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Macroeconomic determinants of NPLs and strategic default

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Macroeconomic determinants of NPLs and strategic default

Abstract

This paper explores the macroeconomic impact of strategic default on non-performing loans (NPLs), addressing a key gap in existing research. Using a novel strategic default proxy developed via principal component analysis (PCA) and a dynamic panel data model, the study reveals a complex temporal relationship. Initially, shocks to strategic defaults lead to a short-term decline in NPL growth, reflecting financial adjustments or delays in recognition, but are followed by a persistent upward trend that significantly weakens loan portfolio quality and financial stability. These findings highlight the need for timely interventions to address misleading short-term stability and mitigate long-term risks. The study also underscores the importance of incorporating behavioural and institutional factors, such as uncertainty and banking leverage, into NPL modelling.

1 Introduction

The growing NPL literature has not considered yet the effect of strategic default behaviour on the NPL phenomenon at the macro level. Micro level studies of strategic default use (proprietary) loan transactional data associated with customer data, demographics, and survey data to identify strategic default incentives. Motivated by their outcomes, and by the necessity for NPLs macro-modelling given regulatory requirements, this paper aims to develop an NPL modelling framework by incorporating the strategic default factor of ex-post credit risk using economy-wide aggregate proxies. The project will investigate a set of proxies associated with the strategic default motives of borrowers within an economy including economic uncertainty and sentiment indices, corruption, rule of law, and governance indicators, real estate prices, dummy variables for foreclosure suspension laws, average banking sector fundamentals as well as gross domestic expenditure on R&D.

2 Strategic default framework:

2.1 Defining strategic default

Strategic default refers to *the intentional decision by a borrower to cease making payments on a loan, despite having the financial capacity to continue doing so* (Guiso et al., 2013). This decision is typically made when the borrower concludes that the financial advantages of defaulting outweigh the potential consequences. Strategic default is most commonly associated with mortgages, particularly in situations where the value of the property has dropped significantly below the outstanding balance on the loan—a scenario often referred to as being "underwater."

At its core, strategic default is a calculated financial decision rather than a response to financial distress. Borrowers who choose to strategically default typically do so after assessing their financial situation and determining that continuing to make loan payments no longer serves their best interests. For instance, consider a homeowner who owes a specific amount on a mortgage, while the current market value of their property has plummeted to half of the amount. In such a case, the homeowner might rationally decide that it makes more sense to default on the mortgage rather than continue paying for an asset that has significantly depreciated in value, leaving them with negative equity.

The most common context for strategic default involves so-called "underwater" loans, where the outstanding loan balance exceeds the current value of the collateral, such as a house. In these situations, borrowers may feel that there is little incentive to continue making payments, as they are effectively paying more than the asset is worth. This lack of equity can drive the decision to default, especially when the prospects of property values recovering seem bleak or too distant (Ganong & Noel, 2020).

Choosing to strategically default on a loan can have serious repercussions for the borrower. One of the most immediate and significant consequences is damage to the

borrower's credit rating, which can make it more challenging or expensive to obtain credit in the future. Additionally, the lender may pursue legal action to recover the outstanding debt, depending on the nature of the loan and the legal framework in the relevant jurisdiction.

In some instances, lenders have the right to seek a deficiency judgment, which is a court order requiring the borrower to pay the difference between the outstanding loan balance and the value of the collateral after it is sold. However, in certain jurisdictions, particularly in the context of residential mortgages, laws may protect borrowers from such judgments, limiting the lender's recourse to the collateral alone.

Strategic default is not merely a financial decision; it also raises significant moral and ethical questions. At its essence, strategic default involves a deliberate decision to break a contractual obligation. Some view this as a legitimate financial choice, particularly in a market environment where both lenders and borrowers engage in transactions with a clear understanding of the associated risks (Ganong & Noel, 2020). Others, however, perceive it as unethical, arguing that it involves a willful failure to honour a commitment.

The debate surrounding strategic default is often framed in terms of the social contract versus individual financial rationality. On one hand, there is the argument that borrowers have a moral duty to repay their debts, honouring the agreements they have entered into. On the other hand, some contend that in a business context, it is expected that both borrowers and lenders will act in their own financial self-interest, and that strategic default is simply an expression of this principle when the balance of incentives shifts (Seiler et al., 2012).

The practice of strategic default can have broader economic implications, particularly during times of financial crisis or in the aftermath of a housing market downturn leading to a financial crisis like the one in 2007/8. If a significant number of borrowers choose to strategically default, this can lead to substantial losses for lenders and contribute to instability within the financial system. Such widespread defaults can exacerbate

economic downturns by further depressing property values and reducing the availability of credit (Scieczka et al., 2011).

In response to the risks posed by strategic defaults, lenders may adjust their practices to mitigate potential losses. This could involve tightening lending standards, increasing interest rates, or requiring larger deposits to protect themselves from the risk of borrowers defaulting on their loans. These measures, while protective for lenders, can also have the effect of making credit less accessible or more expensive for future borrowers (IMF, 2019; ECB, 2024).

Strategic default is a complex and controversial phenomenon that arises when a borrower, despite having the means to continue repaying a loan, opts to default because the economic incentives to do so are stronger than those for maintaining payments (White, 2010). While it is most commonly associated with underwater mortgages, the concept can apply to other types of loans as well. Although strategic default may make sense from a purely financial perspective, it carries significant consequences, including damage to credit ratings, potential legal repercussions, and broader impacts on the economy. Moreover, the decision to strategically default is not just a financial calculation; it also involves navigating moral and ethical considerations, as borrowers weigh their contractual obligations against their own financial interests.

2.2 Literature review

The aim of this section is to offer a concise literature review on strategic default as well as to identify in detail proxies that can be used to describe increasing odd of strategic default for both type of loans, consumer and corporate, in common.

Alderson and Betker (1995) studied the relation between liquidation costs of assets and composition of capital structure for 88 businesses that reorganised after Bankruptcy Code. Liquidation cost is one of the main factors that can determine default if different firms (value of collaterals). They found that liquidation cost is important in determining

the capital structure of the firm and that is significantly negatively related to the proportions of both private and secured debt. High liquidation cost means firms being less likely to have to prepay their debt and higher chances of attraction of new equity capital as part of the reorganisation process hence lower probability of default. Later on the same authors,

Alderson and Betker (1996), underlined the importance all the quality of assets affecting the cost of financial distress and liquidation, and, therefore affecting default rates. On the most interesting finding of the paper is that liquidation costs and research and development expense correlate positively, but weakly. This concludes that gross domestic expenditure on research and development can be a proxy for strategic default.

Allen and Gale (2000) were among the first to examine the role of network structure in financial contagion, finding that incomplete financial networks are more vulnerable to contagion than fully connected ones. Soon after, Eisenberg and Noe (2001) developed a static model of default contagion in financial networks, where agents' ability to repay liabilities depends on their operational cash flows and the payments they receive from others. They demonstrated the existence of a unique clearing payment vector, which could predict chains of defaults.

Elliott et al. (2014) introduced the concepts of integration and diversification in cross-holdings, demonstrating that while integration increases the extent of contagion, it reduces the probability of the initial failure, and diversification reduces exposure between institutions but can amplify default cascades. Acemoglu et al. (2015) extended the Eisenberg-Noe model by incorporating external shocks and showing that connectivity enhances stability up to a point but increases fragility when shocks exceed a certain magnitude.

Further advancing this field, Cabrales et al. (2017) analyzed the optimal financial network structure that maximizes risk-sharing while minimizing risk exposure. To mitigate the domino effect in financial networks, central clearing and targeted interventions aimed at systemically important institutions have been explored. Demange (2018), for example,

introduced the "threat index," which identifies critical agents for targeted cash injections to prevent contagion, following an approach similar to Eisenberg and Noe's (2001).

Finally, Jackson and Pernoud (2020) studied how network structure affects agents' investment strategies and the role of regulatory intervention, contributing to understanding how policy might influence financial stability.

Despite significant advancements, the literature still lacks a comprehensive understanding of how banks would optimally allocate their audit resources when dealing with non-performing loans, especially in the context of strategic default. In such scenarios, banks often do not have accurate information on the true level of strategic default, and companies remain unaware of the audit resources banks are dedicating to monitor them. This uncertainty creates a gap in understanding, which the model presented here aims to address by exploring the optimal allocation of audit resources under these conditions.

2.3 Identifying Strategic Default Proxies

The overarching concept is that strategic default is influenced by two key types of variables: those that hinder loan repayment and those that shape lender sentiment, prompting adjustments in their strategic behaviour and potentially leading to default. Using the literature review along with checking the database of available data for OECD countries we can conclude that the most appropriate proxies to approach strategic default are research and development, bank leverage, uncertainty, and lending rates, each offering insights into how these variables interact with default risk and financial dynamics. I will now explain the connection of these variables with the literature review while the data sourcing will be explained in the data section of this paper, section 4.

- a. Research and development (R&D):

Alderson and Betker (1996) establish a connection between liquidation costs and R&D expenses, finding a weak but positive correlation. This suggests that firms with higher R&D expenditures may face higher liquidation costs, potentially increasing financial distress but also indicating a tendency toward strategic default. The link between R&D and liquidation costs implies that R&D investments may serve as a proxy for strategic behaviour, as firms with significant intangible assets (resulting from R&D) might use default strategically rather than out of necessity.

b. Bank Leverage:

Allen and Gale (2000) and Eisenberg and Noe (2001) provide insights into how financial network structures and interbank relationships can amplify risk. High levels of bank leverage increase vulnerability to financial contagion, as leveraged banks are more exposed to systemic shocks. In addition, Acemoglu et al. (2015) demonstrate that greater connectivity in financial networks (often linked to high leverage) improves stability up to a point but leads to increased fragility when external shocks are severe. This highlights the role of leverage in amplifying or mitigating financial instability. Borrowers might exploit this fragility by defaulting strategically, knowing that banks are likely to renegotiate rather than risk amplifying the contagion.

c. Uncertainty:

Eisenberg and Noe (2001) and Acemoglu et al. (2015) explore how external shocks and cascading defaults in financial networks are heightened in uncertain environments. Banks and firms facing uncertainty in cash flows and repayment chains may adjust their lending strategies or default behaviour.

d. Lending Rates:

Following Alderson and Betker (1994 and 1996), high lending rates influence strategic default by increasing the financial burden on borrowers, making repayment less attractive and incentivising default as a strategic decision to secure better terms or avoid

unsustainable obligations. Furthermore, Elliott et al. (2014) argued that elevated rates often reflect heightened uncertainty or perceived risk, which borrowers may exploit, anticipating that lenders would prefer renegotiation over enforcement to mitigate potential losses or systemic instability.

Another connection identified by Alderson and Betker (1996) work is that stricter credit terms associated with higher rates can push financially constrained borrowers toward default, especially when they perceive opportunities for reorganization or restructuring. This dynamic is further exacerbated in highly leveraged banking systems, where the strain from elevated lending rates increases financial fragility and makes strategic default a more appealing option according to Acemoglu et al. (2015).

To conclude there are clear connections between strategic default, research development, banking leverage, uncertainty, and lending rates. The general idea is that strategic default is affected by two types of variables: variable that inhibit the repayments if the loans and variables affecting the sentiment of the lenders leading them to altering their strategic behaviour and become delinquent by defaulting.

3 Methodology

This paper offers two research contribution in the literature. First, I will be creating a new strategic default index using our 4 proxy variables: R&D (rnd), bank leverage (bankl), uncertainty (uncer) and lending rates (str). To my knowledge, and after studying any literature existing on strategic default, no index like that has ever been created, neither there is a solid theoretical model approaching strategic default. Secondly, I will run a pan-European NPL model including macroeconomic determinants and the aforementioned strategic default index to examine how strategic default affects NPLs. Macroeconomic variables will be included so that I avoid omitted variable bias. The dynamic panel data model will then be estimated with the Holtz-Eakin, Newey, and Rosen (1988) estimator. Both methods discussed will be covered in this section.

3.1 Principal components analysis

Principal Components Analysis (PCA) is a statistical technique used to reduce the dimensionality of a dataset while retaining as much variability as possible. This method is particularly useful when attempting to create a new index from a set of correlated variables, as it allows for the combination of these variables into a single measure that captures the essential information. The process of creating a new index using PCA can be understood through a series of analytical steps, each of which contributes to the construction of a meaningful and interpretable index (Pearson, 1901; Hotelling, 1933).

I will be following Abdi & Williams (2010) and Jolliffe and Cadima (2016) to motivate and explain this method. The first step in creating a new index using PCA involves data preparation. The data, typically a set of variables that are expected to be correlated, which in our case are, must be numeric since PCA operates on numerical values. Before applying PCA, it is crucial to standardise the data, which involves transforming the data such that each variable has a mean of zero and a standard deviation of one. This standardisation is necessary because PCA is sensitive to the scale of the data; without it, variables with larger scales would unduly influence the analysis, leading to misleading results.

Once the data is standardised, the next step is to perform the PCA itself. This begins with the calculation of the covariance matrix, a square matrix that quantifies the extent to which each pair of variables in the dataset varies together. The covariance matrix is central to PCA as it encapsulates the relationships between the variables, allowing for the identification of patterns in the data.

Following the construction of the covariance matrix, the next phase involves the computation of eigenvalues and eigenvectors through eigen decomposition. Eigenvalues indicate the amount of variance captured by each principal component, while eigenvectors, also known as loadings, represent the directions in the data space that correspond to these principal components. Each eigenvector is a linear

combination of the original variables and defines a new axis along which the data can be projected.

The principal components are ordered by the magnitude of their associated eigenvalues, with the first principal component capturing the maximum possible variance in the data. Subsequent components capture progressively less variance, with each component orthogonal to the others. The decision of how many principal components to retain is guided by the proportion of total variance explained by these components. Typically, only the components that account for a significant portion of the variance are selected for constructing the new index. However, in our case we will see that all four variables are kept indirectly proving their significance in explaining strategic default.

To create the new index, the original variables are weighted by the coefficients from the selected principal components. These coefficients are derived from the eigenvectors and represent the contribution of each variable to the principal component. The weighted variables are then summed to form the new index, which is a **linear combination of the original variables**. This index is a single measure that encapsulates the most significant patterns in the data, as identified by the principal components.

The final step in the process involves interpreting the new index. The index created through PCA is a powerful tool for summarising complex data, but its interpretation depends on understanding the underlying principal components. Since each principal component represents a specific pattern of variation within the data, the new index can be interpreted as a measure that reflects these patterns. In practical applications, such an index can be used to rank or classify observations, identify underlying trends, or as a predictor in further analyses.

Given the identification of the proxies from the literature and the methodology of PCA, I can now construct a strategic default index denoted as:

$$Sd = w_1 * rnd + w_2 * bankl + w_3 * uncer + w_4 * str$$

where w_1, w_2, w_3, w_4 are the weights assigned by PCA, optimised to capture the underlying structure of strategic default. This approach enhances interpretability by condensing multiple sources of information into a single index, facilitating more robust empirical analysis while mitigating potential issues of redundancy and noise in the data.

3.2 Dynamic panel data estimator

To examine the impact of strategic default and macroeconomic variables on NPLs, I utilised the Panel Vector Autoregression (PVAR) methodology, where all variables in the system are treated as endogenous. The PVAR approach is the preferred method here since it captures both static and dynamic interdependencies among the variables, allows for unrestricted connections between units, and takes into account unobserved individual heterogeneity across different countries. The PVAR methodology combines the traditional VAR model with a panel data framework, following the PVAR routine introduced by Abrigo and Love (2016).

The Abrigo and Love (2016) PVAR routine offers a sophisticated approach to estimating Panel Vector Autoregression (PVAR) models, blending the flexibility of traditional Vector Autoregression (VAR) models with the advantages of panel data structures. This methodology is particularly valuable for my model aiming to analyse dynamic relationships between multiple variables across different countries over time.

In a VAR framework, each variable in the system is treated as endogenous, meaning its current value is influenced by its **own** past values and the past values **of other** variables in the system. This approach allows for rich modeling of the dynamic interdependencies between the variables. When extended to a panel data setting, which includes both a time-series dimension and a cross-sectional dimension, the resulting model becomes a PVAR. This model can account for heterogeneity across entities (in our case, countries) while still capturing the temporal dynamics within each entity.

The key challenge in PVAR models, as in other dynamic panel data models, is addressing the issue of endogeneity. Endogeneity arises because lagged dependent variables, which are included as regressors, are likely correlated with the error terms. This creates bias in standard estimation techniques such as ordinary least squares (OLS). To address this issue, the Abrigo and Love PVAR routine relies on Generalized Method of Moments (GMM) estimators, specifically the system GMM approach, and more specifically the Arellano and Bover (1995) one. The system GMM estimator uses a combination of first-differenced and level equations, along with lagged values of the endogenous variables as instruments, to control for endogeneity. This method leverages the internal structure of the data, making it possible to handle the endogeneity problem effectively.

The PVAR routine employs the system GMM estimator, which is particularly well-suited to dynamic panel data models. In this context, system GMM involves estimating two sets of equations: the first-differenced equations and the level equations. The first-differencing step helps to eliminate unobserved fixed effects that could otherwise bias the results. Lagged levels of the endogenous variables are used as instruments for the differenced equations, while lagged differences are used as instruments for the level equations. This combination improves the efficiency of the estimation process, particularly in short panels where the time dimension is relatively limited.

The system GMM approach offers several advantages. First, it handles the endogeneity of the lagged dependent variables, which is a critical concern in dynamic models. By using lagged values as instruments, the system GMM estimator helps ensure that the estimated parameters are consistent and unbiased. Second, it addresses the Nickell (1981) bias, a problem that arises when estimating dynamic models with fixed effects using traditional methods. This bias can lead to inconsistent parameter estimates, particularly in panels with a small number of time periods. System GMM corrects for this by utilizing both the differenced and level equations.

Additionally, the Abrigo and Love PVAR routine accounts for unobserved heterogeneity across cross-sectional units through the use of the Helmert transformation. This transformation involves forward mean-differencing, which removes the entity-specific

fixed effects without introducing bias into the instrument set. The transformation also preserves the orthogonality of the instruments, ensuring that they remain valid in the GMM estimation process.

Once the PVAR model has been estimated, one of its key outputs is the generation of Impulse Response Functions (IRFs). These tools are essential for understanding the dynamic interactions between the variables in the model. IRFs trace the effects of a one-time shock to one variable on the future values of all variables in the system, showing how these shocks propagate over time. I will be utilising IRFs in my analysis as well.

3.3 The model

For our analysis we are about to estimate a K-order five-variable model. The model can be generally specified as:

$$Y_{i,t} = c + \sum_{k=1}^K A_k Y_{i,t-p} + n_i + u_{it}, \quad i = 1, \dots, I \text{ and } t = 1, \dots, T \quad (4.1)$$

where $Y_{i,t}$ is the vector of the five endogenous variables (NPL growth, GDP growth, inflation, unemployment and strategic default), c is a vector of constants, A is the matrix of estimated coefficients and n_i and u_{it} are the vectors representing panel fixed effects specific to the dependent variable and the corresponding idiosyncratic error terms, respectively.

Note that in the model we assume that:

$$E(u_{it}) = 0 \text{ as well as } E(u'_{it}u_{it}) = B \text{ and } E(u'_{it}u_{is}) = 0, \text{ for any } t > s$$

We apply a Cholesky decomposition to the variance-covariance matrix of the residuals u_{it} since the actual variance-covariance matrix of the errors is unlikely to be diagonal. This lack of diagonal structure makes it challenging to isolate shocks to any specific VAR error. To address this, we transform the residuals to ensure they are orthogonal,

following the method outlined by Abrigo and Love (2016). Since the dependent variables and their lagged values remain orthogonal, equation 4.1 can be estimated using the Generalized Method of Moments (GMM) approach proposed by Arellano and Bover (1995). For this estimation, lagged values of both the dependent and explanatory variables are employed as instruments. We do that because given the existence of lagged values of the response variable as an explanatory variable, simple OLS estimates would be biased (Abrigo & Love, 2016).

For the results to align with the PVAR methodology, the stability conditions must be satisfied. Specifically, the stability of the PVAR model requires the eigenvalues of the dynamic matrix to have moduli that fall within the unit circle. We will see later on that this condition is met in our estimated model:

4 Data

The NPL data for this paper are the same data used in Giannoulakis (2025). I collected the rest of the data for all the European countries that are OECD (The Organization for Economic Cooperation and Development) members. I decided to use the OECD data base for both macroeconomic and strategic default related variables (with the exception of the uncertainty index) since it will offer a uniform database and there was availability for strategic default related variables. That led to a group of 24 countries: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

The definitions of the new for this paper variables, except uncertainty, I am using are below, taken from the OECD website. In order to approach uncertainty, I am using the economic policy uncertainty index by S. R. Baker, N. Bloom and S. J. Davis (2016).

Real Gross Domestic Product (GDP):

Real gross domestic product (GDP) is the standard measure of the value added created through the production of goods and services in a country during a certain period. Real gross domestic product (GDP) is the standard measure of the value added created through the production of goods and services in a country during a certain period. As such, it also measures the income earned from that production, or the total amount spent on final goods and services (less imports). While GDP is the single most important indicator to capture economic activity, it falls short of providing a suitable measure of people's material well-being for which alternative indicators may be more appropriate. This indicator is based on real GDP (also called GDP at constant prices or GDP in volume), that is, the developments over time are adjusted for price changes. The numbers are also adjusted for seasonal influences (OECD website). The indicator is measured as percentage change from the previous quarter, percentage change from the same quarter of the previous year and volume index (2015=100).

Banking sector leverage:

This indicator presents the ratio between selected financial assets of the banking sector and their total equity; it is also known as the equity multiplier ratio (or financial leverage). This indicator presents the ratio between selected financial assets of the banking sector and their total equity; it is also known as the equity multiplier ratio (or financial leverage). The banking sector covers the central bank, and monetary financial institutions, as well as other financial intermediaries (except insurance corporations and pension funds). The financial assets cover currency and deposits; debt securities; and loans. Total equity relates to the market value of equity, excluding investment fund shares (OECD website).

Unemployment rate:

Unemployment rate is the share of the labour force without work. The labour force is the total number of employees, the self-employed, unpaid family workers and the unemployed.

Unemployed people are those of a working age who do not have a job, are available for work and have taken specific steps to find a job in the previous four weeks. Data are based on labour force surveys (LFS) which contain predominantly monthly and quarterly statistics on the unemployed population by age groups and sex. The uniform application of this definition results in estimates of unemployment rates that are more internationally comparable than estimates based on national definitions of unemployment. This indicator is measured as a percentage of the labour force and is seasonally adjusted (OECD website).

Short-term interest rates:

Short-term interest rates are the rates at which short-term borrowings are effected between financial institutions or the rate at which short-term government paper is issued or traded in the market. Short-term interest rates are generally averages of daily rates, measured as a percentage. Short-term interest rates are based on three-month money

market rates where available. Typical standardised names are "money market rate" and "treasury bill rate" (OECD website).

Inflation rate:

Inflation measured by consumer price index (CPI) is defined as the change in the prices of a basket of goods and services that are typically purchased by specific groups of households. Inflation is measured in terms of the annual growth rate and in index, 2015 base year with a breakdown for food, energy and total excluding food and energy. Inflation measures the erosion of living standards. A consumer price index is estimated as a series of summary measures of the period-to-period proportional change in the prices of a fixed set of consumer goods and services of constant quantity and characteristics, acquired, used or paid for by the reference population. Each summary measure is constructed as a weighted average of a large number of elementary aggregate indices (OECD website).

Gross domestic spending on research and development (R&D):

Gross domestic spending on research and development (R&D) is the total expenditure (current and capital) on R&D in a country. Research and development comprise creative work undertaken on a systematic basis to increase the stock of knowledge, and the use of this knowledge to devise new applications. This indicator includes R&D carried out by all resident companies, research institutes, university, and government laboratories. It includes R&D funded from abroad but excludes domestic funds for R&D performed outside the domestic economy. This indicator is measured in both USD constant prices using 2015 base year and purchasing power parities (PPPs), and as a percentage of GDP. g a sample of prices for a defined set of goods and services obtained in, or by residents of, a specific region from a given set of outlets or other sources of consumption goods and services (OECD website).

Uncertainty:

The Global Economic Policy Uncertainty (GEPU) Index serves as a comprehensive monthly measure of global economic policy uncertainty, extending from January 1997 to the present. It is calculated as a GDP-weighted average of Economic Policy Uncertainty (EPU) indices for 21 countries, including major economies such as the United States, China, Japan, and Germany, as well as a diverse set of emerging and advanced economies like Brazil, India, and Sweden. Together, these countries account for a significant portion of global output—approximately 71% on a purchasing power parity (PPP) basis and 80% at market exchange rates (GEPU website).

Each national EPU index measures the proportion of newspaper articles in a given country that reference a trio of terms related to the economy, policy, and uncertainty in a given month. This methodology reflects the intensity of policy-related economic uncertainty as discussed in the national media. For most countries, the indices are based on a selection of major newspapers, while for China, a hybrid index is created by combining data from the South China Morning Post and various mainland newspapers. Monthly EPU index values are normalized, ensuring consistency and comparability across countries with differing baseline levels of uncertainty.

To construct the GEPU Index, the process begins with normalizing each country's EPU index to a mean of 100 for the period spanning 1997 to 2015. This ensures that country-specific differences in baseline uncertainty levels do not skew the global index. In cases where certain countries have missing data points, a regression-based imputation method is used to estimate these values, creating a balanced panel of monthly EPU index observations for all 21 countries from January 1997 onward. Finally, the GEPU Index is calculated as a GDP-weighted average of the national EPU indices, with GDP data sourced from the International Monetary Fund's (IMF) World Economic Outlook Database.

Two versions of the GEPU Index are available: one based on GDP at current market exchange rates and the other based on PPP-adjusted GDP. The PPP-adjusted version of the index is often considered more appropriate for studying global economic dynamics and specific phenomena like strategic default. Unlike current market exchange rates,

which can fluctuate significantly due to currency movements and speculative pressures, PPP adjustments provide a more stable measure of economic activity by accounting for differences in the cost of living and price levels across countries. This stability ensures that the contribution of each country to the global index reflects its true economic capacity rather than temporary currency distortions.

By weighting countries based on their PPP-adjusted GDP, the index provides a more accurate representation of global economic interdependencies and the strategic considerations that influence default decisions. It ensures that the economic uncertainty of countries with significant real economic output, such as emerging markets with large populations and lower price levels, is appropriately reflected in the global index. This makes the PPP-adjusted GEPU Index a more robust tool for understanding how global economic uncertainty shapes the behavior of nations considering strategic default.

5 Empirical results

We ran a Panel VAR model estimating equation (4.1) where all variables are treated as endogenous following the PVAR routine of Abrigo and Love (2016). The variables in question are NPL first differences (dnpls), GDP growth (ggdp), inflation, unemployment and our strategic default proxy.

The stability of the panel VAR requires the moduli of the eigenvalues of the dynamic matrix to lie within the unit circle. Our model is indeed stable since it satisfies the stability condition given all eigenvalues lie inside the unit circle.

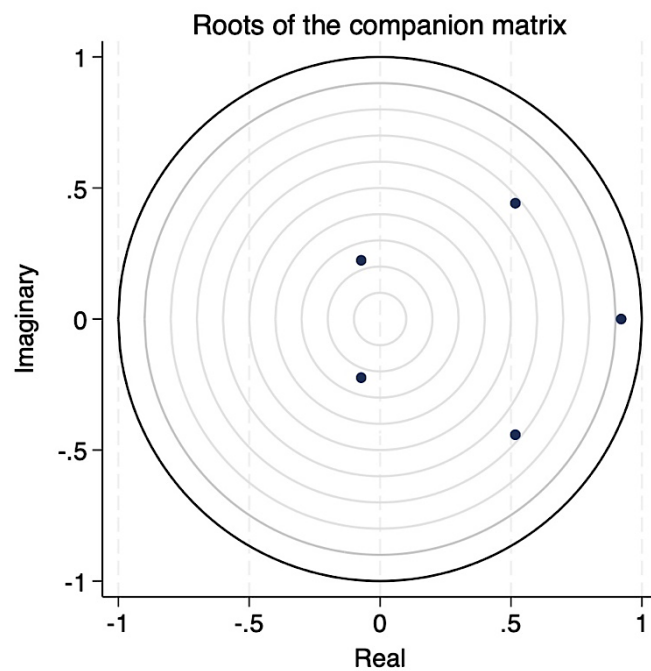


Figure 1 Stability conditions for the panel-VAR model

The appendix for this paper provides detailed estimation results. Our primary focus is to examine the impact of strategic default on the growth of non-performing loans (NPLs). To this end, we have constructed the impulse response functions (IRFs) for this model. While the complete table of IRFs is available in the appendix, we will analyze the IRF of the first difference in non-performing loans (dnpls) in response to a shock in strategic default (SD) in the following discussion.

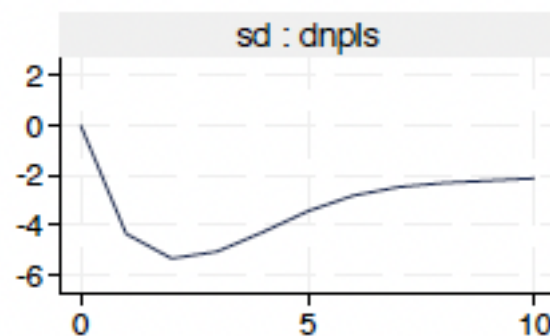


Figure 2 Impulse response function (IRF) of the first difference of non-performing loans (dnpls) to a shock in the strategic default in loans (sd)

The above graph provided shows the impulse response function (IRF) of the first difference of non-performing loans (dnpls) to a shock in the strategic default in loans (sd). What we can see from the graph is having an initial drop, followed by recovery and increase while resulting in a long-term trend. Right after the shock to strategic defaults, there is a noticeable drop in the first difference of non-performing loans. This suggests that initially, the increase in strategic defaults is associated with a reduction in the growth rate of non-performing loans. This could be due to a short-term reaction where defaults lead to fewer new non-performing loans being recorded, possibly because the system or reporting may temporarily be adjusting to the shock.

After the initial drop, the response of non-performing loans (in first differences) starts to increase. This indicates that over time, the shock to strategic defaults begins to contribute to a rising change in non-performing loans, meaning more loans are becoming

non-performing after the initial reaction. The graph shows a steady increase in the response variable, suggesting that the impact of strategic defaults continues to influence the growth in non-performing loans, potentially leading to a worsening in the overall quality of the loan portfolio over time. As far as the whole economy is concerned, the initial drop might reflect an adjustment period where the financial system is coping with the sudden increase in strategic defaults, possibly through tighter credit controls or delays in recognising additional non-performing loans.

As time progresses (medium to long run), the increasing trend in NPL growth indicates that the shock from strategic defaults has a lasting and adverse effect on the loan portfolio's health. The ongoing rise in non-performing loans in subsequent periods suggests that strategic defaults are a significant contributor to the deterioration of loan quality over time.

The results can also have policy implications. Financial institutions might need to implement both immediate and long-term strategies to mitigate the impact of strategic defaults. In the short term, managing the initial shock effectively is crucial to prevent a rapid deterioration in loan quality. Over the longer term, institutions might need to reassess their credit risk models and consider more robust strategies to prevent strategic defaults from leading to sustained increases in non-performing loans.

The IRF graph demonstrates that while there might be an initial adjustment period following a shock in strategic defaults, the longer-term impact is a significant and sustained increase in the rate at which loans become non-performing. This highlights the need for careful monitoring and management of strategic defaults to protect the overall health of the loan portfolio.

6 Conclusion

This paper aimed to bridge a critical gap in the literature by exploring the macroeconomic impact of strategic default on non-performing loans (NPLs). While previous studies have primarily focused on micro-level analyses of strategic defaults using transactional and demographic data, this work expands the scope by introducing a macro-level framework. Through the development of an innovative strategic default proxy using principal component analysis (PCA) and its incorporation into a dynamic panel data model, this paper provides a comprehensive analysis of the dynamic interplay between strategic defaults and NPL growth.

The results highlight a complex, time-sensitive relationship between strategic default and the behaviour of NPLs. In the immediate aftermath of a shock to strategic defaults, the growth rate of NPLs experiences a noticeable decline. This counterintuitive result suggests a short-term adjustment period, during which the financial system may be adapting to the shock. Potential explanations include tightened credit conditions, delays in recognising new NPLs due to operational bottlenecks, or even strategic decisions by financial institutions to manage their portfolios in response to the disruption. This finding underscores the need to understand the transitional dynamics of financial shocks and the temporary buffers that may mask underlying vulnerabilities.

However, this initial period of adjustment is followed by a sustained upward trend in NPL growth. Over the medium to long term, the impact of strategic defaults manifests as a significant and persistent deterioration in the quality of loan portfolios. This trend is indicative of the enduring influence of strategic defaults, which amplify risks within the banking system and contribute to a broader weakening of financial stability. The results align with theoretical expectations, suggesting that strategic default behaviour—driven by factors such as economic uncertainty, banking leverage, and landing rates factors—exerts a lasting and adverse effect on the health of the financial sector.

From a macroeconomic perspective, these findings have several important implications. First, the initial drop in NPL growth following a strategic default shock may lead to a false sense of stability, delaying timely interventions by regulators or policymakers. The subsequent upward trend, however, highlights the necessity of proactive measures to address the root causes of strategic defaults and to mitigate their longer-term impact. Second, the inclusion of behavioural and institutional factors in NPL modelling is critical for accurately capturing the complexity of these dynamics. Indicators such as uncertainty, banking leverage, and unemployment and inflation measures provide valuable insights into the structural and psychological factors that influence borrower behaviour.

This study also offers a robust methodological contribution by developing a strategic default proxy that leverages aggregate economic data and innovative measures such as sentiment indices and banking indicators. By doing so, it paves the way for more sophisticated macroeconomic models that incorporate behavioural dimensions alongside traditional economic variables. This holistic approach is essential for designing effective regulatory frameworks and stress-testing methodologies that can account for the multifaceted nature of financial risk.

Looking ahead, future research could build on these findings in several ways. Cross-country comparisons could reveal how institutional and cultural differences shape the relationship between strategic defaults and NPLs. Additionally, refining the strategic default proxy with more granular or sector-specific data could enhance its predictive power. Investigating the interaction between strategic defaults and broader economic cycles, such as recessions or recoveries, could also provide further insights into how these behaviors evolve in different macroeconomic contexts.

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Appendix

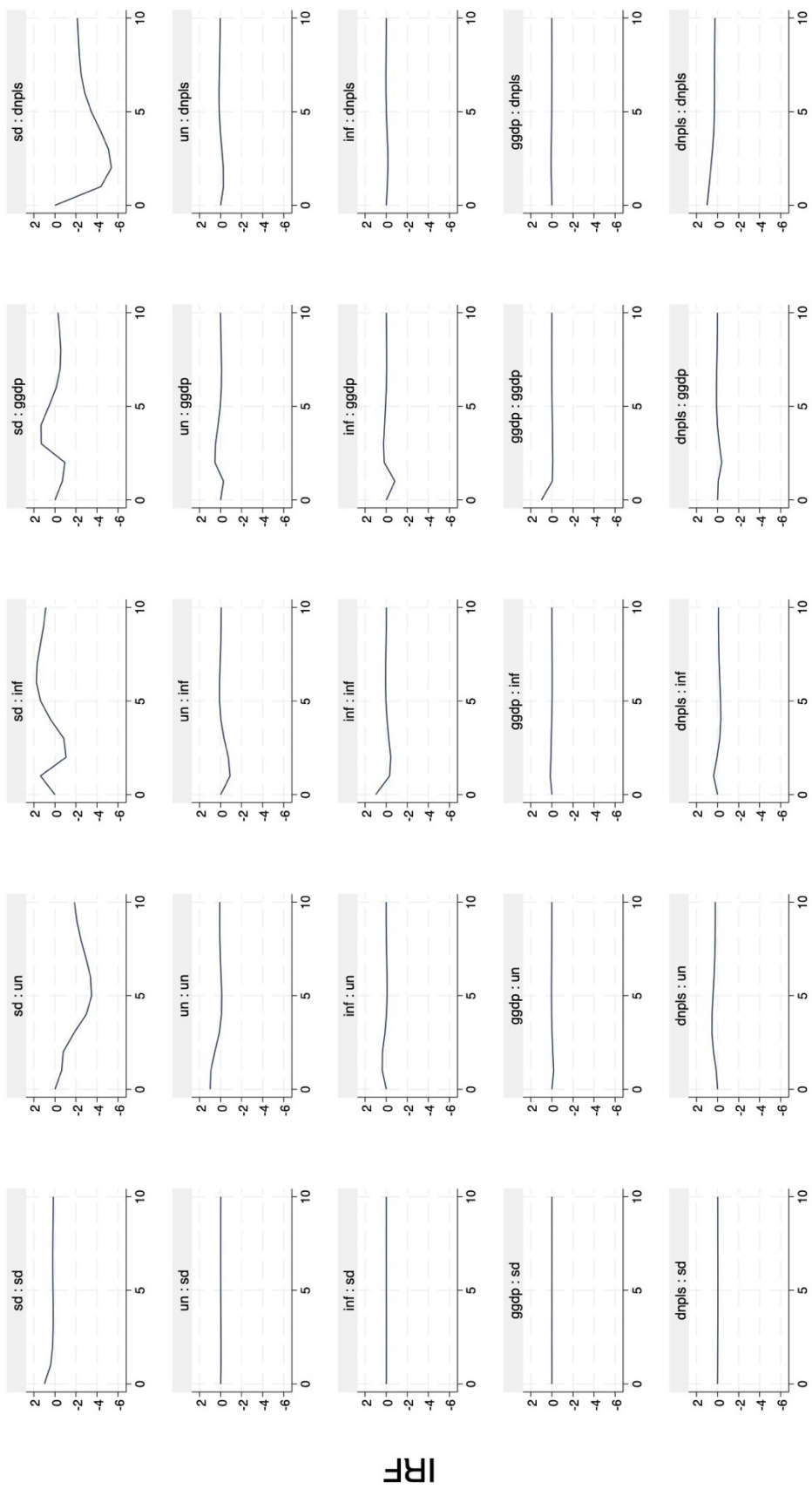
Panel-VAR output:

	(1)	(2)	(3)	(4)	(5)
VARIABLES	dnpls	ggdp	inf	un	str
L.dnpls	0.896*** (0.331)	-0.0575 (0.189)	0.434 (0.290)	0.151*** (0.0551)	0.0788 (0.0557)
L.ggdp	0.0908 (0.230)	-0.0465 (0.0976)	0.137 (0.202)	-0.155*** (0.0442)	0.0407 (0.0404)
L.inf	0.0224 (0.213)	-0.763* (0.403)	-1.515** (0.627)	0.273** (0.118)	-0.333** (0.159)
L.un	-0.186 (0.312)	-0.231 (0.340)	-1.634*** (0.447)	0.872*** (0.0703)	-0.165** (0.0819)
L.str	0.503 (0.594)	-0.107 (0.879)	3.041** (1.278)	0.373* (0.201)	0.866*** (0.301)
Observations	208	208	208	208	208

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 1 Panel VAR output examining the effects of strategic default



IRF

impulse : response

step

Figure 3 IRFs for the strategic default model, for the respective Panel VAR of the previous page