Scaling the Twin Peaks: Systemic Riskand Dual Regulation

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Abstract

In April 2013, the UK implemented a dual-regulation approach to financial services often referred to as twin peaks. In this paper, we assess the impact of the introduction of twin peaks regulation on the systemic risk contributions of UK financial institutions. Using a matched sample of single- and dual-regulated financial institutions, we provide evidence that twin peaks regulation resulted in a relative reduction in systemic risk for dual-regulated firms.

Keywords: bank regulation, financial stability, regulatory model, systemic risk

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1. Introduction

The global financial crisis, beginning from 2007, exposed the fragility of the financial system and highlighted the potential for economic instability resulting from systemic risk. In response to this crisis, sweeping changes to the landscape underpinning financial regulation have been proposed. Central to this emerging regulatory reorientation is the organizational structure of financial regulators, often blamed for sowing the seeds of the crisis. In the United Kingdom, the Financial Services Authority (FSA) has been heavily criticized for deficiencies in safeguarding the financial system prior to the crisis. The Turner Report suggests that the failure of the FSA "to spot emerging issues was rooted in the paucity of macro-prudential, systemic- and system-wide analysis."

Following on the path of early adopters such as Australia and the Netherlands, the UK introduced a so-called twin peaks approach to financial regulation in 2013. The idea of twin peaks regulation was first proposed by Taylor (1995) and denotes a division between prudential regulatory supervision and conduct of business supervision. This separation is grounded in an expectation that a delineation of responsibilities will reduce conflicts of interest, create clear objectives for each regulator and alleviate the danger that one aspect of regulation monopolizes attention (Godwin *et al.*, 2016). In the UK, FSA regulation has been replaced by two separate agencies, the Prudential Regulation Authority (PRA), with responsibility to ensure safety and soundness for the firms it regulates and the Financial Conduct Authority (FCA), responsible for promoting effective competition, ensuring that relevant markets function well and for conduct regulation of all financial services firms (Financial Services Act 2012). At the heart of the twin peaks approach, prudential regulation, referred to by Nier (2009) as "systemic risk regulation," focuses primarily on the harm that firms can cause to the financial system. The objective of this paper is to provide an initial assessment of whether the concentrated focus on prudential regulation under the twin peaks regime resulted in a change to systemic risk for dual regulated firms.

Our identification strategy takes advantage of the 2013 change in UK regulatory structure. Prior to this, financial institutions were regulated for both prudential supervision and financial conduct by the FSA. Post treatment, certain financial firms are subject to twin peaks regulation by two separate entities, the PRA and FCA. In contrast, others are regulated for both prudential and conduct issues by a single regulator, the FCA. Focusing on listed financial institutions and matching using propensity scores, we get a control group of single-regulator firms that look like those which are dual-regulated. A difference-in-differences analysis then demonstrates that, while treated and untreated firms have similar trends in systemic risk prior to the introduction of twin peaks regulation, after treatment a relative reduction in systemic risk for treated firms is observed.

Our paper makes a number of contributions. First, we build on literature assessing the appropriate regulatory architecture for the financial sector (Gaganis and Pasiouras, 2013; Boyer and Ponce, 2012; Dincer and Eichengreen, 2012). Specifically, our identification strategy allows us to isolate the extent to which a change in regulatory architecture impacts systemic risk. Second, we build upon the systemic risk literature, specifically that focused upon ways to reduce such risks (Anginer *et al.*, 2014; Gauthier *et al.*, 2012). Our finding of reduced systemic risk under the twin peaks regulatory architecture echoes previous work highlighting the central importance of regulation in limiting systemic risk (Bostandzic and Weiss, 2018; Weiss *et al.*, 2014). Finally, our paper contributes some initial empirical evidence to the nascent literature debating the merits of twin peaks regulation.

2. Empirical Design

2.1. Model

To examine the impact of the introduction of twin peaks regulation on systemic risk, we employ a difference-in-differences (Diff-in-Diff) setup, comparing systemic risk changes of dual-regulated financial institutions with changes in such risk for a similar group of institutions that are not dual-regulated. We estimate model specifications that are variants of the following form:

$$SR_{i,t} = \delta_0 + \delta_1 Treated_i + \delta_2 Post_t + \delta_3 Treated_i \times Post_t + \mathrm{FE} + \epsilon_{i,t} \quad (1)$$

where $SR_{i,t}$ is the estimate of systemic risk for institution i at time t. *Treated* is a treatment group indicator equalling 1 for financial institutions that are dual regulated by FCA and PRA, and 0 otherwise. *Post* is a dummy indicator that equalling 1 after the twin peaks implementation (i.e., 2013Q2 and onward) and 0 otherwise. FE refers to firm and quarter fixed effects. The coefficient of interest is δ_3, which measures the difference-in-changes in systemic risk for financial institutions that are dual regulated relative to those that are not. If δ_3 is statistically significant, the introduction of twin peaks regulation has an impact on systemic risk for treated financial institutions. The Diff-in-Diff approach ensures model estimation is not biased by permanent and unobserved differences between the treated and control group or by common trends.

2.2. Systemic Risk Measures

We employ the following quantitative measures for systemic risk: Marginal Expected Shortfall (MES), SRISK, and ΔCoVaR. Following Acharya *et al.* (2012), we compute MES as follows:

$$MES_t^i = -E[R_t^i | R_t^m \leqslant q_\alpha] \quad (2)$$

where R_t^i denotes the daily stock return of institution i at time t; R_t^m represents the daily financial services sector market return at time t; and q_α is the α quantile of market return. Setting α=5%, MES is measured as the average firm return during the 5% worst return days for the financial services industry in a quarter. MES quantifies the extent to which an individual institution's stock returns are low when market returns are low.

We calculate SRISK (Brownlees and Engle, 2017), a conditional capital shortfall measure of systemic risk, representing the capital that institution i requires to weather a financial crisis:

$$SRISK_t^i = kDebt_t^i - (1-k)(1 - LRMES_t^i) \times Equity_t^i \tag{3}$$

where k is the prudential capital ratio which equals 8%, $Debt_t^i$ the debt of institution i at time t and $Equity_t^i$ the book value of equity of institution i at time t. $LRMES_t^i$ is the long-run marginal expected shortfall (Acharya *et al.*, 2012) when the financial services sector returns are below –2%, calculated as follows:

$$LRMES_t^i = 1 - exp(-18 \times (-E[R_t^i | R_t^m < -2\%])) \tag{4}$$

We also follow Adrian and Brunnermeier (2016) to estimate the time-varying ΔCoVaR_t for each institution at 5% and 1% levels. Our estimation is based on quantile regressions using daily data.

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \epsilon_t^i \tag{5}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \epsilon_t^{system|i} \tag{6}$$

where X_t^i is the daily return on the market-valued total assets of institution i at time t; X_t^{system} is the daily return of the financial system, calculated as the market value weighted average change in asset values for financial institutions. M_{t-1} is a set of state variables analogous to those suggested by Adrian and Brunnermeier (2016).[1]

[1] The state variables employed are 1) Change in the three-month Treasury bill rate; 2) Change in the yield curve slope, calculated as the spread between the ten-year government bond yield and the three-month Treasury bill rate; 3) A UK specific "TED spread", calculated as the difference between three-month GBP LIBOR rate and three-month Treasury bill rates; 4) Change in the credit spread between BOFA's BAA-rated bonds and the ten-year government bond yield; 5) Market return of MSCI UK index; 6) Real estate sector return in excess of the financial services sector return; and 7) Equity volatility, computed

From estimation of equations (5) and (6) we obtain:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{7}$$

$$CoVaR_t^i(q) = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_t^i(q) + \hat{\gamma}_q^{system|i} M_{t-1} \tag{8}$$

where $\hat{\alpha}_q^i$, $\hat{\gamma}_q^i$, $\hat{\beta}_q^{system|i}$ and $\hat{\gamma}_q^{system|i}$ are coefficients obtained from quantile regressions at the 1% and 5% confidence levels. $\Delta CoVaR_t^i(q)$, which measures the marginal contribution of institution i to the risk of the system at time t, is computed as the difference between $CoVaR_t^i(q)$ conditional on the distress of the institution (i.e., q=1% or 5%) and $CoVaR_t^i(50\%)$ (i.e., the normal state of the institution).

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%) \tag{9}$$

We obtain daily $\Delta CoVaR_t^i(q)$ from the quantile regressions. Since we obtain financial data for each financial institution from Compustat Fundamentals Quarterly, we create the quarterly time-series $\Delta CoVaR_t^i(q)$ and $VaR_t^i(q)$ by taking the mean of $\Delta CoVaR_t^i(q)$ and $VaR_t^i(q)$ for each firm-quarter. To ensure consistency among the systemic risk measures, we scale $VaR_t^i(q)$ and $\Delta CoVaR_t^i(q)$ by –1 such that higher values correspond to greater risk.

2.3. Sample

Systemic risk is calculated using daily stock data from 2011Q2 to 2015Q2 for all UK publicly traded banks, broker-dealers, insurance companies, and investment firms (SIC 6020–6411). We obtain the list of institutions that are regulated by both FCA and PRA from the Bank of England.[2] Daily stock data are obtained from Compustat Global Security Daily and accounting data from Compustat Fundamentals Quarterly. To ensure sufficient data to

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as the 22-day rolling standard deviation of daily equity market returns.

[2]Bank of England (2018). Which firms does the PRA regulate? www.bankofengland.co.uk/prudential-regulation/authorisations/which-firms-does-the-pra-regulate

calculate systemic risk a number of exclusions are employed.[3] The resulting sample consists of 151 financial firms incorporated in the UK. Twin peaks regulation was implemented from April 1^{st} 2013.

The key assumption for obtaining reliable Diff-in-Diff estimates is the parallel trend assumption. That is, in the absence of treatment, the average outcome for treated and control groups should follow parallel paths over time. To deal with selection concerns, we perform propensity score matching in the pre-treatment period (i.e., 2011Q2–2012Q4) to construct a control group of FCA-regulated institutions that look like those which are dual regulated. The propensity score, $p(X_i)$, is the probability of receiving treatment given a vector of covariates X_i, $p(X_i) = Pr(T_i = 1|X_i)$ and estimated using logit.

We match on quarter and institution type (i.e., first 2 digits of SIC code) using a set of matching covariates including book value of assets, market capitalization, trading volume, idiosyncratic volatility, MES, $VaR(5)$ and $\Delta CoVaR(5)$. We perform radius matching that considers all non-treated observations within a specified radius (0.1) around a treated firm's propensity to be dual regulated as control units. Radius matching allows for higher precision than nearest neighbor matching (Huber *et al.*, 2013). Matching is performed with replacement, which means that each non-treated firm can be used as a neighbor for multiple treated firms.[4] The resulting matched sample comprises 16 treated firms and 61 control firms. Table 1 reports the balancing properties of the matching covariates. No statistically significant differences are found between the two samples, providing support for balance between treatment and control samples.

[3]We exclude institutions as follows 1) those which are active for less than 60 trading days in a quarter, 2) those with zero growth in market-valued total assets for more than 60 consecutive trading days in a quarter, 3) returns that are larger than 7 standard deviations, and 4) those come into existence after the treatment year.

[4]Smith and Todd (2005) suggest that this specification should improve accuracy of the matching procedure.

[Table 1 about here.]

3. Results

We use the matched sample to analyze the difference in systemic risk between treated and control firms. Table 2 reports results of the Diff-in-Diff analysis that compares the evolution of systemic risk of treated firms with that from a control group of firms. Standard errors, unless otherwise stated, are clustered at firm level (Petersen, 2009). We use four measures for systemic risk, as detailed in columns 1 to 4 of Table 2. The interaction term is found to be significant and negative across these measures, which indicates that the introduction of twin peaks regulation has been effective in reducing systemic risk overall. An exception is SRISK, where the sample is much reduced due to the availability of accounting data required for estimation. The expected negative sign is found but the t-statistics do not indicate significance.

The finding of altered systemic risk is depicted in Figure 1, which shows the evolution of average systemic risk for the treated and control firms between 2011Q2 and 2015Q2. Both groups have a very similar trend in their contribution to systemic risk in the pre-treatment period, decreasing by around 50% in the period following the sovereign debt crisis. In the post-treatment period, systemic risk increases for both treated and control firms, but while the control increases by over 130%, we observe only an increase of about 5% for treated firms up to 2015Q2. In columns 5 and 6 of Table 2, we also isolate the impact on firm-specific VaR (equation 7), showing that treated firms present reduced tail-risk post treatment.

[Table 2 about here.]

[Figure 1 about here.]

Prior studies suggest that larger banks have significantly higher systemic risk (Laeven *et al.*, 2016). For this reason, we further employ a capitalization-weighted least squares specification to account for possible larger contributions to systemic risk by bigger institutions. The weight is calculated as an institution's average quarterly capitalization divided by the average financial sector total capitalization in the same quarter. Results in Table 3 provide further support for the baseline findings, with an overall increase in the level of significance and statistical power of the test. In particular, SRISK results are now found to have the correct sign and to be significant.

[Table 3 about here.]

4. Concluding Remarks

Consequent to the global financial crisis, the architecture of financial regulation has been comprehensively reformed, with a recent focus on the form of the regulating authorities. In an attempt to ensure that regulators have specific objectives and to reduce the potential for regulatory trade-offs, the UK introduced the so-called twin-peaks regulatory system from April 2013. Central to this approach is a concentrated focus on systemic risk by the prudential regulator. Using the split between single- and dual-regulated financial firms in the UK, we identify a significant beneficial impact of twin-peaks regulation on systemic risk in this jurisdiction.

As highlighted by Schoenmaker and Veron (2018), the majority of European countries maintain an integrated financial supervision structure. While direct cross-border inference from our results may be difficult due to differences in facets such as regulation, law and culture, our findings provide an initial indication regarding the potential for a relative reduction in systemic risk for firms subject to dual regulation. Building upon previous research which has qualitatively debated the merits of the various organizational structures underpinning financial regulation, our contribution lies in the quantitative assessment of twin peaks effectiveness in countering systemic risk.

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Figure 1: Evolution of Systemic Risk (MES) for Treated Group and Control Group

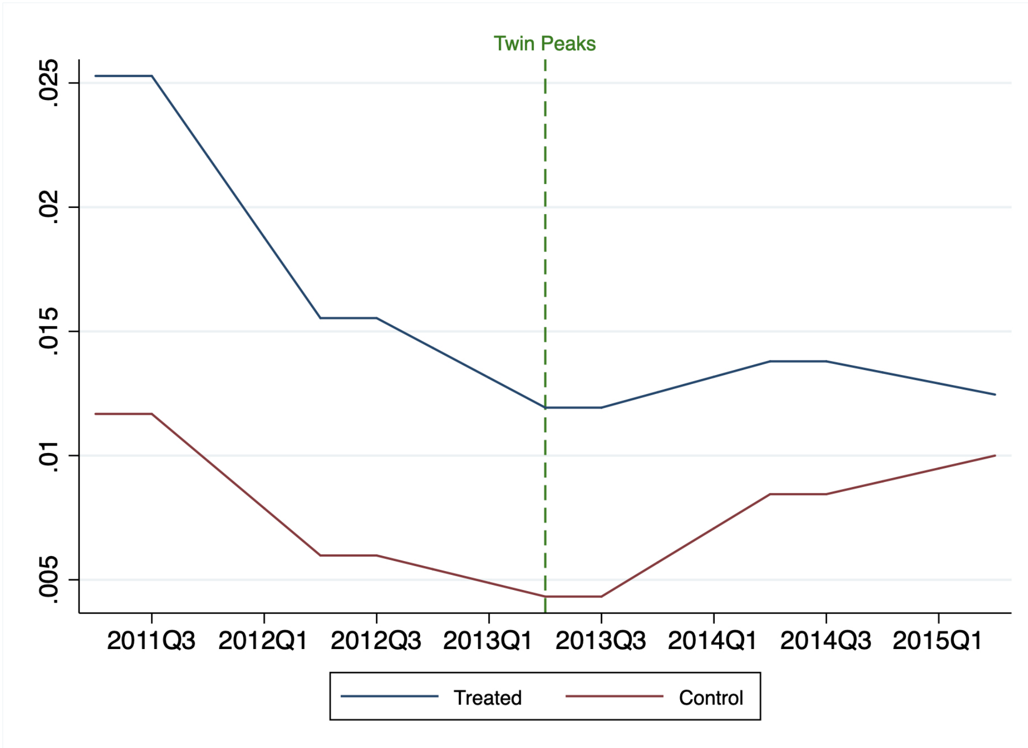

Table 1: Balancing property of the matching covariates

	Treated	Control	Difference	t-statistic	p-value
Book Value of Assets	8.097	7.642	0.455	1.14	0.257
Market Capitalization	13.727	13.406	0.321	0.99	0.322
Trading Volume	5.054	3.164	1.890	0.75	0.455
Idiosyncratic Volatility	0.013	0.013	-0.001	-0.63	0.531
MES	0.017	0.017	0.001	0.24	0.808
VaR(5)	2.849	2.975	-0.126	-0.60	0.546
ΔCoVaR(5)	0.003	0.002	0.000	0.77	0.444

Table 2: Difference-in-differences results

	(1) MES	(2) SRISK	(3) $-\Delta$CoVaR(1)	(4) $-\Delta$CoVaR(5)	(5) $-$VaR(1)	(6) $-$VaR(5)
Treated×Post	-0.005**	-0.001	-0.002**	-0.002**	-0.645*	-0.536*
	[-2.350]	[-1.312]	[-2.474]	[-2.557]	[-1.862]	[-1.793]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,211	542	1,200	1,200	1,200	1,200
R-squared	0.431	0.771	0.711	0.773	0.369	0.462

*** p<0.01, ** p<0.05, * p<0.1; [Robust t-statistics in brackets]

Table 3: Capitalization-weighted least squares difference-in-differences results

	(1) MES	(2) SRISK	(3) $-\Delta$CoVaR(1)	(4) $-\Delta$CoVaR(5)	(5) $-$VaR(1)	(6) $-$VaR(5)
Treated×Post	-0.007**	-0.006*	-0.005***	-0.005***	-1.078***	-0.978**
	[-2.023]	[-1.986]	[-3.017]	[-3.185]	[-2.696]	[-2.621]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,211	542	1,200	1,200	1,200	1,200
R-squared	0.670	0.772	0.737	0.797	0.537	0.675

*** p<0.01, ** p<0.05, * p<0.1; [Robust t-statistics in brackets]