Dynamics Between Economic Policy Uncertainty and Bank's Loan Pricing

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Abstract: This research studies the dynamics between economic policy uncertainty (EPU) and bank's loan pricing at bank-level. To the best of our knowledge, no study has been conducted on the mentioned dynamic relationship and on transmission mechanisms of EPU to loan prices at bank-level. To fill this gap, this research assesses how an EPU shock impacts bank loan prices over time using panel vector autoregressive (PVAR) models. The paper shows that an EPU shock impacts loan prices over time, but this effect is especially concentrated in the short run. On the other hand, monetary policy and financial regulation uncertainty shocks have short- and long-term impacts on loan prices. Additionally, this paper shed light on how an uncertainty shock is transmitted to bank loans, evidencing that liquidity hoarding is a key transmission channel. The novel results obtained offer relevant recommendations to policymakers and regulators as, for example, to promote transparency and predictability in monetary policy and financial regulation, as well as to pay special attention to bank liquidity hoarding, to smooth an adverse policy-related uncertainty shock.

Keywords: policy uncertainty, bank, loan pricing, panel vector autoregressive.

1. Introduction

A highly uncertain global environment reflecting policy-related economic uncertainty became increasingly a reality in recent years. For example, political polarization, trade war, the US sovereign rating downgrade, Brexit, and the US government shutdown, to mention only a few, are events in the political sphere that have led to enormous uncertainty in the context of economic policies. One area where Economic Policy Uncertainty can have a significant impact is the Bank's Loan Pricing. In general terms, the greater the uncertainty, the greater the overall economic risk and, consequently, regardless of the credit risk of each client, the greater the risk premium incorporated into the interest rate of banks' lending operations tends to be.

Few studies were found in the literature regarding the relationship between policy uncertainty and bank loans, documenting a negative impact of an EPU shock on banks' loan growth at aggregate and bank-level (Bordo et al., 2016) and a positive impact on banks' loan interest rate (Ashraf & Shen, 2019). No paper has been found on the dynamic relationship between EPU and loan pricing at bank level; only aggregate-level exist. To the best of our knowledge, there are no empirical studies regarding the transmission channels of policy uncertainty to loans. For example, Ashraf & Shen (2019) postulate, but do not provide empirical evidence, that borrowers' default risk is a transmission channel of EPU to loan pricing. This research fills these literature gaps by measuring the impacts of EPU shock on bank loan pricing over time and assessing the dynamics of transmission of the EPU to the loan price in a bank-level approach. The paper does this using the EPU index of Baker et al. (2016). This index has, among others, the advantage of capturing different types of economic policy uncertainties, such as monetary and fiscal, taxes and government spending, regulation, trade, sovereign debt, and currency crisis, among other.

The literature reports that an increase in EPU promotes a fly to liquidity behavior in banks decision-making (Berger et al., 2022) as a precaution measure, while the deposit maturity shortens, which promotes liquidity risk and impacts banks debt structure (Deng et al, 2023). Therefore, we test if liquidity hoarding, influenced by financial frictions (Almeida et al., 2014), is a transmission channel of EPU to a bank's loan pricing. In short, EPU shocks can be similar to external financial frictions, influencing bank's liquidity hoarding behavior. For example, the interbank market, which is key for liquidity management, can become dysfunctional under stress as interbank interest rates and adverse selection increase (Heider et al., 2015). Another hypothesis tested in this research, based on postulates found in the literature (Ashraf & Shen, 2019), is that borrowers' default risk is a transmission channel of an EPU shock to loan prices.

This research also assesses the dynamic effect of economic policy uncertainties – monetary, fiscal and financial regulation – on loan prices by estimating impulse-response functions. In short, this research contributes to the empirical literature on banking and uncertainty and the knowledge on banking management in several ways by providing: i) information on the dynamics between EPU and loan pricing, ii) quantitative parameters to cope with EPU shocks, and iii) inputs for risk management. Additionally, this research contributes to policymakers, banking regulation and supervision by providing information on how transmission mechanisms of EPU to loan pricing operate to promote a better function of the banking loan market under uncertainty shocks.

The empirical strategy of this research consists of two steps. First, to estimate a conventional panel data model, incorporating individual fixed effects, to confront the results with the empirical literature and, in addition, to robustly select relevant explanatory and control variables to be further incorporated in the dynamics assessment. Second, estimating impulse-response functions, the dynamic relationship between EPU and bank's loan pricing will be studied using panel vector autoregressive (PVAR) models. For the conventional panel data model, results align with the empirical literature, showing that EPU has a positive relationship with loan pricing and that monetary and financial regulation uncertainties have a higher impact on loan price.

The results show that EPU has a positive dynamic relationship with loan pricing in the short-run. One standard deviation shock in EPU increases loan price, achieving a peak after one year, dissipating over time with ups and downs. In short, EPU temporarily impacts loan pricing concentrated in the short run. On the other hand, monetary policy and financial regulation uncertainty shocks have short and long run impacts on loan prices, in which a one-standard-deviation shock increases loan prices over time. In the case of monetary policy uncertainty the shock effect is stronger in the short-run. In financial regulation uncertainty, the effect is stronger in the medium and long run. The effect of fiscal policy uncertainty on loan prices is limited to the short run, reverting after two years.

Evidence obtained supports the hypothesis that liquidity hoarding is a transmission channel of EPU to a bank's loan pricing, as, on the one hand, the impulse-response function shows that in response to a one-standard-deviation shock in EPU, liquidity hoarding increases over time with a peak after one year. Complementary, one standard deviation shock in liquidity hoarding increases loan prices over time. On the other hand, there is no evidence to support the hypothesis that default risk is a transmission channel of EPU to loan pricing, based on postulates found in the literature (Ashraf & Shen, 2019), as the dynamic relationship between both variables didn't exhibit economic meaning.

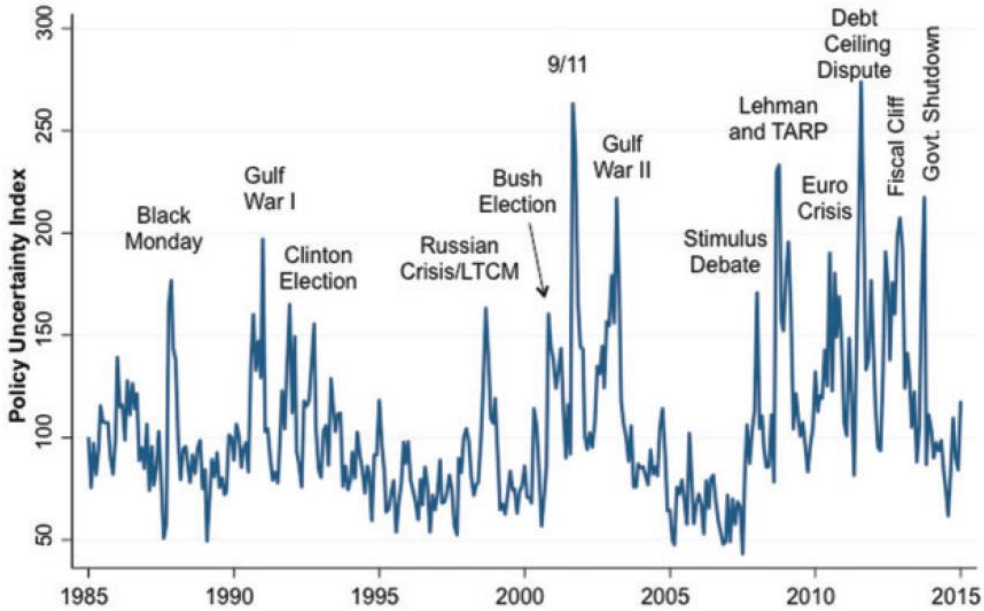
The results bring relevant contributions to policymakers and bank regulation and supervision. First, policymakers and regulators should promote transparency and predictability in monetary policy and financial regulation. Uncertainties in these policies adversely impact bank's loan pricing in the short and long run. Second, under policy-related uncertainty stress, policymakers and regulators should pay special attention to bank liquidity hoarding, a key transmission mechanism of uncertainty to loan pricing. This paper is divided into the following sections: literature review discussing measures and effects of policy uncertainty; modelling and empirical strategy; data; estimation and results; and conclusions.

2. Literature Review

2.1 Measures of policy uncertainty

Baker et al. (2016) developed an EPU index based on textual analysis that is a good proxy for policy-related economic uncertainty, as confirmed by different types of evidences including 12,000 newspaper article readings. The index illustrated in Figure 1 has large historical database across countries and opened the door for new research in several fields, such as economics and finance.

Figure 1 - US Economic Policy Uncertainty Evolution



Source: (Baker et al., 2016).

Bakers et al.'s (2016) economic policy uncertainty index was initially developed for the US, considering ten highly reputable newspapers[1], through which was constructed an index based on the volume of articles discussing economic policy uncertainty, containing the following terms: uncertain, uncertainty, economic, economy, Congress, deficit, Federal Reserve, regulation, legislations, or White House. The index was later extended to various countries and received specific policy uncertainty categories. Baker et al. (2016) also developed a daily EPU index considering 1,500 US newspapers, which monthly average showed to be highly correlated with the monthly EPU index encompassing the ten selected newspapers. The index is also available for eleven types of policy categories by incorporating additional key terms.

[1] USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal

EPU is highly correlated with other measures of economic and policy uncertainties. In fact, similar movements were observed by generating EPU based on left-leading and right-leading newspapers. Additionaly, an extensive audit study of articles selected randomly extracted from the majority of US newspapers was done, under the supervision of students from the University of Chicago, and a convergence of comparison between human and computer generated indexes was observed. Finally, there is also a market validation as EPU was incorporated by data vendors like Bloomberg, Reuters and Haver Analytics (Baker et al., 2016).

Some positive aspects of EPU developed by Baker et al. (2016) are frequently highlighted. They include the idea that it captures economic policy uncertainty, in a way that differs from other indexes like VIX that reflect overall economic uncertainty. Another is that it captures specific categories of economic policy uncertainties, like monetary and fiscal policy uncertainties. Additionaly, it is easy to access a public source free of charge[2]. Moreover, it has long historical data. Finally, it is accurate and is updated on a timely basis every month.

In another line, Jurado et al. (2015) developed an economic uncertainty benchmark to assess the influence of uncertainty in business cycles. Jurado et al.'s (2015) benchmark is computed by extracting forecastable components, concluding that conventional uncertainty proxies are less persistent, especially during recession periods. However, it does not capture specific economic policy uncertainty and is not publicly available and updated like Baker et al.'s (2016) EPU index.

In turn, using a similar methodology developed by Baker et al. (2016) of textual analysis based on news provided by the media, Azzimonti (2018) developed a partizan conflict index (PCI) for the US to capture the uncertainty derived from partizan conflict.

[2] See www.policyuncertainty.com

This is defined as political disagreement about government policy, which is shown to harm investment at the aggregate and firm levels (Azzimonti, 2018). The PCI provides an uncertainty measure to capture precisely the partisan conflict that has been a critical source of uncertainty in the US and worldwide in the context of increasing political polarization. However, the PCI was developed only for the US and does not provide a broad measure of policy uncertainty. In addition, it is not easily accessed, as it demands methodological replication.

Finally, Shoag and Veuger (2016) developed a state-level measure of local economic policy uncertainty. This measure applies Baker et al.'s (2016) methodology, based on media mentions of the word “uncertainty” contextualized by policy. The limitation of such a state-level measure of EPU is the difficulty of separating national and state uncertainty perception and their origins, as they are linked through feedback loops.

2.2 Effects of Policy Uncertainty

The literature documents evidence of policy uncertainty's effects on firms' behavior. Among them, EPU negatively influences future M&A activities at macro and firm levels, mainly because of uncertainty linked with monetary policy, fiscal policy and regulation (Bonaime et al., 2018). Policy uncertainty also affects corporate finance decisions by moderating IPO activities and increasing the cost of capital during government elections, especially if the outcome is highly uncertain (Çolak et al., 2017). Moreover, political uncertainty implies that equity risk premium increases with the rise of stock return volatility and correlations, impacting the cost of capital (Pástor & Veronesi, 2013).

According to the concept of ambiguity developed by Ellsberg (1961), an economic policy uncertainty shock may affect the capacity of banks to estimate probabilities of future scenarios, which may impact loan pricing behavior. In this context, Francis et al.

(2014) found that a firm's exposure to political uncertainty affects the cost of bank loans, in which a one-standard-deviation rise of exposure results in an 11.9 basis points increase in loan spread. In addition, lenders price a firm's political risk faster than investors in the stock market, and banks incorporate its risk into loan pricing.

In another line, D'Mello and Toscano (2020) report a negative relationship between EPU and short-run trade credit in the US, with the firms adjusting their trade credit policy quickly to uncertainty changes. In addition, the evidence obtained by these authors shows that trade credit has a stronger association with monetary, fiscal, tax and regulatory uncertainties. In another study, Bordo et al. (2016) evidenced that policy uncertainty slows bank credit and that lagged uncertainty fluctuations negatively affect bank growth lending rates at cross-sectional and aggregate levels. For large-sized banks, the negative impact of policy uncertainty on loan growth rate is more prominent, being lower for banks that are more capitalized and have higher balance sheet liquidity.

Moreover, Orden-Cruz et al. (2023) reported a positive relationship between EPU and credit risk of US commercial banks, with a more substantial impact on less profitable banks and banks with less solvency. Ashraf and Shen's (2019) findings show that high EPU increases a bank's average loan interest rate, which is a consequence of the rise of borrower default risk reflected on risk premium. Their results show that a one-standard-deviation increase in uncertainty implies a 21.84 basis points rise in the bank's loan average interest rate (Ashraf & Shen, 2019). Higher uncertainty raises firms' default probability and banks' deposit loss risk, which drives agents to require higher premiums to finance banks, reducing bank credit supply and increasing lending rates with a negative impact on investment (Melkadze & Gete, 2018). To the best of our knowledge, no previous study was conducted on the dynamics between EPU and loan pricing and, additionaly, on the transmission mechanisms of EPU to loan. To fill these literature gaps, we develop the following hypothesis.

Hypothesis 1: an EPU shock positively impacts bank's loan pricing over time and through transmission channels.

The primary function of banks is to maintain a system of accounts that allows the transfer of wealth; other functions are to provide services of exchanging deposits and other forms of wealth for currency and portfolio management in which banks purchase securities (Fama, 1980). Risk management assumes a key role for intermediaries, which can be seen as a channel to smooth asymmetric information and frictions of transaction costs (Allen & Santomero, 1998).

Bank funding occurs through deposits, interbank markets, central banks and debt issuance (Camba-Mendez & Mongelli, 2021). The bank lending rate reflects the expected short-run rate, which depends on the access to the interbank market, risk premium, credit risk premium, debt market financial costs, and market power (Camba-Mendez & Mongelli, 2021). Ashraf & Shen (2019) postulate that borrowers' default risk is a transmission channel of EPU to the loan pricing without empirical support. Therefore, we formulate the following hypothesis for empirical testing.

Hypothesis 1A: default risk is a transmission channel of EPU to the bank's loan pricing.

Regarding equity and debt costs implication of political uncertainty, empirical evidence shows that EPU increases underwriting costs in response to the rise of information risk and wakening investor demand, which decreases the willingness of equity increase, as well as long-term and total net debt issuances (Gungoraydinoglu et al., 2017). Paligorova and Santos (2017) found a link between exposure to rollover risk and loan maturity, in which an increase in a bank's short-term uninsured funding results in a drop in the average bank's loan maturity and a steeper loan yield curve. Therefore, borrowers rely more on short-term loans, as they get more attractive compared to the increasing cost of long-term loans, resulting in a higher refinancing risk, and rely more on the bond market to raise longer-term funding (Paligorova & Santos, 2017). Developments in bank's interest rate risk management using tools such as asset securitization, interest rate derivatives and adjustable-rate loans allowed banks to rely less on asset-liability management (ALM) framework, whose objective is to match liability's structure to assets' duration, opening space for an asset-liability mismatch without aggravating bank's overall risk.

In response to an EPU shock, evidence in the literature shows a flight to liquidity effect in bank's decision-making, taking into consideration a broad measure of liquidity - encompassing asset, liability and off-balance sheet activities - which outcome is more prominent in banks with liquidity constraints (Berger et al. 2022). The rise in EPU increases demand deposits and reduces time deposit proportion, changing the structure of deposit maturity as commercial banks fly to liquidity as a precaution measure, which promotes liquidity risk and, thus, impacts the bank's debt structure (Deng et al., 2023). In response to the EPU increase, commercial banks expand bank financial assets sold for repurchase – repo – which functions as short-term funding similar to a financing method with financial assets as collateral.

During crises, banks holding illiquid assets tend to expand cash and drop loans, in particular banks holding more mortgage-backed securities (MBS) and asset-backed securities (ABS); nevertheless, banks more dependent on core deposits and equity capital financing keep lending (Cornett et al., 2011). In the context of liquidity crisis risk, banks have no incentive to sell illiquid assets to avoid fire sales; instead, they tend to spend cash, reduce loan supply, and increase leverage (Diamond & Rajan, 2011). Such behavior can pose risks to a bank's solvency in the future. Interbank markets are key for a bank's liquidity hoarding. Under stress, it can become dysfunctional due to high interbank interest rates and adverse selection that influences the opportunity cost of holding liquidity (Heider et al., 2015). Another source of funding for commercial banks is to issue bonds, which is long-term funding, and to borrow from the Central Bank, which, in general, is only demanded when the other sources of funding are stressed.

Liquidity hoarding can be understood as the decision-making on how a liquid firm's position is planned to be and how to maintain this position over time, which is influenced by current and expected financial frictions (Almeida et al., 2014). We can understand economic policy uncertainty shocks as an external financial friction that may influence a bank's liquidity hoarding behavior and, thus, lending pricing. Therefore, we develop the following hypothesis.

Hypothesis 1B: The Bank's liquidity hoarding is a transmission channel of EPU to the bank's loan pricing.

It is possible to deepen the investigation on the relationship between EPU and loan pricing by assessing the dynamics across EPU and loans at the bank-level and through potential transmission channel components. This novelty is explored in the following topic, describing the empirical strategy.

3 Modeling and Empirical Strategy

A PVAR model is estimated to study the dynamic relationship between EPU and bank's loan pricing, as summarized in Equation 5. Where $\boldsymbol{Y}_{i,t}$ is a vector of bank-level variables, that varies across banks and over time, $\boldsymbol{X}_t$ is a vector of aggregate-level variables that only varies over time, including EPU, $\boldsymbol{v}_i$ is a vector of individual bank fixed-effects, $\boldsymbol{\mu}_{i,t}$ is a vector of idiosyncratic error terms and j is the number of lags of the model. $\boldsymbol{A}_1$,

$\boldsymbol{A}_2$, …, $\boldsymbol{A}_j$ and $\boldsymbol{B}$ are parameters matrices. It is assumed that $E(\boldsymbol{\mu}_{i,t}) = 0$ and $E(\boldsymbol{\mu}'_{i,t}\boldsymbol{\mu}_{i,s}) = 0$.

$$\boldsymbol{Y}_{i,t} = \boldsymbol{Y}_{i,t-1}\boldsymbol{A}_1 + \boldsymbol{Y}_{i,t-2}\boldsymbol{A}_2 + \cdots + \boldsymbol{Y}_{i,t-j}\boldsymbol{A}_j + \boldsymbol{X}_t\boldsymbol{B} + \boldsymbol{v}_i + \boldsymbol{\mu}_{i,t} \qquad (5)$$

The estimation of parameters in equation 5 needs special attention as lagged dependent variables appear in the right-hand of the system of equations, which leads to biased estimates by using ordinary least squares (OLS) estimator (Abrigo & Love, 2016). An alternative is to consider the generalized methods of moments (GMM) proposed by Arellano & Bover (1995) using forward orthogonal deviation (FOD) transformation. Another aspect to consider is that the impulse-response function and the forecast error variance decomposition (FEVD) are affected by the ordering of the endogenous variables in the PVAR model. The variables ordered earlier affect the subsequent ones contemporaneously, as those ordered later affect the previous ones with one lag (Abrigo & Love, 2016).

The general methods of moment estimators lead to consistent estimates, even for short panels, but they incur weak instrument issues if a unit root is present in the model (Abrigo & Love, 2016). Therefore, it is relevant to test for stationarity to ensure that the system of equations is stable before estimating the PVAR model. If stability is observed the PVAR is reversible and can be represented as an infinite-order vector moving-average (Sigmund & Ferstl, 2021), which guarantees that the impulse-response function (IRF) and the forecast-error variance decomposition (FEVD) estimations can be interpreted (Abrigo & Love, 2016).

Before estimating the PVAR model to study the dynamic relationship among variables, a conventional panel model incorporating individual fixed-effects is estimated. This first approach allows for verifying the causal relation between EPU and the bank's loan pricing and other relevant explanatory factors to confront the empirical literature and perform a robust selection of endogenous variables to be incorporated into the PVAR model.

To the best of our knowledge, one of the novelties of the approach adopted in this research is to add value to the literature by performing a bank-level dynamics assessment among EPU, loan pricing and other key explanatory factors, by estimating a panel VAR model, complementing the aggregate-level evaluation found in the empirical literature (Bordo et al., 2016).

Estimating panel vector autoregression models is appropriate for analyzing the dynamics between EPU and banks' loan pricing (Balcilar et al., 2021). The VAR model, initially developed by Sims (1980) for time series analysis, is a powerful tool that is simple to use and interpret. It is helpful as a systematic approach that captures the dynamics among variables (Stock & Watson, 2001) endogenously determined. Techniques to estimate VAR models in panel data, considering individual heterogeneity, were developed by Holtz-Eakin et al. (1988), making it possible to study the dynamics relationship between panel data variables. As panel data usually have a large number of individuals compared to periods, the conventional ordinary least squares (OLS) estimator is not appropriate as it generates substantial asymptotic biases, which was demonstrated analytically by Nickell (1981) using autoregressive panel models with fixed effects. A solution to avoid inconsistent estimates is to use the GMM estimator (Sigmund & Ferstl, 2021) in panel VAR models (PVAR) considered in this research.

Analyzing the impulse-response function to investigate the potential dynamics of EPU shocks on a bank's loan pricing over time is appropriate. Bordo et al. (2016) documented an average reduction of 0.5 percentage points in bank loans in response to a one-standard-deviation shock in EPU, with a peak effect after nine quarters, by estimating an aggregate-level VAR model.

4 Data

The sample frequency starts in 2001, the most extended consolidated historical dataset available for US bank-level data, and continues until 2018 to avoid incorporating noise from COVID-19 shocks from 2019 on. The bank-level data[3] is from the BankFocus database. The aggregate data were collected from the Federal Reserve Bank of St. Louis, FRED economic data, and the World Bank global financial development database.

As summarized in Table 1, the following proxy variables are selected in this research: 1) interest income on customer loans and advances to gross loans ratio as a proxy for bank's loan pricing; 2) natural logarithm of EPU developed by Baker et al. (2016)[4] as a proxy for economic policy uncertainty; 3) interest expense to average interest-bearing liabilities ratio as a proxy for funding cost: 4) loan loss reserves to total assets ratio as a proxy for default risk; 5) liquid assets to total assets ratio as proxy a for liquidity hoarding; 6) total assets to average assets of other banks ratio as a proxy for bank size; 7) return on average equity (ROE); 8) liability to assets ratio, as a proxy for leverage; 9) year-on-year percentage change of seasonal adjusted industrial production index (IPI), as proxy for economic activity; 10) year-on-year percentage change of seasonal adjusted personal consumption expenditure (PCE), as a proxy for inflation; and 11) banking crisis dummy[5].

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[3] Commercial, saving and cooperative US banks.
[4] Monthly extended historical dataset back to 1985 is available at www.policyuncertainty.com
[5] Bank systemic crisis characterized by significant signs of financial distress in the market and significant bank policy intervention.

Table 1 - Proxy variables for modeling

Variable	Description
intloanrate	Bank's loan pricing: interest expenses on loans to total loan ratio
lnepu	Natural logarithm of economic policy uncertainty index
fundingcost	Funding cost: interest expense to average interest-bearing liabilities ratio
lossratio	Borrowers' default risk: loan loss reserves to total assets ratio
liqtytratio	Liquidity hoarding: liquid assets to total assets ratio
banksize	Bank size: total assets to average assets of other banks ratio
roe	Return on average equity
leverage	Liability to assets ratio
ipiyoy	Industrial production year-on-year %change
pce	Inflation: Personal consumption expenditure year-on-year %change
crisisdummy	One if crisis and zero otherwise

The EPU index is released and timely updated with the following categories: monetary policy, fiscal policy, taxes, government spending, health care, national security, entitlement programs, regulation, financial regulation, policy trade, sovereign debt and currency crises. The following categories are considered to investigate the effect of different economic policy uncertainties on bank's loan pricing: monetary policy, fiscal policy and financial regulation.

As summarized in Table 2, the total observations of the data collected are 71,032 after treating for missing values, which were dropped from the dataset. Bank-level data were winsorized at a 1% level in the upper and lower tails. The loan price varies from 1.44% to 10.46%, with 6.15% of the mean and a relatively low standard deviation of 1.36%. The funding cost ranges from 0.1% to 4.19% with 1.43% of the mean and a moderated standard-deviation of 1.02%. The default risk varies from 0.0% to 3.2% with 0.92% of mean and 0.5% of standard deviation. The liquidity ratio has a wide amplitude, ranging from 3.4% to 80.6% with 29.1% of mean and 15.6% of standard deviation.

Table 2 - Descriptive statistics

Variables	Obs	Mean	Std. dev	Min	Max
intloanrate	71,032	6.147	1.363	1.442	10.458
lnepu	71,032	4.500	0.311	4.026	4.900
lnepumonet	71,032	4.298	0.337	3.676	4.823
lnepufiscal	71,032	4.565	0.488	3.731	5.313
lnepufinreg	71,032	4.608	0.651	3.584	5.650
ipiyoy	71,032	0.874	3.772	-11.383	5.559
pce	71,032	4.066	1.756	-1.581	6.525
fundingcost	71,032	1.426	1.020	0.101	4.187
size	71,032	0.305	0.953	0.001	7.552
roe	71,032	8.502	9.281	-40.359	31.349
lossratio	71,032	0.920	0.498	0.000	3.198
liqtytratio	71,032	29.050	15.576	3.385	80.645
leverage	71,032	0.888	0.045	0.214	0.945
crisisdummy	71,032	0.292	0.455	0.000	1.000

The next topic presents the estimation and results based on the empirical strategy defined.

5 Estimation and Results

It is incorporated the following variables in the panel data model: natural logarithm of EPU, funding cost, default risk, liquidity hoarding, bank size and leverage. In addition, it incorporates return on equity as an explanatory variable to control for a bank's profitability, as it influences the cost of bank loans in response to an EPU shock (Francis, Hasan, & Zhu, 2014). Year-on-year industrial production change and inflation are incorporated to control for macroeconomic conditions. A crisis dummy controls for bank crisis. The ordering of the endogenous variables in the PVAR model is defined from the most to the least exogenous ones as follows: EPU, industrial production, inflation, funding cost, size, ROE, loss ratio, liquidity ratio and leverage.

As summarized in the first column of Table 3, with the estimation output, all the explanatory variables are highly significant. In line with the empirical literature (Ashraf & Shen, 2019; Francis, et al., 2014), the estimation result shows that EPU has a positive relationship with loan price, for a one-standard-deviation increase in EPU (0.31), the loan interest rate raises 10 basis points (0.324 x 0.31). For a one-standard-deviation increase in funding cost (1.02), the loan interest rate raises 97 basis points (0.954 x 1.02). For a one-standard-deviation increase in borrowers' default risk (0.5), the loan interest rate raises 30 basis points (0.6 x 0.5). For a one-standard-deviation increase in liquidity hoarding (15.58), the loan interest rate raises 30 basis points (0.019 x 15.58).

Table 3 - Panel estimation

Fixed-effects Number of obs = 71,032 Number of groups = 4,711

R-squared: Within = 0.6864 Between = 0.2050 Overall = 0.4412 Prob > F = 0.0000		R-squared: Within = 0.6929 Between = 0.2138 Overall = 0.4510 Prob > F = 0.0000		R-squared: Within = 0.6858 Between = 0.2024 Overall = 0.4391 Prob > F = 0.0000		R-squared: Within = 0.6852 Between = 0.2038 Overall = 0.4400 Prob > F = 0.0000	
intloanrate		intloanrate		intloanrate		intloanrate	
lnepu	**0.324*** **	**lnepumonet**	**0.41*** **	**lnepufiscal**	**0.197*** **	**lnepufinreg**	**0.172*** **
	(0,010)		0,008		0,006		0,006
fundingcost	**0.954*** **	**fundingcost**	**0.879*** **	**fundingcost**	**0.97*** **	**fundingcost**	**0.948*** **
	(0,003)		0,004		0,003		0,003
lossratio	**0.6*** **	**lossratio**	**0.58*** **	**lossratio**	**0.6*** **	**lossratio**	**0.604*** **
	(0,008)		0,008		0,008		0,008
liqtytratio	**0.019*** **	**liqtytratio**	**0.018*** **	**liqtytratio**	**0.019*** **	**liqtytratio**	**0.019*** **
	(0,000)		0,000		0,000		0,000
size	**0.046*** **	**size**	**0.049*** **	**size**	**0.047*** **	**size**	**0.051*** **
	(0,011)		0,011		0,011		0,011
roe	**0.028*** **	**roe**	**0.027*** **	**roe**	**0.028*** **	**roe**	**0.028*** **
	(0,000)		0,000		0,000		0,000
leverage	**0.253** **	**leverage**	**0.268*** **	**leverage**	**0.22** **	**leverage**	**0.273*** **
	(0,102)		0,101		0,102		0,102
ipiyoy	**0.012*** **	**ipiyoy**	**0.02*** **	**ipiyoy**	**0.01*** **	**ipiyoy**	**0.013*** **
	(0,001)		0,001		0,001		0,001
pce	**0.022*** **	**pce**	**-0.006** **	**pce**	**0.019*** **	**pce**	**0.027*** **
	(0,003)		0,003		0,003		0,003
crisisdummy	**-0.032*** **	**crisisdummy**	**-0.036*** **	**crisisdummy**	**-0.024*** **	**crisisdummy**	**-0.078*** **
	(0,007)		0,007		0,007		0,008
constant	**1.655*** **	constant	**1.617*** **	constant	**2.228*** **	constant	**2.296*** **
	(0,103)		0,096		0,097		0,097
Indiv. FE	yes		yes		yes		yes

Standard errors are shown in parentheses. Statistical significance at 10%, 5% and 1% is denoted

As summarized in Table 3, from columns two to three, it is possible to compare the impacts of different EPU categories on a bank's loan pricing. For a one-standard-deviation increase in monetary policy uncertainty (0.337), the loan price raises 13.8 basis points (0.410 x 0.337). For a one-standard-deviation increase in fiscal policy uncertainty (0.488), the loan price raises 9.6 basis points (0.197 x 0.488). For a one-standard-deviation increase in financial regulation uncertainty (0.651), the loan price raises 11.2 (0.172 x 0.651). Therefore, monetary policy uncertainty has the largest effect on loan price followed by financial regulation uncertainty.

After the conventional panel data approach, which offered statistically and economically significant results in line with the empirical literature, it is possible to deepen the analysis by investigating the dynamic relationship among variables robustly selected. Before estimating the PVAR model using the general methods of moments, it is relevant to test for stationarity to avoid incurring weak instrument issues if a unit root is present in the model (Abrigo & Love, 2016). As summarized in Table 4, for all the endogenous variables considered the null hypothesis of the presence of unit root is rejected for both or one of Phillips-Perron or Dickey-Fuller statistics based on a Fisher-type test, which is more flexible compared to other tests and is supported by general assumptions allowing, for example, unbalanced panels (Choi, 2001).

Table 4 - Unit root tests

Fisher-type unit-root tests
H0: All panels contain unit roots — Nº of panels = 4711
Ha: At least one panel is stationary
Avg nº of periods = 15.08

			Phillips–Perron Statistic	Phillips–Perron p-value	Dickey–Fuller Statistic	Dickey–Fuller p-value
intloanrate	Inverse chi-squared	P	1.29E+04	0.0000	1.26E+04	0.0000
	Inverse normal	Z	-12.8557	0.0000	5.6548	1.0000
	Inverse logit t	L*	-20.5089	0.0000	-8.2638	0.0000
	Modified inv. chi-squared	Pm	25.7902	0.0000	23.6525	0.0000
lnepu	Inverse chi-squared	P	1.21E+04	0.0000	2.21E+04	0.0000
	Inverse normal	Z	-36.2432	0.0000	-81.2365	0.0000
	Inverse logit t	L*	-33.7834	0.0000	-83.1278	0.0000
	Modified inv. chi-squared	Pm	19.5897	0.0000	92.9227	0.0000
fundingcost	Inverse chi-squared	P	1.13E+04	0.0000	1.66E+04	0.0000
	Inverse normal	Z	4.7852	1.0000	-15.5075	0.0000
	Inverse logit t	L*	-8.0576	0.0000	-34.2084	0.0000
	Modified inv. chi-squared	Pm	13.818	0.0000	52.7815	0.0000
lossratio	Inverse chi-squared	P	1.47E+04	0.0000	1.67E+04	0.0000
	Inverse normal	Z	-17.3084	0.0000	-20.6759	0.0000
	Inverse logit t	L*	-24.6103	0.0000	-33.2423	0.0000
	Modified inv. chi-squared	Pm	38.5208	0.0000	53.7329	0.0000
liqtytratio	Inverse chi-squared	P	1.73E+04	0.0000	1.79E+04	0.0000
	Inverse normal	Z	-28.4158	0.0000	-28.6915	0.0000
	Inverse logit t	L*	-39.4399	0.0000	-41.8733	0.0000
	Modified inv. chi-squared	Pm	57.5044	0.0000	62.5114	0.0000
size	Inverse chi-squared	P	4.98E+04	0.0000	5.93E+04	0.0000
	Inverse normal	Z	-108.3019	0.0000	-128.3784	0.0000
	Inverse logit t	L*	-174.6599	0.0000	-214.9777	0.0000
	Modified inv. chi-squared	Pm	295.1649	0.0000	364.9764	0.0000
roe	Inverse chi-squared	P	2.29E+04	0.0000	1.93E+04	0.0000
	Inverse normal	Z	-58.1214	0.0000	-40.4859	0.0000
	Inverse logit t	L*	-70.7036	0.0000	-51.8398	0.0000
	Modified inv. chi-squared	Pm	98.9039	0.0000	72.6003	0.0000
leverage	Inverse chi-squared	P	2.13E+04	0.0000	1.59E+04	0.0000
	Inverse normal	Z	-26.3934	0.0000	-9.3593	0.0000
	Inverse logit t	L*	-47.8731	0.0000	-21.9659	0.0000
	Modified inv. chi-squared	Pm	86.717	0.0000	47.5287	0.0000

AR parameter: Panel-specific — Asymptotics: T -> Infinity
Panel means: Included
Time trend: Not included
Drift term: Not included

			Phillips–Perron Statistic	Phillips–Perron p-value	Dickey–Fuller Statistic	Dickey–Fuller p-value
ipiyoy	Inverse chi-squared	P	3.64E+04	0.0000	5.04E+04	0.0000
	Inverse normal	Z	-126.375	0.0000	-150.525	0.0000
	Inverse logit t	L*	-137.202	0.0000	-199.322	0.0000
	Modified inv. chi-squared	Pm	196.8625	0.0000	299.6593	0.0000
pce	Inverse chi-squared	P	1.93E+04	0.0000	1.63E+04	0.0000
	Inverse normal	Z	-68.4161	0.0000	-46.8605	0.0000
	Inverse logit t	L*	-67.5357	0.0000	-45.2627	0.0000
	Modified inv. chi-squared	Pm	72.3181	0.0000	50.8718	0.0000
lnepumonet	Inverse chi-squared	P	1.52E+04	0.0000	3.86E+04	0.0000
	Inverse normal	Z	-53.7176	0.0000	-81.714	0.0000
	Inverse logit t	L*	-50.4124	0.0000	-143.424	0.0000
	Modified inv. chi-squared	Pm	42.0955	0.0000	213.4139	0.0000
lnepufiscal	Inverse chi-squared	P	1.05E+04	0.0000	2.73E+04	0.0000
	Inverse normal	Z	-27.9247	0.0000	-99.7383	0.0000
	Inverse logit t	L*	-25.2759	0.0000	-105.719	0.0000
	Modified inv. chi-squared	Pm	8.39	0.0000	130.9077	0.0000
lneputax	Inverse chi-squared	P	1.08E+04	0.0000	2.70E+04	0.0000
	Inverse normal	Z	-29.3807	0.0000	-99.3221	0.0000
	Inverse logit t	L*	-26.6448	0.0000	-104.5	0.0000
	Modified inv. chi-squared	Pm	10.0344	0.0000	128.8155	0.0000
lnepugovspen	Inverse chi-squared	P	1.55E+04	0.0000	1.72E+04	0.0000
	Inverse normal	Z	-33.6837	0.0000	-63.9149	0.0000
	Inverse logit t	L*	-42.2342	0.0000	-61.2698	0.0000
	Modified inv. chi-squared	Pm	44.6742	0.0000	57.5573	0.0000
lnepufinreg	Inverse chi-squared	P	8.69E+03	1.0000	1.22E+04	0.0000
	Inverse normal	Z	-12.998	0.0000	-38.093	0.0000
	Inverse logit t	L*	-12.4766	0.0000	-34.5011	0.0000
	Modified inv. chi-squared	Pm	-5.0676	1.0000	20.8847	0.0000

In PVAR models it is recommended to be parsimonious in the lag length decision especially in short panels, as additional lags quickly increase the size of the covariance matrix which can lead to unsatisfactory results by using conventional numerical procedures for inversion (Holtz-Eakin, Newey, & Rosen, 1988). Therefore, a PVAR model is estimated using one lag in this research. Table 5 summarizes the PVAR estimation using the GMM approach, with forward orthogonal deviation (FOD) transformation, including the following endogenous variables: bank's loan pricing, EPU, funding cost, default risk, liquidity hoarding, bank size, ROE, leverage, industrial production and inflation. A crisis dummy was included as an exogenous variable. Individual fixed effects were considered in the estimation.

Table 5 - PVAR estimation output

GMM Estimation

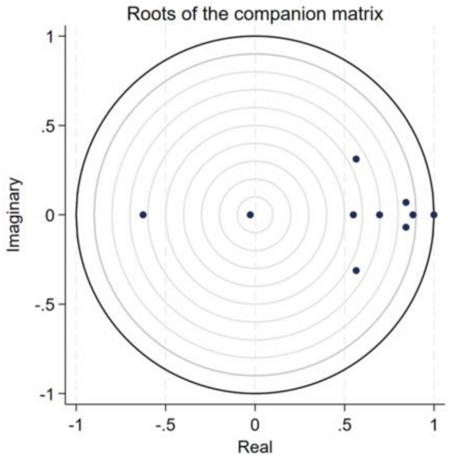
Final GMM Criterion Q(b) = 5.84e-31	No. of obs = 61592
Initial weight matrix: Identity	No. of panels = 4694
GMM weight matrix: Robust	Ave. no. of T = 13.121

Variables	intloanrate	lnepu	ipiyoy	pce	fundingcostw	sizew	roew	lossratiow	liqtytratiow	leveragew
intloanrate (L1)	0.720***	-0.102***	0.660***	0.411***	0.040***	-0.005***	0.647***	-0.016***	0.566***	-0.002***
SE	(0.028)	(0.020)	(0.097)	(0.029)	(0.012)	(0.002)	(0.087)	(0.003)	(0.085)	0.000
lnepu (L1)	1.746***	-1.027***	-8.569***	-3.185***	0.361***	-0.080***	1.233*	-0.021	2.361***	0.023***
SE	(0.209)	(0.146)	(0.770)	(0.239)	(0.094)	(0.019)	(0.633)	(0.027)	(0.636)	(0.003)
ipiyoy (L1)	-0.275***	0.211***	1.497***	0.358***	-0.124***	0.010***	-0.159**	0.005	-0.087	-0.003***
SE	(0.025)	(0.018)	(0.095)	(0.029)	(0.011)	(0.002)	(0.079)	(0.003)	(0.078)	0.000
pce (L1)	0.909***	-0.685***	-4.352***	-0.831***	0.465***	-0.032***	0.748***	-0.027***	0.212	0.008***
SE	(0.081)	(0.056)	(0.301)	(0.093)	(0.036)	(0.007)	(0.248)	(0.011)	(0.247)	(0.001)
fundingcostw (L1)	-0.405***	0.522***	1.999***	0.682***	0.548***	0.021***	-0.579***	0.029***	-0.791***	-0.001
SE	(0.062)	(0.044)	(0.240)	(0.073)	(0.028)	(0.006)	(0.210)	(0.009)	(0.206)	(0.001)
sizew (L1)	-2.292***	1.429***	7.222***	2.369***	-0.979***	0.944***	-1.892*	0.299***	-1.847*	-0.013***
SE	(0.327)	(0.215)	(1.138)	(0.367)	(0.148)	(0.047)	(1.029)	(0.052)	(0.977)	(0.004)
roew (L1)	-0.026***	0.020***	0.110***	0.034***	-0.010***	0.001***	0.535***	-0.003***	-0.039***	0.000***
SE	(0.004)	(0.003)	(0.014)	(0.004)	(0.002)	0.000	(0.016)	(0.001)	(0.012)	0.000
lossratiow (L1)	-0.055	0.081*	1.167***	0.271***	-0.028	-0.006	-0.855***	0.801***	0.898***	-0.002*
SE	(0.064)	(0.047)	(0.228)	(0.068)	(0.029)	(0.005)	(0.232)	(0.011)	(0.197)	(0.001)
liqtytratiow (L1)	0.020***	-0.020***	-0.098***	-0.028***	0.011***	-0.001***	-0.019*	-0.005***	0.875***	0.000***
SE	(0.004)	(0.003)	(0.014)	(0.004)	(0.002)	0.000	(0.011)	0.000	(0.011)	0.000
leveragew (L1)	52.350***	-40.728***	-171.210***	-42.604***	23.691***	-1.816***	61.319***	-1.682***	24.402	1.227***
SE	(4.953)	(3.602)	(19.430)	(5.873)	(2.228)	(0.455)	(15.650)	(0.662)	(15.678)	(0.074)
crisisdummy (L1)	0.930***	-0.489***	-5.974***	-2.628***	0.415***	-0.034***	-1.243***	0.021	1.596***	0.007***
SE	(0.098)	(0.068)	(0.355)	(0.110)	(0.044)	(0.010)	(0.293)	(0.013)	(0.290)	(0.001)
Individual fixed-effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are shown in parentheses. Statistical significance at 10%, 5% and 1% is denoted respectively by *, **, ***.

As summarized in Figure 2, the stability test shows that all the eigenvalues lie inside the unit circle, indicating that the estimated PVAR satisfies the stability condition.

Figure 2 - PVAR Stability test



Eigenvalue stability condition

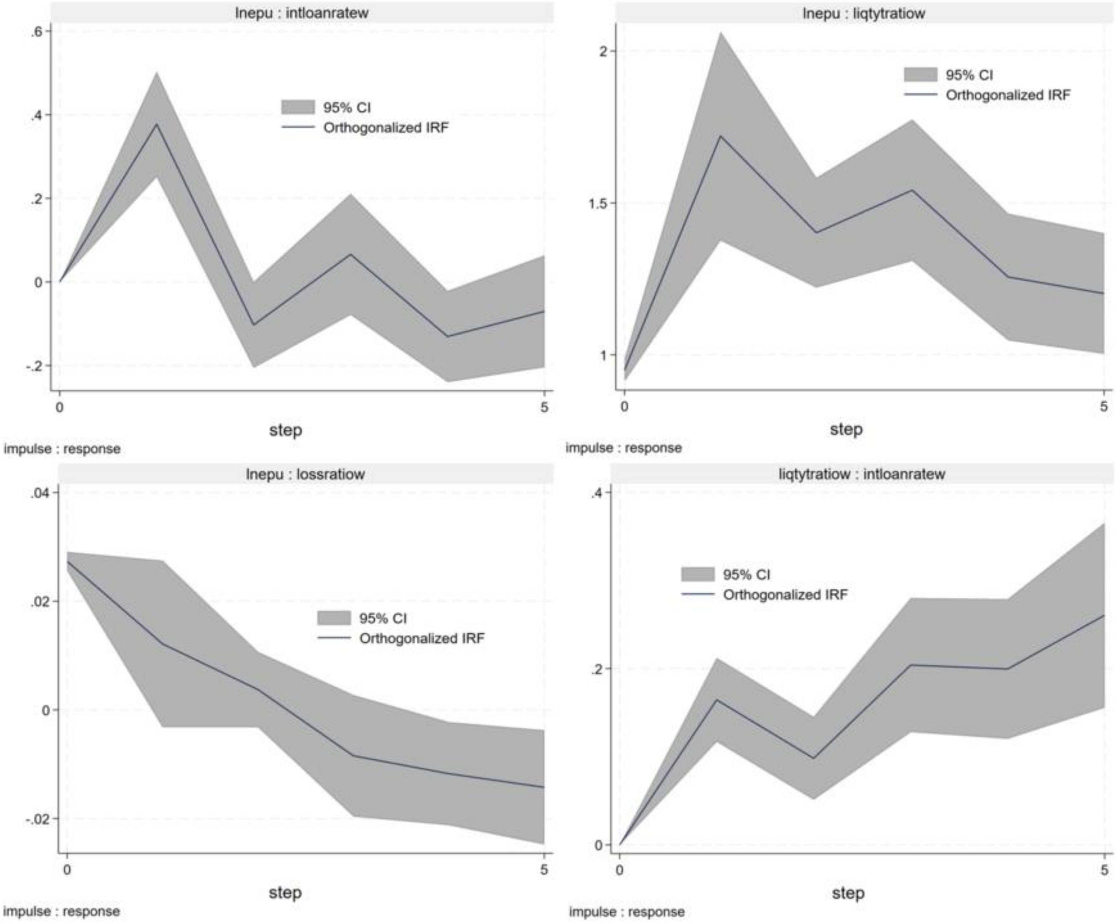
Eigenvalue Real	Imaginary	Modulus
.9991454	0	.9991454
.8822381	0	.8822381
.8429491	-.0694286	.8458035
.8429491	.0694286	.8458035
.6955752	0	.6955752
.5646296	.3119737	.6450846
.5646296	-.3119737	.6450846
-.6260256	0	.6260256
.5490372	0	.5490372
-.0269793	0	.0269793

All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.

As no unit root is present in the baseline model, and the stability condition is observed, it is possible to estimate the orthogonal impulse-response functions. As shown in Figure 3, there is evidence that EPU has a positive dynamic relationship with loan pricing in the short run. A one-standard-deviation shock in EPU increases loan price, achieving a peak after one year, with the shock effect dissipating over time with ups and downs. This result shows that EPU temporarily impacts loan pricing in the short-run.

Evidence shows that liquidity is a transmission channel of EPU to loan pricing. As shown in Figure 3, liquidity exhibits a positive dynamic relationship with EPU, which aligns with the literature, resulting from a fly-to-liquidity behavior in response to an uncertainty shock. A one-standard-deviation EPU shock increases liquidity hoarding, which peaks after one year, gradually decreasing the shock effect over time with ups and downs. In turn, liquidity exhibits a positive dynamics relationship with loan pricing and a one-standard-deviation liquidity shock impacts loan prices over time in the short and medium run. Therefore, under high policy-related uncertainty, policymakers and regulators should pay special attention to bank liquidity hoarding, a key transmission mechanism of uncertainty to loan pricing.

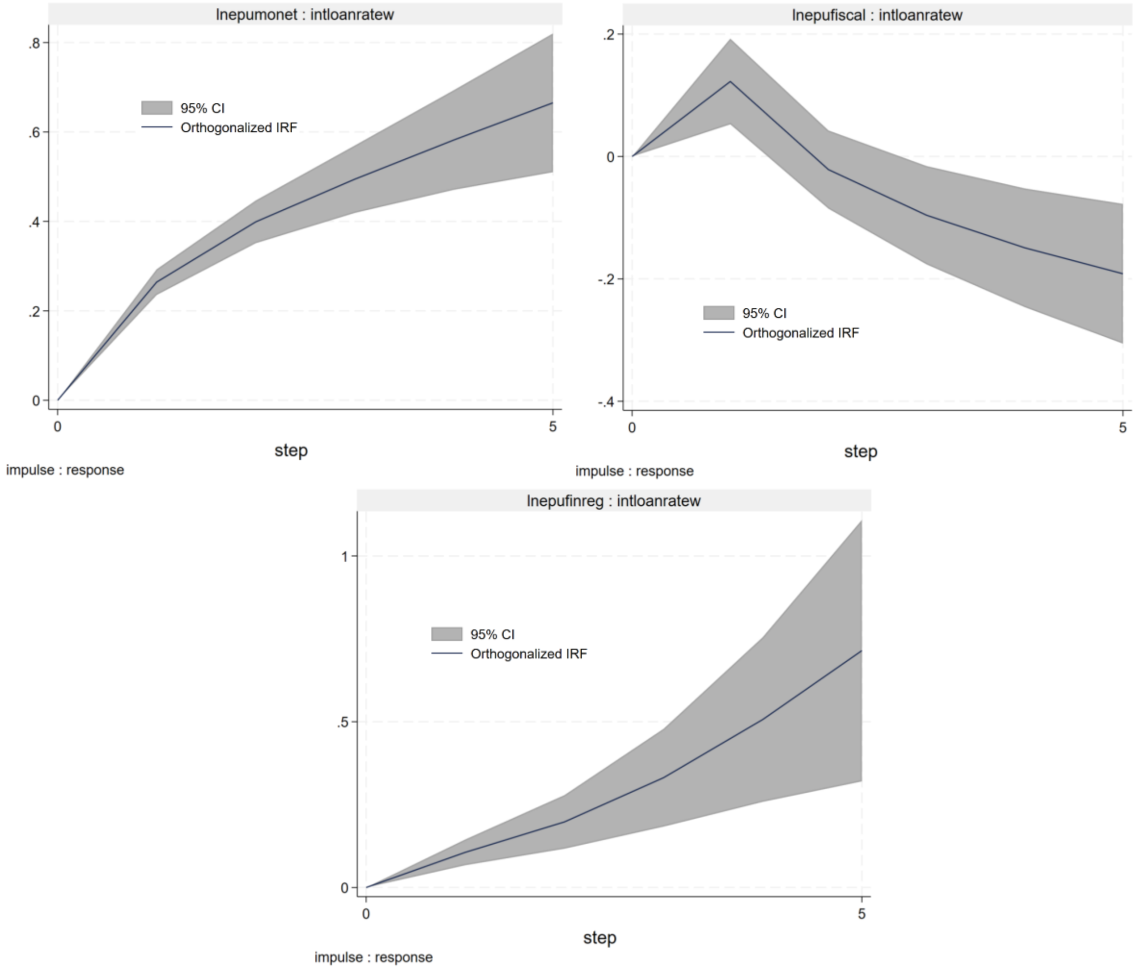
Figure 3 - Impulse-response functions



There is no evidence that default risk is a transmission channel of EPU to loan pricing, as postulated by Ashraf & Shen (2019), as the dynamic relationship between loss ratio and loan pricing didn't exhibit economic meaning. Nevertheless, default risk exhibits a positive dynamics relationship with EPU, as observed in Figure 3, and a one-standard-deviation EPU shock impacts default risk contemporaneously, with the shock effect dissipating gradually over time, which justifies keeping it as a control variable in the model.

To analyze the dynamic relationships between other categories of economic policy uncertainty and loan pricing, PVAR models are reestimated incorporating monetary policy, fiscal policy and financial regulation uncertainties. This also serves as a robustness check for the baseline model. As summarized in Figure 4, a one-standard-deviation shock in monetary policy uncertainty increases loan prices over years following a concave curve. A one-standard-deviation shock in fiscal policy uncertainty increases loan price, achieving a peak after one year and starting to dissipate the shock effect gradually afterwards. A one-standard-deviation shock in financial regulation uncertainty increases loan prices over the years following a convex curve.

Figure 4 - Impulse-response functions



The results show that uncertainties in monetary policy and financial regulation impact short- and medium-term loan pricing. Monetary uncertainty exhibits a faster impact in the short run, as financial regulation exhibits a less intense impact in the short run, accelerating in the medium run. A fiscal uncertainty shock temporarily affects loan prices, concentrated in the short run, with the shock effect dissipating after two years. Therefore, policymakers and regulators should promote transparency and predictability in monetary policy and financial regulation as a policy implication. Uncertainties in these policies adversely impact bank's loan pricing in the short and long run.

6 Conclusions

A highly uncertain global environment reflecting policy-related economic uncertainty has become important in recent years. Examples are political polarization, trade war, the US sovereign rating downgrade, Brexit, US government shutdown. A policy uncertainty shock promotes ambiguity, which is associated with the economic agent's degree of confidence in estimating probabilities (Ellsberg, 1961). Therefore, a rising ambiguous environment makes the basis for an agent's choice less reliable, affecting decision-making. Measures of economic policy uncertainty based on textual analysis emerged (Baker et al., 2016; Jurado et al., 2015), which opened the door for investigating the relationship between EPU and economic and financial decision-making, like bank's loan pricing.

Few studies were found regarding the relationship between policy uncertainty and bank loans. To the best of our knowledge, no study has been conducted on the dynamic relationship between EPU and loan pricing at bank-level; only aggregate-level studies have been found. Regarding the transmission channels of policy uncertainty to loans, to the best of our knowledge, only postulates without empirical studies were found in the literature. This research filled these literature gaps by studying how an EPU shock impacts a bank's loan pricing over time, assessing the dynamics between EPU and loan price at the bank level.

This research's empirical strategy consisted of estimating a conventional panel data model to confront the results with the empirical literature and, in addition, to robustly select relevant explanatory and control variables to be further incorporated in the dynamic assessment. To study the dynamic relationship between EPU and bank's loan pricing, panel autoregressive (PVAR) models and impulse-response functions were estimated.

Results show that EPU temporarily impacts on loan pricing, which is concentrated in the short run. A one-standard-deviation EPU shock increases loan price, achieving a peak after one year, dissipating over time with ups and downs. On the other hand, monetary policy and financial regulation uncertainty shocks have short and long run impacts on loan prices, in which a one-standard-deviation shock increases loan prices over time. In the case of monetary policy uncertainty, the shock effect is stronger in the short run. In the case of financial regulation uncertainty, the effect is stronger in the medium and long run. The effect of fiscal policy uncertainty on loan prices is limited to the short run, reverting after two years.

Evidence supports the hypothesis that liquidity hoarding is a transmission channel of EPU to bank's loan pricing, as the impulse-response function shows that a one-standard-deviation shock in EPU increases liquidity hoarding over time with a peak after one year. Complementary, a one-standard-deviation shock in liquidity hoarding increases loan prices. In short, an EPU shock raises liquidity hoarding, which, in turn, impacts loan pricing as a bank's liquidity behavior has a positive dynamic relation with loan price.

The results bring relevant contributions to policymakers and bank regulation and supervision. First, policymakers and regulators should promote transparency and predictability in monetary policy and financial regulation. Uncertainties in these policies adversely impact bank's loan pricing in the short and long run. Second, under high policy-related uncertainty, policymakers and regulators should pay special attention to bank liquidity hoarding, a key transmission mechanism of policy-related economic uncertainty to loan pricing.

Appendix. PVAR estimation output

Supplementary estimation, including monetary policy, fiscal policy and financial regulation uncertainties in the PVAR model, are summarized in Table A.1, Table A.2 and Table A.3.

Table A.1 - PVAR including monetary policy uncertainty

GMM Estimation

Final GMM Criterion Q(b) = 5.84e-31 No. of obs = 61592
Initial weight matrix: Identity No. of panels = 4694
GMM weight matrix: Robust Ave. no. of T = 13.121

Variables	intloanrate	lnepumonet	ipiyoy	pce	fundingcost	size	roe	lossratio	liqtytratio	leverage
intloanrate (L1)	0.677***	0.1***	1.139***	0.561***	0.053***	-0.002	0.663***	-0.015***	0.497***	-0.003***
SE	(0.019)	(0.006)	(0.049)	(0.021)	(0.012)	(0.002)	(0.086)	(0.004)	(0.084)	(0.000)
lnepumonet (L1)	0.439***	0.425***	-2.861***	-0.989***	0.036	-0.023***	0.188	-0.006	0.623***	0.007***
SE	(0.041)	(0.013)	(0.122)	(0.051)	(0.026)	(0.005)	(0.187)	(0.008)	(0.185)	(0.001)
ipiyoy (L1)	-0.112***	-0.001	0.657***	0.05***	-0.094***	0.002***	-0.051***	0.003***	0.135***	0.000***
SE	(0.004)	(0.001)	(0.015)	(0.006)	(0.003)	(0.000)	(0.022)	(0.001)	(0.021)	(0.000)
pce (L1)	0.389***	0.002	-1.694***	0.145***	0.366***	-0.007***	0.399***	-0.020	-0.496***	0.001***
SE	(0.013)	(0.004)	(0.043)	(0.016)	(0.008)	(0.001)	(0.064)	(0.003)	(0.062)	(0.000)
fundingcost (L1)	-0.141***	0.031***	0.53***	0.155***	0.588***	0.008***	-0.423***	0.026***	-0.427***	0.002***
SE	(0.025)	(0.008)	(0.078)	(0.031)	(0.016)	(0.003)	(0.134)	(0.005)	(0.123)	(0.000)
size (L1)	-1.432***	-0.255***	1.914***	0.51**	-0.886***	0.9***	-1.472	0.288***	-0.639	0.000
SE	(0.220)	(0.057)	(0.583)	(0.242)	(0.138)	(0.052)	(0.986)	(0.052)	(0.893)	(0.003)
roe (L1)	-0.014***	-0.005***	0.034***	0.008***	-0.01***	0.001***	0.539***	-0.003***	-0.023**	0.000*
SE	(0.002)	(0.001)	(0.006)	(0.002)	(0.001)	(0.000)	(0.014)	(0.001)	(0.009)	(0.000)
lossratio (L1)	0.033	0.003	0.762***	0.117***	-0.008	-0.01**	-0.788***	0.8***	1.016***	-0.001
SE	(0.038)	(0.012)	(0.105)	(0.046)	(0.026)	(0.004)	(0.224)	(0.011)	(0.183)	(0.001)
liqtytratio (L1)	0.009***	0.006***	-0.018***	-0.001	0.01***	0.000	-0.023**	-0.004***	0.858***	0.000***
SE	(0.002)	(0.001)	(0.006)	(0.003)	(0.001)	(0.000)	(0.009)	(0.000)	(0.009)	(0.000)
leverage (L1)	28.356***	8.946***	-18.389***	10.521***	21.466***	-0.577***	50.403***	-1.359***	-9.516	0.86***
SE	(1.613)	(0.584)	3.497	(1.705)	(1.152)	(0.166)	(6.825)	(0.287)	(6.827)	(0.037)
crisisdummy	0.438***	0.126***	-3.497***	-1.714***	0.318***	-0.011***	-1.581***	0.027***	0.928***	0.000
SE	(0.029)	(0.009)	(0.088)	(0.037)	(0.019)	(0.004)	(0.137)	(0.006)	(0.130)	(0.000)
Individual fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are shown in parentheses. Statistical significance at 10%, 5% and 1% is denoted respectively by *, **, ***.

Table A.2 - PVAR including fiscal policy uncertainty

GMM Estimation

Final GMM Criterion Q(b) = 4.02e-31 — No. of obs = 61592
Initial weight matrix: Identity — No. of panels = 4694
GMM weight matrix: Robust — Ave. no. of T = 13.121

Variables	intloanrate	lnepufiscal	ipiyoy	pce	fundingcost	size	roe	lossratio	liqtyratio	leverage
intloanrate (L1)	0.764***	-0.218***	0.363***	0.325***	0.055***	-0.007***	0.659***	-0.017***	0.607***	-0.002***
SE	(0.026)	(0.030)	(0.092)	(0.028)	(0.012)	(0.002)	(0.090)	(0.004)	(0.090)	(0.000)
lnepufiscal (L1)	0.715***	-0.422***	-2.792***	-1.244***	0.097***	-0.035***	0.677***	-0.003	1.127***	0.01***
SE	(0.083)	(0.092)	(0.291)	(0.092)	(0.039)	(0.008)	(0.266)	(0.011)	(0.264)	(0.001)
ipiyoy (L1)	-0.23***	0.271***	1.185***	0.269***	-0.109***	0.008***	-0.15***	0.003	-0.047	-0.002***
SE	(0.019)	(0.021)	(0.069)	(0.022)	(0.009)	(0.002)	(0.063)	(0.003)	(0.062)	(0.000)
pce (L1)	0.732***	-0.864***	-3.206***	-0.485***	0.409***	-0.024***	0.69***	-0.022***	0.035	0.006***
SE	(0.057)	(0.063)	(0.204)	(0.064)	(0.027)	(0.005)	(0.186)	(0.008)	(0.184)	(0.001)
fundingcost (L1)	-0.287***	0.683***	1.383***	0.464***	0.575***	0.015***	-0.505***	0.028***	-0.64***	0.000
SE	(0.048)	(0.054)	(0.178)	(0.054)	(0.022)	(0.005)	(0.175)	(0.007)	(0.168)	(0.001)
size (L1)	-2.134***	2.126***	6.421***	2.079***	-0.944***	0.937***	-1.786*	0.297***	-1.64*	-0.011***
SE	(0.304)	(0.313)	(1.006)	(0.329)	(0.143)	(0.048)	(1.013)	(0.052)	(0.955)	(0.004)
roe (L1)	-0.025***	0.032***	0.108***	0.032***	-0.01***	0.001***	0.536***	-0.003***	-0.037***	0.000***
SE	(0.004)	(0.004)	(0.013)	(0.004)	(0.002)	(0.000)	(0.016)	(0.001)	(0.012)	(0.000)
lossratio (L1)	-0.027	0.093	0.952***	0.212***	-0.017	-0.007	-0.852***	0.8***	0.921***	-0.001*
SE	(0.059)	(0.070)	(0.206)	(0.062)	(0.028)	(0.005)	(0.229)	(0.011)	(0.192)	(0.001)
liqtyratio (L1)	0.02***	-0.033***	-0.1***	-0.028***	0.011***	-0.001***	-0.019*	-0.005***	0.874***	0.000***
SE	(0.004)	(0.004)	(0.013)	(0.004)	(0.002)	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)
leverage (L1)	49.304***	-61.932***	-157.089***	-37.116***	23.12***	-1.673***	58.968***	-1.652***	20.097	1.186***
SE	(4.376)	(5.057)	(16.207)	(4.889)	(2.039)	(0.418)	(14.572)	(0.616)	(14.568)	(0.067)
crisisdummy	0.774***	-0.677***	-4.906***	-2.317***	0.361***	-0.028***	-1.282***	0.026***	1.451***	0.005***
SE	(0.077)	(0.083)	(0.265)	(0.084)	(0.036)	(0.008)	(0.241)	(0.011)	(0.237)	(0.001)
Individual fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are shown in parentheses. Statistical significance at 10%, 5% and 1% is denoted respectively by *, **, ***.

Table A.3 - PVAR including financial regulation uncertainty

GMM Estimation

Final GMM Criterion Q(b) = 5.98e-31 — No. of obs = 61592
Initial weight matrix: Identity — No. of panels = 4694
GMM weight matrix: Robust — Ave. no. of T = 13.121

Variables	intloanrate	lnepufinreg	ipiyoy	pce	fundingcost	size	roe	lossratio	liqtyratio	leverage
intloanrate (L1)	0.788***	-0.039***	0.902***	0.509***	0.081***	-0.007***	0.787***	-0.019***	0.547***	-0.002***
SE	(0.025)	(0.005)	(0.071)	(0.021)	(0.012)	(0.002)	(0.090)	(0.004)	(0.088)	(0.000)
lnepufinreg (L1)	0.377***	0.407***	-5.644***	-2.15***	-0.101***	-0.022***	-0.344*	0.013	1.24***	0.008***
SE	(0.061)	(0.012)	(0.182)	(0.058)	(0.030)	(0.006)	(0.208)	(0.009)	(0.201)	(0.001)
ipiyoy (L1)	-0.18***	0.029***	1.449***	0.346***	-0.085***	0.006***	-0.024	0.001	-0.039	-0.002***
SE	(0.015)	(0.003)	(0.046)	(0.014)	(0.007)	(0.001)	(0.053)	(0.002)	(0.051)	(0.000)
pce (L1)	0.622***	-0.14***	-4.626***	-0.956***	0.326***	-0.02***	0.275	-0.015**	0.147	0.005***
SE	(0.051)	(0.010)	(0.155)	(0.048)	(0.025)	(0.005)	(0.176)	(0.007)	(0.171)	(0.001)
fundingcost (L1)	-0.273***	0.095***	1.581***	0.53***	0.586***	0.015***	-0.449**	0.027***	-0.657***	0.000
SE	(0.046)	(0.010)	(0.144)	(0.043)	(0.023)	(0.005)	(0.176)	(0.007)	(0.166)	(0.001)
size (L1)	-2.03***	-0.062	5.155***	1.59***	-0.961***	0.931***	-1.833*	0.3***	-1.343	-0.009**
SE	(0.290)	(0.051)	(0.828)	(0.271)	(0.145)	(0.048)	(1.013)	(0.052)	(0.930)	(0.004)
roe (L1)	-0.024***	0.000	0.063***	0.016***	-0.012***	0.001***	0.531***	-0.003***	-0.029***	0.000***
SE	(0.003)	(0.001)	(0.009)	(0.003)	(0.002)	(0.000)	(0.016)	(0.001)	(0.011)	(0.000)
lossratio (L1)	0.022	-0.034***	1.056***	0.233***	0.000	-0.009**	-0.757***	0.799***	0.951***	-0.001
SE	(0.056)	(0.009)	(0.156)	(0.046)	(0.029)	(0.005)	(0.227)	(0.011)	(0.186)	(0.001)
liqtyratio (L1)	0.019***	0.001	-0.061***	-0.014***	0.012***	-0.001***	-0.014	-0.005***	0.867***	0.000***
SE	(0.003)	(0.001)	(0.010)	(0.003)	(0.002)	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)
leverage (L1)	46.611***	-1.252*	-107.59***	-18.472***	24.177***	-1.511***	62.966***	-1.778***	9.823	1.126***
SE	(3.810)	(0.727)	(12.266)	(3.602)	(1.920)	(0.369)	(13.266)	(0.556)	(12.966)	(0.060)
crisisdummy	0.534***	0.572***	-4.629***	-2.137***	0.305***	-0.016***	-1.619***	0.029***	1.176***	0.002***
SE	(0.053)	(0.009)	(0.149)	(0.048)	(0.026)	(0.006)	(0.176)	(0.008)	(0.167)	(0.001)
Individual fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are shown in parentheses. Statistical significance at 10%, 5% and 1% is denoted respectively by *, **, ***.

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