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Borsa İstanbul Review

Borsa İstanbul Review 23-1 (2023) 203–216
http://www.elsevier.com/journals/borsa-istanbul-review/2214-8450

Full Length Article

Bank contribution to financial sector systemic risk and expected returns: Evidence from large U.S. banks

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Received 22 March 2022; revised 8 October 2022; accepted 8 October 2022
Available online 17 October 2022

Abstract

We estimate the contribution of large U.S. banks to the financial sector systemic risk by using value-at-risk (*VaR*), conditional value-at-risk (*CoVaR*), and two-stage least square (2SLS) methodology. Our sample is the monthly stock returns of 25 large U.S. banks from 1997 to 2021. We find that banks contributing more to the systemic risk have lower future returns on average. We also sort the portfolios' future returns into five pentiles based on systemic risk contribution (*SRC*) and find that portfolios with high SRC earn lower future returns than those with low *SRC*. Our second contribution to the literature is the indication of the endogeneity problem in the *SRC* measures. We suggest an identification strategy for the estimation of *SRC* measures. Our results are contrary to some of the earlier studies, which concluded that the Dodd–Frank act of 2010 failed to eliminate the too-big-to-fail problem in banks. Such studies showed that anticipation of government subsidies has not been eliminated in the form of higher expected returns even for banks contributing more to systemic risk of the financial system. The results in our present study open a new research direction and are useful for investors and policymakers.

JEL classification: G01; G10; G18; G20; G28; G32; G38

Keywords: Systemic risk; Ranking; Financial institutions; Endogeneity

1. Introduction

Since the global financial crisis (GFC), researchers have focused on making new systemic risk measures that could better measure the spillover of the risk from one institution to another. Examples of the systemic risk measures introduced in the literature are delta conditional value-at-risk ($\Delta CoVaR$) by Adrian and Brunnermeier (2011) and marginal expected shortfall by Acharya et al. (2017). These measures are supposed to estimate the spillover of systemic risk from one market to another and vice versa. In the case of financial markets, risk spillover is measured from financial markets to individual financial institutions (banks) and from individual financial institutions (banks) to the financial market. One problem with these measures is that they do not establish causality. Adrian and Brunnermeier (2011) stated that "*Note that the $\Delta CoVaR$ measure does not distinguish whether the contribution is causal or simply driven by a common factor.*" This notion means that the contribution of an individual financial institution toward the aggregate financial market is not necessarily driven by that individual financial institution. Such contribution is measured by $\Delta CoVaR$ of the market conditional on the individual financial institution at or above its *VaR*. As such contribution is not driven by an individual financial institution, these measures cannot be used in causal studies as the coefficients on these measures are unreliable. Consequently, most studies concerning the contribution to systemic risk of financial markets only showed how $\Delta CoVaR$, of the financial market conditional on the individual financial institutions, differs for different financial institutions. These studies did not deal with the issue of causality (Bernal et al., 2014; Girardi & Tolga Ergün, 2013; Karimalis & Nomikos, 2018).

In this article, we suggest the reason behind the lack of causality in systemic risk measures and try to find a solution so

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Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

https://doi.org/10.1016/j.bir.2022.10.002

that these new measures show causal risk spillover effects. We suggest that the lack of causality is caused by the two-sided causality: from the financial market to the individual bank and from individual banks to the financial markets. Owing to these bidirectional causal effects, risk spillover effects, as measured by systemic risk measures, are confounded by risk spillover in the opposite direction. We then use these newly adapted measures of risk spillover in stock pricing specifications of large banks. We test the hypotheses that systemic risk contributions (*SRCs*) of individual banks are priced factors. The finance literature agrees that the large banks in financial markets generate most of the systemic risk in the system and represent most of the market in the financial sector (De Jonghe et al., 2015; bib_laeven_et_al_2014Laeven et al., 2014). In addition, the computational complexity of measuring the systemic risk spillover measures allows selective sampling in studies where *SRC* measures are to be computed.

The literature has discussed intensively the too-big-to-fail (*TBTF*) problem in the banking industry (Mishkin, 2006). The problem lies in the form of deposit insurance, government loans, and government direct assistance to troubled banks. The reason behind the government support is that troubled banks and bank panics can severely hamper the economy. They can trigger recessions by eliminating the information asymmetry solver's role in the banking industry and preventing the efficient flow of finances from lenders to borrowers. Thus, investment in the economy is reduced, leading to economic recessions. All major economic recessions in the last hundred years in the U.S. have started after the financial crises. Therefore, the government tried to avoid these major effects of the failures of large banks by giving subsidies and insurance to the banks. However, the downside of these guarantees is that it creates further information asymmetry problems in the banking system. Banks that expect government assistance in troubled times create moral hazard problems by investing in risky assets (loans). In regular times, without government subsidies and guarantees, these banks would have been managed by the depositors as they would have started withdrawing their deposits from these risky banks. However, the government deposit insurance for the depositors eliminates their incentive to withdraw their money from these troubled banks. Hence, the U.S. government tried to eliminate the *TBTF* problem by strictly monitoring the potentially problematic domestically systemically important financial institutions to overcome these informational problems. The government identified the potential banks that could contribute more to the systemic risk of the financial system and regulated them to strict monitoring and stress-testing under the 2010 Dodd–Frank act. One of the implications of this act is to eliminate the investors' expectations of government subsidies and bailouts.

The term *TBTF* is used implicitly because previous research showed that big banks contribute more to the systemic risk of the financial sector (Laeven et al., 2014). Therefore, in effect, a bank's ability to contribute to the systemic risk creates investors' expectations of government assistance in the event of financial problems. One of the implications of the *TBTF* problem is that investors should value banks that contribute more to the systemic risk higher than other banks. In this study, we test for this implication of the *TBTF* problem. Our sample period allows us to check for the effect of the 2010 Dodd–Frank act on investors' expectations of government bailouts in case of financial problems. We develop direct measures of contribution to systemic risk to measure the contribution to systemic risk. We also identify that previous research neglected the two-sided causality problem when measuring the contribution to the systemic risk and thus its implications. We suggest a solution to this problem using the whole stock market-level *VaR* as an instrumental variable in two-stage least squares (2SLS). Our results suggest that investors value banks that contribute more to systemic risk. However, this relationship holds only in the full period (1997–2021) and in the subsample before 2010 (1997–2009). Consistent with the implications of the Dodd–Frank act of 2010, the investor expectations of lower returns and thus higher value are eliminated in the after 2010 (2010–2021) sample.

Our study makes the following contributions to the existing literature. First, our study adds to the existing literature on the *TBTF* problem by investigating the issue in a unique way. Second, we identify the problems of endogeneity associated with existing "contribution to the systemic risk measures." Third, we suggest a solution to the endogeneity problem by using 2SLS and market *VaR* as an instrumental variables.

The paper is structured as follows. Section 1 is the introduction. Section 2 is the literature review. Section 3 builds the hypotheses. Section 4 describes the data and methodology. Section 5 reports the results and discussion. Section 6 concludes the study.

2. Literature review

First, our study contributes to the systemic risk literature. Lee et al. (2020) found that banks with overconfident chief executive officers contribute more to systemic risk. They used a *CoVaR*-based measure of contribution to measuring systemic risk. Lee (2020) separated the systematic part of the returns from total returns to derive a measure of systemic risk, which they call the Net Systemic Risk. Using a sample of large European banks, Borri and Di Giorgio (2021) found that large banks contribute more to systemic risk. Rahman et al. (2022) computed the contribution of systemic risk of Australian banks and discussed the determinants of *SRC*. They used a copula-based *CoVaR* measure for *SRC* estimation. They found that *SRC* is concentrated in major Australian banks. Xu et al. (2019) used a type of *CoVaR* to estimate the *SRC* in the Chinese market. They ranked institutions in terms of *SRC*. Banulescu and Dumitrescu (2015) suggested component expected shortfall as a measure of the *SRC*. In addition, *SRC* has another type of measure, that is, Shapley value, from the game theory. Many papers used Shapley values as a measure of *SRC* (Shalit, 2020; Tarashev et al., 2016; Zedda & Cannas, 2020). Shapley value is the concept of game theory that attributes the marginal contribution of a player in a cooperative game. It measures the *SRC* as the average contribution of a bank in all possible coalitions.

One criticism of all the above types of studies described in our paper is that these papers did not consider problems of endogeneity in *SRC* measures. The financial sector and systemically important financial institutions (*SIFIs*) interact simultaneously. Hence, a particular measure of the *SRC* for a *SIFI* will be confounded by the effects of the financial sector on the *SIFI*. We argue that clear causality should be established in the measures of *SRC*. We advance the issue of causality in *SRC* measures by discussing the confounding factors and proposing a solution to address the *SRC* measures of these factors.

Our study also contributes to the literature on the expected returns of banks as very few cross-sectional studies regarding bank stock returns exist. Cooper et al. (2003) studied the cross-section of bank stock returns. They found that various ratios related to banking services, noninterest income, loan-loss reserves, earnings, leverage, and standby letters of credit are all univariately important in forecasting the cross-section of bank stock returns. Chen (2011) found that capital ratios predict the cross-section of stock returns in Japan. Gandhi and Lustig (2015) uncovered a size factor in the component of bank returns that is orthogonal to the standard risk factors, including small minus big, which has the right covariance with bank returns to explain the average risk-adjusted returns. Carmichael and Coën (2018) found a real estate factor that predicts the bank returns in a cross-section. The current literature on expected stock returns recognized the extreme risk of the sector, market, and tail risk as priced in expected stock returns. However, the contribution to the systemic risk by individual banks has not been shown to be priced in the expected returns of the banks, although theory predicted this relationship. This case is perhaps caused by the lack of causality in the measures of *SRC*. Our study contributes to this literature by estimating an improved measure of *SRC* and then showing that it is the priced factor for bank stock returns.

Furthermore, our study contributes to research regarding the *TBTF* problem of commercial banks. Barth et al. (2012) contended that *TBTF* is to be contained through regulations, such as Basel 3, the Dodd–Frank act, and the designation of banks as *SIFIs*. Brown (2012) explained the purposes behind the promulgation of the Dodd–Frank act in the case of the *TBTF* problem. Mishkin (2006) explained *TBTF* and how it creates asymmetric information problems. Overall, the literature has conflicting findings about whether the *TBTF* problem persists even after these regulations. The size factor of the bank has been recognized as the main factor behind the *TBTF* problem. The underlying assumption is that all large banks contribute to the systemic risk, and thus, investors expect government subsidies for all large banks and should value all large banks highly. Our study shows that even among large banks, some banks contribute more to the systemic risk than others, and future expected returns are related to this *SRC*. Our measure tries to estimate directly what the size proxies are for. Future research can benefit from *SRC* measures and produce more coherent results about the *TBTF* problem by avoiding the noise in its proxy measure, the size.

3. Data

Our data consist of monthly returns of the 25 largest U.S. banks by size as of year 2007 end. The largest banks were selected because these banks represent most of the market capitalization of the financial industry. Prior research demonstrated that systemic risk is related to the size of the banks (Gandhi & Lustig, 2015). We obtain returns data from the datastream database. The data about the pricing factors are obtained from Kenneth French's data library. Overall, our sample covers the time period from January 1997 to December 2021. One benefit of using the largest banks' sample is that when calculating the impact of systemic risks' contribution on stock price, the impact of small banks is not overrepresented.

4. Methodology

Our methodology consists of estimating the contribution of each individual financial institution to systemic risk using *VaR*, *CoVaR* statistics, and 2SLS methodology. We use the linear regression method and univariate and bivariate portfolio sorts to test our hypotheses.

We run the marginal models on the raw returns data. We use the GJR-GARCH model to filter the time-varying volatility from the data. We follow Huang et al. (2021) and use the following AR (1)-GJR-GARCH (1,1) model.

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \sigma_t z_t \tag{1}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 z_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \gamma \sigma_{t-1}^2 z_{t-1}^2 I(z_t < 0) \tag{2}$$

where z_t is assumed to follow the Gram–Charlier expansion (GCE) distribution function ($z_t \sim \text{GCE}(0, 1, s_t, k_t)$), where GCE distribution function is the distribution function obtained from the GCE (Eqs. (3) and (4)) of the normal density function truncated at the fourth moment. I is an indicator function that takes binary values (1, 0) according to $z_t < 0$ or $z_t \geq 0$, respectively. γ is the coefficient measuring the leverage effect. GCE of normal density functions that truncated at the fourth moment is given by,

$$\begin{aligned} g(z_t|s_t, k_t) &\approx \phi(z)\left[1 + \frac{s_t}{3!}\left(z_t^3 - 3z_t\right) + \frac{k_t - 3}{4!}\left(z_t^4 - 6z_t^2 + 3\right)\right] \\ &= \phi(z_t)\psi(z_t) \end{aligned} \tag{3}$$

where s_t and k_t represent the time-varying third and fourth moments of the return distribution, respectively. Time-varying third and fourth moments are modeled according to Eq. (5) and are estimated jointly using maximum likelihood estimation (MLE) with Eqs. (1) and (2). $\phi(z_t)$ represents the normal distribution probability function. $\phi(z_t)\psi(z_t)$ is not a proper density function, as shown by Leon et al. (2005). Leon et al. (2005) further recommended estimating the following function to obtain the distribution function from the above expansion by normalizing the square of $\psi(z_t)$.

$$GCE(z_t|s_t,k_t)=\phi(z_t)\psi^2(z_t)\left[1+\frac{s_t^2}{3!}+\frac{(k_t-3)^2}{4!}\right]^{-1} \quad (4)$$

We model time-varying skewness and kurtosis as follows:

$$s_t=\lambda_0+\lambda_1 z_{t-1}+\lambda_2 s_{t-1}\;;\; k_t=\eta_0+\eta_1|z_{t-1}|+\eta_2 k_{t-1} \quad (5)$$

Our contribution to the systemic risk measures involves the calculation of *VaR* and *CoVaR* measures. To measure *VaR* from the above distribution function, we need the inverse distribution function for a particular confidence level.

$$VaR_{\alpha,t}=\mu_t+GCE^{-1}_{s_t,k_t}(\alpha)\sigma_t \quad (6)$$

We use the above equation to estimate the value at risk for individual bank returns, financial industry returns (*DJFN* index), and whole stock market returns (*SP500* index). We keep the value of alpha (α) at 1% to estimate *VaR* from the above equation. In Eq. (6), μ_t and σ_t represent the mean and standard deviations of the return series, respectively, which were obtained from the MLE of Eqs. (1), (2) and (5).

We employ the copula functions to estimate the *CoVaRs* in this study. Copula functions estimate the joint probability distribution between two variables as a function of their univariate probability distributions.

$$F_{XY}(x,y)=C(u,v) \quad (7)$$

In Eq. (7), $F_{XY}()$ is the joint distribution function of variables x and y. C(u, v) is the copula function of the two variables x and y, and

$$u=GCE(z_{x,t}|s_{x,t},k_{x,t}) \quad (8)$$

$$v=GCE\left(z_{y,t}\middle|s_{y,t},k_{y,t}\right) \quad (9)$$

This study uses Normal, Student-t, Clayton, rotated-Clayton, Gumbel, and rotated-Gumbel copulas to compute *CoVaRs* and *ΔCoVaRs*. We use $\alpha = 0.01$. Using Eqs. (8) and (9) and the copulas stated above, we estimate the bivariate distribution between u and v in the above equations. We then invert the bivariate distribution function to compute *CoVaR* as $CoVaR = GCE^{-1}(F(CoVaR))$.

In Eqs. (8) and (9), *GCE* is estimated as in Eq. (4) using $s_{x,t}$, $k_{x,t}$, and z_t. We estimate downside *CoVaRs* of DJFN conditional on an individual bank as $CoVaR^d_{b,t}$. The $CoVaR^d_{b,t}$ tells whether the DJFN is in turmoil and if the individual bank is below its *VaR*. We use $\Delta CoVaR^d_{b,t}$, which is *ΔCoVaR* of DJFN conditional on the individual bank, to know how much of the risk of the DJFN is due to the individual bank. We compute the *ΔCoVaR* as follows:

$$\Delta CoVaR^d_{b,t}=\frac{\left(CoVaR^{d,\alpha=0.01}_{b,t}-CoVaR^{d,\alpha=0.5}_{b,t}\right)}{CoVaR^{d,\alpha=0.5}_{b,t}}$$

where the *ΔCoVaR* is the percentage difference of the *CoVaR* of the currency market with $\alpha = 0.01$ from the *CoVaR* of the currency market with $\alpha = 0.5$. We modify $\Delta CoVaR^d_{b,t}$ so as to use it as an *SRC* measure comparable across individual banks. Specifically, we compute

$$DCoVaR^d_{b,t}=CoVaR^{d,\alpha=0.01}_{b,t}-CoVaR^{d,\alpha=0.5}_{b,t} \quad (10)$$

SRC measures employed in this study are related to *VaR* and *CoVaR* calculated using the above methodology. Our first measure of *SRC* is defined as the portion of the DJFN *VaR*, value-at-risk of the financial industry (VaR_{dt}) explained by individual bank *VaR*, value-at-risk of individual banks (VaR_{bit}), in simple linear regression, second term in the right-hand side (RHS) of following equation:

$$VaR_{dt}=a_0+a_{i1}VaR_{bit}+e_{it} \quad (11)$$

In Eq. (11), subscript i is added to represent the individual bank identity. Our second measure of the *SRC* s is obtained similarly by regressing $DCoVaR^d_{b,t}$ on VaR_{bit} and using the portion of $DCoVaR^d_{b,t}$ explained by VaR_{bit}, second term in the RHS of following equation:

$$DCoVaR^d_{b,t}=b_0+b_{i1}VaR_{bit}+e_{it} \quad (12)$$

Endogeneity issues in *SRC* estimation in Eqs. (11) and (12) make the estimation of a_{i1} and b_{i1} biased using simple linear regression. In Eq. (11), the endogeneity arises because of reverse causality as VaR_{dt} is a major determinant of VaR_{bit}. Considering that VaR_{dt} is a major determinant of VaR_{bit}, the $DCoVaR^d_{b,t}$ in Eq. (10) is confounded with the effect of variation in VaR_{dt}. For this reason, we attempt to separate the portion of $DCoVaR^d_{b,t}$ which is explained by VaR_{bit}. We use Eq. (12) for this purpose. However, Eq. (12) suffers from endogeneity for the same reasons as Eq. (11). We try to eliminate endogeneity using 2SLS. We need a valid instrumental variable for 2SLS. We identify *VaR* of the SP500 index, value-at-risk of whole stock market (VaR_{mt}), a potential exogenous instrumental variable in the relationship between VaR_{bit} and VaR_{dt} in the following equation, having problems of reverse causality:

$$VaR_{bit}=c_{i0}+c_{i1}VaR_{dt}+e_{it} \quad (13)$$

VaR_{mt} is the market-level variable and is supposed to be correlated with VaR_{bit} only through its relationship with VaR_{dt}. By using 2SLS, we estimate the unbiased value of c_{i1} in Eq. (13). We adopt the following two-step procedure:

1. We regress VaR_{dt} on VaR_{mt} and obtain the fitted value of the following regression:

   $VaR_{dt}=\alpha_0+\alpha_1 VaR_{mt}+e_t.$

In the above equation, the fitted value of regression consists of the first two terms of the RHS and is represented as follows:

$VaR_{dtf}=\alpha_0+\alpha_1 VaR_{mt}.$

2. We use the fitted value from step 1, VaR_{dtf}, in Eq. (13), in place of VaR_{dt}, to estimate c_{i1a}, in place of c_{i1}.

We then subtract the effect of VaR_{dt} on VaR_{bit} as follows:

$$VaR_{bita}=VaR_{bit}-c_{i1a}VaR_{dt} \quad (14)$$

where VaR_{bita}, *VaR* of bank adjusted for effects of VaR_{dt}, reflects the variation in VaR_{bit} net of effect of variation of VaR_{dt}

on VaR_{bit}. We use VaR_{bita} in place of VaR_{bita} in Eqs. (11) and (12) to estimate a_{i1a} and b_{i1a}, new parameters in place of a_{i1} and b_{i1}, respectively. Our measures of SRC in Eqs. (11) and (12) are calculated as follows:

$$SRC_1 = a_{i1a} VaR_{bit} \tag{15}$$

$$SRC_2 = b_{i1a} VaR_{bit} \tag{16}$$

After computing these measures of endogeneity-corrected SRC_1 *and* SRC_2, we run cross-sectional regressions of individual bank returns on capital asset pricing model (CAPM), Fama-French 3 factor (FF–3F), and Fama-French 5 factor (FF–5F) pricing factors. We also use the univariate and bivariate portfolio sorts and the hypothesis test of the difference between the means of two groups to test the relationship between the *SRC* and cross-sectional stock prices.

Fig. 1(a) and (b) present the line chart of time-varying $DCoVaR^d_{b,t}$ and SRC_1, respectively. Evidently, $DCoVaR^d_{b,t}$ is similar in shape for all of the banks (Fig. 1(a)), although some banks contribute more to the systemic risk than others). However, others may be negatively correlated in the systemic risk event. This finding shows the influence of some common factor on $DCoVaR^d_{b,t}$. Our discussion above argues that variable is VaR_{dt}. Then, Fig. 1(b) shows endogeneity-adjusted $DCoVaR^d_{b,t}$ across the time. The contribution of some banks is positive toward systemic risks, whereas others contribute less in the event of systemic risks.

5. Empirical results

Table 1 presents the descriptive statistics of variables used in the study. These statistics are presented for the full, before-2010, and after-2010 samples. We find that the mean monthly returns of the large banks are positive in the whole sample and for the sample after the GFC but negative for the sample before 2010. Overall, different *VaR* variables show the same trend. The values of *VaR* variables are more negative in the before-2010 sample than the full sample or the after-2010 sample.

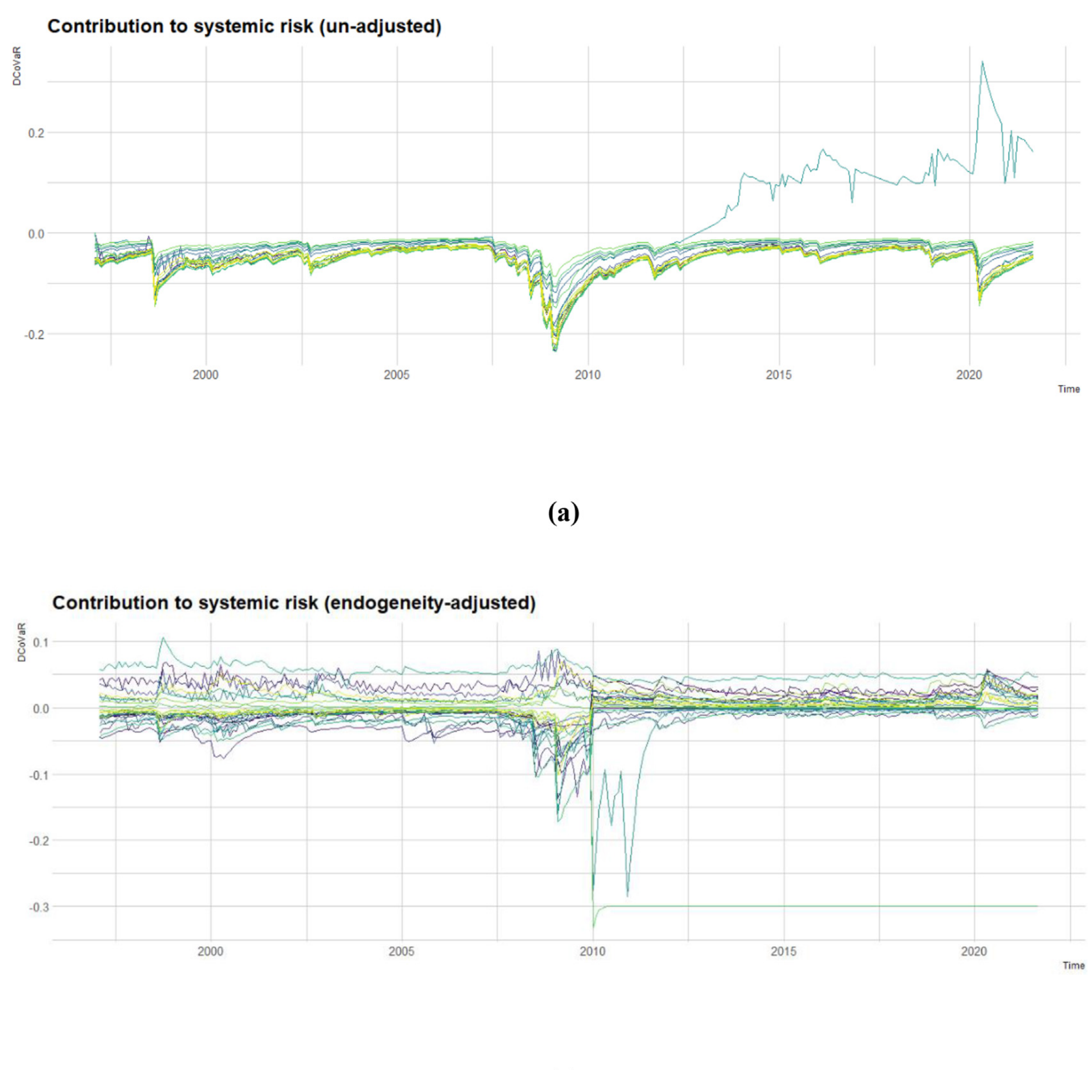

Fig. 1. (a) This figure presents the time-varying $DCoVaR^d_{b,t}$ computed using Eq. (10). (b) This figure presents the time-varying SRC_1 computed using Eq. (15).

Table 1
Descriptive statistics.

Variable	Full Sample					Before 2010					After 2010				
	N	Mean	Std	Min	Max	N	Mean	Std	Min	Max	N	Mean	Std	Min	Max
RET	7400	0.00191	0.098421	−0.99013	0.650588	3875	−0.00212	0.108837	−0.994013	0.546144	3525	0.006342	0.085315	−0.92005	0.650588
$DCoVaR^d_{b,t}$	7400	−0.04650	.0375941	−.235042	0.358231	3875	−.0547621	.0365046	−.2350424	0.000013	3525	−.0404339	.0373384	−.144874	0.358231
VaR_{bit}	7400	−0.33793	0.2753	−0.51817	−0.00184	3875	−0.36288	0.319882	−5.21817	−0.02047	3525	−0.31049	0.212613	−0.24312	−0.00184
VaR_{dt}	7400	−0.24078	0.109818	−0.73111	−0.12296	3875	−0.25745	0.128561	−0.73111	−0.12296	3525	−0.22245	0.080682	−0.49264	−0.1309
VaR_{mt}	7400	−0.17755	0.069674	−0.44643	−0.09881	3875	−0.1953	0.079384	−0.44643	−0.10639	3525	−0.15803	0.050366	−0.38293	−0.09881
RERF	7176	0.004214	0.050918	−2.3581	0.195156	3875	0.00622	0.052146	−0.15933	0.195156	3300	0.002573	0.027325	−0.07688	0.08994
MOM FACTOR	7400	0.330237	5.188234	−34.3	18.2	3875	0.431161	6.358006	−34.3	18.2	3525	0.219291	3.471883	−12.45	10.06
LIQ FACTOR	7175	0.362422	4.814722	−19.4283	19.7956	3875	0.927667	4.936137	−10.0974	19.7956	3300	−0.30131	4.580651	−19.4283	15.6074
MKTRF	7400	0.00706	0.045836	−0.1723	0.1365	3875	0.002552	0.048938	−0.1723	0.1018	3525	0.012016	0.04161	−0.1338	0.1365
SMB	7400	0.002009	0.03205	−0.1539	0.1838	3875	0.003378	0.036753	−0.1539	0.1838	3525	0.000504	0.025833	−0.0832	0.0703
HML	7400	0.000539	0.033303	−0.1402	0.1248	3875	0.003536	0.036452	−0.1111	0.1248	3525	−0.00276	0.029106	−0.1402	0.0821
RMW	7400	0.003038	0.028701	−0.1876	0.1338	3875	0.004452	0.036117	−0.1876	0.1338	3525	0.001484	0.017055	−0.0388	0.0635
CMA	7400	0.001896	0.021086	−0.0678	0.0906	3875	0.003775	0.024833	−0.0678	0.0906	3525	−0.00017	0.015731	−0.0325	0.0477

Notes: Table 1 presents the descriptive statistics of various variables used in the study. The descriptive statistics are provided for the full sample and the subsamples before and after 2010. *RET* is monthly return, $DCoVaR^d_{b,t}$ is the difference in *CoVaR* of the financial sector conditional on a particular bank being in financial distress relative to when the bank is at its average position. VaR_{bit} is 1% value-at-risk of the bank. VaR_{dt} and VaR_{mt} are 1% value-at-risk of the financial sector and the whole stock market, represented by the S&P 500 index, respectively. *MKTRF* is a monthly market return in excess of risk-free return. *SMB*, *HML*, *RMW*, and *CMA* are Fama-French 5 factor model's factors. MOM FACTOR and LIQ FACTOR are the momentum and liquidity factors, respectively.

Table 2 presents the correlation between the variables. The correlation between VaR_{mt} and VaR_{dt} is high (0.8). Overall, the pair-wise correlation between the other variables does not indicate a multicollinearity problem.

Table 3 presents the univariate one-way portfolio sorts of 3-month future returns on the basis of the past one-year average of SRC_1 (columns 2–4) and SRC_2 (columns 5–7). The last two rows of Table 3 present the difference between the average returns of the fifth and first quantiles, including the t statistics of that difference. Columns 2, 3, 5, and 6 show that the difference is statistically significant. Then, columns 4 and 7 present that the difference is statistically insignificant. This result means that the banks that contribute more to the systemic risk in the past one year tend to have lower three-month forward returns for the full sample and before-2010 sample but not for the after-2010 sample.

Table 4 presents one-way portfolio sorts of FF-5F, FF-3F, and CAPM model alpha based on SRC_1. These portfolio sorts are presented for the full, before-2010, and after-2010 samples. The results are consistent with those in Table 3. We find that different portfolios of extreme quantiles are significant in the full and before-2010 samples but not in the after-2010 sample. This finding can be interpreted as the portion of return that cannot be explained by the risk factors is related to SRC_1. For portfolios with strong SRC_1, the alpha is lower than for portfolios with week SRC_1.

Table 6 regresses the returns of the long-short strategy on different pricing factors. The argument behind this strategy is that if the variation in SRC_1 is correlated with the risk factors, then the alpha from such regressions will not be significant. Table 6 shows that alpha coefficients for all models are highly significant (at 1% level). This result shows that the variation in *SRC* is not correlated entirely with the pricing factor, indicating that *SRC* is a separate pricing factor for bank returns.

Table 7 presents the bivariate portfolio sorts of three-month returns in RERF and SRC_1. The purpose of this analysis is to determine if the variation in *SRC* is caused by another controlled factor, *RERF*. We select the *RERF* because earlier tests show that *SRC* explains future returns in the before-2010 sample. Moreover, the *SRC* variation could be because of the real estate factor as the before-2010 sample featured the real estate bubble and crash and consequent financial sector crisis, an event of systemic risk. Our analysis finds that controlling for the *RERF*, the SRC_1 variation is correlated with the three-month return variation as the difference of returns in the second last row for the full and before-2010 samples is evidently insignificant. This finding shows that the variation in *SRC* explains the return variation even after controlling for RERF in five quantiles.

For the robustness of our results, we repeat some of the main tests above using different variables, for example, SRC_2. Table 8 presents the tests performed in Table 5 but with the variable SRC_2. The coefficients of interest are on the variable SRC_{1Y} (mean $SRC1$ over previous one year). For the models relating to the full and before-2010 sample period, we see that SRC_{1Y} is significantly and positively related to various future returns (one month, three months, six months, and one year). This finding shows that our results are not related to a particular proxy for *SRC*.

Table 2
Correlation table.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	*RET*	1.00														
2	SRC_1	0.01	1.00													
3	SRC_2	0.01	0.95	1.00												
4	$\boldsymbol{VaR}_{bit}$	−0.02	0.00	−0.10	1.00											
5	$\boldsymbol{VaR}_{dt}$	−0.02	0.06	0.00	0.63	1.00										
6	$\boldsymbol{VaR}_{mt}$	0.01	0.02	−0.02	0.49	0.80	1.00									
7	*BETA*	0.00	0.18	0.23	−0.19	0.00	0.00	1.00								
8	*RERF*	−0.11	0.00	0.00	0.02	0.04	0.01	0.00	1.00							
9	*MOM FACTOR*	−0.30	0.01	0.00	0.16	0.23	0.20	0.00	0.09	1.00						
10	*LIQ FACTOR*	0.31	0.00	0.01	−0.04	−0.10	−0.13	0.00	−0.28	−0.34	1.00					
11	*MKTRF*	0.49	0.00	−0.01	−0.06	−0.14	−0.08	0.00	−0.08	−0.33	0.31	1.00				
12	*SMB*	0.14	0.00	0.01	−0.04	−0.09	−0.12	0.00	−0.34	−0.02	0.60	0.28	1.00			
13	*HML*	0.36	0.00	0.00	0.01	0.04	0.05	0.00	−0.10	−0.26	0.53	−0.06	0.01	1.00		
14	*RMW*	−0.09	0.00	0.00	−0.01	0.03	−0.01	0.00	0.17	0.07	−0.10	−0.42	−0.46	0.43	1.00	
15	*CMA*	0.03	0.00	0.01	0.00	0.00	−0.03	0.00	−0.15	−0.01	0.35	−0.31	0.01	0.60	0.29	1.00

Table 3
One-way portfolio sorts.

	SRC_1			SRC_2		
	Full Sample	Before 2010	After 2010	Full Sample	Before 2010	After 2010
Strong	−0.00013	−0.00449	0.00431	−0.00144	−0.00296	0.00596
2	−0.00117	−0.00693	0.00470	−0.00194	−0.00777	0.00401
3	−0.00017	−0.00627	0.00606	−0.00127	−0.00906	0.00667
4	0.00052	−0.00565	0.00684	0.00174	−0.00211	0.00569
Week	0.00398	0.00212	0.00588	0.00305	0.00070	0.00544
Week–Strong	0.00469**	0.00670**	0.00151	0.00428***	0.00367***	−0.00051
	(1.98)	(2.13)	(0.4944)	(2.41)	(2.53)	(-1.25)

This table presents the results of the one-way portfolio sorts of 3-month future returns based on the past 1-year average of SRC_1 and SRC_2. The first row presents the strong risk contribution, whereas the fifth row represents the week risk contribution. The row labeled 5–1 represents the difference between portfolios 5 and 1. Columns 2–4 present the one-way portfolio sorts with $SRC_{1,}$ whereas columns 5–7 present the one-way portfolio sorts with SRC_2.

Table 4
One-way portfolio sorts of alpha coefficient.

	Full sample			Before 2010			After 2010		
	FF5-alpha	FF3-alpha	CAPM model	FF5-alpha	FF3-alpha	CAPM-alpha	FF5-alpha	FF3-alpha	CAPM-alpha
Strong	0.00273	0.00238	0.00317	−0.0019	−0.00134	0.00120	0.00794	0.00653	0.00536
2	0.00158	0.00218	0.00275	−0.0038	−0.00232	−0.00061	0.00748	0.00709	0.00643
3	0.00480	0.00451	0.00470	−0.0011	−0.00015	0.00079	0.01127	0.00957	0.00895
4	0.00632	0.00558	0.00449	0.0031	0.00306	0.00106	0.00979	0.00837	0.00825
Week	0.00814	0.00697	0.00692	0.0085	0.00712	0.00650	0.00764	0.00680	0.00738
Week–Strong	0.00558***	0.00458***	0.00374***	0.0105***	0.00847***	0.00529***	0.00030	0.00026	0.00202
	(3.21)	(3.52)	(3.36)	(4.12)	(4.52)	(2.98)	(1.58)	(0.1834)	(1.53)

This table presents the portfolio sort according to SRC_1 of yearly alpha coefficient obtained from the Fama-French 5-factor model, Fama-French 3-factor model, and CAPM model. These estimates are obtained for the full sample (columns 2–4), before-2010 sample (Columns 5–7), and after-2010 sample (Columns 8–10). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

In Table 9, we then run the regressions of various future period returns on various pricing factors used earlier and SRC_{1Y} computed using SRC_1 and SRC_2. The sample period used is the financial crisis of 2007–2009 and 2020. Our results show that SRC_{1Y} is also related to future returns in the crisis period. In Table 10, we run the regressions of the long-short return strategy of three-month future returns computed based on SRC_2. In Table 10, the coefficients on the variable CONS are significant. This result means that the variation in *SRC* is not totally correlated with known pricing factors and that *SRC* determines the future bank stock returns in the cross-sectional regressions.

5.1. Discussion

Our results are different from the recent literature about the situation of the TBTF problem, which describes that the problem continues in the form of expectation of various subsidies, higher risk-taking by TBTF banks, and higher credit ratings for such banks (Afonso et al., 2014; Allen et al., 2018; Kolaric et al., 2021). Some recent papers reported results that are in line with our paper. For example, Berndt et al. (2021) reported a reduction in the market-implied probability of government subsidy after the GFC.

Table 5
Cross-sectional regressions.

	Full Sample					Before 2010				After 2010		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}
MKTRF	0.134***	0.0698**	0.0954***	0.521***	0.220***	0.118**	0.149***	0.847***	0.0507	−0.0241	0.00870	−0.292*
	(3.68)	(2.81)	(5.77)	(4.15)	(4.09)	(2.61)	(5.10)	(4.06)	(0.93)	(−0.98)	(0.48)	(−1.98)
SMB	0.0967*	0.0761**	−0.0418*	−0.00689	0.272***	0.129***	−0.0384	0.326	−0.136	0.106*	0.0740*	0.800**
	(2.00)	(2.88)	(−2.16)	(−0.05)	(4.31)	(3.62)	(−1.54)	(1.70)	(−1.68)	(2.21)	(2.07)	(2.88)
HML	0.0723	0.0916*	−0.0782**	−0.416	0.198*	0.150	−0.103*	0.226	−0.0951	0.0205	−0.0621*	−0.859**
	(1.19)	(2.00)	(−2.70)	(−1.83)	(2.22)	(1.92)	(−2.13)	(0.65)	(−1.23)	(0.52)	(−2.20)	(−2.99)
RMW	−0.0829	−0.0918*	0.00193	−0.474*	0.0339	−0.0547	0.0481	−0.521	−0.163	−0.00309	0.00177	0.550
	(−1.42)	(−2.52)	(0.08)	(−2.34)	(0.39)	(−0.91)	(1.22)	(−1.76)	(−1.66)	(−0.05)	(0.04)	(1.54)
CMA	0.276**	0.0315	0.120***	1.254***	0.0654	−0.0546	0.205***	1.382***	0.918***	0.372***	0.0555	1.634***
	(3.26)	(0.58)	(3.85)	(4.67)	(0.66)	(−0.73)	(4.62)	(3.99)	(6.54)	(5.20)	(1.20)	(3.70)
RERF	0.0445	0.0458**	−0.0112	0.169	0.0750*	0.0657***	0.00113	0.366**	−0.123*	−0.00817	0.0110	0.291
	(1.57)	(2.86)	(−0.86)	(1.59)	(2.24)	(3.49)	(0.08)	(3.00)	(−2.11)	(−0.24)	(0.40)	(1.28)
SRC_{1Y}	0.0221***	0.0240***	0.0260***	0.305***	0.0375***	0.0350***	0.0314***	0.423***	0.00302	0.00356	0.00392	0.0464
	(2.39)	(2.63)	(4.32)	(6.12)	(2.25)	(2.61)	(2.79)	(4.42)	(1.28)	(1.57)	(1.21)	(1.13)
CONS	−0.00142	−0.000406	−0.000482	0.000720	−0.00680***	−0.00530***	−0.00520***	−0.0635***	0.00435*	0.00542***	0.00482***	0.0701***
	(−1.07)	(−0.53)	(−0.88)	(0.16)	(−3.52)	(−4.38)	(−6.22)	(−8.59)	(2.34)	(5.60)	(6.94)	(14.45)
N	6900	6900	6900	6900	3600	3600	3600	3600	3300	3300	3300	3300
R^2	0.06	0.05	0.07	0.05	0.07	0.08	0.07	0.06	0.04	0.05	0.05	0.04

Notes: This table presents the cross-sectional regressions of one-month (RET_{t+1}), three-month ($RET_{3\ m}$), six-month ($RET_{6\ m}$), and one-year future returns (RET_{1y}) on the Fama-French 5-factors, real estate factor, and past one-year average of SRC_1 (SRC_{1Y}). The samples used to perform the regressions are the full sample (1997–2021), the before-2010 sample (1997–2009), and the after-2010 sample (2010–2021). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. The standard errors used are robust standard errors.

Table 6
Long-Short regressions.

	Full sample				Before 2010			After 2010	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Long-Short Returns	Long-Short Returns	Long-Short Returns	Long-Short Returns	Long-Short Returns	Long-Short Returns	Long-Short Returns	Long-Short Returns	Long-Short Returns
MKTRF	0.0205	0.000703	−0.0219	−0.0321	−0.0771***	−0.0992***	0.0673***	0.0768***	0.0871***
	(1.72)	(0.06)	(−1.81)	(−1.55)	(−3.57)	(−4.97)	(4.62)	(5.80)	(6.44)
SMB	0.175***	0.111***	0.0999***	0.286***	0.222***	0.194***	−0.0580*	−0.0579*	−0.0482*
	(8.63)	(7.80)	(7.31)	(9.48)	(10.58)	(10.66)	(−2.40)	(−2.55)	(−1.98)
HML	0.277***	0.179***	0.212***	0.478***	0.392***	0.422***	0.0412*	0.0350*	0.0634***
	(9.85)	(7.78)	(8.71)	(10.72)	(9.60)	(11.09)	(1.98)	(2.21)	(3.30)
RMW	−0.00338	0.0108	−0.0124	−0.0621	−0.0518	−0.0830**	−0.0731**	−0.0750***	−0.0669**
	(−0.17)	(0.58)	(−0.64)	(−1.91)	(−1.56)	(−2.64)	(−2.93)	(−3.44)	(−2.70)
CMA	−0.0134	−0.0161	−0.0203	−0.186***	−0.213***	−0.189***	0.177***	0.163***	0.150***
	(−0.41)	(−0.57)	(−0.69)	(−4.13)	(−5.10)	(−4.83)	(5.15)	(5.96)	(4.46)
LIQUIDITY	−0.000792***			−0.000949***			−0.0000454		
	(−4.60)			(−3.58)			(−0.36)		
MOMENTUM		−0.000220*			−0.000463***			−0.000293*	
		(−2.23)			(−3.59)			(−2.10)	
RERF			0.0504***			0.0515***			0.0425***
			(8.09)			(13.07)			(5.20)
CONS	−0.00437***	−0.00431***	−0.00428***	−0.00710***	−0.00721***	−0.00740***	−0.00235***	−0.00229***	−0.00245***
	(−10.65)	(−10.46)	(−10.41)	(−10.44)	(−10.65)	(−11.36)	(−5.31)	(−5.70)	(−5.58)
N	6900	7125	6900	3600	3600	3600	3300	3525	3300
R_2	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.04	0.04

This table regresses the long-short three-month returns on Fama-French five pricing factors and on liquidity, momentum, and real estate factor separately in three samples. Long-short returns are calculated using a trading strategy that adopts a long position in banks with strong SRC_1 and a short position in banks with week SRC_1. Long-short returns are calculated for three-month future returns each month. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. The standard errors used are robust standard errors.

Table 7
Bivariate portfolio sorts (*RERF v SRC*$_1$).

	Full sample					Before 2010					After 2010				
	RERF					RERF					RERF				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Strong	−0.03153	−0.00872	0.07092	−0.04386	−0.04366	−0.07016	−0.10767	0.06337	−0.17739	−0.09001	0.03169	0.08315	0.07580	0.03468	0.08875
2	−0.03585	−0.03158	0.06728	−0.02381	−0.03576	−0.07318	−0.12469	0.04302	−0.14325	−0.077	0.02523	0.05488	0.08298	0.04644	0.08207
3	0.01668	−0.03486	0.06416	−0.02205	−0.04445	−0.02895	−0.17317	0.03635	−0.12202	−0.09576	0.09135	0.09357	0.08216	0.03675	0.10216
4	0.01116	0.00382	0.06799	−0.01275	−0.05164	−0.04949	−0.11399	0.05588	−0.09433	−0.0988	0.11041	0.11322	0.07583	0.03524	0.08312
Week	0.03071	0.06600	0.10671	0.02681	−0.01025	0.00330	0.04338	0.14349	−0.00583	−0.03873	0.07556	0.08700	0.08291	0.04601	0.07113
Week–Strong	0.06224**	0.07826***	−0.03233	0.07022***	0.03341	0.07346*	0.15105***	0.08012*	0.17155***	0.05127*	0.04387	0.00384	0.00710	0.01133	0.01762
	(2.18)	(2.79)	(1.46)	(2.67)	(1.13)	(1.88)	(2.98)	(1.85)	(3.03)	(1.66)	(1.13)	(0.10)	(0.25)	(0.45)	(0.36)

This table presents the two-way portfolio sorted into five quantiles using *RERF* and *SRC*$_1$. Three-month future return variation caused by the variation in *SRC*$_1$ is tested after controlling for variation in *RERF*. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Robustness tables.

	Full sample					Before 2010				After 2010		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}
MKTRF	0.134***	0.0698**	0.0954***	0.521***	0.220***	0.118**	0.149***	0.847***	0.0506	−0.0242	0.00860	−0.293*
	(3.68)	(2.81)	(5.77)	(4.15)	(4.10)	(2.61)	(5.09)	(4.04)	(0.93)	(0.98)	(0.48)	(1.99)
SMB	0.0967*	0.0761**	−0.0418*	−0.00689	0.272***	0.130***	−0.0382	0.329	−0.136	0.106*	0.0743*	0.803**
	(2.00)	(2.88)	(2.16)	(−0.05)	(4.33)	(3.62)	(−1.53)	(1.72)	(−1.68)	(2.21)	(2.08)	(2.89)
HML	0.0723	0.0916*	−0.0782**	−0.416	0.198*	0.150	−0.103*	0.224	−0.0954	0.0203	−0.0624*	−0.863**
	(1.19)	(2.00)	(−2.70)	(−1.83)	(2.22)	(1.92)	(−2.13)	(0.64)	(−1.23)	(0.51)	(−2.21)	(−3.00)
RMW	−0.0829	−0.0918*	0.00193	−0.474*	0.0343	−0.0546	0.0479	−0.523	−0.163	−0.00271	0.00222	0.555
	(−1.42)	(−2.52)	(0.08)	(−2.34)	(0.39)	(−0.91)	(1.22)	(−1.76)	(−1.65)	(−0.04)	(0.05)	(1.56)
CMA	0.276**	0.0315	0.120***	1.254***	0.0665	−0.0538	0.205***	1.390***	0.919***	0.373***	0.0566	1.647***
	(3.26)	(0.58)	(3.85)	(4.67)	(0.67)	(−0.72)	(4.63)	(4.01)	(6.55)	(5.21)	(1.22)	(3.73)
RERF	0.0445	0.0458**	−0.0112	0.169	0.0751*	0.0657***	0.00116	0.366**	−0.124*	−0.00868	0.0104	0.284
	(1.57)	(2.86)	(−0.86)	(1.59)	(2.24)	(3.49)	(0.08)	(3.01)	(−2.12)	(−0.25)	(0.38)	(1.25)
SRC_{1Y}	0.0221**	0.0240***	0.0260***	0.305***	0.0819**	0.0649***	0.0475***	0.642***	0.0011	0.0023	0.0025	0.0029
	(2.39)	(2.63)	(4.32)	(6.12)	(1.96)	(3.32)	(3.50)	(4.39)	(1.59)	(1.51)	(1.37)	(1.28)
CONS	−0.00142	−0.000406	−0.000482	0.000720	−0.00650***	−0.00506***	−0.00502***	−0.0611***	0.00435*	0.00543***	0.00484***	0.0703***
	(−1.07)	(−0.53)	(−0.88)	(0.16)	(−3.48)	(−4.33)	(−6.19)	(−8.51)	(2.35)	(5.64)	(7.00)	(14.53)
N	6900	6900	6900	6900	3600	3600	3600	3600	3300	3300	3300	3300
R^2	0.04	0.05	0.04	0.05	0.05	0.04	0.05	0.05	0.04	0.04	0.03	0.05

Notes: This table presents the cross-sectional regressions of one-month (RET_{t+1}), three-month ($RET_{3\ m}$), six-month ($RET_{6\ m}$), and one-year future returns (RET_{1y}) on the Fama-French 5-factors, real estate factor, and past one-year average of SRC_2 (SRC_{1Y}). The samples used to perform the regressions are the full sample (1997–2021), before-2010 sample (1997–2009), and after-2010 sample (2010–2021). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. The standard errors used are robust standard errors.

Table 9
Cross-sectional regressions during the financial crisis.

	SRC_1					SRC_2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}	RET_{t+1}	$RET_{3\ m}$	$RET_{6\ m}$	RET_{1y}
MKTRF	0.460***	0.281***	0.384***	2.808***	0.460***	0.281***	0.384***	2.808***
	(5.31)	(4.88)	(9.89)	(8.89)	(5.31)	(4.88)	(9.88)	(8.90)
SMB	0.117	0.667***	0.0578	3.431***	0.116	0.667***	0.0573	3.423***
	(0.57)	(5.75)	(0.69)	(4.90)	(0.56)	(5.73)	(0.68)	(4.87)
HML	−0.0150	−0.428***	−0.608***	−6.772***	−0.0134	−0.425***	−0.605***	−6.737***
	(−0.10)	(−4.68)	(−8.83)	(−11.82)	(−0.09)	(−4.65)	(−8.77)	(−11.72)
RMW	−0.459	−0.917***	−0.561***	−6.155***	−0.458	−0.915***	−0.559***	−6.130***
	(−1.93)	(−5.22)	(−5.16)	(−7.05)	(−1.92)	(−5.21)	(−5.13)	(−7.00)
CMA	0.945**	−0.823**	−0.0110	2.195	0.947**	−0.821**	−0.00870	2.231
	(2.77)	(−3.27)	(−0.08)	(1.78)	(2.78)	(−3.26)	(−0.06)	(1.81)
RERF	0.667***	0.237**	−0.0733	0.125	0.667***	0.237**	−0.0734	0.123
	(5.15)	(3.20)	(−1.18)	(0.23)	(5.15)	(3.19)	(−1.18)	(0.23)
SRC_{1Y}	0.00689***	0.0156***	0.0190***	0.231***	0.0398	0.0526*	0.0612*	0.837**
	(2.62)	(2.92)	(3.43)	(3.90)	(1.48)	(1.74)	(1.90)	(2.97)
CONS	−0.0224***	−0.0209***	−0.0168***	−0.186***	−0.0222***	−0.0207***	−0.0166***	−0.182***
	(−4.76)	(−7.09)	(−7.73)	(−9.59)	(−4.83)	(−7.13)	(−7.64)	(−9.49)
N	1200	1200	1200	1200	1200	1200	1200	1200
R^2	0.05	0.04	0.04	0.06	0.04	0.04	0.04	0.06

Notes: This table presents the cross-sectional regressions of one-month (RET_{t+1}), three-month ($RET_{3\ m}$), six-month ($RET_{6\ m}$), and one-year future returns (RET_{1y}) on the Fama-French 5-factors, real estate factor, and past one-year average of $SRC_{2\ \&\ SRC2}$ (SRC_{1Y}). The samples used to perform the regressions are crisis periods (2007–2009, 2020). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. The standard errors used are robust standard errors.

Table 10
Regression of long-short returns with SRC_2.

	(1)	(2)	(3)	(4)
	Long short returns	Long short returns	Long short returns	Long short returns
MKTRF	0.0441***	0.0586***	0.0763***	0.0264*
	(3.82)	(4.88)	(6.36)	(2.15)
SMB	0.105***	0.0938***	0.208***	0.0971***
	(6.64)	(5.27)	(10.33)	(6.06)
HML	0.170***	0.196***	0.253***	0.159***
	(8.27)	(9.49)	(11.19)	(7.83)
RMW	0.0551**	0.0439*	0.0600**	0.0502**
	(2.94)	(2.23)	(3.20)	(2.65)
CMA	0.114***	0.104***	0.157***	0.130***
	(4.12)	(3.77)	(5.32)	(4.80)
RERF	0.0806***	0.0768***	0.0792***	
	(8.38)	(7.46)	(8.22)	
MOM FACTOR		0.000417**		
		(2.98)		
LIQ FACTOR			−0.00127***	
			(-7.21)	
CONS	−0.00267***	−0.00280***	−0.00267***	−0.00261***
	(−6.64)	(−6.79)	(−6.69)	(−6.50)
N	6900	6900	6900	6900
R^2	0.04	0.04	0.05	0.04

t statistics in parentheses.
$^*p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Our research is different from other papers in that we designate SIFIs through their contributions to the systemic risk of the financial system, whereas many other papers adopt the approach of designating the *SIFI*s, which are domestically systemically important banks. In addition, we measure the implicit government subsidies through lower expected returns and thus higher valuations for SIFIs. Both types of studies could be correct and actually measure different aspects of TBTF subsidies. The better approach will be to repeat these studies by controlling for the differences in the research design and overcoming some of the shortcomings of the previous research, as mentioned in our study.

6. Conclusion

Our study adds new evidence to the literature on *SIFI*s' misvaluation. We find that expected future risk-adjusted returns of the largest U.S. banks are correlated with the *SRC*. Furthermore, these correlations are stronger in the before-2010 sample. Hypothesis tests of differences between means of extreme quantiles in *SRC* also support the results from the cross-sectional regressions. We also identify and correct the problem of causality in previous research because of the simultaneity between financial markets and SIFIs. Our results may be limited to the approach used to estimate *SRC*, although our approach and assumptions are realistic for the findings' empirical research. Our research could be useful for the policymakers, which regulate the financial markets for the elimination of certain problems, such as TBTF. Future research could expand the insights of the current research to other ways that previous research reported SIFIs receiving special status in the economy.

Appendix.

Table A1
Variable definition

Variable	Definition
RET	Ret represents the return on the stock of the bank.
SRC_1	SRC1 represents the measure of systemic risk contribution as computed in Eq. (15).
SRC_2	SRC2 represents the measure of systemic risk contribution as computed in Eq. (16).
VaR_{bit}	This variable represents the value-at-risk computed for the returns of large banks.
VaR_{dt}	This variable represents the value-at-risk computed for the returns on the index representing the whole financial market.
VaR_{mt}	This variable represents the value-at-risk computed for the returns on S&P 500 index.
BETA	Beta is the CAPM-beta and measures the sensitivity of the stock returns to the whole market returns.
RERF	This variable measures the difference in each month between returns for portfolio with highes score and portfolio with lowest score on RER. Here RER is the ratio of real estate assets of a firm.
MOM FACTOR	MOM Factor is Fama-French momentum factor computed as the difference of return between high prior return portfolio and low prior return portfolio.
LIQ FACTOR	LIQ factor is Pástor and Stambaugh (2003) liquidity factor.
MKTRF	MKTRF is market return minus risk-free return.
SMB	SMB is size factor and is the difference in return between small firm portfolio and large firm portfolio when stocks are divided in 10 portfolios based on the size.
HML	HML is value factor and is the difference between return on high B/M stocks and low B/M stocks when stocks are divided into 10 portfolios based on B/M ratio.
RMW	RMW is the return spread of the most profitable firms minus the least profitable firms portfolios in a 10 portfolio sort.
CMA	CMA is the return spread of firms that invest conservatively minus aggressively when sorting is done into 10 portfolios.

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