Do Buffer Requirements for European Systemically Important Banks Make Them Less Systemic?*

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With a panel data model for a sample of listed European banks, we demonstrate that capital requirements for systemically important institutions (SIIs) effectively reduce the perceived systemic risk of these institutions, which we proxy with the SRISK indicator in Brownlees and Engle (2017). We also study the impact of the adjustment mechanisms that banks use to comply with SII requirements. The results show that banks mainly respond to higher SII buffers by increasing their equity. Once we control for the options SIIs employ to fulfill these requirements and SII characteristics, we find a residual effect of having SII status.

JEL Codes: C54, E58, G21, G32.

1. Introduction

The Global Financial Crisis (GFC) made systemic risk a central topic of research and policy. Systemic risk can be analyzed either in its time/cyclical dimension or in its cross-sectional/structural dimension (see European Systemic Risk Board 2013).[1] In this paper

*We thank Ángel Estrada, David Martínez-Miera, Javier Mencía, Carlos Pérez Montes, and seminar participants at the Banco de España for their helpful comments. The opinions expressed in this paper are solely the responsibility of the authors and do not represent the views of the Banco de España. Author e-mails: carmen.broto@bde.es, luisg.fernandez@bde.es, mariya.melnychuk@bde.es@bde.es.

[1]Whereas the time dimension is related to the buildup of risks over time and the procyclical accumulation of financial vulnerabilities, the structural dimension of systemic risk focuses on how a specific shock to the financial system can spread and become systemic (International Monetary Fund 2011).

we focus on this second dimension of systemic risk, specifically on systemically important institutions (SIIs). The GFC evidenced that the failure of these large and complex banks could spill over into the whole financial sector and also harm the real economy. For this reason, these SIIs can be considered to be "too big to fail" and could engage in moral hazard behavior (see Stern and Feldman 2004), so that during boom periods these institutions could have incentives to take excessive risks, as they expect to receive support during crisis episodes. These SII characteristics justify the adoption of specific policy measures.

To address this competitive advantage of SIIs and the associated risk that they create, the Basel Committee on Banking Supervision (BCBS) launched in 2011 its framework for dealing with systemically important banks, with new additional capital requirements with a macroprudential focus (see BCBS 2011).[2] The rationale behind these additional capital buffers for SIIs was precisely to account for the negative externalities stemming from their size and interconnectedness, as well as to increase their resilience and loss-absorbing capacity. Namely, there are two possible structural buffers to address SIIs' particularities: (i) the capital requirements for global systemically important institutions (G-SIIs), which are systemically relevant institutions at the global level,[3] and (ii) the requirements for other systemically important institutions (O-SIIs), which are institutions that are more likely to create risks to financial stability at the national level.[4] In Europe, the region that constitutes the focus of our analysis, G-SIIs are also O-SIIs, and the higher of the two buffers is applied.[5] Additionally, under the CRD IV, the systemic risk buffer

[2]The BCBS framework was implemented in the European Union (EU) with the transposition of Capital Requirements Directive 2013/36/EU (CRD IV), which entered into force in 2013.

[3]Since 2011 the Financial Stability Board (FSB) identifies the list of G-SIIs annually in consultation with the BCBS (see BCBS 2013). The G-SII buffers were first activated in 2016.

[4]Since 2014, O-SIIs are annually selected in accordance with the European Banking Authority (EBA) guidelines (see EBA 2014). These lists and corresponding buffers are revised annually by the national regulatory authorities and communicated to the ESRB, and also submitted to and disclosed by the EBA. O-SII buffers became active in 2016.

[5]The criteria for identifying SIIs, both G-SIIs and O-SIIs, follow an indicator-based measurement approach that takes into account five dimensions of systemic

(SyRB) aims to tackle systemic risks of a long-term structural and non-cyclical nature that are not covered by the CRR.[6] Henceforth, we use the term "SII buffer" to refer to the buffer applicable to SIIs, which is a combination of the O-SII, G-SII, and SyRB capital requirements, depending on the institution and country.[7]

Most of the literature on the effect of higher capital requirements on banks' performance analyzes their impact in general, not that of the SII buffer in particular. These papers tend to conclude that under tighter capital requirements, banks reduce their risk-weighted assets and cut lending in the short run—see, for instance Aiyar, Calomiris, and Wieladek (2014, 2016), Bridges et al. (2014), Gropp et al. (2019), and Mayordomo and Rodríguez-Moreno (2020), among others. However, in the long run capital buffers smooth credit supply cycles and have a positive effect on firm-level aggregate financing and performance (see Drehmann and Gambacorta 2012 and Jiménez et al. 2017).

There is little empirical evidence on the specific impact of SII capital buffers. For instance, there is some literature on the effect of the activation of SII buffers on lending—see Cappelletti et al. (2019, 2020).[8] Additionally, a few studies analyze the impact of SII buffers on banks' solvency and, separately, on the financial markets' response. For instance, Dautović (2020) concludes that an increase in SII buffers was associated with increases in both common equity

importance, namely size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity.

[6]CRR: Capital Requirements Regulation (EU) No. 575/2013. See Article 133 of the CRD IV for further details. Unlike the G-SII and O-SII buffers, the SyRB is an EU instrument beyond the Basel III Framework. It aims to address the risks stemming from structural features that have the potential to amplify shocks and losses such as high indebtedness, interconnectedness, or exposure to common shocks, among others. CRD IV sets out the rules to accumulate this buffer with the G-SII and O-SII buffer rates.

[7]The BCBS calls these two capital requirements the global systemically important bank (G-SIB) buffer and the domestic systemically important bank (D-SIB) buffer, instead of the EU denomination (i.e., G-SII for G-SIB and O-SII for D-SIB)—see BCBS (2012). In this paper we use the latter.

[8]Cappelletti et al. (2019) find that O-SIIs reduce lending to household and financial sectors in the short term, while in the medium term the effect is much smaller and heterogeneous. However, Cappelletti et al. (2020) suggest that O-SIIs curtail lending to credit institutions the most, leaving loan supply to non-financial corporations (NFCs) almost unchanged.

tier 1 (CET1) capital levels and the average risk weights of the asset portfolio.[9] Regarding the impact of SII announcements on financial markets, the empirical evidence suggests that higher capital requirements lead to lower stock prices and credit default swap (CDS) spread increases, although this market response is temporary—see Andrieş et al. (2020) and Gündüz (2020).

The literature on the effect of capital requirements on systemic risk is even scarcer. As far as we know, only Bostandzic et al. (2022) analyze the impact of higher capital requirements on a set of systemic risk measures. These authors use the 2011 EBA capital exercise to conclude that one-off capital increases deteriorate a set of market-based measures of systemic risk. However, SII buffers, which were gradually phased in from 2014, are out of the scope of this analysis. That is, to date, the effectiveness of SII buffers at lowering their systemic risk is still an open question, although this instrument was designed to address the systemic risk posed by these large and interconnected institutions.

Our paper has a dual objective. First, we analyze whether higher capital buffers for SIIs reduce their contribution to systemic risk. For this purpose, we fit a panel data model with fixed effects for all listed European banks, be they SIIs or not. The dependent variable is an indicator that quantifies systemic risk, namely the SRISK indicator in Brownlees and Engle (2017). This metric can be easily computed with publicly available bank- and market-based data. Like other market-based measures, SRISK is available at high frequencies and can be calculated for listed institutions only.[10]

Second, we analyze the impact of the adjustment mechanisms that banks employ to comply with SII buffers on their contribution to systemic risk. Understanding which of these mechanisms dominates banks' behavior toward increases in SII capital requirements is central to evaluating the implications of SII buffers. Broadly speaking, in response to higher capital requirements, banks have four

[9]The findings in Dautović (2020) suggest that banks comply with the regulation by raising equity capital, but at the same time reallocate their portfolio toward riskier assets, thus the overall net effect on solvency is unclear.

[10]Since the GFC, the literature on market-based measures to gauge systemic risk has grown. See Bisias et al. (2012) and Benoit et al. (2017) for two surveys.

main options at their disposal (see Bank for International Settlements 2012, Cohen and Scatigna 2016, and Braouezec and Kiani 2021).[11] Namely, a bank can either (i) issue new equity; (ii) increase its retained earnings; (iii) run down its assets; or (iv) reduce its risk-weighted assets. However, these alternatives have associated costs. For instance, new share issuance might be very costly for banks in the context of EU banks' historically low valuations, especially after the GFC. On the other hand, the retained earnings strategy would be more favorable from a regulator's perspective, but, as in the case of lowering dividends, it might take many years to increase the capital ratio and might lead to negative reaction from investors. Also, if banks' response to the higher requirements is to run down their assets, lending to the real sector could be negatively affected (see Gropp et al. 2019). Finally, shifting the composition of assets toward lower risk-weighted exposures could decrease expected profitability (see Bostandzic et al. 2022).

According to our results, SII buffers do decrease European banks' contribution to systemic risk in the medium term. Furthermore, we find that this effect is partially driven by the increase in banks' equity, and, contrary to Dautović (2020), we do not find evidence that banks take more risks. From a financial stability perspective, this is an important implication that suggests that banks respond to SII buffers as intended. Finally, once we control for the adjustment mechanisms that banks use to comply with the SII buffer, the residual effect of having SII status on perceived systemic risk is still negative and significant. This outcome implies that being an SII provides a positive signal to markets, which further reduces the institution's contribution to systemic risk.

The remainder of the paper is organized as follows. Section 2 describes how we quantify the contribution of a bank to systemic risk by means of the SRISK measure. Section 3 details our data set. Section 4 then describes the empirical model to analyze the relationship between buffers and systemic risk, and Section 5 summarizes the main results. Finally, Section 6 contains our conclusions.

[11] These four possible responses to higher requirements entail the assumption of a constant score, which is the indicator-based measurement that represents its systemic riskiness.

2. SRISK: A Systemic Risk Indicator for Banks

The concept of systemic risk is very complex to capture in a unique framework (see Hansen 2014). In this paper we focus on market-based metrics of systemic distress that allow us to explore the systemic importance of individual banks. Since the GFC, the literature that analyzes such metrics has significantly increased. Broadly speaking, these indicators can be classified into two groups. The first one consists of those metrics that are purely market based, such as the conditional autoregressive value-at-risk (VaR) in Engle and Manganelli (2004), and the ΔCoVaR in Adrian and Brunnermeier (2016), among others. The second set of indicators comprise those metrics that use balance sheet data in addition to market information, such as the marginal expected shortfall (MES) and the systemic expected shortfall (SES) in Acharya et al. (2017) and the SRISK in Brownlees and Engle (2017). We focus on this second type of metrics that associate systemic risk with the capital shortfall of the financial system conditional on the materialization of a systemic event.[12]

More specifically, our dependent variable is systemic risk as proxied by the SRISK indicator in Brownlees and Engle (2017). SRISK is inspired by the SES index in Acharya et al. (2017). Thus, SRISK associates the systemic risk contribution of an institution i with its expected capital shortfall conditional on a severe market downturn. The capital shortfall in t, CS_{it}, is the difference between the market value of equity and a prudential fraction k of the market value of the institution's assets, that is,

$$CS_{it} = k(D_{it} + MV_{it}) - MV_{it}, \tag{1}$$

where D is the book value of total liabilities, MV is the market value of equity, and k is the prudential capital ratio, which is the percentage of total assets that the financial institution holds as reserves

[12] While ΔCoVaR measures the VaR of the financial system conditional on an event affecting a specific bank, SRISK and MES are conditioned by a shock throughout the entire system. Accordingly, the direction of ΔCoVaR is from individual distress to the system, while MES and SRISK measure how much a given financial institution is undercapitalized when the whole financial system is undercapitalized.

because of regulation or prudential management.[13] Brownlees and Engle (2017) define SRISK as the conditional expectation of the future CS in the case of a systemic event, i.e., how much an institution's equity drops below a given fraction of its assets, when there is a crisis affecting the whole financial system, that is,

$$SRISK_{it} = E_t \left[CS_{i,t+h} \mid R_{m,t+1:t+h} < C \right], \tag{2}$$

where $R_{m,t+1:t+h}$ represents the market return between $t+1$ and $t+h$, and C a threshold of market decline over time horizon h, defining a crisis, so that $R_{m,t+1:t+h} < C$ corresponds to the systemic event.

If we assume, like in Brownlees and Engle (2017), that the book value of the bank's liabilities remains fixed during the hypothetical systemic event, this expected capital shortfall can be expressed in terms of the firm equity return conditional on the systemic event, the long-run marginal expected shortfall (LRMES), that is,

$$SRISK_{it} = k(D_{it} + MV_{it}(1 - LRMES_{it})) - MV_{it}(1 - LRMES_{it}), \tag{3}$$

where $LRMES$ denotes the expected drop in the equity value of an institution i when the market falls below a threshold C within time horizon h,

$$LRMES_{it} = -E_t \left[R_{i,t+1:t+h} \mid R_{m,t+1:t+h} < C \right]. \tag{4}$$

$LRMES$, as defined in (4) is non-observable. Following Brownlees and Engle (2017), we estimate $LRMES$ with a dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) model (see Engle 2002, 2009). For further details on the $LRMES$ estimation, see Appendix A.

SRISK has at least four properties that make this indicator an appropriate choice to measure systemic risk. First, it explicitly depends on the size and the degree of leverage of an institution. Second, SRISK can be easily computed with publicly available data.

[13] Brownlees and Engle (2017) call "quasi assets" the sum of book value of liabilities, D, and market value of equity, MV.

Third, as this indicator is also based on market data, it can be available at high frequencies, so that sudden shifts in systemic risk can be detected quickly.[14] Finally, SRISK is a forward-looking measure, as it signals the degree of systemic risk that has not yet materialized, but such risk could lead to economic losses in the event of a severe financial market downturn. However, like other market-based measures, SRISK can only be calculated for listed institutions.[15] Despite its limitations, SRISK is broadly used for empirical purposes by both policymakers and academics.[16]

3. Data and Variables

To test the implications in terms of systemicity of the implementation of SII buffers, we analyze a panel data set of listed banks from 24 European countries. The data set is quarterly and the sample period runs from 2008:Q1 to 2021:Q3.[17] The inclusion of 2020 data in the sample poses sizable challenges, given the sharp changes in a number of variables from the onset of the pandemic that considerably affect the estimates. Our approach to address this issue is to analyze the data set for the complete sample and also for two subsamples: the one that runs from 2008:Q1 to 2019:Q4 and the subsample that corresponds to the pandemic period, from 2020:Q1 to 2021:Q3. As the pandemic represents an exogenous shock independent of the financial cycle, focusing on the first subsample allows us to disentangle the effect of SII buffers in normal times. Specifically, the outbreak of COVID-19 led to an abrupt decrease in banks' market valuations,

[14] While the value of debt is usually available at quarterly frequencies, the market value and the LRMES can be updated daily, which allows us to capture short-term dynamics.

[15] Another limitation of SRISK is that it only reflects the markets' perception on an institution, so that this measure does not allow us to disentangle different risk factors (e.g., contagion, liquidity, solvency, funding, fire sales, etc.). That is, it is less informative than a fully fledged stress test.

[16] See, for instance, Tavolaro and Visnovsky (2014), Grinderslev and Kristiansen (2016), Coleman, LaPlante, and Rubtsov (2018), Engle and Ruan (2019), Bats and Houben (2020), or Brownlees et al. (2020) for some empirical works based on the SRISK indicator.

[17] To minimize the data gaps, especially at the beginning of the sample period where only annual or half-yearly data are available for some banks, we linearly interpolate the missing data to proxy quarterly series.

which held SRISK at historically high levels in 2020:Q1, close to the levels during the 2012 European sovereign debt crisis and above the levels of the 2008–09 Global Financial Crisis.[18] Also, the severity of the shock and the lack of alternative buffers led several countries to release the SII requirements in full or in part in 2020:Q2 as an immediate alternative available to ease the regulatory pressure on their credit institutions.[19]

Our total sample consists of 168 different banks. As Figure 1 shows, since 2008:Q1, when the number of banks was 82, this amount has gradually increased to reach a maximum of 158 banks in 2020:Q1. Subsequently, our sample decreases to 127 banks in 2021:Q3.[20] This sample is fairly representative and accounts for about 80 percent of total EU banks' assets.[21] Our sample consists of all publicly traded European banks reported by Refinitiv Datastream. More specifically, we compare the group of 14 and 52 banks in our sample that have been classified as G-SIIs and O-SIIs, respectively, at any time, and a control group of 102 banks that have never become an SII.[22] We assume that a bank's country is that of its primary listing where its stock is traded. Appendix B details the complete list of banks.

The dependent variable is the systemic risk of each bank as proxied by the SRISK indicator in Brownlees and Engle (2017), which we call $SRISK$, as shown in (3). To compute $SRISK$ we exploit both balance sheet and market data. Regarding balance sheet data, we use total liabilities at the consolidated level. Market data are also at the consolidated level and consist of the market value (MV)

[18]This increase in SRISK was the result of the higher uncertainty around the course of the pandemic that resulted in a sharp decline in stock market performance.

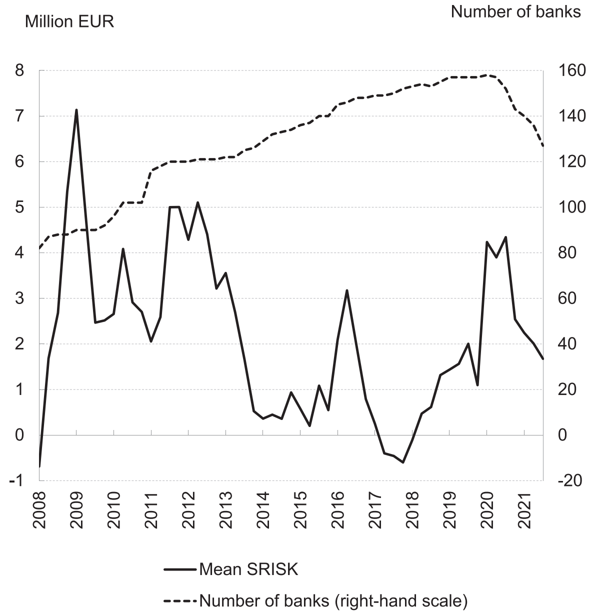
[19]Specifically, Estonia, Finland, Hungary, the Netherlands, and Poland fully or partially released their SII buffers in 2020:Q2. In addition, Cyprus, Greece, Lithuania, Malta, and Portugal postponed the phasing-in of planned O-SII buffers increases by one year (see ESRB 2021).

[20]Not all the banks in the sample continue over the entire period, either because of failures or mergers and acquisitions. This fact explains the gap between the total number of different banks and its peak reached in one quarter.

[21]This evidence is based on the total consolidated assets in 2020 (European Central Bank Statistical Data Warehouse).

[22]Out of these 66 SIIs, 50 are always SIIs (either O-SIIs or G-SIIs) throughout the sample period, while 16 banks have changed their status at any time.

Figure 1. Mean *SRISK* and Number of Banks



Note: Mean *SRISK* and number of banks (right-hand scale) for a panel of 168 European listed banks.

of each bank and the STOXX Europe 600 stock market index. We chose this index as the market index required to calculate LRMES in (4), as shown in Appendix A. We assume that the parameters to compute $SRISK$ in (4) are $k = 4.5\%$ for the capital requirement, $C = 10$ for the market decline threshold, and $h = 22$ business days for the period over which the hypothetical market decline occurs.[23] We calculate $SRISK$ for each listed bank with our own codes.[24]

[23] After several robustness tests, we assume k to be equal to the minimum CET1 ratio in accordance with the Basel III minimum own funds requirement (Pillar 1). In our specification, C and h have the same values as in Brownlees and Engle (2017), while they assume $k = 5.5$.

[24] Our MATLAB codes to compute $SRISK$ are available upon request. Alternatively, $SRISK$ data could be directly obtained from the Volatility Laboratory (V-Lab) (https://vlab.stern.nyu.edu). However, this source does not contain information about all individual listed banks in Europe, and the use of our own codes allows us to better control for the parameters of the indicator.

In line with Bostandzic et al. (2022), we do not restrict $SRISK$ to being positive, that is, it allows us to capture both capital shortfalls and surpluses. Figure 1 depicts the mean $SRISK$ throughout the sample. The average perceived systemic risk of banks as proxied by $SRISK$ increased in 2008 with the GFC, in 2012, coinciding with the European sovereign debt crisis, and also at the beginning of 2020 with the onset of the pandemic.

Our main explanatory variable is the SII buffer rate applied to each systemic bank, which we denote as S_BUF. This variable allows us to disentangle whether SII requirements do influence the systemic importance of the bank. In the EU, SII buffer requirements are set at the individual bank level. We obtain the SII buffer rates from the ESRB website. To calculate S_BUF we account for all the possible combinations to set the SII buffer at the domestic level. Thus, this capital requirement is usually the higher of the G-SII buffer, the O-SII buffer, and the SyRB, although there are some exceptions in certain jurisdictions.[25]

We also analyze whether merely designating the bank as an SII creates a signaling effect, which could be due to the implicit government guarantees in the event of distress, irrespective of the S_BUF level. For this, we define three dummy variables based on the assignment of the SII status by the competent authority—namely, the FSB for G-SIIs and the EBA for O-SIIs.[26] The first one, SII_STAT, takes into account the fact of having SII status. It is a step variable that takes the value of 1 once the EBA or the FSB identifies the bank as an SII and it is equal to 1 while the institution remains on the

[25]For instance, the O-SII buffer was not activated in Denmark or the Czech Republic until the end of 2019, while the SyRB was applied to SIIs in both countries before that date. In Bulgaria, Estonia, and Slovakia, the SyRB is cumulative, and the higher of the O-SII and G-SII buffers are set. Finally, in Bulgaria, Croatia, Estonia, Norway, and Poland all banks—not just SIIs—are subject to the SyRB. For more details, see the annual notifications available on the EBA website and the overview of national macroprudential and capital-based measures updated quarterly by the ESRB.

[26]Our definitions are based on the dates when the SII status is effective. The first G-SII list took effect in January 2012, and since then it is updated annually. The EBA published the O-SII list for the first time on April 25, 2016. However, most competent authorities began to assign the O-SII status in late 2015 (some of them in 2014). In the computation of S_BUF we have checked all notifications that are available on the ESRB website prior to the first EBA list to account for such cases.

SII list. This variable allows us to analyze whether designation as an SII has an impact on the systemicity of the bank, regardless of the buffer level. That is, for bank i in period t we define SII_STAT as

$$SII\_STAT_{it} = \begin{cases} 1 & \text{if designated SII in } t \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

The second dummy variable, SII_IN, is 1 only in the quarter when the bank becomes an SII, while the third one, SII_OUT, takes the value of 1 only when the institution loses SII status. Both SII_IN and SII_OUT allow us to quantify the immediate market reaction after the announcements themselves, which is in line with the empirical approach in Bekaert and Breckenfelder (2019), Andrieş et al. (2020), and Gündüz (2020) to analyze the market reaction to the disclosure of the list of O-SIIs by the EBA. Both binary variables are expressed as follows:

$$SII\_IN_{it} = \begin{cases} 1 & \text{if} \quad SII\_STAT_{it} = 1 \text{ and } SII\_STAT_{it-1} = 0 \\ 0 & \text{otherwise,} \end{cases} \tag{6}$$

$$SII\_OUT_{it} = \begin{cases} 1 & \text{if} \quad SII\_STAT_{it} = 0 \text{ and } SII\_STAT_{it-1} = 1 \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

We also explore whether the different adjustment mechanisms to higher capital requirements affect $SRISK$ once the SII buffer is implemented. Following Cohen and Scatigna (2016) and Braouezec and Kiani (2021), among others, we explore the impact on SRISK of four transmission channels, namely (i) total equity; (ii) retained earnings; (iii) new share issuances; and (iv) the risk-weighted density (RWD).

To check whether SIIs and non-SIIs follow different patterns, Table 1 reports some summary statistics for $SRISK$, the SII buffer level, S_BUF, as well as the four transmission channels for both SIIs and non-SIIs. We analyze the full sample and before and after the pandemic. As expected, the average $SRISK$ is higher for SIIs than for non-SIIs in the entire sample period and the two subperiods. Since the onset of the COVID-19 crisis, SIIs' average $SRISK$

Table 1. Descriptive Statistics of *SRISK*, the SII Buffer Level (*S_BUF*), and Four Transmission Channels

	SIIs				Non-SIIs			
	Mean	**SD**	**Min.**	**Max.**	**Mean**	**SD**	**Min.**	**Max**
A. Full Sample								
SRISK	5,861	18,335	–66,560	90,926	640	6,474	–29,177	85,537
S_BUF	1.2	1.3	0.0	6.5	—	—	—	—
Total Equity	29,880	35,824	137	183,054	4,178	10,627	8	127,892
Retained Earnings	14,724	22,043	–11,715	133,314	2,006	5,186	–21,178	86,138
Risk-Weighted Density (RWD)	42.2	16.1	15.5	86.0	56.3	17.6	3.5	98.3
Equity Issuances	5,807	7,338	0	31,694	546	1871	0	21,594
B. 2008:Q1–2019:Q4								
SRISK	5,011	18,494	–66,560	79,725	712	6,874	–29,177	85,537
S_BUF	1.1	1.3	0.0	5.0	—	—	—	—
Total Equity	32,000	37,100	137	183,000	4,561	11,200	8	128,000
Retained Earnings	15,700	22,900	–11,700	133,000	2,132	5,439	–21,200	86,100
Risk-Weighted Density (RWD)	42.7	16.6	15.5	86.0	57.1	17.6	4.3	98.3
Equity Issuances	6,085	7,301	0	31,694	632	2,062	0.00	21,595
C. 2020:Q1–2021:Q3								
SRISK	8,345	17,653	–14,577	90,926	113	1,748	–6,788	16,780
S_BUF	1.5	1.2	0	6.5	—	—	—	—
Total Equity	23,602	31,145	207	180,427	1,408	2,572	20	20,452
Retained Earnings	11,885	18,964	–11,664	133,314	929	1,635	–1,136	11,873
Risk-Weighted Density (RWD)	40.8	14.5	17.1	77.5	50.4	16.1	3.5	96.6
Equity Issuances	5,080	7,604	0	31,694	290	609	0	3,767

Note: SIIs stands for "systemically important institutions," *SRISK* is the systemic risk of each listed bank as measured by the SRISK indicator in Brownlees and Engle (2017), and *S_BUF* denotes the SII buffer level.

for the pandemic period is much higher than during the first subperiod, while for non-SIIs, this statistic decreased significantly. In other words, during the pandemic, SIIs would have been penalized in terms of systemicity, as measured by $SRISK$, given the drop in their stock prices and market valuations that pushed up the average $SRISK$ from 2020:Q1. Regarding S_BUF, the buffer requirements for SIIs have remained relatively stable in the subsamples. Although the average S_BUF during the pandemic is higher than that of the first subsample, there have been several releases during this last period. Finally, as expected, total equity and equity issuances are, on average, greater for SIIs. Conversely, non-SIIs hold larger shares of risk-weighted assets.[27]

Finally, for the robustness of our results, we also use a set of bank-specific and country-level variables as controls. Specifically, the bank variables consist of the total assets and the return on equity (RoE). Country-level variables allow us to control for the unobserved heterogeneity across countries and comprise (i) macroprudential buffers that are common at national level, namely the countercyclical capital buffer (CCyB),[28] the SyRB, and the capital conservation buffer (CCoB);[29] (ii) real GDP per capita; and (iii) the sovereign CDS spread. See Table 2 for the complete list of variables and data sources.

4. Methodological Approach

The baseline linear panel data model is described by the following expression:

[27] This might be due to different management practices at SIIs as well as the more intense use of internal models when calculating risk-weighted assets.

[28] The total CCyB of a given bank is the average of the CCyB across all countries, weighted by its exposures of the bank in each country. Due to a lack of country-exposures data, we abstract from this complication and only control for the level of the CCyB in its primary listing country.

[29] The adoption of the CCoB was completed in 2015 for the countries with phase-in arrangements, so that since 2015 the CCoB level is 2.5 percent in all jurisdictions. Although this control variable is constant since that date, we consider it given its different dynamics across countries during the phase-in period. The SyRB is non-zero for non-SIIs where this buffer is applied to all banks at the country level.

Table 2. Variable Definitions and Data Sources

Variable	Description	Source
SRISK	Systemic risk contribution of individual banks as proxied by the SRISK indicator (Brownlees and Engle 2017)	Own calculations
Total Liabilities	Quarterly total liabilities at consolidated level, million EUR	S&P Capital IQ
Market Value	Market capitalization, which is the product of share price and the number of ordinary shares in issue, for the last day of each period, million EUR	Refinitiv Datastream
STOXX Europe 600	Stock market index for the last day of each period	Refinitiv Datastream
	SII Characteristics	
S_BUF	Level of structural buffer for SIIs, which is the combination of the G-SII and O-SII buffers and SyRB, for the last day of each period, %	European Systemic Risk Board (ESRB)
SII_STAT	Dummy variable that takes the value of 1 once the bank is designated as an SII in that period and 0 otherwise	European Banking Authority (EBA)
SII_IN	Dummy variable that takes the value of 1 when the bank is designated as an SII and 0 otherwise	European Banking Authority (EBA)
SII_OUT	Dummy variable that takes the value of 1 when the bank stops being designated as an SII and 0 otherwise	European Banking Authority (EBA)

(*continued*)

Table 2. (Continued)

Variable	**Description**	**Source**
	Bank Variables	
Total Equity	Includes par value, paid-in capital, retained earnings, and other adjustments to equity, million EUR	S&P Capital IQ
Retained Earnings	Accumulated net income and dividends, million EUR	S&P Capital IQ
Risk-Weighted Density (RWD)	Total risk-weighted assets, as defined by the latest regulatory and supervisory guidelines, as a percentage of total assets, %	S&P Capital IQ
Equity Issuances	Current value of the share issuance deal, thousand EUR	Dealogic
Total Assets	All assets owned by the company for the last day of each period, as carried on the balance sheet, million EUR	S&P Capital IQ
Return on Equity (RoE)	Net income as a percentage of average equity, %	S&P Capital IQ
	Country Variables	
CCyB	Level of countercyclical capital buffer for the last day of each period, %	European System Risk Board (ESRB)
CCoB	Level of capital conservation buffer, %	European System Risk Board (ESRB)
SyRB	Level of systemic risk buffer if applied to non-SIIs for the last day of each period, %	European System Risk Board (ESRB)
GDP	GDP per capita in purchasing power standards (PPS) with respect to the EU27 average. Average quarter at 2010 = 100	Eurostat
CDS	Sovereign credit default swap (CDS) spreads in basis points	Refinitiv Datastream

$$SRISK_{it} = \alpha_i + T_t + \gamma S\_BUF_{it-1} + \sum_j \beta_j X_{j,it-1} + \sum_k \delta_k Z_{k,it-1} + \varepsilon_{it}, \tag{8}$$

where for all banks $i = 1, \ldots, N$ and periods $t = 1, \ldots, T$, the main explanatory variable is S_BUF to quantify the effect of the introduction of SII capital buffers on a panel of listed banks. The key coefficient in (8) is γ, which can be interpreted as the average effect of a 1 percent increase in SII capital requirements on $SRISK$. Therefore, a negative estimate of γ would suggest that higher SII requirements would lead to a lower contribution to systemic risk as proxied by $SRISK$. Apart from the bank and time dummies, the model includes bank-specific control variables, X_{it}, and country-level variables, Z_{it}, as described in the previous section. We fit the model for the full sample, and also for the two subsamples to characterize the impact of the pandemic on the data set.

Second, we also fit different specifications of the baseline model in (8), replacing S_BUF with the three alternative dummy variables based on the assignment of SII status defined in expressions (5) to (7). Namely, we use the step variable SII_STAT in (5) as an explanatory variable to study whether having SII status influences on the bank systemicity regardless of the SII capital requirement level. Thus, a negative estimate of this coefficient would suggest that being an SII lowers a bank's contribution to systemic risk as proxied by $SRISK$. In other words, being an SII might represent a signaling effect regardless of the buffer level. Further, we explore the possibility that there could be an immediate market response on the announcement of a bank's designation as an SII related to the market perception of its contribution to systemic risk. To this end, we also modify the baseline model in (8) by replacing S_BUF with SII_IN and SII_OUT, as defined in (6) and (7). A positive (negative) estimate of the SII_IN coefficient would indicate that the designation as an SII would immediately increase (decrease) the systemic nature of the bank.

We further study the effect of being identified as an SII over time via local projections (see Jordà 2005). Thus, for quarters $q = 0, 1, 2, \ldots, 12$ we fit the baseline model that considers SII_IN as an explanatory variable instead of S_BUF as follows:

$$SRISK_{it+q} = \alpha_i^q + T_t^q + \lambda^q SII\_IN_{it-1} + \sum_j \beta_j^q X_{j,it-1} + \sum_k \delta_k^q Z_{k,it-1} + \varepsilon_{it+q}. \tag{9}$$

Next, we increase the number of drivers in (8) with the four main options that banks have at their disposal to comply with SII buffers. This specification allows us to disentangle which one dominates in a bank's response in terms of lower systemicity to higher capital requirements. Namely, we explore the impact of four alternative variables entailing changes to the capital structure on $SRISK$: (i) total equity; (ii) retained earnings; (iii) new share issuances; and (iv) risk-weighted density.

$$SRISK_{it} = \alpha_i + T_t + \gamma S\_BUF_{it-1} + \sum_{l=1}^{4} \omega_l C_{l,it-1} + \sum_j \beta_j X_{j,it-1} + \sum_k \delta_k Z_{k,it-1} + \varepsilon_{it}, \tag{10}$$

where $\{C_{l,it}\}_{l=1}^{4}$ denotes the four different channels.

Finally, we check whether decisions by SII banks to comply with capital requirements do have an impact on their systemicity. For this purpose, we also fit the model in (9) with interactions of the variables related to a bank's capital structure and SII_STAT, which is given by

$$\begin{aligned} SRISK_{it} = {} & \alpha_i + T_t + \gamma S\_BUF_{it-1} + \sum_{l=1}^{4} \omega_l C_{l,it-1} \\ & + \sum_{l=1}^{4} \lambda_l (C_{l,it-1} \times SII\_STAT_{it-1}) \\ & + \sum_j \beta_j X_{j,it-1} + \sum_k \delta_k Z_{k,it-1} + \varepsilon_{it}. \end{aligned} \tag{11}$$

This last specification allows us to test for the null hypothesis that the influence of these variables on the systemicity is independent of the SII status. That is, for all the bank capital-related variables l it is possible to test for the following null:

$$H_0 : \lambda_l = 0. \tag{12}$$

Model (11) also allows us to quantify the residual impact of S_BUF on $SRISK$ once we control for capital-related variables. This residual impact of S_BUF could be interpreted as the effect of the SII buffer level itself on a bank's contribution to systemic risk. Finally, we replace S_BUF with SII_STAT in (11) to analyze the significance of having SII status once we also consider all the feasible bank choices to fulfill this capital requirement. This effect could be related to a positive sign for the markets of having SII buffers once we control for bank balance sheet variables.

We estimate this linear fixed-effects panel data model with standard errors robust to serial correlation (clustered at bank level) and heteroskedasticity. Another challenge of the analysis is the possibility of endogeneity problems as a result of reverse causality and omitted variables. Reverse causality could be a concern when analyzing the link between $SRISK$ and S_BUF, as a two-way causality relationship could be feasible. For instance, the national authorities could increase the SII buffer to address a bank's higher systemicity. On the other hand, higher capital requirements for SIIs are likely to influence a bank's systemic nature. This latter direction of causality is precisely the focus of our analysis, and, to minimize the effect of the former, the main variables of interest—S_BUF, SII_IN, and SII_OUT—are lagged one period in specifications (8) to (11). Also, all explanatory variables are lagged one period to limit simultaneity bias. Finally, regarding a possible omitted-variable bias, we consider that our set of explanatory variables contains a sufficient number of relevant drivers to analyze of $SRISK$ and, therefore, we consider that our model is not poorly specified.

5. Results

5.1 Baseline Model: Some Initial Results

Table 3 reports the estimates of the baseline model in (8) for the total sample (panel A), as well as for the subsample before and after the onset of the COVID-19 pandemic (panels B and C, respectively).

Table 3. Estimates of the Baseline Model for the Total Sample and for the Pre- and Post-Pandemic Period

	Full Sample			2008:Q1–2019:Q4			2020:Q1–2021:Q3		
S_BUF	–79.40			–645.5***			–27.16		
	(276.7)			(223.4)			(202.6)		
SII_STAT		–1,303**			–1,767***			756.4	
		(518.3)			(506.8)			(476.0)	
SII_IN			2,120***			2,673***			–486.9
			(597.7)			(697.3)			(654.4)
SII_OUT			–214.3			–420.5			–1225**
			(460.3)			(598.8)			(596.4)
Total Assets	0.039***	0.039***	0.039***	0.034***	0.034***	0.034***	–0.019	–0.019	–0.019
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)
RoE	–8.10***	–8.14***	–8.08***	–7.45**	–7.21**	–7.12**	–1.36	–1.43	–1.34
	(3.01)	(3.01)	(2.99)	(2.99)	(2.91)	(2.89)	(4.35)	(4.33)	(4.35)
CCyB	–499.0**	–513.6**	–522.7*	–439.9*	–679.7***	–722.3**	–411.0	–396.0	–396.8
	(236.1)	(254.0)	(284.2)	(232.7)	(258.7)	(308.2)	(427.2)	(429.9)	(431.1)
SyRB	318.5***	167.9	355.2***	388.3***	413.1***	688.2***	243.8	263.4*	266.3
	(100.6)	(115.3)	(130.5)	(122.3)	(132.0)	(160.3)	(153.1)	(155.9)	(166.4)
CCoB	636.3***	653.9***	617.4***	421.3**	304.1	235.7	—	—	—
	(208.1)	(228.0)	(234.8)	(198.1)	(198.3)	(211.0)	—	—	—
GDPpc	–76.04***	–71.69***	–78.45***	–39.95	–56.64**	–65.93***	–114.6*	–114.1*	–113.5*
	(26.27)	(24.02)	(23.43)	(25.14)	(25.41)	(23.47)	(68.16)	(68.08)	(68.20)
CDS	0.003	–0.013	–0.002	–0.003	–0.043	–0.037	–4.197	–4.307	–4.145
	(0.032)	(0.036)	(0.032)	(0.032)	(0.034)	(0.031)	(10.12)	(10.16)	(10.13)
N	6,487	6,487	6,487	5,501	5,501	5,501	986	986	986
R^2	0.396	0.400	0.397	0.381	0.385	0.380	0.177	0.177	0.177

Note: Dependent variable: systemic risk contribution of individual banks as proxied by the SRISK indicator (see Brownlees and Engle 2017); all explanatory variables are lagged one period; *S_BUF*: SII buffer level; *SII_STAT*: binary dummy, *SII_STAT* = 1 while a bank has SII status; *SII_IN*: binary dummy, *SII_IN* = 1 only in the quarter when a bank becomes an SII; *SII_OUT*: binary dummy, *SII_OUT* = 1 only in the quarter when the bank stops being an SII; RoE: return on equity; CCyB: countercyclical capital buffer; CCoB: capital conservation buffer; GDPpc: GDP per capita; CDS: credit default swap spreads. See Table 2 for a complete description of the explanatory variables and data sources. Standard errors are shown in parentheses. Standard errors are robust to heteroskedasticity and serial correlation. Intercept, time, and bank fixed effects are included but not reported. ***, **, and * refer to significance at 1 percent, 5 percent, and 10 percent level, respectively.

First and most importantly, before the pandemic the increase in the SII buffer level has a negative effect on a bank's contribution to systemic risk, as signaled by the negative and significant estimate of S_BUF. This evidence suggests that higher SII buffers are associated with lower systemic risk. Given that the main objective of SII buffers is to address the systemic riskiness of SIIs, this result means that these capital requirements work as expected over this sample period.[30]

Conversely, during the pandemic the estimate of S_BUF becomes non-significant. This lack of significance also holds for the full sample. The particular dynamics of S_BUF and $SRISK$ during the pandemic explain this result. Thus, during the pandemic the estimate for S_BUF reflects the fact that the released buffers for SIIs in some countries (lower S_BUF) were followed by a reduction in the banks' contribution to systemic risk (lower SRISK) after its peak in 2020:Q1. Therefore, the negative link between the SII buffer level and a bank's contribution to systemic risk identified for the preceding sample does not hold during the pandemic. In fact, this link between S_BUF and $SRISK$ is reversed in those countries that released their SII buffers, so that the lower S_BUF preceded $SRISK$ drops. However, this temporal positive relationship between the two variables does not entail a causality link between them, as the lower $SRISK$ results from the market's correction after the abnormal pattern of $SRISK$ in 2020:Q1.[31] Finally, as the link between S_BUF and $SRISK$ changes during the pandemic, time fixed effects are

[30] According to the estimated coefficient for S_BUF for this subsample, a 1 percentage point (pp) increase in the SII buffer level is associated with a €645.5 million reduction in SRISK. Alternatively, we have fitted the baseline model in (8) with $SRISK$ expressed in logarithms. According to the results, a 1 pp increase in S_BUF is associated with a reduction of 16.4 percent in $SRISK$. The estimates for other coefficients are in line with those presented in Table 3 and are available upon request.

[31] As a robustness check, we have also fit Equation (8) for the full sample with a dummy variable that equals 1 during the COVID period and its interaction with our main explanatory variable, S_BUF. The results are in line with those for separate subsamples presented in Table 3 and are available in Appendix C. As explained, the link between S_BUF and $SRISK$ becomes positive during the pandemic, without involving a causality link between both variables. Besides, the great variety of policy responses implemented by authorities could have also affected in other regressors, which is out of the scope of this article. All in all, we consider it more appropriate to fit the model by subsamples, as in Table 3.

not enough to fully capture the impact of the COVID shock on the variables.

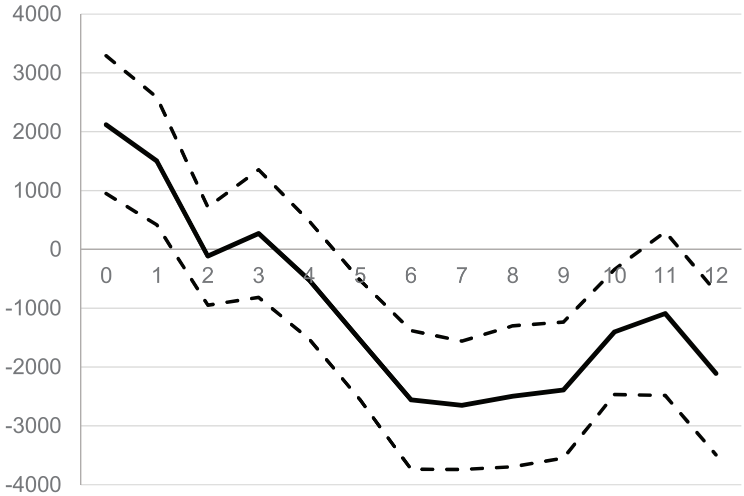
Table 3 also shows that having SII status, irrespective of the buffer level, lowers banks' contribution to systemic risk, as shown by the negative and significant estimates of SII_STAT. This result is to some extent related to Bekaert and Breckenfelder (2019) and Vogel (2020), who find that being designated an SII has different consequences for banks.[32] This outcome holds for the full sample and for the pre-pandemic period, but it becomes non-significant during the pandemic. That is, after the onset of the coronavirus crisis, the contribution of banks to systemic risk was independent of their SII status.[33] From a policy perspective, this significance of having SII status determine the contribution of a bank to systemic risk means that having SII buffers can be interpreted as a signal for the markets of the commitment of these banks to increasing their resilience.

The estimates of SII_IN in Table 3 suggest that the designation as an SII immediately leads to an increase in systemic risk. Conversely, as evidenced by the coefficient of SII_OUT, once the bank ceases to be an SII, its contribution to systemic risk in the next period diminishes. This result is in line with Andrieş et al. (2020) and Gündüz (2020), who find that the initial market reaction to the SII designation tends to be negative given certain stigma effects related to tighter regulation and lower profitability once the requirement is set. To further explore the effect of the designation as an SII over time, we fit model (10), which is inspired by the local projections method (see Jordà 2005). As stated in (10), we consider the baseline equation in (8), and recursively run a set of regressions for the lead dependent variable up to 12 quarters ahead. Figure 2 shows the estimated coefficients of SII_IN and their corresponding 95 percent confidence intervals for the 12 quarters. The initial impact of a bank's SII designation is positive, that is, it is associated with an increase in $SRISK$. However, this effect decreases quickly over

[32]Vogel (2020) concludes that being labeled an O-SII brings a funding cost advantage for deposits, while Bekaert and Breckenfelder (2019) document that bond prices are higher for those banks belonging to the O-SII list.

[33]The subsample after the onset of the pandemic is short and has few new SII designations, which implies a low variation of SII_STAT. This fact complicates the identification, so that the results for this subsample should be interpreted with caution.

Figure 2. Local Projection Estimator of *SII_IN* for 12 Quarters



Note: The unbroken line depicts the local projection estimator for *SII_IN*, a dummy variable that is 1 only in the period when the bank becomes an SII, during 12 quarters for model (9). The broken lines are the 95 percent confidence intervals.

time and becomes negative four quarters later in line with the negative coefficients for S_BUF and SII_STAT. This result suggests that banks adapt to the new capital requirements over time, so that the institutions' contribution to systemic risk eventually decreases.

Finally, as a robustness check, we have also explored whether the estimate of γ in (8) is different for banks of both the peripheral and the core countries. Our results suggest that the country location of the bank does not influence their systemicity once the SII buffer is set.[34]

[34]To this end, we have built two indicator variables. The first one is equal to 1 if a bank's home country is Greece, Italy, Portugal, or Spain, and 0 otherwise, while the second one equals 1 if a bank's jurisdiction is Austria, Belgium, France, Germany, Luxembourg, or the Netherlands, and 0 otherwise. We have interacted these two new variables with S_BUF in (8), as well as with SII_IN and SII_OUT. The estimates, which are available upon request, are not significant or conclusive.

5.2 Additional Insights into the Drivers of the Systemic Risk Driven by Banks

Next, we analyze the potential impact of the adjustment mechanisms that banks use to comply with SII buffer requirements on their contribution to systemic risk. This approach allows us to disentangle which option dominates in banks' response and contributes the most to decreasing their systemicity due to higher capital requirements. As the link between $SRISK$ and S_BUF during the pandemic crisis follows an abnormal pattern, hereafter we focus on the pre-pandemic sample up to 2019:Q4.[35]

Table 4 reports the estimates for model (10), which extends the baseline model (8) by adding the main options for capital adjustment as regressors. The results indicate that higher equity, especially in the form of retained earnings, leads to a lower bank contribution to systemic risk. Also, the coefficient of S_BUF decreases once these variables are included. "De-risking," i.e., a lower risk-weighted density, also diminishes a bank's systemic impact, although this estimate is less significant. Next, we fit the model in (11), which includes the interactions of SII_STAT with banks' capital adjustment options, to distinguish their impact for SIIs and non-SIIs. Table 5 reports the results, which show that the estimated coefficients of the interaction terms are mostly significant, while the estimates for the non-SII group are not, except for the risk-weighted density. This outcome indicates that the impact of these options on a bank's contribution to systemic risk depends on having an SII status.

Specifically, the results in Table 5 indicate that the market perception of systemic risk improves when an SII bank increases its equity.[36] However, the two main drivers of this effect, retained earnings and equity issuances, work in opposite directions. Thus, the increase in SIIs' retained earnings is generally positively perceived by the markets, as signaled by the negative coefficient of its interaction with SII_STAT. One possible interpretation is that in this

[35] This is mainly because the pandemic crisis represents an exogenous shock to banks' market valuations and there was a massive release and other prudential changes to SII buffers in some countries, as explained in the previous subsection.

[36] This finding is in line with Dautović (2020), who suggested that a phased-in increase in capital requirements raises the CET1 capital ratio, thereby improving resilience and loss-absorbing capacity.

Table 4. Estimates of the Baseline Model with Bank Variables Involving Changes to the Capital Structure

	M1	M2	M3	M4	M5	M6	M7	M8
S_BUF	–668.1***	–507.0**	–569.0***	–599.1***	–672.7***	–516.8***	–534.4***	–541.3***
	(228.0)	(196.3)	(193.0)	(217.7)	(228.3)	(194.1)	(191.9)	(190.4)
Total Equity		–0.210**				–0.216**		
		(0.0856)				(0.0858)		
Retained Earnings			–0.220***				–0.203***	–0.204***
			(0.0569)				(0.0657)	(0.0658)
Equity Issuances				–0.196			–0.120	–0.126
				(0.121)			(0.134)	(0.136)
RWD					6.724	21.18*		13.61
					(11.75)	(11.90)		(11.91)
Total Assets	0.035***	0.041***	0.039***	0.034***	0.035***	0.041***	0.038***	0.038***
	(0.005)	(0.007)	(0.004)	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)
RoE	–7.50**	–6.20**	–5.99**	–7.63**	–7.46**	–6.02**	–6.18**	–6.09**
	(3.04)	(2.92)	(2.51)	(3.14)	(3.02)	(2.85)	(2.62)	(2.58)
CCyB	–465.8*	–592.9**	–470.2*	–606.9**	–470.9*	–612.7**	–556.1**	–571.1**
	(244.6)	(234.5)	(245.6)	(239.4)	(246.8)	(235.2)	(243.6)	(247.9)
SyRB	388.6***	371.4***	328.6**	384.7***	386.7***	364.8***	330.8**	326.6**
	(127.5)	(138.4)	(137.2)	(125.6)	(126.8)	(139.2)	(135.2)	(134.6)
CCoB	447.7**	270.2	401.9*	389.9*	453.0**	281.8	370.1*	379.0*
	(210.2)	(196.4)	(210.0)	(201.1)	(208.9)	(195.3)	(202.9)	(202.1)
GDPpc	–40.37	–40.65*	–24.39	–55.29**	–40.36	–40.62*	–34.72	–35.15
	(26.51)	(23.23)	(23.50)	(27.62)	(26.39)	(22.77)	(27.69)	(27.82)
CDS	–0.003	–0.016	–0.026	–0.012	–0.001	–0.009	–0.029	–0.025
	(0.032)	(0.029)	(0.027)	(0.032)	(0.033)	(0.030)	(0.028)	(0.029)
N	5,103	5,103	5,103	5,103	5,103	5,103	5,103	5,103
R^2	0.381	0.403	0.398	0.386	0.381	0.404	0.400	0.401

Note: Dependent variable: systemic risk contribution of individual banks as proxied by the SRISK indicator (see Brownlees and Engle 2017); all explanatory variables are lagged one period; *S_BUF*: SII buffer level; RWD: risk-weighted density; RoE: return on equity; CCyB: countercyclical capital buffer; CCoB: capital conservation buffer; GDPpc: GDP per capita; CDS: credit default swap spreads. See Table 2 for a complete description of explanatory variables and data sources. Standard errors are shown in parentheses. Standard errors are robust to heteroskedasticity and serial correlation. Intercept, time, and bank fixed effects are included but not reported. The sample period runs from 2008:Q1 to 2019:Q4. ***, **, and * refer to significance at 1 percent, 5 percent, and 10 percent level, respectively.

Table 5. Estimates of the Baseline Model with Bank Variables Involving Changes to the Capital Structure and Interactions with SII Status

	M1	M2	M3	M4	M5	M6	M7	M8
S_BUF	–668.1***	–413.1**	–307.8*	–577.6***	–653.9**	–651.9***	–197.0	–204.8
	(228.0)	(180.4)	(162.2)	(206.4)	(257.3)	(207.6)	(172.6)	(230.8)
Total Equity		–0.087				–0.078		
		(0.100)				(0.100)		
Total Equity × *SII_STAT*		–0.069**				–0.079**		
		(0.031)				(0.034)		
Retained Earnings			0.0325				0.159	0.159
			(0.0732)				(0.104)	(0.104)
Retained Earnings × *SII_STAT*			–0.191***				–0.345***	–0.345***
			(0.047)				(0.073)	(0.073)
Equity Issuances				–0.0362			–0.442	–0.447
				(0.342)			(0.294)	(0.299)
Equity Issuances × *SII_STAT*				–0.150			0.555**	0.553**
				(0.246)			(0.238)	(0.246)
RWD					7.084	19.59*		14.93
					(11.44)	(10.60)		(11.84)
RWD × *SII_STAT*					–1.539	19.82*		0.053
					(9.479)	(10.31)		(9.83)
N	5,103	5,103	5,103	5,103	5,103	5,103	5,103	5,103
R^2	0.381	0.418	0.428	0.374	0.381	0.421	0.445	0.445

Note: Dependent variable: systemic risk contribution of individual banks as proxied by the SRISK indicator (see Brownlees and Engle 2017); all explanatory variables are lagged one period; *S_BUF*: SII buffer level; *SII_STAT*: binary dummy, *SII_STAT* = 1 while a bank has SII status; RWD: risk-weighted density; RoE: return on equity; CCyB: countercyclical capital buffer; CCoB: capital conservation buffer; GDPpc: GDP per capita; CDS: credit default swap spreads. See Table 2 for a complete description of explanatory variables and data sources. Standard errors are shown in parentheses. Standard errors are robust to heteroskedasticity and serial correlation. Intercept, time, and bank fixed effects are included but not reported. The sample period runs from 2008:Q1 to 2019:Q4. ***, **, and * refer to significance at 1 percent, 5 percent, and 10 percent level, respectively.

way banks could thus seek to improve their profits, for instance by increasing net interest income or reducing overall operating expenses (see Cohen and Scatigna 2016). Conversely, issuing new equity could be perceived as a less attractive option because of its direct diluting effect on the market value of the existing shares and the uncertainty related to EU banks' post-GFC low valuations. Finally, we do not find a strong link between the risk-weighted density and the level of SRISK, in either SIIs or non-SIIs.[37] Indeed, there is very little empirical evidence of a trade-off between the rise in the risk-weighted density to compensate for the increase in equity (see, for instance, Gropp et al. 2019).

Once we consider the differential impact of these variables for the sample of SIIs, the effect of S_BUF on $SRISK$ substantially decreases and even becomes non-significant in those model specifications that include the interaction of SII_STAT with retained earnings and equity issuances as regressors. In other words, once we control for these drivers, the impact of the SII buffer level on a bank's systemic nature disappears. This indicates that an important part of the decrease in $SRISK$ associated with increases in S_BUF is mediated by increases in equity, particularly via retained earnings.

Finally, Table 6 reports the estimates of model (11) with SII_STAT instead of S_BUF as the main explanatory variable. This approach allows us to disentangle the impact of having SII status on banks' contribution to systemic risk in Table 3 from banks' decisions to adjust their capital to comply with SII requirements.[38] That is, we aim to quantify the residual impact of having SII status once we control for these capital-related variables. Contrary to the results in Table 5 for the SII buffer level, the estimate of SII_STAT is still significant once we include all adjustment options—namely, retained earnings, equity issuances, and share of risk-weighted assets. This result suggests that having SII status is itself positively perceived by markets and decreases the contribution to the systemic risk.

[37]This outcome is to some extent contrary to Dautović (2020), who finds that being an SII is associated with potentially higher risk-taking on average.

[38]Estimates of the interactions of SII_STAT with the different bank-related variables are relatively similar to those reported in Table 6. The main difference is that in Table 6 the link between the proportion of risk-weighted assets and $SRISK$ only holds for SIIs.

Table 6. Estimates of the Baseline Model with Bank Variables Involving Changes to the Capital Structure and Interactions with SII Status

	M1	M2	M3	M4	M5	M6	M7	M8
SII_STAT	–1,873***	–239.5	–92.47	–1,433**	–6,932***	–3,870**	–732.0*	–3,320***
	(512.3)	(589.3)	(456.5)	(630.1)	(1,534)	(1,824)	(420.3)	(1,216)
Total Equity		–0.0945				–0.115		
		(0.103)				(0.108)		
Total Equity × *SII_STAT*		–0.0674*				–0.0456		
		(0.0368)				(0.0415)		
Retained Earnings			0.0327				0.146	0.126
			(0.0795)				(0.105)	(0.109)
Retained Earnings × *SII_STAT*			–0.194***				–0.339***	–0.311***
			(0.0527)				(0.0715)	(0.0782)
Equity Issuances				–0.0923			–0.462	–0.461
				(0.343)			(0.285)	(0.293)
Equity Issuances × *SII_STAT*				–0.0584			0.594**	0.600**
				(0.267)			(0.229)	(0.234)
RWD					–1.020	14.65		9.479
					(10.33)	(10.71)		(11.24)
RWD × *SII_STAT*					110.5***	69.35**		50.06**
					(26.86)	(28.63)		(21.06)
N	5,103	5,103	5,103	5,103	5,103	5,103	5,103	5,103
R^2	0.387	0.416	0.427	0.390	0.404	0.423	0.446	0.449

Note: Dependent variable: systemic risk contribution of individual banks as proxied by the SRISK indicator (see Brownlees and Engle 2017); all explanatory variables are lagged one period; *S_BUF*: SII buffer level; *SII_STAT*: binary dummy, *SII_STAT* = 1 while a bank has SII status; RWD: risk-weighted density; RoE: return on equity; CCyB: countercyclical capital buffer; CCoB: capital conservation buffer; GDPpc: GDP per capita; CDS: credit default swap spreads. See Table 2 for a complete description of explanatory variables and data sources. Standard errors are shown in parentheses. Standard errors are robust to heteroskedasticity and serial correlation. Intercept, time, and bank fixed effects are included but not reported. The sample period runs from 2008:Q1 to 2019:Q4. ***, **, and * refer to significance at 1 percent, 5 percent, and 10 percent level, respectively.

6. Conclusions

In this paper we investigate whether SII buffers are effective at lowering the contribution of these large and complex banks to systemic risk. We also analyze what the possible drivers of the banks' systemicity adjustment are. We proxy banks' perceived systemic risk with the measure SRISK in Brownlees and Engle (2017), the dependent variable of our empirical analysis. This is a broadly used metric of systemic risk that can be easily computed with bank- and market-based data. Then, we fit a number of fixed-effects panel data models to analyze the link between the SII buffer level and having SII status, and the SRISK indicator for a sample of listed European banks from 2008:Q1 to 2021:Q3.

According to our results, there is a negative relationship between the SII buffer level and banks' contribution to systemic risk. Therefore, higher capital requirements for systemic banks achieve the goal sought by regulators, as they lead to a decrease in perceived systemic risk. Furthermore, being designated as an SII also decreases banks' contribution to systemic risk, but this effect is time sensitive. The short-term impact of SII designation on SRISK appears to be positive (i.e., it increases SRISK), potentially due to a market stigma effect, while the medium-term effect, once the bank has had the time to adapt to the higher requirements, turns negative. We then control for the main options banks use to comply with higher SII requirements to further analyze the determinants of this perceived lower systemic risk. The results indicate that an increase in banks' equity through retained earnings is the main driver of this effect. Finally, once we control for these bank-based drivers, the residual effect of having SII status on perceived systemic risk is still negative and significant. This outcome means that being an SII provides a positive signal to markets by further decreasing its contribution to systemic risk.

Our results have important financial stability implications, in particular regarding the discussion of the role of SII buffers as an effective instrument for increasing these banks' resilience and for reducing their need for government interventions. Further research to fully understand the impact of SII buffers would be needed to guide policy responses to address the "too big to fail" status of SIIs. For instance, this paper does not address buffer calibration.

Moreover, impact analysis of SII buffers on different measures of systemic risk, not only the SRISK indicator, would be useful to provide a more holistic view on the implications of SII buffers.

Appendix A. Estimation of the Long-Run Marginal Expected Shortfall (LRMES)

This appendix describes the procedure to estimate the firm equity return conditional on the systemic event, $LRMES$, as defined in (4). $LRMES$ is non-observable and, in line with Brownlees and Engle (2017), we calculate this quantity using a DCC-GARCH model (see Engle 2002, 2009). Following Brownlees and Engle (2017), we denote the logarithmic returns of bank i and market m as $r_{it} = \log(1+R_{it})$ and $r_{mt} = \log(1+R_{mt})$. Conditional on the information set available at $t-1$, I_{t-1}, both variables are jointly distributed and follow an unspecified distribution D with zero mean and time-varying variance and covariance matrix,

$$\left[\begin{array}{c} r_{it} \\ r_{mt} \end{array}\right] \Bigg| I_{t-1} \sim D\left(\mathbf{0}, \left[\begin{array}{cc} \sigma_{it}^2 & \rho_{it}\sigma_{it}\sigma_{mt} \\ \rho_{it}\sigma_{it}\sigma_{mt} & \sigma_{mt}^2 \end{array}\right]\right). \qquad (A.1)$$

The time-varying volatilities are assumed to follow a GJR-GARCH model (Glosten, Jagannathan, and Runkle 1993) model as follows:

$$\sigma_{it}^2 = \omega_i + (\alpha_i + \gamma_i I_{it-1}^-) r_{it}^2 + \beta_i \sigma_{it-1}^2 \qquad (A.2)$$

$$\sigma_{mt}^2 = \omega_m + (\alpha_m + \gamma_m I_{mt-1}^-) r_{mt}^2 + \beta_m \sigma_{mt-1}^2, \qquad (A.3)$$

where $I_{it}^- = 1$ if $r_{it} < 0$ and $I_{mt}^- = 1$ if $r_{mt} < 0$. Next, like in Brownlees and Engle (2017), we define the standardized log returns as $\epsilon_{jt} = \frac{r_{jt}}{\sigma_{jt}}$, while their correlation is given by

$$Corr\left(\begin{array}{c} \epsilon_{it} \\ \epsilon_{mt} \end{array}\right) = \left[\begin{array}{cc} 1 & \rho_{it} \\ \rho_{it} & 1 \end{array}\right] = \mathrm{diag}(Q_{it})^{-1/2} Q_{it} \mathrm{diag}(Q_{it})^{-1/2}, \qquad (A.4)$$

where Q_{it} is the pseudo-correlation matrix with the following expression:

$$Q_{it} = (1-\alpha_{ci}-\beta_{ci})S_i + \alpha_{ci}\left[\begin{array}{c} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{array}\right]\left[\begin{array}{c} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{array}\right]' + \beta_i Q_{it-1}, \qquad (A.5)$$

where S_i is the the unconditional correlation matrix between bank and market-adjusted returns, r_i and r_m, respectively. Using quasi-maximum likelihood, we can estimate the parameters ($\omega_{V,i}$, $\omega_{V,m}$, $\alpha_{V,i}$, $\alpha_{V,m}$, $\gamma_{V,i}$, $\gamma_{V,m}$, $\beta_{V,i}$, $\beta_{V,m}$, α_C, β_C) as well as the time-varying volatilities $\{\sigma_{i,t}, \sigma_{m,t}\}_{t=1,...,T}$ and correlations $\{\rho_{i,t}\}_{t=1,...,T}$. The LRMES can, then, be calculated via simulations. For this purpose, we first compute the standardized innovations,

$$\epsilon_{m,t} = \frac{r_{m,t}}{\sigma_{mt}}, \text{ and } \xi_{i,t} = \left(\frac{r_{i,t}}{\sigma i, t} - \rho_{i,t}\epsilon_{m,t}\right) / \sqrt{1 - \rho_{i,t}^2}, \tag{A.6}$$

for $t = 1, \ldots, T$. To generate joint paths of $\{R_{i,t+l}, R_{m,t+l}\}_{l=1,...,h}$, we first sample with replacement h pairs of standardized returns $\{\epsilon_{m,k}, \xi_{i,k}\}_{k=1,...,h}$. Starting with the estimated $\sigma_{i,T}$, $\sigma_{m,T}$, $\rho_{i,T}$, we can compute $\sigma_{i,T+1}$, $\sigma_{m,T+1}$, $\rho_{i,T+1}$ using expressions from (A.2) to (A.6), and $r_{i,T+1}, r_{m,T+1}$ using the sampled $\{\epsilon_{m,1}, \xi_{i,1}\}$. Iterating, we obtain a simulated sample $\{R_{i,t+l}, R_{m,t+l}\}_{l=1,...,h}$. The LRMES is, then, simply calculated as the average of $R_{i,t+h}$ over paths in which $R_{m,t+h} < C$.

Appendix B. Sample of Listed Banks

- AUSTRIA: Bank für Tirol und Vorarlberg; BAWAG Group; BKS Bank; Erste Group Bank; Oberbank; Raiffeisen Bank International; Volksbank Vorarlberg.
- BELGIUM: Dexia; KBC Group.
- BULGARIA: Bulgarian American Credit Bank; Central Cooperative Bank; First Investment Bank; Texim Bank.
- CROATIA: Privredna banka Zagreb.
- CYPRUS: Bank Cyprus Holdings Public; Hellenic Bank Public.
- CZECH REPUBLIC: Komercní banka; MONETA Money Bank.
- DENMARK: BankNordik; Danske Andelskassers Bank; Danske Bank; Den Jyske Sparekasse; Djurslands Bank; Fynske Bank; GrønlandsBANKEN; Hvidbjerg Bank; Jutlander Bank; Jyske Bank; Kreditbanken; Lån & Spar Bank; Lollands Bank; Møns Bank; Nordfyns Bank; Ringkjøbing Landbobank;

Salling Bank; Skjern Bank; Spar Nord Bank; Sparekassen SjællandFyn; Sydbank; Totalbanken; Vestjysk Bank.
- ESTONIA: AS LHV Group.
- FINLAND: Ålandsbanken; Evli Pankki Oyj; Nordea Bank Abp; Oma Säästöpankki Oyj.
- FRANCE: BNP Paribas; CRCAM de Toulouse 31; CRCAM Paris et IDF; CRCAM d'Ille-et-Villaine; CRCAM du Morbihan; CRCAM de Nord de France; CRCAM Brie Picardie; CRCAM du Languedoc; CRCAM Atlantique Vendee; Crédit Agricole; Natixis; Société Générale.
- GERMANY: Aareal Bank; Comdirect bank; Commerzbank; Deutsche Bank; Deutsche Pfandbriefbk; ProCredit Holding.
- GREECE: Alpha Bank; Attica Bank; Eurobank Ergasias; National Bank Greece; Piraeus Financial Holdings.
- HUNGARY: OTP Bank; Takarék Jelzálogbank Nyrt.
- ITALY: Banca Carige; Banca Finnat Euramerica; Banca Generali; Banca Monte dei Paschi di Siena; Banca Popolare di Milano; Banca Popolare di Sondrio; Banca Profilo; Banca Sistema; Banco BPM Società per Azioni; Banco di Desio e della Brianza; Banco di Sardegna; BPER Banca; Credito Emiliano; FinecoBank; Banca Fineco; Intesa Sanpaolo; Mediobanca Banca di Credito Finanziario; UniCredit; Unione di Banche Italiane.
- LITHUANIA: AB Siauliu Bankas.
- NETHERLANDS: ABN AMRO Bank; ING Groep; Van Lanschot Kempen.
- NORWAY: Aurskog Sparebank; DNB ASA; Høland og Setskog Sparebank; Instabank; Jæren Sparebank; Komplett Bank; Melhus Sparebank; Norwegian Finans Holding; Sandnes Sparebank; Sbanken; Skue Sparebank; Sogn Sparebank; SpareBank 1; SpareBank 1 Helgeland; SpareBank 1 Nord-Norge; Sparebank 1 Nordvest; SpareBank 1 Østfold Akershus; SpareBank 1 Østlandet; SpareBank 1 Ringerike Hadeland; SpareBank 1 SMN; SpareBank 1 SRBank; SpareBank 1 Telemark; Sparebanken Møre; Sparebanken Øst; Sparebanken Sør; Sparebanken Vest; Totens Sparebank; Voss Veksel og Landmandsbank.
- POLAND: Alior Bank; Bank Handlowy w Warszawie; Bank Millennium; Bank Ochrony Srodowiska; Bank Polska Kasa

Opieki; BNP Paribas Bank Polska; Getin Holding; Getin Noble Bank; ING Bank Slaski; mBank; Powszechna Kasa Oszczednosci Bank Polski; Santander Bank Polska.
- PORTUGAL: Banco BPI; Banco Comercial Português; Banco Espírito Santo.
- ROMANIA: Banca Transilvania; BRD Groupe Société Générale.
- SPAIN: Banco Bilbao Vizcaya Argentaria; Banco de Sabadell; Banco de Valencia; Banco Popular Español; Banco Santander; Bankia; Bankinter; CaixaBank; Liberbank; Unicaja Banco.
- SLOVAKIA: OTP Banka Slovensko; Vseobecna uverova banka.
- SWEDEN: Avanza Bank Holding; Collector; Handelsbanken; Skandinaviska Enskilda Banken; Swedbank; TF Bank.
- UNITED KINGDOM: Barclays; HSBC Holdings; Lloyds Banking Group; Metro Bank; NatWest Group; Standard Chartered.

Appendix C. Robustness Exercise: Impact of the Pandemic

Table C.1 shows estimates of the baseline model for the full sample. S_BUF and SII_STAT are interacted with a dummy indicator, $COVID$, that is 1 during the pandemic period and 0 otherwise.

Table C.1. Estimates of Baseline Model for Full Sample

	Full Sample			
	MI	**M2**	**M3**	**M4**
S_BUF	–79.40	–620.5***		
	(276.7)	(222.4)		
S_BUF × *COVID*		1,642***		
		(492.8)		
SII_STAT			–1,303**	–2,406***
			(518.3)	(609.2)
SII_STAT × *COVID*				5,223***
				(1,012)
Total Assets	0.039***	0.038***	0.039***	0.038***
	(0.003)	(0.003)	(0.003)	(0.003)
RoE	–8.10***	–8.14***	–8.14***	–7.79***
	(3.01)	(2.98)	(3.01)	(2.93)
CCyB	–499.0**	–448.6**	–513.6**	–673.6***
	(236.1)	(191.6)	(254.0)	(213.6)
SyRB	318.5***	317.7***	167.9	347.6***
	(100.6)	(115.3)	(115.3)	(101.2)
CCoB	636.3***	704.1***	653.9***	489.7***
	(208.1)	(203.8)	(228.0)	(185.0)
GDPpc	–76.04***	–75.45***	–71.69***	–74.92***
	(26.27)	(25.77)	(24.02)	(22.75)
CDS	0.003	0.005	–0.013	0.001
	(0.032)	(0.031)	(0.036)	(0.032)
N	6,487	6,487	6,487	6,487
R^2	0.396	0.409	0.400	0.430

Note: Dependent variable: systemic risk contribution of individual banks as proxied by the SRISK indicator (see Brownlees and Engle 2017); all explanatory variables are lagged one period; *S_BUF*: SII buffer level; *SII_STAT*: binary dummy, $SII\_STAT = 1$ while a bank has SII status; *COVID*: binary dummy, $COVID = 1$ from 2020:Q1 to 2021:Q3. See Table 2 for a complete description of the explanatory variables and data sources. Standard errors are shown in parentheses. Standard errors are robust to heteroskedasticity and serial correlation. Intercept, time, and bank fixed effects are included but not reported. ***, **, and * refer to significance at 1 percent, 5 percent, and 10 percent level, respectively.

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