193	0.719	0.000	28.574	1.585	1.329	4.829	41.191
EPU	5.070	5.055	4.835	5.419	0.168	0.033	0.476	−0.652
Size	12.719	12.507	8.900	21.585	1.452	0.114	1.418	4.077
ROA	1.077	1.070	−43.025	110.543	1.152	1.070	21.266	2379.0
Solv	11.579	10.920	1.430	76.346	3.435	0.297	4.070	39.873
CAR	17.817	15.801	2.500	152.137	7.509	0.421	3.710	25.558
LDR	0.793	0.814	0.008	2.432	0.193	0.244	−0.342	1.470
GDP	9.928	9.935	9.862	9.986	0.040	0.004	−0.196	−1.263
FFR	1.664	1.690	0.700	2.403	0.555	0.334	−0.179	−1.246
Spread	0.206	0.197	0.103	0.343	0.074	0.357	0.517	−0.775

bank's estimated losses due to the inability of its borrowers to service their debt obligations. This ratio was chosen because when bank credit risks rises, banks are forced to raise loan loss reserves thereby increasing the pressure on capital (Mamonov, 2018). The literature shows this ratio to be representative of bank credit risk (Laidroo & Männasoo, 2017; Mamonov, 2018). The second ratio measures the percentage of loans in which borrowers are in default because they failed to make scheduled payments over a specified period with credit risk being the most common cause of that credit event (Greuning & Bratanovic, 2003). This ratio is often used in the literature as a proxy of bank credit risk (Chi & Li, 2017; Natsir et al., 2019).

In our study, we use bank-specific and external factors as control variables when analysing the effect of EPU on bank credit risk. The literature on the subject suggests the use of the following bank-specific factors as control variables: size (Chi & Li, 2017; Poudel, 2018), return on assets (Chi & Li, 2017; Koju et al., 2018), solvency ratio (Chaibi & Ftiti, 2015; Koju et al., 2018), capital adequacy ratio (Natsir et al., 2019; Loaba & Zahonogo, 2019) and loan to deposit ratio (Chi & Li, 2017; Loaba & Zahonogo, 2019). All of these factors were collected from the Orbis database. With respect to external factors, the following variables are included in our analysis: Gross Domestic Product (Chaibi & Ftiti, 2015; Loaba & Zahonogo, 2019), interest rates (Imbierowicz & Rauch, 2014; Poudel, 2018) and yield spreads (Imbierowicz & Rauch, 2014; Poudel, 2018). The external factor data were obtained from the Federal Reserve Economic Data (FRED, 1991) database[3] of the Federal Reserve Bank of St. Louis.

It should be noted that most of the selected variables were reported on a quarterly basis. Data that were reported on a monthly basis, such as EPU, Interest Rates and Yield Spreads, were averaged to convert them to a quarterly basis. Table 1 summarizes the variables used in this study, their definition and calculation.

Table 2 contains the descriptive statistics of variables used to analyse the impact of EPU on US commercial bank credit risk.

TABLE 3 Bivariate correlations of variables used

Variable	LLRR	NPLR	EPU	Size	ROA	Solv	CAR	LDR	GDP	FFR	Spread
LLRR	1	0.26[a]	−0.01	−0.13[a]	0.04[a]	0.19[a]	0.25[a]	−0.17[a]	−0.03[a]	−0.03[a]	0.02[a]
		(0.000)	(0.254)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
NPLR		1	−0.01[b]	−0.19[a]	−0.13[a]	0.12[a]	0.17[a]	−0.13[a]	−0.03[a]	−0.03[a]	0.02[a]
			(0.036)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
EPU			1	0.02[a]	0.04[a]	0.05[a]	0.02[a]	0.01	0.57	0.51	−0.16[a]
				(0.000)	(0.000)	(0.000)	(0.000)	(0.295)	(0.000)	(0.000)	(0.000)
Size				1	0.12[a]	−0.04[a]	−0.26[a]	0.23[a]	0.03[a]	0.03[a]	−0.02[a]
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
ROA					1	0.11[a]	0.00	0.08[a]	0.05[a]	0.06[a]	−0.01[b]
						(0.000)	(0.839)	(0.000)	(0.000)	(0.000)	(0.012)
Solv						1	0.69[a]	0.02[a]	0.07[a]	0.06[a]	−0.06[a]
							(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
CAR							1	−0.46[a]	0.02[a]	0.02[a]	−0.01[b]
								(0.000)	(0.000)	(0.000)	(0.013)
LDR								1	0.04[a]	0.05[a]	−0.03[a]
									(0.000)	(0.000)	(0.000)
GDP									1	0.87[a]	−0.45
										(0.000)	(0.000)
FFR										1	−0.54[a]
											(0.000)
Spread											1

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.

Observations of Table 2 descriptive statistics note that the mean of credit risk measures is 1.340 for LLRR and 1.193 for NPLR, with the latter presenting a greater dispersion (C.V. = 1.329) and reaching a maximum of 28.574. Regarding EPU, this measure showed lower dispersion, with data being between 4.835 and 5.419 with a mean of 5.070. Related to the bank's specific factors, it is observed that ROA, with a mean of 1.077, is the measure that presents the greatest dispersion (C.V. = 1.070), with data being between −43.025 and 110.543. Likewise, ROA is the measure that shows the greatest asymmetry and the greatest kurtosis where most of the data were to the right of the distribution and highly concentrated around the mean. Finally, in terms of external factors, GDP is the measure with the least dispersion, with FFR and Spread having very similar dispersion levels (C.V. = 0.334 and C.V. = 0.357, respectively).

Table 3 shows the bivariate correlations of the variables used. Most of the correlations are significant at the 5% level or lower, and most are below 0.50. It should be noted that the correlation coefficients between the different variables, in general, are low. Only the correlations between EPU and GDP (0.57), EPU and FFR (0.51), Solv and CAR (0.69), GDP and FFR (0.87) and, FFR and Spread (−0.54) are greater than 0.50, but these are within the 0.90, threshold maximum suggested by Hair et al. (2010). Therefore, the multicollinearity problem does not arise in this study.

4 | METHODOLOGY

We used the panel data approach as the dispersion of the 2994 US commercial banks over different time periods makes this methodology to be more appropriate than transversal analysis and time series analysis (Wooldridge, 2011). This method is one of the most frequently used to analyse bank credit risk (Rose, 2017; Poudel, 2018; Zamore et al., 2019).

In this study, the Hausman test showed that the fixed effects model was more consistent with the sample data we used and therefore that it was our methodological choice.

On the basis of what has been reviewed, the proposed models to identify the impact of EPU on US commercial banks credit risk are the following:

$$\begin{aligned}\mathrm{LLRR}_{it} = {} & \alpha + \beta_1 \mathrm{EPU}_{it} + \beta_2 \mathrm{Size}_{it} + \beta_3 \mathrm{ROA}_{it} + \beta_4 \mathrm{Solv}_{it} \\ & + \beta_5 \mathrm{CAR}_{it} + \beta_6 \mathrm{LDR}_{it} + \beta_7 \mathrm{GDP}_{it} + \beta_8 \mathrm{FFR}_{it} \\ & + \beta_9 \mathrm{Spread}_{it} + v_i + u_{it}, \end{aligned} \quad (1)$$

$$\begin{aligned}\mathrm{NPLR}_{it} = {} & \alpha + \beta_1 \mathrm{EPU}_{it} + \beta_2 \mathrm{Size}_{it} + \beta_3 \mathrm{ROA}_{it} + \beta_4 \mathrm{Solv}_{it} \\ & + \beta_5 \mathrm{CAR}_{it} + \beta_6 \mathrm{LDR}_{it} + \beta_7 \mathrm{GDP}_{it} + \beta_8 \mathrm{FFR}_{it} \\ & + \beta_9 \mathrm{Spread}_{it} + v_i + u_{it}, \end{aligned} \quad (2)$$

where $LLRR_{it}$ and $NPLR_{it}$ are the dependent variables of each model, α is the constant term, β_k is the regression coefficient corresponding to each explanatory variable k, v_i is the constant fixed part of the error that represents the individual effects and u_{it} is the aleatory part of the error. The sub-indices i and t represent, respectively, the cross-sectional dimension and temporal dimension.

5 | RESULTS

Table 4 shows the results obtained for the entire sample and the two credit measures used in this study. It

TABLE 4 Regression results of the influence of EPU on the credit risk of US commercial banks

Variable	LLRR Coef. (*p*-value)	NPLR Coef. (*p*-value)
Const.	4.360[a] (0.000)	12.296[a] (0.000)
EPU_t	0.054[a] (0.000)	0.089[a] (0.007)
Size_t	−0.531[a] (0.000)	−0.482[a] (0.000)
ROA_t	−0.014[a] (0.000)	−0.067[a] (0.000)
Solv_t	−0.027[a] (0.000)	−0.023[a] (0.001)
CAR_t	0.014[a] (0.000)	−0.010[a] (0.005)
LDR_t	−0.875[a] (0.000)	−1.239[a] (0.000)
GDP_t	0.431[a] (0.000)	−0.397 (0.108)
FFR_t	−0.016[a] (0.000)	0.001 (0.934)
Spread_t	−0.071[a] (0.000)	−0.016 (0.823)
R^2	0.928	0.745
F-test (*p*-value)	141.671[a] (0.000)	32.093[a] (0.000)
Hausman-test (*p*-value)	1256.080[a] (0.000)	241.733[a] (0.000)
Number of Obs.	2994	2994

[a]Indicate significance at the 1% level.

has been evidenced that the R^2 of the proposed models is relatively high (0.928 and 0.745) and the regressions are globally significant at the conventional levels. Controlling for the banks' specific factors and external factors, we found that EPU has a significantly positive influence on credit risk with a significance level of less than 1%. This result supports H1 by showing that an increase in EPU increases credit risk in US commercial banks.

Given the two measures selected to represent credit risk, it can be observed that EPU has a greater influence on NPLR than on LLRR. The study finds that an increase of a unit one point of EPU can generate a 5.4% increase in LLRR and 8.9% in NPLR, in both cases with a significance level of less than 1%. Therefore, in general terms, EPU has a bigger impact on credit risk at a later stage when default is real.

Regarding the control variables, we observe an inverse and significant relationship between Size, ROA, Solv and LDR with bank credit risk. However, the sign of the influence of CAR on credit risk has been found to vary depending on the selected credit risk measure. Concerning external factors, GDP, FFR and Spread are found to exert a significant influence on LLRR: the greater the GDP, the greater the size of reserves needed to sustain loan losses. By contrast, an increase in FFR and Spread reduces LLRR.

The aim of this study is not only to evaluate whether EPU may be a relevant factor in a bank's exposure to credit risk but also to consider whether the characteristics of banks could make them more or less vulnerable to this factor. In this part of our analysis, the characteristics of size, profitability and solvency levels of a bank have been considered to determine if these factors impact the effect

TABLE 5 Regression results of the influence of EPU on the credit risk of US commercial banks. Categorized by size

	Small size		Medium size		Large size	
Variable	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**
Const.	6.229[a] (0.000)	21.905[a] (0.001)	4.451[a] (0.000)	12.246[a] (0.000)	6.532[a] (0.000)	14.405[a] (0.000)
EPU_t	0.105[a] (0.000)	0.059 (0.536)	0.049[a] (0.000)	0.136[a] (0.001)	0.027[b] (0.012)	0.054 (0.178)
$Size_t$	−1.133[a] (0.000)	−2.147[a] (0.000)	−0.562[a] (0.000)	−0.2283[a] (0.002)	−0.255[a] (0.000)	0.039 (0.520)
ROA_t	−0.027[a] (0.000)	−0.132[a] (0.000)	−0.008[a] (0.000)	−0.039[a] (0.000)	−0.005[c] (0.068)	−0.037[a] (0.000)
$Solv_t$	−0.054[a] (0.000)	0.007 (0.715)	−0.011[a] (0.000)	−0.067[a] (0.000)	−0.032[a] (0.000)	0.010 (0.240)
CAR_t	0.015[a] (0.000)	−0.021[b] (0.011)	0.007[a] (0.000)	−0.005 (0.249)	0.031[a] (0.000)	0.030[a] (0.000)
LDR_t	−1.143[a] (0.000)	−1.743[a] (0.000)	−1.065[a] (0.000)	−1.136[a] (0.000)	−0.111[a] (0.003)	−0.550[a] (0.000)
GDP_t	0.877[a] (0.000)	0.524 (0.452)	0.462[a] (0.000)	−0.710[b] (0.019)	−0.175[b] (0.038)	−1.465[a] (0.000)
FFR_t	−0.046[a] (0.000)	0.032 (0.519)	−0.016[a] (0.003)	−0.034 (0.115)	0.001 (0.923)	0.014 (0.495)
$Spread_t$	−0.217[a] (0.000)	0.153 (0.473)	−0.053[b] (0.020)	−0.198[b] (0.028)	−0.013 (0.586)	0.102 (0.256)
R^2	0.887	0.674	0.917	0.784	0.976	0.784
F-test (*p*-value)	85.489[a] (0.000)	22.430[a] (0.000)	120.836[a] (0.000)	39.578[a] (0.000)	448.048[a] (0.000)	39.405[a] (0.000)
Hausman-test (*p*-value)	305.811[a] (0.000)	90.128[a] (0.000)	366.242[a] (0.000)	186.255[a] (0.000)	207.446[a] (0.000)	43.205[a] (0.000)
Number of Obs.	749	749	1496	1496	749	749

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.

of EPU on bank credit risk. Thus, we decided to divide the total sample of banks into three parts, considering the 25 and 75 quantiles. The values at the 25 and 75 quantiles are: 11.835 and 13.487 for size, 0.695 and 1.428 for profitability, and 9.98 and 13.12 for solvency.

Table 5 shows the results of the impact of EPU on credit risk in relation to size. Considering the effects of control variables, it can be seen that EPU has a greater impact on the credit risk of the medium size or smaller banks, especially in LLRR. The impact is 3.89 times higher on smaller banks than bigger banks. In particular, in the smallest banks, an increase of a unit one point of EPU results in a 10.5% increase in LLRR. Regarding NPLR, EPU presents a significant influence in only the medium size in which a unit one point EPU increase results in a 13.6% increase in NPLR. These results allow us to not reject H2 since they indicate that the credit risk of smaller banks is more vulnerable to EPU.

-Table 6 contains the results that show the influence of EPU on credit risk, considering the bank specific factor of profitability. Looking at the entirety of regressors' data shows that EPU increases LLRR in all cases with this relationship being stronger in the less profitable banks. In less profitable banks, an increase of a unit one point of EPU results in an increase of 7.6% in LLRR. Regarding NPLR, this study finds that less profitable banks are the only ones in which an EPU increase produces NPLR increases and this impact is higher than LLRR increases. Thus, an increase of a unit one point in EPU leads to an increase of 22.4% in NPLR. This finding supports H3 by showing that the EPU impact is higher in less profitable banks.

Finally, Table 7 presents the results of the EPU impact on credit risk at varying bank solvency levels. It

TABLE 6 Regression results of the influence of EPU on the credit risk of US commercial banks. Categorized by profitability

	Low return		Medium return		High return	
Variable	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**
Const.	5.406[a] (0.000)	13.225[b] (0.042)	4.646[a] (0.000)	14.842[a] (0.000)	5.667[a] (0.000)	12.346[a] (0.004)
EPU_t	0.076[a] (0.001)	0.224[b] (0.018)	0.042[a] (0.000)	0.033 (0.334)	0.052[a] (0.002)	0.054 (0.377)
$Size_t$	−0.645[a] (0.000)	−1.042[a] (0.000)	−0.308[a] (0.000)	0.099 (0.152)	−0.642[a] (0.000)	−0.478[a] (0.000)
ROA_t	−0.022[a] (0.000)	−0.062[a] (0.000)	−0.013[a] (0.000)	−0.187[a] (0.000)	0.001 (0.791)	−0.032[a] (0.000)
$Solv_t$	−0.039[a] (0.000)	−0.006 (0.724)	−0.023[a] (0.000)	0.026[a] (0.006)	−0.017[a] (0.000)	−0.076[a] (0.000)
CAR_t	0.016[a] (0.000)	−0.019[b] (0.015)	0.028[a] (0.000)	−0.008 (0.106)	0.007[a] (0.000)	0.012[b] (0.025)
LDR_t	−0.930[a] (0.000)	−1.682[a] (0.000)	−0.565[a] (0.000)	−0.568[a] (0.000)	−1.110[a] (0.000)	−1.507[a] (0.000)
GDP_t	0.435[a] (0.007)	0.183 (0.791)	0.067 (0.277)	−1.500[a] (0.000)	0.491[a] (0.000)	−0.340 (0.467)
FFR_t	−0.037[a] (0.001)	−0.049 (0.331)	−0.005 (0.235)	0.052[a] (0.004)	−0.009 (0.317)	0.015 (0.652)
$Spread_t$	−0.157[a] (0.001)	−0.270 (0.199)	−0.020 (0.274)	0.250[a] (0.001)	−0.068[c] (0.063)	−0.036 (0.791)
R^2	0.855	0.702	0.948	0.777	0.954	0.766
F-test (*p*-value)	63.850[a] (0.000)	25.602[a] (0.000)	198.115[a] (0.000)	38.052[a] (0.000)	225.450[a] (0.000)	35.620[a] (0.000)
Hausman-test (*p*-value)	341.230[a] (0.000)	68.982[a] (0.000)	243.388[a] (0.000)	33.683[a] (0.000)	477.545[a] (0.000)	227.707[a] (0.000)
Number of Obs.	749	749	1496	1496	749	749

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.
[c]Indicate significance at the 10%.

TABLE 7 Regression results of the influence of EPU on the credit risk of US commercial banks. Categorized by solvency

	Low solvency		Medium solvency		High solvency	
Variable	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**
Const.	3.137[a] (0.000)	12.829[a] (0.003)	3.294[a] (0.000)	9.205[a] (0.002)	7.733[a] (0.000)	23.957[a] (0.000)
EPU_t	0.039[a] (0.001)	0.190[a] (0.003)	0.071[a] (0.000)	0.018 (0.668)	0.043[b] (0.032)	0.100 (0.191)
$Size_t$	−0.313[a] (0.000)	−1.085[a] (0.000)	−0.619[a] (0.000)	−0.140[c] (0.099)	−0.523[a] (0.000)	−0.539[a] (0.000)
ROA_t	−0.040[a] (0.000)	−0.188[a] (0.000)	−0.010[a] (0.000)	−0.053[a] (0.000)	−0.012[a] (0.000)	−0.033[a] (0.001)
$Solv_t$	−0.017[a] (0.000)	−0.042[b] (0.045)	−0.041[a] (0.000)	0.039[a] (0.001)	−0.017[a] (0.000)	−0.040[a] (0.000)
CAR_t	0.014[a] (0.000)	−0.082[a] (0.000)	0.029[a] (0.000)	−0.011[c] (0.096)	0.008[a] (0.000)	−0.000 (0.945)
LDR_t	−0.680[a] (0.000)	−1.482[a] (0.000)	−0.739[a] (0.000)	−1.239[a] (0.000)	−1.091[a] (0.000)	−1.273[a] (0.000)
GDP_t	0.240[b] (0.012)	0.410 (0.398)	0.625[a] (0.000)	−0.567[c] (0.086)	0.116 (0.435)	−1.482[a] (0.009)
FFR_t	−0.014[b] (0.035)	−0.055[c] (0.099)	−0.022[a] (0.000)	0.018 (0.431)	−0.011 (0.302)	0.056 (0.168)
$Spread_t$	−0.037 (0.183)	−0.229 (0.105)	−0.099[a] (0.000)	0.036 (0.708)	−0.053 (0.244)	0.241 (0.159)
R^2	0.873	0.761	0.899	0.728	0.949	0.754
F-test (*p*-value)	74.642[a] (0.000)	34.6891[a] (0.000)	97.280[a] (0.000)	29.187[a] (0.000)	202.342[a] (0.000)	33.321[a] (0.000)
Hausman-test (*p*-value)	168.707[a] (0.000)	131.161[a] (0.000)	796.710[a] (0.000)	37.148[a] (0.000)	256.405[a] (0.000)	97.880[a] (0.000)
Number of Obs.	749	749	1496	1496	749	749

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.
[c]Indicate significance at the 10%.

finds that EPU increases LLRR in all cases with the impact being greater in medium solvent banks (almost double the rest of the banks). An increase of a unit one point of EPU results in an increase of 7.1% in LLRR. But in the case of NPLR, only the less solvent banks are affected by EPU with NPLR increasing by 19%. Therefore, we do not reject H4. The less solvent banks are the ones in which EPU increases both credit risk measures selected, but EPU has a lesser influence on their LLRR.

In summary, this study has confirmed that uncertainty generated by economic policy makers in the US increases US bank credit risk. Considering banks' characteristics of size, profitability, and solvency, the results, a priori, indicate that smaller and lesser profitable and solvent banks suffer the greatest increase in their credit risk when EPU increases.

5.1 | Robustness checks

To analyse the robustness of the analysis, the specification of the variables was modified. Following Pizzi et al. (2020), we considered lagged variables to validate the robustness of the findings. In particular, we analyse the explanatory variables' effects at the moment t-1 on bank credit risk in the moment t. Thus, this specification not only tests our results' robustness, but also allows the evaluation of EPU predictive capacity on US banks' credit risk for the following quarter.

Table 8 presents the results obtained when analysing the predictive capacity of EPU on the credit risk of the US commercial banks. Taking the entire sample and considering the control variables, the results show that EPU has a positive and significant influence in LLRR with a

TABLE 8 Regression results for the robustness check of the influence of EPU on the credit risk of US commercial banks

Variable	LLRR Coef. (*p*-value)	NPLR Coef. (*p*-value)
Const.	4.990[a] (0.000)	10.962[b] (0.036)
EPU_{t-1}	0.034[a] (0.000)	0.029 (0.377)
$Size_{t-1}$	−0.339[a] (0.000)	−0.188[a] (0.002)
ROA_{t-1}	−0.009[a] (0.000)	−0.039[a] (0.000)
$Solv_{t-1}$	−0.026[a] (0.000)	−0.021[a] (0.005)
CAR_{t-1}	0.012[a] (0.000)	−0.010[a] (0.005)
LDR_{t-1}	−0.455[a] (0.000)	−0.919[a] (0.000)
GDP_{t-1}	0.098 (0.464)	−0.642 (0.237)
FFR_{t-1}	−0.004 (0.625)	0.011 (0.733)
$Spread_{t-1}$	−0.091[a] (0.000)	−0.037 (0.613)
R^2	0.929	0.755
F-test (*p*-value)	130.293[a] (0.000)	30.759[a] (0.000)
Hausman-test (*p*-value)	521.660[a] (0.000)	213.845[a] (0.000)
Number of Obs.	2994	2994

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.

significance level of less than 1%. Thus, an EPU increase of a unit one point in t-1 would result in an increase of 3.4% in LLRR in the next quarter. However, there is no significant relationship with NPLR. Therefore, while EPU explains both risk measures, it is only able to predict, in general terms, future credit risk as measured by LLRR.

Based on EPU's ability to predict bank credit risk according to bank size (Table 9), it has been shown that EPU predicts credit risk only in smaller or medium sized banks. Specifically, EPU predicts LLRR in small sized banks with a confidence level greater than 99% and medium-sized banks with a confidence greater than 95%. The relationship is stronger in the former, in which EPU predicts an increase of 10.1% in LLRR. However, with respect to NPLR, a higher EPU increases this credit risk measure in the next quarter, but only in the case of medium sized banks, with an increase of 11.3%. This result shows that EPU only has the ability to predict future credit risk in small or medium sized banks.

Table 10 shows the results of EPU's ability to predict credit risk considering banks' profitability levels. In this case, it has been found that EPU predicts LLRR only in the least profitable banks. In less profitable banks, the increase in the average EPU predicts an increase of 6.7% in LLRR, almost double that of the most profitable banks. However, only in the least profitable banks, EPU has a predictive capacity over NPLR, finding that an increase in EPU is associated with an increase of 15.8% in NPLR in the next quarter.

Based on the above, it is observed that including lags, EPU continues to have a greater impact on bank credit risk in less profitable banks, and shows that banks, with more inefficient asset management, are more vulnerable to EPU.

Finally, when distinguishing by banks' solvency levels (Table 11), it has been found that EPU only predicts credit risk in banks with low solvency or medium solvency. Specifically, EPU can explain the next quarter's LLRR in banks with low and medium solvency levels. However, regarding NPLR, only in the least solvent banks can EPU predicts this measure. In particular, an increase in EPU at $t + 1$ is associated with an increase of 3.1% in LLRR and 18.9% in NPLR in less solvent banks. These results demonstrate that EPU predicts a bank's credit risk to a greater extent if the bank has low solvency levels.

From the results obtained when applying the lag, it has been deduced that, although EPU has a minor impact on credit risk for the next quarter, this impact continues to exist, especially in the LLRR measure. Likewise, by classifying banks by size, profitability, and solvency, it has been shown that profitability and solvency increase their discriminatory power over the initial analysis.

An additional question is whether the differences found when segmenting the sample by size, profitability, and solvency can be considered significant when examining the relationship between EPU and bank credit risk. For this reason, and to achieve greater robustness in our study, the inclusion of interaction terms between Size and EPU, ROA and EPU, and Solv and EPU has been implemented.

Table 12 depicts the results obtained by including the interaction terms in the models. It can be seen that EPU, even after including the interaction terms, maintains its positive and significant impact on credit risk and shows higher coefficients than previous models.

Focusing on the effects of the interaction of EPU with the different characteristics, it is found that the interaction term of EPU with Size has a negative and significant impact on LLRR considering a lag but no significant

TABLE 9 Regression results for the robustness check of the influence of EPU on the credit risk of US commercial banks. Categorized by size

	Small size		Medium size		Large size	
Variable	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**
Const.	8.919[b] (0.012)	12.025 (0.433)	3.564[b] (0.032)	17.567[a] (0.006)	7.093[a] (0.000)	7.190 (0.244)
EPU_{t-1}	0.101[a] (0.000)	−0.048 (0.615)	0.020[c] (0.053)	0.113[a] (0.006)	0.001 (0.896)	−0.035 (0.373)
$Size_{t-1}$	−0.717[a] (0.000)	−1.465[a] (0.000)	−0.422[a] (0.000)	0.053 (0.512)	−0.075[a] (0.000)	0.182[a] (0.004)
ROA_{t-1}	−0.014[a] (0.000)	−0.095[a] (0.000)	−0.006[a] (0.000)	−0.018[a] (0.001)	−0.007[b] (0.021)	−0.009 (0.398)
$Solv_{t-1}$	−0.059[a] (0.000)	0.002 (0.928)	−0.006[b] (0.022)	−0.060[a] (0.000)	−0.028[a] (0.000)	0.014 (0.111)
CAR_{t-1}	0.017[a] (0.000)	−0.012 (0.175)	0.003[a] (0.007)	−0.006 (0.225)	0.029[a] (0.000)	−0.001 (0.855)
LDR_{t-1}	−0.338[a] (0.000)	−1.413[a] (0.000)	−0.774[a] (0.000)	−0.623[a] (0.000)	0.082[b] (0.036)	−0.719 (0.000)
GDP_{t-1}	0.076 (0.834)	0.770 (0.625)	0.365[b] (0.034)	−1.652[b] (0.013)	−0.505[a] (0.005)	−0.846 (0.189)
FFR_{t-1}	−0.010 (0.662)	0.007 (0.944)	−0.010 (0.355)	0.019 (0.638)	0.007 (0.555)	−0.011 (0.774)
$Spread_{t-1}$	−0.278[a] (0.000)	0.051 (0.813)	−0.065[a] (0.005)	−0.192[b] (0.033)	0.013 (0.587)	0.130 (0.131)
R^2	0.885	0.683	0.917	0.792	0.977	0.795
F-test (*p*-value)	76.356[a] (0.000)	21.323[a] (0.000)	110.409[a] (0.000)	37.845[a] (0.000)	417.539[a] (0.000)	38.326[a] (0.000)
Hausman-test (*p*-value)	149.753[a] (0.000)	65.023[a] (0.000)	208.969[a] (0.000)	171.923[a] (0.000)	105.745[a] (0.000)	88.414[a] (0.000)
Number of Obs.	749	749	1496	1496	749	749

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.
[c]Indicate significance at the 10%.

effects are found of its effect on NPLR. This result calls into question the possible consideration of size as a relevant variable in the potential impact of EPU on credit risk. Thus, these results do not allow to reject or not H2 Considering the interaction of EPU with ROA and Solv, it is evident that the interaction with ROA has a negative and significant impact on NPLR in all cases and on LLRR without considering the delay. Regarding the interaction with Solv, a negative and significant impact on credit risk is shown in all cases. Therefore, these results reveal that the higher the bank's profitability and solvency, the lower the impact of EPU on its credit risk.

Therefore, after considering all the analysis, it has been demonstrated that EPU is a relevant factor that should be taken into account by bank managers to control bank credit risk. Regarding the greater or lesser impact of EPU on bank credit risk depending on the entity's characteristics, it can be concluded that EPU has a more significant impact on the credit risk of less profitable and less solvent banks.

6 | DISCUSSION

This study analysed the impact of EPU on one of the most relevant factors when determining the "financial health" of a bank, reflected by its credit risk. This relationship was analysed both globally and after considering the bank's characteristics in question, such as its size, profitability, and solvency.

Taking the US commercial bank as a reference, the results obtained show how, controlling for bank-specific

TABLE 10 Regression results for the robustness check of the influence of EPU on the credit risk of US commercial banks. Categorized by profitability

	Low return		Medium return		High return	
Variable	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**
Const.	5.682 (0.117)	18.716 (0.219)	4.838[a] (0.000)	7.715 (0.143)	5.528[b] (0.039)	13.148 (0.174)
EPU_{t-1}	0.067[a] (0.004)	0.158[c] (0.100)	0.013 (0.115)	−0.028 (0.404)	0.034[b] (0.045)	−0.011 (0.856)
$Size_{t-1}$	−0.466[a] (0.000)	−0.594[a] (0.000)	−0.203[a] (0.000)	0.215[a] (0.003)	−0.357[a] (0.000)	−0.216[c] (0.045)
ROA_{t-1}	−0.010[a] (0.000)	−0.058[a] (0.000)	−0.004 (0.175)	−0.104[a] (0.000)	−0.008[a] (0.001)	0.035[a] (0.000)
$Solv_{t-1}$	−0.033[a] (0.000)	−0.021 (0.272)	−0.013[a] (0.000)	0.030[a] (0.002)	−0.031[a] (0.000)	−0.064[a] (0.000)
CAR_{t-1}	0.014[a] (0.000)	−0.009 (0.277)	0.018[a] (0.000)	−0.021[a] (0.000)	0.008[a] (0.000)	0.005 (0.399)
LDR_{t-1}	−0.518[a] (0.000)	−1.093[a] (0.000)	−0.338[a] (0.000)	−0.502[a] (0.000)	−0.493[a] (0.000)	−1.291[a] (0.000)
GDP_{t-1}	0.154 (0.680)	−0.948 (0.546)	−0.089 (0.501)	−0.892 (0.105)	0.106 (0.703)	−0.761 (0.449)
FFR_{t-1}	−0.023 (0.326)	0.038 (0.698)	0.004 (0.649)	0.012 (0.753)	0.001 (0.933)	0.016 (0.791)
$Spread_{t-1}$	−0.176[a] (0.001)	−0.346 (0.102)	−0.036[b] (0.050)	0.212[a] (0.005)	−0.084[b] (0.024)	−0.043 (0.747)
R^2	0.851	0.711	0.949	0.789	0.955	0.777
F-test (*p*-value)	56.604[a] (0.000)	24.281[a] (0.000)	185.572[a] (0.000)	37.223[a] (0.000)	208.915[a] (0.000)	34.328[a] (0.000)
Hausman-test (*p*-value)	157.710[a] (0.000)	39.704[a] (0.000)	81.357[a] (0.000)	66.260[a] (0.000)	206.256[a] (0.000)	204.266[a] (0.000)
Number of Obs.	749	749	1496	1496	749	749

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.
[c]Indicate significance at the 10%.

factors and external factors, an increase in EPU significantly increases US commercial banks' credit risk. The outcomes have been evidenced to be robust to the inclusion of lags in the explanatory variables and the consideration of interaction terms. This result is in line with Chi and Li (2017), who found this positive relationship for Chinese commercial banks. Regarding what was obtained by these authors, in this study, two early measures of credit risk were considered: Loan loss reserves to gross loans ratio and non-performing loans to gross loans ratio, a ratio that shows a greater probability of losses as a consequence of non-compliance. The results showed how the relationship found between EPU and credit risk was maintained in both measures. Regarding the control variables' influence on credit risk, the results align with the existing literature (Chi & Li, 2017; Chaibi & Ftiti, 2015; Natsir et al., 2019; Imbierowicz & Rauch, 2014).

When evaluating the impact of EPU on bank credit risk and after classifying banks by size, we find how in the smallest banks, EPU has a positive impact on credit risk (measured by loan loss reserves to gross loans ratio), and that it is almost four times higher than in the largest banks. Considering the non-performing loans to gross loans ratio, we have found that an increase in EPU exerts a statistically significant influence on this ratio only in medium-sized banks. A priori, these results support Salas and Saurina (2002) studies, who argued that larger banks take fewer risks. Particularly, these outcomes support the inverse relationship between bank size and credit risk found by Jabra et al. (2017) and the moderating effect of

TABLE 11 Regression results for the robustness check of the influence of EPU on the credit risk of US commercial banks. Categorized by solvency

	Low solvency		Medium solvency		High solvency	
Variable	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**	**LLRR Coef. (*p*-value)**	**NPLR Coef. (*p*-value)**
Const.	2.763 (0.165)	13.033 (0.177)	4.808[a] (0.005)	11.459[c] (0.096)	8.047[b] (0.016)	12.311 (0.319)
EPU_{t-1}	0.031[b] (0.015)	0.189[a] (0.002)	0.036[a] (0.001)	0.005 (0.917)	0.030 (0.156)	−0.100 (0.196)
$Size_{t-1}$	−0.146[a] (0.000)	−0.479[a] (0.001)	−0.441[a] (0.000)	0.061 (0.509)	−0.269[a] (0.000)	−0.291[b] (0.016)
ROA_{t-1}	−0.038[a] (0.000)	−0.201[a] (0.000)	−0.005[a] (0.001)	−0.029[a] (0.000)	−0.006[b] (0.041)	0.017 (0.120)
$Solv_{t-1}$	−0.003 (0.467)	−0.044[b] (0.038)	−0.035[a] (0.000)	0.023[c] (0.076)	−0.024[a] (0.000)	−0.025[b] (0.041)
CAR_{t-1}	0.008[a] (0.003)	−0.053[a] (0.000)	0.027[a] (0.000)	−0.004 (0.561)	0.009[a] (0.000)	−0.006 (0.242)
LDR_{t-1}	−0.482[a] (0.000)	−0.948[a] (0.000)	−0.374[a] (0.000)	−0.716[a] (0.000)	−0.435[a] (0.000)	−1.215[a] (0.000)
GDP_{t-1}	0.047 (0.821)	−0.479 (0.635)	0.224 (0.207)	−1.087 (0.129)	−0.275 (0.423)	−0.530 (0.677)
FFR_{t-1}	−0.006 (0.626)	−0.004 (0.947)	−2.21e-05 (0.998)	0.039 (0.380)	−0.003 (0.882)	−0.007 (0.931)
$Spread_{t-1}$	−0.037 (0.196)	−0.083 (0.545)	−0.103[a] (0.000)	−0.002 (0.988)	−0.096[b] (0.038)	0.065 (0.703)
R^2	0.874	0.777	0.900	0.738	0.949	0.761
F-test (*p*-value)	68.45[a] (0.000)	34.425[a] (0.000)	89.385[a] (0.000)	27.987[a] (0.000)	185.330[a] (0.000)	31.445[a] (0.000)
Hausman-test (*p*-value)	50.505[a] (0.000)	80.407[a] (0.000)	338.371[a] (0.000)	42.305[a] (0.000)	82.401[a] (0.000)	78.862[a] (0.000)
Number of Obs.	749	749	1496	1496	749	749

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.
[c]Indicate significance at the 10%.

bank concentration on the relationship between EPU and banks' non-performing loans showed by Karadima and Louri (2020). These outcomes support the assertion of Tran et al. (2020) regarding the importance of the bank's size in the diversification of income from different activities other than credit interests in the face of high EPU.

Although the previous outcomes remained robust when considering the lagged explanatory variables, when including interaction terms to assess the effect of size on the influence of EPU on credit risk, the results were not conclusive. It was only found that the larger the bank, the smaller the impact of EPU on the future loan loss reserves to gross loans ratio. This result would indicate that the largest banks are more prudent in the face of EPU, accumulating more reserves against possible future losses derived from non-performing loans. Therefore, it cannot be concluded that the larger the bank, the lower the impact of EPU on credit risk, but the opposite cannot be said either.

A bank's profitability is also relevant when determining the impact of EPU on a bank's credit risk. The results obtained in this study show that profitability is negatively associated with banks' vulnerability to EPU. In this classification, no significant influence of EPU was found in the non-performing loan to gross loans ratio for banks with medium or high profitability. This finding remains robust when considering lagged explanatory variables. Furthermore, the indication that the higher the bank's profitability, the lower the impact of EPU on credit risk is also confirmed by evaluating the moderating effect of bank profitability by including in the models the interaction

TABLE 12 Regression results for the robustness check of the influence of EPU on the credit risk of US commercial banks considering interactive terms

Variable	$LLRR_t$ Coef. (*p*-value)	$LLRR_{t+1}$ Coef. (*p*-value)	$NPLR_t$ Coef. (*p*-value)	$NPLR_{t+1}$ Coef. (*p*-value)
Const.	3.408[a] (0.000)	2.745[b] (0.041)	10.260[a] (0.000)	4.188 (0.440)
EPU_t	0.223[a] (0.000)	0.352[a] (0.000)	0.430[c] (0.092)	0.522[b] (0.038)
$EPU_t \cdot Size_t$	0.001 (0.917)	−0.013[a] (0.005)	0.012 (0.513)	0.012 (0.499)
$EPU_t \cdot ROA_t$	−0.038[a] (0.000)	−0.010 (0.113)	−0.218[a] (0.000)	−0.254[a] (0.000)
$EPU_t \cdot Solv_t$	−0.012[a] (0.000)	−0.013[a] (0.000)	−0.022[a] (0.005)	−0.032[a] (0.000)
$Size_t$	−0.533[a] (0.000)	−0.271[a] (0.000)	−0.510[a] (0.000)	−0.249[b] (0.033)
ROA_t	0.178[a] (0.000)	0.044 (0.183)	1.036[a] (0.000)	1.247[a] (0.000)
$Solv_t$	0.032[a] (0.001)	0.039[a] (0.000)	0.090[b] (0.026)	0.145[a] (0.000)
CAR_t	0.014[a] (0.000)	0.012[a] (0.000)	−0.010[a] (0.005)	−0.010[a] (0.005)
LDR_t	−0.872[a] (0.000)	−0.451[a] (0.000)	−1.234[a] (0.000)	−0.910[a] (0.000)
GDP_t	0.440[a] (0.000)	0.156 (0.246)	−0.368 (0.136)	−0.207 (0.703)
FFR_t	−0.018[a] (0.000)	−0.008 (0.316)	−0.005 (0.778)	−0.020 (0.558)
$Spread_t$	−0.082[a] (0.000)	−0.100[a] (0.000)	−0.067 (0.364)	−0.087 (0.235)
R^2	0.928	0.929	0.746	0.756
F-test (*p*-value)	141.899[a] (0.000)	130.419[a] (0.000)	32.166[a] (0.000)	30.889[a] (0.000)
Hausman-test (*p*-value)	1290.480[a] (0.000)	557.835[a] (0.000)	285.317[a] (0.000)	262.046[a] (0.000)
Number of Obs.	2994	2994	2994	2994

[a]Indicate significance at the 1% level.
[b]Indicate significance at the 5% level.
[c]Indicate significance at the 10%.

term of EPU with profitability. The negative relationship between EPU and profitability is aligned with studies conducted in Chinese companies (Guo et al., 2020) and tourism firms (García-Gómez et al., 2021), but the literature in this regard is missing in the banking sector. However, our result supports the Guindos (2019) opinion. The current Vice-president of ECB points to the importance of bank profits as "the first line of defence against losses from credit impairment," a key characteristic to control credit risk in adverse scenarios, such as in times of high EPU.

Finally, when considering a bank's solvency, there is no clear pattern regarding the influence of EPU on the credit risk of commercial banks in the United States. Thus, it has been found that the impact of EPU on the loan loss reserves to gross loans ratio of medium solvency banks is almost double the rest of the banks. However, the least solvent banks are the only ones in which EPU has a significant impact on the non-performing loans to gross loans ratio. This shows that while a bank's solvency level is a key factor in EPU's impact on credit risk, at a more advanced level, a bank's level of solvency is not so

decisive in the accumulation of more reserves for expected credit losses by high EPU levels. These results are robust to the introduction of lagged explanatory variables, even showing how a bank's solvency increases its discriminatory power in the impact of EPU on credit risk compared to the initial analysis. Likewise, when including the interaction term of EPU with a bank's solvency, it is found in all cases that the higher a bank's solvency, the lower the impact of EPU on bank credit risk. In this regard, there is evidence of an inverse relationship between solvency and credit risk in the literature (Lehar, 2005; Baselga-Pascual et al., 2015), but there are no studies about the EPU influence on credit risk when considering a bank's solvency level.

Therefore, based on the outcomes, it can be concluded that EPU is an important factor to consider when analysing bank credit risk, especially in less profitable and solvent banks. We show how EPU not only explains but also predicts a part of bank credit risk.

7 | CONCLUSIONS

Credit risk is one of the most critical issues in bank risk management and essential for their survival, especially in high-risk environments accentuated by higher uncertainty. A growing literature is investigating the impact of EPU on different aspects of banking, but it is scarce about its effects on credit risk. This issue has been addressed in this study in the context of US commercial banks.

The results obtained show how an increase in EPU significantly increases the credit risk of US commercial banks. This relationship has been shown to exist in early measures of credit risk as well as in ratios that show a greater probability of losses as a consequence of non-compliance.

Besides evaluating the influence of EPU on the credit risk of US commercial banks, this study sought to deepen this relationship further, considering the size, profitability, and solvency of banks. The results obtained show that EPU has a greater impact on the credit risk of the less profitable and less solvent banks; however, the results obtained regarding the role of size in this relationship have not been conclusive.

Our findings suggest important implications for both economic policy makers and bank managers. The fact that EPU is positively associated with bank credit risk, one of the most important factors for financial stability, highlights the need for policymakers to pay greater attention to the uncertainty arising from the economic policies implement. The previous financial crisis of 2008 showed the importance of the "health" of banking entities in the economy. This issue is especially important in contexts such as the current one, in which the Covid-19 crisis has led to historic highs in EPU. Furthermore, the predictive capacity of EPU suggests that this measure can be used as a leading indicator of a banking crisis. Regarding bank managers, the findings obtained show the need for these managers to consider EPU levels in their decision making to avoid their consequences on the credit risk of the entity. Moreover, the greatest impact of EPU in less profitable and less solvent banks motivates a greater attention to this segment of the banking market. Along these lines, the findings suggest that bank managers could cushion the possible effects of EPU on credit risk by directing their efforts to improve the bank's profitability and solvency levels.

There remains much to be learned about the influence of EPU on the banking market. The results obtained regarding the influence of EPU on bank credit risk considering the size of the bank show the need for further investigation in this issue. Additionally, further avenues of research may include repeating the tests for a larger sample and allowing for more years of data; studying the impact of economic crises in the relationship between EPU and credit risk; conducting out-of-sample tests in other geographies; testing the findings during the COVID-19 pandemic period; and considering alternative estimating techniques.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Carmen Orden-Cruz https://orcid.org/0000-0002-1411-9286
Jessica Paule-Vianez https://orcid.org/0000-0001-8918-582X
Júlio Lobão https://orcid.org/0000-0001-5896-9648

ENDNOTES

[1] Orbis database is accessible through https://orbis.bvdinfo.com/orbis/Companies/Login?returnUrl=%2Forbis%2FCompanies

[2] US EPU index database is available at https://www.policyuncertainty.com/us_monthly.html

[3] Federal Reserve Economic Database (FRED) database is available at https://fred.stlouisfed.org/

REFERENCES

Adjei, F. A., & Adjei, M. (2017). Economic policy uncertainty, market returns and expected return predictability. *Journal of Financial Economic Policy*, *9*(3), 242–259.

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. *The Journal of Economic Asymmetries*, *20*, e00133.

Apergis, N. (2015). Policy risks, technological risks and stock returns: New evidence from the US stock market. *Economic Modelling*, *51*, 359–365.

Ashraf, B. N., & Shen, Y. (2019). Economic policy uncertainty and banks' loan pricing. *Journal of Financial Stability*, *44*, 100695.

Bachmann, R., Elstner, S., & Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, *5*(2), 217–249.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636.

Baker, S. R., Bloom, N., Davis, S. J. & Terry, S. J. (2020). Covid-induced economic uncertainty (No. w26983). National Bureau of Economic Research.

Basel Committee on Banking Supervision, & Bank for International Settlements (2000). Principles for the management of credit risk. Available at: https://www.bis.org/publ/bcbs75.htm.

Baselga-Pascual, L., Trujillo-Ponce, A., & Cardone-Riportella, C. (2015). Factors influencing bank risk in Europe: Evidence from the financial crisis. *The North American Journal of Economics and Finance*, *34*, 138–166.

Beckmann, J., & Czudaj, R. (2016). Exchange rate expectations and economic policy uncertainty. *European Journal of Political Economy*, *47*, 148–162.

Boahene, S. H., Dasah, J., & Agyei, S. K. (2012). Credit risk and profitability of selected banks in Ghana. *Research Journal of Finance and Accounting*, *3*(7), 6–14.

Bordo, M. D., Duca, J. V., & Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level US evidence over several decades. *Journal of Financial Stability*, *26*, 90–106.

Bouoiyour, J., Selmi, R., & Wohar, M. E. (2018). Measuring the response of gold prices to uncertainty: An analysis beyond the mean. *Economic Modelling*, *75*, 105–116.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, 87–95.

Caglayan, M., & Xu, B. (2019). Economic policy uncertainty effects on credit and stability of financial institutions. *Bulletin of Economic Research*, *71*(3), 342–347.

Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research in International Business and Finance*, *33*, 1–16.

Chi, Q., & Li, W. (2017). Economic policy uncertainty, credit risks and banks' lending decisions: Evidence from Chinese commercial banks. *China Journal of Accounting Research*, *10*(1), 33–50.

Ciccarelli, M., Maddaloni, A., & Peydró, J. L. (2015). Trusting the bankers: A new look at the credit channel of monetary policy. *Review of Economic Dynamics*, *18*(4), 979–1002.

Danisman, G. O., Ersan, O., & Demir, E. (2020). Economic policy uncertainty and bank credit growth: Evidence from European banks. *Journal of Multinational Financial Management*, *57*, 100653.

Demirgüç-Kunt, A., & Huizinga, H. (1999). Determinants of commercial bank interest margins and profitability: Some international evidence. *The World Bank Economic Review*, *13*(2), 379–408.

Federal Open Market Committee (2009), Minutes of the December 2009 meeting. http://www.federalreserve.gov/monetarypolicy/fomcminutes20091216.htm.

FRED (1991). Federal Reserve Economic Database. Available at: https://fred.stlouisfed.org/.

García-Gómez, C. D., Demir, E., Chen, M. H., & Díez-Esteban, J. M. (2021). Understanding the effects of economic policy uncertainty on US tourism firms' performance. *Tourism Economics*, *3148*, 314.

Greuning, H., & Bratanovic, S. B. (2003). *Analyzing and managing banking risk: A framework for assessing corporate governance and financial risk* (2nd ed.). The World Bank.

Guindos, L.D. (2019). Challenges for bank profitability. Speech, OMFIF City Lecture, London, England. https://www.ecb.europa.eu/press/key/date/2019/html/ecb.sp190501~7733ecc1a9.en.html.

Guo, A., Wei, H., Zhong, F., Liu, S., & Huang, C. (2020). Enterprise sustainability: Economic policy uncertainty, Enterprise investment, and profitability. *Sustainability*, *12*(9), 3735.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice hall.

Hammoudeh, S., & McAleer, M. (2015). Advances in financial risk management and economic policy uncertainty: An overview. *International Review of Economics & Finance*, *40*, 1–7.

He, Z., & Niu, J. (2018). The effect of economic policy uncertainty on bank valuations. *Applied Economics Letters*, *25*(5), 345–347.

Hu, S., & Gong, D. (2019). Economic policy uncertainty, prudential regulation and bank lending. *Finance Research Letters*, *29*, 373–378.

Imbierowicz, B., & Rauch, C. (2014). The relationship between liquidity risk and credit risk in banks. *Journal of Banking & Finance*, *40*, 242–256.

International Monetary Fund. (2013). *World economic outlook: Hopes, realities, risks*. IMF Press.

Jabra, W. B., Mighri, Z., & Mansouri, F. (2017). The determinants of credit and insolvency risk of European commercial banks: A dynamic panel data analysis. *International Journal of Monetary Economics and Finance*, *10*(2), 111–143.

Jiang, Y., He, L., Meng, J., & Nie, H. (2019). Nonlinear impact of economic policy uncertainty shocks on credit scale: Evidence from China. *Physica A: Statistical Mechanics and its Applications*, *521*, 626–634.

Jones, P. M., & Olson, E. (2013). The time-varying correlation between uncertainty, output, and inflation: Evidence from a DCC-GARCH model. *Economics Letters*, *118*(1), 33–37.

Jordà, Ò., Richter, B., Schularick, M., & Taylor, A. M. (2017). Bank capital redux: Solvency, liquidity, and crisis (No. w23287). National Bureau of Economic Research.

Karadima, M., & Louri, H. (2020). Economic policy uncertainty and non-performing loans: The moderating role of bank concentration. *Finance Research Letters*, *458*, 1458.

Keynes, J. M. (1936). *The general theory of employment, interest and money*. Macmillan.

Koju, L., Koju, R., & Wang, S. (2018). Macroeconomic and Bank-specific determinants of non-performing loans: Evidence from Nepalese banking system. *Journal of Central Banking Theory and Practice*, *7*(3), 111–138.

La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2002). Government ownership of banks. *The Journal of Finance*, *57*(1), 265–301.

Laeven, L., & Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, *93*(2), 259–275.

Laidroo, L., & Männasoo, K. (2017). Do credit commitments compromise credit quality? *Research in International Business and Finance*, *41*, 303–317.

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, *29*(10), 2577–2603.

Loaba, S., & Zahonogo, P. (2019). Effects of information sharing on banking credit and economic growth in developing countries: Evidence from the west African economic and monetary union. *International Journal of Finance & Economics*, *24*(3), 1079–1090.

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, *36*(4), 1012–1027.

Mamonov, M. E. (2018). Hidden" holes" in the capital of banks and the supply of credit to the real sector of economy. *Voprosy Economiki*, *5*, 49–68.

Miller, S. M., & Noulas, A. G. (1997). Portfolio mix and large-bank profitability in the USA. *Applied Economics*, *29*(4), 505–512.

Natsir, M., Soedarmono, W., Yudhi, W. S. A., Trinugroho, I., & Warokka, A. (2019). Foreign penetration, competition, and credit risk in banking. *Borsa Istanbul Review*, *19*(3), 249–257.

Nguyen, C. P., Le, T. H., & Su, T. D. (2020). Economic policy uncertainty and credit growth: Evidence from a global sample. *Research in International Business and Finance*, *51*, 101118.

Orbis (2022) Orbis database. https://orbis.bvdinfo.com/orbis/Companies/Login?returnUrl=%2Forbis%2FCompanies.

Pastor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, *110*(3), 520–545.

Paule-Vianez, J., Gómez-Martínez, R., & Prado-Román, C. (2020a). Effect of economic and monetary policy uncertainty on stock markets. Evidence on return, volatility and liquidity. *Economics Bulletin*, *40*(2), 1261–1271.

Paule-Vianez, J., Prado-Román, C., & Gómez-Martínez, R. (2020b). Economic policy uncertainty and bitcoin. Is bitcoin a safe-haven asset? *European Journal of Management and Business Economics*, *29*, 347–363.

Peltonen, T. A., Rancan, M., & Sarlin, P. (2019). Interconnectedness of the banking sector as a vulnerability to crises. *International Journal of Finance & Economics*, *24*(2), 963–990.

Pizzi, S., Caputo, F., & Venturelli, A. (2020). Does it pay to be an honest entrepreneur? Addressing the relationship between sustainable development and bankruptcy risk. *Corporate Social Responsibility and Environmental Management*, *27*(3), 1478–1486.

Poudel, S. R. (2018). Assessment of credit risk in Nepali commercial banks. *Journal of Applied and Advanced Research*, *3*(3), 65–72.

Rose, C. (2017). The relationship between corporate governance characteristics and credit risk exposure in banks: Implications for financial regulation. *European Journal of Law and Economics*, *43*(1), 167–194.

Rose, P. S. (1999). *Commercial bank management*. McGraw-Hill.

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, *22*(3), 203–224.

Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, *102*(2), 1029–1061.

Shahzad, S. J. H., Raza, N., Balcilar, M., Ali, S., & Shahbaz, M. (2017). Can economic policy uncertainty and investors sentiment predict commodities returns and volatility? *Resources Policy*, *53*, 208–218.

Sun, X., Yao, X., & Wang, J. (2017). Dynamic interaction between economic policy uncertainty and financial stress: A multi-scale correlation framework. *Finance Research Letters*, *21*, 214–221.

Tran, D., Hoang, K., & Nguyen, C. (2020). How does economic policy uncertainty affect bank business models? *Finance Research Letters*, *9*, 1639.

Tran, D. V. (2020). Economic policy uncertainty and bank dividend policy. *International Review of Economics*, *67*, 339–361.

Uhde, A., & Heimeshoff, U. (2009). Consolidation in banking and financial stability in Europe: Empirical evidence. *Journal of Banking and Finance*, *33*(7), 1299–1311.

Ulrich, M. (2012). Economic policy uncertainty and asset price volatility. Columbia Business School Working Paper.

US EPU, (2022) US EPU Index Database. https://www.policyuncertainty.com/us_monthly.html.

Vogiazas, S. D., & Nikolaidou, E. (2011). Investigating the determinants of nonperforming loans in the Romanian banking system: An empirical study with reference to the Greek crisis. *Economics Research International*, *2011*, 1–14.

Volcker, P. (2012). Unfinished business in financial reform. *International Finance*, *15*(1), 125–135.

Wooldridge, J. M. (2011). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

Zamore, S., Beisland, L. A., & Mersland, R. (2019). Geographic diversification and credit risk in microfinance. *Journal of Banking & Finance*, *109*, 105665.

How to cite this article: Orden-Cruz, C., Paule-Vianez, J., & Lobão, J. (2023). The effect of Economic Policy Uncertainty on the credit risk of US commercial banks. *International Journal of Finance & Economics*, *28*(3), 3420–3436. https://doi.org/10.1002/ijfe.2600