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Nonlinearities between bank stability and income diversification: A dynamic network data envelopment analysis approach

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ABSTRACT

This study contributes to the ongoing debate about the cost-benefit tradeoff of income diversification in banking. Its main objective is to shed light on the non-linear effects of income diversification on the financial stability of a set of European commercial banks during the post-financial crisis period (2010–2019). From an efficiency perspective, we use a three-stage dynamic network slacks-based measure model to assess the financial stability of banks, including non-performing loans as a measure of risk that is carried over between two periods. Then, by performing a panel smooth transition regression model, we investigate the regime-switching behavior of the relationship between income diversification and bank stability by showing how these variables heterogeneously interact with each other. Our findings show that high levels of income diversification negatively and significantly impact bank financial stability regardless of the diversification index used. Important policy implications arise from our findings pertaining to the optimality of income diversification and financial stability of European banks.

1. Introduction

The banking sector plays a crucial role in the sustainable and healthy development of nations. This role is achieved through the efficient allocation of savings and the smooth flow of money and credit to the most beneficial uses of socio-economic activities. Compared to the U.S., where financial markets play a predominant role in financing firms, the European banking sector is still the most important financing channel for the European economy (Lahouel et al., 2022a). The European banking sector has been severely affected by the global financial crises from 2007 to 2010. In addition, many European banks have not been spared by the European economic and financial crisis in Greece, Ireland, Italy, Portugal, and Spain (GIIPS). Since then, economic policymakers in Europe have been preoccupied with how the capitalist system works, how to make the risks of the system more transparent, and specially how to create a more financially stable banking system (Asteriou et al., 2021).

On another note, over the past three decades, the banking industry has experienced changing market conditions, with a trend toward financial liberalization and globalization of banking institutions, which has resulted in a reshaping of the scope of banking from traditional deposit-taking and lending to a range of new business lines (Maudos, 2017; Meslier et al., 2014). Banks have diversified their sources of revenue towards fee and commission-based activities (e.g., insurance, investments, trading securities, brokerage, etc.), which generate non-interest income. As a result of these changes, a large literature on the impact of income diversification on bank financial stability has emerged in developed and developing countries (e.g., Abuzayed et al., 2018; Asteriou et al., 2021; Nguyen et al., 2012; Shaddady and Moore, 2019; Ullah et al., 2021). However, the questions whether income diversification leads to economies or diseconomies for banks remains outstanding (Lahouel et al., 2022a; Saghi-Zedek, 2016). This paper rigorously studies the effects of income diversification on bank stability in a sample of 114 publicly traded European banks over the period 2010–2019. Differently from previous empirical studies, our study adopts an efficiency perspective, based on the dynamic network slacks-based measure model (DNSBM) of Tone and Tsutsui (2014), to measure an indicator of bank stability. Moreover, our study combines the DNSBM with the more robust and flexible panel smooth transition regression (PSTR) model to test the nonlinear impacts of income diversification on bank stability.

For example, some studies demonstrate, consistent with the conventional portfolio theory, that diversification can be effective and desirable because it reduces idiosyncratic risk, improves the risk-return

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profile by broadening the range of investment opportunities, and reduces the expected cost of financial distress when banking operations are spread across different products and industries (Francis et al, 2018). However other studies reported that income diversification is significantly associated with greater income volatility because, in some circumstances, diversification can induce potential agency problems, disperse management resources, and impede rapid responses and organizational flexibility in mitigating risk (Hou et al, 2018; Nguyen et al, 2012). These mixed and inconclusive results can be attributed to two main reasons: i) the way in which financial stability has been measured and, ii) the estimation methods used to date to test the relationship between income diversification and bank financial stability.

First, financial stability is a broad concept that encompasses the different dimensions of the financial system, which covers a range of actors: the financial infrastructures, financial institutions, and financial markets. A myriad of definitions has been attributed to financial stability by government officials, central banks and academics. Nevertheless, there seems to be a broad consensus that financial stability refers to the proper functioning of the institutions and markets that make up the financial system (Crockett, 1997). Houben et al. (2004) define financial stability as the ability of a financial system to allocate resources efficiently, assess and manage financial risks, and absorb shocks. Financial stability can be defined as the absence of financial instability, which refers to certain ideas of market failure or externalities that can potentially affect real economic activity (Ferguson, 2002). Crockett (1997) distinguishes between financial instability in both financial institutions and financial markets. The instability of financial institutions refers to the presence of stresses that prevent financial institutions from meeting their contractual obligations, while the instability in financial markets refers to a situation in which volatile movements in financial assets prices can potentially impinge on real economic activity. This paper focuses on the study of the financial stability of financial institutions, particularly banks. Bank stability has received attention because of the increased leverage inherent in large financial institutions, the shortage of capital and the likelihood of default (Ullah et al., 2021). Bank stability is related to the ability of banks to withstand adverse events, such as crises in the banking system, major policy changes, liberalization of the financial sector and natural disasters (Asteriou et al., 2021). In the literature, the issue of bank stability has been defined within the ambit of bank vulnerability (Houben et al., 2004), bank distress (Wanke et al., 2015), bank failure (Glocker, 2021), bank insolvency (Lepetit and Strobel, 2015), etc. Since financial stability does not have such an easy or universally accepted definition, empirical studies have mainly quantified bank financial stability in terms of risk and profitability (e.g., Abuzayed et al., 2018; Fang et al., 2014; Izzeldin et al., 2021; Maudos, 2017; among others). In the literature, the most popular measure of a financial institution soundness and a banking system financial stability is the Z-score (see Boyd and Runkle, 1993 and Lepetit and Strobel, 2015), a variable that explicitly weigh buffers (capitalization and returns) with the risk potential (volatility of returns). Its popularity stems from its relative simplicity as it only uses accounting information for its calculation. The Z-score is inversely related the probability of a bank's insolvency, which reflects the probability that the value of its assets becomes lower than the value of the debt (Čihák and Hessse, 2010). A higher Z-score corresponds to a lower probability of insolvency risk and a greater financial stability. However, several researchers argue that the Z-score does not necessarily reflect the potential financial stability of a bank (see Čihák et al., 2012; Fang et al., 2011, 2014; Tabak et al., 2012; Tan and Anchor, 2017, among others). For example, the Z-score looks at each bank separately, which may overlook the risk that the failure of one bank could lead to losses for other banks in the system (Čihák et al., 2012). As an absolute measure of financial stability, the Z-score provides little information about the relative financial stability (e.g., the proximity of the different banks to the most financially stable ones). Tabak et al. (2012) argue that the deviation from the bank's current stability and its maximum stability must be considered. In the banking literature, the concept of efficient frontier (i.e., stochastic frontier analysis – SFA and data envelopment analysis – DEA) has been widely used to assess the performance of banks against "best practices" in terms of cost minimization or profit maximization (Henriques et al., 2020). Fang et al. (2014) argue that bank financial stability is a risk-adjusted performance measure that can be estimated using the concept of efficient frontiers. Therefore, in this paper, we employ an advanced DEA model to provide a relative measure of stability. We illustrate, following several studies (e.g., Lahouel et al., 2022a; Fukuyama and Weber, 2015, 2017; Yu et al., 2019) how a dynamic network DEA model can be used to assess a bank financial stability. According to the discussion above, a higher level of efficiency score corresponds to greater financial stability and vice versa.

Second, previous studies have almost exclusively focused on average-based estimators that restrict the shape of the relationship and impose a linear form between exogenous and dependent variables. The main problem is that linear estimation techniques describing the mean effects of exogenous variables on the dependent variable do not account for the heterogeneity of the regression coefficients across the distribution of the dependent variable. Moreover, a number of authors have recognized that the improvement (or degradation) in bank stability, resulting from greater diversification, may be heterogenous across banks and may depend on their ability to capitalize on their diversification strategies (see, Berger et al., 2010; Lahouel et al., 2022a; Maudos, 2017, among others) For instance, Berger et al (2010) argue that the relationship between income diversification and bank stability is non-monotonic. In the same vein, DeYoung and Torna (2013) suggest that bank diversification is rather complex and could be positive and negative, while Lahouel et al. (2020a) and Abuzayed et al. (2018) find a nonlinear relationship between noninterest income and bank financial stability.

One way of recovering from the shortcomings of conventional linear models, which assume that diversification has an invariable and monotonic impact on stability, could be the use of a novel econometric approach capable of providing a comprehensive pattern and an accurate picture of the overall interdependence between income diversification and bank stability. More specifically, in this paper, we employ the nonlinear panel smooth transition regression (PSTR) model, as developed by González et al (2017), and our aim is to re-examine the relationship between income diversification and bank stability. In this regard, the PSTR framework would reveal the complexities of this relationship and would help to avoid any prior shape restriction between the variables, that would be difficult to detect with traditional econometric methods.

This study enriches the existing literature in several ways. First, one of the primary benefits of the PSTR is its flexibility and reliability in capturing both unobserved and time-invariant bank effects in modeling panel data, compared to previous conventional approaches (Lahouel et al, 2020, 2022b; Chiu and Lee 2019). The PSTR framework, unlike linear regression models that implicitly assume nonlinearity between variables, allows for testing of this nonlinearity as well as accounting for regime-switching behavior describing states of banking stability that may be affected by different levels of income diversification.

Second, our study differs from existing studies in the following ways: Whilst most studies consider the Z-score as a *de facto* measure of bank stability or the opposite of distress, this paper follows a new strand in the literature by adopting an efficiency perspective (Avkiran, 2017; Liu et al., 2020; Wanke et al., 2016). We use DEA to calculate a score of bank efficiency by applying the dynamic network slacks-based measure (DNSBM) model. We argue that the relative efficiency scores of banks could be a strong reflection of management's ability to effectively mobilize bank resources to increase revenues and decrease risks, leading to increased financial stability. Since DEA provides efficiency scores, it is useful and necessary to establish the relationship between financial stability on the one hand and the variables leading to this stability such as risk and revenue on the other. In other words, because our DEA model uses inputs and outputs that characterize a bank's risk-profitability trade-off or distress (i.e., non-performing loans for bank risk and net operating income for bank revenue), the relative efficiency scores generated should reflect financial stability. Therefore, we follow Avkiran and Cai (2014) and Wanke et al. (2015) and consider that our DEA model should indicate a bank's effectiveness in minimizing variables related to increasing financial distress (i.e., non-performing loans) and maximizing variables related to increasing financial health (i.e., net operating income). Although there is no universal agreement on the set of variables that increase financial distress or financial health, existing empirical studies assessing bank efficiency show the importance of using non-performing loans as a measure of bank risk that should be incorporated into the analysis of bank efficiency using the DEA approach with undesirable outputs (Fukuyama and Tan 2020). Several studies (see Fukuyama and Matousek, 2017) have called for the inclusion of non-performing loans, as a measure of risk, when estimating bank efficiency, as the omission of non-performing loans from DEA models can provide biased results in bank efficiency analysis. Non-performing loans are considered as undesirable by-products of the lending process because of the asymmetry of information between the borrower and the lender and the uncertainty regarding the soundness of the future conditions of economy (Fukuyama and Weber, 2017). Therefore, we assume that a high level of non-performing loans may induce a high probability of many credit defaults which will affect the financial stability of banks as they will have to accord more resources to reduce non-performing loans. When non-performing loans levels begin to rise, certain steps must be taken to manage them to be kept within tolerance. A bank becomes more concerned and cautious about its lending policy, which may result in a reduction in the amount of lending in the following period (Yu et al., 2019). To provide a more complete representation of a bank's production process, this study develops a three-stage dynamic network model that accounts for non-performing loans, thus allowing for intertemporal resource reallocation, and desirable output of net operating income. Therefore, by gathering the network and dynamic dimensions of the DEA, we provide a more thorough framework of bank stability where interactions between divisions and time periods are considered in efficiency estimates. Accordingly, in assessing bank financial stability (i.e., the risk-return profile of a bank) with the three-stages DNSBM, our approach considers the joint effects of risk and income generation in the efficiency calculation of banks.

The remainder of this paper is organized as follows. The next session presents the research design. Section 3 presents the data and defines the variables of the study. Section 4 provides and discuss the empirical results. Section 5 conclude.

2. Research design

2.1. Measure of bank stability with DEA

DEA is a service management and benchmarking technique originally developed by Charnes et al (1978) to assess efficiency for a set of homogenous decision-making units (DMUs). The DEA has become the most widely used method of assessing efficiency in the banking industry (Paradi and Zhu, 2013; Yu et al, 2019). Given the complexity of production processes within the banking sector, the network DEA, one of the extensions of basic DEA models, has received increasing interest in the pertinent literature (Fukuyama and Matousek, 2017). In the network DEA, a bank's internal structure is segmented into related sub-processes while considering the efficiency of each sub-process as well as the overall efficiency within a single framework. Tone and Tsutsui (2009) designed the slacks-based network approach, where potential slacks of exogenous inputs and final outputs are accounted for in the objective function representing efficiency, and hence non-proportional changes are possible.

Subsequently, Tone and Tsutsui (2014) developed the dynamic network slacks-based measure model (DNSBM) as the combination of network and dynamic DEA models. With its dynamic characteristic, the DNSBM model is presented as an extension of the NSBM model by computing absolute efficiency and changes in sub-processes (divisions) and overall efficiency over multiple time periods. The two-stage DNSBM has received growing interest across bank efficiency studies (see, Avkiran, 2015; Wanke et al 2015, 2016, 2020; Yu et al, 2019, among otehrs). In recent studies, researchers presented the banking production system in three-stage DEA models. For example, Chao et al (2015) divide the production process into capability, efficiency, and profitability sub-processes. They consider non-performing loans and loan loss reserves as carry-overs that capture the dynamics of the transformation process. Mahmoudabadi and Emrouznejad (2019) applied a three-stage DNSBM model to evaluate the efficiency of bank branches in three dimensions: production, intermediation and social welfare. Dia et al (2020) pointed to the fact, that the overall production process of a commercial bank can be divided into three stages: production intermediation, and revenue generation. Based on the methodology presented by Fukuyama and Weber (2010), a three-stage model was developed by Fukuyama and Tan (2020) to analyze input efficiency, stability efficiency and output efficiency of Chinese banks for the period 2007–2017.

Following Fukuyama and Weber (2010, 2012), we consider deposits as an intermediate output generated from the first stage (i.e., the deposit producing stage) using exogenous inputs such labor, physical capital, and equity capital, and an undesirable input generated in a previous period. Then, deposits are used as a free link connecting the first and the second stage (i.e., the intermediation stage) in order to produce two desirable outputs and one undesirable output. The desirable outputs of the second stage are loans and securities, while the non-performing loans are treated as undesirable outputs. Indeed, from the issuance of bank loans, results an undesired jointly by-product – the non-performing loans. Since managers have imperfect and incomplete information about the risk of potential loan applicants, some loans become non-performing (Fukuyama and Weber, 2017). Loans and securities are considered as the free links between the second and the third stage. Regarding the treatment of non-performing loans in dynamic network DEA systems, Chao et al. (2015) explain that some non-performing loans will be written off as bad loans, while the rest will be carried forward to the next period. In this paper, we focus on the co-generation of loans and their non-performing counterparty, while recognizing that banks may have some flexibility in the amortization schedule of non-performing loans for accounting purposes. Recent empirical studies (e.g., Akther et al., 2013; Fukuyama and Matousek, 2017; Fukuyama and Weber, 2015; Lahouel et al. 2022a; Mamatzakis et al., 2016) report the negative and constraining effects of non-performing loans on banks' future production possibilities. For example, Fukuyama and Weber (2017) argue that banks are required to either raise more capital to compensate for non-performing loans or decrease deposits while reducing the loan and investments portfolio to meet regulatory capital requirements. According to Tone and Tsutsui (2014), efficiency measurement of financial institutions based on dynamic network structures should control for bank risk by considering non-performing loans as an undesirable carry-over variable. In addition, undesirable carry-over, including non-performing loans, "*are treated as inputs and their values are restricted to be no greater than the observed ones. Comparative excess in carry-overs in this category is accounted as inefficiency*" (Tone and Tsutsui, 2014; p. 127). Therefore, we follow the recent literature (e.g., Fukuyama and Weber, 2015, 2017; Lahouel et al., 2022a) in considering non-performing loans, that serve as an undesirable link, as an undesirable output generated in stage 2 (i.e., intermediation stage) during period $t-1$ and as an undesirable input to stage 1 (i.e. deposit producing stage) during period t.

In addition, we consider that the ability to generate revenue plays an important role in the overall efficiency of the bank, along with the operational aspects of the production process. Therefore, we extended the previous two-stage literature by adding the revenue generation stage to the network structure. As mentioned by Dia et al. (2020), previous studies have either ignored or combined the revenue generation stage

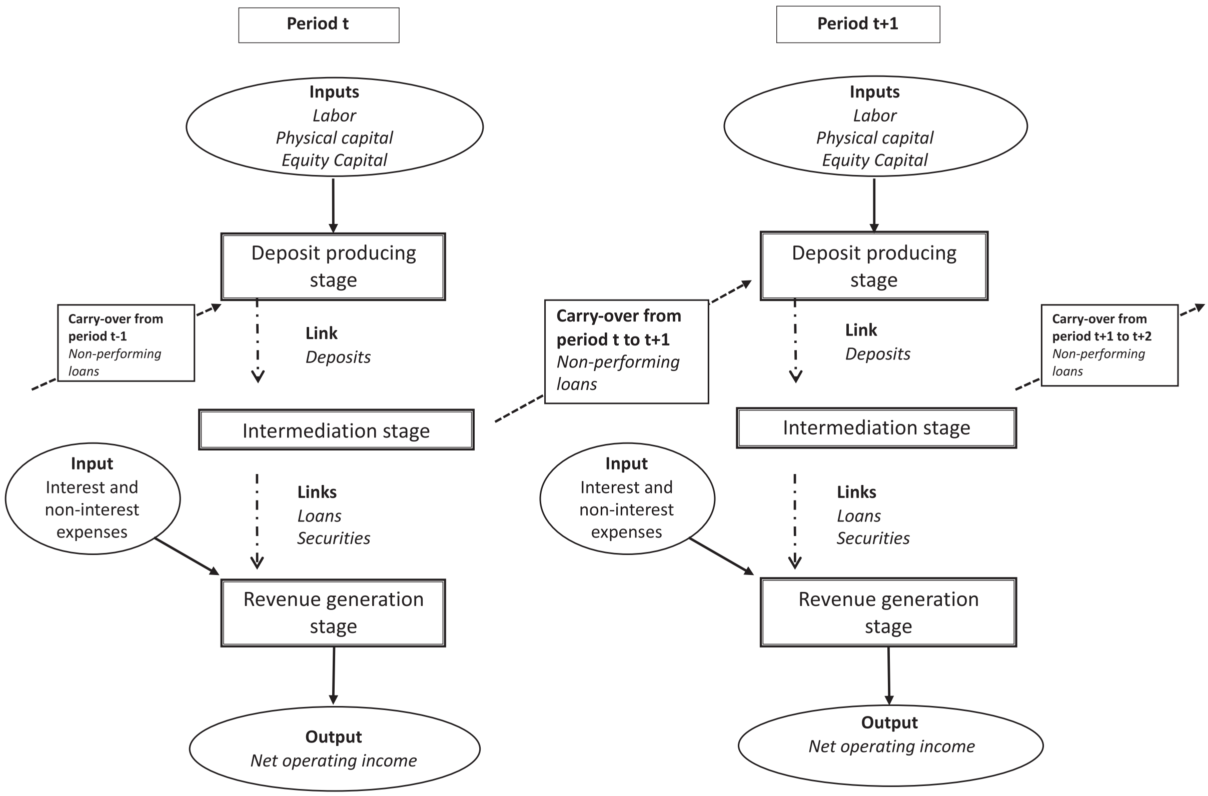

Fig. 1. Three-stage dynamic network bank process.

with other stages. To this end, the efficiency of the third stage is measured by transforming loans, securities investments, and an external input in the form of interest and non-interest expenses into a final output: net operating income. Fig. 1 presents the non-oriented three-stage dynamic network slacks-based measure model. The efficiency scores provided by the DNSBM, which are used as a measure of bank financial stability, are reported in appendix 1.

We consider n DMUs ($j = 1,\dots,n$), which consist of K stages ($k = 1,\dots,K$) over T time periods ($t = 1,\dots,T$). The number of inputs and outputs to stage k represent m_k and r_k, respectively. We denote the link leading from stage k to stage h by $(k,h)_l$ and the set of links by L_{kh}. Then we can define the observed data as follows:

- The set $\left\{x_{ijk}^t \in R_+\right\}$ $(i = 1,\cdots,m_k; j = 1,\cdots,n; k = 1,\cdots,K; t = 1,\cdots,T)$ represents input resource i to DMU_j for stage k in the period t.
- The set $\left\{y_{ijk}^t \in R_+\right\}$ $(i = 1,\cdots,r_k; j = 1,\cdots,n; k = 1,\cdots,K; t = 1,\cdots,T)$ represents output product r from DMU_j for stage k in period t. If some outputs are undesirable, we consider them as inputs to stage k.
- The set $\left\{z_{j(kh)_l}^t \in R_+\right\}$ $(j = 1,\dots,n; l = 1,\dots,L_{kh}; t = 1,\dots,T)$ defines the linking intermediate products of DMU_j from stage k to stage h in period t. Then L_{kh} is the number of items in links from k to h.
- The set $\left\{z_{jk_l}^{(t,t+1)} \in R_+\right\}$ $(j = 1,\cdots,n; l = 1,\cdots,L_k; k = 1,\cdots,K; t = 1,\cdots,T-1)$ represents carry-over of DMU_j, at stage k, from period t to period $t+1$. Then L_k is the number of items in the carry-over from stage k.

The production possibility set $P = \left\{\left(x_k^t, y_k^t, z_{(kh)}^t, z_{i_k}^{(t,t+1)}\right)\right\}(t = 1,\cdots,T)$ under the assumption of variable returns to scale is defined by:

$$x_k^t \ge \sum\nolimits_{j=1}^n x_{jk}^t \lambda_{jk}^t \quad (\forall k, \forall t)$$

$$y_k^t \le \sum\nolimits_{j=1}^n y_{jk}^t \lambda_{jk}^t \quad (\forall k, \forall t)$$

$$z_{(kh)_l}^t = \sum\nolimits_{j=1}^n z_{j(kh)_l}^t \lambda_{jh}^t \quad (\forall l, \forall (k,h), \forall t) \quad (\text{as input to } h \text{ in period } t)$$

$$z_{(kh)_l}^t = \sum\nolimits_{j=1}^n z_{j(kh)_l}^t \lambda_{jk}^t \quad (\forall l, \forall (k,h), \forall t) \quad (\text{as output from } k \text{ in period } t)$$

$$z_{k_l}^{(t,t+1)} = \sum\nolimits_{j=1}^n z_{jk_l}^{(t,t+1)} \lambda_{jk}^t \quad (\forall k_l, \forall k, t = 1,\dots,T-1) \quad (\text{as carry-over from } t)$$

$$z_{k_l}^{(t,t+1)} = \sum\nolimits_{j=1}^n z_{jk_l}^{(t,t+1)} \lambda_{jk}^{t+1} \quad (\forall k_l, \forall k, t = 1,\dots,T-1) \quad (\text{as carry-over to } t+1)$$

$$\sum\nolimits_{j=1}^n \lambda_{jk}^t = 1 \quad (\forall k, \forall t), \quad \lambda_{jk}^t \ge 0 \quad (\forall j, \forall k, \forall t) \tag{1}$$

Where $\lambda_k^t = \left\{\lambda_{jk}^t\right\} \in R_+^n$ is the intensity vector corresponding to stage k ($k = 1,\dots,K$) and t ($t = 1,\dots,T$).

We can express the decision-making unit $DMU_o (o = 1,\cdots,n) \in P^t$ as follows:

$$x_{ok}^t = X_k^t \lambda_k^t + s_{ko}^{t-} \quad (k = 1,\cdots,K; t = 1,\cdots,T)$$

$$y_{ok}^t = Y_k^t \lambda_k^t - s_{ko}^{t+} \quad (k = 1,\cdots,K; t = 1,\cdots,T)$$

$$e\lambda_k^t = 1 \quad (k = 1,\cdots,K; t = 1,\cdots,T)$$

$$\lambda_k^t \ge 0, \; s_{ko}^{t-} \ge 0, \; s_{ko}^{t+} \ge 0, \quad (\forall k, \forall t) \tag{2}$$

where $X_k^t = \left(x_{1k}^t, \cdots, x_{nk}^t\right) \in R^{m_k \times n \times T}$ and $Y_k^t = \left(y_{1k}^t, \cdots, y_{nk}^t\right) \in R^{r_k \times n \times T}$ represent input and output matrices, and s_{ko}^{t-} and s_{ko}^{t+} represent input and output slacks, respectively.

As regard to the linking constraints, we have several opinions. We can apply freely determined linking activities (free), non-discretionary linking activities (fixed), linking activities treated as input to succeeding stage (as input), and the linking activities treated as output from the preceding stage (as output). We apply the assumption of the free link between stages. We can say that the linking activities are freely determined (discretionary) while keeping continuity between input and output.

$$Z^t_{(kh)free}\lambda^t_h = Z^t_{(kh)free}\lambda^t_k \quad (\forall (k,h) free, \forall t) \tag{3}$$

$$Z^t_{(kh)free} = \left(z^t_{1(kh)free}, \cdots, z^t_{n(kh)free}\right) \in R^{L_{(kh)free}\times n}$$

As mentioned by Tone & Tsutsui (2014), this case can serve to see if the current link flow is appropriate or not in the light of other DMUś, i.e. the link flow may increase or decrease in the optimal solution of the linear programs. Between the current link value and the free link value we have a relationship:

$$z^t_{o(kh)free} = Z^t_{(kh)free}\lambda^t_k + s^t_{o(kh)free} \tag{4}$$

Where $s^t_{o(kh)} \in R^{L_{kh}}$ is slack and free in sign.

The DNSBM model can specify the carry-over activities between two periods. The carry-over categories can be classified into four categories: desirable (good), undesirable (bad), discretionary (free) and non-discretionary (fixed). In our study, we apply one undesirable (bad) carry-over activity (i.e., non-performing loans).

The undesirable carry-over can be defined as follows:

$$z^{(t,t+1)}_{ok_lbad} = \sum_{j=1}^{n} z^{(t,t+1)}_{jk_lbad}\lambda^t_{jk} + s^{(t,t+1)}_{ok_lbad} \quad (k_l = 1,\cdots, nbad_k; \forall k; \forall t) \tag{5}$$

$$s^{(t,t+1)}_{ok_lbad} \geq 0 \quad (\forall k; \forall t)$$

Where $s^{(t,t+1)}_{ok_lbad}$ denotes slacks, namely, carry-over excess. The $nbad_k$ indicates the number of undesirable (bad) carry-overs for each stage k.

According to Tone and Tsutsui (2014), we can express the objective function for the overall efficiency in the non-oriented model with only free linking activities and desirable and undesirable carry-over activities as follows:

$$\theta^*_o = min\frac{\sum_{t=1}^{T} W^t\left[\sum_{k=1}^{K} w^k\left[1 - \frac{1}{m_k + nbad_k}\left(\sum_{i=1}^{m_k}\frac{s^{t-}_{iok}}{x^t_{iok}} + \sum_{k_l=1}^{nbad_k}\frac{s^{(t,t+1)}_{ok_lbad}}{z^{(t,t+1)}_{ok_lbad}}\right)\right]\right]}{\sum_{t=1}^{T} W^t\left[\sum_{k=1}^{K} w^k\left[1 + \frac{1}{r_k + ngood_k}\left(\sum_{r=1}^{r_k}\frac{s^{t+}_{rok}}{y^t_{rok}} + \sum_{k_l=1}^{ngood_k}\frac{s^{(t,t+1)}_{ok_lgood}}{z^{(t,t+1)}_{ok_lgood}}\right)\right]\right]} \tag{6}$$

Where, W^t $(t = 1,\ldots,T)$ represents the weight to period t and w^k represents the weight to stage k. These weights satisfy the condition $\sum_{t=1}^{T} W^t = 1$, $\sum_{k=1}^{K} w^k = 1$, $W^t \geq 0$ $(\forall t)$, $w^k \geq 0$ $(\forall k)$. They are supplied exogenously.

A detailed presentation of the DNSBM model can be obtained in Tone and Tsutsui (2014) with regard definitions of period efficiency, divisional (stage) efficiency, and the period-divisional efficiency. For the sake of simplicity, it is omitted from this section.

The DNSBM is executed for the period 2010–2019 and the efficiency scores are calculated separately for each year. The efficiency scores, which are used as a measure of bank financial stability, are reported in appendix 1, which also present their descriptive statistics for the period investigated.

2.2. Empirical model

As we discussed in the introduction, using conventional linear regressions may not be accurate in detecting the true heterogenous impacts of income diversification on bank financial stability (potentially nonlinear). Several authors (e.g., Abuzayed et al., 2018; Berger et al., 2010; Maudos, 2017, among others) point out that it is very likely that the effects of income diversification on bank stability are not monotonic and may be heterogeneous over time and across banks. Hansen (1999) suggests that in cases where the regression functions belong to more than one discrete class, the threshold regression model can be very useful. Therefore, we assume the existence of a threshold level of income diversification at which the pattern of the relationship between income diversification and bank financial stability can change, leading to regime-switching behavior in the relationship. However, we apply the panel smooth transition regression (PSTR) model, developed by González et al (2017), to consider nonlinear relationships between variables as well as to capture the regime-switching behavior respective to a given transition variable. The PSTR model with two extremes regimes and a single transition function can be presented as follows:

$$\begin{aligned} FINSTAB_{i,t} = {} & a_i + b_1DIV_{i,t} + c_1CIR_{i,t} + d_1GROWTH_{i,t} + e_1LEV_{i,t} \\ & + f_1LIQUID_{i,t} + g_1BUIS_{i,t} + + h_1RISK_{i,t} + \left(b_2DIV_{i,t} + c_2CIR_{i,t}\right. \\ & + d_2GROWTH_{i,t} + e_2LEV_{i,t} + f_2LIQUID_{i,t} + g_2BUIS_{i,t} + \\ & \left. + h_2RISK_{i,t}\right) \times G(DIV_{it};\gamma,c) + \varepsilon_{i,t} \end{aligned} \tag{7}$$

for $i = 1,\ldots\ldots,N,$ and $t = 1,\ldots\ldots,T,$ where N and T stands for cross-section and time dimensions of the panel, respectively. $FINSTAB_{i,t}$ and $DIV_{i,t}$ denote bank financial stability and income diversification, respectively. Then, $CIR_{i,t}$, $GROWTH_{i,t}$, $LEV_{i,t}$, $LIQUID_{i,t}$, $BUIS_{i,t}$ and $RIK_{i,t}$ are the control variables, that can affect $FINSTAB_{i,t}$. $\varepsilon_{i,t}$ is the error term. $G(DIV_{i,t};\gamma,c)$ is the transition function illustrating the nonlinear dynamics between the explanatory variables and financial stability. The transition function is bounded between 0 and 1, where c denotes the location parameter (i.e., the threshold level) and γ denotes the slope parameter, which determines the speed of the transition across the regimes.

The PSTR presented in Eq. (7) allows the occurrence of two extreme regimes that are linked with high and low values of the predefined threshold variable $DIV_{i,t}$. Moreover, González et al (2017) specify that $G(DIV_{i,t};\gamma,c)$ can be evaluated with the logistic transition function as follows:

$$G(DIV_{it};\gamma,c) = [1 + exp(-\gamma(DIV_{it-1} - \theta))]^{-1} \tag{8}$$

Where parameter θ is the estimated threshold value.

To test for nonlinear relationships between the variables, a series of preliminary tests describes the empirical procedure. González et al (2017) give details about the procedure for testing the null hypothesis of linearity against a PSTR model. Nevertheless, the test statistics will have a non-standard distribution owing to unidentified nuisance parameters met in the PSTR model under the null hypothesis $H_0 : \gamma = 0$ (i.e., no regime switching effect), also known as Davies (1987) problem. In line with Hansen (1999) and González et al (2017), these nuisance parameters can be solved in respectively the contexts of times series and panel data, by substituting the transition function $G(DIV_{i,t};\gamma,c)$ by its first-order Taylor expansion around the null hypothesis $\gamma = 0$. After reparameterization, it results the following auxiliary regression:

$$\begin{aligned} FINSTAB_{i,t} = {} & a_i + (b_1 + \lambda_0 b_2)DIV_{i,t} + b^*_2DIV_{i,t} \\ & \times q_{i,t} + (c_1 + \lambda_0 c_2)CIR_{i,t} + c^*_2CIR_{i,t} \\ & \times q_{i,t} + (d_1 + \lambda_0 d_2)GROWTH_{i,t} + d^*_2GROWTH_{i,t} \\ & \times q_{i,t} + (e_1 + \lambda_0 e_2)LEV_{i,t} + e^*_2LEV_{i,t} \\ & \times q_{i,t} + (f_1 + \lambda_0 f_2)LIQUID_{i,t} + f^*_2LIQUID_{i,t} \\ & \times q_{i,t} + (g_1 + \lambda_0 g_2)BUIS_{i,t} + g^*_2BUIS_{i,t} \\ & \times q_{i,t} + (h_1 + \lambda_0 h_2)RISK_{i,t} + h^*_2RISK_{i,t} \times q_{i,t} + u_{i,t} \end{aligned} \tag{9}$$

where the parameters $b^*_2, c^*_2, d^*_2, e^*_2, f^*_2, g^*_2, h^*_2$, are the multiple of γ, $\lambda_0 = G\left(q_{i,t} = DIV_{i,t}; \gamma = 0, c\right) = 1/2$, and $u_{i,t} = \varepsilon_{i,t} + R(q_{i,t};\gamma,c)$ is the remainder of the Taylor expansion.

We use the χ^2 LM test version (LM_χ) and the Fisher LM test (LM_F) to test linearity (no regime-switching effect) against the two-regime PSTR model. the statistics of these tests are defined as follows:

$$LM_\chi = \frac{TN(SSR_0 - SSR_1)}{SSR_0} \tag{10}$$

Table 1
Descriptive statistics of inputs and outputs.

Variables	Function	Obs.	Related literature	Mean	S.D.	Max.	Min.
Labor	Input in the first stage	1140	Akhter et al. (2013), Fukuyama and Matousek (2017, 2011), Barros et al. (2012), Fukuyama and Weber (2015, 2017)	24 244	51 262	330 677	38
Physical capital	Input in the first stage	1140	Akhter et al. (2013), Fukuyama and Matousek (2017, 2011), Fujii et al. (2014), Barros et al. (2012)	40 696 271	77 795 217	434 761 762	−2 489 420
Equity capital	Input in the first stage	1140	Akhter et al. (2013), Fukuyama and Weber (2015, 2017)	13 131 456	26 567 017	190 589 024	−7 388 336
Deposits	Free link from first stage to second stage	1140	Akhter et al. (2013), Fukuyama and Matousek (2017, 2011), Barros et al. (2012), Fukuyama and Weber (2015, 2017), Fukuyama and Tan (2020)	100 169 799	213 462 648	1 450 157 968	239 801
Total Loans	Free link from second stage to third stage	1140	Akhter et al. (2013), Barros et al. (2012), Fukuyama and Matousek (2017, 2011)	493 982 179	2 044 223 952	23 288 100 000	139 873
Securities	Free link from second stage to third stage	1140	Akhter et al. (2013), Fukuyama and Matousek (2017), Fukuyama and Weber (2015, 2017)	82 769 166	232 237 357	1 564 494 416	39
Non-performing loans	Carry-over (bad output from second stage of period t to be carried over to the first stage of period t + 1)	1140	Akhter et al. (2013), Fukuyama and Matousek (2017), Fukuyama and Weber (2015, 2017), Fujii et al. (2014), Chiu et al. (2015)	7 211 860	14 623 166	112 731 529	43
Interest and noninterest expenses	Additional input in the third stage	1140	Avkiran and Cai (2014), Wanke et al. (2015, 2016)	7 598 252	17 536 349	124 729 616	12 556
Net operating income	Carry-over (good output from third stage of period t to be carried over to the third stage of period t + 1)	1140	Chiu et al. (2015), Dia et al. (2020), Fernandes et al. (2018), Fukuyama and Tan (2020), Wang et al. (2014)	9 563 863	21 318 531	133 304 993	14 833

$$LM_F = \frac{TN(SSR_0 - SSR_1)/k}{SSR_0/(TN - N - k)} \tag{11}$$

where k is the number of explanatory variables, SSR_0 is the panel sum of squared residuals under H_0(linear panel model with individual effects) and SSR_1 is the panel sum of squared residuals under H_1 (i.e., the PSTR model with two regimes). Under the null hypothesis, the LM_χ is distributed as a $\chi^2(k)$ and the LM_F statistic has an approximate $F(k, TN - N - k)$ distribution. If the null hypothesis is not rejected, we conclude that the model is linear. Second, for heteroscedasticity robustness reasons, we follow González et al (2017) and test the homogeneity using an additional test (*HAC tests*) with two versions[1] (HAC_X) and (HAC_F) for both χ^2 and Fisher tests, respectively.

3. Data and variables

This paper focuses on assessing the impact of income diversification on banks financial stability within a sample of 114 listed European banks over the period 2010–2019. The data set is primarily obtained from Refinitiv Worldscope Fundamentals and is related to commercial banks established in 22 European countries. Appendix 2 shows the breakdown of European commercial banks by country and the representativeness of the sample.

With regard to input and output definitions, the selection criteria are guided by the widely used banking efficiency literature and data availability. Table 1 presents their descriptive statistics and related empirical literature.

In the existing banking empirical literature, there are two general approaches to measure income diversification of banks: (i) through a comprehensive index (Stiroh and Rumble, 2006; Lepetit et al, 2008; Abuzayed et al, 2018; Saghi-Zedek, 2016)) or (ii) by separately assessing a bank's reliance on individual income types other than traditional interest income (Köhler 2015).

In the present study, we consider the structure of income statements by calculating the Adjusted Herfindahl-Hirschman Index (AHHI)[2] for all banks in our sample. We consider a first index (DIV_{NII}) to measure diversification based on accounting figures by distinguishing traditional interest income from non-interest income. Second, because it is not clear how changes between non-interest income activities affect the level of diversification, we follow Hou et al. (2018) and Saghi-Zedek (2016) and calculate the diversification of non-interest income alone using an alternative index *(DIV_{NNII})*.

The two measures of the diversification index are:

$$DIV_{NII} = 1 - \left[\left(\frac{NII}{NOI}\right)^2 + \left(\frac{NNII}{NOI}\right)^2\right] \tag{12}$$

Where $NOI = NII + NNII$, NII is the net interest income, $NNII$ is the net non-interest income, and NOI is the net operating income.

$$DIV_{NNII} = 1 - \left[\left(\frac{FEE}{NNII}\right)^2 + \left(\frac{TRAD}{NNII}\right)^2 + \left(\frac{OTH}{NNII}\right)^2\right] \tag{13}$$

Where $NNII = FEE + TRAD + OTH$, $NNII$ is the net non-interest income, FEE is fees and commission revenue, $TRAD$ is trading revenue from foreign exchange transactions and trading securities, and OTH denotes other non-interest income.

Furthermore, in line with existing literature, we introduce in the regressions a set of control variables relating to bank characteristics that may influence bank financial stability. The cost-to-income ratio (CIR) is used to assess the bank cost efficiency. According to DeYoung and Rice (2004) bank cost efficiency should lead to greater financial stability, as it captures the ability of managers to reduce costs and enhance the quality of non-interest income sources of revenue. To account for bank growth (GROWTH) we use the annual growth in total assets. Abuzayed et al. (2018) find that faster growth can lead to increased investment and diversification opportunities, which can lead to decreased risk. Bank leverage (LEV), which reflects bank capitalization, is proxied by the

[1] HAC stands for Heteroskedasticity and Autocorrelation Consistency. For more details on these two tests, please refer to González et al. (2017).

[2] By construction, AHHI values range from zero to half (Stiroh and Rumble, 2006). When income diversification reaches its minimum, the AHHI is zero. In contrast, it is equal to half when diversification is complete.

Table 2
Variable definitions and descriptive statistics.

Variables	Definition	N	Mean	SD	Min	Max
Dependent variable						
FINSTAB	Financial stability of banks. It is the dependent variable calculated using the three-stage dynamic network slacks-based measure (DNSBM) model	1140	0.0814	0.199	0	1
Independent and transition variables						
DIV_{NII}	Diversification index into non-interest income generating activities Adjusted Herfindahl-Hirschman Index (AHHI): $DIV_{NII} = 1 - \left[\left(\frac{NII}{NOI}\right)^2 + \left(\frac{NNII}{NOI}\right)^2 \right]$	1140	0.397	0.088	0.068	0.499
DIV_{NNII}	Diversification index within non-interest income generating activities Adjusted Herfindahl-Hirschman Index (AHHI): $DIV_{NNII} = 1 - \left[\left(\frac{FEE}{NNII}\right)^2 + \left(\frac{TRAD}{NNII}\right)^2 + \left(\frac{OTH}{NNII}\right)^2 \right]$	1140	0.400	0.136	0.006	0.499
Control variables						
CIR	Bank cost efficiency: ratio of operating costs to total operating income	1140	8.356	53.681	−595.94	1153.60
GROWTH	Bank growth: annual growth rate of the total assets	1140	4.626	10.104	−30.76	81.48
LEV	Bank leverage capturing bank capitalization: ratio of total equity to total assets	1140	7.932	3.735	−5.1	20.82
LIQUID	Bank liquidity capturing bank funding structure: ratio of customer deposits to total assets	1140	55.099	17.718	15.04	97.04
BUS	Bank business model: ratio of total loans to total assets	1140	6.122	14.282	−30.76	99.27
RISK	Bank risk capturing loans quality: ratio of provision for loans to total loans	1140	0.062	0.119	0	1.107

Table 3
Linearity, no remaining nonlinearity tests.

Dependent variable: FINSTAB				
Threshold variables	DIV_{NII} Statistic	p-value	DIV_{NNII} Statistic	p-value
I) Linearity (homogeneity) tests H_0: 1 regime (no transition function) versus H_1: 2 regimes (1 transition function)				
LM_χ	29.04***	0.002	6.321**	0.099
LM_F	3.526***	0.005	0.803**	0.081
HAC_χ	4.151**	0.022	6.385*	0.003
HAC_F	0.681**	0.016	0.014**	0.085
II) No remaining nonlinearity tests H_0: 2 regimes (1 transition function) versus H_1: 3 regimes (2 transition functions)				
LM_χ	21.05*	0.057	55.01	0.111
LM_F	1.441	0.121	3.451	0.129
HAC_χ	16.21	0.226	18.22	0.191
HAC_F	1.035	0.307	2.141	0.323

Notes: H_0: linear model; H_1: PSTR model with at least one threshold. FINSTAB is financial stability, DIV_{REV} is revenue diversification, DIV_{NNII} is revenue diversification within non-interest bank activities, $LM\chi$ is the χ^2 version Lagrange Multiplier test, LM_F is the F version Lagrange Multiplier test, HAC_χ is the χ^2 version of HAC tests, and HAC_F is the F version HAC tests. HAC stands for Heteroskedasticity and Autocorrelation Consistency.

equity-to-total assets ratio. Lepetit et al (2008) argues that lower capital strength reflects riskier banks. Bank funding structure is captured using the ratio of total deposits to total assets. This ratio reflects the level of bank liquidity (LIQUID) and it expected to positively impact the financial stability (Abuzayed et al, 2018). To control for the bank business model (BUS), we use the ratio of total loans to total assets. Finally, bank risk (RISK) is proxied by loans quality which is measured by the ratio of the provision for loans to total loans. The detailed variables definitions and descriptive statistics are provided in Table 2.

4. Empirical results

4.1. Preliminary tests

Before presenting the estimation results, the modeling cycle in PSTR requires different stages of model specification, parameter estimation and model evaluation. The first step in estimating the PSTR model consists of testing the significance of the regime switching, i.e., whether there is a nonlinear relationship between income diversification and financial stability. Table 3 shows the results of the linearity tests against the PSTR model. We find that $LM\chi$ and LM_F are significant at 1% and 5% respectively, which indicate the rejection of the null hypothesis of linearity, then the existence of nonlinearity between income diversification and bank financial stability. This result proves that income diversification heterogeneously impacts financial stability depending on the degree of income diversification (i.e., DIV_{NII} and DIV_{NNII}). In a second step, it is necessary to assess the adequacy of the estimated PSTR model by testing for the absence of residual nonlinearity. As shown in Table 3, our results indicate that the four tests used do not reject the null hypotheses of no remaining nonlinearity. Therefore, we can say that the PSTR model with a single transition function, and containing two extreme regimes, is well suited to study the nonlinear relationship between income diversification and bank financial stability.

4.2. Parameters' estimate and discussion of the results

Table 4 shows the estimation results of the PSTR model with two regimes: *i)* a low regime of income diversification when the diversification index is below the estimated threshold value; and *ii)* a high regime of income diversification when the diversification index is above the estimated threshold value. From the two models (model 1 and model 2), it is clearly observed that the estimated slope parameters are relatively small (i.e., $\gamma = 7.071$ for model 1 and $\gamma = 7.422$ for model 2). This result suggests the presence of a continuum of conditions between the low and the high regimes. In other words, this result indicates that the relationship is nonlinear rather than linear as the impacts of income diversification and bank financial stability move continuously and smoothly between the two regimes (see Fig. 2).

For diversification into non-interest income generating activities (i.

Table 4
Parameter estimation of the PSTR.

Dependent variable: FINSTAB				
Threshold variables	DIV_{NII}(Model 1)		DIV_{NNII}(Model 2)	
	First extreme regime ($b_1, \cdots, h_1$)	Second extreme regime ($b_1 + b_2, \cdots, h_1 + h_2$)	First extreme regime ($b_1, \cdots, h$)	Second extreme regime ($b_1 + b_2, \cdots, h_1 + h_2$)
DIV_{NII}	−0.541	0.082***		
	(0.000)	(0.612)		
DIV_{NNII}			0.309	−0.868 **
			(0.502)	(0.421)
CIR	−0.001	0.001	0.002	0.005
	(0.001)	(0.000)	(0.000)	(0.000)
GROWTH	−0.006	0.008	0.045	−0.012
	(0.002)	(0.002)	(0.034)	(0.071)
LEV	0.001	−0.008*	−0.013	0.001**
	(0.008)	(0.005)	(0.012)	(0.021)
LIQUID	0.001	0.004	0.002	0.003
	(0.002)	(0.001)	(0.002)	(0.001)
BUS	−0.005	0.001	−0.041	0.012
	(0.003)	(0.003)	(0.03)	(0.071)
RISK	0.079	−0.080**	1.089	−0.491**
	(0.812)	(0.123)	(2.273)	(1.248)
Transitions parameters				
Threshold (c)	0.272***		0.319***	
	(0.178)		(0.151)	
Slope (γ)	7.071***		7.422 ***	
	(4.308)		(32.581)	
Standard deviation of the residuals	0.1001		0.1011	

Notes: FINSTAB is bank financial stability measured by the dynamic three-stage network slacks-bases measure model. DIV_{NII} is income diversification into non-interest bank activities measured by the Adjusted Herfindahl-Hirschman Index: $DIV_{NII} = 1 - \left[\left(\frac{NII}{NOI}\right)^2 + \left(\frac{NNII}{NOI}\right)^2 \right]$, with Net Operating Income (NOI) is defined as the sum of Net Interest Income (NII) and Net Non-interest Income (NNII). DIV_{NNII} is income diversification within non-interest bank activities measured by the Adjusted Herfindahl-Hirschman Index: $IV_{NNII} = 1 - \left[\left(\frac{FEE}{NNII}\right)^2 + \left(\frac{TRAD}{NNII}\right)^2 + \left(\frac{OTH}{NNII}\right)^2 \right]$, with *FEE* is fees and commission revenue, *TRAD* is trading revenue from foreign exchange transactions and trading securities, and *OTH* denotes other non-interest income. CIR denotes cost efficiency measured by the ratio of operating costs to total operating income, GROWTH denotes the growth rate of bank total assets, LEV denotes bank capitalization measured by the ratio of total equity to total assets , LIQUID denotes the bank funding structure measured by the ratio of customer deposits to total assets, BUS denotes the bank business model measured by the ratio of total loans to total assets, and RISK denotes bank risk and is calculated by the ratio of provision for loans to total loans. Between parentheses (.) are standard errors. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

e., model 1), we find a negative but insignificant impact of income diversification on bank financial stability under the low-income diversification regime (i.e., $DIV_{NII} < \hat{c} = 0.272$). Once this threshold value is reached and exceeded, under the high-income diversification regime, the impact of additional income diversification on bank financial stability becomes positive and significant at 1% level. Hence, each additional percentage point of income diversification into non-interest income generating activities enhances bank financial stability by 0.082 points. From this result, it is possible to conclude that the relationship between DIV_{NII} and *FINSTAB* follows a U-curve because the relationship between the variables in the low regime is negative while it becomes positive during the high regime. However, this conclusion is incorrect because the analysis must be completed by visualizing the response curve of bank stability to the different values taken by income diversification. In this case, we can actually observe the nature of the entire response of the dependent variable to the effects of the explanatory variable and thus determine the range of true values. From Fig. 3, we can clearly see that, although the relationship follows an upward trend in the high-income diversification regime, the overall response of *FINSTAB* to the impacts of DIV_{NII} remains negative regardless of the regime. Therefore, we must be careful in interpreting the regression results from the PSTR model because the regression coefficients in each of the regimes are relative to the effect of the explanatory variables at the tails of the distribution of the dependent variable, thus allowing a reduced characterization of the relation between variables. Therefore, our empirical results corroborate those of several previous U.S. banking studies, such as Stiroh (2004), Stiroh (2006), and Stiroh and Rumble (2006), which show that a shift to non-traditional income sources worsens the financial stability of banks because not only does the increase in non-interest income negatively impact the risk-return tradeoff, but it also increases the probability of failure. DeYoung and Roland (2001) explain that bank risk does not decrease a result of income diversification, but that a shift to fee-generating activities increases bank profitability by offsetting the increase in risk. Our result is at odds with the traditional intermediation hypothesis that greater involvement in nontraditional activities helps increase a bank's chances of remaining healthy (Diamond, 1984). More significantly, our findings are consistent with European banking studies (e.g., Lahouel et al., 2022a; Lepetit et al., 2008; Maudos, 2017; Mercieca et al., 2007; Saghi-Zedek, 2016, among others) arguing that there is little evidence that benefits from an increase in the share of non-interest income exist.

Referring to the Stiroh studies mentioned above, one possible explanation for our results is that there should be a strong correlation between the sources of interest and non-interest income within European banks over the period explored (i.e., from 2010 to 2019). We should keep in mind that our study spans a post-crisis period characterized by the quantitative easing programs launched by the European Central Bank from 2008 onwards. The decline in interest rates has led banks to move away from traditional intermediation, resulting in a decrease in interest income and an increase in non-interest income. Therefore, if European banks increase the use of cross-selling strategies, their diverse business segments are likely to be exposed to the same economic shocks, especially when the two sources of income become more and more strongly correlated over time. As a result, any potential from income diversification will be neutralized. In similar line of argument, Lepetit et al. (2008) find that banks that offer more nontraditional services are likely to underprice borrower default risk, meaning that loans are likely to be used as a loss leader, raising the issue of weakening financial stability when banks use cross-selling strategies.

About model 2, we find that under the low regime, income diversification within non-interest income (i.e., when DIV_{NNII} is below the threshold $\hat{c} = 0.319$) doesn't have a significant impact on bank stability although its coefficient is positive. However, under the high regime, the relationship between diversification within non-interest income and bank financial stability turns to be significantly negative at 5% level. If we just consider the diversification of the noninterest income the results indicate that each additional percentage point of DIV_{NNII} beyond the threshold ($\hat{c} = 0.319$) reduces financial stability by 0.868 points. Hence, the detailed analysis of individual bank activities provides some evidence that the structure of the non-interest income is relevant since it contributes to increasing risk while leading to greater banking instability. This result is in line with those of Lepetit et al. (2008) who find that increased shares of noninterest income increase accounting return and risk of international banks. Similarly, for American banks,

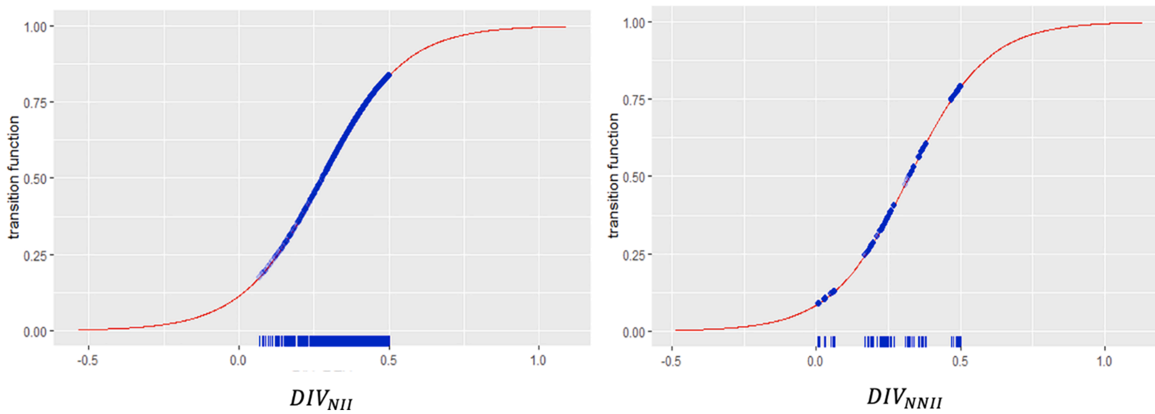

Fig. 2. Estimated transition function of the PSTR model for Bank financial stability. (Note: y axis is the transition function, and × axis is the transition variable.).

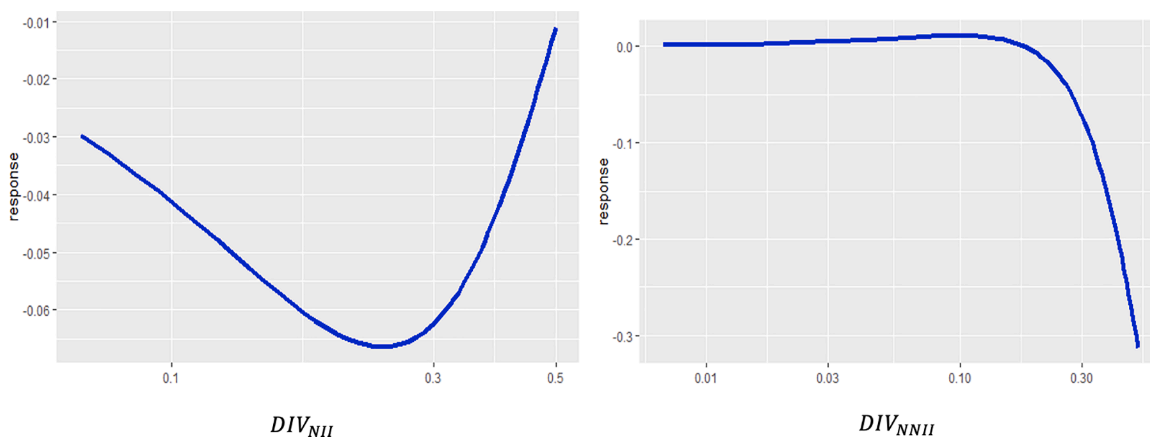

Fig. 3. Response of bank stability to income diversification.

Demirgüç-Kunt and Huizinga (2010) find a risk reducing effects only at very low levels of noninterest income. In the Canadian context, Calmès and Théoret (2012) find that higher shares of noninterest income are associated with both higher risk and higher risk-adjusted profitability. For the Indian Banks, Hidayat et al (2012) conclude that Indian banks that rely more on noninterest income are riskier. Also, Meslier et al. (2014) report a negative effect of a move to fee-based sources of revenue on risk-adjusted profits in Philippine banks. Our results may be driven, as noted above, by a positive correlation between the growth rates of the two sources of income, implying that the demarcation lines between income from lending and non-interest income are blurred due to cross-selling between business segments.

5. Conclusion

The idea of legally limiting banks' engagement in noninterest income has regained popularity after the Global Financial Crisis of 2007–2008, which has been the subject of bank failures around the world. However, the existing empirical literature on bank income diversification provides no clear support for such regulations. Neither evidence for nor against diversification clearly dominates. An important challenge for European policymakers is the design of effective policies that address the financial stability in the banking sector.

This paper contributes to the debates on the relative importance of an optimal portfolio management with regard to the level of non-traditional sources of income and their effects on bank financial stability. Specifically, this paper adopts an operational efficiency perspective that accounts for the bank's risk-return profile across different operating stages. Combining a three-stage DNSBM model with the PSTR model, this paper sheds some light upon the nonlinear relationship between revenue diversification and bank financial stability through the investigation of potential regime-switching behavior of this relationship.

Our study shows that, at higher diversification regimes, European commercial banks do not benefit neither from a shift toward non-interest income nor from a diversification within non-interest activities. Our study reveals the "darker side" of diversification which comes in opposition to the benefits of a portfolio diversification hypothesis. Moreover, our study highlights that the increased complexity of managing a diversified bank can lead to misallocation of resources, dispersion of managerial and organizational skills, and increased asymmetric information, thus generating agency costs that can be sources of banking distress.

Future research should analyze the effects of individual types of noninterest income to capture the sources of the mixed result present in existing empirical results. Doing so, could be helpful to gain more clarity on the effects of diversification on bank stability.

6. Authors' contributions

All authors contributed to the study conception, design and writing. Material preparation, data collection and analysis were performed by

Béchir Ben Lahouel, Lotfi Taleb, and Mohamed Kossai. The current version of the revised manuscript was written and approved by the three authors.

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CRediT authorship contribution statement

Béchir Ben Lahouel: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Software. **Lotfi Taleb:** Data curation, Formal analysis, Methodology, Writing – original draft, Software. **Mohamed Kossai:** Formal analysis, Software, Writing – review & editing, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1

Table A1
Efficiency scores by year.

	Mean	SD	Max	Min
2010	0,291	0,255	1	0,062
2011	0,493	0,194	1	0,076
2012	0,459	0,208	1	0,010
2013	0,511	0,199	1	0,248
2014	0,515	0,196	1	0,256
2015	0,491	0,188	1	0,169
2016	0,490	0,201	1	0,194
2017	0,477	0,197	1	0,169
2018	0,442	0,190	1	0,179
2019	0,455	0,182	1	0,196

Table A2

Table A2
Distribution and representativeness o European commercial banks in the final sample.

Country	Number of all banks	Percentage
Austria	5	4,4%
Belgium	1	0,9%
Denmark	9	7,9%
Finland	3	2,6%
France	13	11,4%
Germany	2	1,8%
Greece	5	4,4%
Hungary	1	0,9%
Ireland	2	1,8%
Italy	12	10,5%
Liechtenstein	1	0,9%
Lithuania	1	0,9%
Netherlands	1	0,9%
Norway	11	9,6%
Poland	10	8,8%
Portugal	1	0,9%
Romania	1	0,9%
Russia	4	3,5%
Spain	6	5,3%
Sweden	3	2,6%
Switzerland	14	12,3%
United Kingdom	8	7,0%
Total	**114**	**100,0%**

References

Abuzayed, B., Al-Fayoumi, N., & Molyneux, P. (2018). Diversification and bank stability in the GCC. *Journal of International Financial Markets, Institutions and Money, 57*, 17–43.
Akther, S., Fukuyama, H., & Weber, W. L. (2013). Estimating two-stage network slacks-based inefficiency: An application to Bangladesh banking. *Omega, 41*(1), 88–96.
Asteriou, D., Pilbeam, K., & Tomuleasa, I. (2021). The impact of corruption, economic freedom, regulation and transparency on bank profitability and bank stability: Evidence from the Eurozone area. *Journal of Economic Behavior & Organization, 184*, 150–177.
Avkiran, N. K. (2017). An illustration of multiple-stakeholder perspective using a survey across Australia, China and Japan. *Annals of Operations Research, 248*(1–2), 93–121.
Avkiran, N. K., & Cai, L. (2014). Identifying distress among banks prior to a major crisis using non-oriented super-SBM. *Annals of Operations Research, 217*(1), 31–53.
Berger, A. N., Hasan, I., & Zhou, M. (2010). The effects of focus versus diversification on bank performance: Evidence from Chinese banks. *Journal of Banking & Finance, 34* (7), 1417–1435.
Boyd, J. H., & Runkle, D. E. (1993). Size and performance of banking firms: Testing the predictions of theory. *Journal of monetary economics, 31*(1), 47–67.
Calmès, C. P. A., & Théoret, R. (2012). *The change in banks' product mix, diversification and performance: An application of multivariate GARCH to Canadian data*. University of Quebec.
Chao, C. M., Yu, M. M., & Wu, H. N. (2015). An application of the dynamic network DEA model: The case of banks in Taiwan. *Emerging Markets Finance and Trade, 51*(sup1), S133–S151.
Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European journal of operational research, 2*(6), 429–444.
Chiu, Y. B., & Lee, C. C. (2019). Financial development, income inequality, and country risk. *Journal of International Money and Finance, 93*, 1–18.
Čihák, M., & Hesse, H. (2010). Islamic banks and financial stability: An empirical analysis. *Journal of Financial Services Research, 38*(2), 95–113.
Čihák, M., Demirgüç-Kunt, A., Feyen, E., & Levine, R. (2012). Benchmarking financial systems around the world. In *World Bank policy research working paper* (p. 6175).
Crockett, A. (1997). Why is financial stability a goal of public policy? *Economic Review-Federal Reserve Bank of Kansas City, 82*, 5–22.
Davies, R. B. (1987). Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika, 74*(1), 33–43.
DeYoung, R., & Roland, K. P. (2001). Product mix and earnings volatility at commercial banks: Evidence from a degree of total leverage model. *Journal of Financial Intermediation, 10*(1), 54–84.
DeYoung, R., & Torna, G. (2013). Nontraditional banking activities and bank failures during the financial crisis. *Journal of Financial Intermediation, 22*(3), 397–421.
Dia, M., Takouda, P. M., & Golmohammadi, A. (2020). Assessing the performance of Canadian credit unions using a three-stage network bootstrap DEA. *Annals of Operations Research*, 1–33.
Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The review of economic studies, 51*(3), 393–414.
Fang, Y., Hasan, I., & Marton, K. (2011). Market reforms, legal changes and bank risk-taking–evidence from transition economies. *Bank of Finland Research Discussion Paper*, (7).
Fang, Y., Hasan, I., & Marton, K. (2014). Institutional development and bank stability: Evidence from transition countries. *Journal of Banking & Finance, 39*, 160–176.
R.W. Ferguson Should Financial Stability Be an Explicit Central Bank Objective?, IMF Conference on Challenges to Central Banking from Globalized Financial Systems, September 16–17 2002 2002 Washington DC.
Francis, B. B., Hasan, I., Küllü, A. M., & Zhou, M. (2018). Should banks diversify or focus? Know thyself: The role of abilities. *Economic Systems, 42*(1), 106–118.
Fukuyama, H., & Matousek, R. (2017). Modelling bank performance: A network DEA approach. *European Journal of Operational Research, 259*(2), 721–732.
Fukuyama, H., & Tan, Y. (2020). Deconstructing three-stage overall efficiency into input, output and stability efficiency components with consideration of market power and loan loss provision: An application to Chinese banks. *International Journal of Finance & Economics.*
Fukuyama, H., & Weber, W. L. (2010). A slacks-based inefficiency measure for a two-stage system with bad outputs. *Omega, 38*(5), 398–409.
Fukuyama, H., & Weber, W. L. (2012). Estimating two-stage network technology inefficiency: An application to cooperative Shinkin banks in Japan. *International Journal of Operations Research and Information Systems (IJORIS), 3*(2), 1–23.
Fukuyama, H., & Weber, W. L. (2015). Measuring Japanese bank performance: A dynamic network DEA approach. *Journal of Productivity Analysis, 44*(3), 249–264.
Fukuyama, H., & Weber, W. L. (2017). Measuring bank performance with a dynamic network Luenberger indicator. *Annals of Operations Research, 250*(1), 85–104.
Glocker, C. (2021). Reserve requirements and financial stability. *Journal of International Financial Markets, Institutions and Money, 71*, Article 101286.
González, A., Teräsvirta, T., van Dijk, D., Yang, Y. (2017). Panel smooth transition regression models. Department of Economics and Business Economics, Aarhus University, CREATES Research Paper 2017-36.
Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics, 93*(2), 345–368.
Henriques, I. C., Sobreiro, V. A., Kimura, H., & Mariano, E. B. (2020). Two-stage DEA in banks: Terminological controversies and future directions. *Expert Systems with Applications, 161*, Article 113632.
Hidayat, W. Y., Kakinaka, M., & Miyamoto, H. (2012). Bank risk and non-interest income activities in the Indonesian banking industry. *Journal of Asian Economics, 23*(4), 335–343.

Hou, X., Li, S., Li, W., & Wang, Q. (2018). Bank diversification and liquidity creation: Panel Granger-causality evidence from China. *Economic Modelling, 71*, 87–98.

Houben, A. G., Kakes, J., & Schinasi, G. J. (2004). Toward a framework for safeguarding financial stability. *IMF Working Papers, 2004*(101).

Izzeldin, M., Johnes, J., Ongena, S., Pappas, V., & Tsionas, M. (2021). Efficiency convergence in Islamic and conventional banks. *Journal of International Financial Markets, Institutions and Money, 70*, Article 101279.

Köhler, M. (2015). Which banks are more risky? The impact of business models on bank stability. *Journal of Financial Stability, 16*, 195–212.

Kunt, A. D., & Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics, 98*(3), 626–650.

Lahouel, B. B., Taleb, L., Kočišová, K., & Ben Zaied, Y. (2022a). The threshold effects of income diversification on bank stability: an efficiency perspective based on a dynamic network slacks-based measure model. *Annals of Operations Research*, 1–38.

Lahouel, B. B., Zaied, Y. B., Managi, S., & Taleb, L. (2022b). Re-thinking about U: The relevance of regime-switching model in the relationship between environmental corporate social responsibility and financial performance. *Journal of Business Research, 140*, 498–519.

Lahouel, B. B., Zaied, Y. B., Song, Y., & Yang, G. L. (2020). *Corporate social performance and financial performance relationship: A data envelopment analysis approach without explicit input* (p. 101656). Finance Research Letters.

Lepetit, L., & Strobel, F. (2015). Bank insolvency risk and Z-score measures: A refinement. *Finance Research Letters, 13*, 214–224.

Lepetit, L., Nys, E., Rous, P., & Tarazi, A. (2008). The expansion of services in European banking: Implications for loan pricing and interest margins. *Journal of Banking & Finance, 32*(11), 2325–2335.

Liu, X., Sun, J., Yang, F., & Wu, J. (2020). How ownership structure affects bank deposits and loan efficiencies: An empirical analysis of Chinese commercial banks. *Annals of Operations Research, 290*(1), 983–1008.

Mahmoudabadi, M. Z., & Emrouznejad, A. (2019). Comprehensive performance evaluation of banking branches: A three-stage slacks-based measure (SBM) data envelopment analysis. *International Review of Economics & Finance, 64*, 359–376.

Maudos, J. (2017). Income structure, profitability and risk in the European banking sector: The impact of the crisis. *Research in International Business and Finance, 39*, 85–101.

Mercieca, S., Schaeck, K., & Wolfe, S. (2007). Small European banks: Benefits from diversification? *Journal of Banking & Finance, 31*(7), 1975–1998.

Meslier, C., Tacneng, R., & Tarazi, A. (2014). Is bank income diversification beneficial? Evidence from an emerging economy. *Journal of International Financial Markets, Institutions and Money, 31*, 97–126.

Nguyen, M., Skully, M., & Perera, S. (2012). Market power, revenue diversification and bank stability: Evidence from selected South Asian countries. *Journal of International Financial Markets, Institutions and Money, 22*(4), 897–912.

Paradi, J. C., & Zhu, H. (2013). A survey on bank branch efficiency and performance research with data envelopment analysis. *Omega, 41*(1), 61–79.

Saghi-Zedek, N. (2016). Product diversification and bank performance: Does ownership structure matter? *Journal of Banking & Finance, 71*, 154–167.

Shaddady, A., & Moore, T. (2019). Investigation of the effects of financial regulation and supervision on bank stability: The application of CAMELS-DEA to quantile regressions. *Journal of International Financial Markets, Institutions and Money, 58*, 96–116.

Stiroh, K. J. (2004). Diversification in banking: Is noninterest income the answer? *Journal of money, Credit and Banking*, 853–882.

Stiroh, K. J. (2006). New evidence on the determinants of bank risk. *Journal of Financial Services Research, 30*(3), 237–263.

Stiroh, K. J., & Rumble, A. (2006). The dark side of diversification: The case of US financial holding companies. *Journal of banking & finance, 30*(8), 2131–2161.

Tabak, B. M., Fazio, D. M., & Cajueiro, D. O. (2012). The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking & Finance, 36*(12), 3366–3381.

Tan, Y., & Anchor, J. (2017). Does competition only impact on insolvency risk? New evidence from the Chinese banking industry. *International Journal of Managerial Finance.*

Tone, K., & Tsutsui, M. (2009). Network DEA: A slacks-based measure approach. *European journal of operational research, 197*(1), 243–252.

Tone, K., & Tsutsui, M. (2014). Dynamic DEA with network structure: A slacks-based measure approach. *Omega, 42*(1), 124–131.

Ullah, A., Pinglu, C., Ullah, S., Qian, N., & Zaman, M. (2021). Impact of intellectual capital efficiency on financial stability in banks: Insights from an emerging economy. *International Journal of Finance & Economics.*

Wanke, P., Azad, M. A. K., & Barros, C. P. (2016). Financial distress and the Malaysian dual baking system: A dynamic slacks approach. *Journal of Banking & Finance, 66*, 1–18.

Wanke, P., Barros, C. P., & Faria, J. R. (2015). Financial distress drivers in Brazilian banks: A dynamic slacks approach. *European Journal of Operational Research, 240*(1), 258–268.

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