Systematic and Unsystematic Determinants of Sectoral Risk Default Interconnectedness

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Abstract

Assessing the financial stability of the banking industry, particularly in credit risk management, has become extremely crucial in times of uncertainty. Given that, this paper aims to investigate the determinants of the interconnectedness of sectoral credit risk default for developing countries. To that purpose, we employ a dynamic credit risk model that considers a variety of macroeconomic indicators, bank-specific variables, and household characteristics. Moreover, the SURE model is used to analyze empirical data. We find the connection between macroeconomic, bank-specific, and household characteristics, and sectoral default risk. The outcomes of macroeconomic factors demonstrate that few macroeconomic determinants significantly influence the sector's default risk. The empirical results of household components reveal that educated households play a substantial role in decreasing sectoral loan defaults interconnectedness and vice versa. While for bank-specific characteristic, we find that greater bank profitability and specialization have substantially reduced loan defaults.

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1 Introduction

Understanding the financial stability of the banking sector, especially in the management of credit risk, is becoming increasingly important, particularly when the industry faces severe events such as Global Financial Crises (GFC) or COVID 19 types of uncertain circumstances (Misman & Bhatti, 2020; Phan et al., 2021). According to the Bank for International Settlement, when a borrower fails to pay back their loan in accordance with the agreed terms, banks are exposed to credit risk. An increase in the risk of ex-post loans is deemed to be one of the primary challenges of the banking sector (Ahmadyan, 2018). More specifically, the ex-post loan risk appears as Non-Performing Loans (NPLs). In evaluating the banking crisis, the size of the non-performing loans (NPLs) is an essential criterion (Reinhart & Rogoff, 2011, 2009). It is possible to use non-performing loan to indicate the beginning of a banking crisis (Louzis et al., 2012).

The exploration of the factors affecting ex-post credit risk is of great significance for regulatory authorities seeking financial stability and effective banks' lending policies (Abid et al., 2014; Tehulu & Olana, 2014). In addition, a timely and clearer understanding of credit risk drivers may be relevant to policies pertaining to risk management. The significance of effective credit risk management encourages notably academics and regulators to examine the determinants of credit risk. It enables to consider a holistic system for credit risk management and to implement it. It is therefore necessary for banks to analyze the main drivers of credit risk in order to manage their functions effectively.

The objective of this study is to explore the factors that determine the dynamic connectivity of the risk of sectoral default in developing countries i.e. Tunisia. To achieve this goal, we employ a dynamic credit risk model, which considers a set of macroeconomic factors, bank-specific variables and household characteristics.

This paper makes contributes to the literature in the following ways. First, to the best of our knowledge, we are the first to investigate the systematic (macroeconomic) and unsystematic (bank specific and household specific) determinants of credit risk together in a developing country setting (i.e. Tunisia). For empirical data analysis, SURE model is employed. A key advantage of the SURE setting is that it allows for correlated errors between equations. That is, a seemingly unrelated regression (SURE) modelling yields estimators at least asymptotically more efficient than Ordinary least squares (OLS) regression. Secondly, we links two strands of the literature (financial contagion and credit risk) to provide a better understanding of how systematic and idiosyncratic contagion works in the banking sector. Using this, we discuss how contagion spread through the interconnectedness of the sectoral credit default.

Our empirical findings can be summarized as follows. First, the results show that few macroeconomic determinants are of significant concern for sector's default risk and their effects vary little across sector loan type. In addition, our findings show that sectoral credit default risk is more responsive to idiosyncratic component whether through household specific explanatory factors or bank-specific characteristics making them well suited for our understanding of sectoral interconnectedness.

The empirical results indicate that younger, lower and middle-income with less qualified households play a significant role in increasing sectoral loan defaults interconnectedness while for bank-specific characteristics. Third, we find that greater bank profitability and specialization has substantially significant reducing effect on loan defaults.

The paper proceeds as follows: Sect. 2 includes a review of the existing literature, Sect. 3 describes data, key variables measurement, and descriptive statistics. Section 4 presents methodological approach. Section 5 discusses the findings of the study and Sect. 6 concludes the paper.

2 Research Background and Related Studies

Credit risk management practices has drawn the interest of many developed and developing countries, academicians and financiers. The literature argues that the credit risk or non-performing loan of banks are an unintended result of the credit activity of banks. In such circumstances, the assessment of default risk should not be sought solely on the basis of systemic factors that are external to the banking sector. As such, it is important for banks to evaluate whether and how the financial characteristics of banks and household factors, combined, could be a potential risk driver when it comes to the factors that influence credit risk. Mainly two sets of drivers that explain non-performing loans, notably systematic macroeconomic factors and bank-specific or institutional unsystematic indicators are identified in the extant studies. Systematic factors that affect the probability of borrowers paying their debts. These variables include, among others, macroeconomic indicators such as GDP growth, employment, stock market index, inflation rate and exchange rate. On contrary, unsystematic factors focus on specific factors affecting individuals (i.e. the personality of individuals, financial solvency, credit insurance) and companies (i.e. managerial practices, financial status, funds sources and financial reporting, ability to repay the loan and industry-specific factors) (Klein, 2013). The connection between the quality of bank loans and macroeconomic variables is indisputable (Fallanca et al., 2021). While assessing the credit risk, it is necessary to consider macroeconomic factors because fluctuations in macroeconomic indicators such as adverse changes occur in inflation and unemployment rates may contribute to banking crisis (Chaibi & Ftiti, 2015). Although most countries have a banking crisis due to some common causes. However, each country has some specific factors that increase the risk of contributing to the banking crisis. Real GDP growth, inflation, unemployment rate and exchange rate are therefore chosen in this study as macroeconomic factors to determine their strength in influencing the credit risk in Tunisia. As for macroeconomic determinants, the findings of Ghosh (2015) indicate that higher real GDP and real personal income growth rates decrease non-performing loans, whereas non-performing loans are substantially increased by inflation, unemployment and public debt. Washington (2014) argues that non-performing loans in Kenya are adversely affected by unfavorable economic conditions, along with the lack of risk management skills and the high lending rates charged. In addition, prior literature suggests that some specific features of banks are related to problems with loans. Further,

Berger and DeYoung ([1997](#)) emphasis on the interactions between banks' specific characteristics, performance indicators and bad loans. As pointed out by Berger and DeYoung ([1997](#)), possible mechanisms are worth formulating. More precisely, they state that the potential factors that lead to problem loans are 'bad timing', 'bad management', 'skimping', 'moral hazard' and 'capital adequacy'. Most studies dealing with the determinants of credit risk have presumed that macroeconomic or other bank-specific variables are observed as explanatory determinants, taking into account the aggregate level of non-performing loans. Warue ([2013](#)) claims that, relative to macroeconomic factors, bank-specific factors lead to non-performing loans with greater magnitude.

This paper extends and complement the aforementioned studies by considering the data relating to the banks of a developing country. In fact, Tunisia provides a good setting for our empirical testing for at least three reasons. First, a common feature of all past studies is that they focus on cross-country analyses and therefore do not provide insight on the role of country specific factors of credit risk. Second, the choice of the Tunisian context find it roots by the importance of NPLs. Being a small open developing country with quite concentrated bank with respect to the supply of business loans and fragmented financial system, Tunisia would provide new insight on the impact of Npls on sectoral credit default.

Much has been written about the unprecedented surge in non-performing loans. According to a report by Standard & Poor's (2011), the Tunisian banks have 'the appetite for high risk'. Subsequently, Moussa ([2019](#)) among others, found that Tunisian banking sector remains characterized by a high credit risk compared to the Middle East-North Africa (MENA) countries. In a related report by the WordBank ([2014](#)), shows evidence that the ultimate controller of three largest government-owned banks still imposes great influence on external governance mechanisms. Accordingly, the credit risk dimension has been aggravated more by the introducing a system of granting credit without guarantee from the state-owned banks. In this context, bank regulations enacted or enforced to maximize the interests of a particular group. Furthermore, politically connected firms were favored over non-connected peers in granting access to bank financing.

It is worthwhile to note at this point that regulation policies and legislation framework has been taken to avoid financially distressed conditions through the transformation of capital markets, better institutional environments, bank consolidation, loan restructuring procedures and portfolio sanitation of NPLs. Despite the gradual but far-reaching financial reforms in response to the extensive political involvement of former regime's members that seek favorable financial regulatory conditions, the banking system still crucially affected by the credit risk and non-performing loans still remains at high level (Belaid et al., [2017](#)). In particular, the tremendous supply of credit, particularly from public banks, has recently culminated in a very high non-performing loan ratio of 14.6% in December 2018, compared to 13.5% in 2017 and 12% in 2012 (Salem et al., [2020](#)).

Third, the choice of Tunisia add an additional perspective to this literature by focusing on aspects of macro prudential policy following radical changes to the socioeconomic system. In fact, Tunisia as a small open economy at the forefront of the Arab Spring provides an interesting case study to assess the link between

macro prudential regulation and state-business relationships encapsulated in the term cronyism and favoritism. Such principles are particularly important in macro prudential policy and must be further integrated to design a satisfactory stress-testing framework. With the notable exception of Chekir and Diwan (2012), Acemoglu et al. (2018) who studied the extent of business privileges in Egypt, a very little quantitative information still exists on the prevalence and economic significance of state business relationships in the Arab spring Region. Our paper goes beyond to contribute to the macro prudential policy literature. It presents in a well-established dynamic credit risk model, the multifaceted interactions between macroeconomic and financial market development in which cronyism is a widespread phenomenon. Cronyism permeates most of the financial sector environment and provides an additional context to understand to what extent these failures will challenge policy makers to revisit their regulatory framework and to adopt effective macro prudential policy.

3 Data and Variables Measurement

For our analyses we use monthly data over the period 2005–2018. We compile data from the National Institute of Statistics public databases (INS), Tunisian central bank financial statistics bulletin, and various bank annual reports. Since 2005, the Regulatory Committee of Tunisian central bank has required all commercial banks to bimonthly report their operational details and make their financial performance as well as loan subscriber classification information available to the public. The above process allows the collection of the maximum number of reliable observations for non-listed small-and medium-sized banks.

3.1 Measurement of Variables

In the relevant literature, four popular proxies of banks' asset quality are used to measure credit risk. These are a change of expected default frequencies (EDF), loan loss provisions(LLPs), loss given default (LGD), and non-performing loans(NPLs) (see (Beck et al., 2015; Ghosh, 2015, 2017; Kanas & Molyneux, 2018). Due to data availability and the lack of a harmonized definition of credit risk proxies, we construct monthly series of sectoral default frequencies by using the share of non-performing loans (NPLs) in outstanding credit (i.e., Non-Performing Loans/total gross loans).[1] We group the longest feasible NPLs series into the following sectors: Agriculture and Fishing (AGR), Construction (CONSTR), Energy (ENRG), Manufacturing (MANF), Mining (MMP), Tourism (TRSM), Transport (TRANS), Trade(TRD) and Household (HH).

However, aside from our main variable of interest, one is also interested in identifying the factors that determine credit risk. We outline the steps we took to capture

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[1] We consider loans and non-accrual loans that have been left unpaid or delinquent in repaying the interest debt either entirely or partially for at least 90 days or more relatively long period risk driver.

two broad sets of drivers that explain NPLs, namely, the systematic macroeconomic factors and the bank-specific or institutional unsystematic factors.

In our setting, we consider several macroeconomic conditions that have empirical evidence to affect loan quality. To avoid the problem of a certain degree of arbitrariness in choosing variables of interest, we rely on extant literature in influencing NPLs. Among the well-known macroeconomic variables, we choose the real GDP growth, unemployment rate, exchange rate and the change in inflation (CPI) rates as the primary macroeconomic determinants of NPLs following (Cifter et al., 2009; Espinoza & Prasad, 2010; Nkusu, 2011) and (Škarica, 2014). For instance, as for Real GDP growth, a negative relationship is shown with (Jakubík & Reininger, 2013; Ekanayake & Azeez, 2015; Koju et al., 2018) while (Klein, 2013) reported a positive relationship. Alternatively, in an extensive study (Ghosh, 2015) finds that inflation and unemployment significantly increase NPLs. However, in the view of Warue (2013), there is no clear evidence that inflation was related to NPLs.

Interestingly, certain recent articles advocate those non-performing loans are an unintended consequence of banks' credit activities (Lafuente et al., 2019). Thus, assessing default risk should not be sought exclusively among systematic factors, which are exogenous to the banking industry. As such, when it comes to the factors that may have an impact on credit risk, the literature reviews should take into consideration whether and how banks' financial characteristics and household characteristics, taken together, could be possible. To provide additional insights on the above issues and to implement the model dynamically, our empirical strategy involves the measurement of the following banks' financial variables.

Following (Klein, 2013; Ekanayake & Azeez, 2015; Koju et al., 2018), we employ the total loans-to-total assets ratio as a proxy of lending specialization. It is worth stressing that a higher share of loans in the bank's asset portfolio leads to considerable dependence on lending. Therefore, the more banks are involved in lending, the more can monitor such loans better and further prevent banks' assets from becoming defaultable (Ghosh, 2017). Next, we examine whether credit risk originates in the quality of credit. We follow the standard convention of Espinoza and Prasad (2010), Messai and Jouini (2013), Nikolaidou and Vogiazas (2013) and assume that credit quality is measured by provision for loan and lease losses-to-total loans. The key point, though, is that banks with poor credit quality remarkably display the high probability of occurrence of moral hazard in consumer credit by increasing the riskiness of their loan portfolio. As a consequence, risk managers and regulators should expect higher NPLs (Keeton, 1999).

We further examine whether banking diversifying strategy influences credit risk. Much like (Louzis et al., 2012), we use the share of non-interest income-to-total income as proxies for bank diversification. Theoretically, it is unclear whether or not diversification has a positive or negative impact on banking risk, and so far, empirical evidence has remained inconclusive. In particular, proponents of diversification suggest that more diversification in banks can improve loan quality, leading to lower insolvency risks and credit risk Saunders et al. (2014). Therefore, we assume a negative impact of diversified banks on NPLs. A different view posits that diversification might also lead to systemic risks during the crisis, as it entails a contagion effect (Kayed & Hassan, 2011; Wagner, 2010; Slijkerman et al., 2013).

Table 1 Descriptive statistics for Npls ratios (%) per type of sector

Variables	No of observations	Mean	Standard deviation	Maximum	Minimum
NPLs_AGR & FISH	8743	14.135	9.560	20.659	16.897
NPLs_CONSTR	8746	12.642	5.102	18.338	6.474
NPLs_ENRG	8745	30.732	12.057	44.509	22.396
NPLs_MANF	8746	13.014	6.868	20.132	9.115
NPLs_MINIG	8745	13.346	11.918	17.192	15.010
NPLs_TRSM	8745	28.472	20.094	30.134	19.118
NPLs_TRSAN	8745	14.315	13.072	16.508	10.396
NPLs_TRADE	8745	14.278	11.156	16.543	9.816
NPLs_HH	8743	31.047	6.523	43.111	22.047

Agriculture and Fishing (AGR), Construction (CONSTR), Energy (ENRG), Manufacturing (MANF), Mining (MMP), Tourism (TRSM), Transport (TRANS), Trade(TRD) and Household (HH)

We complement the above analysis with bank profitability. In practical terms, we can define bank profitability by return on assets (ROA), i.e., net income divided by total assets. This parametrization finds its roots in the 'bad management' hypothesis of Berger and DeYoung (1997) and Podpiera and Weill (2008); Gulati et al. (2019). When backtesting this assumption, we posit that highly profitable banks have fewer incentives to engage in high-risk activities, therefore, one may expect to reduce their NPLs. Other than that, low cost-efficiency and poor monitoring in banks would cause a rise in NPLs.

Household-related creditworthiness variables are collected from the monthly statistical bulletin of the Tunisian national statistics institute. For analysis, we draw on the extant literature to identify the expected sign between factors dealing with households and NPLs. More precisely, we build on earlier findings of DeVaney et al. (2007) and Crook et al. (2007), establishing a positive relationship between the age of the household head and the creditworthiness. Therefore, we expect that younger people are more disposed to borrow, whereas older people tend to save their income. Furthermore, As argued by Crook (2006), the growth of the size of a household are primarily a result of the arrival of new children. Given this, we expect that an increase in the size of a family lowers household debt capacity. Such a phenomenon can be seen in Tunisia. In fact, the average age of the labor force is very young, and children of households do not become independent as soon as they receive their own revenues. In this sense, we conjecture a positive relationship between the household size and their ability to service loans. As alluded to earlier, we shed light on the plausible causes for a rise in the rate of nonperforming loans(NPLs) with the education level of the household head. In a close line of research, Crook (2006), and DeVaney et al. (2007), find that the rise of the income level of the individual is perpetually dependent on the increase of schooling years. Basically, we expect a negative association between the high education level of a household head and its default. Overall, by establishing the parsimonious properties of all variables, one

Table 2 Descriptive statistics for banks' financial data and macro variables

Variables	Description	Expected sign	Mean	Std dev	Max	Min
Panel A: Bank variables						
Specialization	Total loans-to-total assets ratio	−	− 0.164	7.144	0.659	0.046
Credit quality	Loans loss provision-to-total loans	±	0.002	0.009	0.338	1.766
Diversification	Non-interest income-to-total income	±	− 1.245	0.304	0.509	0.396
Profitability	Return on assets (ROA)	−	− 0.134	4.510	0.132	0.115
Panel B: Macro variables						
Real GDP growth	Month-to-month growth	−	8.7121	2.0219	10.20	6.22
Inflation	Month-to-month growth	+	2.3820	6.23	20.05	− 4.10
unempl. rate	Month-to-month growth	+	10.068	4.072	19.39	3.508
Exchange rate	Month-to-month growth	±	4.55	0.18	5.2	3.99

The table reports statistics that describe the sample. In particular, panel A reports the results for banks' financial data while panel B shows the results for macro variables

Table 3 Descriptive statistics of the sampled households

Variables	Description	Expected sign.	Mean	Standard deviation	Max	Min
Income	Households'total income	±	3.822	2.064	34.0	0.3
Family size	Number of children	±	0.82	5.102	1	0
Age	Age of household heads (years)	±	36.06	4.082	69	30
Education	The education level of the head	±	1.02	0.625	2	1

Educational level is divided into below high school (Non univ), and undergraduate or postgraduate (univ), assigning value 1, 2 respectively; Family size is divided into with or without children and assigned 0 and 1, respectively. In the household survey, credit accessed were asked for households whose head is between 30 and 69 years

should keep in mind their expected relationships with the NPLs throughout the discussion of the results.

3.2 Descriptive Analysis

To develop some basic intuition for the data, we provide summary statistics for each category of the NPL ratios over the entire sample period in Table 1. Interestingly, at first glance, we may note a high degree of heterogeneity among sector's Nonperforming loans. Pointedly, we observe that manufacture and construction have, on average, the lowest NPLs while in energy and households, NPLs, is very high. From a comparative perspective, it is obvious to note that energy and households sectors' credit default has higher volatility. The considerable variation around the averages

default loans motivate us to look again at the factors that may trigger the risk of default.

Tables 2 and 3 summarizes Bank-level data as well as Household characteristics and provides an overview of their expected relations to non-performing loans. Interestingly, households income and age appear higher in terms of the mean and with the later taking the lead. On the other hand, the variability in Age and education is low, indicating little spread from their corresponding means. Regarding the standard deviation, Family size has the highest value, followed by age, while that for education has the lowest. As for Bank specific and macro variables, it seems that GDP and unemployment provides the highest sample mean of 10.06 and 8.71, while Exchange rate has the lowest sample mean of 4.55. Consistent with the sample mean, inflation is the riskiest macro variables as shown by a standard deviation of 6.23. From Panel A of Table 2, observe that, expect the bank quality variables, the mean of Specialization and profitability are close to zero, which shows that the both variable may be co-move. Overall, the most striking feature is that all bank variables have expected sign. Unsurprisingly, given these attractive features in sign, it seems that these variables move closely and synchronously.

4 Methodological Approach

4.1 SURE Models

Consider the estimation of the average default rate for sectoral s with the following logistic functional form:

$$p_{s,t} = \frac{1}{1 + e^{y_{s,t}}} \tag{1}$$

where $p_{s,t}$ refers to the default rate in industry s observed at time t while $y_{s,t}$ is the sector specific index, whose parameters will be estimated, with $s,(s = 1, n)$ indicates the number of sectors. Further, Misina et al. (2006) note that the performance of the SURE estimator can be enhanced by modeling defaults rates with non-linear logistic function, thus for interpretation purposes, we use its logit-transformed value $y_{s,t}$ as the dependent variable, such that for each $s,(s = 1, \dots 9)$, the index $y_{s,t}$ is given by the inverse of the logistic function in the above equation. This is formalized in the following equation:

$$Ln(p_{s,t}) = Ln\left(\frac{1 - p_{s,t}}{p_{s,t}}\right) = y_{s,t} \tag{2}$$

In applied settings, we make use of Seemingly Unrelated Regression (SUR), firstly discussed by Zellner (1962), to estimate the set of industry-specific equations. The SUR method (or JGLS, Joint Generalized Least Squares) represents a generalisation the OLS method which comprises several regression equations and increases efficiency if the equations have different regressors (Wang, 2010; Kubáček, 2013; Sun et al., 2014; Kurata & Matsuura, 2016). Moreover, the key feature of the SUR model is that it allows each equation to have its own explanatory variables (unlike,

for instance, a VAR model) therefore accounting for possible correlation among equation error terms. We refer to Zhao and Xu (2017), Sheng and Sharp (2019), Hou and Zhao (2019), Jiang et al. (2020) and references therein for details on SUR models and their application. We define each sectoral index as follows:

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\begin{aligned}
y_{s,t} =\beta_{s,0} + \sum_{k=1}^{q} \rho_{s,k} y_{s,t-k} + \sum_{r=1}^{n} \beta_{s,r} x_{r,t} \\
+ \sum_{j=1}^{3} \theta_{s,j} f_{s,t} + v_{s,t} + a_b X_t^b + a_h X_t^h + \epsilon_{s,t}
\end{aligned}
\tag{3}
$$

where the dependent variable $y_{s,t}$ is the ratio of NPL to total loans outstanding in sector s, $(s = 1, \dots 9)$ at time t. To enhance the accuracy of our estimates, we assume that the logit transformed default rate $y_{s,t}$ drivers by its past dynamics. This allows us to investigate the persistence and transmission under the role of exogenous shocks.

Correspondingly, we assume a set of systematic risk factors, $(x_i = x_{1,t}, x_{2,t} \dots, x_{s,t})$ and their lags for n independent macroeconomic indicators, capturing the variability of the sectoral default rate on credit risk due to the systematic components with the vector of coefficients $\beta_s = (\beta_{s,1}, \beta_{s,2}, \beta_{s,n})$ to be estimated.

In addition, assuming that sectoral default rate, $y_{s,t}$, becomes more pronounced given households and bank specific characteristic, we therefore proxy a broad set of bank, X_t^b and households, X_t^h controls.

Accounts of the fact that poorly specified regressions that neglect contagion effects in banks credit risk models could ensue in underestimation of the tail probabilities of the credit loss distribution, thus resulting in insufficient capital provisions to buffer actual losses. We follow the methodology used by Pesaran et al. (2004) and include a parameters vector θ that captures lagged contagion effects,[2] In this setting, let also $\epsilon_{s,t}$ be the error term that account for idiosyncratic factors while $v_{s,t}$ corresponds to systematic factors.

5 Empirical Results

At the beginning of our empirical investigation, we start by investigating the impact of the macroeconomic environments on the nonperforming loans. Next, we consider the impact of other relevant bank and households' specific factors. In the last part of this section, we explore the feedback from different sectors-specific defaulted loans. One should note again that this aspect remain largely under-explored in the extant literature.

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[2] We only include first order lag of contagion effects.

Table 4 SUR model results: Macro systematic component

Variables	AGR &FISH	INDUSTRY				SERVICES			HH
		CONSTR	ENRG	MANF	MIN	TRSM	TRANS	TRADE	
Constant	34.119	4.372	8.706	15.66	16.746	17.410	25.472	34.470	14.465
	(1.58)	(0.07)	(1.27)	(1.39)	(0.63)	(0.69)	(0.91)	(1.40)	(0.89)
$NPL(t-1)$	0.520**	0.523**	0.473***	0.519**	0.512***	0.542***	0.539**	0.543***	0.502***
	(3.16)	(4.32)	(8.45)	(3.24)	(8.24)	(7.25)	(3.25)	(6.15)	(5.25)
GDP									
Mov(2)	− 0.039**	− 0.078**	− 0.109***					− 0.182**	
	(− 1.75)	(− 2.31)	(− 1.31)					(− 2.51)	
Mov(3)				− 0.061**		− 0.021**			− 0.031**
				(− 2.60)		(− 1.53)			(− 2.41)
Mov(4)						− 0.104**		− 0.145**	
						(− 2.65)		(− 2.42)	
Log (Inflation)	0.74**	0.31**	3.34**	1.51**	0.81**	2.53***	0.82**	2.13**	2.75***
	(0.63)	(0.42)	(1.42)	(0.81)	(0.73)	(1.72)	(0.70)	(1.42)	(1.86)
U									
Mov(2)	0.009**	0.008**	0.003***					0.140***	
	(0.05)	(0.01)	(0.02)					(0.14)	
Mov(3)				0.161		0.021			
				(0.60)		(0.03)			
Mov(4)					0.144		0.045**		
					(0.20)		(0.12)		
EX									
Mov(2)	− 0.030**	− 0.024**	− 0.018**					− 0.109***	− 1.860*
	(− 0.75)	(− 0.31)	(− 0.10)					(− 0.30)	(− 2.51)
Mov(3)				− 2.061**		− 2.021**			

Table 4 (continued)

Variables	AGR &FISH	INDUSTRY				SERVICES			
		CONSTR	ENRG	MANF	MIN	TRSM	TRANS	TRADE	HH
Mov(4)				(− 1.60)	− 1.164**	(− 1.03)	− 0.452**		
					(− 1.90)		(− 1.82)		

This table reports SURE estimation results of Eq. (1) where non-performing loans to total loans (NPLs) is the dependent variables for sector s at month t. The NPL$(t−1)$ is lagged dependent variables. Detailed definitions for each variable can be found in Sect. 3. Mov(x) means moving average of the variable over the recent x month. t-statistics are between parentheses. Statistical significance indicates ***1%; **5%; *10%

5.1 Macroeconomic Conditioning

Table 4 presents the estimation results for the baseline models with macroeconomic variables. An interesting finding here is that parameter estimates are statistically significant and its sign is as expected.[3] It is also worth noting that the statistical significance of the coefficients on our measure of non performing loans vary extensively by loan sector.

In particular, the conditioning one lags of the dependent variable in the set of regressors that have statistically significant (at the 1% level) coefficients are those for energy, Mining, tourism, trade sectors and households while the others sectors remains significant at the 5% level. Indeed, regardless of the specification and the statistically significant differences, the results suggests that a substantial part of risky loans are being approved to mortgages, business and consumer loans. This evidence is bolstered by the fact that we adopt a sectoral disaggregated approach in our analysis.

Importantly, with respect to the point estimates, our results show that the previous month's NPLs ratio affect the current and to some extent the future ratio of NPLs with a degree of persistence accounted in the range 0.47–0.54% points. Comparing the size of the persistence effect in our study with aforementioned analysis, our results represents an advance over previous research which recorded no such default loans cluster in a relatively short time period. Broadly speaking, this preliminary evidence supports the view that banks with a high share of defaulted loans in their balance sheet tend to have substantial time to reduce such NPLs. Apparently, this behavior can be rationally expected from the adjustment to the long-run equilibrium.[4]

In terms of magnitude effects, most of sectoral NPLs shows high persistence. Pointedly, in all specifications, it can be seen that a coefficients estimations of ρ is between 0 and 1 which in turn implies persistence of credit risk default before they are written off in the long-run.

Our results show that, on the other hand, not all the systematic factors are significant determinant of impaired loans which is in line with the findings of Jakubík and Reininger (2013). Focusing on specific macro-fundamentals driven of default loans, it is notable that GDP growth, have the most noticeable effect confirming the effect of the phase of the cycle on credit defaults (Cifter et al., 2009; Nkusu, 2011; Louzis et al., 2012; Castro, 2013; Jakubík & Reininger, 2013).

Our results also indicate that both inflation and exchange rate are associated with credit risk. These findings are in line with the evidence of Fofack (2005); Castro (2013), pointing to the vulnerability of highly concentrated banks in developing economies to negative welfare effects of export-oriented firms. Furthermore, the positive association between inflation and Npls, although it appears to be slightly higher compared to their counterparts macro-factor, corroborates the findings of Ghosh (2017) but contrast those of Klein (2013), Škarica (2014).

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[3] Note that all SURE models were estimated with a constant.

[4] NPLs are not immediately affected by the Changes in banks' balance sheet or macroeconomic dynamics but after some time lag.

In other words, with this notable characteristics of macroeconomic variables, we contend that implicit government guarantees can cause a distortion of a competitive environments with small banks. Mishkin (1999), Cerasi and Daltung (2000), Farhi and Tirole (2012). To be more precise, an inherent feature of such a conjuncture, is that politically connected banks contribute to the rise in Npls by channeling government-sponsored credit guarantees to entrepreneurs with close relationships to the government which translate later into greater downward spiral in quality of loans and to higher systemic risk (Kroszner, 2010).

The economic significance of our results is also consistent with competition-fragility view reported by Dick (2006) for the USA, Yeyati and Micco (2007) for Latin America, Jiménez et al. (2013) for Spain, Agoraki et al. (2011) for Eastern and Central European countries, Kouki and Al-Nasser (2017), Akande et al. (2018) for SSA, and (Soedarmono & Tarazi, 2016) for countries of Asia and the Pacific.

It is noteworthy that the consideration of unemployment does not, however, have such a marked effect on default loans. As shown in in Table 4, the coefficients estimates although not always statistically significant in all specification, tend to displays somewhat small increase in default risk. Additionally, based on last column of of Table 4, it can be seen that the coefficients of households' NPLs are negative and statistically significant at 10%. This is surprising to the extent that one would expect that a rise in unemployment alter households' ability to service their debts and intuitively, one can infer a positive effect on credit risk. An alternative explanation, however, is that bank loans are mostly extended to high-skilled workers from the middle class with long-term fixed contract. Equally important, this evidence suggests that unemployment does not, however, have such a marked effect households' NPLs.

So far, we have provided evidence of high degree of heterogeneity in behavior of the coefficients. It cannot be ruled out, however, that the share of defaulted loans are related through their exposure to common risk factors, and the co-movements of few factors induce the correlated sectoral defaults.

5.2 Banking-Industry Idiosyncratic Component

In this section, we investigate the determinants of sectoral defaults loans using an upgraded SURE model with banking-industry specific data. The results of the estimation are displayed in Table 5.

Gleaning first at the *quality* of credit variable, it can be argued that a deterioration of the bank credit quality significantly increases NPLs across all specification. Specifically, the coefficient of loan-loss provision, capturing inferior credit quality remains positive with a 1% rise increasing sectoral NPLs by 0.11–0.35 percentage points. This is especially important, given that our data support the "'moral hazard hypothesis[5]'" of Berger and DeYoung (1997) and matching the findings of Ghosh (2015) and Messai and Jouini (2013).

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[5] moral hazard incentives seems to be the explanation of why banks' managers increase the riskiness of their loan portfolio under thinly-capitalization.

Table 5 SUR model results: Bank idiosyncratic component

Variables	AGR&FISH	INDUSTRY				SERVICES			
		CONSTR	ENRG	MANF	MIN	TRSM	TRANS	TRADE	HH
Constant	− 0.783***	− 57.07****	15.70***	13.20***	10.43***	13.25***	12.45***	− 1.071	2.641
	(1.28)	(4.02)	(3.53)	(4.35)	(4.02)	(4.02)	(4.85)	(− 1.10)	(4.43)
NPL($t − 1$)	1.088***	0.635***	0.846***	0.880***	0.841***	0.511***	0.737***	0.742***	0.5745***
	(0.12)	(0.05)	(0.14)	(0.11)	(0.06)	(0.15)	(0.06)	(0.08)	(0.09)
Specialization									
Log (Loans-to-Assets)	− 1.473**	− 2.53***	− 4.522***	− 2.160***	− 4.146***	− 1.584***	− 1.524***	− 2.482***	2.108**
	(− 4.32)	(− 5.41)	(− 6.35)	(− 4.84)	(− 6.11)	(− 4.44)	(− 4.43)	(− 4.92)	(5.77)
Credit quality									
Log (Loan loss provisions to total loans)	0.251***	0.261***	0.242***	0.245***	0.227***	0.358***	0.346***	0.117***	0.257***
	(4.43)	(10.01)	(7.73)	(5.69)	(2.59)	(8.43)	(7.30)	(2.98)	(2.10)
Log (Diversification)	0.017	0.078	0.022	0.174	0.020	0.340	0.004	0.049	0.057
	(0.17)	(1.01)	(0.26)	(0.47)	(0.38)	(1.61)	(0.02)	(1.25)	(0.21)
Profitability									
Log(Return on Assets)	− 1.191***	− 1.252***	− 2.109**	− 1.065***	− 2.282**	− 2.354**	− 1.163***	− 1.241***	− 2.320***
	(− 2.26)	(− 2.29)	(− 5.17)	(− 2.04)	(− 5.25)	(− 5.43)	(− 2.24)	(− 2.27)	(− 5.40)

This table reports SURE estimation results of Eq. (1) where non-performing loans to total loans (NPLs) is the dependent variables for sector s at month t. The $NPL(t − 1)$ is lagged dependent variables. Detailed definitions for each variable can be found in Sect. 3. t-statistics are between parentheses. Statistical significance indicates ***1%; **5%; *10%

As for *diversification*, the coefficients of the non-interest income ratio are neither statistically significant nor has the expected negative sign, suggesting a countertendencies to the degree of risk-taking from banks. In keeping with earlier findings, we find evidence in favor of potential "'dark sides" hypothesis of diversification, see, e.g. (Stiroh, 2004). Pointedly, one may argue that banks undertake loan diversification where regulatory managers many not be perfectly experienced. This is again intuitive and points possibly to the effect of diversification reflected by an increase in bank's default risk. It should be also emphasized that our findings is coherent with the evidence showed (Louzis et al., 2012) for the for Greek and Czech banking industry.

In the same vein, Loans-to-asset may be a complementary proxies illustrating the "'specialization effect" on the corporate sectoral default. As can be seen in Table 5, the coefficients of loans-to-assets is negative and significant at 1% in all corporate sector-level. That is, for the full sample, a rise by 1% in banks assets portfolio, would negatively and significantly reduce NPLs by 2.16–4.52 percentage points in corporate sector while for services sector, it yields a drop of loans default in the range of 1.52–2.48 percentage points. It is also hinted by results reported in column 9 of Table 5 that Loans-to-asset ratio positively affects non-performing households' loans. The positive relationship indicates that lax credit standards' hypothesis of Keeton (1999) is likely to holds but contrast the findings of Espinoza and Prasad (2010), Jakubík and Reininger (2013), Klein (2013) on panel of European countries.

Finally, bank profitability seems to take crucial role as it significantly reduces sectoral impaired loans in regression models. The result indicates that a rise by 1% in ROA reduce the NPLs by 1.06–2.35 percentage points. The relatively high magnitude of persistence of the coefficient underlines the observation that highly profitable banks have fewer incentives to approve more loans to risky borrowers and therefore are exposed to lower default risk. This finding is in accordance with previous studies, such as those of Louzis et al. (2012), Klein (2013), Messai and Jouini (2013), Ghosh (2017).

5.3 Households' Specific Idiosyncratic Component

The results of the empirical analysis so far are supportive of bank-specific variables impact on default risk. To get more insight on the magnitude of the impact in comparative perspective, we further examine how household-related variables affect credit risk. Table 6 presents the results of this regression. As would be expected, household characteristics are contemporaneously positively associated with default risk. The evidence of its positive impact can generally support the implications of the theoretical model. The results, which are presented in Table 6, show that the sign of the coefficient of the variable aging is positive and statistically significant at the 1% level. As can be seen from Table 6, a one percent rise in age of household heads increase the probability of default risk across age groups by the range of 0.02–2.65%.

Table 6 SUR model results: Household idiosyncratic component

Variables		NPLs Household
Constant		2.6683***
		(9.22)
NPL($t - 1$)		0.539***
		(18.44)
Income	1000–1500	0.197***
		(1.116)
	2000–2500	0.407
		(0.120)
	2500	0.376**
		(0.139)
Family size		0.297***
		(0.122)
AGE	30–39	2.659***
		(22.259)
	40–49	1.241***
		(20.192)
	50–59	0.198***
		(18.042)
	60–69	0.025***
		(10.020)
Education level	Univ	0.013**
		(1.054)
	Non-Univ	0.057***
		(1.157)

Note: This table reports SURE estimation results of Eq. (1) where non-performing loans to total loans (NPLs) for Household is the dependent variable for sector s at month t. The NPL(t-1) is lagged dependent variables. Detailed definitions for each variable can be found in Section 3. t-statistics are between parentheses. Statistical significance indicates *** 1%; ** 5%; * 10% while reference age is between 30-69 and reference income: more than 1500 dinars

In fact, results show that older households group tend to have lower default rate than younger households. Accordingly, when investigating the differential impact across credit-accessed households age groups, the estimated results reveal that defaulted loans are highest among households aged 30–39 (at 2.65 percentage points). Table 6 further indicates that on average, default fall to 1.24 % for households aged 40–49; 0.19 % for households aged 50–59 and 0.02 percentage points for households aged 60–69. This finding could be attributed to the fact that, older household heads has less risk appetite in terms of incentive to ask for credit because

they are more settled and their saving rates remain more stable. This argument is supported by the findings of Barslund and Tarp (2008).

As for income variable, the results shows that default risk expands with the income gap between households. As can be seen in Table 6, components of household income ranging from 2000 to 2500 TND[6] and more than 2500 TND has limited and statistically insignificant impacts on impaired loans. In contrast, the extent of impact tends to increase with less than 1500 TND. Therefore, one can interpret the estimation result as evidence of more household heterogeneity with income groups. These impacts are partly explained by the fact that High-income households are more attainable to repay on schedule than middle-income households, who in similar fashion are able to repay than low income households. This Findings corroborate with the outcomes suggested by Rubaszek and Serwa (2011) which indicate that widen income gap between lowest income and highest income households will eventually lead to strong uncertainty in the repayment behavior of the latter.

As for the education level of household Head. We find as expected a positive association between the level of qualifications and credit risk default. As the results in the Table 6 show, the coefficient of Non-university educated households variable is significantly positive at the 1% level, suggesting that borrower's default loans are more likely to increase with lower levels of education.

Lastly, we turn to evaluating risk defaults with the number of children in the family. As we can see from Table 6, family size increase the incidence of default. Pointedly, the cause to this unusual phenomenon can be attributed to the fact that children raise the demand for loans and consequently leading to an overall rise in non-performing loans. In the short, our findings confirm that the lower distribution of income groups, younger households and lower education level makes the largest contributions in explaining the effects of household characteristics on default loans risk. To pin down the causal effects, we investigate in next section the contagion channel.

5.4 Contagious Defaulting Behavior

In order to obtain a more complete view of sectoral defaults interconnectedness, it is certainly desirable to consider the idiosyncratic component of contagious effects. From an economic point of view, this gives a voice to the data to capture the essentials of credit risk interconnectedness.

Table 7 shows that in all columns (1)–(9), the coefficient of contagious is positive and statistically significant either at 1% or 5% level. In terms of magnitude of the coefficients, the estimation results show that at corporate level, the effect of contagion is strongest in energy sector, yet it also seems that contagion was considerably stronger for tourism service sector level. From Table 7, we glean that a percentage point increase in lagged sectoral default in mining sector leads to relatively higher interconnectedness in energy and tourism sector. However for the remaining

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[6] The Tunisian dinar is commonly abbreviated TND.

Table 7 SURE Contagion estimations

Variables	AGR & FISH	INDUSTRY				SERVICES			
		CONSTR	ENRG	MANF	MIN	TRSM	TRANS	TRADE	HH
NPLs_AGR & FISH($t-1$)				0.071**					
				(1.85)					
NPLs_CONSTR($t-1$)	0.228***				0.037***				
	(1.20)				(1.03)				
NPLs_ENRG($t-1$)						0.007***	0.016***		0.385**
						(2.29)	(0.15)		(2.43)
NPLs_MANF($t-1$)									0.352***
									(1.90)
NPLs_MINIG($t-1$)		0.182	0.530***			0.445**			0.370***
		(0.59)	(2.53)			(2.31)			(2.16)
NPLs_TRSM($t-1$)				0.187***			0.041***	0.070***	0.552***
				(2.42)			(0.23)	(0.95)	(3.11)
NPLs_TRSAN($t-1$)	0.060***								
	(0.03)								
NPLs_TRADE($t-1$)	0.250**								
	(0.16)								
NPLs_HH($t-1$)		0.240***	0.271***			0.194***			
		(0.90)	(4.92)			(3.27)			

This table reports SURE estimation results of Eq. (1) where non-performing loans to total loans (*NPL*) is the dependent variables for sector *s* at month *t*. The NPL($t-1$) is lagged dependent variables. Detailed definitions for each variable can be found in Sect. 3. t-statistics are between parentheses. Statistical significance indicates ***1%; **5%; *10%
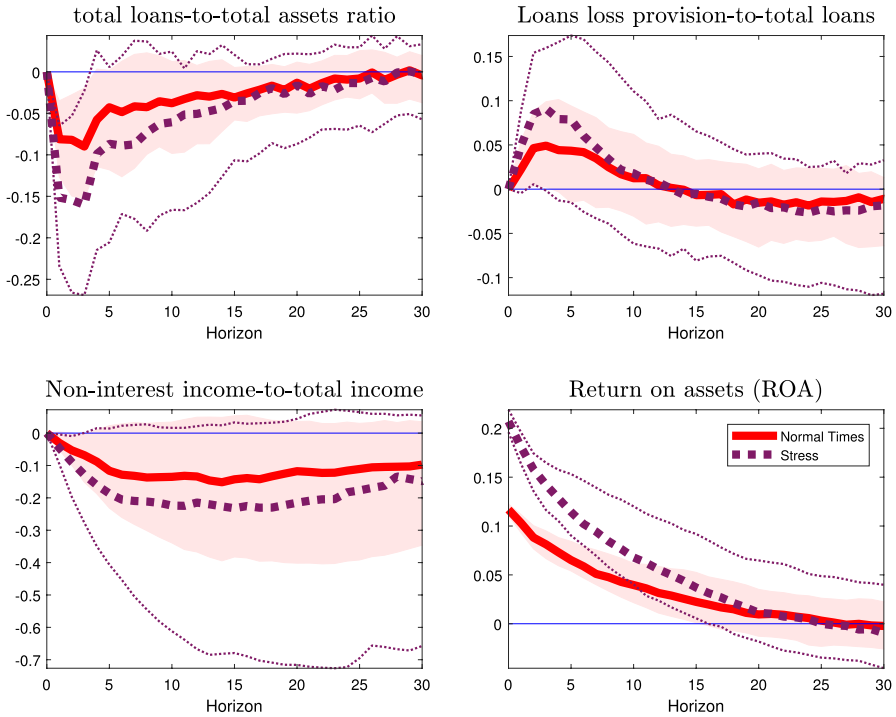
Fig. 1 Stress scenarios based on simulated 1% distribution tail of banks characteristics variables

corporate sector, evidence of contagion effects is not apparent. We can see from column 7 and 8 of Table 7 that transport and trade sector are perceived as less interconnected in terms of credit risk. Eventually, we can observe in column (9) that household idiosyncratic component also exhibits the highest level of extremal dependence with Tourism and energy sector. This further suggests that sectoral default is not due only to the common dependence to macroeconomic and financial variables but stemming from households characteristic.

In general terms, the evidence presented so far points to a pattern of contagion at the sectoral level occurring over the sample period. Furthermore, it is likely that there exists the so-called sectoral risk-taking sharing, which is further amplified by the default intensities of corporations. A similar outcome has been described by Hussain Shahzad et al. (2019), showing that short-run spillover among credit market sectors intensifies during global and Eurozone crisis periods.

5.5 Monte Carlo Design and Experiment

Taking in account the framework outlined in the previous section, we propose a stress test exercises of credit risk based on scenario analysis. We will first outline the criteria used in designing relevant stress scenarios and then provides a brief comparison between a baseline and distressed scenarios.
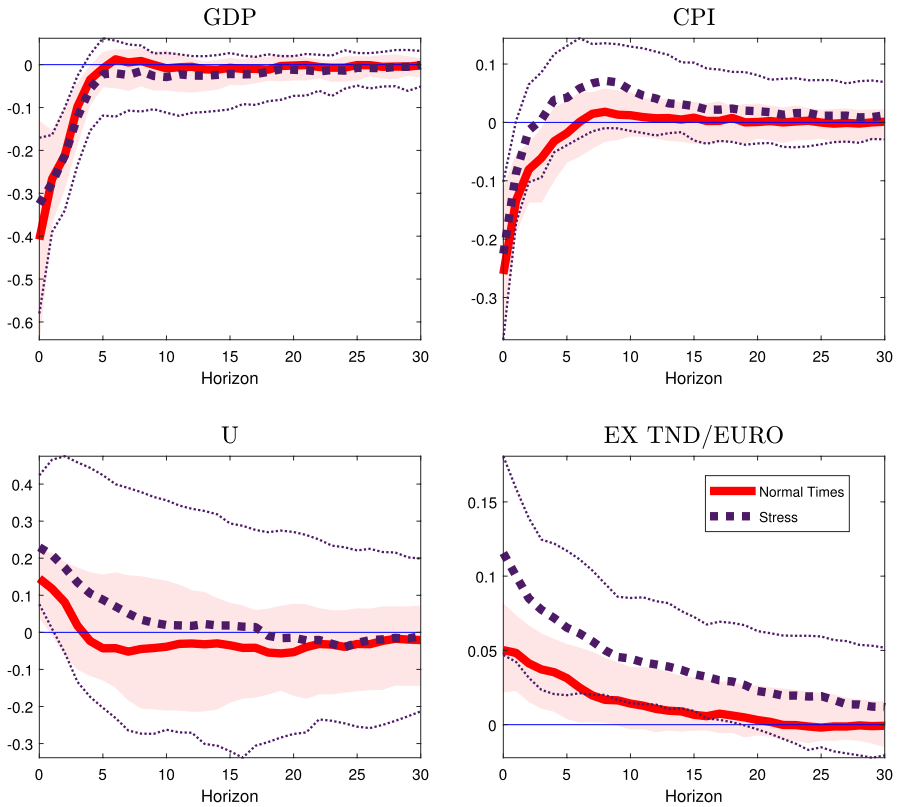
Fig. 2 Stress scenarios based on simulated 1% distribution tail of Macro variables

As an adverse stress scenario, we consider several hypothetical shocks. Following (Ven et al., 2018), the harmful situation is based on the tail value of the unconditional probability distribution of a systematic macro component, two hypothetical shocks on the macroeconomic variables are introduced. For real GDP growth, a shock of 7% in each of the four consecutive quarters starting from 2018 Q4 to 2019 Q3 and after one year, the real GDP growth returns to its trend and grows on average by 0.5% the subsequent quarters. However, for exchange rate, we introduce a nominal shock to the TND/EURO exchange rate by 15% in the first quarter starting from 2018 Q4, 20% the second quarter of the forecast horizon and for the rest of the periods, the exchange rate depreciates on average by 4.6%, as in the baseline case.

The above analysis is repeated for the construction of scenarios stress tests related to idiosyncratic components. We consider the 1% "harmful" tail of the unconditional distribution of each bank variable. Pointedly, these structural shocks are sufficiently large to be considered abnormal.

The results are pictorially represented in Figs. 1 and 2. Several observations can be made. First, from the pictorial representations of sectoral default, it does
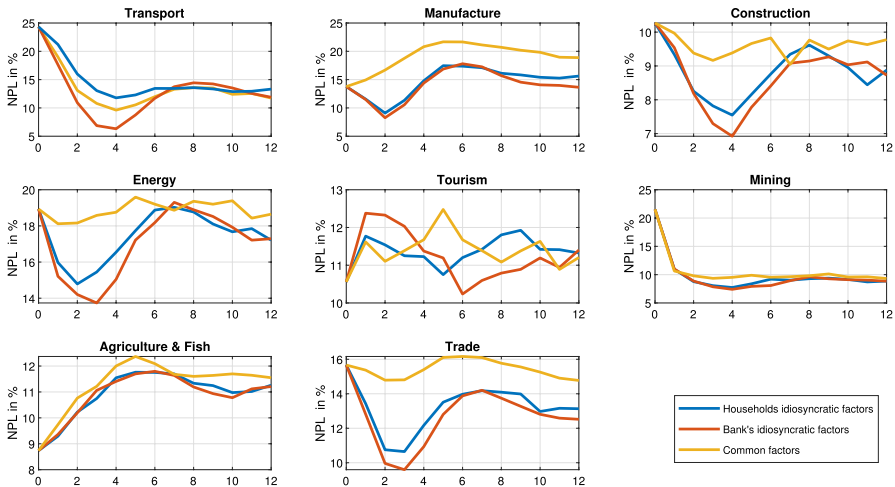
Fig. 3 Simulating the sectoral default-related components

appear that stress tests work as intended on connectedness. Second, the pattern of NPLs under distressed macroeconomic scenarios appear economically sensible as it contrasts sharply with macro-dynamics.

As illustrated in Fig. 2, compared to baseline (normal) scenario, credit default risk under distressed scenarios do not track as closely with macro dynamics as it does with bank characteristic variables portrayed in Fig. 1. Therefore, at most, one can only claim that there is probably some evidence of sectoral interconnectedness due to the idiosyncratic component. Overall, the empirical outcomes of our analysis strengthen the evidence in Salem et al. (2020) showing that a significant and negative relationship between economic growth and Non-Performing Loans (NPL) ratio, which is very robust during the political crisis of 2011.

To provide more comprehensive portrait on what may lie behind the clear-cut trend over the stress period, it is worth looking at each of the components behind the sectoral evolution of default. Figure 3 plots the contribution of each element in the evolution of the sector's default rate. The yellow lines in the graph represent the contribution of common macro factors while the red and blue lines are bank-specific factors and household-specific factors. Strikingly, our graph again points toward a fundamental dependence of default risk to idiosyncratic component. As shown in Fig. 3, NPLs ratios changes widely across sectors under the idiosyncratic component while almost shock to common factors similarly drives the NPLs ratios in all the sectors. Considering the behavioural pattern of common factors, we notice some obvious rise to extraordinary levels in the first four quarters, and after ten quarters, their negative impact dissipates. Interestingly, the connectedness of default risk is easily affected by the changes in the household's conditions, showing obvious time-varying characteristics. As we

see clearly, in all subgraphs, household idiosyncratic component is a short-run information transmitter.

Further analysis through graphical illustration reveals that an increase of the household's factor by one standard deviation increases NPLs approximately to the regions of 20–30% for household, 10.1–20.3% for mining and manufacture, 15–19.1% for energy and 10.7–12.3% for tourism respectively. Taken together, these impulse response (IRFs) suggest that sectoral defaulted loans are not due to commonality but rather linked to the idiosyncratic component of banks and household's fundamentals. This can be considered a further indication that sectoral interconnectedness has occurred.

In short, looking at the results pertaining to the full sample period, it is worth interpreting our results by keeping in mind the idea that during periods of financial markets crises, credit risk interconnectedness between sectors are higher and this is often a key element in the underestimation of sector's default risk in stress periods.

6 Conclusion

The aim of this paper was to investigate the factors that determine the dynamic connectedness of sectoral default risk in the case of merging countries. To reach this end, we use a dynamic credit risk model that takes into account a set of macroeconomic factors, bank-specific variables and households characteristic.

We find the interconnectedness between macroeconomic, bank-specific and household factors and sectoral default risk. The results demonstrate that few macroeconomic determinants do significantly influence the sector's default risk. More specifically, we confirm the effect of macroeconomic variables, particularly the real GDP growth rate on almost all sectoral NPLs while for exchange rate and inflation, we find a strong effect on household, energy, tourism and trade, but to a lesser extent on transport and construction sectoral defaulted loans. Moreover, little dependency is found between the unemployment rate and the sector's non-performing loans.

By exploring bank-specific variables, the results provide evidence for the significant positive effect of credit quality on sectoral default, where poor credit quality appeared to have higher impacts in the energy and mining sectors. Moreover, we find that greater bank profitability and specialization lowers sectoral credit default risk. Turning towards the effect of the household variables on sectoral default probability, we find statically and economically significant explanatory power. Considering the level of education, the results suggest that university-educated households ensure little defaulting behavior, but poorly educated households both are more likely to experience default.

From the above findings, policy recommendations can be drawn for improving early-warning measures of systemic vulnerabilities. First, countries such as Tunisia have very low credit information sharing coverage, hence banking supervisory authorities and/or financial markets regulators must enact laws that will expand the coverage and scope of information towards household's creditworthiness. This way, policymakers could identify the loan type that is likely to generate the

non-performing loan. This is notably important as rapid demographic changes have a sizeable impact on the the individual income. These implications suggested that more effort should be placed on macroprudential policy. Given that this paper's approach explicitly links systematic (macroeconomic) and unsystematic (bank-specific) factors to extract the driving forces of NPLs, it lends itself to the ongoing discussion about the effectiveness of bank supervision. As such, policymakers will have to put their efforts into developing a framework that increases the severity of stress testing scenarios or activating pre-existing macro-prudential tools to cope with sectoral interconnectedness.

Finally, attention needs to be paid to governance mechanisms. The policymakers must improve their quality of governance by monitoring state-owned banks' risk appetite, and the level of competition is a crucial consideration for the country. That being said, an open banking environment encourages competition. It is therefore essential for the governments and policymakers in Tunisia to decrease the governance risk and increase competition to improve banks 'financial stability and reduce their risk of default.

Declarations

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