Financial stability, liquidity risk and income diversification: evidence from European banks using the CAMELS–DEA approach

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Abstract

Liquidity risk was at the heart of 2007–2008 global financial crisis, which has led to a series of financial institutions failure. We test whether and how liquidity risk impacts European banks' stability (i.e., a bank risk-return profile) under different levels of engagement in non-traditional banking activities after the global financial crisis and during the implementation of the Basel III liquidity rules. To calculate financial stability, we adopt an efficiency perspective based on the combination of the CAMELS rating system with the data envelopment analysis technique. We implement a nonlinear panel smooth transition regression approach, where transitional factors of income diversification are endogenously captured from the data. We find that, liquidity risk stemming from liquidity creation has a positive impact on bank stability, implying that income diversification can serve as a "buffer" through which banks can ensure their liquidity creation and offset for the compression of intermediation margin in lending and deposit activities. This suggests that diversification does not impede the ability of banks to operate with lower liquidity holdings but allows them to make greater use of their balance sheets to fulfill their primary roles of credit provision and liquidity creation. The results offer interesting implications for regulators and bank managers in managing liquidity risk.

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1 Introduction

The modern theory of financial intermediation suggests that the main objective of the banking sector in the economy is the creation of liquidity. Through maturity transformation, banks' monetary activities occur on both sides of the balance sheet. Banks create liquidity on the balance sheet by financing their risky, illiquid long-term assets, i.e. loans, with liquid short-term liabilities, i.e. deposits (Diamond & Dybvig, 1983). However, liquidity creation is risky because banks become less liquid when depositors claim their funds at an inopportune time, making it difficult for banks to meet their financial obligations by immediately selling illiquid assets (Diamond & Rajan, 2001). Therefore, liquidity risk arises from the creation of liquidity that can increase the likelihood of the bank's illiquidity. An illiquid bank means that it cannot raise adequate funds, either by increasing its liabilities or by converting its assets quickly at a reasonable price (Chen et al., 2018). Therefore, illiquidity is considered the main source of bank vulnerability and insolvency (Acharya & Naqvi, 2012; Berger & Bouwman, 2017).

The global financial crisis of 2007–2009 showed that the failure of financial institutions was due to liquidity risk (DeYoung & Jang, 2016). The turmoil in the financial markets has revealed the importance of effectively managing liquidity risk for the proper functioning of the banking sector and the economy. Since banks are inherently exposed to liquidity risk (Holmström & Tirole, 2000), liquidity risk management is essential not only to determine their direction, but also to ensure their stability (Zheng & Cronje, 2019). Following the crisis, financial organizations such as the Basel Committee on Banking Supervision (2010) suggested active liquidity risk management through the introduction of two liquidity principles, namely the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), as part of the Basel III regulations. The newly mandated liquidity restrictions require banks, while remaining financially stable and profitable, to hold more liquid assets than in the past, thereby addressing short- and long-term liquidity mismatches (Dietrich & Wanzenried, 2014). While the Basel III funding standards are generally expected to have a positive effect on banks, particularly by introducing more capital and liquidity efficient business models, their effects are hardly studied (Dietrich & Wanzenried, 2014). However, the new liquidity requirements may undermine the core function of the banking system (i.e., creating liquidity by collecting customer deposits and then lending to the economy), which may lead to reduced profitability and compressed lending margins. Several researchers emphasize the need to consider the trade-off between new liquidity requirements and profitability (e.g., Allen et al., 2012; Bordeleau & Graham, 2010; King, 2013). They warn that if the results of the implementation of the new liquidity requirements are not carefully monitored, evaluated, and, if necessary, modified, the remedy of the newly introduced regulations will prove to be worse than the harm. In other words, liquidity regulations should make banks more resilient to liquidity shocks, but at the cost of reducing banks' profitability in normal times since liquid assets have a lower liquidity premium than illiquid assets.

Following the introduction of Basel III regulations, a limited number of studies have been conducted to examine the impacts of liquidity risk on bank stability. In most empirical studies, liquidity has been included as an additional explanatory variable for bank stability, and there has been little discussion of the results for the estimated parameter (Bordeleau & Graham, 2010). Little consensus has been reached to date, and three types of conclusions emerge. The

first group of studies suggests that increased liquidity holdings have a negative impact on the stability of banks and may lead to their failure. Indeed, the availability of liquid assets encourages banks to assume more risk by allocating excessive loans (Acharya & Naqvi, 2012; Imbierowicz & Rauch, 2014; Nguyen et al., 2017; Wagner, 2007). In addition, because liquid assets have lower returns than other assets, the cost of holding liquid assets can hurt profitability. The second group of studies argues that liquid assets serve as a 'buffer' during periods of instability by increasing bank resilience and decreasing the probability of bank failure (Acharya and Mora, 2015; DeYoung & Jang, 2016). The third group of studies suggests that increasing liquidity may have a nonlinear impact on bank stability. Several researchers consider the presence of a trade-off between the short-term profitability gains of reducing liquidity and the longer-term performance benefits of insuring against liquidity shortages. For example, Ehiedu (2014) highlights the importance of balancing profit maximization with holding sufficient liquidity. Bordeleau and Graham (2010) argue that increasing liquid assets would improve a bank's profitability as long as the marginal benefit of holding additional liquid assets outweighs the opportunity cost of their low relative return.

Given the ambivalence of the previous results, the first objective of this study is to fill the research gap regarding the impact of liquidity risk on bank stability. However, existing studies almost universally ignore the role of income diversification as a factor that may influence the relationship between liquidity risk and bank stability. Specifically, there could be nonlinear effects of the relationship between liquidity risk and bank stability under different levels of income diversification, which is absent from the existing literature. The literature on bank diversification offers valuable insights for our study in two ways. On the one hand, income diversification plays a risk-absorbing role, as diversification into non-traditional banking activities can allow banks to grow, achieve efficiencies through economies of scale and scope, reduce total volatility and insolvency risk, achieve capital savings, and enhance stability (Köhler, 2014; Moudud-Ul-Huq et al., 2018; Saghi-Zedek, 2016). Therefore, diversified banks are more likely to create liquidity, as they are more financially stable than other banks in terms of meeting depositors' withdrawal demands and providing liquidity to borrowers (Hou et al., 2018). On the other hand, many studies find that income diversification has negative effects on bank stability. The increase in non-interest income is related to the deterioration of the risk-return profile (DeYoung & Rice, 2004; Stiroh, 2006). Stiroh (2015) concludes that diversification is ineffective in reducing earnings volatility, pooling resources and managerial capabilities, improving operational stability, and maximizing stakeholder wealth. As a result, income diversification may disperse managerial skills, leading to higher organizational coordination costs and, in turn, an inability to meet the liquidity demands of depositors and borrowers, thereby undermining bank liquidity creation. Based on the above discussion, ignoring the role of income diversification could lead to incomplete and, at times, incorrect conclusions and implications about the effects of liquidity risk, arising from liquidity creation, on bank stability. Thus, the first objective of this paper is to empirically examine the nonlinear impacts of liquidity risk on bank stability under different levels of income diversification. Empirical evidence is provided within a balanced panel data of European commercial bank over the period 2010–2019. The focus on European banks is justified by the fact that new liquidity measures inspired by the Basel III regulatory framework may have more salient impacts on banking stability in the European context. Indeed, the financial system in Europe is bank-oriented, which means that a "credit crunch" environment can be a drag on investment activity in the real economy and thus a barrier to economic growth (Roulet, 2018). Discussions on the Basel III accords were initiated in 2009 before being legally adopted in 2011 by the European Union countries. In 2013, national jurisdictions began applying additional capital adequacy rules. The years 2014 and 2015 saw the application of the liquidity coverage

ratio (LCR) and the net stable funding ratio (NSFR) by national jurisdictions. Banks will have to comply with all Basel III regulatory requirements, considering the maximum thresholds, by the end of 2019.

The second objective of this paper is to extend the existing literature on gaps in the measurement of bank stability.[1] To this end, following Avkiran and Cai (2014) and Wanke et al., (2015, 2016), we adopt a CAMELS–DEA scoring system as a stability indicator. To predict financial distress from firm characteristics, existing studies have largely relied on the Z-score (Altman, 1968; Altman et al., 1977), which reflects the probability of bank failure. However, Shaddady and Moore (2019) note that additional sources of risk, such as market risk or management risk sensitivity, are not included in the Z-score because it is based purely on accounting and auditing variables in its construction. As a result, the CAMELS rating system categories appear to play an important role in bank failure detection due to their ability to include the total functionality of the bank (Avkiran & Cai, 2014; Männasoo & Mayes, 2009). To date, there is little empirical literature on combining CAMELS and DEA to detect bank failures and thus measure their stability.

Our study contributes to the literature in terms of theoretical and methodological aspects. First, this study is the first to examine the nonlinear effects of liquidity risk on financial stability under different levels of income diversification. To the best of our knowledge, previous studies have examined the relationship between only two of the three variables without ever combining them in a single model. To fill this gap, we consider the effects of income diversification on the relationship between liquidity risk and bank stability.

Second, existing studies primarily assume linear relationships between variables and employ linear approaches that reflect the average behavior of the sample under the assumption of homogeneity of the link between liquidity risk and bank stability. However, linear models fail to identify the limitations of possible improvements in expected outcomes from the expansion of priors (Busse et al., 2016). In this regard, estimates derived from linear models can lead to misleading interpretations, incorrect theoretical propositions, and flawed management recommendations (Latan et al., 2018). To address this issue, rather than relying on a single description of the central sample behavior, this study contributes to the existing literature by exploring the nonlinear relationship between liquidity risk and bank stability under different degrees of income diversification using the more flexible and reliable panel smooth transition regression (PSTR) model developed by González et al. (2005). Our study has the advantage of showing the presence of regime-switching behavior in the relationship between liquidity risk and bank stability and that the effects of this relationship vary and depend on their positioning (i.e., below, or above) the threshold levels of income diversification. Therefore, the PSTR model could be a useful method to provide an accurate picture on the overall interaction between the variables considered as it reveals the intricacy of the relationships between liquidity risk, bank stability, and income diversification that would be difficult to obtain with traditional econometric approaches (Lahouel et al., 2022a). Unlike polynomial models, PSTR overcomes any prior constraints (e.g., linear forms) on the relationship between variables, making it a more intuitive and reliable framework (Cheikh & Zaied, 2020; Namouri et al., 2018) capable of accurately capturing the impacts of liquidity risk on bank stability. Furthermore, the PSTR model allows capturing both unobserved and time-invariant bank effects in modeling panel data. In addition, the PSTR frameworks enables for a smooth change of the slope coefficient when switching from one regime to another, as the threshold value of the transition variable is not given a priori but generated endogenously from the model (Lahouel et al., 2022c).

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[1] In this paper, bank stability is conceived as the opposite of bank distress and failure.

Third, unlike previous studies that relied on the Z-score and various financial ratios, we combine CAMELS and DEA to measure bank stability. Indeed, CAMELS components are incorporated as input, output, and carryover variables in the dynamic slacks-based measure (DSBM) model as proposed by Tone and Tsutsui (2010). This represents a contribution to the current theoretical literature on bank efficiency measurement.

The remainder of this paper is organized as follow. Section 2 presents a literature review. Section 3 presents the methodologies employed in this paper. The empirical results are reported in Sect. 4. Robustness tests are presented in Sect. 5. Section 6 concludes the paper.

2 Literature review

2.1 The relationship between liquidity risk and bank stability

Intermediation for financial markets is the specific role of commercial banks through which they create liquidity. Because banks conduct deposit-taking and lending activities to provide market liquidity, they are exposed to liquidity risk (Zheng & Cronje, 2019; Diamond and Rajan, 2000). Liquidity risk can be defined in the context of banks' ability to sell their illiquid assets at market prices in a short period of time and in the context of banks' ability to cover their liquidity needs from depositors' withdrawals. The first liquidity risk is called market liquidity risk while the second is called funding liquidity risk. These two types of risk are complementary because the ease of trading securities leads to the ease of obtaining funds to trade those securities (Marozva, 2015). In this regard, this paper focuses on funding liquidity risk. Therefore, funding liquidity risk is defined as the inability of a bank to meet funding demands for asset increases and immediately meet its obligations without incurring intolerable costs (Drehmann & Nikolaou, 2013); thus, failure to meet this requirement triggers liquidity risk.

As they provide liquidity, banks must be stable because they play a crucial role in financing the economy and supporting economic growth. A financial banking system is stable when it can provide continuous support to the economy. While the stability of financial institutions refers to the absence of stress, the stability of financial markets refers to the absence of excessive asset volatility or crisis (Crockett, 1997). Emphasizing the importance of bank stability, several authors propose applying this concept to assess how well a bank manages liquidity risk (Dietrich & Wanzenried, 2011; Djebali & Zaghdoudi, 2020; Shaddady and Moore, 2019). In fact, Arif and Anees (2012) argue that a bank with good quality assets, high returns, and sufficient capital can nevertheless fail if it does not maintain adequate liquidity.

The number of studies specifically examining the actual impact of liquidity risk on bank stability[2] remains limited. However, the debate is still ongoing because the empirical results are mixed. One group of academics suggests that liquidity risk has a negative impact on bank stability. Several arguments have been put forward in this regard. A highly liquid bank may suffer opportunity costs because liquid assets, such as cash and government securities, have a relatively low liquidity premium compared to illiquid assets. As a result, banks' interest margins tend to be negatively affected by increased liquidity. In addition, higher liquidity increases liquidity risk, which leads banks to finance their assets with a higher interest rate in the financial markets (Chen et al., 2018). Therefore, higher liquidity risk is expected to have a negative effect on banks' profitability. In addition, although liquid assets are considered a

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[2] In this study bank stability refers to the risk-return profile of a bank. A bank is called stable when it is financially profitable and less risky.

'buffer' in the event of liquidity shocks, holding high levels of liquid assets can affect the degree of banks' incentive to take risks (Chen et al., 2020). Wagner (2007) theoretically shows that banks with abundant liquidity tend to increase their lending activities, which can lead to bank failure through their increased funding gap. Similarly, Acharya and Naqvi (2012) argue that during a market downturn, commercial banks receive abundant deposits that are transformed into additional loans, which increases liquidity risk. Furthermore, in the presence of deposit insurance, banks pay less attention to the quality of loans, which creates moral hazard that encourages banks to take excessive risks (Chen et al., 2020).

A second group of scholars argue that liquidity risk has a positive influence on bank stability. Berger et al. (1995) suggests that banks with a high level of liquid assets enjoy a better perception in funding markets, which reduces their funding costs and increases their profitability. Kosmidou (2008) finds that banks with low liquidity have a lower return on assets (ROA). Özşuca and Akbostancı (2016) study the behavior of Turkish banks with respect to Turkey's monetary policy risk-taking channels during 2002–2012. They find that large, well-capitalized and liquid banks decrease the probability of their failure.

A third group of studies suggests that liquidity risk may have a nonlinear impact on bank stability. Several researchers suggest that banks should manage the trade-off between short-term income from holding liquid assets and long-term profitability gains from hedging against liquidity shocks. It is necessary to balance profit maximization with sufficient liquidity (Ehiedu, 2014). Bordeleau and Graham (2010) find that profitability is improved for more liquid banks, but there is a point at which holding additional liquid assets decreases bank profitability. They argue that liquidity risk has a nonlinear relationship with bank profitability because banks hold high levels of liquid assets until the opportunity costs of their low relative returns outweigh their marginal benefits. More recently, Djebali and Zaghdoudi apply the PSTR model to examine the effects of liquidity risk and credit risk on banking stability in the MENA region. They find that the relationship between banking stability and the two types of risk is nonlinear and characterized by the presence of two regimes. In the low regime, risks have a positive impact on banking stability. However, their influence becomes detrimental in the high regime.

2.2 The impact of income diversification on bank stability and liquidity risk

In this section, we review the literature to examine why and how income diversification affects liquidity risk and bank stability. There are direct and indirect influences of income diversification on bank stability. Regarding direct effects, following the deregulation in the United States and Europe in the 1980s and after the global financial crisis of 2007–2009, a large body of research has examined the impacts of income diversification on banking stability. Most empirical studies agree that non-interest activities not only generate higher returns, but also additional risk due to their uncertain nature (Lepetit et al., 2008; Moudud-Ul-Huq et al., 2018; Saghi-Zedek, 2016). According to Stiroh (2015), income diversification can have both benefits and costs. One strand of the literature on banking diversification suggests that it improves both profitability and stability. In fact, income diversification is thought to reduce risk concentration and thus the likelihood of financial distress. For example, some studies show, consistent with conventional portfolio theory, that diversification can be efficient and cost-effective because it reduces idiosyncratic risk, improves the risk-return profile by expanding the range of investment opportunities, and reduces the expected cost of financial vulnerability when banking operations are spread across a variety of products and services, such as securities, insurance, foreign exchange, and investment management, as

well as several off-balance-sheet activities (Abedifar et al., 2018; DeYoung & Torna, 2013). Nonetheless, banks can benefit from risk diversification if non-interest income streams are not correlated with interest income. Rather than simply lending funds, income diversification allows banks to benefit from economies of scale, less costly supervision, and more efficient use of management skills (Diamond, 1991; Meslier et al., 2014).

On the contrary, income diversification can be costly because of increased agency problems in diversified activities. Agency conflicts can emerge in large organizations not only because it is difficult to align the incentives of insiders and outsiders, but also because it is not easy to balance interests across divisions and across customers (DeYoung & Torna, 2013; Jensen & Meckling, 1976). Similarly, Laeven and Levine (2007) argue that agency costs, which arise from increasing information asymmetries resulting from over-reliance on non-traditional revenue sources, dominate the benefits of business diversification or economies of scope. Acharya et al. (2006) find that increasing non-interest income decreases financial performance, as diversification reduces incentives to monitor bank loans (resulting in a lower quality loan portfolio and reduced profits). Stiroh and Rumble (2006) find that a higher share of non-interest activities in U.S. financial holding companies improves profitability but also increases risk. Similarly, Williams (2016) finds that diversification into non-interest income worsens the risk-return profile of Australian banks.

Based on this literature, the direct effects of income diversification on bank stability are still undecided. According to Maudos (2017), the benefits of diversification do not necessarily apply to all banks. In this sense, Berger et al. (2010) suggests that bank stability should be non-monotonically related to income diversification, as institutions may be better than others at managing the process of diversification strategies, which determines the level of the risk-return profile.

Diversification could also indirectly influence banking stability through liquidity risk. The mixed results on the impact of income diversification on banking stability produce opposing projections on the link between non-traditional banking activities and liquidity creation. On the one hand, the benefits of diversification tend to stimulate liquidity creation. On the other hand, the potential drawbacks of diversification may mitigate the primary function of banks (Dang, 2020). A recent study by Tran (2020) made two assumptions regarding these two opposing predictions. First, under the diversification-liquidity expansion hypothesis, Tran (2020) suggests that diversified banks are more prone to increasing their liquidity buffers since they enjoy high stable income streams and a low probability of failure. According to portfolio theory, income diversification acts as a risk absorber, since the combination of imperfectly correlated, non-traditional activities is generally expected to reduce the variance of returns. Furthermore, Diamond (1984) suggests that diversified banks experience a more stable supply of credit under aggregate shocks, resulting in less risky cash flows attributed to loan portfolios. As a result, diversified banks with stronger financial bases are expected to create more liquidity, which in turn means assuming additional liquidity risk, as they are better able to meet depositors' demands for withdrawal of funds and provide liquidity to borrowers.

Second, under the diversification-liquidity contraction hypothesis, Tran (2020) suggests that diversification negatively affects liquidity creation, which in turn leads to a decrease in bank liquidity risk. In theory, it is commonly accepted that banks can create liquidity by collecting deposits from their customers and then lending to the economy at an interest rate. Thus, a shift to non-traditional sources of income can destroy this essential function. Hou et al. (2018) argue that the results of diversification do not necessarily translate into risk reduction if managerial expertise is lacking in the newly adopted segments. Therefore, income diversification may disperse organizational skills, increase coordination costs, and

weaken financial stability by failing to meet depositors' demand for liquidity while impeding liquidity creation.

To the best of our knowledge, the empirical literature on the effects of bank diversification on liquidity creation has been surprisingly unnoticed by academics so far, except for related work by Hou et al. (2018), Tran (2020) and Dang (2020). To examine the reciprocal relationship between bank diversification and liquidity creation, Hou et al. (2018) use the panel vector autoregression model and find that income diversification into non-traditional activities reduces bank liquidity creation. Similarly, using a large panel of U.S. bank holding companies from 2001 to 2015, Tran (2020) provides evidence of lower liquidity creation for higher diversification. Finally, using a dataset of Vietnamese commercial banks from 2007 to 2018, Dang (2020) finds that liquidity creation decreases with income from non-traditional banking segments.

Based on the above literature, we show that bank income diversification could have an important influence in exploring the effects of liquidity risk on bank stability. To the best of our knowledge, no study has so far examined the influence of income diversification on the relationship between liquidity risk and bank stability. Our study aims to fill this gap in the literature.

3 Methodology

This study combines the data envelopment analysis (DEA) technique with the CAMELS scoring system to calculate the dependent variable, which is bank stability. Then, bank stability is regressed on liquidity risk and income diversification and other determinants (in a second step), to study the effects of bank diversification on the relationship between liquidity risk and bank stability. The panel smooth transition model (PSTR) is applied for estimation.

The PSTR is increasingly used in recent empirical studies within various disciplines (i.e., environmental economics, management sciences, finance, economics, etc.). For example, Namouri et al. (2018) examined the threshold effects of investor sentiment in stock market. Cheikh and Zaied (2020) explored the threshold effects of inflation on exchange rate pass-through for a set of transition economies. As part of a test of the environmental Kuznets curve (EKC) hypothesis in MENA countries, Lahouel et al. (2021) used the PSTR model to study the elasticity of income on environmental performance with respect to the decomposing factors of green productivity growth. Their findings show the presence of a double threshold when technical change and scale change are taken as transition variables, then leading to an inverted N-shaped curve between country income and environmental performance. More recently, Lahouel et al. (2022b) used the PSTR model to examine the nonlinear impacts of environmental sustainability on firm competitiveness, using an efficiency perspective. Lahouel et al. (2022a, 2022b, 2022c) examined the potential regime switching behavior and the nonlinear relationship between environmental corporate social responsibility and financial performance using the PSTR model. In the banking sector, Lahouel et al. (2022a) employed the PSTR model to examine the threshold effects of income diversification on bank stability. They find that higher levels of income diversification worsen bank stability in the European context.

3.1 Bank stability: a CAMELS–DEA approach

DEA is a non-parametric frontier approach originally developed by Charnes et al. (1978) to evaluate the efficiency of a set of decision-making units (DMUs). DEA has the advantage of

not assuming a prior functional form for the production process unless a simple assumption of piecewise linear connections of DMUs on the frontier is made. DEA has become one of the most widely used methods for measuring bank efficiency (Antunes et al., 2021; Fukuyama & Weber, 2017).

DEA has become a valuable technique for bank regulators, particularly when they seek to identify best and worst practices within a group of banks (Avkiran & Cai, 2014; Kaffash et al., 2018). The first step in DEA is to establish the vectors of inputs and outputs. Then, the analyst should identify the appropriate DEA model. Traditional DEA models (i.e., CCR and BCC[3]) deal with the measurement of the relative efficiency of DMUs regarding multiple inputs and multiple outputs. The CCR and BCC are radial models because they measure the radial efficiency of inputs (input-oriented) or outputs (output-oriented) by assessing the ratio of inputs to be contracted or the ratio of outputs to be increased for the evaluated DMU to become efficient. One limitation of radial models is that radial efficiency does not account for all the inefficiency of a DMU (Lahouel et al., 2022b). Slacks must be considered simultaneously with radial efficiency to identify the "true" projection of a DMU. To overcome this issue, Tone (2001) developed the non-radial model called slacks-based measure (SBM), which uses the term "slacks" to illustrate the excesses of inputs and the shortfalls of outputs and deals with them directly. However, the SBM model is static as it analyses a single moment in time. It uses data from the years independently of each other, with efficiency calculated for each year separately. To remedy this problem, Tone and Tsutsui (2010) developed the dynamic slacks-based measure (DSBM) model to measure changes in efficiency over time through carry-over variables that connect the production function in two consecutive periods. Tone and Tsutsui (2010) state that future levels of inputs and outputs are influenced by these carryovers, which act as intermediate inputs or outputs.

Our DEA model uses the variables representing the CAMELS rating system as a starting point to define the inputs and outputs to be used in this study. Although the CAMELS rating system is valued by regulators and supervisors to monitor bank stability, the initial variables used in its determination are not publicly disclosed (Jin et al., 2011). Therefore, we select the proxy for each category based on the availability of data in the Bankscope database and with reference to previous studies. The CAMELS acronym indicates capital adequacy (C), asset quality (A), management efficiency (M), earnings (E), liquidity (L), and sensitivity to market risk (S). We apply the methodology used by Wanke et al., (2015, 2016) to emulate the CAMELS rating system under the DSBM model. As a result, capital adequacy (C) is captured by total equity and is treated as a desirable output in DSBM because more equity is likely to reduce financial distress. Asset quality (A) is proxied by loan loss reserves, which is treated as un undesirable carry-over (input) to be minimized because less loan loss reserves means less financial distress. Likewise, management efficiency (M), which is proxied by total non-interest expenses, is treated as an undesirable input. Earnings (E), treated as a desirable carry-over (output), is proxied by total net income. Liquidity (L) is treated as a desirable output and is proxied by the level of liquid assets. Finally, sensitivity to market risk (S) is an additional desirable output, which is proxied by total assets because it has been documented in previous studies that total assets are negatively related to default risk (Avkiran & Cai, 2014; Wanke et al., 2015). Our CAMELS–DEA model is estimated by solving the linear programming problem as shown in Fig. 1.

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[3] CCR and BCC are the initial DEA models that were developed by Charnes et al. (1978) and Banker et al. (1984). While the former considers the constant return to scale (CRS) assumption, the latter overcomes this drawback and introduce the variable return to scale (VRS).
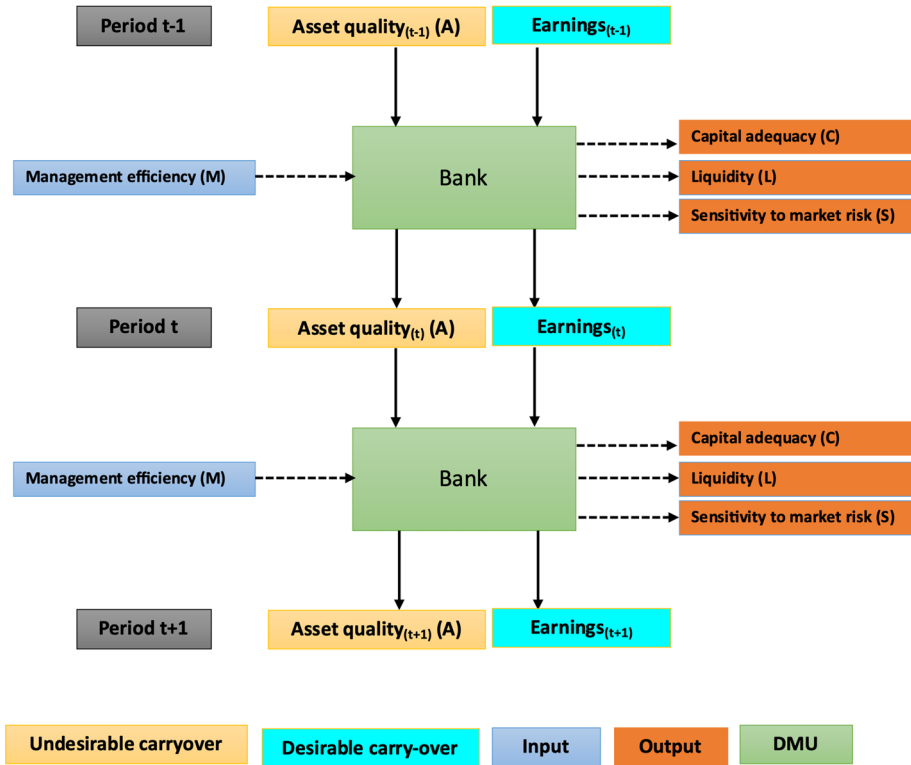
Fig. 1 CAMELS–DEA under the DSBM model

We consider n DMUs ($j = 1,…,n$) over T time periods ($t = 1,…,T$). At each term, DMUs have common m inputs ($i = 1,…,m$), p non- discretionary (fixed) inputs ($i = 1,…,p$), s outputs ($i = 1,…,s$) and r non-discretionary (fixed) outputs ($i = 1,…,r$). Let $x_{ijt}(i = 1,…,m)$, $y_{ijt}(i = 1,…,p)$, and $y_{ijk}^{fix}(i = 1,…,r)$ denote the observed (discretionary) input, non-discretionary input, (discretionary) output and non-discretionary output values of DMU j at term t, respectively. We symbolize the four-category links as z^{good}, z^{bad}, z^{free}, $and z^{fix}$. In order to identify them by term (t), DMU (j) and item (i), we employ, for example, the notation z_{ijk}^{good} ($i = 1,…,ngood; j = 1,…,n; t = 1,..., T$) for denoting good link values where $ngood$ is the number of good links. These are all observed values up to the term T. The production possibilities $\{x_{it}\}$, $\left\{x_{it}^{fix}\right\}$, $\{y_{it}\}$, $\left\{y_{it}^{fix}\right\}$, $\left\{z_{it}^{bad}\right\}$, $\left\{z_{it}^{good}\right\}$, $\left\{z_{it}^{free}\right\}$, $\left\{z_{it}^{fix}\right\}$, are defined by:

$$x_{it} \geq \sum_{j=1}^{n} x_{ijt}\lambda_j^t \qquad (i = 1, ..., m; t = 1, ..., T)$$

$$x_{it}^{fix} = \sum_{j=1}^{n} x_{ijt}^{fix}\lambda_j^t \quad (i = 1, ..., p; t = 1, ..., T)$$

$$y_{it} \leq \sum_{j=1}^{n} y_{ijt}\lambda_j^t \qquad (i = 1, ..., s; t = 1, ..., T)$$

$$y_{it}^{fix} = \sum_{j=1}^{n} y_{ijt}^{fix}\lambda_j^t \quad (i = 1, ..., r; t = 1, ..., T)$$

$$z_{it}^{good} \leq \sum_{j=1}^{n} z_{ijt}^{good}\lambda_j^t \quad (i = 1, ..., ngood; t = 1, ..., T) \qquad (1)$$

$$z_{it}^{bad} \geq \sum_{j=1}^{n} z_{ijt}^{bad}\lambda_j^t \quad (i = 1, ..., nbad; t = 1, ..., T)$$

$$z_{it}^{free} : free \qquad (i = 1, ..., nfree; t = 1, ..., T)$$

$$z_{it}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix}\lambda_j^t \quad (i = 1, ..., nfix; t = 1, ..., T)$$

$$\sum_{j=1}^{n} \lambda_j^t = 1 \qquad (t = 1, ..., T)$$

where $\lambda^t \in R^n (t = 1,...,T)$ is the intensity vector for the term t. The last constraint corresponds to the variable returns-to-scale assumption. If we delete these constraints, we have the constant returns-to-scale model. The continuity of link flows between terms t and $t + 1$ can be ensured by the following condition:

$$\sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_j^t = \sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_j^{t+1} \quad (\forall i; t = 1, ..., T - 1) \qquad (2)$$

where the symbol α designates fix, good, bad, fix, or free.

Using these expressions for production, we can express DMUo ($o = 1,..., n$) as follows:

$$x_{iot} = \sum_{j=1}^{n} x_{ijt}\lambda_j^t + s_{it}^- \qquad\qquad (i = 1, ..., m; t = 1, ..., T)$$

$$x_{iot}^{fix} = \sum_{j=1}^{n} x_{ijt}^{fix}\lambda_j^t \qquad\qquad (i = 1, ..., p; t = 1, ..., T)$$

$$y_{iot} = \sum_{j=1}^{n} y_{ijt}\lambda_j^t - s_{it}^+ \qquad\qquad (i = 1, ..., s; t = 1, ..., T)$$

$$y_{iot}^{fix} = \sum_{j=1}^{n} y_{ijt}^{fix}\lambda_j^t \qquad\qquad (i = 1, ..., r; t = 1, ..., T)$$

$$z_{iot}^{good} = \sum_{j=1}^{n} z_{ijt}^{good}\lambda_j^t - s_{it}^{good} \qquad\qquad (i = 1, ..., ngood; t = 1, ..., T)$$

$$z_{iot}^{bad} = \sum_{j=1}^{n} z_{ijt}^{bad}\lambda_j^t + s_{it}^{bad} \qquad\qquad (i = 1, ..., nbad; t = 1, ..., T)$$

$$z_{iot}^{free} = \sum_{j=1}^{n} z_{ijt}^{free}\lambda_j^t + s_{it}^{free} \qquad\qquad (i = 1, ..., nfree; t = 1, ..., T)$$

$$z_{iot}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix}\lambda_j^t \qquad\qquad (i = 1, ..., nfix; t = 1, ..., T)$$

$$\sum_{j=1}^{n} \lambda_j^t = 1 \qquad\qquad (t = 1, ..., T)$$

$$s_{it}^- \geq 0, \ s_{it}^+ \geq 0, \ s_{it}^{good} \geq 0, \ s_{it}^{bad} \geq 0 \ and \ s_{it}^{free} : free \ (\forall i; t)$$

$$(3)$$

where s_{it}^-, s_{it}^+, s_{it}^{good}, s_{it}^{bad}, $and \ s_{it}^{free}$ are slacks denoting, respectively, input excess, output shortfall, link access, and link deviation.

According to Tone and Tsutsui (2010), the overall efficiency of DMUo ($o = 1,..., n$), in the non-oriented model with, can be defined by solving the following program:

$$\theta_o^* = \min \frac{\frac{1}{T}\sum_{t=1}^{T} w^t \left[1 - \frac{1}{m+nbad}\left(\sum_{i=1}^{m} \frac{w_i^- s_{it}^-}{x_{iok}^t} + \sum_{i=1}^{nbad} \frac{s_{it}^{bad}}{z_{iot}^{bad}} \right) \right]}{\frac{1}{T}\sum_{t=1}^{T} w^t \left[1 + \frac{1}{s+ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{it}^+}{x_{iok}^t} + \sum_{i=1}^{ngood} \frac{s_{it}^{good}}{z_{iot}^{good}} \right) \right]} \qquad (4)$$

subject to (2) and (3), where w^t, w_i^-, and w_i^+ are the weights to term t, input i, output i, which are supplied exogenously according to their importance and satisfy the conditions as

$$\sum_{t=1}^{T} w^t = T, \ \sum_{i=1}^{m} w_i^- = m, \ and \ \sum_{i=1}^{s} w_i^+ = s, \ respectively. \qquad (5)$$

This model deals with excesses in input resources and undesirable (bad) links and shortfalls in output products and desirable (good) links in a single unified scheme. Using an optimal solution $\{\lambda_o^{t*}\}$, $\{s_{ot}^{-*}\}$, $\{s_{ot}^{+*}\}$, $\{s_{ot}^{good*}\}$, $\{s_{ot}^{bad*}\}$, $\{s_{ot}^{free*}\}$, to (4), (2), and (3), the non-oriented term efficiency is defined by:

$$\theta_{ot} = \min \frac{1 - \frac{1}{m+nbad}\left(\sum_{i=1}^{m} \frac{w_i^- s_{iot}^{-*}}{x_{iot}} + \sum_{i=1}^{nbad} \frac{s_{it}^{bad*}}{z_{iot}^{bad}} \right)}{1 + \frac{1}{s+ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{iot}^{+*}}{y_{iot}} + \sum_{i=1}^{ngood} \frac{s_{it}^{good*}}{z_{iot}^{good}} \right)} (t = 1, \ldots, T) \qquad (6)$$

For the sake of simplicity several details of the DSBM have been omitted in this section. They can be obtained from Tone and Tsutsui (2010).

3.2 Sample selection and data specification

The objective of this study is to examine how income diversification affects the relationship between liquidity risk and banking stability. We adopt a balanced panel dataset of 176 European banks over the period 2010–2019. The dataset is mainly obtained from the Bankscope database and covers commercial banks established in 32[4] European countries.

There are several reasons for choosing this sample. The first reason is to isolate the effects of the global financial crisis of 2007–2009. The second reason is related to the availability and accessibility of data prior to the year 2010. Thus, after eliminating missing values and outliers, our sample consists of a balanced panel of 1760 bank-year observations. The third reason is that, in EU countries, non-financial firms are more dependent on bank credit as a source of financing than in another context, such as the United States, where financial markets play a predominant role in financing firms. The final reason concerns the intrinsic characteristics of the European banking system. Although it appears to be structurally homogeneous, it is nevertheless composed of banks with important operational differences and different resilience capacities to risk (Galletta & Mazzù, 2019).

Table 1 presents the descriptive statistics for the variables used in our econometric model (see Sect. 3.3). The dependent variable, financial stability (FINSTAB) is measured by the CAMELS–DEA rating system using the DSBM model of Tone and Tsutsui (2010). The DSBM is executed for the period 2010–2019 and the efficiency scores are calculated separately for each year. The annual average efficiency scores, which are used as a measure of bank financial stability, are reported in Table 6 of the appendix. For the explanatory variable Liquidity risk (LIQR), we follow Saunders and Cornett (2006) and use the 'financing gap' method, which is defined as the difference between average bank loans and average bank core deposits. DeYoung and Jang (2016) reported that the funding gap is in line with the spirit of the Basel III net stable funding ratio (NSFR) regulation that banks hold sufficient stable funding (e.g., core deposits) to fully fund their illiquid assets (e.g., loans). Accordingly, to obtain a meaningful analysis, the funding gap is normalized by total average assets and is calculated as follows:

$$FGR = \frac{AL - ACD}{ATA} \tag{7}$$

where FRG denotes the financing gap ratio that measures LIQR, AL denotes the average loans, ACD denotes the average core deposits, and ATA denotes the average total assets. According to Saunders and Cornett (2006) a higher value of FGR indicates a greater degree of liquidity risk to which the bank is exposed.

For the second explanatory variable, income diversification (DIV), we follow the previous literature and consider the structure of income statements (e.g., Lahouel et al., 2022a; Lepetit et al., 2008; Saghi-Zedek, 2016; Stiroh & Rumble, 2006) by calculating the adjusted Herfindahl–Hirschman Index (AHHI) for all banks in our sample. DIV is calculated as follows:

$$DIV = 1 - \left[\left(\frac{NII}{NOI} \right)^2 + \left(\frac{NNII}{NOI} \right)^2 \right] \tag{8}$$

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

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[4] Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Liechtenstein, Lithuania, Malta, Monaco, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom.

Table 1 Descriptive statistics of variables used in the PSTR model

Variables	Description	N	Mean	SD	Min	Max
Bivariate model						
FINSTAB	Dependent	1,760	.467	.372	0	1
LIQR	Explanatory 1	1,760	3.255	10.411	− 76.383	152.582
DIV	Explanatory 2	1,760	.375	.108	0	0.5
Multivariate model						
SIZE	Control	1,760	16.882	2.024	12.118	21.720
CIR	Control	1,760	8.700	96.553	− 1740.221	2886.074
GROWTH	Control	1,760	6.373	15.168	− 43.33	140.72
CAP	Control	1,760	8.460	3.735	− 5.1	20.82
FUNDS	Control	1,760	55.099	4.790	− 85.72	30.64
BM	Control	1,760	72.496	18.085	3.13	334.345
LOANR	Control	1,760	.068	.223	0	6.067
LOANQ	Control	1,760	1.042	2.607	− 2.53	78.56
ROA	Control	1,760	.747	3.944	− 135.22	44.48
MTB	Control	1,760	1.016	1.373	− 11.03	18.64

FINSTAB is bank financial stability measured by the dynamic network slacks-based measure model. LIQR denotes liquidity risk and is measured using the "financing gap" ratio method: $FGR = \frac{AL-ACD}{ATA}$, with AL the average loan, ACD the average core deposits, and ATA the average total assets. DIV 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). SIZE denotes the bank size measured by the natural logarithm of bank total assets, CIR denotes cost efficiency proxied by the cost-to-income ratio and measured the ratio of operating costs to total operating income, GROWTH denotes the growth rate of bank total assets, CAP denotes bank capitalization measured by the ratio of total equity to total assets, FUNDS denotes the bank funding structure measured by the ratio of total customer deposits to total assets, BM denotes the denotes the bank business model measured by the ratio of total loans to total assets, LOANR denotes loan risk and is measured by the ratio of non-performing loans to total loans, LOANQ denotes loan quality and is measured by the ratio of loan loss provisions to total loans, ROA denotes return on assets and is measured as the ratio of net income to total assets, MTB denotes the market-to-book ratio to control for the market financial performance

Looking at the indicators of interest, we could realize some notable features of the European banking industry. Financial stability has an average of 46.7% with a large standard deviation suggesting that CAMELS–DEA rating system varies widely across banks. There is a considerable difference in liquidity risk across banks. By construction the AHHI values vary from zero and a half. When income diversification reaches its minimum, the AHHI is equal to zero and when there is a complete diversification, the AHHI is equal to a half. Hence, DIV is about 0.375 on average, which means that the European banks are increasingly diversified with a further focus on nontraditional banking activities. Regarding the control variables, it is shown that the cost-to-income ratio (CIR) and the ratio of total deposits to total assets (BM) are characterized by a higher dispersion, which dispersion clearly shows that we are investigating the effect of liquidity risk on bank stability using an heterogenous panel data.
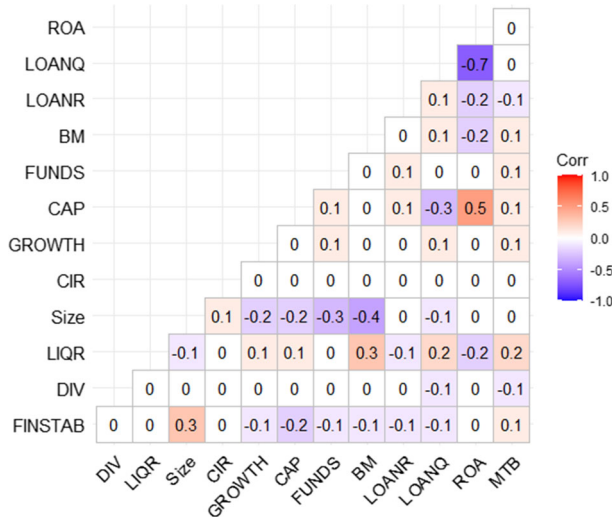
Fig. 2 Correlation matrix

The cross-correlation matrix between the variables is illustrated in Fig. 2. It shows the absence of any correlation between the dependent variable (FINSTAB) and the two variables of interest (DIV and LIQR). For control variables, only a negative correlation is detected between LOANQ and ROA, and a positive correlation between CAP and ROA.

To examine the possible nonlinear relationships between liquidity risk and bank stability under different levels of income diversification, we use an econometric technique that is more suitable for nonlinear relations, namely the panel smooth transition regression (PSTR) model. Compared to the abrupt transition of Hansen's (1999) panel threshold regression model, the PSTR is more general without any restrictions on the transition function. This transition function in Hansen's (1999) regression model depends only the threshold level and the transition variable. The advantage of the PSTR model is that it adds a variable that captures the speed of the transition between the regimes, which ensures smoothing in most cases.

Following González et al. (2005), who extended the Hansen's (1999) panel threshold regression (PTR) model, this study adopts a two-regime PSTR model with fixed effects as follows:

$$FINSTAB_{i,t} = a_i + b_1 LIQR_{i,t} + c_1 DIV_{i,t}$$
$$+ \left(b_2 LIQR_{i,t} + c_2 DIV_{i,t} + \right) \times G\left(DIV_{it}; \gamma, c \right) + \varepsilon_{i,t} \quad (9)$$

for $i = 1,\ldots,N$, and $t = 1,\ldots,T$, where N and T stands for cross-section and time dimensions of the panel, respectively. $FINSTAB_{i,t}$, $LIQR_{i,t}$ and $DIV_{i,t}$ and denote bank financial stability, liquidity risk and income diversification, respectively. $\varepsilon_{i,t}$ is the error term. The transition function $G\left(DIV_{i,t}; \gamma, c \right)$, that drives the nonlinear dynamics between $LIQ_{i,t}$ and $FINSTAB_{i,t}$, is a continuous function of the transition variable $DIV_{i,t}$ and it is bounded between 0 and 1, where c denotes the location parameter (i.e., the threshold level) and the slope parameter γ determines the speed of the transition across regimes.

The PSTR model (Eq. 9) considers two extreme regimes that are linked with high and low values of $DIV_{i,t}$. Moreover, González et al. (2017) consider that $G\left(DIV_{i,t}; \gamma, c \right)$ is to be

evaluated via the logistic transition function as follows:

$$G(DIV_{it}; \gamma, c) = \left[1 + exp(-\gamma(DIV_{it-1} - \theta))\right]^{-1} \tag{10}$$

where parameter θ is the estimated threshold value.

The empirical procedure consists of a series of tests to show whether a nonlinear relationship exists between variables. The procedure for testing the null hypothesis of linearity against a PSTR model is described in González et al. (2005, 2017). However, 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. These nuisance parameters are then solved, in line with Hansen (1999) and González et al. (2017) in respectively time series and panel data contexts, by replacing the transition function $G(q_{it}; \gamma, c)$ by its first-order Taylor expansion around the null hypothesis $\gamma = 0$.[5]

To test the linearity against the PSTR model with two regimes, we, first, use the χ^2 LM test version (LM_χ) and the Fisher LM test (LM_F). Their statistics are defined as follows:

$$LM_\chi = \frac{TN(SSR_0 - SSR_1)}{SSR_0} \tag{11}$$

$$LM_F = \frac{TN(SSR_0 - SSR_1)/k}{SSR_0/(TN - N - k)} \tag{12}$$

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[6] (HAC_X) and (HAC_F) for both χ^2 and Fisher tests, respectively.

4 Empirical results

4.1 Panel unit root tests

According to González et al. (2005, 2017),[7] before estimating the PSTR model, it is required to test the stationarity of each variable in the model. In the present study we employ the two first-generation unit root tests which assume the existence of cross-sectional independence, Levin et al. (2002) (LLC) test and the Im et al. (2003) (IPS) test. The results of these two tests are presented in Table 2 and shows that our variables are stationary in levels.

4.2 Linearity (homogeneity) and misspecification tests

Once the stationarity of the variables has been tested, the first step in estimating the PSTR model is to check whether or not the regime switching is significant, i.e., whether there is a

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[5] For more details about the procedure please refer to González et al. (2005, 2017).

[6] For more details on these two tests, please refer to González et al. (2017)

[7] The PSTR specification procedures are based on the assumption that all variables in Eq. (1) are I(0) stationary in level (González et al., 2005, 2017).

Table 2 Results of the panel-data unit root tests in level and in first difference

	Description	LLC	LLC (Δ)	IPS	IPS (Δ)
FINSTAB	Dependent	-2.8179^{***}	-8.081^{***}	-2.0275^{**}	-8.585^{***}
		(0.002)	(0.000)	(0.023)	(0.000)
LIQR	Explanatory 1	2.0163^{**}	-4.1579^{***}	7.754^{**}	2.0925^{***}
		(0.041)	(0.000)	(0.041)	(0.000)
DIV	Explanatory 2	-2.2659^{***}	-6.8251^{***}	6.4239^{**}	-3.548^{***}
		(0.004)	(0.000)	(0.031)	(0.000)
SIZE	Control	-1.0120^{***}	-4.6323^{***}	0.7053^{**}	-10.148^{***}
		(0.09)	(0.000)	(0.028)	(0.000)
CIR	Control	-2.0998^{***}	-6.1255^{***}	-3.527^{***}	-9.103^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
GROWTH	Control	-3.0426^{***}	-5.615^{***}	-0.293^{**}	-9.086^{***}
		(0.0004)	(0.000)	(0.034)	(0.000)
CAP	Control	-0.0179^{***}	-10.701^{***}	-1.892^{**}	-10.192^{***}
		(0.002)	(0.000)	(0.032)	(0.000)
FUNDS	Control	1.3763	-4.989^{***}	10.754^{**}	-2.018^{***}
		(0.145)	(0.000)	(0.041)	(0.000)
BM	Control	-0.1059^{***}	$-148,251^{***}$	3.4239^{**}	-6.548^{***}
		(0.004)	(0.000)	(0.039)	(0.000)
LOANR	Control	-0.0120^{***}	-3.6323^{***}	0.7753^{**}	-9.8480^{***}
		(0.006)	(0.000)	(0.028)	(0.000)
LOANQ	Control	-4.0991^{***}	-7.185^{***}	-2.587^{***}	-10.263^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
ROA	Control	-3.046^{***}	-7.155^{***}	-0.009^{**}	-9.016^{***}
		(0.0000)	(0.000)	(0.024)	(0.000)
MTB	Control	-3.125^{***}	-8.1055^{***}	-2.125^{***}	-8.061^{***}
		(0.000)	(0.000)	(0.000)	(0.000)

FINSTAB is bank financial stability measured by the dynamic network slacks-based measure model. LIQR denotes liquidity risk and is measured using the "financing gap" ratio method: $FGR = \frac{AL-ACD}{ATA}$, with AL the average loan, ACD the average core deposits, and ATA the average total assets. DIV 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). SIZE denotes the bank size measured by the natural logarithm of bank total assets, CIR denotes cost efficiency proxied by the cost-to-income ratio and measured the ratio of operating costs to total operating income, GROWTH denotes the growth rate of bank total assets, CAP denotes bank capitalization measured by the ratio of total equity to total assets, FUNDS denotes the bank funding structure measured by the ratio of total customer deposits to total assets, BM denotes the denotes the bank business model measured by the ratio of total loans to total assets, LOANR denotes loan risk and is measured by the ratio of non-performing loans to total loans, LOANQ denotes loan quality and is measured by the ratio of loan loss provisions to total loans, ROA denotes return on assets and is measured as the ratio of net income to total assets, MTB denotes the market-to-book ratio to control for the market financial performance. LLC and IPS denote, respectively, Levin et al. (2002) and Im et al. (2003) panel unit root test. *** and ** indicate statistical significance at 1 and 5 percent level of significance, respectively

Table 3 Linearity tests

Dependent variable: FINSTAB

Model	Bivariate model		Multivariate model	
	Statistic	p value	Statistic	p value
(I) Linearity (homogeneity) tests H_0: 1 regime (no transition function) versus H_1: 2 regimes (1 transition function)				
LM_χ	20.34***	0.000	5.212**	0.099
LM_F	4.031***	0.000	2.057**	0.012
HAC_χ	5.150**	0.012	5.317**	0.033
HAC_F	0.826**	0.012	0.011**	0.086
(II) No remaining nonlinearity tests H_0: 2 regimes (1 transition function) versus H_1: 3 regimes (2 transition functions)				
LM_χ	12.15	0.052	50.31	0.113
LM_F	1.048	0.128	4.409	0.119
HAC_χ	12.51	0.221	12.28	0.195
HAC_F	1.995	0.257	1.108	0.316

H_0: linear model; H_1: PSTR model with at least one threshold. FINSTAB is bank financial stability, LM_χ 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 Consistent

*** and ** indicate statistical significance at 1 and 5 percent level of significance, respectively

nonlinear relationship between income diversification, liquidity risk and financial stability. Table 3 shows the results of the linearity tests against the PSTR, as well as the specification tests for the absence of residual nonlinearity. The results indicate that the null hypothesis of linearity can be strongly rejected, thus, providing evidence of nonlinearity between the three variables in the model (bivariate model). As can be seen from Table 3, the LM_χ, LM_F, HAC_X and HAC_F tests reject the linearity between variables at the 1% and 5% significant levels. Accordingly, this result suggests that the influence of income diversification on the relationship between liquidity-risk and bank stability is not constant and monotonic. The impact of liquidity risk on bank stability changes with the different levels taken by income diversification.

Before discussing the estimated results, we need to assess the adequacy of the estimated PSTR model by testing the constancy of the parameters and the absence of remaining non-linearity. Following González et al. (2017), we use additional versions of the HAC test[8] for heteroskedasticity-robustness. The results in Table 3 show that these tests fail to reject the null hypotheses of parameter constancy and no remaining nonlinearity. Therefore, we find that the nonlinear relationship between income diversification, liquidity risk, and financial stability would be best explored by a PSTR model with a single transition function, which is characterized by the presence of two extreme regimes.

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[8] HAC stands for Heteroskedasticity and Autocorrelation Consistency.

4.3 Parameters' estimate

The parameter estimation of our bivariate PSTR model is presented in Table 4 where income diversification (DIV) is considered as the transition variable. The nonlinear least squares (NLS) method was used to estimate the parameters of Eq. (9) after removing individual effects.

In the first extreme regime, when the value of the transition variable (DIV) is less than the estimated threshold value (θ), the transition function approaches zero, and then the coefficients on income diversification and liquidity risk are b_1 and c_1, respectively. In the second regime, the transition function approaches unity when the value of the transition variable is greater than the estimated threshold value (θ). The coefficients of the two explanatory variables are captured by ($b_1 + b_2$) and ($c_1 + c_2$), respectively. The estimated value of the slope parameter $\gamma = 20.09$ is relatively small, suggesting that the transition function is continuous and smooth (see Fig. 3). Therefore, the impacts of income diversification and liquidity risk on bank stability smoothly switch from the first regime to the second regime depending on the threshold level of income diversification. This result is of great importance as it proves that the PSTR model is more reliable than linear models in detecting nonlinear relationships between variables. Moreover, this result is important for policy makers who should consider the degree of income diversification when implementing liquidity creation strategies.

Table 4 Parameter estimation of the PSTR (bivariate model)

Dependent variable: FINSTAB		
	First extreme regime	Second extreme regime
LIQR	0.0025** (0.062)	0.0012*** (0.076)
DIV	− 0.2574** (0.291)	0.01049** (0.212)
Transition's parameters		
Threshold (c)	0.3233*** (0.109)	
Slope (γ)	20.09*** (58.25)	
Standard deviation of the residuals	0.2218	

FINSTAB is bank financial stability measured by the dynamic network slacks-based measure model. LIQR denotes liquidity risk and is measured using the "financing gap" ratio method: $FGR = \frac{AL-ACD}{ATA}$, with AL the average loan, ACD the average core deposits, and ATA the average total assets. DIV 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). Between parentheses (.) are standard errors. *** and ** indicate statistical significance at 1 and 5 percent level of significance, respectively
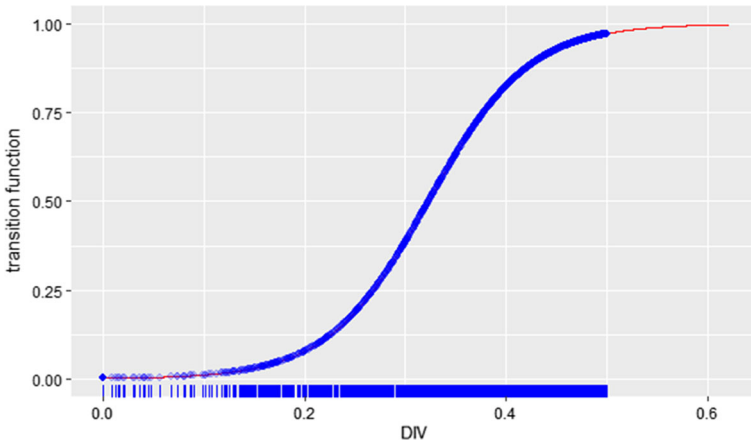
Fig. 3 Estimated transition function of the PSTR model for bank stability in the bivariate model (*Note*: the y axis is the transition function, and the x axis is the transition variable.)

The coefficients on liquidity risk are significantly positive in both regimes, suggesting that, regardless of the level of income diversification, liquidity creation has a positive impact on bank stability. We note that the positive effect of liquidity creation is higher in the first regime than in the second.[9] This result is in accordance with the diversification-liquidity expansion hypothesis put forward by Tran (2020). This means that by taking on the role of liquidity creation, diversified banks are using more of their balance sheets to perform their core functions. At least, two main mechanisms explain our findings. First, income diversification is likely to decrease agency frictions between bank creditors and managers, leading to reduced risk. Indeed, managers who are subject to moral hazard, are called upon to convince outside creditors, they are holding a buffer of safe assets with transparent value in order to promote bank stability. As a result, diversified banks can enhance the credibility of their lending decisions and borrower monitoring by overcoming information asymmetry, as they are able to retrieve borrower information and reuse it cost-effectively for non-interest banking activities (Diamond, 1984). Conversely, credit risk management and financial stability are improved, with stable credit supply and reduced correlation of loan returns, when diversified banks profitably use information from non-traditional banking activities in their lending decisions (Acharya et al., 2006). Second, income diversification is seen as a "buffer" through which banks can ensure their liquidity creation and compensate for the compression of intermediation margin in lending and deposit activities. In that respect, moving away from traditional intermediation activities changes the banks' need to hold liquid assets in order to reduce underinvestment risk. For example, it is common for banks to have to reject profitable loan applications if external funding is expensive, forcing them to hold a buffer of securities that can be liquidated on demand despite the opportunity cost of holding low yielding securities. Diversification could reduce this motive, as it helps reduce the volatility and correlation of financing and investment opportunities by allowing investments to be financed through the internal capital market instead of liquidating securities (Houston et al., 1997; Kashyap & Stein, 2000). Hence, diversification spurs banks' financial stability while creating liquidity for the economy. Therefore, our findings are consistent with those of Chavaz (2017) that diversification gains enable banks to operate with lower liquidity holdings, allowing them to

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[9] $b_1 = 0.0025$ in the first regime and $(b_1 + b_2) = 0.0012$ in the second regime.
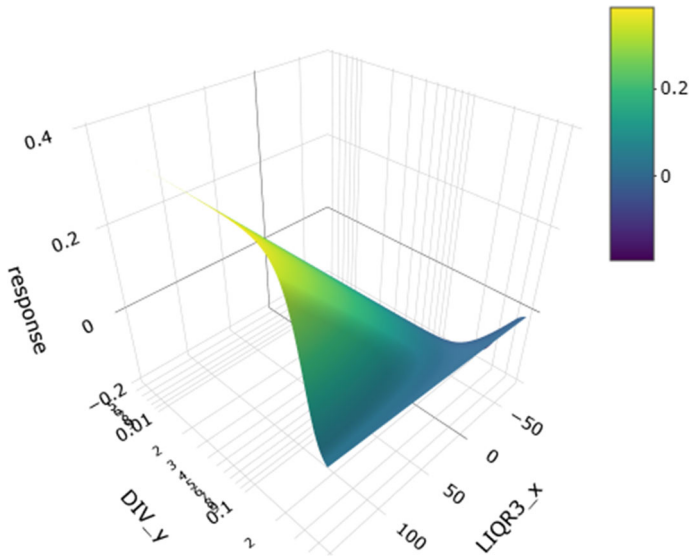
Fig. 4 Response of bank stability to liquidity risk in the bivariate model

use their balance sheets more to fulfill their primary roles of providing credit and creating liquidity. Finally, our results provide consistent evidence that diversified as well as less diversified banks can create liquidity for the economy while maintaining a satisfactory degree of financial stability.

This finding is illustrated graphically in Fig. 4, which shows the way liquidity creation positively impacts bank stability under different levels of income diversification.

Regarding the effect of income diversification on bank stability, Table 4 reports that the relationship between income diversification and bank stability is characterized by the presence of a threshold effect ($\hat{c} = 0.3233$). The estimation shows that income diversification exerts a negative and significant effect on bank stability below the optimal threshold, while this effect becomes positive and significant for high levels of income diversification. Therefore, the relationship between income diversification and bank stability can be described by a U-shaped curve, as shown in Fig. 5. However, this result should be interpreted with caution because Fig. 5 shows that the effect of diversification is negative overall and only becomes positive on the extreme right side of the spectrum. The U-shaped relationship does not mean that all banks with a diversification level below the threshold level benefit from diversification. Therefore, the main impact of diversification on bank stability is negative. This result is consistent with previous studies that argue that high levels of non-interest-based activities worsen the risk-return profile. For instance, our results corroborate those of Nguyen et al. (2012) that income diversification has no clear value-added and that higher levels of revenues from nontraditional banking activities are related to worse risk-adjusted earnings. We explain our findings as follow. First, many existing empirical studies support the argument that increased agency costs, arising from increasing information asymmetries, dominate any benefits from income diversification or economies of scope (e.g., Lahouel et al., 2022a; Lepetit et al., 2008). However, although we noted earlier that income diversification can reduce agency costs between creditors and bank managers, our results support the evidence
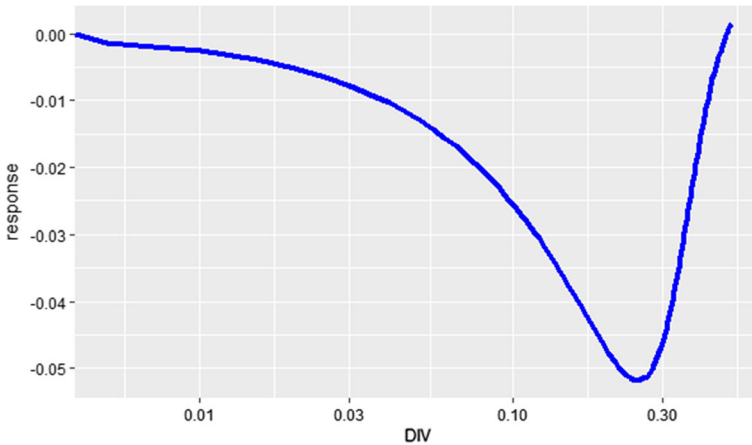
Fig. 5 Response of bank stability to income diversification in the bivariate model

of increased agency conflicts resulting from managers' discretionary decisions to undertake value-reducing investments (Berger & Ofek, 1995) when it is difficult to align insider and outsider incentives. It is very likely that the private benefits that managers obtain from diversification exceed their private costs. Thus, an inefficient diversification strategy, even one that leads to a deterioration in shareholder value (risk-shifting and suboptimal investment problems), can be adopted and maintained by managers. Indeed, managing a diversified bank provides certain advantages to managers such as power and prestige, entrenchment, and compensation arrangements, as well as reduced risk in managers' non-diversified personal portfolios (Tran, 2020). Second, although the recommendations on restricting the non-interest activities of commercial banks following the post-crisis regulatory reforms in Europe (e.g., Basel III requirements), the significant negative effects of income diversification on bank stability can be, in part, explained by the various quantitative easing programs launched by the European Central Bank since 2008. To put it quite plainly, the downward trend in long-term interest rates after the global financial crisis has influenced the behavior of European banks, which have turned away from less profitable and less attractive financial intermediation activities to non-interest generating activities. As a result, it is very likely that increased competition for non-interest income sources will lead to market share saturation in this market segment, making European banks more fragile in terms of profitability and solvency. Bank stability may be jeopardized because increased competition may undermine the relationships between banks and customers that arise from lending activity and reduce the ability of banks to internalize the benefits of building these relationships, thereby creating incentives for banks to impose greater credit rationing.

5 Robustness check

To examine the robustness of our PSTR model presented in the previous section, we perform an additional analysis to assess the sensitivity of our results to an alternative model. It is important to note that omission variable bias could be raised when applying a bivariate PSTR model (Chiu & Lee, 2019).

Thus, consistent with Lahouel et al. (2022a), we introduce into the regressions the vector $X_{i,t}$ of control variables that are related to the characteristics of the banks and that can influence the relationships between the initial variables of the bivariate model. We add the natural logarithm of total assets to account for bank size (SIZE), the cost-to-income ratio (CIR) to measure the bank cost efficiency, the annual growth in total assets as a proxy of bank growth (GROWTH), the equity-to-total assets ratio expressing bank capitalization (CAP), the ratio of total deposits to total assets to account for the funding structure (FUNDS), the ratio of total loans to total assets to control for bank's business model (BM), then ratio of non-performing loans to total loans to control for loan risk (LOANR), the ratio of loan loss provisions to total loans to account for loan quality (LOANQ), the return on assets ratio to account for bank accounting financial performance (ROA), and the market-to-book ratio to control for the market financial performance (MTB). In addition, Following González et al. (2005), we introduce a set of year dummies to capture the exogenous macroeconomic shocks, attributed to the 2010–2011 European sovereign debt crisis, that might impact the dependent variable bank stability. Indeed, the financial stability of European banks was largely affected by sovereign debt problems in many EU countries after the global financial crisis of 2007–2008 (Roulet, 2018).

The panel fixed effects multivariate PSTR model can be written as follows:

$$FINSTAB_{i,t} = a_i + \pi d_t + b_1 LIQR_{i,t} + c_1 DIV_{i,t} + + \left(b_2 LIQR_{i,t} + c_2 DIV_{i,t} +\right)$$
$$\times G\left(DIV_{it}; \gamma, c\right) + \sum_{j=1}^{p} \theta_j X_{i,t}^{j} + \varepsilon_{i,t}$$
(13)

where d_t denotes the vector of year dummies.

Table 5 reports the results for the multivariate model and shows the presence of a regime switching behavior of all variables under different levels of income diversification (see Fig. 6). Our findings suggest that the impacts of the omission variable bias are important in our study. Indeed, the multivariate model confirmed the estimated coefficients of liquidity risk obtained from the bivariate PSTR model in Table 4 (see Fig. 7). In addition, the multivariate model provides better illustration of the actual impacts of income diversification on bank stability. Results in Table 5 confirm our first impression about the negative influence of income diversification on bank stability. Now, we can clearly see that income diversification has a negative and significant effect on bank stability in both regimes (see Fig. 8). Also, Table 5 presents the coefficient estimates of the year dummies. The coefficient estimates suggest the presence of exogenous shocks attributed to the 2010–2012 European sovereign debt crisis. Indeed, Table 5 shows that European banks' financial stability has been negatively and significantly affected by the propagation of the European debt crisis that occurred in late 2009. In particular, the effects of the crisis began to take effect in Europe at the beginning of 2010 and lasted until 2012. However, the negative effects of this exogenous shock on financial stability become insignificant from 2013 where for the first time since 2007 and for all the public accounts of the euro zone, the debt fell in 2013, heralding an end to the crisis.

Table 5 Parameter estimation of the PSTR model (multivariate model)

Dependent variable: FINSTAB			
	First extreme regime	Second extreme regime	Fixed effect model
LIQR	0.0041** (0.062)	0.0019*** (0.076)	–
DIV	− 0.2782* (0.291)	− 0.05075** (0.212)	–
SIZE			0.1085 (0.022)
CIR	–	–	0.0001 (0.000)
GROWTH	–	–	0.0001 (0.0006)
CAP	–	–	0.0137** (0.006)
FUNDS	–	–	0.0007 (0.001)
BM	–	–	0.009*** (0.014)
LOANR	–	–	− 0.059*** (0.039)
LOANQ	–	–	− 0.003*** (0.005)
ROA	–	–	0.007*** (0.004)
MTB	–	–	0.0142** (0.007)
Yr_2010	–	–	− 0.081*** (0.032)
Yr_2011	–	–	− 0.145* (0.023)
Yr_2012	–	–	− 0.123** (0.023)
Yr_2013	–	–	0.003 (0.031)
Yr_2014	–	–	− 0.071 (0.042)
Yr_2015	–	–	− 0.023 (0.025)
Yr_2016	–	–	− 0.028 (0.012)
Yr_2017	–	–	− 0.047 (0.041)
Yr_2018	–	–	− 0.053 (0.021)

Table 5 (continued)

| Dependent variable: FINSTAB			
	First extreme regime	Second extreme regime	Fixed effect model
Yr_2019	–	–	− 0.021 (0.044)
Threshold (c)	0.324*** (0.052)		
Slope (γ)	20.09*** (58.25)		
Standard deviation of the residuals	0.2218		

Note: FINSTAB is bank financial stability measured by the dynamic network slacks-based measure model. LIQR denotes liquidity risk and is measured using the "financing gap" ratio method: $FGR = \frac{AL-ACD}{ATA}$, with AL the average loan, ACD the average core deposits, and ATA the average total assets. DIV 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). SIZE denotes the bank size measured by the natural logarithm of bank total assets, CIR denotes cost efficiency proxied by the cost-to-income ratio and measured the ratio of operating costs to total operating income, GROWTH denotes the growth rate of bank total assets, CAP denotes bank capitalization measured by the ratio of total equity to total assets, FUNDS denotes the bank funding structure measured by the ratio of total customer deposits to total assets, BM denotes the denotes the bank business model measured by the ratio of total loans to total assets, LOANR denotes loan risk and is measured by the ratio of non-performing loans to total loans, LOANQ denotes loan quality and is measured by the ratio of loan loss provisions to total loans, ROA denotes return on assets and is measured as the ratio of net income to total assets, MTB denotes the market-to-book ratio to control for the market financial performance. ***, **, and * indicate statistical significance at 1, 5, and 10 percent level of significance, respectively. Between parentheses (.) are standard errors
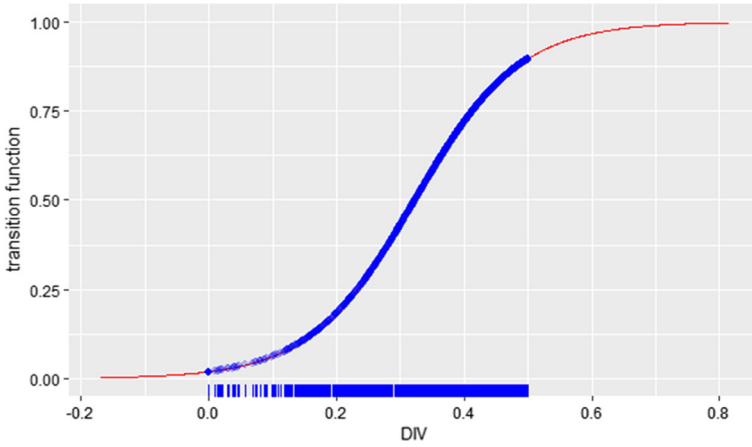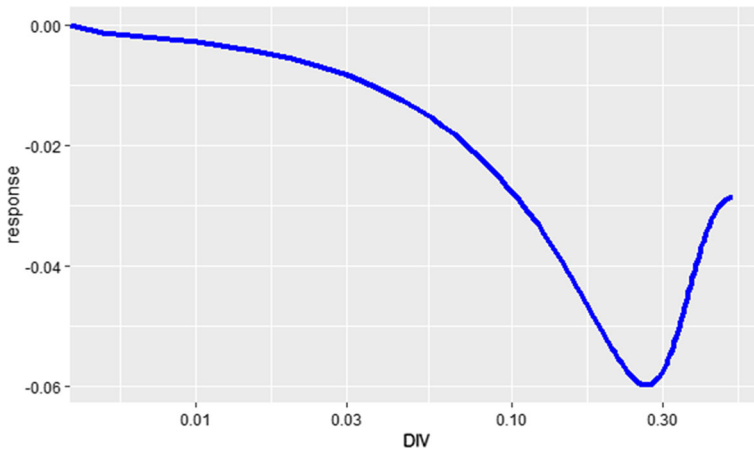
Fig. 6 Estimated transition function of the PSTR model for Bank financial stability (*Note*: the y axis is the transition function, and the x axis is the transition variable.)
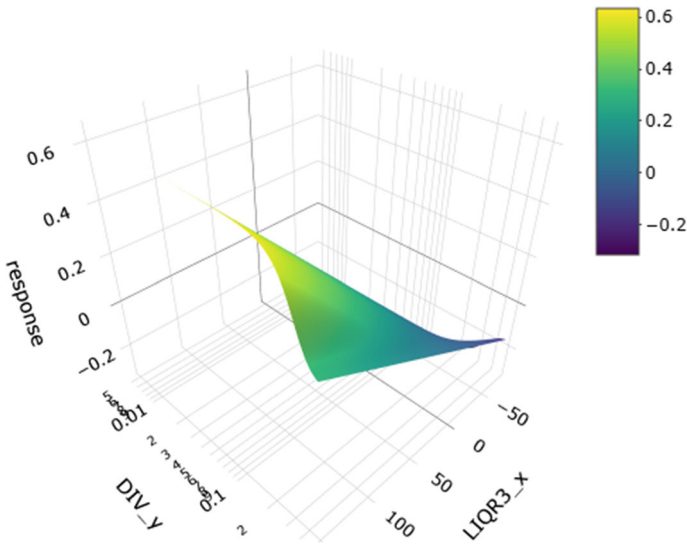
Fig. 7 Response of bank stability to liquidity risk in the multivariate model

Fig. 8 Response of bank stability to income diversification in the multivariate model

6 Conclusions

The debate on the impact of liquidity risk on bank stability has received renewed attention since the recent financial crisis, which led to bank failures around the world. Although this strand of research has emerged strongly recently, a comprehensive framework on how and when liquidity risk affects bank stability remains outstanding. The novelty of this paper is to incorporate income diversification as a third variable that may influence the relationship between liquidity risk and bank stability. Because the results of empirical studies on the relationships between these variables are mixed and sometimes nonlinear, we sought to better understand the threshold effects of income diversification. Therefore, we applied more sophisticated techniques than those used so far, combining the CAMELS–DEA scoring system with the PSTR model to show the nonlinear effects of liquidity risk on bank stability under different levels of income diversification.

Our main empirical findings are summarized as follows. First, liquidity risk stemming from liquidity creation has a positive and significant nonlinear effect on bank stability, regardless of the level of income diversification. We conclude that diversification strategies do not destroy the primary function of commercial banks, which is liquidity creation. On the contrary, diversified banks should have a stable credit supply, which can reduce the volatility of interest income from lending activities. Second, we find that income diversification exerts a negative nonlinear effect on bank stability. Our results are consistent with the prevailing evidence related to the "dark side of diversification", as the combination of interest and non-interest income does not generate any portfolio diversification benefits.

Financial stability is reached when the financial system, which includes financial intermediaries, markets, and market infrastructures, becomes able to withstand shocks and adjust financial unsteadiness. However, it is necessary to distinguish financial instability from simple financial volatility which describes the temporary and low-amplitude fluctuations of financial variables around their average value (generally measured and assessed by the variables' variance). Financial stability has several implications on macroprudential policies because it contributes to the achievement of several macroprudential policies targets. It can prevent the excessive accumulation of risks, linked to external factors and market failures, to smooth the financial cycle. Besides, it aims to strengthen the resilience of the financial sector and

limit contagion effects. Financial stability has a potential impact on fostering a system-wide perspective in financial regulation to create an appropriate set of incentives for market participants.

From a policy perspective, the results of this paper are relevant given the BASEL III capital and liquidity constraints following the global financial crises. The empirical results of this paper suggest that banks that are exposed to higher liquidity risk may have an incentive to diversify further into non-traditional banking activities, as income diversification can serve as a precaution to absorb the liquidity risk that results from liquidity creation. However, while higher levels of income diversification improve bank stability through liquidity creation, they lead to bank failures.

The main limitation of our study is the lack of a market risk and macro-economic controls that should be overcome in future studies. An interesting avenue for future research could be the integration of the network structure provided by the DEA technique when calculating bank stability. A study based on a network dynamic CAMELS–DEA could be of great contribution to the measurement of bank efficiency. Moreover, it will be interesting to consider heterogeneity across banks and take advantage of the possibilities provided by the meta-frontier DEA models. Finally, the PSTR framework may offer many possibilities regarding the use of additional transition variables, such as market competition, market power, bank size, bank lending in terms of loan quality and interest spread, ownership structure, etc.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [BBL], [LT], [YBZ], and [SM]. The current version of the manuscript was written and approved by all authors.

Declarations

Conflict of interests The authors declare that they have no conflict of interests.

Appendix

See Table 6.

Table 6 Efficiency scores

Year	Mean	Min	Max	SD
2010	0.421	0.001	1	0.349
2011	0.388	0.015	1	0.371
2012	0.477	0.007	1	0.368
2013	0.478	0.025	1	0.386
2014	0.434	0.008	1	0.389
2015	0.499	0.019	1	0.370
2016	0.511	0.021	1	0.368
2017	0,549	0.021	1	0.368
2018	0.540	0.021	1	0.367
2019	0.445	0.006	1	0.354

References

Abedifar, P., Molyneux, P., & Tarazi, A. (2018). Non-interest income and bank lending. *Journal of Banking & Finance, 87*, 411–426.

Acharya, V. V., Hasan, I., & Saunders, A. (2006). Should banks be diversified? Evidence from individual bank loan portfolios. *The Journal of Business, 79*(3), 1355–1412.

Acharya, V. V., & Mora, N. (2015). A crisis of banks as liquidity providers. *The Journal of Finance, 70*(1), 1–43.

Acharya, V., & Naqvi, H. (2012). The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle. *Journal of Financial Economics, 106*(2), 349–366.

Allen, B., Chan, K. K., Milne, A., & Thomas, S. (2012). Basel III: Is the cure worse than the disease? *International Review of Financial Analysis, 25*, 159–166.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589–609.

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). ZETATM analysis A new model to identify bankruptcy risk of corporations. *Journal of Banking & Finance, 1*(1), 29–54.

Antunes, J., Hadi-Vencheh, A., Jamshidi, A., Tan, Y., & Wanke, P. (2021). Bank efficiency estimation in China: DEA-RENNA approach. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-04111-2

Arif, A., & Anees, A. N. (2012). Liquidity risk and performance of banking system. *Journal of Financial Regulation and Compliance, 20*(2), 182–195.

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.

Basel Committee on Banking Supervision. (2010). *Basel III: International framework for liquidity risk measurement, standards and monitoring*. Bank for International Settlements.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science, 30*(9), 1078–1092.

Berger, A. N., Hasan, I., Korhonen, I., & Zhou, M. (2010). *Does diversification increase or decrease bank risk and performance? Evidence on diversification and the risk-return tradeoff in banking*. Bank of Finland Discussion Papers Series No. 9/2010.

Berger, A. N., & Bouwman, C. H. (2017). Bank liquidity creation, monetary policy, and financial crises. *Journal of Financial Stability, 30*, 139–155.

Berger, A. N., Herring, R. J., & Szegö, G. P. (1995). The role of capital in financial institutions. *Journal of Banking & Finance, 19*(3–4), 393–430.

Berger, P. G., & Ofek, E. (1995). Diversification's effect on firm value. *Journal of Financial Economics, 37*(1), 39–65.

Bordeleau, É., & Graham, C. (2010). *The impact of liquidity on bank profitability* (No. 2010-38). Bank of Canada.

Busse, C., Mahlendorf, M. D., & Bode, C. (2016). The ABC for studying the too-much-of-a-good-thing effect: A competitive mediation framework linking antecedents, benefits, and costs. *Organizational Research Methods, 19*(1), 131–153.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*(6), 429–444.

Chavaz, M. (2017). *Liquidity holdings, diversification, and aggregate shocks*. Bank of England. Working paper 698.

Cheikh, N. B., & Zaied, Y. B. (2020). Revisiting the pass-through of exchange rate in the transition economies: New evidence from new EU member states. *Journal of International Money and Finance, 100*, 102093.

Chen, I. J., Lee, Y. Y., & Liu, Y. C. (2020). Bank liquidity, macroeconomic risk, and bank risk: Evidence from the Financial Services Modernization Act. *European Financial Management, 26*(1), 143–175.

Chen, Y. K., Shen, C. H., Kao, L., & Yeh, C. Y. (2018). Bank liquidity risk and performance. *Review of Pacific Basin Financial Markets and Policies, 21*(01), 1850007.

Chiu, Y. B., & Lee, C. C. (2019). Financial development, income inequality, and country risk. *Journal of International Money and Finance, 93*, 1–18.

Crockett, A. (1997). Why is financial stability a goal of public policy? *Economic Review-Federal Reserve Bank of Kansas City, 82*, 5–22.

Dang, V. D. (2020). Do non-traditional banking activities reduce bank liquidity creation? Evidence from Vietnam. *Research in International Business and Finance, 54*, 101257.

Davies, R. B. (1987). Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika, 74*(1), 33–43.

DeYoung, R., & Jang, K. Y. (2016). Do banks actively manage their liquidity? *Journal of Banking & Finance, 66*, 143–161.

DeYoung, R., & Rice, T. (2004). Noninterest income and financial performance at US commercial banks. *Financial Review, 39*(1), 101–127.

DeYoung, R., & Torna, G. (2013). Nontraditional banking activities and bank failures during the financial crisis. *Journal of Financial Intermediation, 22*(3), 397–421.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies, 51*(3), 393–414.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy, 99*(4), 689–721.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy, 91*(3), 401–419.

Diamond, D. W., & Rajan, R. G. (2000). A theory of bank capital. *The Journal of Finance, 55*(6), 2431–2465.

Diamond, D. W., & Rajan, R. G. (2001). Liquidity risk, liquidity creation, and financial fragility: A theory of banking. *Journal of Political Economy, 109*(2), 287–327.

Dietrich, A., & Wanzenried, G. (2011). Determinants of bank profitability before and during the crisis: Evidence from Switzerland. *Journal of International Financial Markets, Institutions and Money, 21*(3), 307–327.

Dietrich, A., & Wanzenried, G. (2014). The determinants of commercial banking profitability in low-, middle-, and high-income countries. *The Quarterly Review of Economics and Finance, 54*(3), 337–354.

Djebali, N., & Zaghdoudi, K. (2020). Threshold effects of liquidity risk and credit risk on bank stability in the MENA region. *Journal of Policy Modeling, 42*(5), 1049–1063.

Drehmann, M., & Nikolaou, K. (2013). Funding liquidity risk: Definition and measurement. *Journal of Banking & Finance, 37*(7), 2173–2182.

Ehiedu, V. C. (2014). The impact of liquidity on profitability of some selected companies: The financial statement analysis (FSA) approach. *Research Journal of Finance and Accounting, 5*(5), 81–90.

Fukuyama, H., & Weber, W. L. (2017). Measuring bank performance with a dynamic network Luenberger indicator. *Annals of Operations Research, 250*(1), 85–104.

Galletta, S., & Mazzù, S. (2019). Liquidity risk drivers and bank business models. *Risks, 7*(3), 89.

González, A., Teräsvirta, T., vanDijk, D. (2005). *Panel smooth transition regression models*. SEE/EFI Working Paper Series in Economics and Finance, No. 604.

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.

Holmström, B., & Tirole, J. (2000). Liquidity and risk management. *Journal of Money, Credit and Banking, 32*, 295–319.

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.

Houston, J., James, C., & Marcus, D. (1997). Capital market frictions and the role of internal capital markets in banking. *Journal of Financial Economics, 46*(2), 135–164.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics, 115*(1), 53–74.

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

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305–360.

Jin, J. Y., Kanagaretnam, K., & Lobo, G. J. (2011). Ability of accounting and audit quality variables to predict bank failure during the financial crisis. *Journal of Banking & Finance, 35*(11), 2811–2819.

Kaffash, S., Kazemi Matin, R., & Tajik, M. (2018). A directional semi-oriented radial DEA measure: An application on financial stability and the efficiency of banks. *Annals of Operations Research, 264*(1), 213–234.

Kashyap, A. K., & Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review, 90*(3), 407–428.

King, M. R. (2013). The Basel III net stable funding ratio and bank net interest margins. *Journal of Banking & Finance, 37*(11), 4144–4156.

Köhler, M. (2014). Does non-interest income make banks more risky? Retail-versus investment-oriented banks. *Review of Financial Economics, 23*(4), 182–193.

Kosmidou, K. (2008). The determinants of banks' profits in Greece during the period of EU financial integration. *Managerial Finance, 34*(3), 146–159.

Laeven, L., & Levine, R. (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics, 85*(2), 331–367.

Lahouel, B. B., Zaied, Y. B., Yang, G. L., Bruna, M. G., & Song, Y. (2021). A non-parametric decomposition of the environmental performance-income relationship: Evidence from a non-linear model. *Annals of Operations Research, 313*, 1–34.

Lahouel, B. B., Taleb, L., Kočišová, K., & Zaied, Y. B. (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*. https://doi.org/10.1007/s10479-021-04503-4

Lahouel, B. B., Taleb, L., Zaied, Y. B., & Managi, S. (2022b). Business case complexity and environmental sustainability: Nonlinearity and optimality from an efficiency perspective. *Journal of Environmental Management, 301*, 113870.

Lahouel, B. B., Zaied, Y. B., Managi, S., & Taleb, L. (2022). 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.

Latan, H., Jabbour, C. J. C., de Sousa Jabbour, A. B. L., Renwick, D. W. S., Wamba, S. F., & Shahbaz, M. (2018). 'Too-much-of-a-good-thing'? The role of advanced eco-learning and contingency factors on the relationship between corporate environmental and financial performance. *Journal of Environmental Management, 220*, 163–172.

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.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics, 108*(1), 1–24.

Männasoo, K., & Mayes, D. G. (2009). Explaining bank distress in Eastern European transition economies. *Journal of Banking & Finance, 33*(2), 244–253.

Marozva, G. (2015). Liquidity and bank performance. *International Business & Economics Research Journal (IBER), 14*(3), 453–562.

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.

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.

Moudud-Ul-Huq, S., Ashraf, B. N., Gupta, A. D., & Zheng, C. (2018). Does bank diversification heterogeneously affect performance and risk-taking in ASEAN emerging economies? *Research in International Business and Finance, 46*, 342–362.

Namouri, H., Jawadi, F., Ftiti, Z., & Hachicha, N. (2018). Threshold effect in the relationship between investor sentiment and stock market returns: A PSTR specification. *Applied Economics, 50*(5), 559–573.

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.

Nguyen, M., Perera, S., & Skully, M. (2017). Bank market power, asset liquidity and funding liquidity: International evidence. *International Review of Financial Analysis, 54*, 23–38.

Özşuca, E. A., & Akbostancı, E. (2016). An empirical analysis of the risk-taking channel of monetary policy in Turkey. *Emerging Markets Finance and Trade, 52*(3), 589–609.

Roulet, C. (2018). Basel III: Effects of capital and liquidity regulations on European bank lending. *Journal of Economics and Business, 95*, 26–46.

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

Saunders, A., & Cornett, M. M. (2006). *Financial institutions management: A risk management approach*. McGraw-Hill.

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

Stiroh, K. J. (2015). Diversification in banking. In A. N. Berger, P. Molyneux, & J. O. S. Wilson (Eds.), *The Oxford handbook of banking* (2nd ed., pp. 219–243). Oxford University Press Inc.

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.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130*(3), 498–509.

Tone, K., & Tsutsui, M. (2010). Dynamic DEA: A slacks-based measure approach. *Omega, 38*(3–4), 145–156.

Tran, D. V. (2020). Bank business models and liquidity creation. *Research in International Business and Finance, 53*, 101205.

Wagner, W. (2007). The liquidity of bank assets and banking stability. *Journal of Banking & Finance, 31*(1), 121–139.

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.

Williams, B. (2016). The impact of non-interest income on bank risk in Australia. *Journal of Banking & Finance, 73*, 16–37.

Zheng, C., & Cronje, T. (2019). The moderating role of capital on the relationship between bank liquidity creation and failure risk. *Journal of Banking & Finance, 108*, 105651.