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THE IMPACT OF COMPLEX FINANCIAL INSTRUMENTS ON BANKS' VULNERABILITY: EMPIRICAL EVIDENCE ON SSM BANKS

by Tommaso Perez* and Francesco Potente** (coordinators),
Andrea Carboni**, Alberto Di Iorio*** and Jacopo Raponi**

Abstract

Level 2 (L2) and Level 3 (L3) assets and liabilities represent a substantial portion of European banks' balance sheets, and valuing them is extremely difficult, since no liquid market prices are available. This paper relies on a large panel of euro-area banks between 2014 and 2019, and two different econometric frameworks, in order to estimate the relationship between the holdings of selected instruments (L2, L3 and Non-Performing Loans, NPLs) and banks' key performance and risk profile metrics, namely Credit Default Swaps (CDSs), Price-to-Book (PtB) ratios and Z-scores. It finds that larger holdings of L2 tend to be associated with higher CDSs, at least in the short run, while larger amounts of NPLs and L3 tend to characterize banks with higher CDSs, lower PtB ratios and worse Z-scores, other things being equal.

JEL Classification: G21, G28, C33, M41.
Keywords: fair value accounting, Level 2 instruments, Level 3 instruments, non-performing loans, prudential regulation, panel data models.
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Contents

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1. Introduction[1]

Roca, Potente et al. (2017) highlighted the lack of transparency and the risks surrounding the valuation of complex financial products, focusing on both Level 2 (L2) and Level 3 (L3) instruments. These categories encompass a certain degree of illiquidity and opacity, and their classification might be biased by opportunistic valuation practices, given that the underlying accounting framework leaves room for discretion.[2] Therefore, closer scrutiny of both types of instrument by banking supervisors is more than desirable: this might imply, among other things, tailored data collection and a structured framework for their use in supervisory activity. Indeed, one of the supervisory priorities for policy action in recent years has been to focus more closely on financial risks, to enhance the assessment of illiquid and opaque instruments on banks' balance sheets.

Valuation uncertainties can be exacerbated in times of stress (ESRB, 2020; IMF, 2020), when liquidity also tends to evaporate quickly. The reasons for extending research in this field have not therefore diminished after the spillovers of the Covid-19 crisis across the financial markets.

A growing, albeit still scarce, stream of literature has focused on the potential impact of complex financial instruments on perceptions of banks' vulnerability by external investors. Goh et al. (2015) and Short (2012) argued that market concerns about illiquidity and information risk drive market valuations, as the market price of one dollar invested in L1 assets tends to be greater than one dollar invested in L2 and L3 assets. Riedl and Serafeim (2011) and Huang et al. (2016) found evidence that L3 assets increase firms' cost of equity capital. Other authors (Glaser et al., 2013; Mohrmann and Riepe 2019; D'Apice et al., 2016), detected a positive relationship between exposure to L3 assets and various measures of banks' default risks.

More recently, the ECB (2019) investigated the impact of L2 and L3 holdings on price-to-book (PtB) values over a sample of 106 Significant Institutions. The analysis confirmed a statistically significant negative relationship between L3 holdings and PtB ratios, with greater economic significance in periods of high market volatility. However, the study did not provide conclusive evidence about holdings of L2 assets. Carboni et al. (2020) found that L3 assets and liabilities show a positive relationship with the probability of abrupt changes in banks' share prices. Furthermore, Ciocchetta (2020) found a statistically significant relationship between the PtB and non-performing

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[1] The views expressed in the paper are those of the authors alone and do not necessarily represent those of the Bank of Italy or the Eurosystem. We wish to thank P. Angelini, F. Cannata, A. De Vincenzo, R. Roca, E. Sette, A. Carboni, A. Carella and M. L. Bianchi for their comments and suggestions.

[2] In some circumstances, banks might also suspend trading in complex financial products in order to avoid the emergence of mark-to-market losses, keeping book valuations artificially high (Milbradt, 2012).

loan (NPL) ratio, suggesting possible similarities between complex financial products and NPLs, with respect to the market perception of banks' vulnerability.

The scope of this paper is to add some empirical evidence to the analysis carried out by Roca, Potente et al. (2017). To this end, we compare the impact on banks' risk profile of both L2 and L3 instruments with that stemming from large holdings of NPLs. Our study includes data collected before and after the entry into force of IFRS9 (1 January 2018), which replaced the International Accounting Standard (IAS) 39 related to the requirements for the recognition and measurement of financial assets, financial liabilities, and some contracts to buy or sell non-financial items.

Relying on supervisory reporting and the market data available for SSM banks, we test several econometric specifications potentially able to 'capture' the relationship between banks' financial vulnerability and holdings of complex financial instruments and NPLs. In particular, a number of metrics of vulnerability of banks, such as Credit Default Swaps (CDS), PtB and Z-scores, are regressed against holdings of both NPLs and L2/L3 instruments, adopting different econometric frameworks, Fixed effects and Correlated Random Effects panel estimations. The latter allow for disentangling across time and cross section effects.

Across time, we find that holdings of L2 tend to be associated with higher CDS, while L3 holdings show a positive correlation with default risk (lower Z-scores). From a cross section perspective, larger amounts of L3 instruments and NPLs tend to characterize banks with higher CDS, lower PtB and, as far as NPLs are concerned, higher default risk. Large holdings of specific L2 categories tend to produce mixed results.

This paper is structured as follows: Section 2 provides a descriptive comparison of L2 and L3 instruments, and NPLs, in terms of amounts, distribution and concentration across different jurisdictions and banks; Section 3 illustrates the models adopted and the results of the analysis; Section 4 concludes.

2. A comparison of L2/L3 and NPLs: stylized facts

The definition of L2 and L3 instruments is based on the accounting framework (e.g. IFRS13). According to the current rules, financial instruments have to be classified in either of these categories when fair value is not directly observed in active markets.[3] More specifically, L2 products are priced using directly or indirectly observable inputs; L3 instruments are priced using unobservable inputs, since market reference data are either not available or are not sufficiently reliable. In both cases, they need to be valued using the best information available about the assumptions market participants would adopt when pricing them.

L2 and L3 categories include a wide range of financial products, with different levels of valuation complexity and uncertainty (from plain vanilla IRS to structured products with exotic payout). Furthermore, some of them are originated by (large) bespoke transactions; therefore, they tend to be illiquid and, in a number of cases, not easily transferable without substantial markdowns with respect to their book values. For this reason, L2 and L3 instruments share similar valuation uncertainties with NPLs: in fact, NPLs represent instruments with a material degree of uncertainty about recovery values, and their secondary market is illiquid, with buyers requiring an extra return rewarding information asymmetries, in the same vein as L2 and L3 instruments.

As of December 2019, the value of L2 and L3 financial instruments held by the selected SSM significant institutions[4] amounted to around €5.9 trillion,[5] representing several times the amount of net NPLs (€267 billion).[6]

As already mentioned, while the valuation risk embedded in L3 instruments is widely recognized, the L2 category includes products with different degrees of illiquidity. The granularity of current standard supervisory reporting allows the identification of the following categories for L2 assets and liabilities: debts, equities, derivatives, hedge accounting and loans (Chart 1). Derivatives are, by far, the most represented category, followed by loans.[7]

Holdings of L2/ L3 assets and liabilities are geographically concentrated, as are NPLs: more than 70% of the entire SSM exposures to L2 and L3 instruments stem from just two jurisdictions

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[3] Assets and liabilities traded in active markets are instead classified as Level 1.

[4] Data are drawn over a sample of 105 Significant Institutions adopting the IFRS framework. Source FINREP.

[5] L2 and L3 instruments, of which €3.1 trillion and €2.8 trillion respectively for assets and liabilities. L3 instruments alone account for €349 billion, of which €184 billion in assets and €165 billion in liabilities.

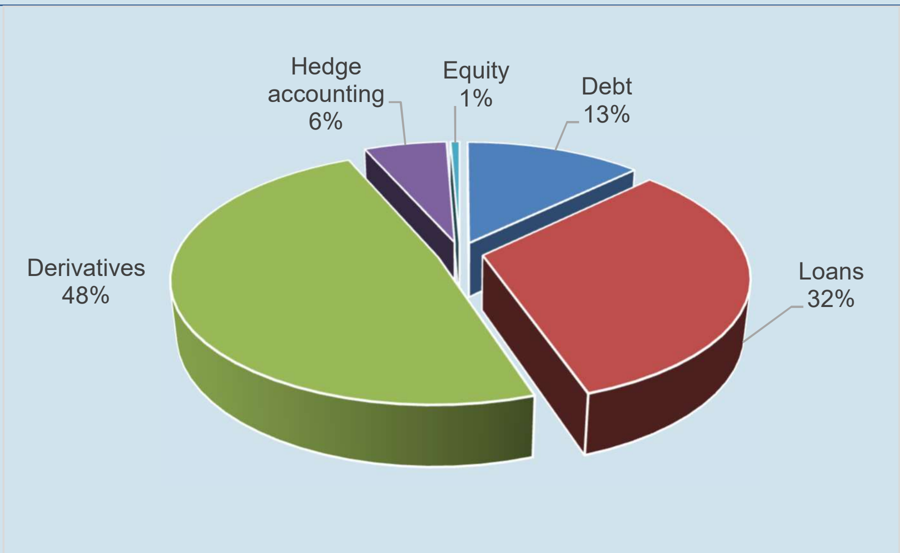
[6] Net NPLs are computed by subtracting from the gross carrying amount of non-performing loans the accumulated impairments, according to the FINREP definitions.

[7] Financial instruments, following fair value hierarchy, are reported at fair value, according to the FINREP definitions.

(France and Germany). This compares with more than 70% of net NPLs held by banks located in Italy, France, Greece and Spain (Chart 2a and 2b).[8] Furthermore, the composition of L2 asset and liabilities differs widely among SSM countries (Chart 3).

Chart 1

Distribution of L2 assets and liabilities among SSM banks

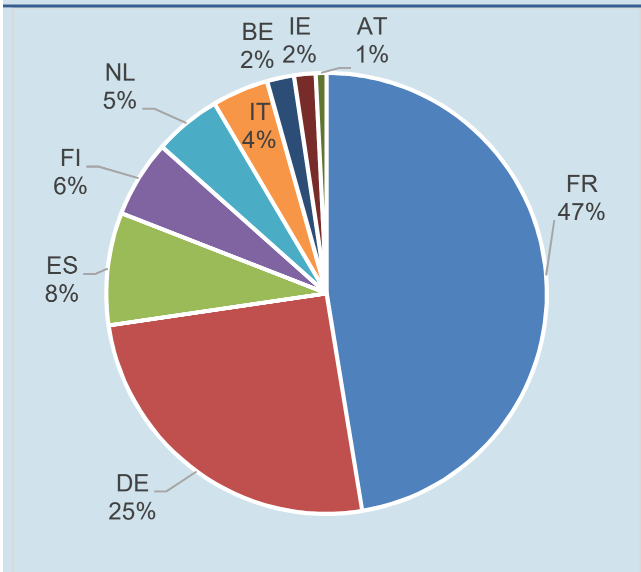


Source: FINREP. Data as of 31 December 2019. Data refer to L2 assets and liabilities on a sample of 105 SSM Significant Institutions (adopting the IFRS framework).

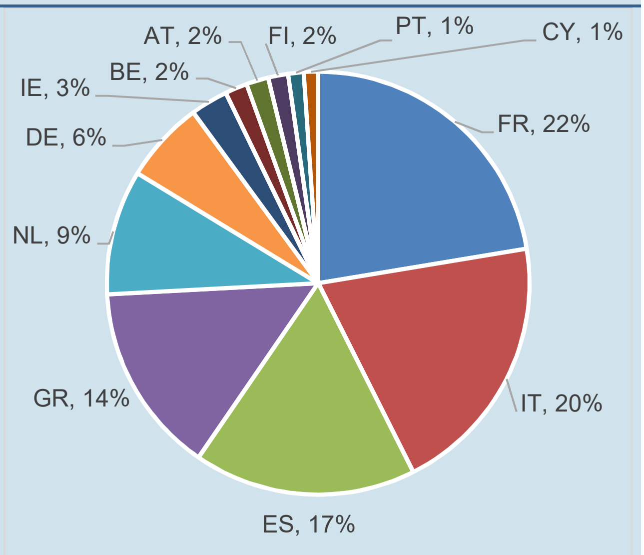
Chart 2

Distribution of L2 and L3 assets and liabilities, and net NPLs among SSM banks

(a) L2 and L3 assets and liabilities



(b) Net NPLs

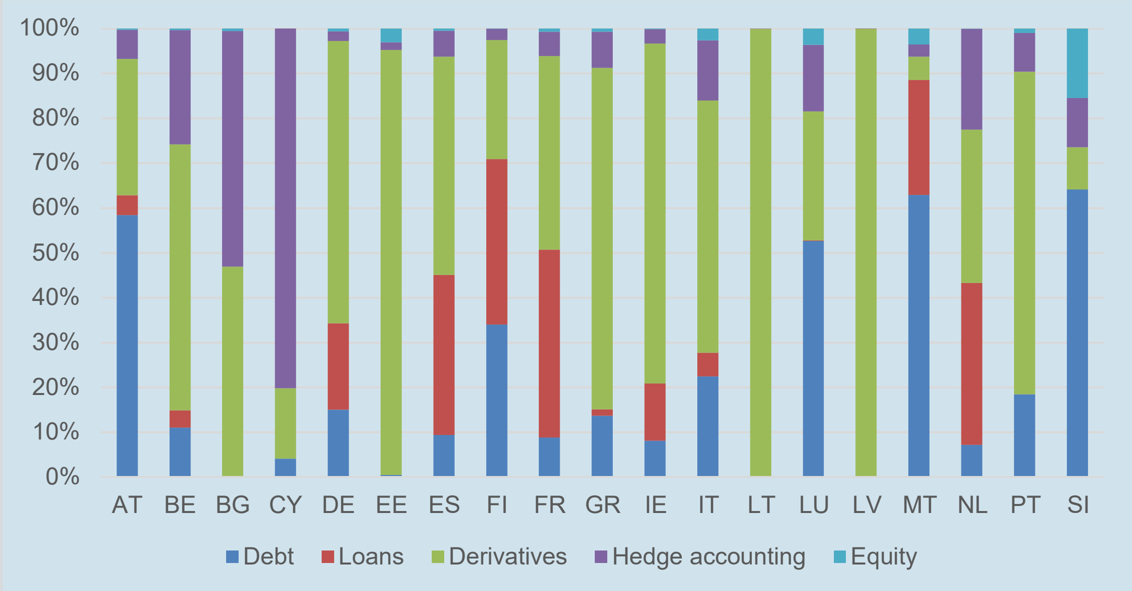


Source: FINREP. Data as of 31 December 2019. Data refer to L2 and L3 assets and liabilities, and net NPLs of 105 SSM Significant Institutions.

[8] Holdings in different jurisdictions are expressed in absolute values and not in comparison to the sizes of the respective jurisdictions (e.g. holdings divided by total assets/loans), since we are only interested in the comparative concentration of NPLs and L2/L3 holdings across jurisdictions.

Chart 3

Classification of L2 instruments across SSM countries



Source: FINREP. Data as of 31 December 2019. Data refer to L2 and L3 assets and liabilities, and net NPLs of 105 SSM Significant Institutions.

L2 and L3 instruments are mostly held by a small number of large banks. In particular, the amount held by the top 18 SSM banks[9] – in terms of L2 and L3 holdings on total assets – represents 77% of the overall amount of L2/ L3 assets and liabilities over the selected sample. On the other hand, net NPLs[10] held by the top 18 banks – in terms of net NPL holdings relative to total assets – represent 27% of overall net NPLs over the selected SSM banks. Among these banks, the ratio between the amount of L2 and L3 assets and liabilities and (two times) CET1, averages 4.9 (in aggregate terms). This average effect hides a substantial heterogeneity across banks, with values as high as 10 and as low as 2 (Chart 4a); on the other hand, the ratio between net NPLs and capital is much lower. In particular, net NPLs to CET1 ratios range from 0.3 to 1.5, with an average of around 0.6 (Chart 4b).

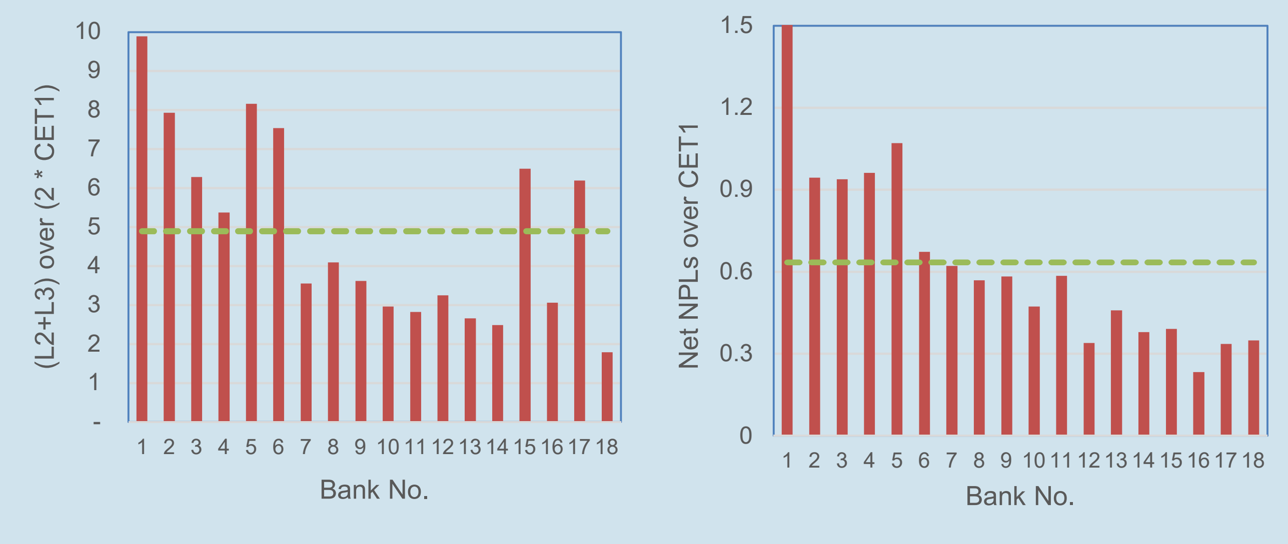
To sum up, both amounts of L2/L3 and NPLs – which share a certain degree of opacity, illiquidity and valuation difficulty for external investors – are material for large SSM banks (with L2/L3 representing multiples of net NPLs), as well as geographically concentrated. Finally, the ratio between L2/L3 and capital is higher than the ratio between net NPLs and capital, for banks with the highest share of respectively L2/L3 and net NPLs on total assets.

[9] Similar choice as in Roca, Potente et al. (2017).
[10] We compare net NPLs with L2/L3 since their amount represents the residual risk borne by banks for valuation uncertainties on deteriorated loans.

Chart 4

L2 and L3 assets and liabilities, and net NPLs with respect to CET1

(a) L2 and L3 assets and liabilities | (b) Net NPLs



Source: SNL. Data as of 31 December 2019. Data refer to the largest 18 SSM banks in terms of either L2 or L3 holdings with respect to total assets or in terms of net NPLs with respect to total assets. The dotted lines represent averages.

3. How L2/L3 instruments and NPLs might affect banks' financial vulnerability

The following empirical analysis aims to corroborate the hypothesis that potential risks stemming from NPLs and L2/L3 instruments might affect banks' financial soundness.

In particular, we rely on both accounting and market indicators to test the hypothesis that a large amount of complex and opaque products entails an increasing level of financial vulnerability. In addition, we adopt different model specifications in order to investigate the issue from different perspectives (i.e. across time and cross section). We use a panel dataset of quarterly supervisory data (FINREP/COREP) and market data (Bloomberg) for SSM banks, from September 2014 to December 2019.[11]

Given the uncertainty surrounding the identification of a measure of 'financial soundness', we rely on different market- and accounting-based proxies: CDS, PtB and Z-scores.[12] CDS and PtB are expressed as quarterly averages of daily values. In particular, to take into account the publication lag of the balance sheet data, we average data over the period that starts one month before and ends two

[11] See the annex for further details.

[12] The Z-score, computed as in D'Apice et al. (2016), is an accounting-based indicator of the (normalized) economic and capital buffer the institution has: the higher the Z-score, the more sound an institution is.

months after the end of a quarter.[13] Z-scores are calculated as the sum of returns on assets (ROA) and the equity to assets ratios, divided by the standard deviations of ROA.[14] The idea behind this indicator is that higher values of ROA (i.e. higher profitability), coupled with a larger amount of own funds (i.e. a larger capital position) and a lower volatility of ROA (i.e. more stable profitability) should imply a lower default risk: the higher the Z-score, the lower the default risk. Because the empirical distributions of CDS and Z-scores show a heavy positive skewness, we employ the natural logarithm of these variables to obtain more symmetric distributions. For the sake of simplicity, from now on, CDS and Z-scores will refer to their logarithmic transformations.

The number of banks in the sample varies according to data availability (in particular market data) over the sample period, giving rise to an 'unbalanced panel' (see Tables A2 and A3 for more details): CDS and PtB data are available for only 50 and 41 banks respectively.

We consider the ratio over total equity of the 'risk factors' (i.e. net NPL, L2 and L3), since the risk to the banks' financial soundness stemming from these instruments depends both on their amount and on their incidence over own funds. Our hypothesis is that the risk profile might be negatively affected by large holdings of NPLs, L2 and L3, to the extent that the amount of own funds proves insufficient to absorb potential losses related to their depreciation. Furthermore, provided that we include both L2/L3 assets and liabilities as potential risk factors, we divide them by twice the amount of own funds.[15]

Pooling the data across the entire panel, the net NPL ratio over own funds averages 0.45, with a maximum of 3.48; total L2 and L3 represent on average 1.28 and 0.11 times own funds, with a peak of 17.65 and 3.03, respectively (see Table A.2 in the annex for further details).[16] These numbers confirm that net NPLs, L2 and L3 are unevenly distributed among SSM banks.

In Table 1 we report the decomposition (within-between) of the variability of data. In particular, the within variability expresses that of data across time (considering just the time series dimension of available data), while the between variability expresses that across banks (considering just the cross section dimension of the panel). As expected, the within variability is significantly

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[13] As a rule, the publication date and the accounting date of balance sheet data are not the same, with the former coming after the latter: hence, the definition of publication lag. For the sake of clarity, for example the PtB or CDS value for Dec 31 20XX is obtained as the average of daily values over the period Dec 1 20XX – Feb 28 20(XX+1). This way of constructing the dependent variables partially addresses the publication lag issue, and is consistent with the forward-looking nature of market prices.

[14] ROA is calculated as the ratio of the sum of the operating income over the current quarter and the three previous ones to the average of the total assets in a given year. The standard deviation of ROA is calculated year by year.

[15] For the sake of the analysis, we consider a measure of 'accounting equity', expressed as the sum of capital, reserves and net income.

[16] See also analogous statistics of ratios on total assets in Table A.3.

lower than the between variability: quarterly accounting data are clearly time-varying slowly, since banks tend to change the structure of their balance sheet with low frequency.

Table 1

Variance decomposition of some variables of interest

Variable	Std. Dev.		Variable	Std. Dev.	
CDS	**Overall**	1.04	L2	**Overall**	2.03
	between	*0.95*		*between*	*1.92*
	within	*0.38*		*within*	*0.67*
PtB	**Overall**	0.37	L3	**Overall**	0.25
	between	*0.34*		*between*	*0.22*
	within	*0.14*		*within*	*0.10*
Z-score	**Overall**	1.28	NPL ratio	**Overall**	0.58
	between	*1.08*		*between*	*0.53*
	within	*0.78*		*within*	*0.23*

Against this backdrop, we consider it appropriate to follow two econometric approaches for the estimates. The first approach is a simple, standard fixed effects model; the second is a correlated random effects model or hybrid model[17] (for more details see Mundlak, 1978; Chamberlain, 1982; Wooldridge, 2016) to take into account the difference in variability within and between observed in the data set.

In the fixed effects model (FE), a gold standard default in econometrics, part of the variability of dependent variables, not explained by the selected time-varying explanatory variables (i.e. time-invariant unobserved heterogeneity), is captured by a 'fixed' parameter (a constant), which accounts for the effects of the entire time-invariant variables for each individual bank. On the one hand, the presence of this parameter limits endogeneity concerns related to 'omitted variable bias'.[18] On the other hand, it is not possible to disentangle the individual effects related to potentially different time-invariant variables, since all the variability is absorbed by the fixed effect. Furthermore, the fixed effects estimator uses the 'within variability' (time dimension) cutting out the 'between variability'

[17] In a random intercept setting, correlated random effect and hybrid models are equivalent (Schunck, 2013). Throughout this paper, we will refer to the random effect model and to the hybrid model interchangeably.

[18] Endogeneity issues may arise in any case if the error term and predictors are correlated; for example, in the presence of omitted time-varying variables.

(cross section dimension).

Correlated random effect (CRE) models assume a specific correlation among observations. This class of model allows for a flexible specification of both within and between effects, resulting in a more general approach than the classic random effect model (RE).[19] In light of the characteristics of our dataset, which exhibits a much higher variance across banks than across time, it makes sense to investigate both data dimensions (time-series and cross-section) through a CRE framework, rather than through a FE model that focuses only on the time dimension (i.e. 'within variability').

In static panel models, cross section estimates tend to capture long-term effects, while 'within' estimates (and fixed effects model estimates) tend to capture short-term relationships.[20]

3a. Standard approach

We start by using a standard panel regression with fixed effects, where the variables concerning financial vulnerability selected (CDS, PtB, Z-score) are regressed against specific risk factors, typically considered by market analysts: net NPLs, L2/L3 assets and liabilities over own funds (NPL ratio, L2 and L3 respectively); control variables, affecting banks' resilience to the aforementioned risk factors, are then added. In particular, we consider: i) the level of own funds with respect to total assets (Equity to asset); ii) a proxy for efficiency – yearly non-interest expenses over total assets (NonInterestExp) – and one for profitability – return on equity (ROE); and iii) a scale factor, the natural logarithm of the overall amount of assets (Size). We also introduce iv) the implied volatility index (v2x), calculated from the Eurostoxx 50 index options, to control for market risk aversion. To ensure that the model takes into account regional differences and possible time trends, we consider a country-year interaction term.[21] Finally, we add a dummy variable to control for the introduction of IFRS9, taking value 1 after the end of 2017 (0 otherwise).[22] This allows us to control for the effects generated by changes in accounting rules that might have caused a 'one-off' reclassification of fair value and amortized cost, with a break in the historical series.

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[19] A classic random effect estimator is a weighted average of the within and between estimator and assumes that both the (within and between) effects must be equal. If this assumption holds, using both sources of information (time-series and cross-section) results in a more efficient estimator than the fixed effect estimator (within) or the between estimator.

[20] Egger and Pfaffermayr (2005).

[21] This variable is defined as an interaction term between the calendar year, to which the observation is referred, and the country of the considered bank. In the CRE model, where coefficients of time-invariant variables can be estimated, we opt to introduce the main effects of respectively the year variable and the country one.

[22] It is worth noting that, due to the quarterly frequency and the unbalanced sample, the effect of the IFRS9 dummy is not absorbed by the individual effects.

Formally, our fixed effects model is expressed as follows:

$$Financial\ vulnerability_{i,t} = \alpha_i + \beta_1 Npl\_ratio_{i,t} + \beta_2 L2_{i,t} + \beta_3 L3_{i,t} +$$
$$+ \beta_k Control\ variables_{i,t,k} + \beta_{mj}(Country_m x\ year_j) + \gamma IFRS9 + constant + \varepsilon_{i,t},$$

where *i* indexes the bank, *t* the quarter. We also propose an augmented specification of the equation, in order to identify whether specific categories of L2 products might contribute more than others to the financial vulnerability of banks. Based on the granularity available in the supervisory reporting, we replace the broad L2 category in the equations with FINREP subcategories: Equities, Debts, Derivatives, Hedge Accounting items and Loans.

The main results of the estimates are summarized in Table 2. As already mentioned, they tend to represent short-run results.

The L2 coefficient is statistically significant in equation 1, with a positive sign: an increase in holdings of L2 instruments tends to be accompanied by a deterioration in the market risk perception of a bank (higher CDS). Considering the different categories of L2 financial instruments, an increase in L2 derivatives holdings, which represent the largest chunk of L2 assets and liabilities (see Figure 1), appears to be associated with larger CDS spreads (see equation 4). L2 hedge accounting instruments are positively correlated with CDS and negatively with PtB (see equations 4 and 5).

An increase in the amounts of L3 is associated with lower Z-scores (higher default risk),[23] as suggested by the sign and the statistical significance of the related coefficients in equations 3 and 6.

NPL ratios do not show any statistically significant coefficients. This result might appear counterintuitive; however, an increase in net NPLs vis-à-vis own funds might not be conclusive *per se* in terms of banks' vulnerability, as, for example, the increase in net NPLs might be compensated by an increase in real guarantees.

[23] See also D'Apice et al. (2016).

Table 2

Fixed effects model

VARIABLES	(1) CDS	(2) PtB	(3) Z-score	(4) CDS	(5) PtB	(6) Z-score
NPL ratio	0.00706	0.00908	-0.00909	0.0246	0.00871	0.0591
	(0.0671)	(0.0325)	(0.236)	(0.0683)	(0.0320)	(0.274)
Size	0.332	-0.120	-0.661	0.229	-0.105	-0.616
	(0.268)	(0.0811)	(0.628)	(0.264)	(0.0795)	(0.621)
L2	0.0473***	-0.00118	-0.0628			
	(0.0176)	(0.0151)	(0.0943)			
L3	-0.680	0.233	-0.664**	-0.712	0.114	-0.817**
	(0.447)	(0.256)	(0.316)	(0.426)	(0.246)	(0.371)
Equity to asset	-4.876***	1.026	6.980	-5.167***	0.819	6.778
	(1.633)	(0.924)	(6.548)	(1.669)	(0.892)	(6.453)
NonInterestExp	-2.269	-7.164	-20.83	-1.487	-7.502	-20.02
	(3.747)	(7.045)	(22.64)	(3.882)	(7.095)	(22.66)
ROE	-0.118	0.217***	1.871***	-0.0648	0.203***	1.809***
	(0.422)	(0.0652)	(0.553)	(0.424)	(0.0644)	(0.557)
IFRS9	-0.431***	-0.190	1.113*	-0.422***	-0.190	1.122*
	(0.147)	(0.118)	(0.597)	(0.145)	(0.117)	(0.608)
v2x	0.0130***	-0.00287***	-0.00249	0.0119***	-0.00238**	-0.00192
	(0.00178)	(0.000949)	(0.00232)	(0.00175)	(0.000927)	(0.00234)
L2 equity				-0.0477	-0.560	-0.137
				(0.969)	(0.349)	(2.270)
L2 derivative				0.0730*	-0.0166	-0.0490
				(0.0371)	(0.0217)	(0.132)
L2 loan				-0.00144	0.000606	0.00112
				(0.0464)	(0.0260)	(0.235)
L2 hac				0.723**	-0.284***	-0.455
				(0.323)	(0.103)	(0.329)
L2 debt				0.0861	-0.0221	-0.0663
				(0.131)	(0.0797)	(0.271)
Observations	684	637	1,477	684	637	1,477
R-squared	0.688	0.568	0.295	0.691	0.579	0.299
Number of groups	50	41	98	50	41	98

Note: Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

As regards the control variables, an increase in ROE is associated with higher values of both PtB ratios (see equations 2 and 5) and the Z-scores (see equations 3 and 6). A higher market risk aversion, as measured by the v2x index, tends to be associated, as expected, with higher CDS spreads (see equations 1 and 4) and lower PtB (see equations 2 and 5). A stronger capital position (as measured by a higher Equity to asset ratio) tends to be associated with lower CDS spreads (see equations 1 and 4). The dummy variable related to the introduction of the IFRS9 standard appears significant in most cases.

3.b. Correlated random effect model

As previously stated, the FE estimator exploits only one source of variability (i.e. within variability across the time dimension). In a panel setting including two sources of variability, time series and cross section, where the latter appears to predominate, a Random Effects (RE) estimator exploits the data more efficiently than the FE. However, in order to get consistent estimates in an RE framework, some assumptions must hold, namely the lack of correlation between time-varying explanatory variables and the individual time-invariant characteristics, which, in an RE setting, are seen as random variables. In our set up, where individuals are represented by banks, this might be an unrealistic assumption, since some explanatory variables (i.e. the accounting ones) can be correlated with some time-invariant bank features, such as management styles, business models and so on. For this reason, we resort to a CRE model that introduces some additional explanatory variables as a proxy for the time-invariant individual features of the bank, thus allowing us to explicitly model the correlation between individual effects and explanatory variables.[24]

Table 3 summarizes the main results of within estimates, where coefficients represent the across time relationship between dependent variables (financial vulnerability indicators) and explanatory variables (e.g. L2, L3 or net NPLs) for each single individual (bank). As already mentioned, ‘within estimates’, like FE estimates, also tend to represent short-run results.

[24] In CRE models, the average over time (individual average) of explanatory variables is introduced alongside other predictors. The individual average acts as a proxy for the time-invariant characteristics of the predictors that covariate with the individual effects. The idea behind this approach is intuitive: if a non-null correlation between (time-constant) individual effects and (time-varying) explanatory variables exists, it must exist for each time. This implies that there is a non-null correlation between the individual effects and the average over time of the explanatory variables. Hence, introducing time-averaged predictors explicitly controls for correlation between time-constant heterogeneity and predictors. Unlike what happens in a classic random effect estimation problem, in CRE an assumption of equality of within and between effects does not exist, so that we have two sets of parameters: one set is composed by the within (across-time) relationship coefficients, the other by those of the between (cross-section) one.

Table 3

Correlated Random Effects model[25]
(Within effects)

VARIABLES	(7) CDS	(8) PtB	(9) Z-score	(10) CDS	(11) PtB	(12) Z-score
NPL ratio	-0.0400	-0.0280	0.0167	-0.0130	-0.0324	0.0522
	(0.102)	(0.0267)	(0.174)	(0.108)	(0.0309)	(0.205)
L2	0.0398*	-0.0107	-0.0913			
	(0.0220)	(0.0207)	(0.0841)			
L3	-0.705	0.339	-0.713*	-0.643	0.159	-0.865**
	(0.706)	(0.214)	(0.366)	(0.738)	(0.255)	(0.393)
Equity to asset	-3.660	0.249	7.470	-3.476	-0.0737	7.183
	(2.273)	(1.115)	(5.962)	(2.296)	(1.077)	(5.944)
NonInterestExp	8.005	-17.95**	-8.512	7.274	-19.15***	-7.886
	(6.088)	(7.122)	(27.31)	(6.208)	(6.767)	(27.45)
ROE	-0.314	0.272**	2.232***	-0.323	0.285**	2.220***
	(0.525)	(0.135)	(0.751)	(0.538)	(0.131)	(0.739)
IFRS9	-0.156***	-0.194***	0.494***	-0.154***	-0.195***	0.499***
	(0.0473)	(0.0259)	(0.136)	(0.0463)	(0.0255)	(0.140)
v2x	0.0135***	-0.00295***	-0.00181	0.0135***	-0.00280***	-0.00126
	(0.00159)	(0.000866)	(0.00256)	(0.00156)	(0.000850)	(0.00255)
L2 equity				1.519	-0.301	0.477
				(1.766)	(0.315)	(1.938)
L2 derivative				0.117**	0.00562	-0.0330
				(0.0582)	(0.0190)	(0.117)
L2 loan				-0.0168	-0.0366	0.0563
				(0.0944)	(0.0326)	(0.219)
L2 hac				-0.128	-0.249***	-0.505**
				(0.388)	(0.0938)	(0.257)
L2 debt				-0.150	0.00356	-0.300
				(0.155)	(0.0968)	(0.237)
Observations	684	637	1,477	684	637	1,477
Number of groups	50	41	98	50	41	98

Note: Robust standard errors are in parentheses. The variable Size is not reported in this table because it is estimated as in a RE model due to its low *within* variability; *** p<0.01, ** p<0.05, * p<0.1.

Across time, the estimated coefficients suggest the existence, on average, of a positive relationship between holdings of L3 instruments and default risk: higher L3 are associated with lower Z-scores (see equations 9 and 12). By the same token, higher L2 holdings, and in particular L2

[25] R-squared are not reported in the table, since CRE models are estimated through GLS; hence, the classic R-squared properties do not hold. We do not resort to pseudo R-squared measures, because they would not be comparable to those provided in the Fixed Effect model.

derivatives, tend to be associated with higher CDS spreads (see equations 7 and 10). Similarly, an intensification in the use of hedge accounting practices across time tends to be associated with lower PtB (see equation 11) and higher default risk (lower Z-score, see equation 12); this result might be explained if the wider use of hedge accounting techniques is interpreted as an attempt to only partially offset increased risks. Other possible explanations may include expectations of reduced margins of profitability or increased counterparty risk, to the extent that hedge accounting exposures are not settled with Central Clearers. Across the time-dimension NPLs do not seem to affect the risk profile of a bank significantly, according to the selected risk measures, similar to the FE framework results.

As regards the control variables: an increase in ROE comes with higher PtB ratios (see equations 8 and 11) and a decrease in the default risk, measured by higher Z-scores (see equations 9 and 12). An increase in market risk aversion, as measured by the v2x index, tends to be associated with higher riskiness perceived by the market (higher CDS, see equations 7 and 10; lower PtB, see equations 8 and 11); the dummy variable related to the introduction of the IFRS9 standard appears significant in most cases.

As already stated, across-time relationships might show a low explanatory power of the phenomenon at hand, probably as a consequence of the slow rate of change of some independent variables across time, such as L2, L3 and Net NPLs, and the limited length of the sample. Table 4 shows the main results of between estimates, where coefficients represent the cross section relationship among dependent (financial vulnerability indicators) and independent variables. As already mentioned, they also tend to reflect longer-term relationships than FE and within estimates.

According to this analysis, *ceteris paribus*: i) banks with intrinsic higher net NPL ratios tend to have wider CDS spreads (see equations 7' and 10'), lower PtBs (see equations 8' and 11') and higher risks of default, as measured by lower Z-scores (see equations 9' and 12'); ii) similarly, larger amounts of L3 are associated with higher CDS (see equations 7' and 10') and lower PtB ratios (see equations 8' and 11'); iii) larger holdings of L2 debt instruments tend to characterize banks with lower PtB and higher default risks, as measured by lower Z-scores (see, respectively, equations 11' and 12').

Table 4

Correlated Random Effects model

(Between effects)

VARIABLES	(7') CDS	(8') PtB	(9') Z-score	(10') CDS	(11') PtB	(12') Z-score
NPL ratio	0.427***	-0.330**	-0.987***	0.348**	-0.498***	-1.145***
	(0.137)	(0.167)	(0.322)	(0.142)	(0.143)	(0.346)
L2	0.0309	0.0399	-0.0584			
	(0.0253)	(0.0364)	(0.0510)			
L3	0.749***	-0.918**	-0.352	1.164***	-0.875*	0.124
	(0.248)	(0.398)	(0.339)	(0.387)	(0.517)	(0.394)
Equity to asset	6.887***	1.483	-1.947	5.335*	1.376	-2.400
	(2.592)	(1.681)	(2.102)	(3.192)	(1.721)	(2.030)
NonInterestExp	1.061	-1.897	-12.51	-0.439	10.75	-19.63
	(8.156)	(7.446)	(12.60)	(8.306)	(8.465)	(12.34)
ROE	-4.445***	2.240**	7.573**	-4.771***	2.005**	6.857*
	(1.482)	(1.001)	(3.477)	(1.408)	(0.795)	(3.574)
IFRS9	-1.633	0.238	-3.447***	-0.357	0.510	-3.147***
	(1.449)	(0.933)	(0.525)	(1.529)	(0.648)	(0.653)
v2x	-0.540**	-0.383*	0.813***	-0.655***	-0.291*	0.779**
	(0.219)	(0.206)	(0.311)	(0.234)	(0.150)	(0.333)
L2 equity				0.856	-0.739	0.180
				(0.724)	(1.366)	(2.239)
L2 derivative				-0.0596	0.161***	-0.0679
				(0.0509)	(0.0497)	(0.0500)
L2 loan				0.0409	0.305**	0.234
				(0.0887)	(0.124)	(0.200)
L2 hac				-1.486	1.079***	-0.218**
				(0.921)	(0.236)	(0.0988)
L2 debt				0.202	-0.711**	-0.312**
				(0.162)	(0.352)	(0.145)
Observations	684	637	1,477	684	637	1,477
Number of groups	50	41	98	50	41	98

Note: Robust standard errors are in parentheses. The variable Size is not reported in this table because it is estimated as in a RE model due to its low *within* variability; *** p<0.01, ** p<0.05, * p<0.1.

An intensive use of L2 derivatives and hedge accounting techniques, which are often closely intertwined, provides counterintuitive evidence from a cross section perspective, since they tend to be associated with higher values of PtB (see equation 11'). One possible explanation for this is that huge amounts of L2 derivatives characterize banks with business models perceived as more profitable by the market (with higher PtB), other things being equal. In addition, larger amounts of L2 classified as loans tend to be associated with higher PtB values (see equation 11'). Also in this case, the trading of loans might lift the market perception in terms of expected profitability, in a longer-term perspective. On the other hand, lower Z-scores (higher default risks) tend to characterize banks making an extensive use of hedge accounting instruments (see equation 12'), as in the across time results.

As regards the control variables, a structurally larger ROE tends to be associated with lower CDS (see equations 7' and 10'), higher PtB (see equations 8' and 11') and lower default risk (see equations 9' and 12'). Market risk aversion, as measured by the v2x index, provides mixed evidence: it tends to be associated with lower PtB (see equations 8' and 11'), but lower CDS (equation 7') and higher Z-scores (see equations 9' and 12').[26] The dummy variable related to the introduction of the IFRS9 standards appears significant exclusively in equation 9' and equation 12'.

The impact on banks' financial vulnerability of the selected 'risk factors' (NPLs, L2, L3) can be summarized as follows (see table A4 in the Annex):

i) across time (FE and CRE within estimates, short term results), statistical evidence suggests that higher L2 holdings (overall) are associated with higher CDS spreads (see equations 1 and 7); this phenomenon is particularly evident for L2 derivatives (see equations 4 and 10) and L2 hedge accounting instruments (see equation 4). Furthermore, larger amounts of L2 hedge accounting instruments tend to be associated with lower PtB (see equations 5 and 11) and higher default risk (lower Z-scores, see equation 12). Bigger L3 holdings tend to come with higher default risk (lower Z-scores, see equations 3, 6, 9 and 12). NPL ratios are uncorrelated with the financial vulnerability indicators selected in our dataset;

ii) across banks (between estimates, longer term results), L2 holdings (without distinction among categories) appear to be uncorrelated with the selected financial vulnerability indicators. This could depend on different impacts (positive or negative) on financial vulnerability indicators arising from specific L2 categories. In fact, considering different L2 categories provides mixed evidence: on the one hand, L2 debts are associated with lower PtB (see equation 11') and higher default risks (lower Z-scores, see equation 12'). On the other hand, holdings of L2 derivatives show a positive correlation with PtB (equation 11'), as do hedge accounting instruments; the latter, however, also show a positive correlation with default risk (lower Z-scores, see equation 12'); L2 loans show a positive correlation with PtB. With respect to NPLs, banks with structurally higher

[26] The v2x index, our proxy of risk aversion, is a Eurozone index; for each time, we have the same risk aversion for all individuals: in other words, each bank experiences the same risk aversion. Hence, in a balanced panel, the v2x index between effect would be zero. In our case of an unbalanced panel, the risk aversion also varies across banks, but its coefficient may not have a direct interpretation.

net NPL ratios tend, as expected, to show lower PtB (see equations 8' and 11'), wider CDS spreads (see equations 7' and 10') and higher risks of default (lower Z-scores, see equations 9' and 12'). Finally, it is confirmed that L3 holdings are negatively correlated with PtB (see equations 8' and 11'); they also tend to be positively correlated with CDS (see equations 7' and 10').

4. Conclusions

The amount of complex financial products is rather sizeable across SSM banks. In our sample, in particular, they amount to around €5.6 trillion of L2 (assets and liabilities) and €349 billion of L3 (assets and liabilities) respectively, representing several times the amount of net NPLs (€267 billion), as of December 2019. Furthermore, their holdings are concentrated in just a few jurisdictions. Consequently, from a supervisory perspective, it is worth understanding whether and to what extent their amount might impact banks' risk profile.

Following previous qualitative analyses and a recent stream of literature, we carry out an econometric analysis to investigate the potential impact of both categories of instruments on banks' vulnerability, leveraging different econometric methodologies. In particular, we stress the importance of analyzing these phenomena also from a cross section perspective, given the slow rate of change of some explanatory variables over time and the limited length of the sample.

Some results are in line with previous studies. In particular, L3 holdings tend to be associated with higher default risk, as measured by Z-scores and also suggested by D'Apice et al. (2016). By the same token, they might characterize banks with lower PtB, other things being equal, as it may also be argued in ECB (2019). High NPL ratios tend to be associated with lower PtB, as in Ciocchetta (2020), but also with a higher default risk and CDS.

Other results, to the best of our knowledge, are innovative. In particular, we find that, in the across-time estimates, an increase in L2 holdings (overall) might come with higher CDS spreads. Considering single L2 categories, this is true for L2 derivatives and hedge account instruments (with the latter also showing a negative correlation with PtB).

The cross section dimension assessment (longer-term perspective) paints a slightly different picture: L2 holdings (without distinction among categories) appear to be uncorrelated with the selected financial vulnerability indicators. This could depend on different impacts (positive or negative) on financial vulnerability indicators arising from specific L2 categories. On the one hand, L2 debts are associated with lower PtB and higher default risks; on the other hand, holdings of L2 derivatives show a positive correlation with PtB, as for hedge accounting instruments; the latter, however, also show a positive correlation with default risk.

From a policy perspective, these empirical results confirm that a high supervisory focus on NPLs, L2 and L3 is justified, since large holdings of potentially illiquid instruments are likely to affect the risk profile of banks. As far as the broad area of L2 instruments is concerned, mixed empirical evidence suggests that only specific supervisory investigation techniques might allow plain vanilla to be disentangled from more exotic products, whose risks, theoretically, might be similar to those stemming from L3 instruments.

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Annex

Table A.1

Variable name	Variable description
L2	Total L2 instruments (assets and liabilities) on total equity (doubled)
L3	Total L3 instruments (assets and liabilities) on total equity (doubled)
Equity_to_asset	Total common equity on total assets
NonInterestExp	Annualized non-interest expenses on total assets
Size	Natural logarithm of total assets
NPL ratio	Net NPLs on total equity
L2 equity	Equity assets classified as L2 on total equity
L2 derivative	Derivatives instruments (assets and liabilities) classified as L2 on total equity (double)
L2 loan	Fair Value loans and deposits classified as L2 on total equity (double)
L2 hac	Hedge accounting derivatives (assets and liabilities) classified as L2 on total equity (double)
L2 debt	Debt and residual instruments classified as L2 (assets and liabilities) on total equity (double)
ROE	Return on equity
v2x	End of quarter value of Vstoxx index (eurozone implied volatility index)
CDS	3 months daily average of CDS quoted spread (natural logarithm)
Z-score	Natural logarithm of (ROA + Equity/Total Assets) / Std. Dev.(ROA)
PtB	3 months daily average of price-to-book

Table A.2

Summary statistics

(Pooled data. Sample period: Q3 2014 – Q4 2019. See Table A.1 for variables definitions.)

Variable	Obs	Mean	Std. Dev.	Min	Max
Size	1,955	25.00	1.58	21.51	28.45
NPL ratio	1,905	0.45	0.58	0.00	3.48
L2	1,954	1.28	2.03	0.00	17.65
L3	1,953	0.11	0.25	0.00	3.03
Equity to asset	1,954	0.08	0.04	0.02	0.38
ROE	1,955	0.03	0.07	-0.66	0.62
NonInterestExp	1,955	0.01	0.01	0.00	0.05
L2 equity	1,954	0.02	0.09	0.00	2.31
L2 derivative	1,954	0.57	1.23	0.00	13.98
L2 hac	1,954	0.19	0.65	0.00	6.71
L2 loan	1,954	0.21	0.50	0.00	3.49
L2 debt	1,954	0.30	0.60	0.00	5.92
v2x	1,955	0.19	0.06	0.12	0.32
CDS	875	4.71	1.04	2.98	8.32
PtB	787	0.68	0.37	0.01	1.86
Z-score	1,511	4.62	1.28	-0.69	9.15

Table A.3

Summary statistics

(Pooled data. Sample period: Q3 2014 – Q4 2019. Values in percentage points.)

Variable	Obs	Mean	Std. Dev.	Min	Max
NPL ratio_ta	1,905	3.60	5.40	0.00	41.00
L2_ta	1,954	6.80	8.60	0.00	61.50
L3_ta	1,953	0.60	1.10	0.00	10.20
L2 equity_ta	1,954	0.10	0.60	0.00	16.70
L2 derivative_ta	1,954	3.10	5.10	0.00	48.70
L2 loan_ta	1,954	1.10	2.60	0.00	18.30
L2 hac_ta	1,954	0.80	1.60	0.00	16.40
L2 debt_ta	1,954	1.50	2.80	0.00	25.40

Note: variables considered in this table are constructed as those of Table A.1 where the total of assets replaces the total equity. Here comes the suffix "ta".

Table A.4

Summary of significant estimated coefficients relevant variables

	Fixed effects model			Correlated Random Effects model					
				Within			*Between*		
	(1) CDS		(3) Z – score	(7) CDS	(8) PtB	(9) Z-Score	(7’) CDS	(8’) PtB	(9’) Z-score
NPL ratio							0.427***	-0.330*	-0.987***
L2	0.0473***			0.0398*					
L3			-0.664**			-0.713*	0.749***	-0.918**	

	(4) CDS	(5) PtB	(6) Z-score	(10) CDS	(11) PtB	(12) Z-score	(10’) CDS	(11’) PtB	(12’) Z-score
NPL ratio							0.348**	-0.498***	-1.145***
L2 equity									
L2 derivative	0.0730*			0.117**				0.161***	
L2 hac	0.723**	-0.284***			-0.249***	-0.505**		1.079***	-0.218**
L2 loan								0.305**	
L2 debt								-0.711**	-0.312**
L3			-0.817**			-0.865**	1.164***	-0.875*	

Note: *** p<0.01, ** p<0.05, * p<0.1.