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Are we living in an illusion?

A fresh look at the importance of bank capital in the quest for stability

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Abstract

Using a sample of 2,350 listed banks from 51 countries in 1990-2018, we find that changes in capital or even the amount of capital itself is not significantly related to concurrent changes in the banks' probability of default. We combine four methods to deal with endogeneity issues (effect of unobserved confounders and reverse causality): linear models with fixed effects, novel instrumental variables in 2SLS analyses, generalised method of moments, and structural equation modelling. Hence, our conclusions can be seen as evidence of the lack of causal impact from capital to bank stability. This could be explained by the possibility of higher risk taken to cover the cost of capital offsetting the loss absorption benefits of capital and by different loss perceptions of shareholders that may reduce their incentives to monitor bank managers. Our results are corroborated by several robustness tests involving different capital and stability measures and alternative model specifications. In an additional step, we also show that promoting changes in other aspects normally considered by regulators and supervisors (asset quality, management quality, earnings, liquidity risk, and sensitivity to market risk) does not lead to higher stability either. In sum, we contribute to the literature by applying original approaches for causal inference in the context of bank capital and stability. For regulators, we leave a message indicating that the prevalent regulatory framework is likely based on an illusion given that making banks increase their capital does not necessarily make them more resilient.

JEL codes: G21, G28

Keywords: bank capital; financial stability; endogeneity

1. Introduction

For at least two centuries, bank capital has been a key element of banking regulation in its efforts to promote financial stability (Rae, 1886, pp. 258-265; Grossman, 2010; Turner, 2014). Nowadays, the benefits of bank capital are taken for granted by regulators worldwide (see, e.g., BCBS, 2011). Memmel and Raupach (2010, p. 509), for example, state that bank capital ratio is a “natural indicator of soundness”.

Yet the banks that failed during the Global Financial Crisis normally had more capital than the levels required by regulators not only in the pre-crisis period but also in the new version of the regulation issued after the crisis (Gorton, 2012; Flannery and Giacomini, 2015). This casts doubt on the belief that bank capital would be the key aspect (or even an effective one) driving stability. As a matter of fact, Thompson (1991), Rochet (1992) and Roy (2005) have shown evidence that increasing capital not always results in lower probability of bank failure. Still, a regulatory reform has recently been announced (BCBS, 2017) bringing a further increase to the capital holdings required from banks (PwC, 2017).

Moreover, even if capital is relevant in this context, academic studies have presented conflicting conclusions on the association between capital and stability (see discussions, e.g., in Shrieves and Dahl, 1992; Berger, Herring and Szegö, 1995; Santos, 2001; and Barth, Caprio Jr and Levine, 2006, pp. 53-54). On the one hand, the findings in Jahankhani and Lynge (1980), Holmstrom and Tirole (1997), Calomiris and Manson (2003), Calomiris and Wilson (2004), Kick and Koetter (2007), Agoraki, Delis and Pasiouras (2011), Allen, Carletti and Marquez (2011), Mehran and Thakor (2011), and Thakor (2012), among others, support the regulatory expectations by showing that more capital is related to higher bank stability.

On the other hand, there is a myriad of studies suggesting the opposite effect, i.e., more capital would lead to more risk-taking (e.g., Pettway, 1976; Kahane, 1977; Koehn and Santomero, 1980; Lam and Chen, 1985; Kim and Santomero, 1988; Gennotte and Pyle, 1991; Besanko and Kanatas, 1996; Jacques and Nigro, 1997; Blum, 1999; Altunbas et al., 2007; Jokipii and Milne, 2011[1]). Although an increase in risk associated with higher capital may seem counterintuitive, this could be due to the fact that raising capital is expensive and banks try to offset that extra cost by investing in more profitable assets, which happen to be the riskiest ones. Another possibility would be explained by a mean-variance interpretation of the relationship between capital and risk (as in Kahane, 1977; Koehn and Santomero, 1980; Kim and Santomero, 1988). In this case, bank leverage and risk-taking would become substitutes given regulatory constraints on capital. Hence, banks forced to increase capital would reach their optimal risk level by increasing risk. Miller (1995) adds that asking banks to have more capital does not prevent embezzlement (a common cause of bank failures) or excessive risk-taking given the safety-net options available nowadays.

Naturally, the different findings in the literature could be due to the different samples and/or methods used in those studies. These possibilities may be – at least partially – explained by the fact that the relationship between bank capital and stability is endogenous, which involves two main aspects that could vary in different samples or could be captured by alternative approaches in a different way. First, the relationship observed between bank capital and stability may be jointly driven by other factors that could be the actual cause of changes in both capital and stability given that the decision made by bank managers regarding the level of capital held (which is normally higher than the regulatory minimum) may be strongly associated with other decisions that also affect bank stability. For example, the banks with more capital could be the ones with lower risk aversion and/or more capable managers, which in turn would make default less likely. Therefore, banks' resilience would come from their low-risk appetite and/or skilled managers, not from capital. If this is the case, our banking regulatory system could be based on an illusion.

[1] In a particular sub-period tested, Jokipii and Milne (2011) identify a negative relation between capital buffer and risk but, in most of the sample period considered in their analyses, the association is positive.

Second, the association between capital and risk could reflect a relationship going from the latter to the former (i.e., an impact in the opposite direction of that implied in the regulatory reasons for controlling capital). The possibility of such reverse causality can be illustrated by most of the explanations for a positive correlation between capital and risk summarised in Shrieves and Dahl (1992, pp. 442-443). The regulatory pressure on banks close to the minimum level who increase risk-taking in the presence of good investment opportunities would lead those banks to increase capital in order to avoid penalties from supervisors in the event of losses that could drive their capital to a point below the required threshold. Also, higher capital levels could be a response of banks to increased risk in order to reduce bankruptcy costs. Moreover, managerial risk aversion could make bank managers increase capital to offset high risk taken with a view to preventing personal losses resulting from their institutions' insolvency. We notice that in these cases the narrative goes from risk-taking to the determination of the capital level.

This issue boils down to the question whether bank capital itself can help promote stability. This is a causality question. As discussed in detail ahead (Section 2), the analyses in many studies in this area do not allow us to answer this question given that endogeneity is not (properly) treated (e.g., Shrieves and Dahl, 1992; Jacques and Nigro, 1997; González, 2005; Altunbas et al., 2007; Brewer III, Kaufman and Wall, 2008; Gropp and Heider, 2010; Francis and Osborne, 2012; Dagher et al., 2016). Hence, we cannot conclude whether or not the association between capital and risk (stability) shown in these analyses is causal.

We aim at shedding light on this discussion by using different methods to assess the potential impact of *changes* in capital on *changes* in bank stability (initially proxied by banks' probability of default). We focus on changes because, in comparison with variables in levels, they (changes) are more intrinsically related to the concept of causality (Cox, 2013). In the context of banking, the difference between having and changing capital is briefly mentioned in Miller (1995).

We contribute to the literature and to the practitioners' understanding of the role of capital in the promotion of stability by treating the endogeneity between capital and stability with the use of complementary methods (fixed effects, instrumental variables and structural equation modelling – besides the Generalised Method of Moments in additional analyses). Such effort combining these approaches, which cover different aspects of endogeneity, cannot be found in the existing literature in the area. We also propose novel instruments to capture exogenous variations of capital, which can be applicable to future studies in this area. In addition, we further investigate whether other aspects considered by banking regulators and supervisors (asset quality, management quality, earnings, liquidity risk, and sensitivity to market risk) have a beneficial impact on stability. To our knowledge, a causal assessment involving these factors simultaneously has not yet been carried out in the literature. We emphasise that, while the literature has also investigated the effect of bank capital on systemic stability (e.g., Gorton, 2012; Anginer, Demirgüç-Kunt and Mare, 2018), we are concerned with the risk of individual bank failures.

Our analyses are based on a sample of 2,350 listed banks headquartered in 51 countries. The sample period goes from 1990 to 2018. Our results, supported by many robustness tests, indicate that the association between capital and bank stability is likely driven by latent confounders affecting those two variables, which means that changing capital does not lead to changes in stability. This contradicts the common sense according to which capital by itself would be relevant to the improvement of stability. Moreover, none of the additional factors evaluated appears to effectively contribute to higher stability.

It is worth noting that, as in Shrieves and Dahl (1992) and Berger and Bouwman (2013) for example, we focus on the capital held by banks, not on the capital required by regulators. Although the effective capital levels are partially driven by regulatory requirements, they are only lower bounded and the excess capital normally kept by banks is discretionary (Berger et al., 2008). This active management of capital reinforces the importance of investigating the impact of capital on stability because such practice raises the possibility that banks could potentially affect their own resilience by means of frequent changes in their capital (should capital be a relevant cause of stability). Another important aspect of our study refers to the fact that banking regulation, which relies heavily on capital, implies the idea of intervention. So, causal inference is extremely important in this case given that policy evaluations aim at quantifying the changes in effects following changes in potential causes, i.e., interventions (Cox, 2013). In sum, given our empirical findings, to show evidence that bank capital does not impact stability is the first step to motivate academics, regulators, and policy-makers to look for factors that can actually improve stability. Our main objective is to contribute to this first step.

The importance of our study is also related to corporate governance in the context of bank capital as the literature has shown conflicting evidence of the influence of governance structures on bank capitalisation. Anginer et al. (2016), for instance, suggest that good corporate governance (in terms of board size, CEO-chairman separation and absence of anti-takeover provisions) favouring shareholders' interests by intending to increase bank valuation should result in lower bank capital ratios, which in turn would negatively affect financial stability. In contrast, Baumann and Nier (2003) and Brewer III, Kaufman and Wall (2008), for example, find that improvements in governance structures are associated with higher capitalisation in banks. This is explained by the fact that better governance enhances risk identification and discipline, which would lead to the need of higher capital ratios to guarantee stability. Our analyses can therefore help in understanding the possible effects of corporate governance on stability via changes in bank capital.

The remainder of this paper is organised as follows. Section 2 discusses how the literature has dealt with the endogeneity of capital when evaluating its relationship with stability. Section 3 introduces the data and the methods used in our analyses. In Section 4, the main results are presented and discussed. Section 5 reports several robustness tests while Section 6 concludes.

2. Bank capital, stability and endogeneity

As explained in Wooldridge (2010, pp. 54-55), endogeneity may arise as a consequence of three issues: omitted variables, simultaneity, and measurement error. In the first case, variables not included in the analyses (regressions) may be related to the main independent variable(s) of interest. This would mean that those omitted variables may be driving the co-movement of the dependent and the independent variables. In other words, such situation could (partially or totally) explain the correlation observed between the variables analysed in the regressions. In our case, as briefly mentioned in Section 1, this could result from the existence of variables unobservable to researchers (e.g., managers' preferences or bank strategies) that could affect both the banks' capital level and their stability.

Simultaneity (also known as reverse causality) happens when the dependent variable and one (or more) of the independent variables concomitantly affect each other. In terms of bank capital and stability, as discussed in Section 1, an example would be when, due to an increase in risk-taking (therefore, reducing stability) banks increase their capital ratios (e.g., Shrieves and Dahl, 1992). Consequently, in principle, we would not be able to disentangle the influence of capital on stability (the one we are interested in) from the effect taking place in the opposite direction (i.e., from the latter to the former).

Measurement error is concerned with inaccuracies in the value of independent variables that can end up in the error term of the regression and be related to the true (unobserved) values of those variables. Hence, the omitted difference can be driving both the dependent and the respective independent variables, leading to the aforementioned issue regarding omitted variables. Considering that we use secondary data in our empirical analyses and would not have access to the precise measures of the main variables in our study, we focus on the other two sources of endogeneity, which are much more commonly discussed in the literature. These two aspects should cover most of the potential problems due to the endogeneity of capital especially because when treating the omitted variables bias we would be, to some extent, avoiding the effects of inaccurate measures included in the omitted variables (error term of our regressions). The endogenous nature of capital has been discussed in the literature (e.g., Koehn and Santomero, 1980; Kim and Santomero, 1988; Rochet, 2015; Dagher et al., 2016). Even when endogeneity is not explicitly mentioned, the arguments and conclusions in some studies on capital and risk-taking (stability) indicate its presence. VanHoose (2007), for example, claims that the reaction of banks (in terms of changing risk-taking) when capital increases depends on banks' risk aversion. Since this is normally an omitted factor in empirical analyses, it could act as an unobserved confounder driving both capital and risk levels, which would refer to one of the reasons for endogeneity discussed earlier. Bertrand and Schoar (2003) show that managers' preference (normally, an omitted variable) impacts bank capital structure and risk-taking where less risk averse managers choose more aggressive strategies and higher leverage. According to Rochet (1992), different conclusions regarding the relationship between capital and risk are due to the assumptions of complete or incomplete markets. Shrieves and Dahl (1992) emphasise that the theories leading to contradictory conclusions regarding the relationship between capital and risk-taking are not mutually exclusive as capital and risk decisions depend on bank characteristics. In these two studies, the issues considered (market completeness and bank characteristics) could be seen as other unobserved influences on the association between bank capital and risk-taking.

Before we consider the attempts in the relevant literature to overcome the threats posed by endogeneity, it is worth noting that, in theoretical studies, causal relationships are normally embedded in the models proposed (e.g., Kahane, 1977; Koehn and Santomero, 1980; Kim and Santomero, 1988; Gennotte and Pyle, 1991; Calem and Rob, 1999; Blum, 1999; Hellmann, Murdock and Stiglitz, 2000; Mehran and Thakor, 2001; Thakor, 2012). This also applies to analyses based on equilibrium models such as the Dynamic Stochastic General Equilibrium (DSGE) models (see references summarised in Dagher et al., 2016). Hence, causality is only implicitly assumed and we know that assumptions (and intuition) may well be wrong even if they sound plausible. These studies are important as they suggest possible explanations for relationships involving bank capital but many of the theories proposed therein have not yet be tested empirically in a way that would allow us to analyse the reliability of their implicit causal claims.

We therefore focus on empirical studies as they are based on external information (i.e., data) that do not entirely depend on the narrative and assumptions presented by authors. Although many empirical studies in this area only measure the correlation between bank capital ratios and the other variables of interest, such as stability (see, e.g., discussion in Rochet, 2015), a number of analyses have aimed at tackling endogeneity in order to obtain credible conclusions on the impact of capital. However, a close look at their approaches indicates that this is not completely achieved. Shrieves and Dahl (1992), Jacques and Nigro (1997), Rime (2001) and Altunbas et al. (2007), for instance, consider the simultaneous relationship (reverse causality) between capital and risk by means of partial adjustment models (2SLS or 3SLS) and Seemingly Unrelated Regressions but do not address the possible influence of omitted confounders (common causes driving both capital and risk). Despite this limitation, the aforementioned authors describe their results as an indication of impact (i.e., a causal interpretation). Similarly, González (2005) uses a 2SLS method to investigate the relationship between banking regulation and risk-taking via charter value but does not control for unobserved bank characteristics that could be driving charter value and risk-taking in both stages. The analyses in Francis and Osborne (2012) have similar limitations although the authors also use a fixed-effects model and the Generalised Method of Moments (GMM). Nevertheless, these two approaches do not overcome the endogeneity threat completely. While fixed-effects only control for non-time-varying unobserved factors, the instruments in GMM (normally lags of variables in the model) are relatively weak as GMM estimates only minimise the correlation between the potentially endogenous covariates and the error term rather than guaranteeing a zero correlation between them (see, e.g., Hayashi, 2000).

In the linear models used in Brewer III, Kaufman and Wall (2008), neither the possibility of confounders driving capital and risk nor the possible reverse causality between them is taken into account. Gropp and Heider (2010) take a further step by controlling for the influence of bank non-time-varying omitted factors (fixed-effects) in the relationship between capital ratio and risk (among other relevant determinants of capital) but still do not show any effort to preclude the influence of time-varying omitted variables or reverse causality.

Acosta-Smith, Grill and Lang (2021), on the other hand, endeavour to prevent the possibility of reverse causality but neglect the role of omitted variables. Moreover, the treatment (leverage ratio in Basel III affecting more leveraged banks, i.e., those below the requirement level) in their difference-in-differences analyses is not random. This may bias their conclusions as the treatment and control groups may have different latent features (e.g., a more or less aggressive profile), which would be the actual reason for the differences found (Atanasov and Black, 2016). Fixed-effects and GMM are also used but, as discussed above, they have significant limitations in dealing with endogeneity. Therefore, in this case, another approach such as 2SLS with instrumental variables would be necessary as well.

GMM is also employed by Davis, Karim and Noel (2020) but these authors supplement their analyses with Panel Vector-Autoregressive (PVAR) models, which despite their causal interpretation in that study, are actually related to prediction (impulse-response), not causality (see Maziarz, 2020, pp. 65-71). Thus, the potential role of latent factors acting on capital and risk remains as a possibility.

Instrumental variables may help us to overcome the challenges posed by endogeneity. However, to find instruments that comply with all the necessary conditions is a Herculean task. Taking Berger and Bouwman (2013) as an example, one of the instruments used for capital is the ratio of citizens older than 64 in the regions where a bank operates. It relies on the fact that elderly individuals invest in equities more than younger people but the authors do not consider the fact that the ratio of senior citizens could change due to changes in the fraction of younger people who could move in/out the respective regions in response to their macroeconomic conditions or specific events (e.g., closures or opening of new factories). Such unobserved conditions/events would then simultaneously drive the instrument and the dependent variable in that study (bank performance). Consequently, this would cast doubt on the conclusion that bank capital per se would be affecting bank performance. The second instrument, the state income tax paid by banks, would discourage banks from having large capital buffers because, contrary to interest on debt, dividend payments are not tax deductible. However, this instrument is unlikely to be applicable to many other samples (countries) as it is too specific to the US taxation system. As explained in Section 3.2.2, in our study, we also make use of instruments (among other approaches) but they are more likely dissociated from unobserved factors driving capital and our dependent variable (stability) and their reasoning can be applied to any banking system (country).

Natural experiments are another option to tackle endogeneity but, despite being very rare, they are usually based on stressful scenarios, which do not represent healthy banks in normal conditions (e.g., with full access to equity markets). Therefore, their results tend not to be applicable to the great majority of cases observed in the banking industry (Dagher et al., 2016). When it comes to the treatment of reverse causality, the use of lagged independent variables has been very common in the bank capital literature (e. g., Berger et al., 2008; Gropp and Heider, 2010; Francis and Osborne, 2012; Acosta-Smith, Grill and Lang, 2021) because past independent variables (e.g., capital ratio at time *t-1*) could not be determined or caused by a dependent variable (e.g., risk) happening at time *t*. Despite this appealing argument, such framework normally lacks economic significance in the context of the impact of capital on bank risk given that changes in the latter are a consequence of concurrent changes in the former. For instance, in terms of the loss absorption capacity of capital, the probability of default (risk) of banks in a particular period reflects the capital level of those banks in the same period. To some extent, in this study, we relax the need of lagging independent variables in order to prevent reverse causality. This is the case because two of the methods used ahead, apart from accounting for the potential influence of omitted variables, allow us either to argue against that possibility in a logical way (particular instruments used) or to select a best-fit model among options including scenarios of reverse causality (structural equation modelling). Thus, our results will reflect the banking environment in a more realistic way as compared to most of the existing literature.

3. Data and Methods

3.1. Data

Our original data set comprises 2,512 active and inactive listed banks from 98 countries. However, in order to allow for variation across institutions in each country, we restrict our sample to countries with data for at least 10 banks.[2] Then, we end up with 2,350 active and inactive listed banks headquartered in 51 countries. A list of these countries and their number of banks is presented in Appendix A. Only listed banks are considered because the stability measures used in our analyses are based on stock market data. The sample period spans from 1990 to 2018, the first and the last years, respectively, for which information on the stability measures used was available when the data was collected.

Data on the alternative dependent variables (banks' probability of default and credit default swap spread) is obtained from the Credit Research Initiative (CRI) of the Risk Management Institution (RMI) at the University of Singapore (https://nuscri.org/en/). The accounting data is downloaded from OSIRIS/Bureau van Dijk (BvD). Relevant information on the countries is

[2] In robustness tests presented in Section 5, we further reduce our sample to countries with at least 20 banks (besides a minimum number of bank-year observations).

retrieved from the World Bank database (https://data.worldbank.org/) and the Capital IQ database.

To remove outliers, we winsorise the data at the 1st and 99th percentiles. Bank-specific data from different sources were matched by means of the ISIN codes of financial institutions.

3.2. Methods

3.2.1. Fixed effects

We start our analyses by controlling for possible unobserved time-invariant factors in the following baseline fixed-effects model:

$$\Delta PD_{i,t} = \beta_0 + \beta_1 \Delta C_{i,t} + \beta_2 C_{i,t} + \beta_3 A_{i,t} + \beta_4 M_{i,t} + \beta_5 E_{i,t} + \beta_6 L_{i,t} + \beta_7 S_{i,t} + \beta_8 Size_{i,t} + \beta_9 \Delta GDP_{j,t} + \beta_{10} \Delta Stock\_index_{j,t} + \mu_i + \theta_j + \tau_t + \varepsilon_{i,t}, \quad (1)$$

where the subscripts i, t and j refer to bank i, year t, and country j, respectively. For convenience, these subscripts are omitted from the description of the variables as their meaning should be straightforward. ΔPD at time t represents the variation of a bank's probability of default (PD) from the end of year t-1 to the end of year t, calculated as $(PD_t - PD_{t-1})/PD_{t-1}$. The PD estimations follow the Merton Model (see, for instance, Duan, Sun and Wang, 2012).

ΔC at time t, our main independent variable, is the variation of capital (C) between years t-1 and t. It is calculated as $(C_t - C_{t-1})/C_{t-1}$. Three key measures of capital are used in our analyses: total equity divided by total assets, where total equity = total common shares + total preferred shares; total capital ratio is equal to the sum of all items accepted as regulatory capital (sum of Tier 1, Tier 2, and Tier 3 Capital) divided by total assets; and Common Equity Tier 1 (CET1) divided by total assets, where CET1 = total equity - preferred shares.[3]

[3] As discussed, for example, in Shrieves and Dahl (1992), market values of capital measures would be preferred but unfortunately they are not available.

Capital at level (*C*) is also included in the regression (the three aforementioned measures are tested). *A* is asset quality (Total Impaired Loans and Assets divided by Total Assets). *M* stands for management quality (proxied by Cost-to-Income Ratio = Interest and Related Expense + Non-Interest Expense) divided by (Interest Income + Non-Interest Income). *E* is earnings (Return on Equity = Net Income divided by Common Stock + Preferred Stock). *L* represents liquidity (Liquid Assets divided by Total Deposits). *S* is sensitivity to market risk (Assets Held for Sale divided by Total Assets). These controls, including capital, form the CAMELS acronym and, besides having been constantly used to explain banks' probability of default (or similar concepts) in the literature (e.g., Cole and White, 2012; Klomp and de Haan, 2012; Duchin and Sosyura, 2014; Kick and Prieto, 2015; Khan, Scheule and Wu, 2017), they have also been used by bank supervisors in the assessment of the financial institutions (Jacques and Nigro, 1992; Duchin and Sosyura, 2014).

In addition, we control for bank size (*Size*), which is measured by the natural logarithm of total assets. This variable has been shown to be highly associated with bank risk (and, therefore, *PD*); see, among many others, Gonzalez (2005), Altunbas et al. (2007), Klomp and de Haan (2012), Berger and Bouwman (2013). *ΔGDP* and *ΔStock_index* are the annual changes in the Gross Domestic Product (GDP) and in the main stock index of the respective country from year *t-1* to year *t*. These two factors have been considered to be potentially important indicators of bank stability (e.g., Acosta-Smith, Grill and Lang, 2021).[4] βs are the parameters to be estimated. μ, θ and τ are bank-, country-, and time(year)-fixed effects, respectively.[5] ε is the error term.

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[4] Due to the lack of data for many countries, we are not able to use other macro factors such as those used in Acosta-Smith, Grill and Lang (2021). We reckon that this should not substantially affect our results because these factors become omitted variables in our models and we are using different approaches to control for the influence of unobserved factors. Other potentially relevant controls such as ownership structure (e.g., whether single shareholders have a relatively high percentage of voting rights) faces a similar issue regarding the lack of data for banks in many countries in our sample. Hence, such controls also become unobserved factors, the influence of which is taken into account in our models.

[5] An interaction term between time and country fixed effects would help to represent relevant financial/economic factors specific for each country in specific periods. However, given the number of periods and countries in our data set, the number of interaction terms is not supported by the version of the software used (Stata/IC).

It is worth noting that the independent variables are in the same period as the dependent variable because this specification is more representative of the decisions made by banks and of the dynamics we aim to investigate. Although using lagged independent variables is a common strategy in empirical research in this area, it would not have economic meaning in our case. Furthermore, the possibility of reverse causality in our baseline model (i.e., changes in *PD* determining changes in capital) will be checked by means of additional methods, including the use of instrumental variables (Section 3.2.2) and structural equation modelling (Section 3.2.3).

3.2.2. Instrumental variables

3.2.2.1. Model

The linear model introduced in the previous section controls for non-time-varying unobserved factors (e.g., bank culture) that could affect both the capital level chosen by banks and their probability of default. Nevertheless, that model does not account for the possible influence of time-varying unobserved factors. To deal with this issue, we employ the two stage least squares approach with instrumental variables (2SLS-IV). The first and the second stages are respectively:

$$\Delta C_{i,t} = \alpha_0 + \alpha_1 IV_{i,j,t-1} + \alpha_2 C_{i,t} + \alpha_3 A_{i,t} + \alpha_4 M_{i,t} + \alpha_5 E_{i,t} + \alpha_6 L_{i,t} + \alpha_7 S_{i,t} + \alpha_8 Size_{i,t} + \alpha_9 \Delta GDP_{j,t} + \alpha_{10} \Delta Stock\_index_{j,t} + \mu_i + \upsilon_{i,t} \qquad (2)$$

and

$$\Delta PD_{i,t} = \gamma_0 + \gamma_1 \widehat{\Delta C}_{i,t} + \gamma_2 C_{i,t} + \gamma_3 A_{i,t} + \gamma_4 M_{i,t} + \gamma_5 E_{i,t} + \gamma_6 L_{i,t} + \gamma_7 S_{i,t} + \gamma_8 Size_{i,t} + \gamma_9 \Delta GDP_{j,t} + \gamma_{10} \Delta Stock\_index_{j,t} + \mu_i + \vartheta_{i,t}. \qquad (3)$$

IV represents the instrumental variables explained in the next section. $\widehat{\Delta C}_{i,t}$ is the change in capital (from year *t-1* to year *t*) predicted in the first stage, Eq. (2). α and γ are the parameters to be estimated. υ and ϑ are error terms. The meaning of the subscripts and the other variables follows the presentation just after Eq. (1). γ_1 in Eq. (3) is the main coefficient of interest as it indicates the causal impact of changes in capital on changes in banks' probability of default.

3.2.2.2. Instruments

Our instrument is related to the arguments regarding regulatory pressure discussed, for example, in Marcus (1983, p. 1229) and the conclusions therein suggesting that, when assessing a bank, regulators and supervisors are more concerned about its capital relative to peers than about its capitalisation per se. In fact, we add that this argument can be extended to market pressure as well given that there is evidence that banks are also influenced by market discipline when defining their capital levels (see, e.g., Berger, Herring and Szegö, 1995; Dowd, 2000; Marini, 2003; Ashcraft, 2008; Grossman, 2010, pp. 147-149).

For a bank *i* operating in a country *j*, we build measures combining two factors that would influence the bank's decision regarding its capital level in year *t*. The first factor is the distance of bank *i*'s capital in year *t-1* to the mean capital ratio of the banking system in country *j* in the same period. The second factor refers to the dispersion (standard deviation) of the distribution of capital in the country *j*'s banking system in year *t-1*. Our first instrument, (IV^{mean_disp}) is then an interaction term where the two aforementioned factors are multiplied by each other:

$$IV_{i,j,t-1}^{mean\_disp} = (C_{i,t-1} - \bar{C}_{j,t-1}) * \sigma(C_{j,t-1}).$$

C is the capital of the bank represented by the IV. $\bar{C}$ is the average capital of the banking system in country *j* while σ represents the standard deviation of the distribution of bank capital in that country in the given period. To keep consistency with the previous explanation, the instrument's formula is presented in terms of year *t-1*, which means that this value is used in the analyses concerning the relationship between probability of default and capital in year *t*. We use lagged measures of the IVs to reflect the fact that the capital level of banks in a particular period can only be learned by their competitors when the period in question is over.

The first aspect considered in the IV calculation (distance between the bank capital and the mean capital in the respective banking system) implies that the smaller the value of the first term in the IV's formula ($C_{i,t-1} - \bar{C}_{j,t-1}$), the bigger is the incentive for a bank to increase its capital in the subsequent period. The second aspect considered (dispersion of capital in the banking system) suggests that, if the capital level is similar across banks (a low standard deviation in the distribution of capital), any fall would be noticeable by regulators, supervisors and the market in general. On the other hand, when the dispersion is large, it is easier for banks to disguise the low level of their capital. Hence, as in the previous case, this term also has an expected negative relation with the capital held by banks: the smaller the capital dispersion, the more incentive banks have to increase their capital. In sum, both terms are expected to be negatively associated with the change in capital in the following period (year).

Recall that our reasoning is based on the importance of banks comparing their capital levels to those of their peers. In the instrument presented above, such comparison is made in line with the average (mean) capital in the whole banking system where a bank operates. Nevertheless, other criteria for comparing capital ratios are possible. We therefore propose an alternative IV where the motivation for a bank to adjust its capital would come from the rank-order position of its capital in comparison with their competitors:

$$IV_{i,j,t-1}^{perc\_disp} = (C_{i,j,t-1}^{perc}) * \sigma(C_{j,t-1}),$$

where $C_{i,j,t-1}^{perc}$ is the percentile of bank i's capital ratio in the distribution of capital in the banking system of country *j* in year *t-1*. The second term is identical to that in the previous instrumental variable ($IV_{i,j,t-1}^{mean\_disp}$). Also, as before, the expected relationship between this percentile-based instrument and the banks' capital level one period later is negative. For example, the smaller $IV_{i,j,t-1}^{perc\_disp}$ is, the more need bank *i* has to increase its capital at time *t*. This is because a small value of the IV would tend to indicate that the bank has little capital as compared with most of its competitors at the same time that the capital dispersion in its country is low (so that the capital deficiency of bank *i* would be easily noticed by external stakeholders). Initially, the two IVs introduced above ($IV_{i,j,t-1}^{mean\_disp}$ and $IV_{i,j,t-1}^{perc\_disp}$) will be used together when estimating our 2SLS-IV models. Although the simultaneous use of these two instruments may seem redundant, they seem to convey different information to a certain degree. That is, the perceptions of a bank in terms of capital ranking and the distance to the mean capital in its banking system are not necessarily the same as they depend on the capital dispersion (volatility) around the capital level of that specific bank. For instance, a small change in the distance to the mean capital could lead to a change of many positions in the capital ranking of a bank (when there is a concentration of banks with capital ratios similar to the bank in question) or lead to no change in the ranking (when there are no other banks with capital ratios close to the capital of the bank considered).[6] This reasoning is corroborated by our empirical results, which show that the correlation between those two instruments is not very high (between 0.65 and 0.70 according to the capital measure used). This indicates that the rank position (percentile) as compared to peers is not the same as the distance to mean capital in the banking system. Hence, it is reasonable to use those two instruments together when they pass the necessary overidentification tests (which is the case in most of our initial results – as shown ahead).[7] However, when the two instruments do not pass the overidentification tests, we report the results based on one of them only. These alternative results also work to alleviate any remaining concerns over the possible redundancy in the joint use of those two IVs.

Additionally, for the purpose of robustness tests we consider other variants of these instruments. One of them replaces the mean capital in $IV_{i,j,t-1}^{mean\_disp}$ with the median capital of

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[6] This is still valid if we consider scenarios with a same volatility of capital ratios in the whole banking system. An equal volatility could be observed in the two situations described if, for example, the dispersion of capital at values away from the capital of the bank analysed is different in such a way that the overall dispersion remains constant.

[7] We also consider the possibility of a triple interaction term: $(C_{i,t-1} - \bar{C}_{j,t-1}) * C_{i,j,t-1}^{perc} * \sigma(C_{j,t-1})$. It would confirm our main findings presented ahead but in around half of the tests (including different measures of capital and stability), it does not pass the weak identification test.

the respective banking systems ($IV_{i,j,t-1}^{median\_disp}$). We also calculate instruments only using the first component of each of the IVs presented above. That is, we ignore the second term regarding capital dispersion and calculate the instrument based on the bank i's capital percentile or the distance between the bank's capital and the mean (median) capital in the respective country. Hence, we have another three instruments: $IV_{i,j,t-1}^{perc} = (C_{i,j,t-1}^{perc})$, $IV_{i,j,t-1}^{mean} = (C_{i,t-1} - \bar{C}_{j,t-1})$, and $IV_{i,j,t-1}^{median} = (C_{i,t-1} - C_{j,t-1}^{M})$, where $C_{j,t-1}^{M}$ is the median capital of the whole banking system in country j in period t-1 and the other terms follow the same definitions above. For any of the previous IV alternatives, as described above, we see that their values in period *t-1* provide a motivation for banks to adjust their capital in period t. This is the first condition for a valid instrument. Also, it is reasonable to assume that the position of a bank's capital in relation to its peers would not affect other issues linked to its probability of default. A bank's PD is normally affected by internal issues or exogenous shocks. In general, neither of these two aspects could be driven by the exact position of the capital level of a bank among other banks in the same market. Thus, we would not expect alternative channels connecting an IV to PD, except for the capital of the bank in question (the endogenous variable). This means that the proposed IVs comply with the exclusion restriction condition.

Also, our IVs greatly depend on the actions of other banks in *t-1*. Many possible events (especially unobserved ones) influencing the PD of a particular bank are internal to that bank and could therefore be seen as disassociated from the capital level of that bank in comparison with other banks. The same is true for macro events (shocks). Moreover, it is worth noting that many of the issues not included in our analyses that could affect banks' PD take place in period t. Given that the IVs are measured in *t-1*, it is natural to accept that those unobserved factors do not drive the IVs. Together, the arguments in this paragraph indicate that our IVs and the outcome analysed (PD) do not share omitted common causes, which reinforces the notion that our IVs are exogenous to the multiple issues involved in the endogenous relation between banks' capital and their probability of default.

Lastly, it is important to note that the temporal nature of the IVs (being determined before all the other variables in the model) helps to preclude the possibility of reverse causality from probability of default to capital ratios given that the variation of capital considered will come from the variation of the IVs.

3.2.3. Structural Equation Modelling

We use structural equation modelling (SEM) to test alternative models indicating the potential presence of omitted factors and the direction of the relationships among variables (e.g., which variables more likely affect the other variables). Simultaneous linear equations for hypothetical relationships (theoretical models) across variables are run and the implied covariance among the variables in each model is compared with the covariance of the data in hand. The closer the fit, the better. For more details on SEM and its application in this context, see, for instance, Mulaik (2009) and Pearl (2009, pp. 133-172, 366-374).

In our particular case, we aim at finding out what combination of relationships is more likely among changes in capital, changes in probability of default and (possibly) unobserved factors that could be driving the two previous variables. As a supplementary tool for our IV analyses, SEM can give us additional evidence to argue against the possibility of reverse causality between probability of default and capital (i.e., the impact going from the former to the latter). It also helps us to test the possible influence of omitted common drivers of those two variables. We focus on the two main variables analysed (changes in bank's probability of default and in capital), while treating the control variables introduced in Eq. (1) as exogenous. A latent variable potentially driving both variables of interest is also considered as a possibility in some cases.

The possible scenarios (theoretical models) are presented in Figure 1, where each panel shows an alternative relationship (or combination of relationships). As before, the main variables of interest are ΔC and ΔPD (the percentage variations in capital and banks' probability of default, respectively, from the end of year *t-1* to the end of year *t*). U is one or more unobserved variables related to year *t* that might be a common cause of *ΔC* and *ΔPD*. The arrows represent the direction of the relationship (i.e., the end pointed towards the affected variable). Every variable with an arrow pointing to it becomes a dependent variable in an equation that will be part of the set of regressions to be run for a model. The variables which the arrows depart from are the independent variables in the respective regressions.

Panel A refers to the case where *ΔC* affects *ΔPD* without any influence of latent factors. Panel B shows an association in an inverse direction (from *ΔPD* to *ΔC*), still with no omitted factors influencing the main variables. Panels C and D represent situations where *ΔC* and *ΔPD* share common causes (U) besides one of them affecting the other one, the only difference between the panels being the direction of the relationship between the two main variables. Panel E follows the same idea of the two previous cases except that it has a reciprocal relationship between *ΔC* and *ΔPD* (i.e., they affect each other). Panel F shows a case in which *ΔPD* and *ΔC* are exclusively driven by unobserved factors; that is, those two variables are correlated but do not affect each other.

[Insert Figure 1 here]

After running the equations corresponding to each of the models in Figure 1, we should generate three metrics for identifying the best-fit-model: Akaike's information criterion (AIC), Bayesian information criterion (BIC), and the coefficient of determination (CD). As explained in Acock (2013, pp. 23-24), when it comes to information criteria measures, the lower the AIC and the BIC scores, the more suitable the model is. The higher CD is, the better its model is.

3.2.4. Generalised Methods of Moments

Although our main objective in this study is to investigate the potential impact of changes in capital on changes in banks' probability of default (PD), we take additional steps to check whether other relevant factors (AMELS from the CAMELS acronym presented before and bank size) could lead to changes in banks' PD.[8]

As in the case of capital, the relationship between changes in PD and changes in each of the candidate factors is also endogenous, which means that we would need instruments for each of the factors. Given that finding IVs for those variables is very challenging, we adopt the Generalised Methods of Moments (GMM) as it gives us more flexible alternatives to select instruments. Following the recommendations in the literature (e.g., Cameron and Trivedi, 2005, p. 743), we use lagged values of the endogenous variables (i.e., the candidate factors) as their respective instruments.[9]

We first run tests considering only one of the factors as endogenous while taking the other candidates and the country-specific variables introduced in Eq. (1) as exogenous. Then, in a final test, we include all of the candidates (CAMELS and bank size) as simultaneously endogenous variables.

Hence, our general GMM model uses the same dependent and independent variables presented in Eq. (1) except that the time- and country-fixed effects are not included because, in our data set, they would make the number of regressors outnumber the number of instruments, in which case it would not be possible to run the instrument validation tests. We repeatedly run the GMM regression

$$\Delta PD_{i,t} = \phi_0 + \phi_1 \Delta C_{i,t} + \phi_2 C_{i,t} + \phi_3 A_{i,t} + \phi_4 M_{i,t} + \phi_5 E_{i,t} + \phi_6 L_{i,t} + \phi_7 S_{i,t} + \phi_8 Size_{i,t} + \phi_9 \Delta GDP_{j,t} + \phi_{10} \Delta Stock\_index_{j,t} + \nu_{i,t} \quad (4)$$

[8] In fact, we also include the 'C' (capital) of CAMELS in our GMM analyses, which ends up working as a robustness test in relation to our previous analyses (fixed-effects and 2SLS-IV) especially because GMM helps with precluding the possibility of Nickell bias (Nickell, 1981).

[9] To reduce the possibility of overfitting the endogenous variables and weakening the Hansen test of joint validity of the instruments (Roodman, 2009), we use the *collapse* Stata command, which prevents an excessive number of instruments (i.e., not all lags of the endogenous variables are used as instruments).

replacing ΔC with the variation of one the other factors (*AMELS* and *Size*) and keeping all the control variables. Later, we run a model including all the variations and all the controls, where the instruments for the variation of each candidate factors are the lags of their respective variations. The variables in Eq. (4) are defined just after Eq. (1). Here, ϕ are the coefficients to be estimated and ν is the error term.

4. Results and discussion

4.1. Summary statistics

The descriptive statistics of the main variables used in our study are presented in Table 1. To help with the distinction between the different roles of the variables, they are split into three panels. In Panel A, we present *PD* and ΔPD, which are related to the dependent variable in our models (the former used to calculate the latter, which is the dependent variable). Panel B shows capital and variations in capital, the latter being the main independent variable in our study, calculated from the former, which is also used as a control variable. The other controls appear in Panel C.

Overall, there are no noticeable inconsistencies. The only issue that may deserve an additional explanation is the highest values of the variations in ΔPD. The considerably high values observed are due to the small values of (already winsorised) *PD*. For example, a change from 0.000003 to 0.000075, which means a variation of +2400% (ΔPD = 24). We opt for not further winsorising ΔPD because this would distort the nature of the data analysed as such oscillations in relatively small values of *PD* are common for the banks in our data set. Note that, for all maturities of *PD*, ΔPD has relatively high standard deviations as compared to its respective mean. This helps explain the maximum values of that variable. Also, looking at their 75th percentiles, we see that the extreme values reported in the last column of Table 1 do not cover a significantly high proportion of the distributions of ΔPD.[10] Additionally, the information provided in Table 1 is supplemented with visual descriptive statistics (histograms) presented in Appendix B.

The correlations among the independent variables in Table 2 show that there is no evidence of multicollinearity in our data set. The only values standing out as relatively high (above 0.60) are four correlations involving the capital ratios considered (pairs: variations in total equity and in CET1, variations in total capital and in CET1, total equity and CET1 in levels, and total capital and CET1 in levels). This is not worrying nevertheless given that these variables are not used together in our regressions (i.e., they are alternative measures of a same variable, capital).

Furthermore, as shown in Table 3, the negative correlations between the three measures of capital and the four maturities of probability of default used in our study could suggest a beneficial impact of capital on banks' stability. Being all statistically significant at the 1% level, the values could lead us to assume that by increasing capital, banks would become more stable. However, as it is well known, linear correlation is a very rough measure of association, especially when one is interested in understanding impact. Our analyses ahead will shed light on the nature of this relationship.

[Insert Tables 1, 2 and 3 here]

4.2. Baseline results (fixed-effects model)

The model presented in Eq. (1) is run for the three capital ratios (as a function of total assets) introduced in Section 3.2.1 (total equity, *TEq_ta*; total regulatory capital, *TCap_ta*; Common Equity Tier 1, *CET1_ta*) and four *PD* maturities (1 month, 3 months, 6 months and 12 months, where the last is our preferred option as it is the time horizon normally considered in regulatory

[10] A supplementary information: the average values of the 90th and 95th percentiles of ΔPD for the four maturities considered are 2.64 and 5.25, which indicate variations much less drastic than the maximum values shown in Table 1.

requirements - see, e.g., BCBS, 2011). As the *PD* data is originally provided in monthly frequency and the other variables used in our models are annual, for each of the four maturities considered, the *PD* values in our regressions are the annual averages of the respective monthly PDs.

Table 4 shows the results of our fixed-effects model. Each panel refers to one of the capital measures. Standard errors are initially clustered by banks but, in robustness tests, clusters by banks and countries are also considered. The main independent variable of interest, changes in capital (ΔC), is not statistically significant in any of the 12 specifications tested. This means that, when controlling for latent time-invariant factors, changing capital does not affect changes in banks' probabilities of default. Although the signs of the ΔC coefficients do not coincide across all *PD* maturities, all of them are insignificant, which is the key point related to the main objective of this paper. In Section 4.5, this will be further discussed and analysed in view of the relevant literature after we have presented supplementary results based on another two methods, which will allow us to have a more complete view of the relationship investigated.

Even though we do not focus on the relationship between the capital level and changes in *PD*, we highlight that in most of the scenarios considered, the amount of capital a bank has is not related to variations in *PD*.

[Insert Table 4 here]

4.3. Instrumental variables

In the previous section, we only control for the potential effect of time-invariant unobserved factors. We now use instrumental variables with a view to also controlling for the presence of time-varying omitted factors that could be driving changes in *PD* and in capital.

Whenever the first two instruments ($IV_{i,j,t-1}^{mean\_disp}$ and $IV_{i,j,t-1}^{perc\_disp}$) presented in Section 3.2.2.2 pass the Hansen J overidentification test at the 5% level, they are used together in our 2SLS model. This is the case in most of the specifications shown in Table 5. When they do not pass the tests, we report the results based on one of them only ($IV_{i,j,t-1}^{mean\_disp}$). Alternative instruments are used in robustness tests.

[Insert Table 5 here]

As in the fixed-effects analyses, the results in Table 5 are organised in three panels (one for each capital measure) and four *PD* maturities are considered. In the first stage, the IVs' coefficients in all specifications have the expected sign (negative) as discussed in Section 3.2.2.2 and the F statistics are above 10, which reinforces the statistical validity of the instruments (Angrist and Pischke, 2009).[11]

Moreover, in all scenarios, the Kleibergen-Paap rk Wald F statistic is bigger than the critical values required to the rejection of the weak identification test.[12] Hence, we can reject the hypothesis that our equations are weakly identified.

None of the coefficients of the main variable of interest in the second stage, $\widehat{\Delta C}$ (exogenous change in capital estimated in the first stage), is statistically significant, which corroborates the findings based on our fixed-effects model. This is further evidence that changes in capital per se seem not to affect changes in banks' probability of default. The potential reasons for this will be discussed in detail in Section 4.5, when we will be able to consider and compare the results based on three approaches. Again, although out of the main scope of this study, the results concerning capital levels also show no significant relationship with changes in *PD*.

In short, our instruments help to overcome concerns regarding endogeneity in terms of reverse causality and association with omitted variables that could be driving changes in both capital and stability (*PD*). As for the former, all the IVs are determined one period before the stability measure used and therefore it is reasonable to assume that they are not influenced by the

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[11] In each panel, for *ΔPD_6m* and *ΔPD_12m*, the results of the first stage concerning the three measures of capital are the same because their regressions are based on the same sample and have the same variables (note that, in each panel, the sample size for *ΔPD_1m* and *ΔPD_3m* is different). Nevertheless, the results of their second stages are clearly distinct.

[12] In the IV tests run throughout this paper (including the initial analyses and the robustness tests), the highest critical values reported in the regression outputs, in general, vary between 17 and 19.

dependent variable (changes in probability of default). As for the latter, the characteristics of the IVs discussed in Section 3.2.2.2 indicate that they are not related to unobserved factors that would influence variations in capital and stability. Therefore, the results presented here add credibility to our conclusions regarding the impact (rather than simple association) of (changes in) capital on (changes in) stability.

4.4. Testing different relationship structures

We test the six possible relationships between changes in capital and in banks' probability of default depicted in Figure 1. The values of the relevant comparative statistics (see Section 3.2.2.3) for the six models tested are reported in Table 6. The model represented in Panel F of Figure 1 is preferred because it has the lowest AIC and BIC values and the highest CD value (while this particular measure has the same value as that in other models). This best-fit scenario indicates that changes in capital and changes in probability of default are more likely jointly driven by unobserved factors rather than directly affect each other (in one or both directions).

[Insert Figure 1 and Table 6 here]

Overall, this supports the results based on the instrumental variables analyses where, given the features of the IVs employed, we concluded that the lack of association between the main variables applied for either direction of the relationship (i.e., from capital to probability of default or vice versa). Moreover, although we had shown statistically significant negative correlations between capital and probability of default (Table 3), the results in this section suggest that such correlations are due to the influence of unobserved common causes. This is also in line with the fixed-effects and IV results according to which there is no direct impact of bank capital on probability of default.

4.5. Analyses of the baseline results

Taken together, our results imply that promoting changes in bank capital does not directly affect bank stability even though those two variables are (negatively) correlated. Our confidence in this conclusion is enhanced by the use of three methods (alongside a fourth one considered in Section 5.2), which deal with endogeneity in different ways. The results from 2SLS-IV, for example, are only valid for banks whose capital decisions are driven by regulatory and market pressures as implied by the instruments used. The other methods employed in this study do not rely on this assumption.

Although this conclusion may sound implausible as it goes against the status quo in this field, in fact, it is in line with other studies that found no significant relationship between bank capital and risk (Thompson, 1991; Rochet, 1992; Roy, 2005) or claim that capital may not be an essential requirement to achieve stability (Gorton, 2012, pp. 151-164). To a certain extent, we could also associate our findings with those in studies indicating that, although relevant, capital is not sufficient to ensure resilient banking systems (Kahane, 1977; Barth, Caprio Jr and Levine; 2006, p. 66). While we focus on individual bank failures, our results are also consistent with those in Jordà et al. (2021) who find that higher bank capital is not related to lower risk of banking crisis.

Recall that, as discussed earlier, the two main reasons for believing that increasing capital would lead to safer banks are the loss-absorption capacity of capital and the skin-in-the-game incentives it would give shareholders to monitor bank managers in order to prevent excessive risk-taking. Nonetheless, other factors would also play a role in this relationship. For instance, given that capital is more expensive than debt, it would be natural to expect that banks who increase their capital ratios would seek more profitable opportunities (which are normally riskier) to increase their income and be able to pay the dividends expected by shareholders. This helps explain why a number of studies have found a positive relation between bank capital and risk-taking (Pettway, 1976; Kahane, 1977; Koehn and Santomero, 1980; Lam and Chen, 1985; Kim and Santomero, 1988; Gennotte and Pyle, 1991; Besanko and Kanatas, 1996; Jacques and Nigro, 1997; Blum, 1999; Altunbas et al., 2007; Jokipii and Milne, 2011). The increase in risk-taking would then counterbalance banks' higher loss absorption capacity due to the additional capital raised. In other words, those banks would be more prepared for facing higher losses but the probability of such losses happening would also increase. These offsetting forces could keep the banks' probability of default virtually unaltered. Consequently, stability (fairly constant) would be independent of capital (which would be changing).

In terms of the skin in the game explanation, we understand that capital is not causally relevant because what should matter is the ratio between the amount invested by each shareholder (especially the major ones) and their respective total wealth rather than the ratio between the level of capital and debt in their banks. This explanation is supported by the findings in Grossman (2001), according to whom extended liability (i.e., shareholders being responsible for covering losses above what they invested in the banks) is more effective than single liability (i.e., shareholders' losses is limited to the amount invested by them) at controlling risk-taking (at least in periods not affected by crises). Obviously, this does not mean that extended liability is an infallible solution to instability but it tends to be more efficient than limited liability (Macey and Miller, 1992; Grossman, 2001; Mitchener and Richardson, 2013; Turner, 2014, pp. 108-120). Moreover, as suggested by Rochet (2015), a direct effect of the skin in the game on risk-taking would only be expected if we factor in the capital held by top managers of banks given that, normally, shareholders are not able to influence the decisions made by banks (i.e., by their top managers). Additionally, we should consider that increasing capital can possibly lead to a reduction in the voting rights of the existing shareholders. As a consequence, this reduces their means to put pressure on managers. It is also worth noting that, as pointed out by Saunders, Strock and Travlos (1990), limited liability could actually encourage shareholders to increase risk in order to maximise their investment value given that their losses are curbed. In our view, this expected benefit can help counterbalance any risk aversion coming from the possibility of higher losses due to capital increments. Since we do not have the necessary data to test the hypotheses raised above, this is left for further research.

In sum, our findings can be explained by the possibility of higher risk taken by banks to offset the higher cost of capital as compared to debt and by the little incentive for most shareholders to monitor bank managers given that increasing capital levels as a function of banks' assets or debt does not seem to threaten shareholders as much as if those levels were increased as a function of their personal wealth. Thus, the presumed effects of capital on stability are not observed in practice.

5. Robustness and additional tests

5.1. Robustness tests

5.1.1. Alternative measure of bank risk

We employ credit default swap (CDS) spread as an alternative proxy of bank risk. CDS spread is directly related to corporate probability of default (see a detailed presentation in Chan-Lau, 2013, pp. 61-74). Four maturities are used: one, two, three and five years.[13]

We replicate our analyses based on three methods used previously. In all cases, the findings of our baseline exercises are confirmed. Tables 7 (fixed-effects) and 8 (2SLS-IV) show that changes in capital (besides capital level) are not statistically significant when explaining changes in CDS spread. Moreover, in Table 8, we see that all the instruments pass all the necessary validation tests. Table 9 corroborates the initial findings according to which changes in capital and in stability are most likely driven by unobserved common causes (i.e., scenario F based on Figure 1 has the lowest AIC and BIC values alongside the highest CD value possible).

[Insert Tables 7, 8 and 9 here]

[13] Regressions concerning the four-year maturity were also run but, due to space constraints, they are not reported. Their results are in line with the conclusions presented in this section.

We clarify that Z-score (for a survey, see, e.g., Lepetit and Strobel, 2013) would initially be an additional option for an accounting measure of stability but it could not be used in our case because capital (one of the components of the Z-score formula) is on the right-hand side of our regressions (variation and level).

5.1.2. Alternative instruments

Besides the two IVs used in our original analyses, other alternatives to those instruments are tested. Altogether, we consider the six individual IVs defined in Section 3.2.2.2 and six pairs combining some of them: $IV_{i,j,t-1}^{perc\_disp}$ and $IV_{i,j,t-1}^{mean}$, $IV_{i,j,t-1}^{perc\_disp}$ and $IV_{i,j,t-1}^{median}$, $IV_{i,j,t-1}^{perc}$ and $IV_{i,j,t-1}^{mean}$, $IV_{i,j,t-1}^{perc}$ and $IV_{i,j,t-1}^{median}$, $IV_{i,j,t-1}^{perc\_disp}$ and $IV_{i,j,t-1}^{perc\_median}$, and $IV_{i,j,t-1}^{perc\_disp}$ and $IV_{i,j,t-1}^{perc\_mean}$, where the last pair was used in our initial IV analyses. Given that the exact benchmark used by banks when deciding their capital levels is normally unknown to external stakeholders, testing these multiple possibilities improves the reliability of our results.

Changes in capital are *not* statistically significant in 218 out of the 244 models[14] for *ΔPD* and *ΔCDS* with statistically valid IVs. This represents a ratio of 89.33% models with valid IVs where both the measure of capital and its variation are *not* statistically significant. More specifically, recalling that our tests are focused on changes in capital, we see that exogenous changes in capital do not affect changes in bank risk (proxied either by probability of default or CDS spread). So, our main conclusions remain unaltered in the great majority of robustness tests using alternative instruments. Due to space constraints, these results are not reported here but are available upon request.

[14] In total, considering the 12 possibilities of instruments, there are 288 models for the four maturities of *PD* and *CDS* shown in our previous results.

5.1.3. Possible influence of the global financial crisis years

The global financial crisis (GFC) 2007-2008 may have distorted the relationship between bank capital and banks' risk of failure due to the massive losses suffered by banks in that period (therefore increasing their probability of default and drastically wiping out their capital) and the capital injections promoted by the government and central banks of some countries (so, an unusual increase of capital in a short period). To make sure this has not affected our baseline results we re-run our fixed-effects and 2SLS-IV analyses by adding a dummy equal to 1 in years 2007 to 2009 (2009 is also considered a GFC year because the consequences of the crisis relevant to our study could still be noticed in that year). Tables 10 (fixed-effects) and 11 (2SLS-IV) show different conclusions about the importance of the GFC to the variations in banks' probability of default. While, in the fixed-effects, the GFC dummy is only significant in one scenario, it is significant in all 2SLS-IV specifications. Nevertheless, it has not affected our original results as the changes in capital remain statistically insignificant in both tables. Additionally, capital in level is also insignificant in most of the scenarios and all the instruments pass the necessary validation tests reported in Table 11.

[Insert Tables 10 and 11 here]

5.1.4. Other alternatives

To test if the lack of impact from capital to stability is due to the quantitative easing tools adopted in many countries during and after the GFC, we run our baseline models for the period before 2008. In that period, we only have enough data for one measure of capital (*TEq_ta*). In all scenarios tested (i.e., *PD* maturities), the coefficients of ΔC and C remain insignificant. Alternatively, note that, since we control for country fixed effects, we are able to take into account the fact that not all countries in our sample have adopted quantitative easing practices. We repeat our fixed-effects and 2SLS-IV analyses by removing countries with data for less than 20 banks and alternatively with less than 200 bank-year observations. This aims at avoiding the influence of countries with little data that could prevent us from identifying relevant variations across banks or over time. Our results remain consistent with our original findings (see, for example, Tables 12 and 13 where we report the results for the12 countries[15] in our sample with at least 200 bank-year observations).

[Insert Tables 12 and 13 here]

Studies in this area have suggested a non-linear relationship between bank capital and risk (e.g. Gennotte and Pyle, 1991; Calem and Rob, 1999). Hence, our previous findings could be explained by a non-linear relationship between capital and stability not captured in our models. To test this possibility, we add a quadratic term (ΔC^2) to our baseline models (fixed effects and 2SLS-IV). In all scenarios, the coefficients of ΔC, ΔC^2 and C are statistically insignificant, which reinforces our initial results.[16]

While our baseline fixed-effects and 2SLS-IV results are based on standard errors clustered by banks only, clustering standard errors by bank and country does not affect our conclusions (these results are available upon request).

5.2. Additional tests (searching for other factors potentially affecting stability)

As mentioned earlier, CAMELS are used by supervisors and researchers to predict bank distress. Given that our main findings suggest that changes in capital (C in CAMELS) do not directly cause changes in banks' probability of default, a natural question would be whether the other five factors (asset quality, management quality, earnings, liquidity, and sensitivity to market risk) would play a relevant role in this context. Like capital, all these aspects are endogenous because they are possibly related to omitted variables (e.g., managers' skills) that also affect bank stability. An appropriate treatment of these jointly endogenous factors would

[15] Brazil, Canada, China, France, Germany, India, Indonesia, Japan, Switzerland, Turkey, United Kingdom and United States.

[16] By further adding C^2 to the regressions, we find that all the coefficients of the main variables of interest (ΔC and ΔC^2) remain insignificant. To save space, we do not present tables with these results but they are available upon request.

require specific instruments for each of them. Considering that finding these instruments is not a trivial task, we resort to GMM to investigate this relationship. As before, we focus on the changes of the variables of interest. To mimic our baseline regressions with one endogenous variable only, we start with individual models following Eq. (4) where each of the CAMELS factors and size (another aspect highly related to banks' stability) are separately taken as endogenous one by one. We then run the model assuming all those seven variables are jointly endogenous.[17]

The results are presented in Tables 14 and 15, where bank stability is respectively proxied by probability of default and credit default swap spreads. The three capital measures used in our baseline analyses are included in this additional exercise. We show the results for changes in bank stability in the one-year horizon as this is the period normally considered in regulations such as the Basel Accords. In the scenarios with all the independent variables seen as simultaneously endogenous, we only report the results where the instruments pass all the necessary validation tests. This explains why a few scenarios for jointly endogenous variables (two in Table 14 and one in Table 15) are not reported. Note that columns (1) to (3) in both tables work as other robustness tests for the potential impact of changes in capital on bank stability (i.e., a method not tried before).

In general, the results indicate that changes in the factors considered tend not to have an impact on bank stability. The only exceptions are changes in total regulatory capital in an individual analysis for CDS (weakly significant –see column (2) of Table 15) and changes in earnings in a joint analysis for PD (see column (10) of Table 14). Hence, in general, even factors commonly associated with bank stability seem not to have a causal effect on it. Nevertheless, differently from the findings for capital in Section 4, which are based on much more detailed tests (including the corroborative evidence from columns (1) to (3) in Tables 14 and 15), the

[17] These models cannot include time- and/or country-fixed effects because the regressors would outnumber the instruments, which is not allowed in GMM.

additional results in this section are primarily presented with a view to inspiring future discussions and motivating the search for factors that actually influence bank stability.

We emphasise that, according to the statistics shown at the bottom of the tables (p-values > 0.10), we do not reject the null hypotheses saying that the instruments are statistically valid. In terms of testing the possibility of error autocorrelation, we focus on the Arellano-Bond test AR(2). Taking the 5% significance level as an example, p-values above the related threshold (0.05) would indicate that the null hypothesis (autocorrelation does not exist) should not be rejected, meaning that our instruments comply with the GMM condition regarding the absence of correlation between errors two periods apart (Arellano and Bond, 1991, p. 281).

6. Conclusions

The idea that increasing capital makes banks healthier is appealing. Capital absorbs losses (which delays distress) and, in principle, would give shareholders incentives to monitor bank managers with a view to preventing high risk-taking (therefore, reducing the possibility of distress). However, such relationship may not be causal as other (unobserved) factors could be driving it.

Our results based on four methods (fixed-effects, 2SLS-IV, structural equation modelling, and generalised methods of moments) suggest that changing capital does not affect bank stability. Their association seems to be purely correlational. Considering that we have treated the possible effects of endogeneity (omitted variables and reverse causality) and that we have focused on changes of the variables studied, we can interpret our results as causal. We also find that factors other than capital commonly taken into account by bank supervisors and researchers (AMELS as explained in the paper and size) do not affect stability either, although these particular findings should be taken with caution as they are based on GMM only.

While we do not show what factors could be used in banking regulation in order to make banks safer, this study is still important because it warns policy-makers and regulators about the lack of causal link between factors currently considered by financial regulators and supervisors. Hence, many of these regulatory initiatives may be ineffective even though unobserved issues have guaranteed stability part of the time. This said, a natural further step in this area would be to search for factors and aspects that actually improve bank stability (rather than simply co-moving with stability). This is not a trivial task as endogenous relations may affect the results in empirical analyses but it is essential in the quest for stability. This is indeed a promising area of research with big potential of impact.

Moreover, conditional on data availability, additional analyses could empirically test the hypotheses raised in the discussion of our results, namely: (i) extended liability is what matters for shareholders in terms of motivations for monitoring bank managers (rather than the ratio of capital to total assets or debt), (ii) the skin-in-the-game reason for reducing risk-taking only works for the level of equity held by top managers, and (iii) other factors drive the association between capital and banks' probability of default. Also, since in this paper we deal with the capital banks have (which is determined by a combination of internal and external forces), another possibility would be to study the specific (causal) impact of regulatory interventions concerning higher capital requirements. This should account for the fact that Basel recommendations in terms of capital requirements have been implemented in different ways in different countries. Such additional analyses would even allow us to further check the consistency of the instruments used here given that their rationale (regulatory and market pressure) may vary across countries.

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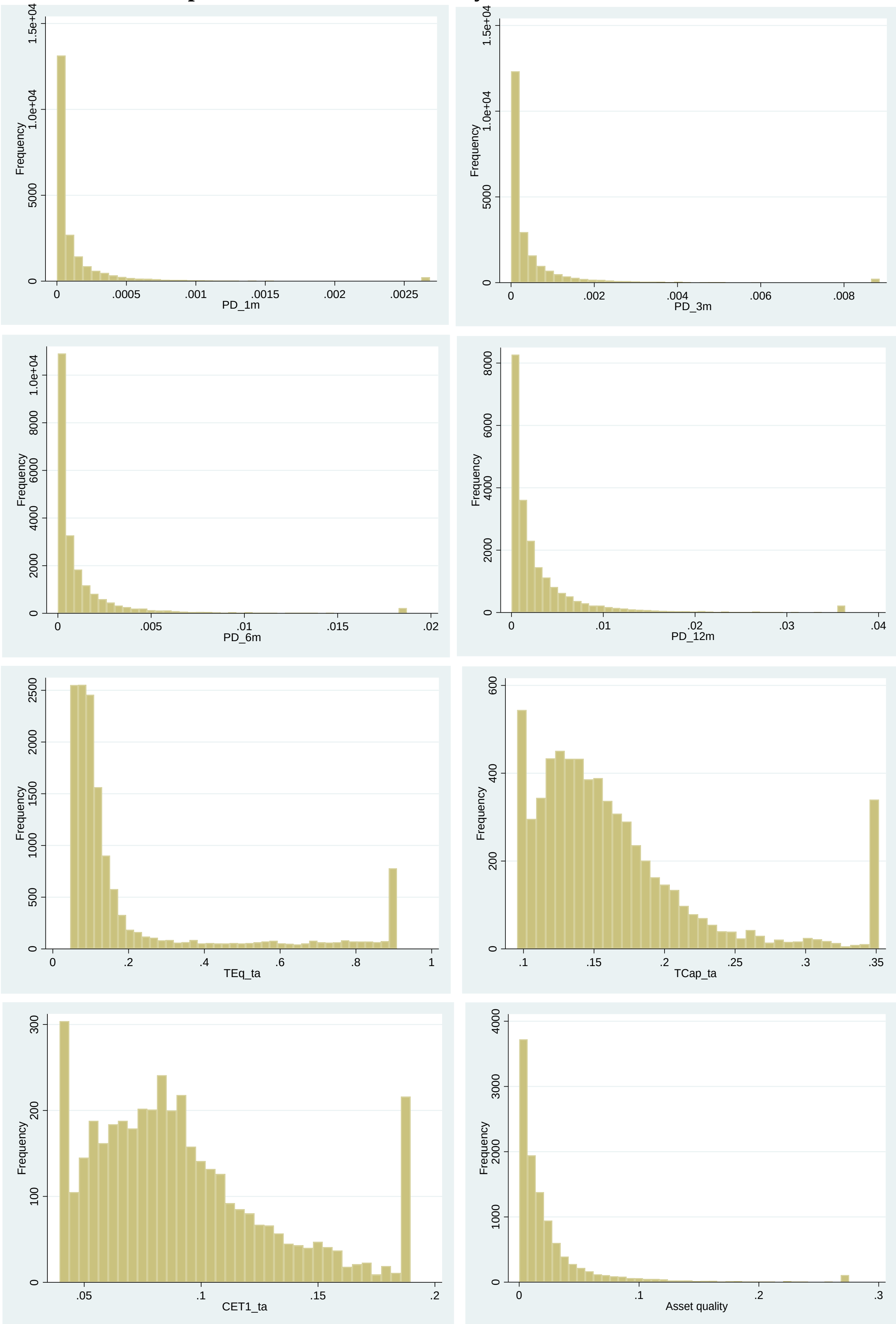
Appendix A

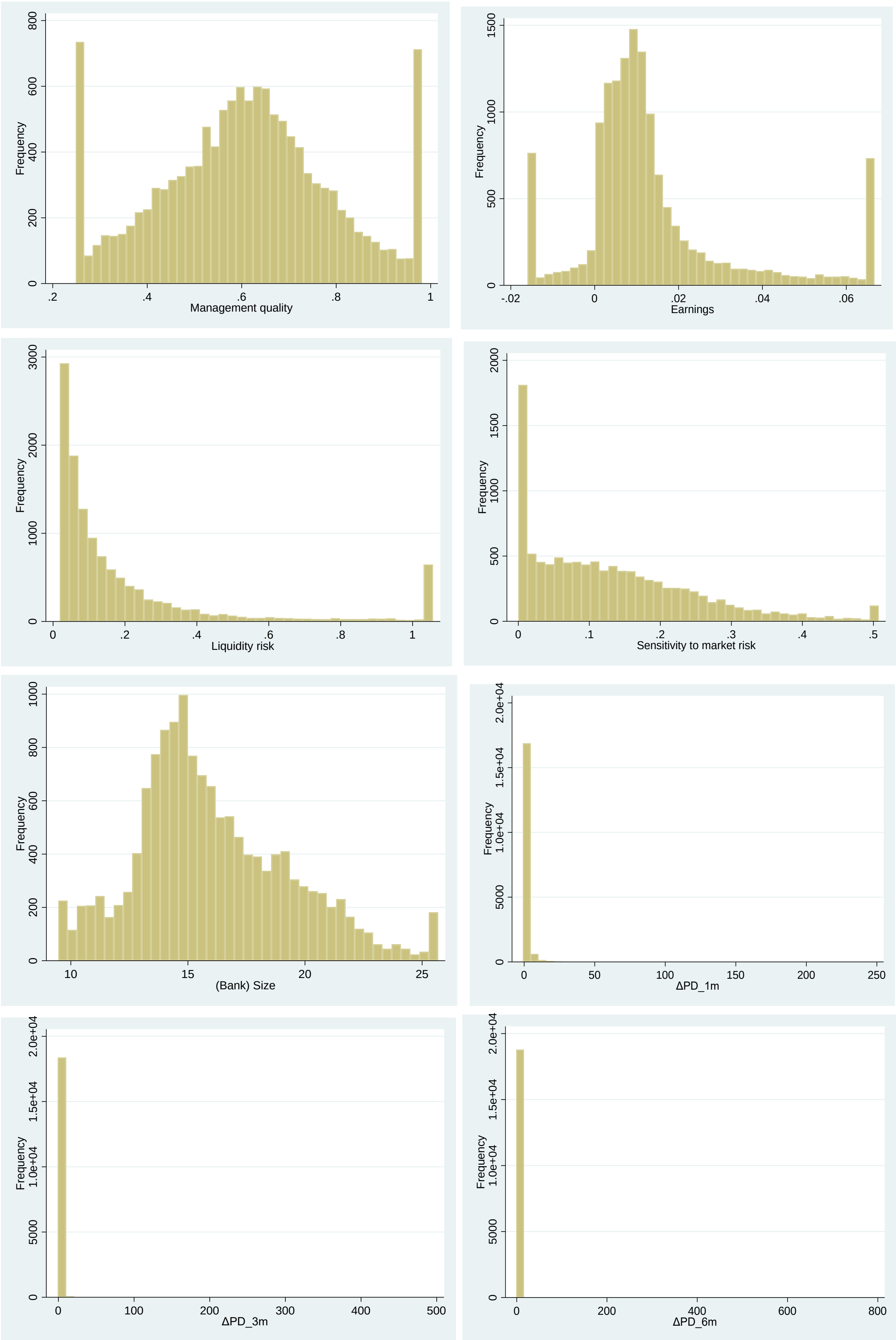
List of countries and number of banks in the sample used in the baseline analyses

Country	Number of banks	Country	Number of banks
Australia	23	Morocco	13
Bahrain	14	Nigeria	21
Bangladesh	50	Norway	28
Bermuda	21	Oman	19
Brazil	21	Pakistan	34
Canada	18	Philippines	23
Cayman Islands	12	Poland	15
Chile	10	Qatar	11
China	68	Republic of Korea	44
Colombia	11	Russian Federation	17
Croatia	12	Saudi Arabia	12
Denmark	27	Singapore	11
Egypt	28	South Africa	15
France	34	Spain	10
Germany	38	Sri Lanka	36
Hong Kong	24	Sweden	10
India	74	Switzerland	37
Indonesia	65	Taiwan	32
Israel	10	Thailand	33
Italy	32	Tunisia	19
Japan	171	Turkey	53
Jordan	25	United Arab Emirates	25
Kenya	10	United Kingdom	45
Kuwait	28	United States of America	918
Malaysia	14	Vietnam	14
Mexico	15	TOTAL	2,350

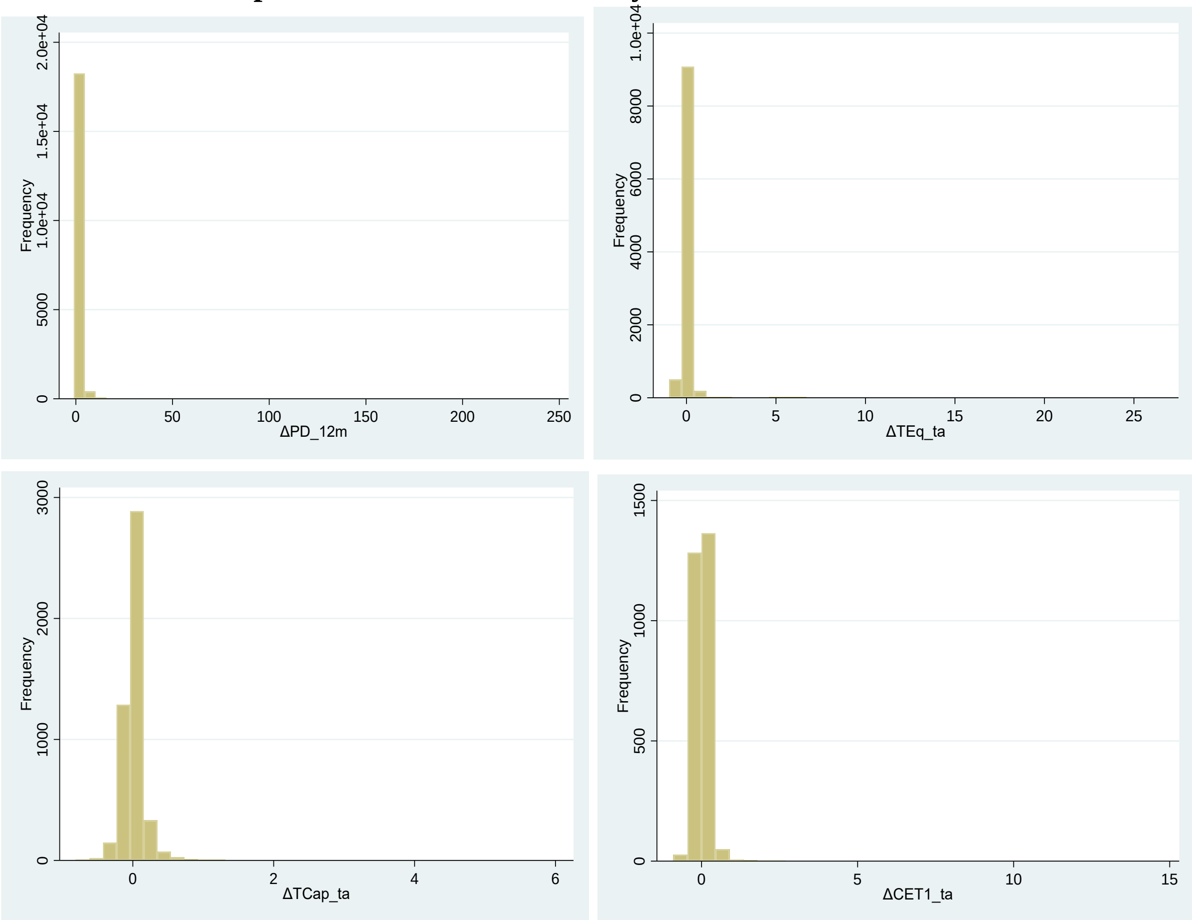
Appendix B
Visual representation of the summary statistics of the main variables



Appendix B (continuation)
Visual representation of the summary statistics of the main variables



Appendix B (continuation)
Visual representation of the summary statistics of the main variables



PD is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *TEq_ta* is calculated as total equity divided by total assets, *TCap_ta*, is the total capital ratio (the sum of all items accepted as regulatory capital divided by total assets), and *CET1_ta* is given by Common Equity Tier 1 divided by total assets. *A* is asset quality (total impaired loans and assets divided by total assets). *M* is management quality (measured by Cost-to-Income Ratio = Interest and Related Expense + Non-Interest Expense) divided by (Interest Income + Non-Interest Income). *E* is earnings (Return on Equity = Net Income divided by Common Stock + Preferred Stock). *L* is liquidity (liquid assets divided by total deposits). *S* is sensitivity to market risk (Assets Held for Sale divided by Total Assets). Bank *Size* is calculated as the natural logarithm of total assets. *ΔPD* are the variations of *PD* (from the end of year *t-1* to the end of year *t*) in the respective time windows reported for *PD*. *ΔTEq_ta*, *ΔTCap_ta* and *ΔCET1_ta* are respectively the percentage variations (from the end of year *t-1* to the end of year *t*) of the three aforementioned capital measures.

Table 1. Summary statistics of the main variables

Variable	N	Mean	Stdev	Min	25 pct	Median	75 pct	Max
				Panel A. Probability of default				
PD_1m	21,402	0.0002	0.0004	<0.0001	<0.0001	<0.0001	0.0001	0.0027
PD_3m	21,402	0.0006	0.0012	<0.0001	<0.0001	0.0001	0.0005	0.0089
PD_6m	21,402	0.0013	0.0027	<0.0001	0.0001	0.0004	0.0013	0.0187
PD_12m	21,402	0.0033	0.0056	<0.0001	0.0004	0.0014	0.0037	0.0363
ΔPD_1m	18,807	0.8741	5.5325	-1.0000	-0.6004	-0.1372	0.7799	233.0000
ΔPD_3m	18,807	0.4419	5.6621	-1.0000	-0.5609	-0.1090	0.6137	459.2108
ΔPD_6m	18,807	0.5285	5.4609	-0.9956	-0.5214	-0.1615	0.3823	721.8889
ΔPD_12m	18,807	0.5061	3.6621	-0.9954	-0.4366	-0.0213	0.5166	235.3607
				Panel B. Capital				
TEq_ta	20,180	0.2107	0.2471	0.0458	0.0759	0.1039	0.1737	0.9085
TCap_ta	6,515	0.1646	0.0625	0.0955	0.1226	0.1485	0.1835	0.3520
CET1_ta	4,091	0.0918	0.0390	0.0394	0.0632	0.0844	0.1101	0.1896
ΔTEq_ta	16,005	0.1804	1.4971	-0.9712	-0.0659	0.0000	0.0670	26.9571
ΔTCap_ta	4,807	0.0174	0.2106	-0.8089	-0.0549	0.0034	0.0672	6.1231
ΔCET1_ta	2,745	0.0209	0.3898	-0.9012	-0.0708	0.0000	0.0650	14.3699
				Panel C. Controls				
A	13,682	0.0261	0.0419	0.0001	0.0047	0.0124	0.0278	0.2753
M	16,274	0.6157	0.2417	0.0185	0.4861	0.6095	0.7223	0.9812
E	17,121	0.0131	0.0324	-0.0160	0.0041	0.0096	0.0166	0.0667
L	15,364	0.2549	0.4976	0.0049	0.0465	0.0988	0.2268	1.0570
S	13,557	0.1306	0.1150	0.0000	0.0343	0.1072	0.1979	0.5076
Size	17,180	16.0533	3.2999	9.4648	13.8528	15.4535	18.1365	25.6752
ΔGDP	21,202	0.0271	0.0231	-0.0389	0.0164	0.0265	0.0403	0.0849
ΔStock_index	20,739	0.0673	0.2078	-0.4221	-0.0619	0.0899	0.1994	0.5680

N is the number of observations. Stdev is standard deviation. Min and Max are the minimum and maximum values, respectively. 25 pct and 75 pct are the 25th and the 75th percentiles. *PD* is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *ΔPD* are the variations of *PD* (from the end of year *t-1* to the end of year *t*) in the respective time windows. *ΔTEq_ta*, *ΔTCap_ta* and *ΔCET1_ta* are respectively the percentage variations (from the end of year *t-1* to the end of year *t*) of total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *A* is asset quality (total impaired loans and assets divided by total assets). *M* is management quality (measured by Cost-to-Income Ratio = Interest and Related Expense + Non-Interest Expense) divided by (Interest Income + Non-Interest Income). *E* is earnings (Return on Equity = Net Income divided by Common Stock + Preferred Stock). *L* is liquidity (liquid assets divided by total deposits). *S* is sensitivity to market risk (Assets Held for Sale divided by Total Assets). Bank *Size* is calculated as the natural logarithm of total assets. *ΔGDP* and *ΔStock_index* are the annual changes in the Gross Domestic Product (GDP) and in the main stock index of the respective country from year *t-1* to year *t*. Data is winsorised at the 1st and 99th percentiles (except for the variation – *Δ* – values which are already based on winsorised values).

Table 2. Correlation matrix – main independent variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) *ΔTEq_ta*	1.000													
(2) *ΔTCap_ta*	0.469	1.000												
(3) *ΔCET1_ta*	0.934	0.656	1.000											
(4) *TEq_ta*	0.285	0.057	0.273	1.000										
(5) *TCap_ta*	0.085	0.164	0.208	0.573	1.000									
(6) *CET1_ta*	0.260	0.086	0.245	0.891	0.602	1.000								
(7) *A*	0.067	0.035	0.084	0.198	0.013	0.195	1.000							
(8) *M*	-0.144	-0.049	-0.070	-0.139	0.057	0.049	0.056	1.000						
(9) *E*	0.132	-0.001	0.108	0.348	0.136	0.349	-0.167	-0.430	1.000					
(10) *L*	0.042	0.015	0.017	0.494	0.494	0.250	0.101	0.062	0.129	1.000				
(11) *S*	-0.072	0.025	0.053	-0.233	-0.079	-0.079	-0.137	0.060	-0.107	-0.164	1.000			
(12) *Size*	-0.074	0.044	0.021	-0.402	-0.120	-0.293	0.014	-0.212	-0.022	-0.052	-0.086	1.000		
(13) *ΔGDP*	-0.031	-0.033	-0.023	-0.035	-0.025	-0.010	-0.032	-0.209	0.105	-0.024	-0.052	0.300	1.000	
(14) *ΔStock_index*	0.027	0.036	0.031	0.003	0.010	-0.020	-0.065	0.016	0.030	0.000	0.073	-0.016	0.078	1.000

ΔTEq_ta, *ΔTCap_ta* and *ΔCET1_ta* are respectively the percentage variations (from the end of year *t-1* to the end of year *t*) of total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *A* is asset quality (total impaired loans and assets divided by total assets). *M* is management quality (measured by Cost-to-Income Ratio = Interest and Related Expense + Non-Interest Expense) divided by (Interest Income + Non-Interest Income). *E* is earnings (Return on Equity = Net Income divided by Common Stock + Preferred Stock). *L* is liquidity (liquid assets divided by total deposits). *S* is sensitivity to market risk (Assets Held for Sale divided by Total Assets). Bank *Size* is calculated as the natural logarithm of total assets. *ΔGDP* and *ΔStock_index* are the annual changes in the Gross Domestic Product (GDP) and in the main stock index of the respective country from year *t-1* to year *t*. Except for the pairs *ΔTCap_ta-E*, *ΔTCap_ta-L*, *ΔTCap_ta-S*, *ΔCET1_ta-L*, *ΔCET1_ta-Size*, and *TCap_ta-A*, which are not statistically significant, all the correlations between the main bank-specific variables are significant at the 5% level.

Table 3. Correlation between capital and probability of default

	PD_1m	*PD_3m*	*PD_6m*	*PD_12m*
TEq_ta	-0.0852	-0.0873	-0.0928	-0.1072
TCap_ta	-0.089	-0.093	-0.0996	-0.1128
CET1_ta	-0.1154	-0.1196	-0.1262	-0.1387

TEq_ta is total equity divided by total assets. *TCap_ta* is the total capital ratio (the sum of all items accepted as regulatory capital) divided by total assets. *CET1_ta* is Common Equity Tier 1 divided by total assets. *PD_1m*, *PD_3m*, *PD_6m*, and *PD_12m* are banks' probability of default over 1, 3, 6, and 12 months, respectively. All correlation coefficients are statistically significant at the 1% level.

Table 4. Baseline results (fixed-effects model)

	Panel A				*Panel B*				*Panel C*			
Capital measure	*TEq_ta*				*TCap_ta*				*CET1_ta*			
Dependent variable	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔC	**1.0054**	**0.5657**	**0.5729**	**0.4077**	**0.6845**	**-0.2700**	**0.1995**	**0.1982**	**0.1238**	**-0.4903**	**-0.2338**	**-0.1171**
	(0.8546)	**(0.7583)**	**(0.5416)**	**(0.3299)**	**(0.4741)**	**(0.6145)**	**(0.3339)**	**(0.2344)**	**(0.3943)**	**(0.4503)**	**(0.3160)**	**(0.2207)**
C	-0.1193	-1.9886	-3.7822	-2.2614	0.6793	4.6979	0.9543	0.2375	4.6522	11.4359*	8.0928*	4.4586
	(4.6484)	(4.7233)	(4.2206)	(2.2627)	(2.1119)	(4.1321)	(2.0508)	(1.4414)	(5.4573)	(6.5689)	(4.7271)	(3.2047)
No. obs.	14,895	15,042	15,088	15,088	2,509	2,573	2,592	2,592	1,398	1,460	1,478	1,478
No. banks	2,265	2,287	2,296	2,296	659	698	704	704	458	498	504	504
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0865	0.0344	0.0175	0.0260	0.0537	0.0367	0.0547	0.0751	0.0492	0.0404	0.0545	0.0750

This table shows the regression results of the baseline model, Eq. (1). *PD* is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *ΔPD* is the variation of *PD* (from the end of year *t-1* to the end of year *t*). *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. No. obs. is the total number of bank-year observations. FE stands for fixed-effects. Numbers in parentheses are robust standard errors clustered by banks. * indicates coefficients statistically significant at the 10% level. For convenience, the values of greatest interest (regarding *ΔC*) are presented in bold.

Table 5. Results of the original two-stage-least-squares model with instrumental variables

	Panel A				*Panel B*				*Panel C*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						First stage						
Dep variable	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*
IV^{mean_disp}	-5.444***	-2.773***	-2.757***	-2.757***	-13.615***	-1.597***	-1.610***	-1.610***	-64.016***	-82.094***	-82.164***	-82.164***
	(0.351)	(0.229)	(0.227)	(0.227)	(3.111)	(0.550)	(0.537)	(0.537)	(20.955)	(19.590)	(19.561)	(19.561)
IV^{perc_disp}		-3.486***	-3.491***	-3.491***	-1.591***	-13.624***	-13.582***	-13.582***	-7.973***			
		(0.311)	(0.306)	(0.306)	(0.5480)	(3.115)	(3.057)	(3.057)	(1.676)			
F statistic	30.28	39.54	40.40	40.40	80.03	80.82	80.68	80.68	37.18	11.57	11.55	11.55
						Second stage						
Dep variable	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*
$\widehat{\Delta C}$	**0.9739**	**-1.378**	**-0.356**	**0.030**	**0.660**	**-.0290**	**0.261**	**0.189**	**-0.667**	**-0.4604**	**-0.381**	**-0.221**
	(1.4946)	**(1.253)**	**(0.675)**	**(0.334)**	**(0.494)**	**(0.820)**	**(0.358)**	**(.264)**	**(0.609)**	**(0.651)**	**(0.402)**	**(.288)**
C	0.3127	5.360	-1.509	-1.307	0.622	3.589	0.149	0.036	4.173	3.113	4.729	2.295
	(7.1532)	(6.691)	(4.350)	(2.170)	(2.435)	(3.303)	(1.984)	(1.526)	(6.078)	(5.255)	(4.748)	3.328
No. obs.	14,645	14,792	14,836	14,836	2,354	2,400	2,418	2,418	1,257	1,299	1,316	1,316
No. banks	2,015	2,037	2,044	2,044	504	525	530	530	317	337	342	342
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F	240.849	159.968	163.094	163.094	275.123	278.374	278.068	278.068	163.186	17.561	17.643	17.643
Hansen J stat	n/a	3.105	2.724	2.028	1.265	1.627	2.531	2.966	3.539	n/a	n/a	n/a
Hansen J p-val	n/a	0.078	0.099	0.154	0.261	0.2022	0.112	0.0850	0.0599	n/a	n/a	n/a

This table reports the results of the 2SLS-IV model presented in Eqs. (2) and (3). *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. *PD* is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *ΔPD* is the variation of *PD* (from the end of year *t-1* to the end of year *t*). IV^{mean_disp} and IV^{perc_disp} (based on year *t-1*) are the first two instruments introduced in Section 3.2.2.2. When they together pass the Hansen J overidentification test, both are used. Otherwise, we only use the former one. $\widehat{\Delta C}$ is the ΔC estimated in the first stage. N. obs. is the total number of bank-year observations. FE stands for fixed-effects. K-P Wald F stands for the Kleibergen-Paap rk Wald F statistic. Numbers in parentheses are robust standard errors clustered by banks. *** indicates coefficients statistically significant at the 1% level (to maintain consistency with other tables, ** and * are not used in this table). For convenience, the values of greatest interest (regarding $\widehat{\Delta C}$) are presented in bold.

Table 6. Testing alternative relationships between changes in capital and in probability of default

Relationship	Panel - Fig. 1	AIC	BIC	CD
Direct impact of *ΔC* on *ΔPD*	A	157,376.06	157,395.31	0.000
Direct reverse impact (from *ΔPD* on *ΔC*)	B	157,636.96	157,656.20	0.000
Joint impact of *ΔC* and U on *ΔPD*	C	-19,774.28	-19,748.15	1.000
Joint impact of *ΔPD* and U on *ΔC*	D	-19,773.95	-19,747.81	1.000
Joint impact of U on *ΔC* and *ΔPD* with reciprocal effect between *ΔC* and *ΔPD*	E	-19,767.53	-19,741.39	1.000
U driving *ΔC* and *ΔPD*	F	-25,929.360	-25,896.69	1.000

ΔC and *ΔPD* are the percentage variations in capital and in banks' probability of default, respectively, from the end of year *t-1* to the end of year *t*. Changes in the PD regarding the 1-year time window (*ΔPD_12m*) are used as an example in this case. AIC, BIC and CD stand for Akaike's information criterion, Bayesian information criterion, and coefficient of determination, respectively.

Table 7. Fixed-effects model with an alternative risk measure (CDS spread)

	Panel A				*Panel B*				*Panel C*			
Capital measure	*TEq_ta*				*TCap_ta*				*CET1_ta*			
Dependent variable	*ΔCDS_1y*	*ΔCDS_2y*	*ΔCDS_3y*	*ΔCDS_5y*	*ΔCDS_1y*	*ΔCDS_2y*	*ΔCDS_3y*	*ΔCDS_5y*	*ΔCDS_1y*	*ΔCDS_2y*	*ΔCDS_3y*	*ΔCDS_5y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔC	**0.1088**	**0.0587**	**0.0368**	**0.0178**	**0.1367**	**0.0938**	**0.0807**	**0.0661**	**-0.2044**	**-0.1085**	**-0.0733**	**-0.0338**
	(0.1404)	**(0.0781)**	**(0.0532)**	**(0.0322)**	**(0.1736)**	**(0.1215)**	**(0.0959)**	**(0.0715)**	**(0.1845)**	**(0.1279)**	**(0.0990)**	**(0.0704)**
C	-1.4322	-0.9727	-0.7947	-0.6013	-0.1263	-0.3348	-0.4039	-0.4129	4.5603	2.7289	2.1044	1.3712
	(1.2848)	(.7819)	(0.5797)	(0.4004)	(1.0060)	(0.7307)	(0.5925)	(0.4455)	(4.3340)	(3.1975)	(2.5190)	(1.8152)
No. obs.	5,223	5,223	5,223	5,223	2,551	2,551	2,551	2,551	1,443	1,443	1,443	1,443
No. banks	1,304	1,304	1,304	1,304	691	691	691	691	487	487	487	487
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0515	0.0689	0.0847	0.1128	0.0901	0.0967	0.1047	0.1146	0.0778	0.0925	0.1075	0.1297

This table shows the regression results of the baseline model, Eq. (1), when the original dependent variable (*ΔPD*) is replaced with *ΔCDS*. *CDS* is the average credit default swap spread in year *t* considering the maturities indicated (1, 2, 3 and 5 years). *ΔCDS* is the variation of *CDS* (from the end of year *t-1* to the end of year *t*). *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. No. obs. is the total number of bank-year observations. FE stands for fixed-effects. Numbers in parentheses are robust standard errors clustered by banks. None of the coefficients shown are statistically significant. For convenience, the values of greatest interest (regarding *ΔC*) are presented in bold.

Table 8. Two-stage-least-squares model with instrumental variables for an alternative risk measure (CDS spread)

	Panel A				*Panel B*				*Panel C*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						First stage						
Dep variable	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*
IV^{mean_disp}	-5.553***	-3.286***	-3.286***	-3.286***	-12.267***	-12.267***	-12.267***	-12.267***	-11.986***	-11.986***	-11.986***	-11.986***
	(0.615)	(0.299)	(0.299)	(0.299)	(2.305)	(2.305)	(2.305)	(2.305)	(3.776)	(3.776)	(3.776)	(3.776)
IV^{perc_disp}		-3.342***	-3.342***	-3.342***					-192.295***	-192.295***	-192.295***	-192.295***
		(0.510)	(0.510)	(0.510)					(20.940)	(20.940)	(20.940)	(20.940)
F statistic	46.27	40.09	40.09	40.09	12.21	12.21	12.21	12.21	32.43	32.43	32.43	32.43
						Second stage						
Dep variable	*ΔCDS_1y*	*ΔCDS_2y*	*ΔCDS_3y*	*ΔCDS_5y*	*ΔCDS_1y*	*ΔCDS_2y*	*ΔCDS_3y*	*ΔCDS_5y*	*ΔCDS_1y*	*ΔCDS_2y*	*ΔCDS_3y*	*ΔCDS_5y*
$\widehat{\Delta C}$	**0.334**	**0.075**	**0.098**	**0.106***	**-0.295**	**-0.213**	**-0.160**	**-0.106**	**-0.126**	**0.011**	**0.046**	**0.084**
	(0.382)	**(0.140)**	**(0.092)**	**(0.058)**	**(0.229)**	**(0.162)**	**(0.129)**	**(0.097)**	**(0.361)**	**(0.250)**	**(0.193)**	**(0.134)**
C	-1.427	-0.620	-0.630	-0.564	0.733	0.302	0.105	-0.049	2.410	1.029	0.722	0.262
	(0.382)	(0.846)	(0.639)	(0.485)	(1.250)	(0.924)	(0.747)	(0.560)	(4.079)	(2.968)	(2.248)	(1.578)
No. obs.	4,981	4,981	4,981	4,981	2,386	2,386	2,386	2,386	1,286	1,286	1,286	1,286
No. banks	1,062	1,062	1,062	1,062	526	526	526	526	330	330	330	330
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F	81.621	64.002	64.002	64.002	28.311	28.311	28.311	28.311	106.405	106.405	106.405	106.405
Hansen J stat	n/a	1.680	0.427	0.201	n/a	n/a	n/a	n/a	0.009	0.102	0.311	0.297
Hansen J p-val	n/a	0.1950	0.513	0.654	n/a	n/a	n/a	n/a	0.927	0.749	0.577	0.586

This table reports the results of the 2SLS-IV model presented in Eqs. (2) and (3) replacing the original dependent variable (*ΔPD*) with *ΔCDS*. *CDS* is the average credit default swap spread in year *t* considering the maturities indicated (1, 2, 3 and 5 years). *ΔCDS* is the variation of *CDS* (from the end of year *t-1* to the end of year *t*). *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. IV^{mean_disp} and IV^{perc_disp} (based on year *t-1*) are the first two instruments introduced in Section 3.2.2.2. When they together pass the Hansen J overidentification test, both are used. Otherwise, we only use the former one. $\widehat{\Delta C}$ is the *ΔC* estimated in the first stage. N. obs. is the total number of bank-year observations. FE stands for fixed-effects. K-P Wald F stands for the Kleibergen-Paap rk Wald F statistic. Numbers in parentheses are robust standard errors clustered by banks. *** and * indicate coefficients statistically significant at the 1% and 10% levels (to maintain consistency with other tables, ** is not used in this table). For convenience, the values of greatest interest (regarding $\widehat{\Delta C}$) are presented in bold.

Table 9. Testing alternative relationships between changes in capital and in credit default swap spreads

Relationship	Panel - Fig. 1	AIC	BIC	CD
Direct impact of *ΔC* on *ΔCDS*	A	158,500.57	158,519.91	0.001
Direct reverse impact (from *ΔCDS* on *ΔC*)	B	158,568.93		0.001
Joint impact of *ΔC* and U on *ΔCDS*	C	-21,113.44	-21,087.20	1.000
Joint impact of *ΔCDS* and U on *ΔC*	D	-21,106.74	-21,080.50	1.000
Joint impact of U on *ΔC* and *ΔCDS* with reciprocal effect between *ΔC* and *ΔCDS*	E	-21,061.79	-21,035.55	1.000
U driving *ΔC* and *ΔCDS*	F	-24,589.16	-24,549.80	1.000

ΔC and *ΔCDS* are the percentage variations in capital and in credit default swap spreads related to banks, respectively, from the end of year *t-1* to the end of year *t*. Changes in 1-year CDS spreads (*ΔCDS_1y*) are used as an example in this case. AIC, BIC and CD stand for Akaike's information criterion, Bayesian information criterion, and coefficient of determination, respectively.

Table 10. Fixed-effects model with dummy for the global financial crisis

	Panel A				*Panel B*				*Panel C*			
Capital measure	*TEq_ta*				*TCap_ta*				*CET1_ta*			
Dependent variable	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔC	**1.005**	**0.5657**	**0.5729**	**0 .4077**	**0.6845**	**-0.2700**	**0.1995**	**0.1982**	**0.1238**	**-0.4903**	**-0.2338**	**-0.1171**
	(0.8546)	**(0.7583)**	**(0.5416)**	**(.3299)**	**(0.4741)**	**(0.6145)**	**(0.3339)**	**(0.2344)**	**(0.3943)**	**(0.4503)**	**(0.3160)**	**(0.2207)**
C	-0.1193	-1.989	-3.7822	-2.2614	0.6793	4.6979	0.9543	0.2375	4.6522	11.4359*	8.0928*	4.4586
	(4.6484)	(4.7233)	(4.2206)	(2.2623)	(2.112)	(4.1321)	(2.0508)	(1.4414)	(5.4573)	(6.5689)	(4.727)	(3.2047)
GFC_dummy	-3.7590	-3.2745	-2.9046	2.0185**	-0.2978	-0.0848	1.2912	0.6169	-0.0048	-0.0139	-0.1362	-0.0328
	(2.7750)	(2.0436)	(1.5341)	(0.9414)	(0.5966)	(0.5069)	(1.3241)	(0.5111)	(0.0036)	(0.0255)	(0.1461)	(0.0436)
No. obs.	14,895	15,042	15,088	15,088	2,509	2,573	2,592	2,592	1,398	1,460	1,478	1,478
No. banks	2,265	2,287	2,296	2,296	659	698	704	704	458	498	504	504
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0865	0.0344	0.0175	0.0260	0.0537	0.0367	0.0547	0.0751	0.0492	0.0404	0.0545	0.0750

This table shows the regression results of the baseline model, Eq. (1) including a dummy for the global financial crisis period (2007-2009). *PD* is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *ΔPD* is the variation of *PD* (from the end of year *t-1* to the end of year *t*). *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. No. obs. is the total number of bank-year observations. FE stands for fixed-effects. Numbers in parentheses are robust standard errors clustered by banks. * and ** indicate coefficients statistically significant at the 10% and 5% levels, respectively. For convenience, the values of greatest interest (regarding *ΔC*) are presented in bold.

Table 11. Two-stage-least-squares model with dummy for the global financial crisis

	Panel A				*Panel B*				*Panel C*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	First stage											
Dep variable	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*
IV^{mean_disp}	-3.429***	-3.323***	-3.324***	-3.324***	-15.858***	-15.880***	-15.827***	-15.827***	-64.016***	-82.094***	-82.164***	-82.164***
	(.378)	(0.338)	(0.333)	(0.333)	(2.927)	(2.929)	(2.890)	(2.890)	(20.955)	(19.590)	(19.561)	(19.561)
IV^{perc_disp}	-2.960***	-2.937***	-2.926***	-2.926***					-7.973***			
	(0.296)	(0.292)	(0.290)	(0.290)					(1.676)			
F statistic	39.01	44.96	45.80	45.08	45.05	45.25	45.09	45.09	37.18	11.57	11.55	11.55
	Second stage											
Dep variable	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*
$\widehat{\Delta C}$	**0 .264**	**-0.730**	**0.084**	**0.262**	**0.553**	**-0.413**	**0.140**	**0.087**	**-0.667**	**-0.460**	**-0.380**	**-0.221**
	(1.194)	**(1.155)**	**(0.623)**	**(0.311)**	**(0.521)**	**(0.815)**	**(0.389)**	**(0.285)**	**(0.609)**	**(0.651)**	**(0.402)**	**(0.288)**
C	3.146	2.884	-3.125	-2.164	1.347	4.294	1.185	0.735	4.172	3.112	4.729	2.295
	(6.177)	(6.160)	(4.194)	(2.118)	(2.520)	(3.309)	(2.108)	(1.598)	(6.078)	(5.255)	(4.748)	(3.328)
GFC_dummy	4.302***	4.073***	2.739***	1.425***	0.727***	0.580***	1.202*	0.691***	0.564***	0.364***	0.049***	0.031***
	(0.791)	(0.856)	(0.536)	(0.248)	(0.203)	(0.186)	(0.675)	(0.246)	(0.144)	(0.107)	(0.021)	(0.010)
No. obs.	14,645	14,792	14,836	14,836	2,354	2,400	2,418	2,418	1,257	1,299	1,316	1,316
No. banks	2,015	2,037	2,044	2,044	504	525	530	530	317	337	342	342
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F	137.155	157.388	160.874	160.874	29.352	29.394	29.989	29.989	163.186	17.561	17.643	17.643
Hansen J stat	0.210	0.020	0.003	0.138	n/a	n/a	n/a	n/a	3.539	n/a	n/a	n/a
Hansen J p-val	0.647	0.887	0.956	0.711	n/a	n/a	n/a	n/a	0.060	n/a	n/a	n/a

This table reports the results of the 2SLS-IV model presented in Eqs. (2) and (3) including a dummy for the global financial crisis period (2007-2009). *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. *PD* is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *ΔPD* is the variation of *PD* (from the end of year *t-1* to the end of year *t*). IV^{mean_disp} and IV^{perc_disp} (based on year *t-1*) are the first two instruments introduced in Section 3.2.2.2. When they together pass the Hansen J overidentification test, both are used. Otherwise, we only use the former one. $\widehat{\Delta C}$ is the *ΔC* estimated in the first stage. N. obs. is the total number of bank-year observations. FE stands for fixed-effects. K-P Wald F stands for the Kleibergen-Paap rk Wald F statistic. Numbers in parentheses are robust standard errors clustered by banks. *** and * indicate coefficients statistically significant at the 1% and 10% levels, respectively. For convenience, the values of greatest interest (regarding $\widehat{\Delta C}$) are presented in bold.

Table 12. Fixed-effects model without the countries with less than 200 observations

	Panel A				*Panel B*				*Panel C*			
Capital measure	*TEq_ta*				*TCap_ta*				*CET1_ta*			
Dependent variable	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔC	**1.6731**	**0.7493**	**0.8661**	**0.6434**	**2.6799**	**-1.5320**	**0.4644**	**0.4450**	**0.0756**	**-1.0261**	**-0.3702**	**-0.1501**
	(1.9280)	**(1.6879)**	**(1.1837)**	**(0.7170)**	**(2.1741)**	**(2.2543)**	**(1.3113)**	**(0.9041)**	**(0.5826)**	**(1.0590)**	**(0.5063)**	**(0.3150)**
C	6.0965	2.3158	-2.1150	-1.4216	3.9438	12.8236	4.7779*	2.4149	28.2263	14.8748	24.5613*	17.0451*
	(7.9016)	(9.5607)	(7.2591)	(3.7738)	(2.9990)	(8.8431)	(2.6653)	(1.7454)	(19.9763)	(26.6282)	(13.3282)	(8.9502)
No. obs.	12,911	13,054	13,092	13,092	1,080	1,142	1,153	1,153	377	438	448	448
No. banks	1,785	1,807	1,815	1,815	288	327	332	332	173	213	218	218
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.1008	0.0352	0.0186	0.0255	0.0575	0.0377	0.0617	0.0716	0.0424	0.0792	0.0650	0.0669

This table shows the regression results of the baseline model, Eq. (1) removing the countries with less than 200 observations. *PD* is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *ΔPD* is the variation of *PD* (from the end of year *t-1* to the end of year *t*). *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. No. obs. is the total number of bank-year observations. FE stands for fixed-effects. Numbers in parentheses are robust standard errors clustered by banks. * indicates coefficients statistically significant at the 10% level. For convenience, the values of greatest interest (regarding *ΔC*) are presented in bold.

Table 13. Two-stage-least-squares model without countries with less than 200 observations

	Panel A				*Panel B*				*Panel C*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						First stage						
Dep variable	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTEq_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔTCap_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*	*ΔCET1_ta*
IV^{mean_disp}	-4.981***	-1.956***	-1.948***	-1.948 ***	-0.558*	-0.574*	-0.580*	-0.580*	-132.57***	-132.46***	-132.35***	-132.35***
	(0.329)	(0.165)	(0.162)	(0.162)	(0.319)	(0.325)	(0.313)	(0.313)	(5.098)	(5.102)	(5.124)	(5.124)
IV^{perc_disp}		-3.623	-3.628	-3.628	-9.928***	-10.004***	-9.984***	-9.984***				
		(0.332)	(0.325)	(0.325)	(3.201)	(3.248)	(3.182)	(3.182)				
F statistic	38.73	62.77	64.06	64.06	30.64	31.12	31.05	31.05	113.67	113.31	113.18	113.18
						Second stage						
Dep variable	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*	*ΔPD_1m*	*ΔPD_3m*	*ΔPD_6m*	*ΔPD_12m*
$\widehat{\Delta C}$	**0.994**	**-1.945**	**-0.650**	**-0.120**	**2.099**	**-1.634**	**0.182**	**0.098**	**0.272**	**-0.729**	**-0.345**	**-0.136**
	(2.143)	**(1.782)**	**(0.992)**	**(0.486)**	**(1.902)**	**(3.306)**	**(1.186)**	**(0.843)**	**(0.361)**	**(1.373)**	**(0.552)**	**(0.334)**
C	6.782	8.864	-1.237	-0.553	3.917	11.706	3.885	2.340	13.135*	-20.928	12.339	8.868*
	(9.358)	(10.629)	(7.518)	(3.817)	(3.547)	(8.202)	(2.847)	(2.067)	(7.792)	(48.202)	(8.179)	(5.094)
No. obs.	12,732	12,875	12,911	12,911	994	1,038	1,048	1,048	293	334	343	343
No. banks	1,606	1,628	1,634	1,634	202	223	227	227	89	109	113	113
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P Wald F	228.764	243.733	249.395	249.395	58.325	60.820	60.129	60.129	676.244	673.865	667.15	667.15
Hansen J stat	n/a	3.260	3.367	3.099	2.917	1.612	3.675	2.552	n/a	n/a	n/a	n/a
Hansen J p-val	n/a	0.071	0.066	0.078	0.088	0.204	0.055	0.110	n/a	n/a	n/a	n/a

This table reports the results of the 2SLS-IV model presented in Eqs. (2) and (3) removing the countries with less than 200 observations. *C* represents capital, which is measured in three alternative ways: total equity divided by total assets (*TEq_ta*), total capital ratio (*TCap_ta*, equal to the sum of all items accepted as regulatory capital divided by total assets), and Common Equity Tier 1 divided by total assets (*CET1_ta*). *ΔC* is the variation of capital from the end of year *t-1* to the end of year *t*. *PD* is the annual average of monthly banks' probability of default in the periods indicated (1, 3, 6 and 12 months). *ΔPD* is the variation of *PD* (from the end of year *t-1* to the end of year *t*). IV^{mean_disp} and IV^{perc_disp} (based on year *t-1*) are the first two instruments introduced in Section 3.2.2.2. When they together pass the Hansen J overidentification test, both are used. Otherwise, we only use the former one. $\widehat{\Delta C}$ is the *ΔC* estimated in the first stage. N. obs. is the total number of bank-year observations. FE stands for fixed-effects. K-P Wald F stands for the Kleibergen-Paap rk Wald F statistic. Numbers in parentheses are robust standard errors clustered by banks. *** and * indicate coefficients statistically significant at the 1% and 10% levels (to maintain consistency with other tables, ** is not used in this table). For convenience, the values of greatest interest (regarding $\widehat{\Delta C}$) are presented in bold.

Table 14. Results of the analyses based on GMM (probability of default)

Dependent variable	*ΔPD_12m*									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔTEq_ta	1.0930									0.2714
	(0.9946)									(0.5504)
ΔTCap_ta		2.2831								
		(1.5277)								
ΔCET1_ta			1.6957							
			(2.2317)							
ΔA				0.0057						0.0010
				(0.0077)						(0.0033)
ΔM					0.0007					-0.0026
					(0.0272)					(0.0196)
ΔE						0.0002				-0.0004**
						(0.0004)				(0.0002)
ΔL							0.0008			0.1096
							(0.0091)			(0.1176)
ΔS								0.0009		-0.0007
								(0.0010)		(0.0006)
ΔSize									-3.7169	-8.6379
									(3.1295)	(33.1510)
No. of observations	15,088	12,592	11,478	14,854	15,049	15,068	14,986	14,687	15,088	14,515
No. of banks	2,296	1,704	1,504	2,256	2,282	2,289	2,277	2,253	2,296	2,225
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of instruments	25	25	25	25	25	25	25	24	25	160
Arellano-Bond test AR(2) p-val	0.788	0.410	0.311	0.443	0.692	0.365	0.898	0.597	0.869	0.549
Hansen test of Overid. Restrictions p-val	0.086	0.687	0.986	0.495	0.853	0.580	0.600	0.440	0.534	0.769
Diff-in-Hansen test exclud. group p-val	0.092	0.618	0.986	0.577	0.799	0.502	0.579	0.385	0.455	0.838
Diff-in-Hansen test Difference p-val	0.217	0.793	0.457	0.156	0.963	0.897	0.407	0.576	0.963	0.160

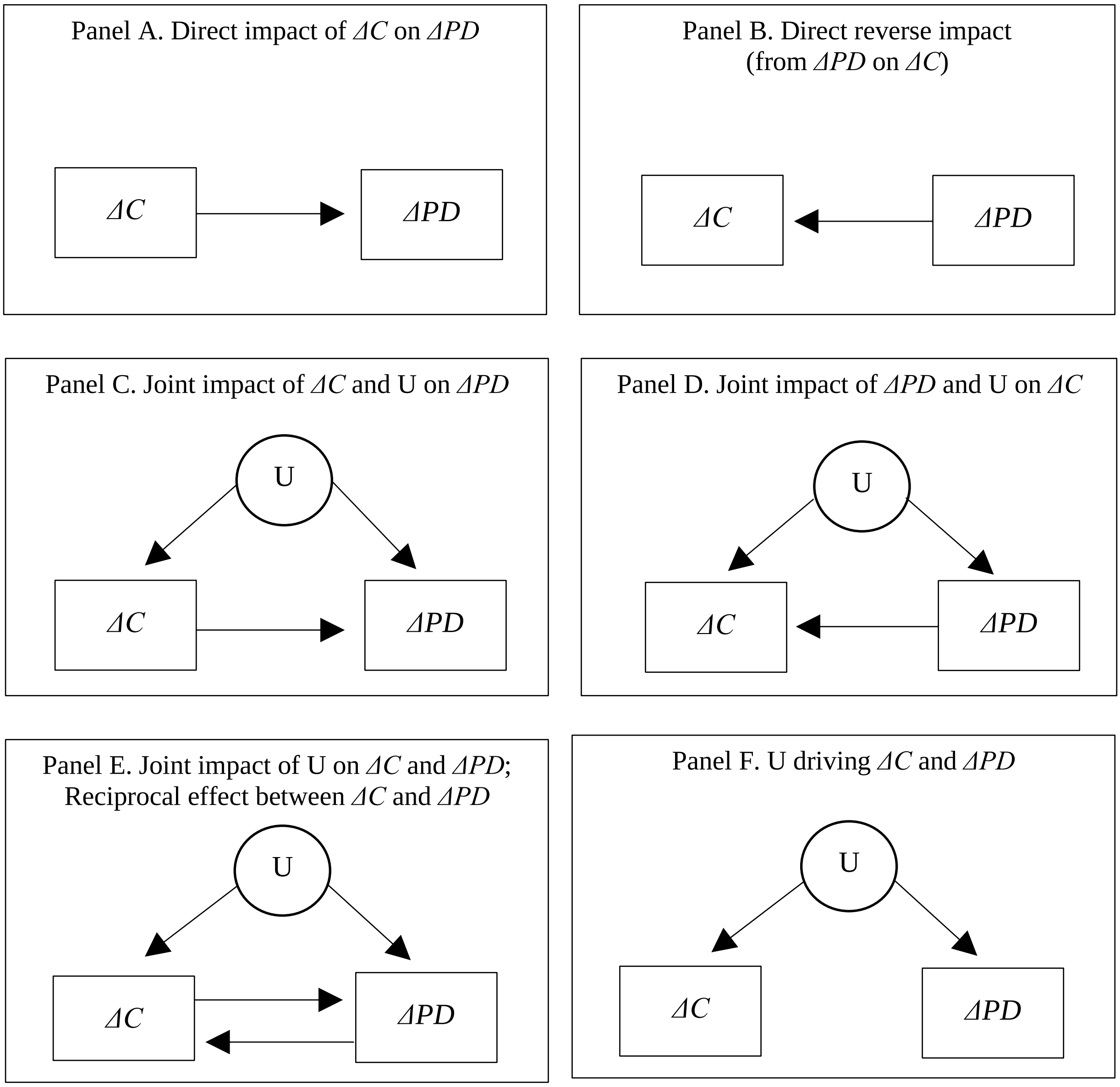
This table presents the regression results of GMM model introduced in Eq. (4). All regressions control for the CAMELS variables and size in levels. *Δ* represents the variation in the respective variables from the end of year *t-1* to the end of year *t*. *PD* is bank's probability of default. As defined in Section 3.2.1, just after Eq. (1): *TEq*_ta is total equity divided by total assets; *ΔTCap_ta* is the total (regulatory) capital divided by total assets; and *CET1_ta* is Common Equity Tier 1 divided by total assets; *A* is asset quality; *M* is management quality; *E* is earnings; *L* is liquidity; *S* is sensitivity to market risk; and *Size* is bank size. The two models with the variation of all CAMELS and size as endogenous where *TCap_ta* and *CET1_ta* are the proxies of capital are not reported because their instruments do not pass all the necessary validation tests. Corrected standard errors are reported in parentheses below the coefficient estimates. ** indicates statistical significance at the 5% level (to maintain consistency with the other tables in this paper, * and *** are not used here).

Table 15. Results of the analyses based on GMM (credit default swap spread)

Dependent variable	*ΔCDS_1y*										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔTEq_ta	-0.4451									0.2389	
	(1.2699)									(0.2788)	
ΔTCap_ta		7.4098*									
		(3.5359)									
ΔCET1_ta			1.7111								0.4216
			(4.6112)								(0.9052)
ΔA				0.0080						0.0064	0.0282
				(0.0074)						(0.0052)	(0.0642)
ΔM					-0.0080					-0.0077	-0.0102
					(0.0413)					(0.0163)	(0.0445)
ΔE						0.0203				-0.0051	-0.0088
						(0.0168)				(0.0027)	(0.0064)
ΔL							0.0048			0.1758	0.4103
							(0.0073)			(0.1105)	(0.2665)
ΔS								0.0001		0.0006	-0.0027
								(0.0007)		(0.0006)	(0.0035)
ΔSize									-5.1452	1.3161	17.4961
									(4.2309)	(23.157)	(20.263)
No. of observations	15,223	12,551	11,443	15,003	15,177	15,207	15,139	14,833	15,223	14,655	11,353
No. of banks	2,304	1,691	1,487	2,263	2,292	2,300	2,286	2,262	2,304	2,239	1,466
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of instruments	25	24	24	25	25	25	25	24	25	154	79
Arellano-Bond test AR(2) p-val	0.656	0.584	0.461	0.418	0.299	0.809	0.848	0.765	0.872	0.385	0.177
Hansen test of Overid. Restrictions p-val	0.975	0.813	0.876	0.634	0.964	0.767	0.982	0.758	0.763	0.815	0.894
Diff-in-Hansen test exclud. group p-val	0.961	0.842	0.825	0.570	0.944	0.701	0.980	0.738	0.696	0.814	0.819
Diff-in-Hansen test Difference p-val	0.752	0.269	0.973	0.688	0.863	0.868	0.483	0.432	0.880	0.474	0.870

This table presents the regression results of GMM model introduced in Eq. (4) using credit default swap (*CDS*) spread as proxy of bank risk. All regressions control for the CAMELS variables and size in levels. *Δ* represents the variation in the respective variables from the end of year *t-1* to the end of year *t*. As defined in Section 3.2.1, just after Eq. (1): *TEq*_ta is total equity divided by total assets; *ΔTCap_ta* is the total (regulatory) capital divided by total assets; and *CET1_ta* is Common Equity Tier 1 divided by total assets; *A* is asset quality; *M* is management quality; *E* is earnings; *L* is liquidity; *S* is sensitivity to market risk; and *Size* is bank size. The model with the variation of all CAMELS and size as endogenous where *TCap_ta* is the proxy of capital is not reported because their instruments do not pass all the necessary validation tests. Corrected standard errors are reported in parentheses below the coefficient estimates. * indicates statistical significance at the 10% level (to maintain consistency with the other tables in this paper, ** and *** are not used here).

Figure 1. Possible relationships between changes in capital and in banks' probability of default



ΔC and ΔPD are the percentage variations in capital and banks' probability of default, respectively, from the end of year t-1 to the end of year t. The arrows indicate the direction of the relationship (e.g., $\Delta C \rightarrow \Delta PD$ indicates an impact of ΔC on ΔPD). U (taking place in year t) is one or more unobserved variables that may be the actual reason for the co-movement of ΔC and ΔPD. For estimation purposes, all the independent variables in levels in our baseline model – Eq. (1) – are included in the models above (although not shown in the diagrams) as exogenous variables.