PRIFYSGOL BANGOR / BANGOR UNIVERSITY

PRIFYSGOL BANGOR UNIVERSITY

The Impact of Regulatory Reforms on European Bank Behaviour: A Dynamic Structural Estimation

Jones, Laurence; Alsakka, Rasha; ap Gwilym, Owain; Mantovan, Noemi

European Economic Review

DOI:
https://doi.org/10.1016/j.euroecorev.2022.104280

Published: 01/11/2022

Publisher's PDF, also known as Version of record

Cyswllt i'r cyhoeddiad / Link to publication

Dyfyniad o'r fersiwn a gyhoeddwyd / Citation for published version (APA):
Jones, L., Alsakka, R., ap Gwilym, O., & Mantovan, N. (2022). The Impact of Regulatory Reforms on European Bank Behaviour: A Dynamic Structural Estimation. *European Economic Review*, *150*, [104280]. https://doi.org/10.1016/j.euroecorev.2022.104280

Hawliau Cyffredinol / General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal ?

Take down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

11. Nov. 2022

European Economic Review 150 (2022) 104280

Contents lists available at ScienceDirect

European Economic Review

journal homepage: www.elsevier.com/locate/eer

The impact of regulatory reforms on European bank behaviour: A dynamic structural estimation

Laurence Jones [a], Rasha Alsakka [a,*], Owain ap Gwilym [a], Noemi Mantovan [b]

[a] Bangor Business School, Bangor University, United Kingdom
[b] The University of Liverpool, United Kingdoom

ARTICLE INFO

JEL classification:
G15
G21
G24

Keywords:
Discrete choice dynamic programming (DCDP)
Bank behaviour
Bail-in regime
Basel III regulation
Credit rating regulation

ABSTRACT

This paper develops a dynamic structural model of bank behaviour. Banks can vary their financing structure, business model and decide on rating solicitation, in the presence of costly debt, corporation tax, insolvency costs and convex adjustment costs. The model is then simulated to examine the impact of regulation on banks' behaviour. A bail-in regime leads to reduced bank lending activity, while having little impact on bank insolvency rates. Stringent capital requirements reduce bank insolvency rates in a crisis period, while mitigating the reduction in lending activity due to an increased uptake in marginal investments. More lenient credit ratings are associated with increased bank failures. These findings offer wide-ranging implications for policy makers and the banking industry.

1. Introduction

Failures of large financial institutions during the 2008-2010 financial crisis exacerbated the crisis, caused significant damage in the real economy and resulted in increased sovereign credit risk (Acharya et al. (2014), Berger et al. (2019)). To prevent future repeats, regulators responded via several channels. The outcomes of European regulatory initiatives were particularly evident in three distinct areas: (i) European Banking Union, including a bail-in regime, (ii) capital requirement regulations (Basel III) and (iii) reforming the role of credit rating agencies (CRAs). This study builds and estimates a dynamic structural model of bank behaviour and uses the model to simulate counterfactual scenarios in which these three key regulatory reforms are implemented prior to the financial crisis, thereby enabling investigation of the resultant impact on banks' performance, risk and lending activity.

The first issue of interest is the Single Resolution Mechanism (SRM) of the European Banking Union. Its Bank Recovery and Resolution Directive (BRRD) contains provisions for a bail-in mechanism commencing from 2015, which aims to shift the burden of bank failure from the taxpayer to equity holders and bondholders. Given the potential losses for shareholders in the event of insolvency, this mechanism should impact upon bank decision-making. Secondly, the Basel III common equity capital ratio (CET1), planned to be fully implemented by 2025, increased the proportion of equity that banks are required to hold. While this requirement placed a constraint upon banks, it could impact their risk-taking behaviour. Thirdly, in September 2009, European regulators implemented new reforms of the credit rating industry, the newly created European Securities and Markets Authority (ESMA) assumed responsibility for regulating CRAs operating in Europe. Increased scrutiny and oversight of CRAs could lead to more conservative ratings (Bannier et al., 2010), which would impact banks' behaviour and performance.

* Corresponding author at: Bangor Business School, Bangor University, Hen Goleg, Bangor, Wales, LL57 2DG, United Kingdom.
E-mail address: r.alsakka@bangor.ac.uk (R. Alsakka).

https://doi.org/10.1016/j.euroecorev.2022.104280
Received 15 February 2021; Received in revised form 1 September 2022; Accepted 4 September 2022
Available online 13 September 2022
0014-2921/© 2022 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

With much of the regulation only recently (or yet to be) fully enacted, there is much debate on its implications. For example, the bail-out of two Italian banks in June 2017 and a German bank in December 2019 raised questions on the effectiveness of BRRD and its bail-in regime. Similarly, the optimal capital ratios that banks should adopt to effectively prevent insolvency, the impact of the recent CRA regulation on bank ratings and the influence of ratings on banks' behaviour, are subject to ongoing discussions among regulators, market participants and academics. Ensuring financial stability is a vital topic, given banks' crucial influence on the economy, hence the debates on the optimum design of regulatory regimes are still ongoing.[1] This paper contributes to the understanding of the regulation's impact on bank's decision-making and the wider consequences for the economy.

We build and estimate a Discrete Choice Dynamic Programming (DCDP) model of bank behaviour.[2] To the best of our knowledge, this is the first paper to apply this methodology to bank decision-making.[3] We apply the model in the presence of several frictions, whereby banks are rational, forward-looking agents that must make a sequence of dynamic decisions to maximise their current and discounted future return on equity. Banks must decide on whether to (i) vary the extent of debt financing, (ii) adjust their business activities towards lending or non-interest income and (iii) solicit a credit rating. The model is estimated using the simulated method of moments (SMM), as in Hennessy and Whited (2005).[4]

We employ data for an extensive sample of banks from 27 European countries for the period 2004-2019. Data up to 2015 is used to estimate the model, through matching several moments (see Section 6.1), including a wide range of time-varying bank characteristics during pre-crisis, peak-crisis and post-crisis episodes in our sample period.[5] We replicate key mechanisms and feedback loops in the data, e.g. the ability for a bank's decisions to impact its credit rating, which in turn can impact the bank's cost of debt and hence its profitability. We then run counterfactual scenarios to assess difference policy outcomes.

Firstly, we examine what would have been the impact of the increased cost of insolvency induced by European bail-in regulation, had it been implemented prior to the crisis in 2005. There is strong evidence that the bail-in regime may affect lending in the real economy. The model predicts the adoption of higher optimal capital ratios (consistent with Berger et al. (2019) and Leanza et al. (2021)), driven by reduced debt levels, but little impact on bank insolvency rates during crisis periods (contrary to Dam and Koetter (2012)). Yet, this comes at the cost of a slight reduction in long term profits and banks shifting away from lending.

Secondly, we investigate potential outcomes if the Basel III capital requirements had been in place since 2005. The simulations show a larger increase in bank capital and a larger decrease in bank debt (double in size) than that stimulated from the bail-in regime. Stronger bank stability during the financial crisis is revealed, with a lower number of insolvent banks. Banks seek alternative ways to maintain their profitability, given that their leverage has been constrained, which has a crucial impact on lending activity in the economy.

Bahaj and Malherbe (2020) argue that stringent capital requirements lead to two competing effects, (i) The *composition effect*, where funds are more expensive as they are funded by a greater proportion of equity, and (ii) the *forced safety effect*, whereby banks internalise a greater proportion of profits from marginal investments due to reduced bankruptcy risk. Our results are consistent with the *forced safety effect*, with banks increasing their lending and investment activity, after an initial adjustment period, counter to that predicted by the composition effect alone. Conversely, we find that the increased aversion to bankruptcy under the bail-in regime acts to offset the *forced safety effect* from voluntarily higher capital ratios.

Lastly, we consider the impact of CRA reforms and show that banks react to changes in CRA rating practices via their actions in the debt/deposit market, adding to uncertainty in banks' lending activity. An increase (decrease) in CRA conservatism is associated with an increase (decrease) in a bank's cost of debt and a fall (increase) in the proportion of banks that choose to solicit a rating.

Our results underline the importance of understanding the mechanisms through which regulation can impact bank decision-making behaviour and performance. By building and estimating a dynamic model, we replicate various influential relationships, investigate the underlying mechanisms, and eliminate endogeneity issues. It allows us to observe not only the direct impact of the regulation (e.g. capital ratios or bail-in policy), but also how this can have knock-on implications to other less anticipated aspects of bank behaviour and be able to form an ample spectrum prediction of the policy changes. This provides a strong framework to consider the real effects of bank decision-making in the economy.

We contribute to ongoing debates about banking and credit rating regulations on multiple fronts. First, contrary to previous literature (see for example, Dam and Koetter (2012)), we find that bail-in reforms that raise the cost of bankruptcy are less effective at curbing insolvency rates than regulators have hoped. Second, we further the debate on the efficacy of the new capital requirements by providing evidence that they are very effective at preventing insolvency (consistent with Berger and Bouwman (2013); Miles et al. (2013)) with no negative impact on bank profitability. Third, we show that the introduction of capital requirements, and to a lesser extent the bail-in regime, cause an initial reduction in bank lending in the real economy, in line with Gropp et al. (2019). However, this

[1] In the US, for example, the debate over whether to repeal the bail-in regime for large bank holding companies continues (e.g. Berger et al., 2019).

[2] Technically, banks make one discrete choice (whether to be rated or not) and two continuous discretised choices (business model and amount of debt). Nevertheless, we refer to our model as a DCDP because we follow a solution structure typical to DCDP models, with full backward recursion using the Expected Maximum (EMax) and interpolation, as in Keane and Wolpin (1994).

[3] Very few papers in banking have used dynamic programming (e.g. Egan et al. (2017), De Nicolo et al. (2014)) However, these studies calibrated a proposed model rather than conducting estimation (see Section 5).

[4] Hennessy and Whited (2005) explain that the advantage of SMM over IV and OLS regressions is that it does not suffer from simultaneity problems because it does not require any of the zero-correlation restrictions that are needed by the latter methods.

[5] Data from 2004 to 2015 is used for main estimations, and data from 2016-2019 is used for an external validity exercise (Section 6.3).

appears to be mitigated under the capital requirements, as a subsequent increase in bank lending is observed, providing evidence for the presence of the *forced safety effect* proposed by Bahaj and Malherbe (2020). Finally, we contribute to the sparse literature on how the recent rating industry reforms (see Opp et al, 2013) have influenced banks' behaviour and performance, revealing that the regulation has a spill over effect causing an increase in bank insolvency rates, a reduction in bank profitability and a short-term reduction in bank lending in the real economy.

The remainder of the paper is organised as follows. Section 2 reviews the literature, Section 3 describes the sample and the illustrative analysis, and Section 4 outlines the model. Section 5 outlines the empirical strategy, while Section 6 discusses the model fit and parameter estimates. Section 7 presents the counterfactual scenarios involving regulatory changes, and Section 8 concludes.

2. Literature review

Theoretical and empirical research on dynamic corporate finance has grown dramatically (e.g. Strebulaev and Whited, 2011, Egan et al., 2017; Bahaj and Malherbe, 2020). A body of literature has developed that utilises dynamic structural models to examine firm financing. Gomes (2001) calibrates a dynamic model of firm financing costs and investment decisions. Cooley and Quadrini (2001) calibrate a dynamic model of firm financing with financial market friction, industry dynamics and persistent shocks. Hennessey and Whited (2005) examine firm leverage utilising a dynamic trade-off model with corporate income tax, financial distress costs, endogenous choice of leverage and equity flotation costs, and then utilise SMM to estimate the model using actual data.

A separate strand of literature focuses on regulatory changes in response to the 2008 financial crisis such as bail-in mechanisms and reformed capital requirements. The potential for a bail-in resolution shifts the burden of losses from the government to equity and debt holders first (Conlon and Cotter (2014)). The increased burden on these stakeholders could reduce bank risk taking, e.g. Hilscher and Raviv (2014) show that a bail-in regime could be an effective tool for stabilizing financial institutions. However, DeYoung et al. (2013) find that increased government intervention can make banks more risk insensitive and increases insolvency risks. Attaoui and Poncet (2015) report that firms' total market values are larger in the presence of write-down debt, such as the bail-in requirement. Berger et al. (2019) examine the impact of US regulatory efforts by developing a dynamic model of optimal regulatory design that examines three scenarios of bailout, bail-in and no regulatory intervention. They show that regulatory intervention is always optimal and that only the bail-in provides incentives for banks to build up capital reserves pre-emptively. Further, the literature on banks' capital requirements shows that well capitalised banks have improved performance and lower insolvency rates (Berger and Bouwman (2013), Miles et al. (2013)). Gropp et al. (2019) show that banks react to higher capital requirements by reducing their risk-weighted assets, leading to reduced bank lending. Bahaj and Malherbe (2020) argue that higher capital requirements influence a bank's decision to invest in marginal loans in two ways. Firstly, the *composition effect* implies that a bank's cost of capital is increased by holding a larger proportion of equity, reducing the likelihood of banks' investment in marginal loans. Secondly, the *forced safety effect* implies that safer banks expect to internalise a greater proportion of the return from marginal loans when avoiding bankruptcy,[6] increasing the likelihood of banks' investment in marginal loans.

There is sparse literature on the recent regulatory reforms of CRAs. Bannier et al. (2010) show that ratings which expose a CRA to greater scrutiny tend to be downward biased (more conservative) and that the effect is stronger for more opaque industries (such as banking), yet they do not explore the impact of regulation. We extend their logic and argue that increased oversight of CRAs will strengthen this downward rating bias. Hence, an increase in conservatism is likely to result in lower bank ratings. This will influence bank behaviour because ratings are a strong determinant of the cost of debt.

While the literature includes several models of banking behaviour (e.g. Calem and Rob (1999), Repullo (2004), De Nicolo et al. (2014), DeYoung et al. (2015), Egan et al. (2017)), they are static, purely theoretical or produce calibrations. DeYoung et al. (2015) estimate a static structural model of bank portfolio lending and show that US community banks reduced their business lending during the global financial crisis. Repullo (2004) builds a theoretical model of imperfect competition in banking where banks can invest in a prudent or a gambling asset under either a flat-rate capital requirement or deposit rate ceilings. De Nicolo et al. (2014) and Calem and Rob (1999) calibrate dynamic models of banking; the former study examines the impact of micro prudential bank regulations on bank lending, while the latter creates a dynamic portfolio choice problem facing banks. Egan et al. (2017) also calibrate a structural model of the US banking sector that examines bank runs in the presence of insured and uninsured depositors and produce evidence for higher capital ratios.

Our work aims to shed light on the impact of new regulatory reforms on banking behaviour, something on which there is still not consensusn in the literature, by focusing on the mechanisms consistent with an estimated dynamic model, using DCDP methodology, which has been most frequently applied in labour economics, starting with Keane and Wolpin (1994, 2009).[7]

3. Data description and illustrative analysis

The sample includes banks from 27 EU countries during the period 2004 to 2019. Data from 2004 to 2015 are used for estimation, while data from 2016 to 2019 are set aside to be used for external validity analysis (see Section 6.3). The variables' definitions and data

[6] Banks with a higher capital requirement are less likely to default, whereby the taxpayer would receive the marginal loan's payoff, and more likely to realise these payoffs themselves, thereby increasing their expected value to the bank.

[7] DCDP has been used extensively in several research areas, including labour economics, industrial organisation, and political economy (Keane and Wolpin (2009)).

Table 1
Sample summary statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Rating	6,418	4.90	1.03	1	7
Equity	29,565	583,000,000	1,480,000,000	3,658,058	14,400,000,000
Debt	29,803	9,010,000,000	28,900,000,000	8,638,128	303,000,000,000
Total Assets	30,464	24,400,000,000	135,000,000,000	3,576,329	3,100,000,000,000
Gross Loans to Total Earning Assets	26,728	61.62%	27.36%	0.34%	100.00%
Equity to Total Assets	29,509	12.61%	12.01%	1.06%	81.93%
Expenses (% TA)	7,345	2.93%	3.34%	0.11%	28.59%
Rated Choice	30,631	20.95%	40.70%	0	1
Y return	22,692	4.94%	6.16%	0.11%	43.90%
X return	18,364	5.45%	2.74%	1.29%	21.44%
ROE	24,509	6.68%	10.49%	-36.77%	48.67%
ROA	24,261	0.67%	1.26%	-4.02%	8.74%
Cost of Debt	27,462	2.07%	1.34%	0.10%	7.54%
Sovereign Rating	30,631	43.95	10.07	1	52

This table reports the summary statistics for the dataset. The data sample includes EU banks from 2005 to 2015. See Table A1 for variables' definitions. Rating summary statistics are shown for only rated institutions, the credit rating is mapped onto a 7-point scale, see Table 6. For unrated financial institutions *Rating* is assigned a value of 0.

sources are reported in Panel A of Table A1 in the Appendix. Similar to Hennessy and Whited (2005), banks with total assets of less than two million Euros and equity less than one million Euros are excluded.[8] Observations that fail to obey standard accounting identities are excluded. Annual bank observations that have more than three of the following data items missing are also omitted: equity, debt, gross loans to total assets, cost of debt, return on loans, return on non-interest activities, interest rate and sovereign rating.[9] The resulting dataset is an unbalanced panel of banks with between 812 and 2,824 observations per year, and a total of 36,674 bank-year observations.[10] The summary statistics for the data are reported in Table 1. Bank size shows the greatest degree of variation with the standard deviation being very large relative to the mean, caused by having various bank types within our sample, such as small community banks, large investment banks and retail institutions. Return on Equity ROE and Return on Assets ROA (both profitability measures) also exhibit large degrees of variation with their standard deviations being larger than their means. The return of Y (non-interest income) also notably exhibits greater variation and standard deviation relative to the mean than the return of X (loan return), which indicate that it is typically riskier business. There is also a good level of variation in both bank ratings, the decision to be rated and the level of capital held by banks (ETA).

The key trends in the data over time can be observed in Fig. 1. The proportion of banks that are rated (*Rated)* remains relatively steady throughout the sample period (see Fig. 1a), exhibiting only a slight decrease in 2010 onwards that corresponds to falling rating levels (see Fig. 1b). Both *Debt* and *Business Model* (GL-TEA) vary significantly over time (see Figs. 1f and 1d respectively). *Debt* exhibits an initial rise, which is then reversed when the 2008 financial crisis hits. *Business Model* shows an initial growth towards loan making activity which again reverses following the 2008 financial crisis.

3.1. Illustrative analysis

In this section, we analyse the relationships between the key variables. The dynamics within the data are then used, along with theories from prior literature, to guide the process of modelling bank behaviour. As a precursor to specifying a theoretical model, an illustrative analysis is conducted. This involves a series of OLS and ordered logit regressions which explore the relationship between various components in the dynamic model (Table 2 includes a list of Equations).

The first set of estimated regressions investigates the return generated from bank loans, which is calculated following Kwast (1989):

$$X_{i,t} = \frac{Total\ interest\ income}{Gross\ Loans} = 2\frac{TII_{i,t}}{\left(GL_{i,t} + GL_{i,t-1}\right)} \tag{1}$$

The results reported in Panel A of Table 3 suggest that: (i) loan rates are lower following periods of high market volatility, (ii) loan rates are positively associated with interest rates and (iii) banks located in countries with high sovereign credit rating levels tend to have higher returns on loans.

Secondly, we consider the determinants of non-interest activities income. The return on non-interest activities (*Y*) in the sample is

[8] All variables, e.g. debt, equity, total assets, are denominated in Euros.

[9] To eliminate outliers, the top and bottom 2% is trimmed off all the variables, except return on loans, return on non-interest activities and gross loans to total assets, for which 3% is trimmed off the top. Also, it should be noticed that 'Rating' summary statistics are only reported for rated institutions and hence there is a lower number of observations. There is also less data available on banks' Expenses (% TA) and hence a lower number of observations.

[10] The lowest number of banks is for the year 2019, which is not used for estimation purposes, but only for external validity. Moreover, the data is adjusted to 2015 prices using a GDP inflator from the World Bank and OECD national accounts data. The summary statistics of variables and the list of banks included in our sample are available on request.

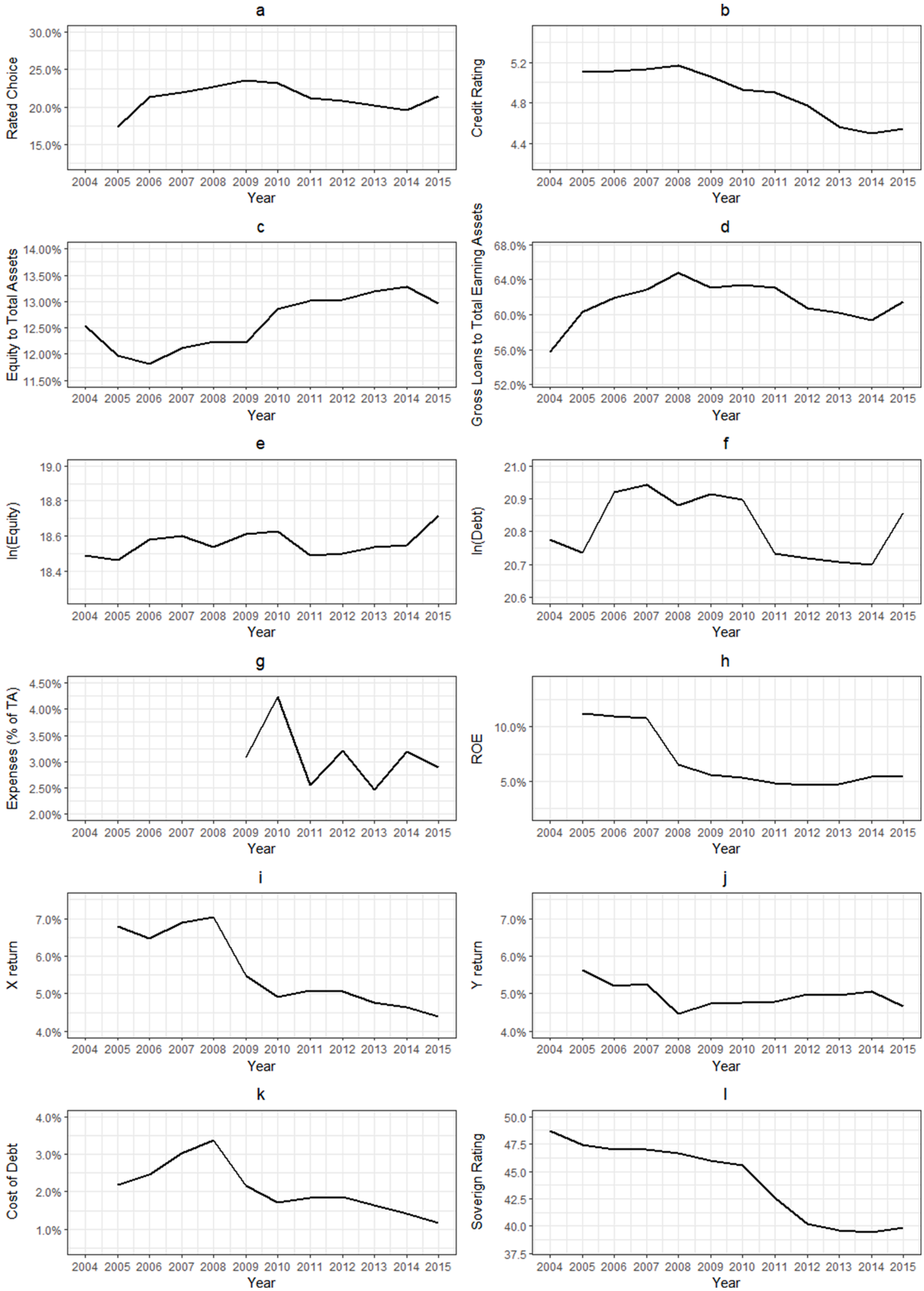

Fig. 1. Key variable trends
The Fig. shows the transition of the Rated Choice, Rating levels, Equity to Total Assets, Gross Loans to Total Earning Assets (Business Model), ln (Equity), ln(Debt), Expenses as percentage of total assets, ROE, X return, Y return, Cost of Debt and the Sovereign Credit Rating over time throughout the sample. See Table A1 for variables' definitions.

Table 2
Illustrative analysis equations.

Dependent Variable	Equation
Credit rating	$CR_{i,t} = \beta_{CR,0}(1 - Rated_{i,t-1}) + \beta_{CR,1} CR_{i,t-1} Rated_{i,t-1} + \beta_{CR,2} Ec_{i,t} + \beta_{CR,3} SR_{i,t} + \beta_{CR,4} \lambda_{i,t} + \beta_{CR,5} \left(\frac{TA_{i,t}}{Eq_{i,t-1}}\right)^2 + \varepsilon_{CR,1}$
Return on loans	$X_{i,t} = \beta_{X,0} + \beta_{X,1} \left(\frac{Ec_{i,t} + Ec_{i,t-1} + Ec_{i,t-2}}{3}\right) + \beta_{X,2} IR_{i,t} + \beta_{X,3} SR_{i,t} + \varepsilon_{X,1}$
Return on non-interest activities	$Y_{i,t} = \beta_{Y,0} + \beta_{Y,1} SR_{i,t} + \beta_{Y,2} Ec_{i,t} + \varepsilon_{Y,2}$
Equity	$\Delta Eq_{i,t} = NI_{i,t} - Div_{i,t} + SC_{i,t}$
Dividends	$Div_{i,t} = \beta_{Div,1} Eq_{i,t-1} + \beta_{Div,2} NI_{i,t}$
Share capital	$SC_{i,t} = \beta_1 TA_{i,t}$
Expenses	$EXPS_{i,t} = \beta_{Ex,0} TA_{i,t} = \beta_{Ex,0}(Eq_{i,t-1} + D_{i,t})$
Cost of debt	$COD_{i,t} = \beta_{COD,0} + \beta_{COD,1} IR_{i,t} + \beta_{COD,2} CR_{i,t} + \beta_{COD,3}(1 - Rated_{i,t}) + \beta_{COD,4} Ec_{i,t} + \beta_{COD,5} \left(\frac{TA_{i,t}}{Eq_{i,t}}\right) + \beta_{COD,6} \lambda_{i,t} + \beta_{COD,7} SR_{i,t}$

The table presents the Equations used in the illustrative analysis to investigate the connections between various components of the model. Variable definitions can be found in Table A1. For the purposes of the exploratory regressions, a linear relationship is assumed between CR and cost of debt. However, the actual relationship appears to be exponential, with the change in bond spread between higher rating categories (e.g. AAA and AA) being much smaller than lower rating categories (e.g. BBB and BB). Hence the actual model employs an exponential relationship (shown in the model section).

Table 3
Ratings and returns

Panel A: Return on loans								
	OLS Coeff	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**
Interest rate	56.314***	2.59	0.573***	30.16	56.314***	2.59	0.606***	31.41
Financial crisis moving average	-0.849**	-2.49	-0.0002***	-3.66				
Financial crisis					0.120**	2.49	-0.0003***	-7.50
Sovereign rating	0.003**	2.41	0.00007*	1.79	0.003**	2.41	0.00008*	1.85
Constant	17.115**	2.49	0.045***	25.13	-2.988**	-2.46	0.047***	26.25
Country * Year FE	Yes		No		Yes		No	
Observations	18,364		18,364		18,364		18,364	
R^2	29.4%		12.5%		29.4%		12.7%	
Panel B: Return on non-interest activities return								
	OLS Coeff		**t-stat**		**OLS Coeff**		**t-stat**	
Sovereign rating	-0.005		-1.29		0.0003***		3.54	
Financial crisis	-0.009*		-1.87		-0.0004***		-6.43	
Constant	0.445*		1.68		0.047***		14.56	
Country * Year FE	Yes				No			
Observations	22,692				22,692			
R^2	5.3%				0.4%			
Panel C: Credit rating								
	Ordered Logit Coeff		**z-stat**		**Ordered Logit Coeff**		**z-stat**	
Not Rated	20.580***		33.21		21.519***		36.01	
Rating	4.273***		45.75		4.422***		48.07	
Financial crisis level	-0.061		-0.20		0.012**		2.43	
Sovereign Rating	0.182		0.52		0.083***		17.11	
Total assets to equity squared	5e-07		0.47		2e-07		0.48	
Gross Loans to total assets	-0.547***		-3.42		-0.247		-1.75	
Country * Year FE	Yes				No			
Observations	5,597				5,597			
R2	65.75%				60.58%			

This table reports the results of regressions that examine the underlying relationship for return on loans (Panel A), return on non-interest income (Panel B) and credit rating levels (Panel C) using a sample of EU banks during 2005 to 2015. For equations see Table 2, and for variables' definitions see Table A1. 7-notch numerical credit rating scale is used (AAA/Aaa = 7, AA+/AA/AA-/Aa1/Aa2/Aa3 = 6 … CCC+/Caa1/CCC/Caa2/, CCC-/Caa3, C/SD/CC/D = 0). 'Not Rated' is a dummy that takes a value of 1 when the firm is not rated and zero when rated. In Panel C, we used 'Not Rated' because the 'Rated' variable is collinear with the 'Rating' variable. Standard errors are clustered by bank and ***, **, * represent significance at the 1%, 5% and 10% levels respectively.

Table 4
Equity, dividends and share capital.

Panel A: Equity						
	OLS Coeff	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**
Net Income	1.205***	5.99	1.169***	6.00	1.206***	5.99
Dividend Paid	-1.150***	-3.70	-1.118***	-3.69	-1.151***	-3.70
Change in share capital	0.419***	3.53	0.408***	3.55	0.419***	3.53
Constant	1.357e+08	1.06	-8202043*	-1.96		
Country * Year FE	Yes		No		Yes	
Observations	6,637		6,637		6,637	
R-squared	27.9%		26.3%		28.7%	
Panel B: Dividends						
	OLS Coeff		**t-stat**	**OLS Coeff**		**t-stat**
Equity	0.004*		1.87	0.005**		2.10
Net Income	0.390***		12.57	0.405***		13.48
Country * Year FE	Yes			No		
Observations	6,976			6,976		
R-squared	58.9%			56.6%		
Panel C: Share capital						
	OLS Coeff	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**
Total Assets	0.002***	5.94	0.002***	6.04	0.002***	5.94
Constant	-1,441,671	-0.16	-1,325,922	-0.27		
Country * Year FE	Yes		No		Yes	
Observations	24,022		24,022		24,022	
R-squared	4.9%		4.9%		5.0%	

This table presents the results of the regressions that model the change in equity, using a sample of EU banks during 2005 to 2015. The dependent variables are equity, dividends and share capital for Panel A, B and C respectively. For equations see Table 2 and for variables' definitions see Table A1. Standard errors are clustered by bank and ***, **, * represent significance at the 1%, 5% and 10% levels respectively.

calculated following Kwast (1989),[11] whereby the total non-interest income is used:

$$Y_{i,t} = \frac{Total\ non\ interest\ income}{TA - Gross\ Loans} = 2\frac{TNII_{i,t}}{\left(\left(TA_{i,t} + TA_{i,t-1}\right) - \left(GL_{i,t} + GL_{i,t-1}\right)\right)} \tag{2}$$

The results from the regressions reported in Panel B of Table 3 reveal that: (i) banks in countries with stronger economic conditions generate more non-interest income and (ii) non-interest income fell during the financial crisis.

The third set of estimated regressions explores the variables associated with banks' credit ratings. The results reported in Panel C of Table 3 suggest that (i) credit ratings are 'sticky', i.e. depend upon their past values; (ii) bank credit ratings are lower during crisis periods; (iii) banks located in countries with higher sovereign credit ratings tend to have higher credit ratings, consistent with a sovereign-bank rating ceiling (e.g. Almeida et al., (2017)); (iv) traditional banks tend to have lower credit ratings than fee-based banks.[12]

The relationship between change in equity and other key variables is estimated. The results are presented in Panel A of Table 4 and confirm that equity increases with positive net income and injections of share capital, and equity falls when issuing dividends. Next, we analyse bank dividend payments (Panel B of Table 4) and find that: (i) companies with more equity tend to issue more dividends and (ii) banks tend to issue more dividends in profitable years. Moreover, larger companies issue more share capital (Panel C of Table 4).

The definition of 'debt' includes both debt and deposits. As expected, we find that banks' operating expenses do indeed scale with firm size (Panel A of Table 5). In addition, a t-test is performed examining whether banks that changed their debt or business model incurred higher expenses (consistent with adjustment costs in the literature (e.g. Gomes (2001), Hennessy and Whited (2005, 2007)). The results in Panel B of Table 5 show that banks that decide to substantially change their debt (large increase or decrease) incur additional expenses (1.154% increase in expenses as a percentage of total assets). There is also an increase in expenses (0.231%) associated with a 1% shift in the bank's business model, either a shift to more lending activities or a shift to more non-interest activities. Following De Nicolò et al. (2014) and Hennessy and Whited (2005), we include corporation tax in the model. However, the tax rate varies across countries and years, therefore we employ the weighted average corporation tax for banks in the sample and find it to be

[11] Non-interest activities are defined here as business activities which do not involve lending. In Section 4, when considering bank business models, our focus is on the ratio of Gross Loans to Total Assets as a more direct lending-related measure. The assumption of categorizing bank assets into two different types (often termed safe and risky) is consistent with earlier research (e.g. Gennaioli et al. (2013), Hanson et al. (2015)).

[12] In Panel C of Table 3, the results which include Country*Year FE naturally show that the financial crisis and sovereign rating variables lose their statistical significance as the cross-sectional variation is captured entirely by the Country*Year FE variation. The results are illustrative to further confirm the impact of both a bank's past ratings and business model on its current rating. When Country*Year FE are excluded to allow for country-year variation, the impacts of these variables are significant.

Table 5
Expenses, ajustment costs and tax.

Panel A: Banks' expenses								
	OLS Coeff	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**
Total assets (t)	0.010***	11.49	0.010***	11.49	0.011***	12.97	0.010***	12.12
Constant			1.255e06	0.32			6.441e07***	10.44
Country * Year FE	Yes		Yes		No		No	
Observations	7,632		7,632		7,632		7,632	
R-squared	40.0%		34.2%		38.1%		33.3%	
Panel B: t-test of expenses and adjustment costs								
				Expenses to Total Assets				
		No change		**Large change**		**Difference**	**t stat**	
Debt	Obs	2,494		813				
	Coef	2.619%***		3.773%***		1.154%***	9.04	
Business Model	Obs	2,079		959				
	Coef	2.654%***		2.885%***		0.231%**	2.10	
Panel C: Cost of debt regressions								
	OLS Coeff	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**	**OLS Coeff**	**t-stat**
IR	2.314	1.56	0.887	0.55	0.420***	55.41	0.420***	27.94
Rating	-0.001***	-2.80	-0.003***	-3.89	-0.001***	-2.74	-0.004***	-4.98
Not rated	-0.026***	-6.04	-0.036***	-4.06	-0.033***	-7.48	-0.046***	-4.93
Financial Crisis	0.003	1.03	0.0001	0.03	0.00002	1.58	0.0001***	5.29
Total Assets to Equity	-2e-07	-0.03	0.00003	0.85	8e-06	0.79	0.00005*	1.81
Gross Loans to Total Assets	0.041***	13.77	0.040***	6.64	0.026***	9.19	0.026***	4.57
Sovereign Rating	-0.0002**	-2.34	-0.00006	-0.32	0.00006	0.66	0.0003*	1.81
Constant	-0.074	-0.95	0.005	0.05	0.013***	40.82	0.014***	21.62
Country * Year FE	Yes		Yes		No		No	
Bank rated at some point	No		Yes		No		Yes	
Observations	19,923		5,651		19,923		5,651	
R-squared	46.7%		44.4%		33.4%		31.2%	

Panel A presents the results of fixed effect OLS regressions that model banks' expenses, using a sample of EU banks during 2005 to 2015. Panel B shows a t-test of expenses to total assets ratio (%) for banks with and without a large change in debt or business model. Panel C present the results of regressions that model banks cost of debt. For equations see Table 2, and for variables' definitions see Table A1. Standard errors are clustered by bank and ***, **, * represent significance at the 1%, 5% and 10% levels, respectively.

28.86% (using 30,508 observations).

For the cost of debt, the results (in Panel C of Table 5) reveal that (i) the cost of debt increases with interest rates (consistent with expectations); (ii) the cost of debt increases during crisis periods (as funding is scarcer and drives up the cost of debt); (iii) higher rated firms experience a lower cost of debt (consistent with the literature on debt markets); (iv) more highly leveraged banks (increased credit risk) incur increased costs of borrowing; and (v) loan-focused banks incur higher costs of borrowing compared to trading or fee focused institutions.

4. Theoretical model

This section outlines the components of the discrete dynamic model of bank behaviour. The economy is populated by $i \in I$ banks. Each bank i maximises its present and future profitability (ROE) in each period $t = 1, \dots, T$ (DeYoung et al. (2015) and Egan et al. (2017)). Banks raise funds and engage in a combination of lending and non-interest activities. Choices are made by banks at the beginning of the period prior to the realization of the time-variant shocks. This follows the standard approach in the literature (Bakke and Gu (2017), Calem and Rob (1999), DeAngelo et al. (2011), De Nicolò et al. (2014), Hennessy and Whited (2005)).

The first choice a bank makes in each period is whether to increase or decrease the amount of debt, denoted as $\widetilde{D}_t$. The benefit of greater leverage arises from increased resources available to invest in assets, and therefore a bank may achieve a higher ROE. However, higher leverage increases the risk of financial distress, especially during times of high loan failure (e.g. a financial crisis) and therefore has an adverse impact on its credit rating and hence cost of debt. Also, having lower levels of debt may reduce the risk of insolvency, and can lead to a higher credit rating and lower cost of debt. The second choice a bank makes in each period is whether to vary the type of business it conducts, deciding between loans and non-interest activities to maximise its ROE. This decision is denoted by $\widetilde{\lambda}_t$. Shifting to increasingly non-interest activities may pay off in the current period but could impact a bank's credit rating and cost of debt in the future. The third choice a bank makes in each period is whether to solicit a rating from a CRA, with $CR_t \in \{0,1\}$. A bank may solicit a rating to achieve enhanced access to capital markets and lower the cost of debt.

Any profit or loss is carried over to the following period, impacting the bank's equity. The model also includes costly debt (D), corporation taxes (Tax), dividends (Div), share capital (SC), expenses ($EXPS$) and bankruptcy costs (χ). It contains four potential shocks, one each on X_t and Y_t returns, on expenses and on the credit rating, (see Eqs. (9), (12), (16) and (20)).

ROE is a common metric for bank success and influences managerial remuneration (e.g. Doucouliagos et al. 2007). Therefore, each bank attempts to maximise both the profit (ROE) in each period ($t = 0,\dots,T$) and a discounted stream (δ is the discount rate) of expected future profits (in periods $t+1$ to T) associated with decisions (d_t) made in each period subject to the period's state space I_t:[13]

$$\max_{d_t}\left\{ROE_{d_t}(I_t)+E\left[\sum_{\tau=t+1}^{T}\delta^{\tau-t}ROE_{d_t}(I_t)|I_t,d_t\right]\right\} \tag{3}$$

Following Keeley and Furlong (1990), we define the return on equity as:

$$ROE_{i,t}=\frac{[TI_{i,t}-TE_{i,t}]\times(1-Tax)}{Eq_{i,t-1}} \tag{4}$$

Where Tax represents the tax rate, which is assumed constant over the time period, $TI_{i,t}$ is the total income, $TE_{i,t}$ is the total expenses and $Eq_{i,t-1}$ is the equity at the start of the period. If the bank equity falls below zero then it is classed as insolvent and ceases trading. In this case it is awarded an insolvency penalty (β_{IC}) as in Egan et al. (2017).

The bank's income derives from loans and non-interest activities. The returns on loans and non-interest income activities are $X_{i,t}$ and $Y_{i,t}$ respectively, with $\sigma_{x,i,t}$ and $\sigma_{y,i,t}$ standard deviations, where $\sigma_y > \sigma_x$. The proportion of gross lending to total assets (GL-TA) is given by $\lambda_{i,t}$. The distribution of assets is then scaled up by the total assets $TA_{i,t}$, which is given by the sum of equity ($Eq_{i,t}$) and debt ($D_{i,t}$, which includes both debt and deposits).

$$TI_{i,t}=\left(X_{i,t}\lambda_{i,t}+Y_{i,t}(1-\lambda_{i,t})\right)*TA_{i,t}=\left(X_{i,t}\lambda_{i,t}+Y_{i,t}(1-\lambda_{i,t})\right)*\left(Eq_{i,t}+D_{i,t}\right) \tag{5}$$

$TI_{i,t}$ is the overall income from the combination of assets stated (adapted from Kwast's (1989) definition[14]). The business model, $\lambda_{i,t}$, (GL-TA) will change as follows:

$$\lambda_{i,t}=\lambda_{i,t-1}+\beta_{\lambda,1}\left(\widetilde{\lambda}_{i,t}\right) \tag{6}$$

$\beta_{\lambda,1}$ represents the proportional increase/decrease associated with the corresponding business model decision $\widetilde{\lambda}_{i,t}$. Therefore, the banks' businesses comprise: (i) traditional lending activities, and (ii) non-interest activities, which include securities and investment banking (e.g. Abedifar et al. (2018)). If the bank is mainly engaged in traditional lending activities, λ will be relatively high.

The bank incurs two types of expenses: (i) financing costs (as in Gomes (2001)), where the cost of debt depends on macro-economic conditions (interest rate, sovereign rating), bank credit rating and bank size (see Section 4.2), and (ii) operating expenses ($EXPS$). These operating expenses scale with firm size and include adjustment costs (as in Gomes (2001), Hennessy and Whited (2005, 2007)) associated with changing the proportion of debt financing and the business model (see Section 4.3). The resultant equation follows:

$$TE_{i,t}=COD_{i,t}*D_{i,t}+EXPS_{i,t}*TA_{i,t} \tag{7}$$

COD is the cost of debt for bank i in period t. A bank's debt will change as follows:

$$D_{i,t}=D_{i,t-1}(1-D\_decay)*\left[1+\beta_{D,1}\left(\widetilde{D}_{i,t}\right)\right] \tag{8}$$

Where $D_{i,t-1}$ is the debt at time $t-1$, $\beta_{D,1}$ is the proportional increase/decrease in debt associated with the corresponding debt choice $\widetilde{D}_{i,t}$. We follow a standard assumption in the literature that debt decays over time, due to loans (debt) reaching maturity. Following De Nicolò et al. (2014) and Hennessy and Whited (2005), we model the decay over time using the coefficient D_decay which represents the annual proportion of maturing debt.

4.1. Asset return

The assumption of categorizing bank assets into two different types (often termed safe and risky) is consistent with earlier literature (e.g. Benhabib at al. (2016), Gennaioli et al. (2013), Hanson et al. (2015)). First, we model the return on loans assuming (as in DeYoung et al. (2015)) that the probability of loan defaults depends on the economic conditions, both in the country and in the wider (European) economy, as follows:

$$X_{i,t}=\beta_{X,0}+\beta_{X,1}\left(\frac{Ec_{i,t}+Ec_{i,t-1}+Ec_{i,t-2}}{3}\right)+\beta_{X,2}IR_{i,t}+\beta_{X,3}SR_{i,t}+\varepsilon_X \tag{9}$$

Ec is a measure of the financial crisis (using the VSTOXX European market volatility index and is exogenous) and captures the wider economic uncertainty. We apply a 3-year moving average to reflect past economic conditions affecting the current loan default rate.

Interest rate (IR) changes are modelled as:

$$IR_{i,t}=IR_{i,t-1}+\varepsilon_{IR} \tag{10}$$

[13] It should be noted that in the general Bellman formulation in Eq. (3), we do not add the subscript i to indicate that the maximisation problem is faced by each bank, as this is common practice in the literature (see for example Keane and Wolpin, 1994). As shown in Eq. (4), the maximization problem is faced by each bank in a longitudinal (rather than time series) framework.

[14] $E(R) = \lambda E(RS) + (1-\lambda)E(RNS)$, where RS is return on securities activities and RNS is return on non-securities activities.

Sovereign rating (*SR*) captures the country's economic conditions. Countries with low sovereign credit rating have a much higher country risk factor and a correspondingly higher loan default rate. The sovereign rating changes as follows:

$$SR_{i,t} = SR_{i,t-1} + \varepsilon_{SR} \tag{11}$$

This study follows Gennaioli at al. (2013) and Hanson et al. (2015) in modelling the return of non-interest activities as a function of economic conditions. Three categories of economic conditions, good state (growth), bad state (down-turn) and recession, are employed. The return from non-interest activities is therefore modelled as follows:

$$Y_{i,t} = \beta_{Y,0} + \beta_{Y,1}SR_{i,t} + \beta_{Y,2}Ec_{i,t} + \varepsilon_Y \tag{12}$$

4.2. Cost of debt

This is modelled in two parts, as it includes all the pre-existing debt $\Omega_{i,t}$ and new debt ω taken during the current period (e.g. Bahai and Malherbe (2020)).[15] The cost of the total debt $\Phi_{i,t}$will depend on components:

$$COD_{i,t}(\Phi_{i,t}) = (1-\theta_{i,t})^*COD_{i,t}(\Omega_{i,t}) + \theta_{i,t}{}^*COD_{i,t}(\omega_{i,t}) \tag{13}$$

Where $\theta_{i,t}$ is the proportion of new debt. This modelling strategy enables keeping track of the proportion of debt incurred in the period (a current decision) and past accumulated debt.[16] The cost of existing debt depends on current interest rates and the wider economic environment (as this determines the availability of funds and hence the price) and the FI's credit risk (captured by either their Credit Rating or other indicators) and is modelled as:

$$\begin{aligned} COD_{i,t}(\Omega_{i,t}) &= \beta_{COD,0} + \beta_{COD,1}IR_{i,t} + \beta_{COD,2}Ec_{i,t} \\ &+Rated_{i,t}\left[\beta_{COD,3}e^{\beta_{COD,4}CR_{i,t}} + \beta_{CRA\ Fee}\right] \\ &+(1-Rated_{i,t})\left[\beta_{COD,5} + \beta_{COD,6}TA_{i,t} + \beta_{COD,7}SR_{i,t}\right] \end{aligned} \tag{14}$$

Increased interest rates ($IR_{i,t}$) raise the cost of borrowing for all market participants. This is supported by Merton (1974) who states that the cost of a firm's debt will depend on the interest rate and the volatility of the firm's value (or its business risk) as measured by the variance. Moreover, the firm's business risk will vary with the economic conditions (Ec_t).

For rated banks the terms $\beta_{COD,3}e^{\beta_{COD,4}CR_{i,t}}$ capture the impact of the credit rating on the cost of debt, which can be positive or negative.[17] Credit ratings are a key determinant of the cost of a firm's debt in capital markets (e.g. Almeida et al. (2017)).[18] The CRA fee is also included and is set as 0.0675% of the size of the issue.[19] The regression results support the above relationship (see Section 3.1).

For unrated banks, the first additional terms ($\beta_{COD,3}e^{\beta_{COD,4}CR_{i,t}}$) are replaced with the constant $\beta_{COD,5}$. The term $\beta_{COD,6}TA_{i,t}$ is included to capture the additional cost to larger banks of being unrated, which arises as larger firms typically use more long-term debt (Custódio et al., 2013). Large debt issuance without a credit rating is highly unusual, as it would require the institution to offer a significant premium on their debt to attract investors. This term represents that premium and the value is fixed from the data. As no credit rating is present, bond investors will also consider the financial state of the host country when evaluating the credit risk. We include the term $\beta_{COD,7}\,SR_{i,t}$ to account for the country level risk factor.

A bank's cost of newly added debt will impact both the bank's decisions regarding whether to solicit a credit rating and to issue new debt. Different factors are considered when estimating the cost of new debt issuance and hence the cost of issuing new debt is modelled as:

$$COD_{i,t}(\omega_{i,t}) = COD_{i,t}(\Omega_{i,t}) + \beta_{COD,8}\left(\frac{TA_{i,t}}{Eq_{i,t}}\right) + \beta_{COD,9}\lambda_{i,t} \tag{15}$$

We include the additional two terms $\beta_{COD,8}\left(\frac{TA_{i,t}}{Eq_{i,t}}\right)$ and $\beta_{COD,9}\lambda_{i,t}$, as in addition to a bank's credit rating, investors consider other key risk indicators including the bank's leverage (Berger and Bouwman (2013)) and its type (Altunbas at al. (2017)) when evaluating credit risk.

[15] Bahaj and Malherbe (2020) distinguish between new loans generated in that period and existing legacy loans already on the banks' balance sheet.

[16] Computational limitations do not allow keeping track of each past period's cost of debt separately.

[17] Ratings have a non-linear relationship with the cost of debt. The exponential constant $\beta_{COD,4}$ is fixed from the data and not changed during the estimation. The scaling constant $\beta_{COD,3}$ is estimated.

[18] Elton et al. (2001) show that bonds from financial sector companies with lower ratings have significantly higher rates (than highly rated FIs) and therefore those companies have significantly higher cost of debt. Elton et al. (2001) show that the spread from Treasury bonds is roughly twice as large for financial sector corporations rated BBB as for those rated AA (on bonds with a maturity of less than 10 years).

[19] S&P's rating fee for corporates (at the time of writing).

4.3. Expenses and taxation

Bank expenses are modelled as a function of size and adjustment costs. Firstly, we assume that expenses will scale with size (see Section 3.1). We also follow a standard assumption in the literature (Gomes (2001), Hennessy and Whited (2005, 2007)) whereby businesses incur *adjustment costs*, either *fixed* or *convex* (Strebulaev and Whited (2011)). This study opts for *convex* adjustment costs as they better capture the size of the change. The adjustment costs apply to both a change in the debt level and a change in the business model. Debt adjustment costs arise from the costs associated with accessing capital markets and of issuing debt at different maturities. There are costs associated with shifting the emphasis of the banking business from lending to more non-interest focused business or vice versa.[20]

$$EXPS_{i,t} = \left(\beta_{Ex,0} + \beta_{Ex,1}\left[\beta_{D,1}\left(\widetilde{D}_{i,t}\right)\right]^2 + \beta_{Ex,2}\left[\beta_{\lambda,1}\left(\widetilde{\lambda}_{i,t}\right)\right]^2 + \varepsilon_{exps}\right) * \left(Equity_{i,t-1} + Debt_{i,t}\right) \tag{16}$$

Further, we include a corporation tax of 28.9% (see Section 3.1), close to the value used by Hennessy and Whited (2005) (of 30%).

4.4. Equity, dividends and share capital

The bank's equity can change over time, as in De Nicolò et al. (2014) and Peura and Keppo (2004).[21] Equity is more expensive than debt (e.g. DeYoung et al. (2015)).[22] Hennessy and Whited (2005) show that it is generally optimal to leave debt outstanding than to replace with equity. Therefore, in our model, if banks wish to raise additional capital, they can choose to raise debt. Further, banks pay dividends to shareholders, and we match the average dividend pay-out each period dependent on bank size and net income. Banks also receive a modest input of share capital, dependent on the size of the bank.[23]

Consistent with the literature, banks retain earnings which are then reinvested with a view to increasing the value of equity (e.g. De Nicolò at al. (2014) and Repullo (2004)). The next period's equity level is modelled as:

$$Eq_{i,t} = Eq_{i,t-1} + NI_{i,t} - Div_{i,t} + SC_{i,t} \tag{17}$$

Where $Div_{i,t}$ is the dividend issued by the bank and $SC_{i,t}$ is the change in share capital. This relationship is shown to hold in the data (see Section 3.1). We also include the total dividends. A simple estimation of the average dividend paid each year is included, based on the size of the bank's equity and the net income generated that year.

$$Div_{i,t} = \beta_1 Eq_{i,t-1} + \beta_2 NI_{i,t} \tag{18}$$

Higher profits lead to the firm being able to pay (or pay a larger) dividend that period and as such β_2 is positive. This positive relationship between revenue and dividends is shown by Dickens at al. (2002) and others. The relationship in the above equation is fully supported by the data (see Section 3.1). Due to limitations in computational power, share capital cannot be specified here as a choice variable, so the average amount of share capital of each institution is estimated based on their characteristics and this is then matched to the actual data. The trend shown in the data is that larger banks issue more share capital at each offering. The relationship is modelled as:

$$SC_{i,t} = \beta_1 TA_{i,t} = \beta_1\left(Eq_{i,t-1} + D_{i,t}\right) \tag{19}$$

4.5. Bank credit ratings

A bank's credit rating is a metric that captures the probability that the bank will be unable to repay its debts in full and on time. Ratings are used in a variety of areas, from determining bond spreads in capital markets to being embedded in government regulation. As such, a bank's credit rating has a significant impact on its activities. The greatest impact is on the bank's cost and availability of debt. Banks require a credit rating to access capital markets and to be able to issue bonds in a cost-effective manner. A poor rating can limit the potential investors in a bank's debt and require the bank to offer a premium to attract more risk-tolerant investors. Many studies show that credit ratings significantly impact the cost of debt (e.g. Almeida et al. (2017), Elton et al. (2001), Nozawa (2017)).

Various factors affect the rating that a bank will be assigned. Leverage captures the capital structure and is a strong determinant of bank risk (Berger and Bouwman (2013). White and Cole (2012), and others, find that higher capital levels improve banks' performance

[20] A t-test confirms that banks that make large changes to their debt level have significantly higher expenses as a proportion of their total assets. A t-test confirms that banks that make a large shift towards lending activity (or towards non-interest activities) have higher expenses than those that make no change to their business model.

[21] The literature typically models the change in equity as $Equity_t = Equity_{t-1} + Net\ income_t - Dividends_t + Change\ in\ share\ capital_t$. Individual models vary as to whether they include estimates for the dividends paid and the change in share capital. We apply Peura and Keppo's (2004) model as it is the most appropriate in our setting.

[22] Specifically, that the opportunity cost of capital is larger than the interest rate on deposits.

[23] Since equity is more expensive than debt, if a bank wishes to raise more funds, we assume this would be done via raising debt. Thus, we do not include the change in share capital as a choice variable. Yet, since share capital does change over time, we choose to model the overall average change each period based on a bank's size.

during the financial crisis. We capture this by using the ratio of total assets to equity, following Hau at al. (2013). Bank business models are also known to have an impact on their riskiness (Altunbas at al., 2017). The rating is also highly dependent on its past value and is affected by the financial crisis (market volatility, captured by VSTOXX). Finally, risk can be transferred from sovereigns to banks through a rating channel (e.g. Almeida et al. (2017)) whereby the sovereign rating normally acts as an upper bound for the bank rating. It is then necessary to include the sovereign rating of the bank's host country to capture any such transmission of risk. A bank's credit rating is therefore modelled as:

$$CR_{i,t} = \beta_{CR,0}\left(1 - Rated_{i,t-1}\right) + \beta_{CR,1}CR_{i,t-1}Rated_{i,t-1} + \beta_{CR,2}Ec_{i,t} + \beta_{CR,3}SR_{i,t} + \beta_{CR,4}\lambda_{i,t} + \beta_{CR,5}\left(\frac{TA_{i,t}}{Eq_{i,t-1}}\right)^2 + \varepsilon_{CR} \tag{20}$$

Where $Rated_{i,t-1}$ is a dummy variable equal to 1 if the bank was rated in the previous period. $\varepsilon_{CR,1}$ is a shock that captures the uncertainty facing banks when predicting their rating levels.

4.6. Constraints

Banks are subjected to a regulatory minimum capital ratio, which is the minimum ratio of equity to total assets.[24]

$$\frac{Eq_{i,t}}{TA_{i,t}} \geq \min\left(\frac{Eq}{TA}\right) \tag{21}$$

During our sample period, two sets of capital requirements prevailed in Europe. First, Basel II brought in an initial common equity tier 1 capital ratio of 2% in 2006.[25] Second, the equity tier 1 capital ratio was extended by the Basel III regime to 4.5% in 2013.[26] These capital constraints are explicitly included in the base model. Simulated scenarios are implemented, through which we examine what would have been the impact on banks' choices and overall outcomes if capital requirements regulation would have been introduced before the crisis and if the regulation would have been more stringent (e.g. 7% as opposed to 2%); see Section 7.2 for a full description of the simulated scenarios.

4.7. Shocks structure and expectations formation

The distribution of the temporary shocks on banks' credit rating, expenses, returns on loans and returns on non-loan activities is joint normal $(\varepsilon_{CR},\ \varepsilon_X, \varepsilon_Y, \varepsilon_{exps}) \sim (0, \Sigma)$ with covariance matrix $\Sigma = AA'$ where A is the Cholesky decomposition. A is restricted for identification reasons so that:

$$A = \begin{bmatrix} a_{CR} & 0 & 0 & 0 \\ 0 & a_X & 0 & 0 \\ 0 & a_{XY} & a_Y & 0 \\ 0 & 0 & a_{YExp} & a_{Exp} \end{bmatrix}$$

Thus, two non-diagonal elements of the lower triangular matrix are non-zero, allowing the estimation of covariance between returns on loans and returns on non-interest activities, and between returns on non-interest activities and expenses. During the estimation process, we investigated the role of more covariance elements but found them non-identified and therefore restricted them to zero.

On the other hand, shocks to the interest rate and sovereign credit rating are subject to Markov processes. In each period, banks face a uniform independent probability of their interest rate and sovereign credit rating transitioning to a different category. The probability of moving to another category depends on the category that they currently reside in, and the probabilities differ according to the time period of the model (pre/peak/post crisis). These probabilities are not estimated as they do not depend directly on banks' choices but are calculated from the data.[27] It is possible that lower-level shocks, such as regional shocks to lending, could affect the behaviour of banks, but it not feasible to add them to the model due to computational limitations. Moreover, adding too many shocks would likely have consequences for identification.

Banks form expectations about future macroeconomic conditions with imperfect foresight. The model is split into three major periods: pre-crisis (2004-2007), peak crisis (2008-2010) and post crisis (2011-2015). Each period has separate interest rate and sovereign credit rating transition probabilities. This allows bank to anticipate the short-term changes, but not the long term. Banks then generate their expectations based upon the setting. As such, banks in the pre-crisis years are unable to anticipate the financial crisis and assume that the crisis level (*Ec*), measured by the European Volatility Index (see Table A1), will not change substantially. Prior to the

[24] We employ total assets instead of risk weighted assets, as it was not possible to include risk weightings in our model and framework. Banks can still breach the limit involuntarily, for example, if an unexpected negative shock causes the bank to make a loss leading to a fall in capital and hence breach the regulatory limit.

[25] EU Directive 2006/49/EC of 14th June 2006.

[26] EU No 575/2013 Article 92 of 26th June 2013.

[27] For brevity, we do not report the six transition probabilities tables, which are available upon request.

Table 6
State space and choice variables.

Variable	Symbol	Number of Categories	Categories
Time	*T*	13	One category for each year in the model.
Equity	*Eq*	30	The average equity value for each 1/30th percentile, from €0 to €4b
Debt	*D*	30	The average debt value for each 1/30th percentile, from €0 to €67b
Gross loans to total assets	λ	14	The average equity value for each 1/14th percentile. From 0.3% to 95.5%
Credit rating	*CR*	8	0 = Not Rated, 1-7 represent the Credit Rating category on a 7 point scale.
Financial crisis period	*Period*	3	Pre, peak or post crisis period.
Sovereign rating	*SR*	4	Average sovereign rating of *23.2, 35.6, 45.5, 52* on the 52-point CCR rating scale.
Interest rates	*IR*	5	Average interest rate of *0.2%, 0.7%, 1.5%, 2.9%, 5.0%.*
Debt Choice	$\tilde{D}$	5	Divided the distribution of debt in: -inf to -5%, -5% to 0%, 0% to 5%, 5% to 90%, 90% to inf change in debt.
BM Choice	$\tilde{\lambda}$	5	Divided the distribution of BM in: -inf to -7.5%, -7.5% to -2%, -2% to 2%, 2% to 7.5%, 7.5% to inf change in business model.
Rated Choice	*Rated*	2	Rated vs not rated

The table defines the state space and choice category variables employed in the model. Debt and BM Choice are each interpolated from 5 onto 41 separate debt and BM choice levels. The 52-point comprehensive credit rating (CCR) scale used for Sovereign Rating is defined as: AAA/Aaa = 52, AA+/Aa1 = 49, AA/Aa2 = 46 …, CCC+/Caa1, CCC/Caa2, CCC-/Caa3 = 4, C/SD/CC/D = 1, then we add +1/+2 for positive outlook/watch signals and deduct -1/-2 for negative outlook/watch signals.

crisis, banks expect that the values of *Ec* for 2008 onwards will assume the rolling average of the past four periods (Ec_{t-1} to Ec_{t-4}), which mirrors the lack of expectations for future market volatility and of the crisis.[28] With the onset of the crisis, banks amend their expectations and anticipate recovery and a diminishing crisis level, with the value of *Ec* being exogenously set to match the actual annual average European Volatility, VSTOXX, level. Therefore, during the peak-crisis and post-crisis periods, banks expect a recovery and can anticipate the gradual decrease of the financial crisis level but are not able to predict the long-term interest rate and sovereign rating movements.

5. Empirical strategy

We employ the simulated method of moments (SMM) (McFadden, 1989; Pakes and Pollard, 1989) to estimate the DCDP model, which allows a theoretical model to be explicitly incorporated in the empirical analysis, and it relies on the discretization of the decision space. The main advantage of using a Dynamic Structural Estimation (DSE) approach over a reduced form one is the exploration of the mechanism that produces observed outcomes (Low and Meghir, 2017). Therefore, this approach enables moving beyond the conclusions of a study that provides reduced-form causal relationships. Moreover, even though dynamic models are applied in the banking literature (e.g. De Nicolo et al. (2014)), these have not been be fully estimated.[29]

We set the largest possible choice and state space given computational limits,[30] thus having three contemporaneous choice dimensions: amount of debt, business model, and whether to solicit a rating, producing a total of 3,362 possible choices in each year. Table 6 shows the possible choices and states. Banks face one discrete choice of whether to be rated or not; and they face two continuous discretized choices with regards to whether to acquire new debt and their business model. Each of these categories is discretized into five possible categories in the backward recursion. However, by using interpolation we allow banks to choose between 41 possible levels of percentage change in the amount of debt, 41 possible levels of percentage change in the business model, and whether to be rated.

The state space is also discretised, whereby the amount of debt and the business model are divided into 30 and 15 categories respectively, while the credit rating level is divided into 8 categories.[31] Moreover, the state space includes equity (30 categories), interest rate (5), sovereign rating (4), financial crisis (3) and time (13) for a total of 3.931 billion (non-interpolated) and 264.3 (interpolated) billion possible future paths.

We take several steps to ensure that we minimize initial and final conditions irregularities, as follows. First, we match the decisions of banks from 2005 to 2015 but simulate the same from 2004 to 2017, to reduce initial and final conditions' irregularities. Second, we use initial conditions for banks' characteristics based on the sample in the initial year of 2004, whereby banks are split into 50 categories by percentile (0-2%, 2-4% etc) based on the size of their total assets. Banks in the simulation are then randomly assigned a size category (1-50) and average debt level, equity level, and a credit rating for that category. Moreover, banks are assigned a business

[28] The values for 2004 to 2007 are anticipated with perfect foresight and set exogenously to match the actual annual average of the European Volatility level (VSTOXX).

[29] The models are only calibrated and do not calculate any standard errors for the parameters.

[30] Technically, the set of *Emax*'s could not exceed 3.93 billion, as this was the maximum number possible when simulated using an Intel I7-8700k, 16 GB ram and a NVidia Titan Xp GPU.

[31] This includes 7 rating categories (AAA/Aaa = 7, AA+/AA/AA-/Aa1/Aa2/Aa3 = 6 … CCC+/Caa1/CCC/Caa2/ CCC-/Caa3/C/SD/CC/D = 1) and 0 for non-rated.

Table 7
Table of moments.

Panel A: Profitability, return on loans and non-interest activity return						
Moment	**Pre-Crisis (2006)**		**Peak Crisis (2007-2010)**		**Post Crisis (2011-2015)**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
Return on Equity (%)	10.95	11.00	7.07	6.10	5.01	4.91
	(9.94)	(27.69)	(10.27)	(23.99)	(10.28)	(25.25)
Return on Assets (%)	0.98	1.21	0.66	0.64	0.57	0.37
	(1.14)	(2.00)	(1.17)	(1.88)	(1.31)	(1.91)
Return of X (%)	6.46	7.91	6.03	6.98	4.79	5.26
	(2.98)	(2.88)	(2.73)	(3.05)	(2.44)	(3.02)
Return of Y (%)	5.21	6.57	4.81	5.97	4.90	5.74
	(6.06)	(4.20)	(5.96)	(4.29)	(6.21)	(4.26)
Panel B: Bank characteristics and behaviour						
Moment	**Pre-Crisis**		**Peak Crisis**		**Post Crisis**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
Equity	18.58	18.64	18.60	18.64	18.55	18.54
	(1.76)	(1.96)	(1.76)	(2.01)	(1.82)	(2.07)
Debt	20.82	20.92	20.83	20.84	20.66	20.76
	(2.09)	(2.65)	(2.10)	(2.54)	(2.11)	(2.49)
Business Model (%)	61.94	62.58	63.53	64.85	60.95	60.17
	(27.77)	(29.46)	(27.70)	(28.83)	(26.34)	(29.38)
Equity to Total Assets (%)	11.82	11.86	12.36	12.71	13.10	12.96
	(11.00)	(8.46)	(11.95)	(8.96)	(12.36)	(12.02)
Dividends (% of TA)	0.63	0.73	0.62	0.70	0.53	0.65
	(0.96)	(0.50)	(1.16)	(0.50)	(0.97)	(0.55)
Share Capital (% of Equity)	0.38	1.45	1.11	1.25	1.46	1.37
	(2.91)	(0.96)	(2.93)	(0.88)	(3.08)	(0.79)
Solvency (%)	100.00	99.58	97.80	94.96	95.83	94.21
Panel C: Credit ratings, cost of debt and expenses						
Moment	**Pre-Crisis**		**Peak Crisis**		**Post Crisis**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
Average rating	5.11	4.97	5.07	5.01	4.66	4.92
	(0.91)	(0.79)	(0.93)	(0.81)	(1.12)	(0.74)
Rated / Total (%)	21.39	18.76	21.14	22.63	20.66	20.98
Cost of Debt - rated (%)	2.46	4.38	2.95	4.40	1.66	3.04
	(1.00)	(1.06)	(1.45)	(1.07)	(1.24)	(0.68)
Cost of Debt - unrated (%)	2.44	4.11	2.79	3.80	1.57	2.86
	(1.08)	(1.13)	(1.47)	(0.89)	(1.14)	(0.67)
Cost of Debt - no extra debt (%)	2.75	2.59	2.89	3.46	1.90	3.19
	(1.18)	(0.96)	(1.43)	(0.90)	(1.27)	(1.08)
Expenses (% of total assets	na	2.64	2.93	2.33	2.93	2.17
	na	(1.19)	(3.34)	(1.11)	(3.34)	(1.08)
Panel D: Wider economy (not estimated)						
Moment	**Pre-Crisis**		**Peak Crisis**		**Post Crisis**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
IR (%)	2.98	4.37	2.90	3.22	0.74	0.68
Sovereign rating	46.99	47.28	46.30	46.13	40.35	41.18

The table shows the mean values and the standard deviations (in brackets) for the simulated and actual moments. na: Data on expenses was not available in the pre-crisis period. The data sample includes EU banks from 2005 to 2015. See Table A1 for variables' definitions.

model drawn from a set of 10 categories, based on the average business model in each percentile category (0-10%, 10-20% etc) in 2004. Finally, each bank is assigned a random interest rate and sovereign rating category drawn from a 2-dimensional grid of probabilities based on the categories found in the real data in 2004.

Third, we implement final conditions by setting the EMAX in the final period to:

$$EMAX(CAPT) = gammaD[\widetilde{D}_{CAPT}] + gammaBM[\widetilde{\lambda}_{CAPT}] + gammaCR[\widetilde{CR}_{CAPT}] \tag{22}$$

Where *gammaD* is a set of parameters that are assigned if the bank chooses a debt choice (-1, 0, 1, 2). *gammaBM* is a set of parameters that are assigned if the bank chooses BM choice (-1, 0, 1, 2). *gammaCR* is a parameter that is assigned if the bank chooses to be rated in the final period. The values of *gammaD, gammaBM* and *gammaCR* are then estimated and reported in Table 9.

In order to estimate the model, the first step is to build a dynamic structural model of optimal bank financing and investment policy under several constraints, including: costly debt, corporate taxation, credit ratings, convex adjustment costs and bankruptcy costs. Bank managers attempt to maximise their return on equity (ROE) subject to the frictions and restrictions detailed in the model (see Section 4). The second step is to code the model to generate a simulated panel data set, whose moments can then be compared to the actual panel data. The third step consists of adjusting the parameters of the model, until the distance between the two sets of moments

Table 8
Table of annual moments.

Panel A: Credit ratings, ROE, return on loans and return on non-interest activities

Moment	Credit Rating		ROE (%)		Return on loans (%)		Return on non-interest activities (%)	
	Actual	Simulated	Actual	Simulated	Actual	Simulated	Actual	Simulated
2005	5.11	5.09	11.23	14.37	6.80	7.29	5.63	6.64
2006	5.12	4.97	10.95	11.00	6.46	7.91	5.21	6.57
2007	5.13	4.94	10.77	11.58	6.89	8.00	5.25	6.40
2008	5.17	5.09	6.56	6.91	7.04	8.01	4.47	5.79
2009	5.06	5.06	5.57	1.11	5.48	6.24	4.73	5.68
2010	4.93	5.16	5.34	4.69	4.90	5.58	4.76	6.02
2011	4.90	4.73	4.81	-1.63	5.08	5.25	4.78	5.42
2012	4.78	4.93	4.65	1.62	5.05	5.22	4.99	5.61
2013	4.57	4.93	4.76	8.85	4.76	5.29	4.97	5.92
2014	4.50	4.91	5.39	9.99	4.63	5.25	5.06	5.97
2015	4.54	4.91	5.51	5.93	4.40	5.27	4.67	5.80

Panel B: Cost of debt, debt, equity and capital ratio

Moment	Cost of debt – rated (%)		Equity (log)		Equity to total assets (%)	
	Actual	Simulated	Actual	Simulated	Actual	Simulated
2005	2.46	3.60	18.46	18.60	11.98	11.75
2006	2.76	4.38	18.58	18.64	11.82	11.86
2007	3.34	4.89	18.60	18.66	12.11	12.42
2008	3.58	4.96	18.54	18.66	12.24	13.26
2009	2.51	4.43	18.61	18.61	12.22	12.76
2010	2.06	3.54	18.63	18.60	12.86	12.40
2011	2.11	4.36	18.49	18.52	13.01	12.77
2012	2.18	3.30	18.50	18.48	13.03	12.76
2013	1.75	2.77	18.54	18.53	13.19	12.90
2014	1.53	2.76	18.55	18.57	13.28	13.09
2015	1.29	3.36	18.71	18.59	12.97	13.28

Panel C: Debt, Business Model and Rated Choice

Moment	Debt (log)			Business Model (%)			Choice - Rated (%)		
	Actual	Simulated	t-stat	Actual	Simulated	t-stat	Actual	Simulated	Chi2
2005	20.74	20.86	2.22	60.32	59.58	-1.02	17.33	23.33	15.73
2006	20.92	20.92	0.15	61.94	62.58	0.78	21.39	18.76	4.6
2007	20.94	20.91	-0.41	62.91	67.04	6.05	22	24.05	0.22
2008	20.88	20.83	-0.88	64.79	65.21	0.22	22.73	22.55	0.05
2009	20.91	20.80	-1.8	63.07	64.18	0.94	23.61	22.69	6.09
2010	20.90	20.81	-1.44	63.38	62.87	-1.55	23.16	20.5	2.14
2011	20.73	20.74	0.16	63.09	61.87	-2.61	21.25	23.36	3.9
2012	20.72	20.71	-0.06	60.71	60.68	-0.79	20.89	20.55	0.45
2013	20.71	20.73	0.49	60.24	59.73	-1.47	20.25	22.1	0.53
2014	20.70	20.78	1.54	59.34	59.34	-0.57	19.57	21.32	0.87
2015	20.86	20.83	-0.55	61.45	59.16	-4.09	21.44	19.93	0.82

The average of various annual characteristics generated by the model and those observed in the actual data. The data sample includes EU banks from 2005 to 2015. See Table A1 for variables' definitions.

is minimized by convergence, thereby yielding consistent estimates for the unknown parameters (as in Hennessy and Whited (2005, 2007)).

We use an interpolated backwards recursion method to conduct the estimation. This involves first solving the model, for estimated parameters, by backwards recursion. To do this, we use the full numerical solution method where the expected maximum (*Emax)* function is solved at every $t = 1,\ldots,T$, as pioneered by Keane and Wolpin (1994). The *Emax* function is the expected utility, i.e. predicted ROE, associated with any given choice in any state space for the bank. Using interpolation, we are able to map the 3.931 billion components of the *Emax* on a finer grid and banks can make choices that are in between multiple state spaces, leading to a final state space of 264.3 billion. After the *Emax* is calculated, the model is forward simulated, using the interpolated possible future expected maximum ROE that applies to each state. In this way the simulated panel data is obtained. The objective of SMM is to estimate a set of structural parameters by matching a set of simulated moments to a corresponding set of data moments (see Section 6.1). By varying the parameters, the distance between corresponding moments can be reduced. We build the variance covariance matrix and from that calculate the parameter standard errors.

We add three more measures to mitigate the effects of working within a finite timeframe. First, we increase the number of simulated years beyond the period used for matching by two years. This step is taken to ensure that simulated banks do not drastically change their behaviour in the last year of matched moments as they still perceive a future that affects their choices. Second, to further tackle finite time, we implement final conditions, which consists of matching a final value function for each current state (similar to Keane and Wolpin (2000), see Section 5). This further ensures that in the years approaching the final one, matched banks do not take decisions as if there was no future and that their behaviour is consistent with previous years' behaviour. Finally, to ensure these mitigating measures work as intended, robustness tests are conducted to increase the number of years on a reduced model. While it is not possible to add more years to the whole simulated model given computational limitations, it is possible to shut down one set of

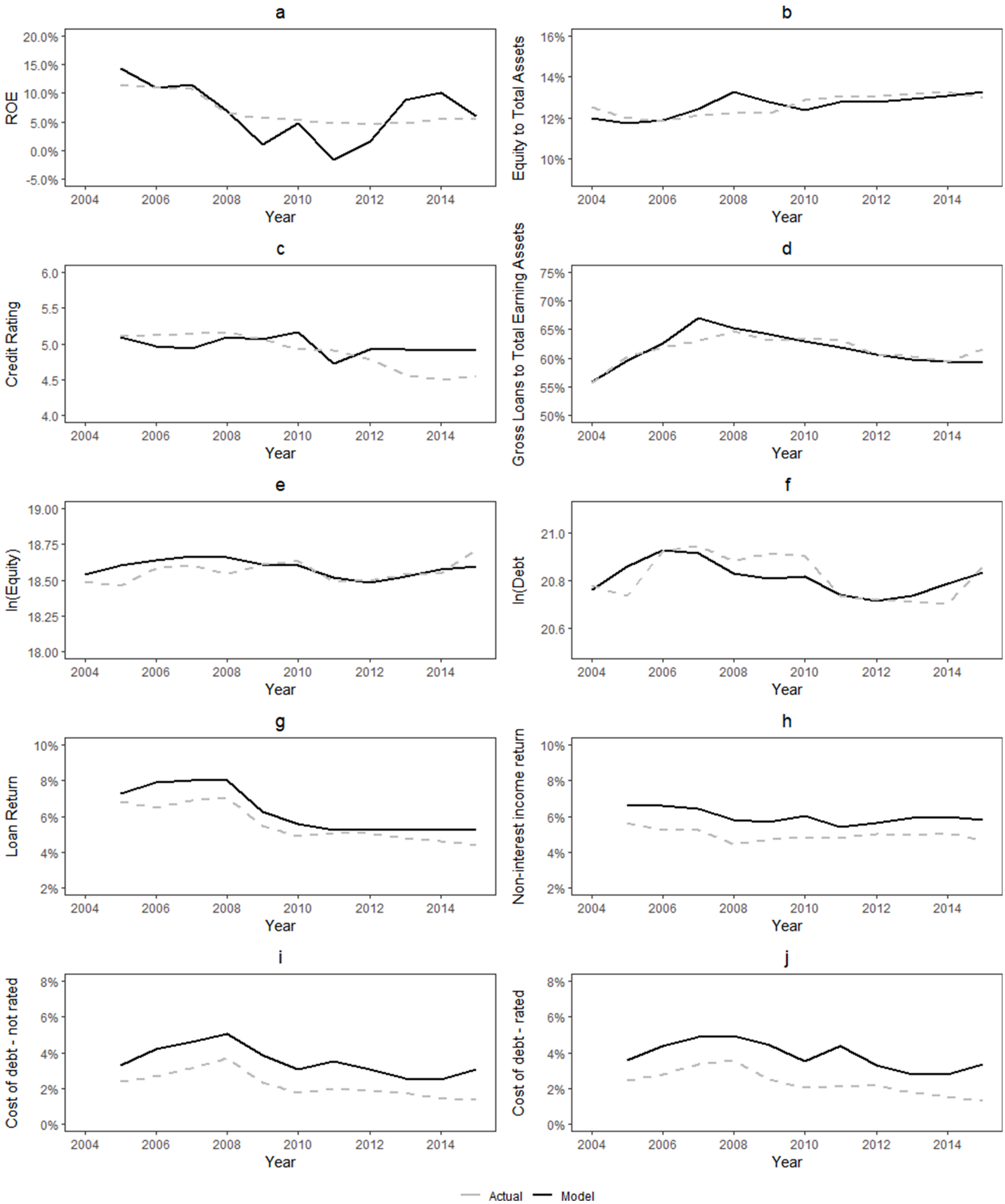

Fig. 2. The behaviour of variables over time
The Fig. shows the change in the various bank characteristics over time. See Table A1 for variables' definitions.

decisions at the time and add 10 years to the simulations. This enables us to compare the difference between the results for the simulations between the two models (smaller model with original number of years versus smaller model with added number of years). Results show that increasing the number of years does not significantly affect banks' choices within the model.

Standard errors are calculated as the square root of the ratio between the diagonal of the variance covariance matrix and the number of simulated banks. The variance covariance matrix is $Q_s(W) = \left(1 + \frac{1}{S}\right)\left[\frac{\partial(\theta_0)'}{\partial\theta} W^{Opt} \frac{\partial(\theta_0)'}{\partial\theta}\right]^{-1}$, where S is the number of simulations (6,121*10), $\frac{\partial(\theta_0)}{\partial\theta}$ is the first derivative of the vector of moments m with respect to the vector of parameters θ. W^{Opt} is the optimal weighting matrix, the iterated variance-covariance (VC) estimator of W. This is calculated using a two-step procedure (see Gourieroux, et al. (1993)), which is then iterated to increase robustness and efficiency (as suggested by Jalali et al. (2015), among others). In order to calculate the optimal weighting matrix, we use the following steps: (i) calculate the VC matrix using the identity matrix, (ii) calculate the weighting matrix as the inverse of the VC matrix, (iii) this new weighting matrix is then used to recalculate the VC matrix. Steps 1-3 are then repeated for 200 iterations, until there is no longer improvement in the standard errors.

6. Results

6.1. Moments, model fit and parameters

Tables 7 and 8 present the moments used in the estimation and compare the simulated with actual values. Fig. 2 shows a series of moments over time.[32] Table 7 examines the average of key variables across time periods and Table 8 displays the annual values. Overall, the model fit follows closely the actual data. Looking first at profitability, the model matches well the actual bank profitability (*ROE* and *ROA*) (Panel A of Table 7), with only an underprediction of *ROE* during the crisis period. This initial fall in *ROE* is influenced by the modelled deteriorating market conditions captured by lower sovereign ratings (*SR*) and higher crisis levels (*Ec*) which exhibit themselves in declining asset returns. Declining market conditions also increase the likelihood that banks will fail to make the payments on their debt and hence drive up the cost of debt (*COD*) as banks are forced to offer higher compensation for the increased risk (see Section 4.2). The combination of lower asset returns, and higher cost of funds means that banks generate lower profits (*ROE*). The trend is somewhat reversed when the market recovery begins.

The model also matches the returns on lending activity and returns on non-interest activities in both the crisis periods and annually, with an overall slight overprediction of returns. The model correctly replicates the fall in non-interest activity during the financial crisis and the collapse in loan returns following 2008. The returns from lending activity fall in response to deteriorating economic conditions (*Ec* increasing, *SR* decreasing) and collapsing interest rates (*IR*). In the model, non-interest activities depend directly upon the economic market conditions (see Section 4.1), whereby declining sovereign ratings (*SR*) and rising crisis levels (*Ec*) result in a steady, but less severe, fall of non-interest income.

Secondly, the model matches equity levels almost exactly, capturing the overall rise throughout the sample (partly attributable to accumulated profits from higher ROE) and the dip during the European sovereign debt crisis (as profits collapsed). Similarly, for debt, the model captures the fall from 2007 to 2011, due in part to the 2008 financial crisis whereby banks reduced their debt in response to the lack of good business opportunities (replicated in the model by falling asset returns). The model also captures the stability of the market conditions from 2011 onwards as banks recover and market uncertainty decreases, and hence banks take on more debt to fund further business. This is reflected in the moments both in each period (Panel B of Table 7) and annually (Panel C of Table 8, where a t-test shows no significant differences in means). The model captures the trends in bank business model, which saw a proportional shift towards lending activities in the first half (2005-2008) and then a shift to reduced lending activity in 2009-2015.[33] Panel C in Table 8 shows that there are no statistically significant differences between the simulated and actual moments relating to business model and debt, implying that the simulated data match those points very closely. The model also accurately matches the increase in capital ratios following the implementation of Basel II in 2006 and Basel III in 2013 (Table 8, Panel B), which are included within the baseline model and limit the minimum capital ratio that banks may deliberately choose to adopt. The model matches the dividends issued by banks, but slightly over predicts the proportion of share capital issued in the pre-crisis period (Panel B of Table 7).

Thirdly, the model replicates the changing CRA behaviour throughout the sample, capturing the reduced credit ratings during the European sovereign debt crisis (Table 8, Panel B) and matching the standard deviation as well as the proportion of banks soliciting a rating from CRAs (Table 7, Panel C). The model correctly matches the annual average proportion of banks that choose to be rated, with χ^2 statistics showing significant difference only in 2005 (Table 8, panel C).[34] The decision to solicit a rating impacts banks' current and future cost of debt and by extension their profitability. The model is reasonably successful in matching the cost of debt for rated and unrated banks as well as for banks that issue no extra debt in each period (Table 7, Panel C). The simulated cost of debt for rated banks is overpredicted in every year (Table 8, Panel B), but the percentages are rather small. The operating expenses incurred by banks are also matched for two of the three periods (Table 7, Panel C), showing a slight underprediction.

The parameters estimated using the SMM method are reported in Table 9. Key unobservable parameters are the convex adjustment costs of debt ($\beta_{Ex,1}$), which is -0.007 times the percentage change in Debt squared, and of business model ($\beta_{Ex,2}$), which is 1.320 times

[32] In both Figs. 1 and 2, the change in ROA over time is not shown here as its behaviour mirrors that of ROE and hence in the interests of brevity we focus on ROE as a profitability measure.

[33] This change is captured in the model as banks shift preferences between the two activities depending on which they perceive to be more remunerative. This is initially loan activity prior to the financial crisis, but due to the fall in interest rates and poorer economic conditions (also captured in the model), fee income achieves greater relative importance.

[34] While it is recommended to use a χ^2 statistic for discrete choices as in Heckman and Walker (1990), continuous discretized choices, such as business model and debt can be analysed with a t-test for differences in means.

Table 9
Table of Parameters.

Group	Variable	Parameter	Value	Standard error
Panel A: Credit rating, return on loans and return on non-interest activities				
Group	**Variable**	**Parameter**	**Value**	**Standard error**
Credit rating	$(1\text{-}Rated_{i,t-1})$	$\beta_{CR,0}$	1.070***	0.000
	$Rated_{i,t-1}$	$\beta_{CR,1}$	0.210**	0.000
	$Ec_{i,t}$	$\beta_{CR,2}$	-0.006***	0.000
	$SR_{i,t}$	$\beta_{CR,3}$	0.094***	0.000
	$\lambda_{i,t}$	$\beta_{CR,4}$	-0.116***	0.000
	$\left(\frac{TA_t}{Eq_{t-1}}\right)^2$	$\beta_{CR,5}$	-0.001***	0.000
Return on loans	Constant	$\beta_{X,0}$	0.015***	0.000
	$Ec_{i,t}$	$\beta_{X,1}$	-0.0002***	0.000
	$IR_{i,t}$	$\beta_{X,2}$	0.606***	0.000
	$SR_{i,t}$	$\beta_{X,3}$	0.0004***	0.000
Return on non-interest activities	Constant	$\beta_{Y,0}$	-0.003***	0.000
	$SR_{i,t}$	$\beta_{Y,1}$	0.001***	0.000
	$Ec_{i,t}$	$\beta_{Y,2}$	-0.0004***	0.000
Panel B: Debt, dividends and share capital				
Group	**Variable**	**Parameter**	**Value**	**Standard error**
Debt	Debt decay	D_decay	0.066***	0.000
Dividends	Eq_{t-1}	$\beta_{Div,1}$	0.045***	0.000
	NI_t	$\beta_{Div,2}$	0.110***	0.000
Share capital	TA_t	$\beta_{SC,1}$	0.001***	0.000
Panel C: Expenses, tax, cost of debt and insolvency				
Group	**Variable**	**Parameter**	**Value**	**Standard error**
Expenses	TA_t	$\beta_{Ex,0}$	0.011***	0.000
	$[\beta_{D,1}(\widetilde{D}_t)]^2$	$\beta_{Ex,1}$	-0.007***	0.000
	$[\beta_{\lambda,1}(\widetilde{\lambda}_t)]^2$	$\beta_{Ex,2}$	1.320***	0.000
Corporate Tax	Tax	$\beta_{Tax,0}$	0.289***	0.000
Cost of debt	Constant	$\beta_{COD,0}$	-0.005***	0.000
	$IR_{i,t}$	$\beta_{COD,1}$	0.120***	0.000
	$Ec_{i,t}$	$\beta_{COD,2}$	0.001***	0.000
	Credit rating linear parameter	$\beta_{COD,3}$	0.395***	0.000
	Credit rating exponential parameter	$\beta_{COD,4}$	-0.746***	0.000
	$(1\text{-}Rated_{i,t})$	$\beta_{COD,5}$	0.001***	0.000
	$(1\text{-}Rated_{i,t}) \times TA_{i,t}$	$\beta_{COD,6}$	0.329 ***	0.000
	$(1\text{-}Rated_{i,t}) \times SR_{i,t}$	$\beta_{COD,7}$	0.001 ***	0.000
	$\left(\frac{TA_{i,t}}{Eq_{i,t}}\right)$	$\beta_{COD,8}$	0.0001***	0.000
	$\lambda_{i,t}$	$\beta_{COD,9}$	0.019***	0.000
Insolvency cost	Insolvency cost	$\beta_{IC,0}$	0.311***	0.001
Panel D: Choleski Elements				
Group	**Variable**	**Parameter**	**Value**	**Standard error**
	CR shock	a_{11}	0.371***	0.000
	X shock	a_{22}	0.013***	0.000
	Y shock	a_{33}	0.018***	0.000
	X Y shock	a_{32}	0.004***	0.000
	Expenses shock	a_{44}	0.007***	0.000
	Expenses Y shock	a_{43}	0.00003***	0.000
Panel E: End Function				
Group	**Variable**	**Parameter**	**Value**	**Standard error**
Debt Choice	*gammaD1*	$\beta_{gammaD,1}$	0.265***	0.000
	gammaD2	$\beta_{gammaD,2}$	-0.032***	0.000
	gammaD3	$\beta_{gammaD,3}$	0.070***	0.000
	gammaD4	$\beta_{gammaD,4}$	0.188***	0.000
BM Choice	*gammaBM1*	$\beta_{gammaBM,1}$	0.230***	0.001
	gammaBM2	$\beta_{gammaBM,2}$	0.339***	0.000
	gammaBM3	$\beta_{gammaBM,3}$	0.206***	0.001
	gammaBM4	$\beta_{gammaBM,4}$	-0.066***	0.000
CR Choice	*gammaCR1*	$\beta_{gammaCR,1}$	0.165***	0.000

The table displays the estimated structural parameters estimated with their standard errors and t statistics. The parameters correspond to the symbols used in the theoretical model (see Section 4). The term $(1\text{-}Rated_{i,t})\times TA_{i,t}$ is scaled by the constant 1e-12 to account for bank sizes being in the billions. See Table A1 for variables' definitions. ***, **, * represent significance at 1%, 5% and 10% respectively.

the percentage change in GL-TA squared.[35] Additionally, we estimate the theoretical cost of insolvency to be 0.311 times the firm equity, which not only encapsulates the firm's financial insolvency costs, but also the very strong aversion of shareholders to insolvency.

6.2. Identification

Central to evaluating the model are the moments utilized. We estimate 46 parameters using 116 moments, which are chosen to provide strong identification by being closely related to the parameters. Overidentification is very common when using SMM, as parameters are reduced as much as possible to improve identification, and the number of moments can be bigger compared to parameters, given that not all moments are orthogonal. Moreover, to calculate the standard errors, all parameters in an SMM estimation must be identified. The set of moments used in the estimation are both static and dynamic and are split into four groups. The first group contains moments that are linked to profitability (ROE, ROA) and income from banking activities, and these are used to identify the parameters associated with loan income, non-interest activity income, the correlation between shocks affecting the two and dividends.

The second group contains moments that are used for examining bank behaviour. These include the time varying levels of bank's debt and equity, in addition to the business model, ratio of equity to total assets over time, value of dividends paid, share capital issued by banks over time and the insolvency rates in each period. These moments enable a clear identification of bank capital ratios, the unobservable cost of insolvency, the weight that CRAs place on various factors and the decision by a bank to solicit a rating.

The third group of moments examines bank credit ratings, cost of debt and expenses. These moments identify the impact of sovereign ratings, economic uncertainty, bank business models and capital ratios on credit ratings assigned to banks. Additionally, they enable identification of the relationship between a bank's cost of debt and its rating and the impact that interest rates, economic uncertainty and capital ratios have on a bank's cost of debt. They also aid in identifying the unobservable impact of debt and business model decisions on bank expenses and the additional impact on their cost of debt arising from being a larger unrated bank. The last group of moments tracks the interest rate levels and sovereign ratings generated by the model to ensure that they closely follow the actual behaviour in the economy.

It should be noted that we limit the estimation to only those model moments and parameters that are based on bank behaviour, which are indicated in Table 7. While a wider range of other moments are calibrated, they are not used for calculating the model's standard errors in order to avoid identification issues. This additional matching includes moments related to interest rate, sovereign rating, financial crisis status, return to non-lending activities, net income, distribution across rating categories, cost of debt by rating category and cost of debt by debt category for unrated banks. Only the parameters indicated in Table 9 are estimated. Others are simply calibrated or obtained from the data. These include: CRA fee, the discount factor, transition probabilities for interest rate and sovereign shocks, onset of the financial crisis.

6.3. External validity

In order to analyse the robustness of the results, we perform several tests. First and most importantly we investigate whether the parameters are valid outside the period estimated. This is a particularly important test given the finite time horizon of the model. To test whether estimation results are valid externally, we extend the initial data for the subsequent period of 2016 to 2019, for the same sample of banks. Then, we compare moments from the data with moments obtained from our model, using the estimated parameters, updating only external parameters such as interest rates and country risk. Leaving aside four years of data to use as external validity reveals the power of prediction of the estimated model, which can easily be applied to other timeframes.[36] Table 10 reports the outcome of the external validity exercise. Apart from a couple of exceptions discussed below, moments and choices follow closely the actual moments in the periods considered. Of course, a perfect match should not be expected in an external validity analysis, but the exercise should indicate whether parameters are still implying a reasonable fit outside the period considered.

We divide the results in five panels: panel A contains profitability (ROA and ROE), Return on loans and Return on non-interest activity. Except for the ROE, which is more sensitive in our model, all the other moments in this panel are close to the actual moments. The higher ROE that arises in the latter three years (2017-2019) appears to be driven by the widening gap between relatively stable asset returns (X and Y) and falling cost of debt. Intuitively, ROE is very sensitive to the spread between the two, whereby a small variation can have a large impact upon bank profitability.

Panel B includes moments relative to Equity, Debt, and Business model. The moments show overall similar patterns compared to the data. The same is true for Panel C, which contains Equity to Total Assets (ETA), Dividends and Share capital. On the other hand, Panel D which contains cost of debt, for rated and not rated companies, deserves some discussion. The simulated cost of debt is higher than in the actual data, likely because of the extremely low cost of debt observed in light of the negative interest rate policy implemented by the European Central Bank and other central banks. However, it should be noted that the pattern over the years is correct, with a decrease in cost of debt after 2016.

Finally, Panel E, which includes Solvency, Expenses, average Rating and proportion of banks that choose to solicit a rating, shows

[35] Following De Nicolo et al. (2014), the discount factor (δ) is set at 0.95.

[36] It should be noted that the current number of years used in the estimation are at the limit of what is computationally feasible, given the large state space. Therefore, it would have not been possible to add these extra years to the estimated sample without somehow reducing drastically the state space or number of choices.

Table 10
External validity.

Panel A: Profitability, return on loans and non-interest activity return								
Moment	**ROE (%)**		**ROA (%)**		**Return on loans (%)**		**Return on non-interest activities (%)**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
2016	6.8	4.6	0.6	0.3	4.1	5.1	4.7	5.8
2017	6.6	13.2	0.6	1.0	3.7	5.1	4.8	6.2
2018	6.7	10.9	0.6	0.9	3.5	5.1	4.8	6.1
2019	6.6	12.1	0.6	1.0	3.4	5.1	5.0	6.1

Panel B: Equity, Debt and Business Model						
Moment	**Equity (log)**		**Debt (log)**		**Business Model (%)**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
2016	19.4	19.1	21.8	21.6	56.0	58.2
2017	19.5	19.2	21.8	21.6	56.6	57.8
2018	19.5	19.2	21.8	21.6	59.9	56.2
2019	19.5	19.3	21.8	21.6	60.2	54.7

Panel C: Equity to Total Assets, Dividends, Share Capital						
Moment	**ETA**		**Dividends (% of TA)**		**Share Capital (% of Equity)**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
2016	10.5	9.4	4.1	5.5	1.6	1.4
2017	10.7	10.1	4.5	6.8	1.4	1.4
2018	10.6	9.9	4.1	6.2	1.5	1.4
2019	10.9	10.2	4.5	6.4	1.6	1.4

Panel D: Cost of debt				
Moment	**Cost of debt - rated (%)**		**Cost of Debt - Not Rated (%)**	
	Actual	**Simulated**	Actual	**Simulated**
2016	1.8	3.2	1.3	3.9
2017	1.5	2.3	1.3	3.1
2018	1.5	2.4	1.1	3.5
2019	1.6	2.3	0.9	3.1

Panel E: Solvency, Expenses, Average Rating, Rated								
Moment	**Solvency (%)**		**Expenses (%)**		**Average Rating**		**Choice Rated (%)**	
	Actual	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**	**Actual**	**Simulated**
2016	99.8	99.1	2.4	2.1	4.7	4.7	24.2	28.6
2017	99.8	99.0	2.3	2.1	4.7	4.8	24.2	28.7
2018	99.8	99.6	2.3	2.1	4.8	4.9	23.1	30.5
2019	99.9	99.3	2.3	2.2	4.3	4.9	25.5	33.5

The average of various annual characteristics generated by the model and those observed in the actual data. The data sample includes EU banks from 2015 to 2019. See Table A1 for variables' definitions.

simulated moments that are very close to the actual ones in the model. Further, bank choices including the decision to be rated, vary their business model and debt levels, follow the data very closely. This suggests that the validity of our estimated model is not limited to the period considered, implying that the model and parameters can be used to simulate counterfactual scenarios reliably.

7. Simulated experiments

This section develops applications of the model which provide insights on the link between banks and the real economy. We focus on three distinct regulatory reforms: (i) a bail-in regime, (ii) capital requirement regulations (Basel III) and (iii) reforming the credit rating industry. The following sub-sections run counterfactual scenarios that examine the impact of each regulatory effort in turn on bank decision-making behaviour in the real economy. We particularly focus on how the various regulatory efforts affect banks' performance and behaviour, including: lending activity, profitability, insolvency, cost of debt and systemic impact.

In order to perform the counterfactual scenarios, we follow a three-step procedure. First, the target aspect of the baseline model is modified (increasing the bankruptcy penalty, change in capital requirements and change in credit rating regulation, respectively). Second, the model is simulated using the estimated parameters and the new shock. Lastly, the output of the simulation is compared to the one from the baseline model.

7.1. Bail-in regime

This section considers the influence of bailout and bail-in upon banks' behaviour in the real economy, e.g. lending and systemic risk. In the aftermath of the global financial crisis, there was much criticism of decisions to bail-out banks, with association to an increase in banks' risk-taking behaviour (Dam and Koetter (2012)) and an increase in sovereign credit risk (Acharya et al. (2014)). DeYoung et al. (2013) show that increased confidence in a bail-out makes bank debt holders more risk insensitive, reduces banks' exposure to market discipline and encourages bank managers to take greater insolvency risks. European regulators established a new bail-in regime (from January 2015) as part of the European Banking Union, which shifts the penalty for bankruptcy from the tax payer, via government bailouts, to equity holders first and creditors second.[37] The result being that both shareholders and junior creditors will stand to lose more should the bank become insolvent, thereby having increased "skin in the game". With more at stake, the increased concerns of shareholders will act to rein in banks' risk-taking activity.

However, there is currently no consensus on how best to design or amend such a regime. The bail-out of two Italian banks in June 2017 and a German bank in December 2019, raised concerns on the effectiveness of the European bail-in regime. Berger et al. (2019) highlight the US regulatory debate on replacing the bail-in requirement for large bank holding companies. Yet, preliminary evidence from other studies is positive. Hilscher and Raviv (2014) find that the bail-in could be an effective tool for stabilizing financial institutions. Attaoui and Poncet (2015) show that firms' total market values are larger in the presence of bail-in mechanisms. The introduction of the bail-in reduces the safety net for banks and should, through increased insolvency costs, result in lower insolvency rates and a reduced cost to governments (Conlon and Cotter (2014)) and taxpayers, thus resulting in a positive social outcome.

In our first counterfactual scenario we ask: "what would have been the impact of the presence of the bail-in regime before and during the global financial crisis?" To simulate this scenario in the model, the theoretical cost of insolvency for a bank is increased.[38] Fig. 3 illustrates the impact of a 50% and a 20% increase in the theoretical cost of insolvency.[39] The 50% increase elicits consistent changes, but larger in magnitude than those for the 20% increase. We discuss here the impact of a 50% increase in the theoretical cost of insolvency.

In an initial adjustment period, banks are increasingly conservative because of the increased bankruptcy costs, choosing not to raise additional funds (debt) to invest in anticipation of future profits. Higher capital ratios and less debt benefit them in the peak and post crisis periods, resulting in a short-term increase in profits (Fig. 3a). Consistent with the reduction in debt levels, a fall in the percentage of banks that choose to obtain a rating from CRAs (by 0-0.5%, Fig. 3d) is observed, as the need to access debt markets is reduced.

Following the initial adjustment period (2008 onwards), the more conservative banks maintain a new higher optimal capital ratio, which is consistent with Berger et al. (2019) and Leanza et al. (2021), achieved by reducing debt levels by 0.15% (Fig. 3h). Banks achieve slightly higher profit levels, ROE, by around 0.2% (Fig. 3a).[40] The higher profits result in more retained earnings and equity levels rises over time (2011 onwards, Fig. 3g).

Fig. 3c shows a minimal change in credit ratings (~1%), which is very substantially different to the 3-4 notch lower ratings predicted by Henriques' (2011) survey. This very slight change is stimulated by increased capital ratios but is somewhat mitigated by the increased portfolio risk. Importantly, banks are shifting their business activities more aggressively to seek higher profits. Fig. 3e shows the slightest reduction in insolvency rates (2-5%), which is in contrast with the results generated under the capital requirement regime. This indicates that the higher capital ratios implemented voluntarily under a bail-in regime are insufficient to significantly guard against the risk of bankruptcy, particularly with an increase in portfolio risk. Fig. 3f provides a clear downward trend in lending. This increased shifting of activities is an attempt to counter the falling profits caused by reduced leverage and indicates that banks seek to maximise their profit through other avenues.

In brief, the increased cost of insolvency causes banks to shift to higher optimal capital ratios and a more conservative long-term outlook. However, there are indications of a shift away from lending, associated with maintaining profit levels, and no material improvement in insolvency rates. This strongly suggests that the bail-in mechanism may affect bank's lending activities. The result is stronger for a greater increase in perceived insolvency costs.

7.2. Capital requirement regulations

This section addresses the effects of capital adequacy regulations on lending and other aspects of bank behaviour. During the financial crisis, many banks were undercapitalised and there was substantial evidence that well capitalised banks demonstrated better performance (Berger and Bouwman (2013) and Miles et al. (2013)). Over the past decade, there has been a substantial change in the approach to capital requirements.[41] In Europe, regulators strengthened capital requirements by adopting Basel II which brought in a common equity tier 1 capital ratio of 2% in 2006, and then by adopting Basel III in 2013 which raised the level to 4.5% with an additional capital conservation buffer of 2.5% bringing the total common equity ratio to 7.0%. Academics have also argued that banks

[37] The mechanism of the European bail-in is as follows: The bail-in is triggered when a bank suffers a loss of >8% of its assets. This causes a write-down of assets to occur, principally the equity and subordinated debt. Once the write-down has occurred, the bank is recapitalised to 10.5% common equity capital ratio (CET1) through the conversion of the remaining subordinated debt and part of the senior unsecured debt. In effect, this causes the losses of the bank to first be taken by shareholders and then by its creditors (see Hüser et al. (2018)). It was not possible to directly model this specific mechanism as the different debt types could not be separated. Instead, the increased cost of bankruptcy to equity holders is captured via the inclusion of an additional insolvency term.

[38] In practice, this means that the value of the insolvency penalty (i.e. the coefficient of β_{IC}, see Section 4) was increased.

[39] 1%, 5%, 10% and 100% adjustments are also examined and produce coherent results (available on request).

[40] For brevity, we focus on ROE as a measure of profitability.

[41] The baseline model includes the capital requirements that were in place during the timeframe as they are introduced, see Section 4.6.

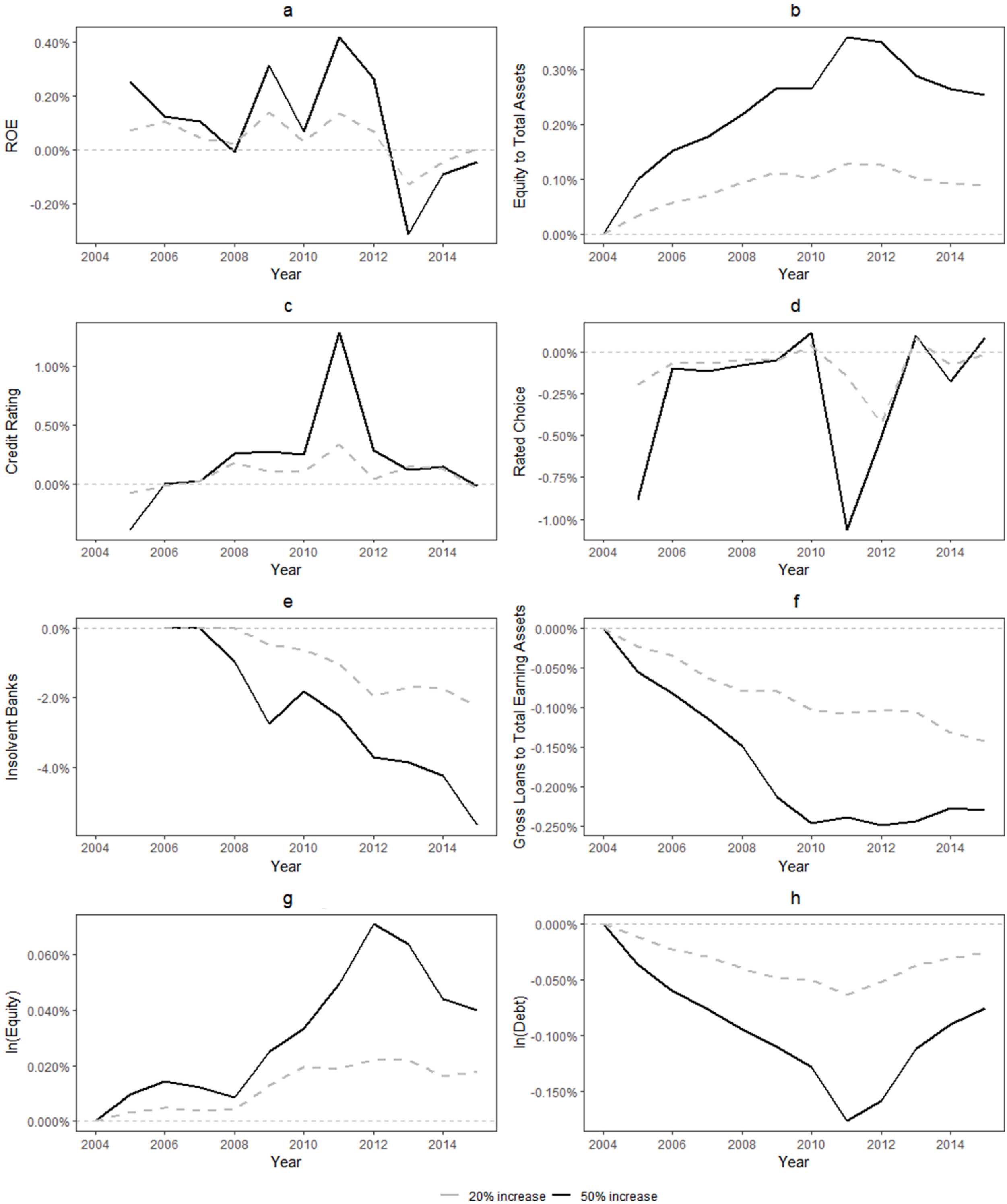

Fig. 3. Banks' responses to a Bail-in penalty
The Figures show how bank characteristics, and hence behaviour, change in response toto a 50% (Solid Line) and 20% (Dashed Line) increase in the theoretical cost of insolvency. Figs. 3a, 3b, 3d, and 3f (Return on equity, Equity to total assets, Rated Choice, and Gross loans to total assets) show the actual change in the value of the variable (e.g. ROE falling from 7% to 5%, would be a -2% change). Figs. 3c, 3e, 3g and 3h (Credit rating, Insolvency, ln(Equity), ln(Debt)) show the percentage change in the variable (e.g. credit rating falls from 6 to 5, would be a -16.66% change). Fig. 3e shows the percentage change in the number of insolvent banks each year.

should be financed with more equity (Bhagat and Bolton (2014)) and questioned whether the existing regulation goes far enough (Miles et al. (2013)). In this analysis, we consider the following counterfactual scenarios: ''how would banks' behaviour have differed if the Basel III CET1 requirement of the initial 4.5% or the full 7% had been in place since 2005?''.[42] The results are reported in Fig. 4.

Firstly, under the 4.5% CET1 scenario, there is an initial adjustment period (2008 onwards) whereby banks adopt higher capital ratios to comply with the higher requirements (Fig. 4b). The average increase of 2.5% is nearly ten times greater than that stimulated by the baseline bail-in case (Section 7.2). This fall is driven by a 1% reduction in debt (Fig. 4h). We also report a temporary boost to profits (Fig. 4a) caused by stronger stability in the crisis periods. Yet, after the initial adjustment period, under the capital requirement regime, capital ratios trend back towards those of the original model (Fig. 4b). This is driven by a steady increase in debt, as banks increase their leverage closer to the new limit in search of greater profits, and contrasts with the effects of the bail-in where, following the initial period, capital ratios remain at the new optimal level for the subsequent period. This implies that capital regulation merely constrains bank capital ratios and does not necessarily impact the underlying risk-taking behaviour. We observe the consequentially improved credit ratings by 2-4% (i.e. half of one notch, Fig. 4c), which are warranted due to a large drop in the number of insolvent banks (40% less, Fig. 4e), as banks perform much better during the peak and post crisis periods as they have a larger capital buffer to rely on. Consistent with the case of the bail-in regime, a 4.5% CET1 causes banks to increasingly shift business away from lending (Fig. 4f).

The second simulated scenario of 7.0% CET1 requirement elicits consistent, yet stronger results. Fig. 4 shows a rise in banks' average equity to total assets of 3%, a similar change in profits and a fall in debt levels of 1.25% at the end of the implementation period. We show strong bank stability during the peak and post crisis periods, with the number of insolvent banks falling by up to 40%. Significantly, this is not greater than under the 4.5% CET1 requirement, suggesting that the majority of the marginal benefit from increased capital has been realised by the initial 4.5% increase and that there is little benefit to insolvency rates of increasing to 7%. Further, the corresponding fall in capital ratios and rise in debt levels are consistent. Consistent with the first scenario of 4.5% CET1, the number of banks that choose to be rated falls dramatically as banks lower their debt levels more substantially and require less access to capital markets. Bank ratings are also much more sensitive to the European sovereign debt crisis. Due to banks' increased capital levels, greater emphasis falls on country level factors becoming increasingly important in determining the bank ratings. The prior impact on the real economy is further strengthened in the second scenario as banks switch more rapidly away from lending.

Following Bahaj and Malherbe (2020), we test whether stringent capital requirements lead to the *forced safety effect,* and to what extent this dominates over the *composition effect*. Similarly, to Bahaj and Malherbe (2020),[43] our banks expect a higher likelihood of survival due to the increased capital ratios, and hence expect to internalise a greater proportion of the profits from marginal investments making them more attractive. The simulations confirm this, are consistent with the *forced safety effect,* and show (following an initial adjustment period) a steady increase in the amount of debt held (Fig. 4h), which corresponds to a greater level of investment and lending.

In short, if the Basel III capital requirements of 4.5% and 7% had been in place since 2005, the impact on bank behaviour would have been substantial. It would have resulted in larger increases in bank capital ratios and a greater decrease in bank debt (5-10 times greater than that elicited by the presence of a bail-in regime). We find stronger bank stability during the peak and post crisis periods, with a lower number of insolvent banks. Unlike the effect of the bail-in (which results in a new equilibrium), the impact of more stringent capital requirements on marginal return, business model and leverage diminishes slightly following the initial adjustment period, but the effect is greater in magnitude compared to the bail-in scenario. Banks seek alternative ways to maintain profitability, which has a crucial effect on lending activity.

7.3. Change in credit rating behaviour

CRAs were widely criticised for their role in the financial crisis, and regulators were left in no doubt that inflated ratings had a significant impact (Bolton et al. (2012)). Consequently, recent regulatory changes in the EU (CRA I, II and III) and in the US (Dodd-Frank Act) have targeted CRAs and their behaviour. Greater oversight of CRAs has, particularly in the EU, arguably resulted in increased rating conservatism (i.e. unjustifiably lower ratings). This arises as CRAs lower their ratings as a reaction to the increased scrutiny and to the potential penalties for over-rating (Bannier et al. (2010)). It is important to consider how a change in CRA rating behaviour can spill over and impact the behaviour of the rated entities (banks). In modelling this shock to bank debt/deposits, we consider the following counterfactual scenarios: (i) an increase in rating conservatism, whereby we examine the case that bank ratings are 1-notch lower and (ii) increasingly lenient CRAs which assign higher credit ratings, whereby we examine the case that bank ratings are 1-notch higher.[44]

In the first scenario, more conservative CRAs issue 1-notch lower ratings, which causes a rise in banks' cost of debt which depends upon their credit rating, stimulating a fall in profits (ROE) in the subsequent periods (Fig. 5a). Banks are roughly 15%-20% less likely to solicit ratings (Fig. 5d) as there is less benefit from doing so. Since ratings significantly impact a banks' cost of debt and add to uncertainty for banks' lending activities, banks initially shift towards non-interest income activities (0.40% change, Fig. 5f), but when the

[42] Under this simulation, banks cannot deliberately choose to reduce their capital ratio below this threshold; however, it could still be broken as a result of unanticipated shocks (see Section 4.6).

[43] Bahaj and Malherbe (2020) compare the case of investing in the marginal loan versus the case of not investing the funds. We compare the decision to increase overall investment versus the case of decreasing investment.

[44] We also examine 0.5 and 2-notch lower and higher rating and the results (available on request) are consistent.

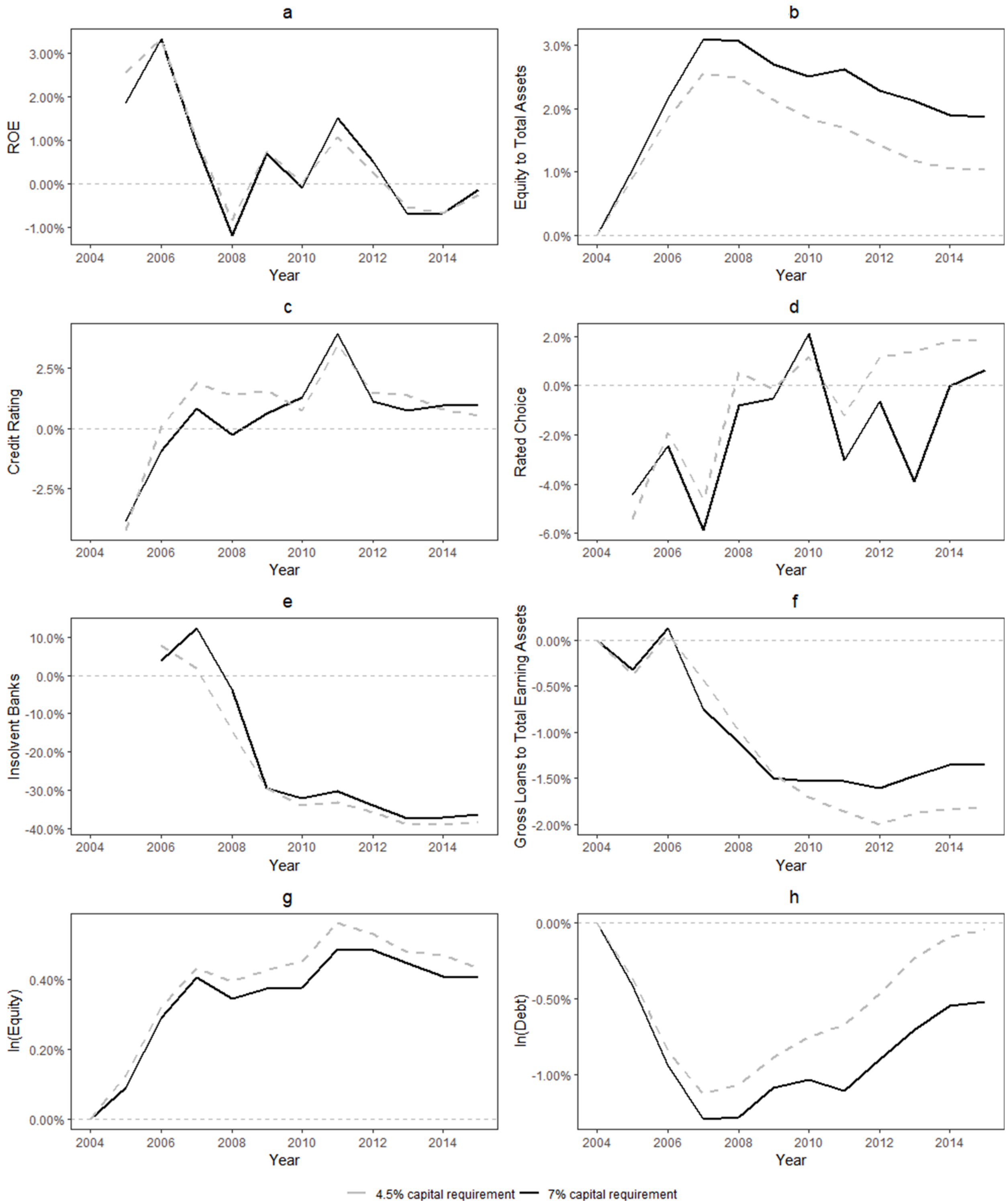

Fig. 4. Banks' responses to a change in capital requirements
The figures show how bank characteristics, and hence behaviour, change in response to the Basel III CET1 capital requirement of the initial 4.5% (Dashed line) and the full capital requirement of 7% (Solid Line) had been in place since 2005. Figs. 4a, 4b, 4d, and 4f (Return on equity, Equity to total assets, Rated Choice, and Gross loans to total assets) show the actual change in the value of the variable (e.g. ROE falling from 7% to 5%, would be a -2% change). Figs. 4c, 4e, 4g and 4h (Credit rating, Insolvency, ln(Equity), ln(Debt)) show the percentage change in the variable (e.g. credit rating falls from 6 to 5, would be a -16.66% change).

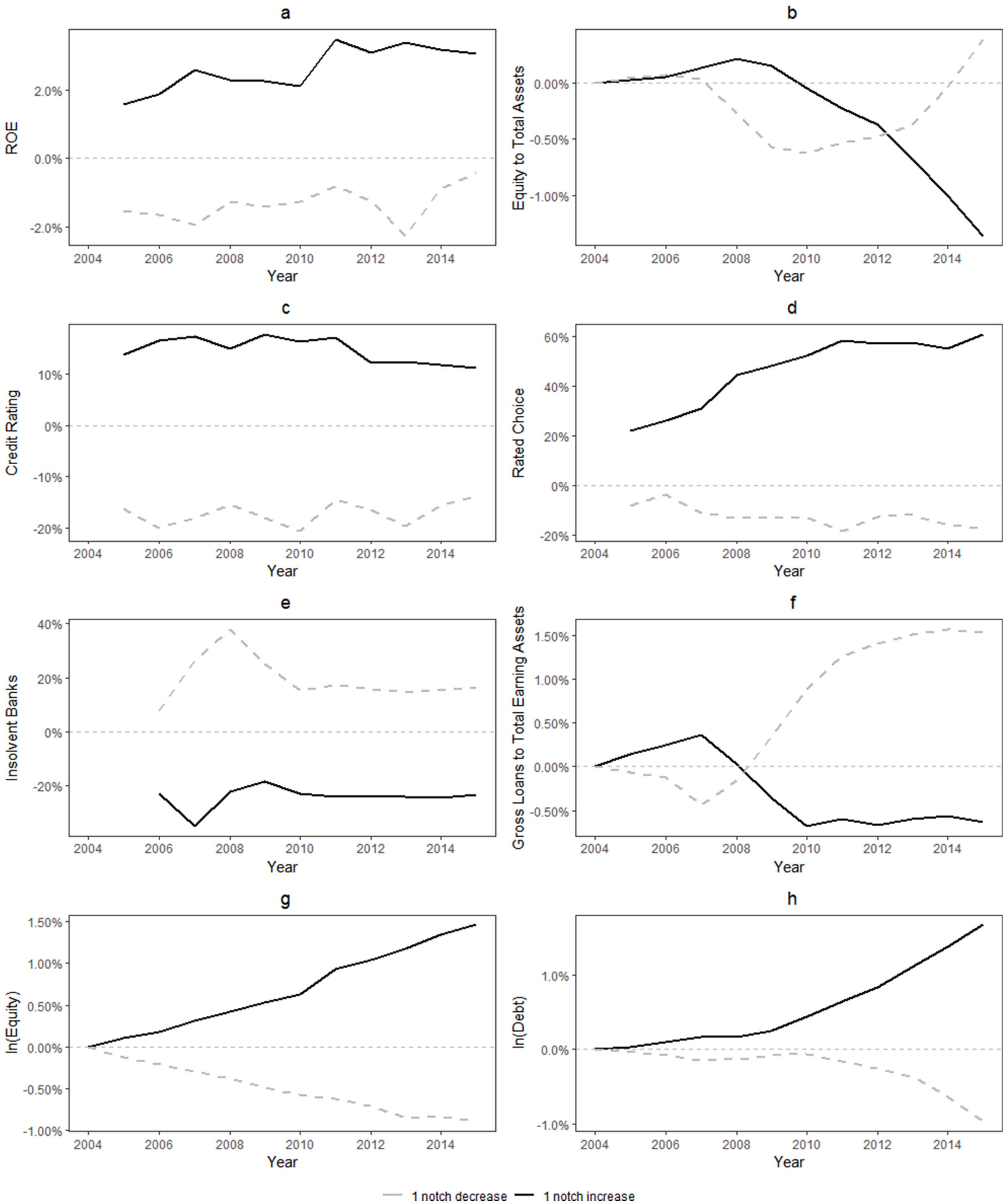

Fig. 5. Banks' responses to a change in CRA conservatism
The figures show how bank characteristics, and hence behaviour, change in response to (i) 1-notch lower ratings, i.e. an increase in rating conservatism (Dashed Line) and (ii) 1-notch higher ratings, i.e. increasingly lenient CRAs (Solid Line). Figs. 5a, 5d, 5e, and 5f (Equity to total assets, Rated Choice, cost of debt and Gross loans to total assets) show the actual change in the value of the variable (e.g. ROE falling from 7% to 5%, would be a -2% change). Figs. 5b, 5c, 5g and 5h (Insolvency, Credit rating, ln(Equity), ln(Debt)) show the percentage change in the variable (e.g. credit rating falls from 6 to 5, would be a -16.66% change).

crisis hits, this trend reverses and they shift back towards lending. Banks struggling to improve their ratings and facing a higher cost of debt suffered more during the crisis, with a resultant ~20% increase in the number of insolvent banks (Fig. 5e).

In the second examined scenario, increasingly lenient CRAs issue 1-notch higher ratings, which lowers banks' cost of debt, causing banks to solicit a rating from CRAs more often during non-crisis periods (up to 20%-60% more, Fig. 5d). Banks take advantage of the cheaper debt by increasing debt levels and hence reducing their capital ratios (1% lower at the end of the sample, Fig. 5a). Banks utilise the cheaper debt, but don't increase their overall lending compared to the base case (Fig. 5f).

In brief, the simulated increase (decrease) in CRA conservatism predicts an increase (decrease) in a bank's cost of debt and reduces (increases) the proportion of banks that solicit a rating. Yet, a systematic increase in rating conservatism adds to uncertainty for banks' lending activity. Banks react to changes in CRA behaviour via their actions in the debt/deposit market and by the manipulation of their capital ratios, which can result in an increased rate of insolvency during crisis periods. The shock to debt/deposits induced by a change in CRA practices has a meaningful impact on banks' risk taking and their role in the economy.

8. Conclusions

The 2008 financial crisis led to the widespread collapse or restructuring of important financial institutions, which exacerbated the crisis and caused further damage to European economies through sovereign-bank linkages. Recent European regulatory efforts have sought to reform the banking industry and to mitigate bank risk-taking behaviour to prevent a future re-occurrence. We use a DCDP model to simulate counterfactual scenarios that examine the potential influence of pre-crisis adoption of (i) a European bail-in regime, (ii) Basel III capital requirements, and (iii) the reform of the credit rating industry, on bank behaviour in the real economy.

To the best of our knowledge, this is the first time a DCDP is applied to a banking problem. Most theoretical models in banking are set with an infinite time horizon (De Nicolo et al. (2014)), usually implying iteration around a fixed point, with a two-step procedure with convergence of the value function. As a result, infinite time horizon models tend to be calibrated or estimated for a small number of parameters without allowing the estimation of all parameters of the model. Our choice contrasts with this, by estimating a large number of parameters by fitting several moments. This allows generating an extensive working framework that can be used to reveal robust effects for the possible regulatory scenarios under investigation. Such a framework provides very close matching because banks observe the actual shock in each year and are able to modify their behaviour according to the actual conditions, without the need for a general optimal policy rule.

The main disadvantage of using such a framework is the need to work within a finite time frame. If we could have used an infinite time approach, we would have probably been able to obtain more consistent rules about banks' behaviour across a longer time frame. However, we believe that the estimation of the main parameters would have not been dramatically changed by this. Moreover, we believe that a finite horizon model is appropriate for simulating banks' choices in practice. While it is true that banks do not expect an end period to their operations, it is also true that, in practice, they make decisions using their current state-dependent situation and their expectations for the future, which are based on a finite number of years (see for example McKinsey's Global Banking Annual Review of 2021 that contains forecasts until 2027).[45] Adding final conditions to the model, which ensures that simulated banks do not take decisions as if there was no future, helps to reinforce the appropriateness of using a finite time horizon.

The results from the counterfactual scenarios modelled are as follows. Firstly, we find that a bail-in regime (with increased costs of insolvency) leads to the adoption of higher optimal capital ratios but only a slight reduction (2% and 4% respectively) in bank insolvency rates during the peak and post crisis periods. Banks shift away from lending, which is associated with maintaining profit levels, i.e. the bail-in regime influences lending activity in the real economy. This effect scales with the perceived increase in insolvency costs.

Secondly, we find that hypothetical earlier adoption of Basel III capital requirements (of 4.5% and 7%) lead to a stronger increase in bank capital ratios (2.5% and 3% higher respectively) driven by a fall in debt financing that results in stronger bank stability in the subsequent period (up to 40% fewer insolvent banks). There is evidence of diminishing marginal returns with the effect of capital ratios on bank insolvency rates and the effect is greater in magnitude compared to the bail-in scenario. Crucially, banks seek alternative ways to maintain profitability, which has a detrimental effect on lending activity in the real economy. We find evidence supporting the *forced safety effect* (Bahaj and Malherbe, 2020), which causes banks to take up marginal investments, hence increasing lending activity, when stringent capital requirements are in place.

Lastly, we show that banks compensate for changes in CRA practices via their manipulation of their capital ratios and their actions in debt/deposit markets. Any systematic shift to increasingly conservative rating practice adds to uncertainty for banks' lending activity.

In general, the results demonstrate the importance of understanding the interactions between regulatory changes and the dynamics of banks' decision-making and risk taking, and hence their role in the real economy. Our dynamic framework allows us to explore mechanisms and feedback processes that would simply not be possible to consider using a static framework such as reduced form estimates. We conclude that the counterfactual early implementation of the bail-in and higher capital requirements would have a positive impact by reducing bank insolvency rates, particularly during crisis periods and hence reducing the burden on governments and the real economy. Regulators should exercise caution in considering how capital requirements can potentially induce banks to shift business away from lending, and to seek other (potentially risker) means to maintain their profitability. Regulators should balance the

[45] For details, see: https://www.mckinsey.com/industries/financial-services/our-insights/global-banking-annual-review.

reduction in insolvency rates (which exhibit diminishing returns) against the fall in bank sizes and profits. The findings imply a potentially effective method of mitigating banks' risk-taking by combining increased capital requirements with the introduction of a bail-in regime. The increased responsibility of equity holders for losses complements the increased "skin in the game" caused by greater levels of capital and is necessary to ensure a shift to a reduced risk-taking equilibrium. The reduction in risk and therefore insolvency should result in a reduced burden on taxpayers, on sovereign credit risk and thereby benefit the real economy. The results also imply that CRA reforms should deter rating leniency, as it may lead to increased bank insolvency rates.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2022.104280.

Appendix

Table A1

Table A1
Variables and equations.

Variable	Symbol	Source	Units	Description
Total assets	*TA*	BankScope/ BankFocus	Euros	Total assets of the bank
Equity	*Eq*	BankScope/ BankFocus	Euros	Equity of the bank
Debt	*D*	BankScope/ BankFocus	Euros	Total Assets – Equity. Debt denotes both debt and deposits.
Return on equity	*ROE*	BankScope/ BankFocus	Percentage	Net income divided by shareholders equity and is a measure of bank performance.
Return on Assets	*ROA*	BankScope/ BankFocus	Percentage	Net income divided by total assets and is a measure of bank performance.
Gross loans to total assets	λ	BankScope/ BankFocus	Ratio	The proportion of lending activities
Credit rating	*CR*	BankScope/ BankFocus	Numerical Scale	Ratings from S&P, Moody's and Fitch. If ratings from multiple CRAs were available, the average was used
Rated	*Rated*	BankScope/ BankFocus	Dummy	1 if bank is rated, zero otherwise
Return on loans	*X*	Calculated from data	Percentage	Return generated from loan activity
Return on non-interest activities	*Y*	Calculated from data	Percentage	Return generated from non-interest income activities
Net income	*NI*	BankScope/ BankFocus	Euros	Net income generated by the bank.
Cost of debt	*COD*	Calculated from data	Percentage	Calculated as total interest expense/debt
Dividends	*Div*	BankScope/ BankFocus	Euros	Dividends paid by the bank
Share capital	*SC*	BankScope/ BankFocus	Euros	Calculated as the change in share capital
Financial crisis level	*Ec*	VSTOXX	Index	European market volatility index.
Sovereign rating	*SR*	S&P Capital IQ	Scale	S&P sovereign ratings
Interest rates	*IR*	DataStream	Percentage	Interest rates for each country and the Eurozone
Inflator		World Bank	Ratio	GDP inflator from the World Bank national accounts data
Equity to total assets	*ETA*	Calculated	Ratio	The ratio of bank equity to its total assets.
Insolvency	*Insolvency*	Calculated	Dummy	Dummy variable 1 if the bank is insolvent, 0 otherwise.
Regulation	*Regulation*	Calculated	Dummy	Dummy variable 1 following the passage of the regulation and 0 prior.

This table describes the data sources and definition of variables (Panel A) and equations estimated in the illustrative analysis (see Section 3.1). θ is the proportional increase in debt. BankScope, one key source of our main dataset, is currently renamed Moody's BankFocus and used to extend the data for the external validity exercise (Section 6.3). The VSTOXX is an index of 30-day option implied volatility in the EURO STOXX 50 indices and is designed to reflect the market expectations of volatility

References

Abedifar, P., Molyneux, P., Tarazi, A., 2018. Non-interest income and bank lending. J. Bank. Finance 87, 411–426.
Acharya, V., Drechsler, I., Schnabl, P., 2014. A Pyrrhic victory? Bank bailouts and sovereign credit risk. J. Finance 69 (6), 2689–2739.
Almeida, H., Cunha, I., Ferreira, M.A., Restrepo, F., 2017. The real effects of credit ratings: The sovereign ceiling channel. J. Finance 72, 249–290.
Altunbas, Y, Marqués-Ibáñez, D., Manganelli, S, 2017. Realized bank risk during the great recession. J. Financ. Intermediation 32, 29–44.
Attaoui, S., Poncet, P., 2015. Write-down bonds and capital and debt structures. J. Corp. Finance 35, 97–119.
Bahaj, S., Malherbe, F., 2020. The forced safety effect: How higher capital requirements can increase bank lending. J. Finance 75, 3013–3053.

Bakke, T., Gu, T., 2017. Diversification and cash dynamics. J. Financ. Econ. 123, 580–601.
Bannier, C.E., Behr, P., Güttler, A., 2010. Rating opaque borrowers: Why are unsolicited ratings lower? Rev. Finance 14 (2), 263–294.
Benhabib, J., Miao, J., Wang, P., 2016. Chaotic banking crises and regulations. Econ. Theory 61, 393–422.
Berger, A.N., Himmelberg, C.P., Roman, R.A., Tsyplakov, S., 2019. Bank bailouts, bail-ins, or bankruptcy? A dynamic model and empirical tests of optimal regulatory design. Working Paper. University of South Carolina and European Central Bank.
Berger, A.N., Bouwman, C.H.S., 2013. How does capital affect bank performance during financial crises? J. Financ. Econ. 109, 146–176.
Bhagat, S., Bolton, B., 2014. Financial crisis and bank executive incentive compensation. J. Corp. Finance 25, 313–341.
Bolton, P., Freixas, X., Shapiro, J., 2012. The credit ratings game. J. Finance 67 (1), 85–111.
Calem, P., Rob, R., 1999. The impact of capital-based regulation on bank risk-taking. J. Financ. Intermediation 8, 317–352.
Cooley, T.F., Quadrini, V., 2001. Financial markets and firm dynamics. Am. Econ. Rev. 91 (5), 1286–1310.
Conlon, T., Cotter, J., 2014. Anatomy of a bail-in. J. Financ. Stability 15 (2014), 257–263.
Custódio, C., Ferreira, M.A., Laureano, L., 2013. Why are US firms using more short-term debt? J. Financ. Econ.s 108, 182–212.
Dam, L., Koetter, M., 2012. Bank bailouts and moral hazard: Evidence from Germany. Rev. Financ. Stud. 25 (8), 2343–2380.
De Nicolò, G., Gamba, A., Lucchetta, M., 2014. Microprudential regulation in a dynamic model of banking. Rev. Financ. Stud. 27, 2097–2138.
DeAngelo, H., DeAngelo, L., Whited, T.M., 2011. Capital structure dynamics and transitory debt. J. Financ. Econ. 99, 235–261.
DeYoung, R., Gron, A., Torna, G., Winton, A., 2015. Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis. J. Finance 70, 2451–2488.
DeYoung, R., Kowalik, M., Reidhill, J., 2013. A theory of failed bank resolution: Technological change and political economics. J. of Financ. Stability 9, 612–627.
Dickens, R.N., Casey, K.M., Newman, J.A., 2002. Bank dividend policy: Explanatory factors. Quart. J. Bus. Econ. 41, 3–12.
Doucouliagos, H., Haman, J., Askary, S., 2007. Directors' remuneration and performance in the Austrailian banking sector. Corporate Governance Int. Rev. 15 (6), 1363–1384.
Egan, M., Hortaçsu, A., Matvos, G., 2017. Deposit competition and financial fragility: Evidence from the US banking sector. Am. Econ. Rev. 107 (1), 169–216.
Elton, E.J., Gruber, M.J., Agrawal, D., Mann, C., 2001. Explaining the rate spread on corporate bonds. J. Finance 56, 247–277.
Gennaioli, N., Shleifer, A., Vishny, R.W., 2013. A model of shadow banking. J. Finance 68, 1331–1363.
Gourieroux, C., Monfort, A., Renault, E., 1993. Indirect inference. J. Appl. Econ. 8 (S1), S85–S118.
Gropp, R, Mosk, T., Ongena, S., Wix, C., 2019. Banks response to higher capital requirements: Evidence from a quasi-natural experiment. Rev. Financ. Stud. 32, 266–299.
Gomes, J.F., 2001. Financing investment. Am. Econ. Rev. 91, 1263–1285.
Hanson, S.G., Shleifer, A., Stein, J.C., Vishny, R.W., 2015. Banks as patient fixed-income investors. J. Financ. Econ. 117, 449–469.
Hau, H., Langfield, S., Marques-Ibanez, D., 2013. Bank ratings: What determines their quality? Econ. Policy 28, 289–333.
Heckman, J.J., Walker, J.R., 1990. The relationship between wages and income and the timing and spacing of births: Evidence from Swedish longitudinal data. Econometrica: J. Econometr. Soc. 58 (6), 1411–1441.
Hennessy, C.A., Whited, T.M., 2005. Debt dynamics. J. Finance 60, 1129–1165.
Hennessy, C.A., Whited, T.M., 2007. How costly is external financing? Evidence from a structural estimation. J. Finance 62, 1705–1745.
Henriques, R., 2011. The great bank downgrade: What bail-in regimes mean for senior ratings? JP Morgan Chase Europe Credit Research.
Hilscher, J., Raviv, A., 2014. Bank stability and market discipline: The effect of contingent capital on risk taking and default probability. J. Corp. Finance 29, 542–560.
Hüser, A.C., Hałaj, G., Kok, C., Perales, C., Kraaij, A.V.D., 2018. The systemic implications of bail-in: A multi-layered network approach. J. Financ. Stability 81–97.
Jalali, M.S., Rahmandad, H., Ghoddusi, H., 2015. Using the method of simulated moments for system identification. Analytical Methods for Dynamic Modelers. MIT Press, pp. 39–69.
Keane, M.P., Wolpin, K.I., 1994. The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence. Rev. Econ. Stat. 76 (4), 648–672.
Keane, M.P., Wolpin, K.I., 2000. Eliminating race differences in school attainment and labor market success. J. Labor Econ. 18 (4), 614–652.
Keane, M.P., Wolpin, K.I., 2009. Empirical applications of discrete choice dynamic programming models. Rev. Econ. Dyna. 12 (1), 1–22.
Keeley, M.C., Furlong, F.T., 1990. A re-examination of mean-variance analysis of bank capital regulation. J. Bank. Finance 14, 69–84.
Kwast, M.L., 1989. The impact of underwriting and dealing on bank returns and risks. J. Bank. Finance 13, 101–125.
Leanza, L., Sbuelz, A., Tarelli, A., 2021. Bail-in vs bail-out: Bank resolution and liability structure. Int. Rev. Financ. Anal. 73, 101642.
Low, H., Meghir, C., 2017. The use of structural models in econometrics. J. Econ. Perspect. 31 (2), 33–58.
McFadden, D., 1989. A method of simulated moments for estimation of discrete response models without numerical integration. Econometrica 57 (5), 995–1026.
Merton, R.C., 1974. On the pricing of corporate debt: The risk structure of interest rates. J. Finance 29, 449–470.
Miles, D., Yang, J., Marcheggiano, G., 2013. Optimal bank capital. Econ. J. 123, 1–37.
Nozawa, Y., 2017. What drives the cross-section of credit spreads? A variance decomposition approach. J. Finance 72 (5), 2045–2072.
Opp, C.C., Opp, M.M., Harris, M., 2013. Rating agencies in the face of regulation. J. Financ. Econ. 108, 46–61.
Pakes, A., Pollard, D., 1989. Simulation and the asymptotics of optimization estimators. Econometrica 57 (5), 1027–1057.
Peura, S., Keppo, J., 2004. Optimal bank capital with costly recapitalization. Rev. Econ. Stud. 71, 285–315.
Repullo, R., 2004. Capital requirements, market power, and risk-taking in banking. J. Financ. Intermediation 13, 156–182.
Strebulaev, I.A., Whited, T.M., 2011. Dynamic models and structural estimation in corporate finance. Foundations Trends Finance 6, 1–163.
White, R.A., Cole, J.L., 2012. Déjà vu all over again: The causes of U.S. commercial bank failures this time around. J. Financ. Serv. Res. 42, 5–29.