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ON THE IMPORTANCE OF TRADITIONAL LENDING
ACTIVITY FOR BANKING SYSTEMS STABILITY

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In this paper, we analyzed the role of banks' traditional lending on systemic stability. Firstly, we quantified the effect of correlation among banks' results on systemic risk through Monte Carlo simulation. Secondly, we verified how traditional lending affects banks' results correlation. Finally, combining the two effects, we assessed the importance of bank traditional lending on financial stability. Our results suggest that banks devoting a higher share of their assets to traditional lending show a lower correlation of their comprehensive income, thus having a mitigation effect on systemic stability.

Keywords: Banking; systemic risk; Monte Carlo simulation; correlation.

JEL Classification: G21, G28, G17.

1. Introduction

Bank traditional lending is typically considered as fundamental for sustaining the real economy. What is less evident is that it also provides a significant contribution to systemic stability.

After the Great Financial Crisis, the Basel Committee on Banking Supervision (2005) introduced several proposals to reduce both the banks' probability of default and its possible impact on the financial system. The resilience of the EU banking sector has been strengthened following the Basel III agreement, which contributed to enhance banks' loss-absorbing capacity through the introduction of potential capital buffers in addition to the minimum capital requirements, i.e. the capital conservation

buffer, the countercyclical buffer, the global systemically important institution buffer and the systemic risk buffer. In fact, capital buffers are macro-prudential instruments, whose aim is to decrease bank systemic risks deriving from pro-cyclicality and excessive credit growth during an expansion phase. Furthermore, Basel III introduced new liquidity constraints and a minimum leverage ratio calculated on non-risk-based exposures to counteract the excessive deleveraging processes. The reforms are detailed and discussed in the economic review of the financial regulation agenda (see European Commission 2014) and entered into force in January 2014 with the Capital Requirements Directive IV (CRD IV)[a] and the Capital Requirements Regulation (CRR).[b] Benczur *et al.* (2017) performed a detailed quantitative assessment of the reduction in public finance costs brought about by the introduction of these rules, and the analysis of Parrado-Martínez *et al.* (2019) reports that the European banking system shows a relative reduction of its risks from 2011 to 2016. According to their study, this reduction has been motivated to some extent by a decrease in the asset portfolio risk, but mainly by a higher banking capital.

However, in terms of macro-prudential regulation, the debate is open on how to strengthen the stability of a banking system for a given stability level of individual banks and on how to minimize the impact of possible banking crises.

For the purposes of our analysis, the term contagion refers to the risk that one financial institution's failure leads to the default of others through a domino effect in the interbank market, as defined in Allen *et al.* (2012). The recent literature, starting from the seminal paper of Allen & Gale (2000), reports that two components are fundamental in determining contagion risks, namely the correlation among banks' results, and the linkages through direct (interbank) and indirect (market) exposures.

On one hand, correlation plays a fundamental role for contagion risk, because if banks tend to react in the same way to the business cycle and common external shocks, then the system is exposed to a lower number of crises, but more intense as more banks are involved at the same time. Thus, correlation mainly sets favorable conditions for contagion to start.

On the other hand, direct or indirect links among banks have the role of transmitting the crises' effects from one troubled bank to the others, inducing further weakening or defaults.

Correlation is often included in system modeling, as banks operating in a specific system are exposed to the same business cycle, at least in part. It means that customer defaults will occur more often in some years (crises) than in others (booms), thus affecting banks' results.

The effect of this exposure to common risk sources, as to say, the exposure to possible common shocks, translates in the risk of a simultaneous weakening of a significant part of the banking system. In such a situation, even a single banking crisis can affect the other banks by (direct or indirect) contagion, since their loss

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[a] Directive 2013/36/EU.
[b] Regulation (EU) No 575/2013.

absorbing capacity is already weakened. It is evident that the higher the number of banks involved and the deeper the impact of the common shock, the higher the risk of contagion. The role played by this parameter is, thus, of fundamental significance.

To analyze the role of bank traditional lending on financial system stability, we first verified how traditional lending affects banks' results correlation. Then, we quantified the effect of the correlation of banks' results on systemic risk, detailing its effects and its relations to the specific structure of assets and liabilities of each bank. To this end, we used a Monte Carlo simulation-based approach that allows us to split the systemic risk in an idiosyncratic component that is mainly driven by bank capital level and asset riskiness, and a contagion component, driven by correlation and direct or indirect linkages among banks. Finally, we assessed the impact of bank traditional lending on financial stability to provide a clearer picture of the process, and to have some hints on how to limit contagion risks and its disruptive effects on the banking and financial system.

The remainder of the paper is structured as follows. Section 2 report a literature review. Section 3 describes the methodology and the simulation model used for testing the correlation effects on systems stability. Section 4 presents an empirical application to a sample of Italian banks and discusses the results of our analysis. Section 5 analyzes the economic significance and policy implications based on the results of our research, and Sec. 6 concludes.

2. Literature Review

Our analysis is directly linked with the research stream focused on the effect of the business models' evolution on banks' results correlation.

Within the literature studying the (increasing) interconnection of banks over time, Nijskens & Wagner (2011) have verified that the introduction of credit risk transfer activities has increased their correlation, while reducing the single bank risk. Patro *et al.* (2013) analyzed the correlations of equity returns between 1988 and 2008 reporting that correlations are an important indicator of systemic risk. Kreis *et al.* (2018) perform a thorough analysis of the correlations over an extensive period, from 1980 to 2016, which reports that systemic risk was not significant until 2007, but, since then, it has become highly significant as a result of both the increase in the estimated weight of the common factors (correlation) and of their nonlinear impact on systemic risk.

Our analysis is in line with this research stream, aimed at verifying if the traditional lending activity can mitigate the impact of common risk factors, and linked with the theoretical network analysis that modeled contagion risks in banking systems.

In theoretical terms, Elsinger *et al.* (2006) have already acknowledged that the correlation between banks' results and common risk variables affects the probability of simultaneous crises with significant systemic effects, reporting that "between the two leading sources of systemic risk, the correlation is much more important than financial exposures." A more detailed description of this effect is in Co-Pierre (2013), whose analysis reports that in the case of "pure" interbank contagion the shock

concentrated on a single bank impacts on the other banks through interbank losses, while in the case of a common shock all banks are hit by the simultaneous loss of a fraction of their capital. Furthermore, even when the shock only brings to default a small number of banks, a large number of banks become more vulnerable, and if contagion is triggered, it typically induces a large number of defaults and high system losses. Similar effects are found when considering simultaneous direct and indirect linkages by Cifuentes *et al.* (2005).

With regard to the common variables influencing the results of banking activities, Allen *et al.* (2012), in their paper focused on asset commonality, show that the composition of banks' asset structures interacts with the funding maturity in determining systemic risk. Acharya & Yorulmazer (2008) model the correlation among bank returns based on the characteristics of loans that compose the banks' portfolios showing that correlation can be considered the ex-ante aspect of systemic risk as it affects the likelihood of joint failure of banks.

Regarding indirect contagion, Siedlarek & Fritsch (2019) report that institutions holding broadly similar portfolios can be simultaneously affected by a drop in prices for one asset class.

Frey & Hledik (2014) argue that similar asset positions across banks can determine a higher correlation between bank asset returns and financial stability.

About the common risk sources, some papers, such as Karimzadeh *et al.* (2013) verified that the yearly changes in GDP are strictly related to bank yields, risk and loan losses. Similarly, the analyses of Demirguc-Kunt & Huizinga (2000) and Bikker & Hu (2002) suggest that bank profitability is related to the business cycle. Athanasoglou *et al.* (2008) verified the role of some important variables that influence bank results, confirming that the economic cycle significantly influences bank profits. Albertazzi & Gambacorta (2009) specify that the pro-cyclicality of bank profits is due to two different effects, the first related to the profitability of lending, which in particular has a positive effect on the interest margin, while the second effect is linked to the quality of the assets, which affects the losses on receivables and consequently on the related provisions.

3. Methodology

As a first analysis, we evaluated the effects of correlation among banks' results on financial systems stability.

According to the literature presented in the previous paragraph, the results of the banks can be represented as the weighted sum of two components, an idiosyncratic factor, and a common factor. To this end, we denote bank i results for year s, L_{is}, as follows:

$$L_{is} = \rho_i \mathrm{com}_s + \sqrt{1 - \rho_i^2} d_{is}, \tag{3.1}$$

where ρ_i represents the weight of the common factor com_s, and $\sqrt{1 - \rho_i^2}$ represents the weight of the idiosyncratic factor d_{is}. The above formula evidences that com_s and

d_{is} are mutually independent variables, and that ρ_i represents the correlation between L_{is} and com_s as in Drehman & Tarashev (2013) and in Frey & Hledik (2014).

The estimation of ρ_i can be based on the correlation of assets returns, which, in turn, can be estimated either on market values, as in Hull & White (2004), or on balance sheet values, and more specifically on the profits, as in Meiselman *et al.* (2018), and as we do in this paper.

For testing the effects of different correlation levels of banks' results on the system stability, as it is not possible to rely on actual data, we developed a Monte Carlo based simulation exercise, carried out through the Leave-One-Out methodology proposed in Zedda & Cannas (2020).

The basic idea under the Leave-One-Out method is the comparison between the performance of the whole banking system, and that of the same system when excluding one bank. In this way, it is possible not only to assess which is the contribution to systemic risk of each bank, but also to specify the bank's risk contribution due to the risk of idiosyncratic defaults (stand-alone contribution), and the contribution due to its role in the crises transmission (contagion risk contribution), which is useful for this study. In fact, we have to consider two interconnected effects influencing the contagion risk contribution of each bank. The first is due to the correlation between the considered bank results and the common factor, the second is due to the easing of contagion, as a consequence of the (average) correlation level of the other banks in the system. To analyze these effects, we developed two sets of simulations. In the first one, we tested for the effect of a change in each bank correlation with the common risk sources changing it uniformly for all banks in the system. In particular, we set correlation respectively to 40%, 50%, 60%, 70%, 80% and 90%, considering both its impact on the whole system and on each of the considered banks.

The systemic risk contribution of each bank h can be represented as:

$$\text{Sys}_i = \alpha_i + \beta_i \text{corr}, \tag{3.2}$$

where:

Sys_i is the systemic risk contribution of bank i;

α_i is the constant term for bank i;

corr is the correlation (of all banks) to the common factor, and β_i is the i bank coefficient (sensitivity) to it, which is estimated through an OLS regression.

In the second simulation set, we tested for the influence of the correlation level when it is different for each bank while keeping it in a predefined range.

In this case, the systemic risk contribution of each bank h can be represented as:

$$\text{Sys}_i = \alpha_i + \beta_i \text{corr}_i + \gamma_i \text{corr}_{\text{avg}}, \tag{3.3}$$

where:

α_i is the constant term;

corr_i is the correlation between bank i and the common factor, and β_i represents its coefficient (sensitivity);

$\mathrm{corr}_{\mathrm{avg}}$ is the average correlation of all banks in the system to the common factor, and γ_i represents the i bank coefficient (sensitivity) to it.

Based on these simulations results, we verified which of the two correlation components, corr_i or $\mathrm{corr}_{\mathrm{avg}}$, influences more the system's stability.

The second step of the analysis consists in testing for the relationship between the loans' incidence on total assets and the banks' results correlation, proxied employing the comprehensive income correlation.

To do that, we computed the year-on-year variation of comprehensive income V_{is} for each bank i and each year s, proxying the banks' results L_{is} by means of the comprehensive income R_{is} as follows:

$$V_{is} = \frac{R_{is} - R_{i(s-1)}}{R_{i(s-1)}}, \tag{3.4}$$

where R_{is} is the comprehensive income of bank i for year s.

Then, we estimated the average annual values of V_{is}, namely $\bar{V}_s$, for the whole sample, and computed the correlation between the $\bar{V}_s$ values and the V_{is} values, obtaining for each bank a proxy of its correlation with the banking system ongoing over time.

4. Data and Results

4.1. *The sample*

The analysis was carried out on a balanced panel of 233 Italian banks and banking groups, selecting from the whole Italian banking system the ones for which all the needed data were available for the years from 2011 to 2017 on Orbis Bank Focus, and with an incidence of loans from 40% to 90%.[c,d]

The summary data are shown in Tables 1 and 2.

The values in Table 1 show that the system experienced a progressive reduction in the riskiness of the assets from 2011 to 2017, as estimated by its average probability to default (Assets PD), and, starting from 2013, a progressive recapitalization.

Table 2 reports some details on the distribution of the same variables for 2017, showing a rather wide dimensional range, a high number of small banks and a significant diversification of both capitalization level and interbank exposures, which

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[c] Missing values is the main reason for exclusion. The average incidence of gross loans on total assets was around 60%. Just 38 banks reported an incidence of gross loans on total assets lower than 40%, mainly referring to entities classified as banks, even if their main activity is not the typical commercial banking. So, for avoiding a subjective selection, we excluded all banks with an incidence of gross loans on total assets lower than 40%.

[d] The variables extracted from Orbis Bank Focus are Total transitional capital, Total assets, Bank deposits, Net loans and advances to banks. The assets PD is computed as in de Lisa *et al.* (2011), based on Total assets and Total risk-weighted assets — transitional or on some estimation of the latter based on CET1 value and ratio or on Tier1 value and ratio.

Table 1. Sample summary (average values).

	Banks number	Assets PD %	Total capital mn. €	Total assets mn. €	Interbank deposits mn. €	Interbank loans mn. €
2011	233	0.004897	797	11,181	1636	694
2013	233	0.003839	757	10,702	1458	634
2015	233	0.002983	768	10,898	1286	731
2017	233	0.002691	822	11,484	1660	1001

Table 2. Sample summary for 2017.

	Assets PD %	Total capital mn. €	Total assets mn. €	Interbank deposits mn. €	Interbank loans mn. €
Min	0.000340	5	29	0	1
1st quartile	0.001933	32	311	24	17
median	0.002481	61	703	81	41
3rd quartile	0.003226	137	1647	237	102
Max	0.007800	64,454	836,790	123,244	72,462

are variously asymmetric. Overall, the sample is sufficiently diversified to validate the correlation effect and to show its impact on different banking structures.

4.2. *Uniform variation of correlation across all banks*

As a first step, we analyzed the effect of correlation of banks' results on systemic risk.

In doing so, we firstly verified the effects of correlation on the selected banking system and then detailed its effect on single banks.

4.2.1. *System effects*

The first part of this analysis aims to verify the effect of different correlation levels on the whole system riskiness.

The Leave-One-Out simulation exercise is performed by uniformly setting the correlation to the common risk sources for all banks respectively to 40%, 50%, 60%, 70%, 80% and 90%. Theoretical statistics and literature report that more correlated shocks are expected to induce a lower number of crises, but more intense, and involving several banks at the same time. As previous literature (Zedda & Cannas 2020) reports that results are different for distinct crises dimension, we focused our analysis on cases when the financial stability is significantly threatened; therefore, we selected for the crises with a total loss of more than 10 bn. euro.

Our results, reported in Fig. 1, confirm that while the stand-alone risk contributions due to the risk of idiosyncratic defaults are not significantly affected by correlation, contagion risks are highly and progressively enhanced by correlation, confirming its role of catalyst to contagion.

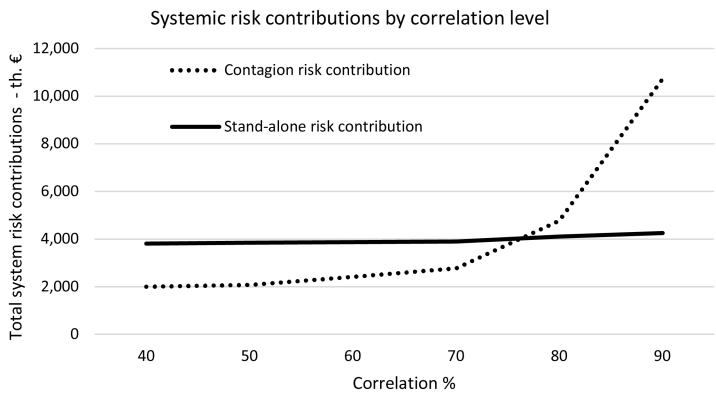Table 3 reports the same results in table form.

Fig. 1. Expected excess losses in case of crisis. Note that a higher correlation induces higher contagion risks.

Table 3. Leave-One-Out systemic risk contributions, by correlation level, th. €.

	$\rho = 40\%$	$\rho = 50\%$	$\rho = 60\%$	$\rho = 70\%$	$\rho = 80\%$	$\rho = 90\%$
Contagion risk contributions	1999	2076	2414	2775	4768	10,719
Stand-alone risk contributions	3813	3845	3874	3901	4107	4255
Total systemic risk contributions	5811	5921	6288	6676	8874	14,974

4.2.2. *Effects on single banks*

The stand-alone risk contributions, obtained without taking into account contagion effects, generate rather stable results as expected and already recorded for the entire system, with small variations, almost partially attributable to the uncertainty margin always present in Monte Carlo simulations.

It is instead interesting to analyze the effect of correlation on banks' risk contributions to contagion, which show very different results (see Appendix A for details), partially due to the different banks' dimensions, but also to other effects, as in the example presented in Table 4.

In this case, bank 62 reports the highest contagion risk contribution when the correlation level is set to 40%. However, as correlation increases, the difference from bank 133 lowers, and for a correlation of 90% is bank 133 the one reporting the higher contagion risk contribution.

Table 4. Contagion risk contribution, by bank, by correlation level, th. €.

	$\rho = 40\%$	$\rho = 50\%$	$\rho = 60\%$	$\rho = 70\%$	$\rho = 80\%$	$\rho = 90\%$
Bank 62	9.9	10.3	11.8	13.1	20.4	34.0
Bank 133	3.7	3.9	4.7	5.7	11.1	35.2

This effect can be explained by the different bank sensitivity to correlation, which brings bank 62 contributions to grow from 9.9 to 34, so around 3.5 times higher. In contrast, bank 133 sensitivity to correlation is substantially higher, bringing its contributions from 3.7 to 35.2, so 9.5 times higher.

What is less evident is why different banks are characterized by different sensitivity to correlation, and if these different effects mainly depend on the considered bank correlation to the common factor or on the (average) whole system correlation to it.

4.3. *Regression analysis*

To understand which variable influences the bank sensitivity to correlation, we performed the other 10 sets of simulations, setting different correlation levels for each bank. Furthermore, we computed a standard OLS regression on the simulated results (contagion risk contributions for each bank) in which the risk contribution of the i bank on simulation j, Sys_{ij}, is set as a dependent variable, and explained by the same bank correlation coefficient, corr_{ij}, multiplied by its sensitivity coefficient, β_i, and the average correlation of all the banks in the system $\mathrm{corr}_{\mathrm{avg}j}$, multiplied by its sensitivity coefficient, γ_i.

Thus, the regression is based on the following equation:

$$\mathrm{Sys}_{ij} = \alpha_i + \beta_i \mathrm{corr}_{ij} + \gamma_i \mathrm{corr}_{\mathrm{avg}j} + \varepsilon. \tag{4.1}$$

Results, as reported in Table 5, show that the average system correlation mainly influences each bank's risk contribution. The β_i coefficients are significant in just a small number of cases, and its average t-ratio is of 0.31. In contrast, the γ_i coefficients are almost always highly significant, reporting an average t-ratio of 4.37, evidencing that average correlation is more important than direct correlation in determining contagion risk contributions for the considered sample.

The subsequent analysis is devoted to test the relationship between the loans' incidence on total assets and the comprehensive income correlation. For doing this,

Table 5. Results of OLS regression of contagion risk contributions on correlation coefficients.

Percentile	β_i				γ_i				R^2
	Coeff.	Std. Error	t-ratio	p-value	Coeff.	Std. Error	t-ratio	p-value	
10	−5.73	0.96	−1.11	0.08	4.22	1.14	2.33	0.00	0.424
20	−2.96	1.62	−0.63	0.19	7.33	2.17	3.41	0.00	0.569
30	−0.80	2.46	−0.27	0.27	12.18	3.14	3.96	0.00	0.606
40	−0.03	3.48	−0.01	0.35	17.48	4.53	4.26	0.00	0.620
50	0.76	4.80	0.33	0.45	25.29	6.28	4.57	0.00	0.627
60	1.51	6.92	0.57	0.55	32.12	8.45	4.95	0.00	0.635
70	3.40	9.23	0.82	0.62	48.55	11.87	5.34	0.00	0.647
80	6.69	14.12	1.16	0.76	75.38	18.39	5.71	0.00	0.660
90	16.76	24.96	1.68	0.89	142.38	29.71	6.23	0.02	0.681
Average	*8.36*	*11.43*	*0.31*	*0.47*	*59.17*	*14.60*	*4.37*	*0.03*	*0.60*

Table 6. Regression of correlation of comprehensive income on the average loans share of total assets.

	Coefficient	Std. Error	t-ratio	p-value
Const	1.63091	0.155294	10.50	1.68e-21***
Loans/TA	−1.64826	0.237783	−6.932	3.75e-11***
R-squared	0.1656	Adjusted R-squared		0.1622

Notes: ***signals parameter significance at 1%, **significance at 5% and *significance at 10%.

we performed an OLS regression for testing the explanatory power of loans incidence on the different correlation levels of banks' comprehensive income (as detailed at the end of Sec. 3).

Results show that the comprehensive income correlation is significantly explained by the average loans share (Loans/TA, see Table 6), with a negative coefficient, meaning that the higher the loans incidence on total assets in the system, the lower the correlation.[e]

The same results are shown in Fig. 2, where the banks reporting a lower incidence of loans on total assets show a higher correlation coefficient, and *vice versa*, banks with a higher incidence of loans show lower, and even negative, correlation.

Fig. 2. Year-on-year correlation of comprehensive income and incidence of gross loans on total assets for a sample of 233 Italian banks.

[e] The regression values only show that correlation on banks' results and their loans share are correlated among them. However, it is essential to remind that the banks' assets often include long-term loans, so the previous years' investment choices significantly influence banks' results. Consequently, it can be reasonable to consider that correlation on results is more likely to be the effect of portfolio choices than vice versa.

Table 7. Regression of income correlation to banks input variables.

	Coefficient	Std. Error	t-ratio	p-value
Const	1.90637	0.219711	8.677	7.67e-16***
Loans/TA	−1.19701	0.326031	−3.671	0.0003***
Av_AssetsPD	−34.7904	21.5509	−1.614	0.1078
Log Av TA	−0.0329286	0.0171619	−1.919	0.0563*
R-squared	0.184	Adjusted R-squared		0.174

In order to consider the possible effect of dimension and assets riskiness on the previous outcome, we computed a robustness check including as control variables the average assets riskiness (in terms of its average Probability to Default, PD) and the logarithm of the average total assets value (from 2011 to 2017). Table 7 presents the results, which confirm the role of loan incidence as the main driver of the comprehensive income correlation, with a negative effect. Dimension just shows a significance at the lower level, while the riskiness of the assets is never significant.

Table 8. Regression of income correlation to banks' input variables.

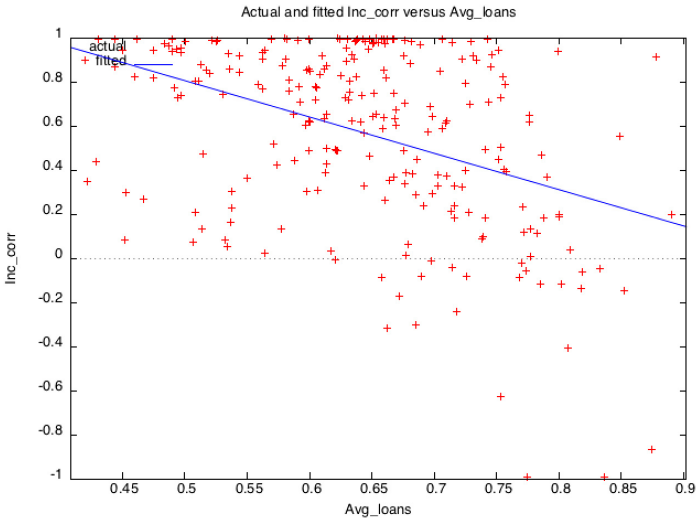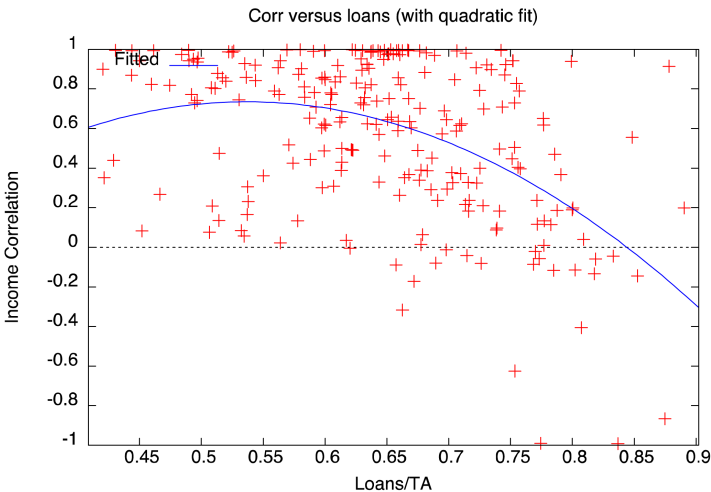|	Coefficient	Std. Error	t-ratio	p-value
Const	−1.20395	0.784951	−1.534	0.1265
Loans/TA	8.59422	2.39959	3.582	0.0004***
Sq_Loans/TA	−7.64316	1.85692	−4.116	5.39e-05***
Av_AssetsPD	−32.8636	20.8430	−1.577	0.1162
Log Av TA	−0.0297083	0.0166125	−1.788	0.0751*
R-squared	0.241	Adjusted R-squared		0.227

Fig. 3. Year-on-year correlation of comprehensive income and incidence of gross loans on total assets for a sample of 233 Italian banks with quadratic fit.

As a further test, we also included the income correlation squared values for testing for its nonlinear incidence.

Results presented in Table 8 and Fig. 3 show that the inclusion of the squared value of the loans incidence enhances the determination coefficient, incidentally lowering the significance of dimension.

5. Policy Implications

Macro-prudential regulation aims to reduce the systemic risk and its negative impact on the real economy in case of crises through instruments that mitigate the losses transmission role of the banks. Academic studies have already signaled the tendency towards the progressively increasing importance of the common risk sources in determining banking systems riskiness.

Consequently, the theme is very significant, raising the question of how it is possible to reduce systemic risks when interventions have to be taken at single bank level, that is to say, how to drive macro effects just intervening at the micro level. In this sense, the empirical analysis reported above can provide useful information to policy-makers to address macro-prudential regulation. On one hand, regarding simulation exercise results, we can notice that systemic risk increases significantly as banks' correlation with the common risk sources rises. On the other hand, the regression results suggest that the traditional lending activity, by decreasing the correlation of the results over banks, also reduces contagion risks.

In fact, our empirical research adds new information on the systemic risk evaluation and suggests a way to reduce it, which can be achieved by pushing banks to raise their share of loans on total assets. To this end, one significant possibility within the regulation tuning relies on the correction of capital requirements for credit risk, taking into account the negative effects of correlation on systemic risk.

Briefly, a reduction of risk weighting for loans, possibly balanced by symmetrical rising in the risk weighting of other and more correlated asset categories, can induce banks to devote a higher share of their assets to traditional lending. It goes in the same direction as the SME support factor[f] introduced by the European Commission in the recent update of the Basel regulatory framework.[g]

6. Conclusions

In the current macro-prudential regulation framework, policy-makers mainly focus on the role of interconnectedness in the stability of banking systems.

In this paper, we analyzed the role of traditional bank lending in terms of its effect on systemic risk, passing by its effect on banks' results correlation with common risk sources. Results show that systemic risk grows significantly as the correlation

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[f]It consists of a reduction factor for loans to small and medium enterprises of 0.7619. It aims to reduce capital requirements on exposures to firms with a turnover of below EUR 50 million.

[g]Art. 501, Regulation (EU) No 575/2013 (CRR).

between banks' results and common risk sources increases, and that banks devoting higher shares of their assets to traditional lending present a lower correlation with the common risk sources.

Regression results suggest that the effect of correlation is substantially neutral for each bank's stability as a single; they only show its effects on the contagion risk contributions, i.e. the risk for each bank to turn out a contagion vehicle within the system.

Interestingly, our empirical findings suggest that a higher loans' share on banks' total assets mitigates the crises propagation within the banking network and reduces, as a consequence, the systemic risk. This means that limiting the supervision of each bank stability as a single, as in the Basel II approach, or just considering systemic risk through the banks' interlinkages, as in Basel III, determines a significant lack of information and excludes one fundamental component of systemic risk.

Concerning policy implications, our empirical results imply that a banking regulation framework aimed to incentive the traditional lending activity can reduce systemic risk without a further increase of capitalization requirements, while contributing to an effective sustainment of the real economy.
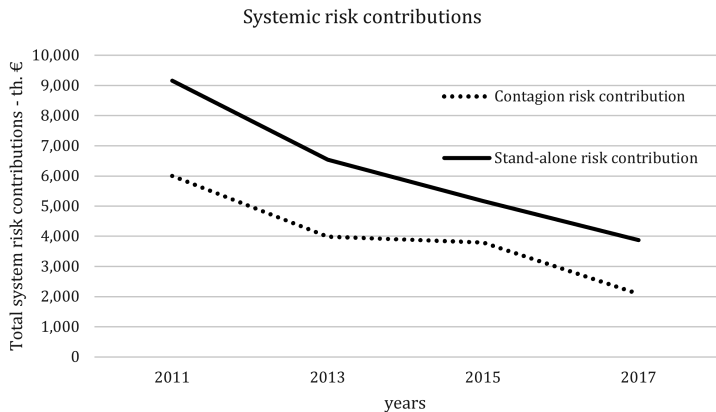
Appendix A.

Fig. A.1. Evolution of systemic risk contributions over time from 2011 to 2017.

Leave-One-Out **contagion** risk contributions, by correlation intensity, by bank.

Correlation %	90	80	70	60	50	40
Whole System risk	*10,719*	*4768*	*2775*	*2414*	*2076*	*1999*
Bank 1	643.5	249.4	128.2	104.7	84.6	80.2
Bank 2	441.4	188.3	100.2	82.1	67.4	64.1
Bank 3	352.1	159.0	86.4	71.4	59.2	56.3
Bank 4	299.2	139.7	77.2	64.2	53.7	51.2
Bank 5	261.8	125.5	70.2	58.8	49.5	47.3
Bank 6	274.4	120.1	65.3	54.5	45.8	43.8
Bank 7	238.4	108.5	60.5	50.9	43.0	41.2
Bank 8	195.2	98.3	56.4	47.8	40.6	38.9
Bank 9	180.3	91.9	53.1	45.2	38.4	36.8
Bank 10	167.8	86.4	50.2	42.8	36.5	35.0
Bank 11	157.0	81.6	47.7	40.8	34.8	33.4
Bank 12	147.1	77.4	45.5	38.9	33.2	31.9
Bank 13	138.4	73.0	43.4	37.2	31.8	30.5
Bank 14	132.1	70.1	41.6	35.8	30.6	29.4
Bank 15	130.6	67.3	39.9	34.3	29.4	28.2
Bank 16	116.8	65.4	39.4	34.0	29.0	27.8
Bank 17	108.9	58.9	36.1	31.4	27.0	25.9
Bank 18	109.5	59.2	35.6	30.8	26.5	25.4
Bank 19	111.4	57.0	34.3	29.7	25.6	24.5
Bank 20	100.8	55.0	33.2	28.9	24.8	23.8
Bank 21	97.2	53.1	32.2	28.0	24.1	23.1
Bank 22	92.6	51.2	31.1	27.1	23.4	22.4
Bank 23	90.1	49.6	30.2	26.4	22.7	21.8
Bank 24	86.9	48.0	29.3	25.6	22.1	21.2
Bank 25	84.0	46.6	28.5	24.9	21.5	20.6
Bank 26	81.5	45.2	27.7	24.3	20.9	20.1
Bank 27	78.0	43.8	26.9	23.6	20.4	19.6
Bank 28	75.6	42.6	26.2	23.0	19.9	19.1
Bank 29	74.0	41.4	25.5	22.4	19.4	18.6
Bank 30	72.0	40.3	24.9	21.9	18.9	18.2
Bank 31	69.8	39.2	24.3	21.4	18.5	17.8
Bank 32	66.8	38.1	23.6	20.8	18.0	17.3
Bank 33	65.5	37.2	23.1	20.4	17.6	17.0
Bank 34	63.0	36.2	22.5	19.9	17.2	16.6
Bank 35	66.0	35.5	22.0	19.5	16.8	16.2
Bank 36	61.1	34.6	21.6	19.1	16.5	15.9
Bank 37	59.4	33.8	21.1	18.7	16.2	15.6
Bank 38	57.9	33.0	20.6	18.3	15.8	15.2
Bank 39	56.5	32.2	20.2	17.9	15.5	14.9
Bank 40	54.5	31.5	19.7	17.5	15.2	14.6
Bank 41	48.3	29.5	19.0	17.0	14.8	14.2
Bank 42	52.8	30.2	18.9	16.8	14.6	14.1
Bank 43	51.4	29.5	18.6	16.5	14.3	13.8
Bank 44	50.6	28.9	18.2	16.2	14.1	13.5
Bank 45	48.5	28.3	17.8	15.9	13.8	13.3
Bank 46	48.1	27.7	17.5	15.6	13.5	13.0
Bank 47	48.5	27.1	17.1	15.3	13.3	12.8
Bank 48	45.3	26.6	16.8	15.0	13.0	12.6

(*Continued*)

Correlation % *Whole System risk*	90 *10,719*	80 *4768*	70 *2775*	60 *2414*	50 *2076*	40 *1999*
Bank 49	45.1	26.1	16.5	14.7	12.8	12.4
Bank 50	44.1	25.6	16.2	14.5	12.6	12.1
Bank 51	43.1	25.0	15.9	14.2	12.4	11.9
Bank 52	42.9	24.6	15.6	14.0	12.2	11.7
Bank 53	462.0	79.3	26.5	20.9	19.3	18.5
Bank 54	40.0	23.6	15.0	13.5	11.7	11.3
Bank 55	39.2	23.2	14.8	13.2	11.5	11.1
Bank 56	39.6	22.8	14.5	13.0	11.3	10.9
Bank 57	39.2	22.4	14.3	12.8	11.2	10.8
Bank 58	37.7	22.0	14.0	12.6	11.0	10.6
Bank 59	36.9	21.6	13.8	12.4	10.8	10.4
Bank 60	37.2	21.2	13.5	12.2	10.6	10.3
Bank 61	35.5	20.7	13.3	11.9	10.4	10.1
Bank 62	34.0	20.4	13.1	11.8	10.3	9.9
Bank 63	35.9	20.2	12.9	11.6	10.1	9.8
Bank 64	32.9	19.7	12.7	11.4	10.0	9.6
Bank 65	32.2	19.4	12.5	11.2	9.8	9.5
Bank 66	40.3	19.3	11.7	10.5	9.2	9.0
Bank 67	31.8	18.8	12.1	10.9	9.5	9.2
Bank 68	32.0	18.5	11.9	10.7	9.4	9.0
Bank 69	30.6	18.1	11.7	10.5	9.2	8.9
Bank 70	29.1	17.8	11.5	10.4	9.1	8.8
Bank 71	31.0	17.5	11.3	10.2	8.9	8.6
Bank 72	28.4	17.2	11.1	10.1	8.8	8.5
Bank 73	28.7	17.1	11.0	9.9	8.7	8.4
Bank 74	28.8	16.7	10.8	9.8	8.6	8.3
Bank 75	28.1	16.3	10.6	9.6	8.4	8.1
Bank 76	27.1	16.2	10.5	9.5	8.3	8.0
Bank 77	27.6	15.9	10.3	9.3	8.1	7.9
Bank 78	26.7	15.7	10.2	9.2	8.1	7.8
Bank 79	26.1	15.5	10.0	9.1	8.0	7.7
Bank 80	24.9	14.8	9.8	8.9	7.8	7.6
Bank 81	449.0	74.8	24.6	21.1	14.7	14.4
Bank 82	24.5	14.7	9.5	8.7	7.6	7.4
Bank 83	26.1	14.6	9.4	8.5	7.5	7.3
Bank 84	23.8	14.3	9.3	8.4	7.4	7.2
Bank 85	25.4	14.2	9.1	8.3	7.3	7.1
Bank 86	23.0	13.8	9.0	8.2	7.2	7.0
Bank 87	23.7	13.6	8.9	8.0	7.1	6.9
Bank 88	21.8	13.4	8.7	7.9	7.0	6.8
Bank 89	22.0	13.2	8.6	7.8	6.9	6.7
Bank 90	21.7	13.1	8.5	7.7	6.8	6.6
Bank 91	21.7	12.8	8.3	7.6	6.7	6.5
Bank 92	20.3	12.5	8.2	7.5	6.6	6.4
Bank 93	22.2	12.4	8.1	7.4	6.5	6.3
Bank 94	20.1	12.2	8.0	7.3	6.4	6.2
Bank 95	20.2	12.0	7.9	7.2	6.3	6.1
Bank 96	20.9	11.9	7.8	7.1	6.2	6.0
Bank 97	45.4	13.2	7.7	6.9	6.1	5.9
Bank 98	19.0	11.5	7.5	6.9	6.1	5.9

(*Continued*)

| Correlation % | 90 | 80 | 70 | 60 | 50 | 40 |
Whole System risk	*10,719*	*4768*	*2775*	*2414*	*2076*	*1999*
Bank 99	21.9	10.9	7.5	6.7	5.9	5.7
Bank 100	17.7	11.1	7.3	6.7	5.9	5.7
Bank 101	17.7	11.0	7.2	6.6	5.8	5.6
Bank 102	18.0	10.9	7.1	6.5	5.7	5.6
Bank 103	17.6	10.7	7.0	6.4	5.7	5.5
Bank 104	17.6	10.5	6.9	6.3	5.6	5.4
Bank 105	18.2	10.4	6.8	6.2	5.5	5.3
Bank 106	19.2	10.3	6.7	6.1	5.4	5.3
Bank 107	17.8	10.1	6.6	6.0	5.3	5.2
Bank 108	16.2	9.9	6.5	6.0	5.3	5.1
Bank 109	54.3	11.1	6.3	5.5	5.0	4.8
Bank 110	15.2	9.6	6.3	5.8	5.1	5.0
Bank 111	20.6	9.7	6.2	5.7	5.0	4.9
Bank 112	15.2	9.3	6.1	5.6	5.0	4.8
Bank 113	15.0	9.2	6.1	5.6	4.9	4.8
Bank 114	14.9	9.1	6.0	5.5	4.8	4.7
Bank 115	15.8	8.9	5.8	5.4	4.7	4.6
Bank 116	13.4	8.7	5.8	5.3	4.7	4.6
Bank 117	14.4	8.7	5.7	5.2	4.6	4.5
Bank 118	13.3	8.5	5.6	5.2	4.6	4.4
Bank 119	16.8	8.6	5.6	5.0	4.5	4.3
Bank 120	12.1	8.1	5.4	5.0	4.4	4.3
Bank 121	13.0	8.1	5.4	4.9	4.4	4.2
Bank 122	14.5	8.0	5.3	4.9	4.3	4.2
Bank 123	12.9	7.9	5.2	4.8	4.3	4.1
Bank 124	13.1	7.8	5.1	4.7	4.2	4.1
Bank 125	13.2	7.7	5.1	4.7	4.1	4.0
Bank 126	12.2	7.5	5.0	4.6	4.1	4.0
Bank 127	13.7	7.5	4.9	4.5	4.0	3.9
Bank 128	14.6	7.9	4.8	4.5	3.9	3.8
Bank 129	12.1	7.2	4.8	4.4	3.9	3.8
Bank 130	14.7	8.0	4.7	4.3	3.8	3.7
Bank 131	11.3	7.0	4.6	4.3	3.8	3.7
Bank 132	11.5	6.9	4.6	4.2	3.7	3.6
Bank 133	35.2	11.1	5.7	4.7	3.9	3.7
Bank 134	10.7	6.7	4.4	4.1	3.6	3.5
Bank 135	11.2	6.6	4.4	4.0	3.6	3.5
Bank 136	10.3	6.4	4.3	4.0	3.5	3.4
Bank 137	12.3	6.5	4.2	3.9	3.4	3.3
Bank 138	9.3	6.2	4.1	3.8	3.4	3.3
Bank 139	9.9	6.2	4.1	3.8	3.3	3.3
Bank 140	11.5	6.8	4.0	3.7	3.3	3.2
Bank 141	12.4	6.1	4.0	3.7	3.2	3.2
Bank 142	9.4	5.8	3.9	3.6	3.2	3.1
Bank 143	9.4	5.8	3.8	3.5	3.2	3.1
Bank 144	10.4	5.8	3.8	3.5	3.1	3.0
Bank 145	8.6	5.6	3.7	3.4	3.0	3.0
Bank 146	11.9	5.2	3.6	3.3	3.0	2.9
Bank 147	8.6	5.4	3.6	3.3	3.0	2.9
Bank 148	8.9	5.3	3.5	3.3	2.9	2.8

(*Continued*)

Correlation % *Whole System risk*	90 *10,719*	80 *4768*	70 *2775*	60 *2414*	50 *2076*	40 *1999*
Bank 149	10.3	5.3	3.5	3.2	2.9	2.8
Bank 150	8.7	5.2	3.4	3.2	2.8	2.7
Bank 151	9.5	5.3	3.4	3.1	2.8	2.7
Bank 152	7.6	5.0	3.3	3.1	2.7	2.7
Bank 153	8.3	4.9	3.2	3.0	2.7	2.6
Bank 154	6.9	4.7	3.2	3.0	2.6	2.6
Bank 155	9.1	4.7	3.1	2.9	2.6	2.5
Bank 156	9.8	4.8	3.1	2.8	2.5	2.5
Bank 157	7.3	4.5	3.0	2.8	2.5	2.4
Bank 158	7.4	4.5	3.0	2.8	2.5	2.4
Bank 159	7.1	4.4	2.9	2.7	2.4	2.4
Bank 160	8.2	5.1	2.9	2.7	2.4	2.3
Bank 161	11.0	4.5	2.8	2.6	2.3	2.3
Bank 162	6.7	4.1	2.8	2.6	2.3	2.2
Bank 163	5.8	4.0	2.7	2.5	2.2	2.2
Bank 164	6.2	4.0	2.6	2.5	2.2	2.1
Bank 165	5.8	3.9	2.6	2.4	2.2	2.1
Bank 166	7.9	3.9	2.6	2.4	2.1	2.1
Bank 167	−6.4	1.1	1.4	1.5	1.5	1.5
Bank 168	60.3	7.9	2.7	1.6	1.5	1.5
Bank 169	5.5	3.6	2.4	2.2	2.0	1.9
Bank 170	6.6	3.5	2.4	2.2	2.0	1.9
Bank 171	5.7	3.4	2.3	2.1	1.9	1.9
Bank 172	5.7	3.4	2.3	2.1	1.9	1.8
Bank 173	4.5	3.3	2.2	2.1	1.8	1.8
Bank 174	5.0	3.3	2.2	2.0	1.8	1.8
Bank 175	5.1	3.2	2.1	2.0	1.8	1.7
Bank 176	5.5	3.1	2.1	1.9	1.7	1.7
Bank 177	5.5	3.1	2.0	1.9	1.7	1.7
Bank 178	4.8	3.0	2.0	1.9	1.7	1.6
Bank 179	4.9	2.9	2.0	1.8	1.6	1.6
Bank 180	5.8	2.9	1.9	1.8	1.6	1.5
Bank 181	3.7	2.7	1.9	1.7	1.5	1.5
Bank 182	10.4	3.7	1.9	1.7	1.5	1.5
Bank 183	4.4	2.6	1.8	1.7	1.5	1.5
Bank 184	4.1	2.6	1.7	1.6	1.4	1.4
Bank 185	3.2	2.5	1.7	1.6	1.4	1.4
Bank 186	−48.3	−0.4	1.1	0.8	0.5	0.5
Bank 187	5.0	2.4	1.6	1.5	1.4	1.3
Bank 188	3.4	2.4	1.6	1.5	1.3	1.3
Bank 189	2.9	2.3	1.5	1.4	1.3	1.3
Bank 190	3.5	2.2	1.5	1.4	1.2	1.2
Bank 191	44.6	2.9	−0.2	−0.6	−0.3	−0.1
Bank 192	3.4	2.1	1.4	1.3	1.2	1.1
Bank 193	4.7	2.1	1.4	1.3	1.1	1.1
Bank 194	2.7	1.9	1.3	1.2	1.1	1.1
Bank 195	4.1	2.0	1.3	1.2	1.1	1.0
Bank 196	3.1	1.9	1.3	1.2	1.0	1.0
Bank 197	2.6	1.8	1.2	1.1	1.0	1.0
Bank 198	55.0	5.8	1.0	0.7	0.6	0.6

(*Continued*)

Correlation % *Whole System risk*	90 *10,719*	80 *4768*	70 *2775*	60 *2414*	50 *2076*	40 *1999*
Bank 199	−33.0	−4.0	−0.6	−0.1	0.2	0.2
Bank 200	2.5	1.6	1.1	1.0	0.9	0.9
Bank 201	131.9	11.7	−0.2	−0.6	−0.2	−0.1
Bank 202	3.3	1.5	1.0	1.0	0.9	0.8
Bank 203	12.3	1.7	1.0	0.9	0.8	0.8
Bank 204	1.8	1.4	1.0	0.9	0.8	0.8
Bank 205	2.1	1.4	0.9	0.9	0.8	0.8
Bank 206	175.5	15.4	0.6	−1.0	−0.6	−0.4
Bank 207	51.1	6.1	1.7	0.9	0.7	0.8
Bank 208	2.4	1.2	0.8	0.8	0.7	0.7
Bank 209	8.8	2.0	1.0	0.7	0.6	0.6
Bank 210	1.7	1.1	0.8	0.7	0.6	0.6
Bank 211	2.5	1.1	0.8	0.6	0.6	0.6
Bank 212	1.8	1.0	0.7	0.6	0.6	0.6
Bank 213	40.7	3.8	0.2	0.1	0.1	0.2
Bank 214	4.1	0.7	0.6	0.5	0.5	0.5
Bank 215	0.1	0.7	0.5	0.5	0.5	0.5
Bank 216	1.3	0.8	0.5	0.5	0.5	0.5
Bank 217	1.2	0.8	0.5	0.5	0.4	0.4
Bank 218	23.1	2.9	0.1	0.0	0.1	0.0
Bank 219	41.3	6.1	0.9	0.2	0.1	0.1
Bank 220	0.9	0.6	0.4	0.4	0.4	0.4
Bank 221	14.1	−0.1	0.0	0.0	0.1	0.1
Bank 222	68.3	3.3	−0.3	−0.4	−0.3	−0.2
Bank 223	129.8	16.0	1.0	−0.3	−0.5	−0.5
Bank 224	3.9	1.0	0.3	0.2	0.2	0.2
Bank 225	−0.5	0.3	0.2	0.2	0.2	0.2
Bank 226	7.3	0.8	0.3	0.2	0.2	0.2
Bank 227	3.5	0.7	0.3	0.2	0.1	0.1
Bank 228	0.4	0.3	0.2	0.2	0.1	0.1
Bank 229	314.9	33.9	4.9	1.4	0.4	0.2
Bank 230	0.8	0.2	0.1	0.1	0.1	0.1
Bank 231	50.4	4.4	0.6	0.0	0.0	0.0
Bank 232	3.1	0.4	0.1	0.1	0.0	0.0
Bank 233	−0.6	0.0	0.0	0.0	0.0	0.0

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