

ONLINE APPENDIX:

Do capital requirements make banks safer?

Evidence from a quasi-natural experiment

January 3, 2021

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A Robustness

The main specification in the paper is given by:

$$Y_{i,t} = \alpha_i + \sum_{k \neq 2011q2} \beta_k \mathbf{1}_{t=k} + \sum_{k \neq 2011q2} \gamma_k (\mathbf{1}_{t=k} \times EBA_i) + \epsilon_{i,t} \quad (1)$$

where i indexes bank and t indexes time. $Y_{i,t}$ are different regulatory and non-regulatory risk-measures. $\mathbf{1}_{t=k}$ represents year-quarter dummies and EBA_i is an indicator for whether bank i is an EBA bank or not. α_i indicate bank fixed-effects.

A.1 Placebo-exercise

To alleviate concerns that exposure to the sovereign debt crisis is driving our results, we undertake a placebo exercise where we compare the relative evolution of risk measures at the onset of the sovereign debt crisis. Specifically, we estimate

$$Y_{i,t} = \alpha_i + \sum_{k \neq 2009q4} \beta_k \mathbf{1}_{t=k} + \sum_{k \neq 2009q4} \gamma_k (\mathbf{1}_{t=k} \times EBA_i) + \epsilon_{i,t} \quad (2)$$

focusing on the period from Q1:2009 to Q4:2010 whenever bank shares data are available. We focus on solvency risk, systemic risk measures, and the market capitalization of banks. The results are shown in Figure 1, 2, and 3. Across all figures, there are no clear signs that there is an increase in risk measures or a decline in market capitalization at the start of the sovereign debt crisis. This provides additional support for our interpretation of the increase in risk measures and decline in market capitalization highlighted in the main text being driven by higher capital requirements.

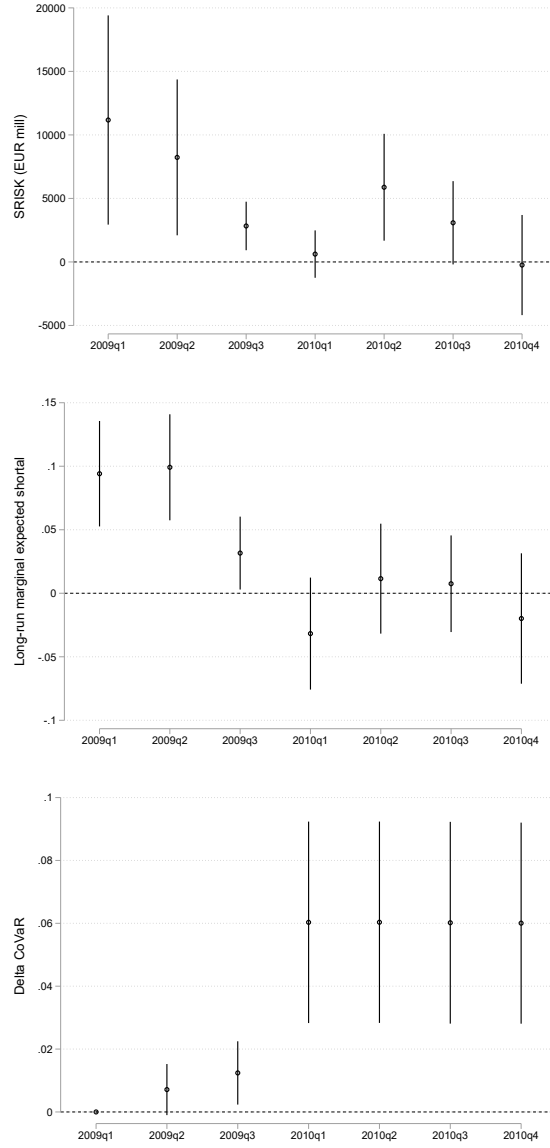


Figure 1: This figure shows the evolution of SRISK, LRMES, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (2). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

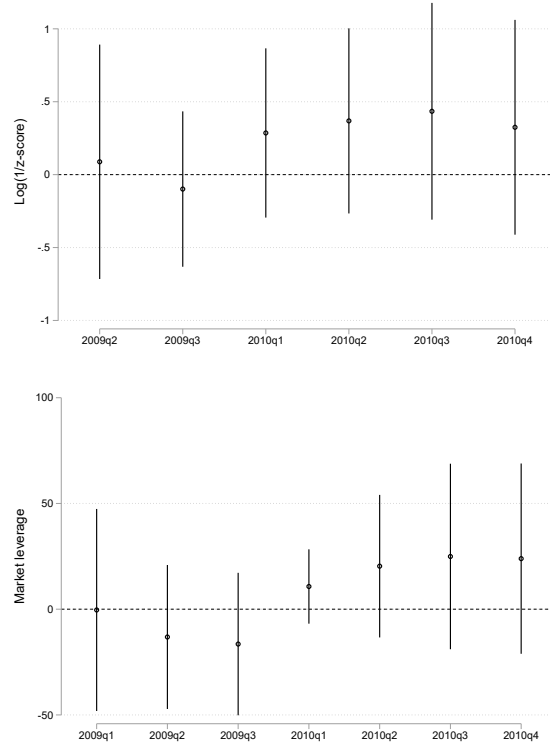


Figure 2: This figure shows the evolution of z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (2). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

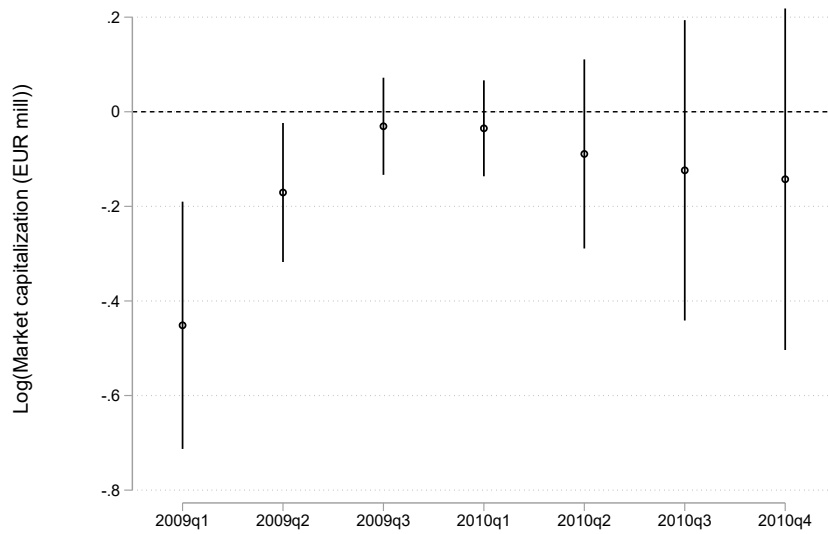


Figure 3: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (2) using the log of market capitalization as outcome variable. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.2 Within EBA-comparison

In this section, we adopt an alternative identification approach. Specifically, we focus only on EBA-banks and investigate whether the evolution of the various outcome variables we consider varies with the CT1 capital ratio in Q4:2010. We normalize our new treatment intensity variable by taking its inverse, so that a higher value correspond to higher treatment intensity. Specifically, we now estimate

$$Y_{i,t} = \alpha_i + \sum_{k \neq 2011q2} \beta_k \mathbf{1}_{t=k} + \sum_{k \neq 2011q2} \gamma_k (\mathbf{1}_{t=k} \times (1/CT_{i,2010})) + \epsilon_{i,t} \quad (3)$$

where $CT_{i,2010}$ is Core Tier 1 ratio of bank i by the end of 2010. Figures 4, 5 and 6 plot the estimated coefficients from equation (3). The estimates are qualitatively similar to those in the main text, although there are generally less precise estimates. Perhaps the key qualitative differences can be seen when we consider pure equity tail risk and systematic risk. The effect on Value-at-Risk is no longer statistically significant, whereas the effect on the equity beta is more delayed. Results for the solvency and systemic risk measures are close to the ones described in the main text.

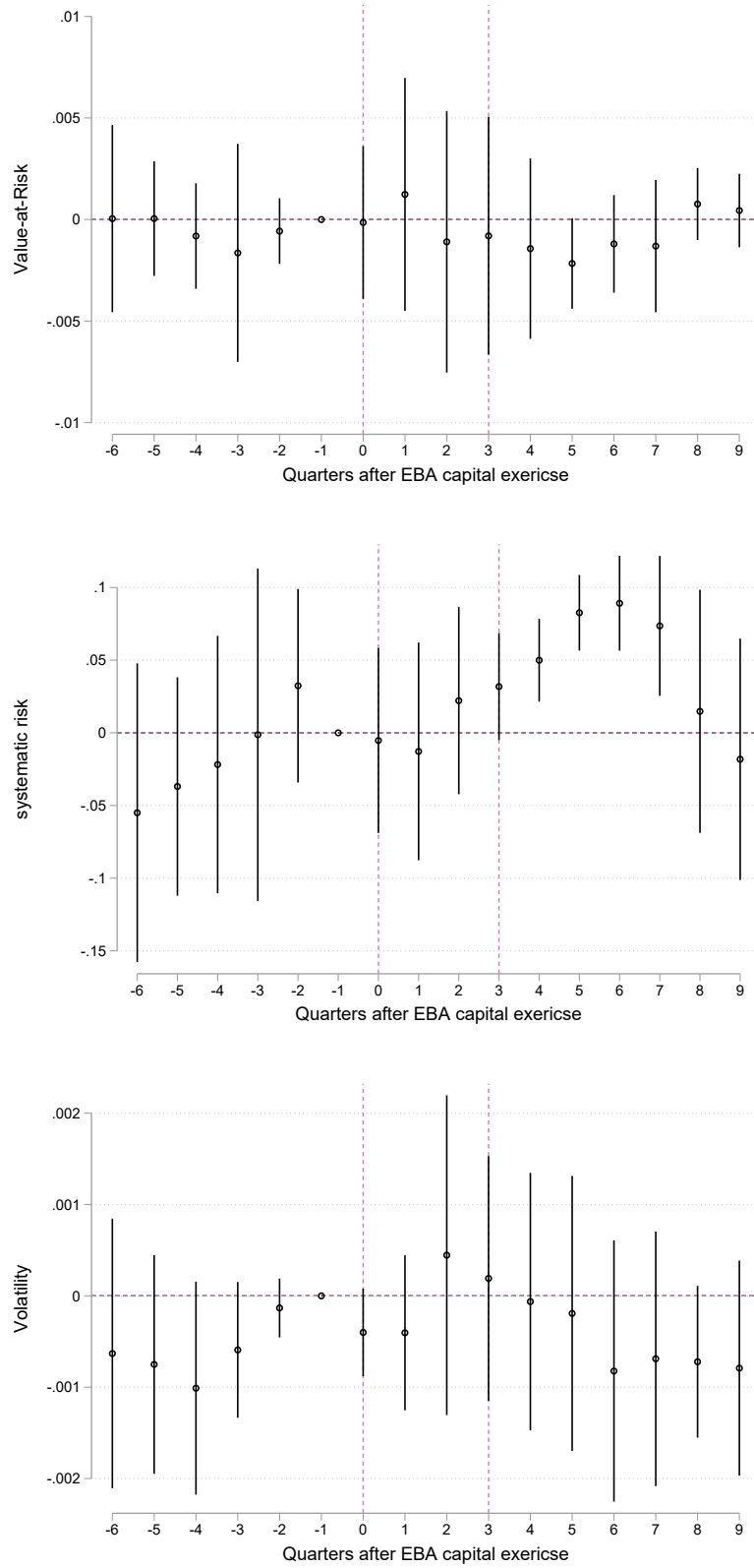


Figure 4: This figure shows the evolution of VaR, systematic risk (beta), and stock return volatility. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (3). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

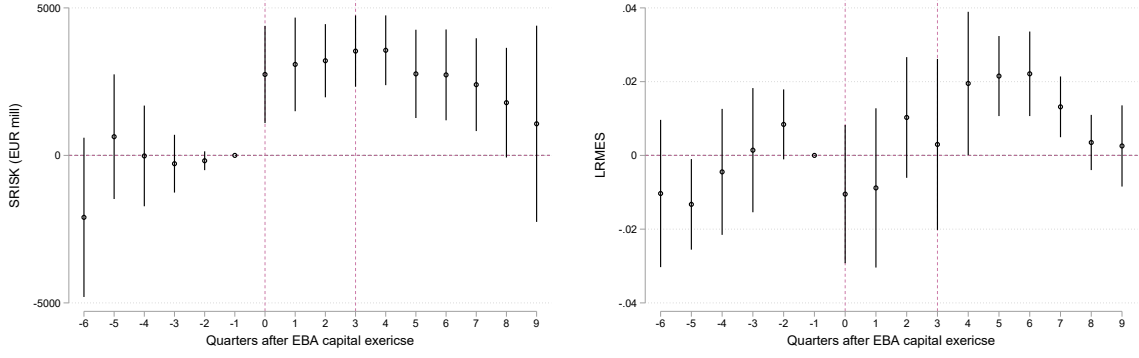


Figure 5: This figure shows the evolution of SRISK, LRMEs, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (3). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

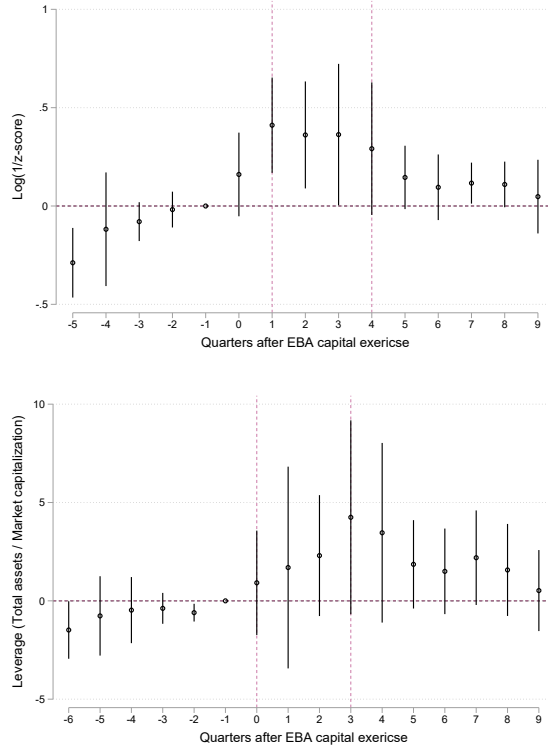


Figure 6: This figure shows the evolution of (inverse) z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (3). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

Finally, in order to show that the increase in risk measures in this narrow sample is driven by the market capitalization of banks, we show the estimated dynamic effects on market capitalization in Figure 7. As in the main text, treated banks experience a more severe decline in their market capitalization during the capital exercise.

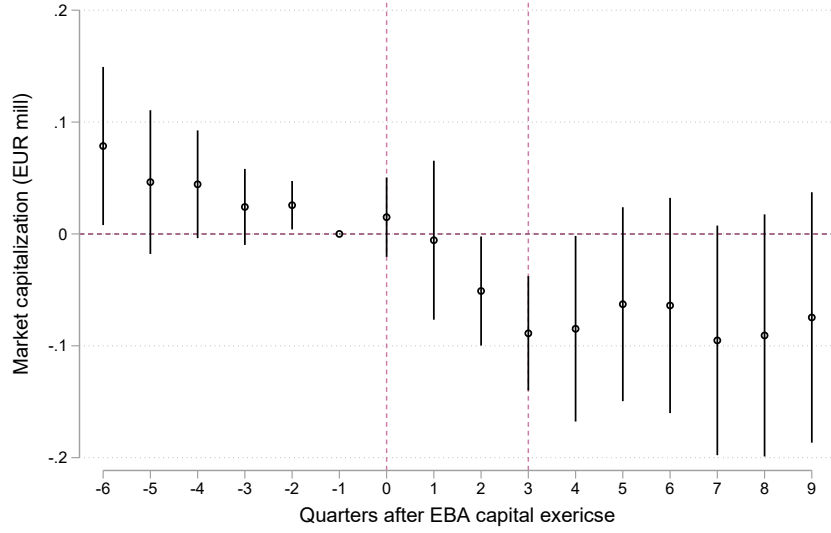


Figure 7: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (3) using the log of market capitalization as outcome variable. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.3 Narrow sample

In this subsection, we perform an additional robustness analysis where we redo our analysis on a narrow subsample of banks. Specifically, we consider only three banks on both sides of the threshold within each country. For countries for which we have less than six banks, we keep the same sample as in the main text. With country \times year-quarter fixed effects, this ensures that we essentially estimate the difference between the three EBA banks that are closest to the threshold with the three closest non-EBA banks within each country. Figures 8, 9, 10 and 11 show dynamic treatment coefficients from estimating equation (1) using this subsample. The results remain qualitatively and quantitatively similar to those reported and discussed in the main text.

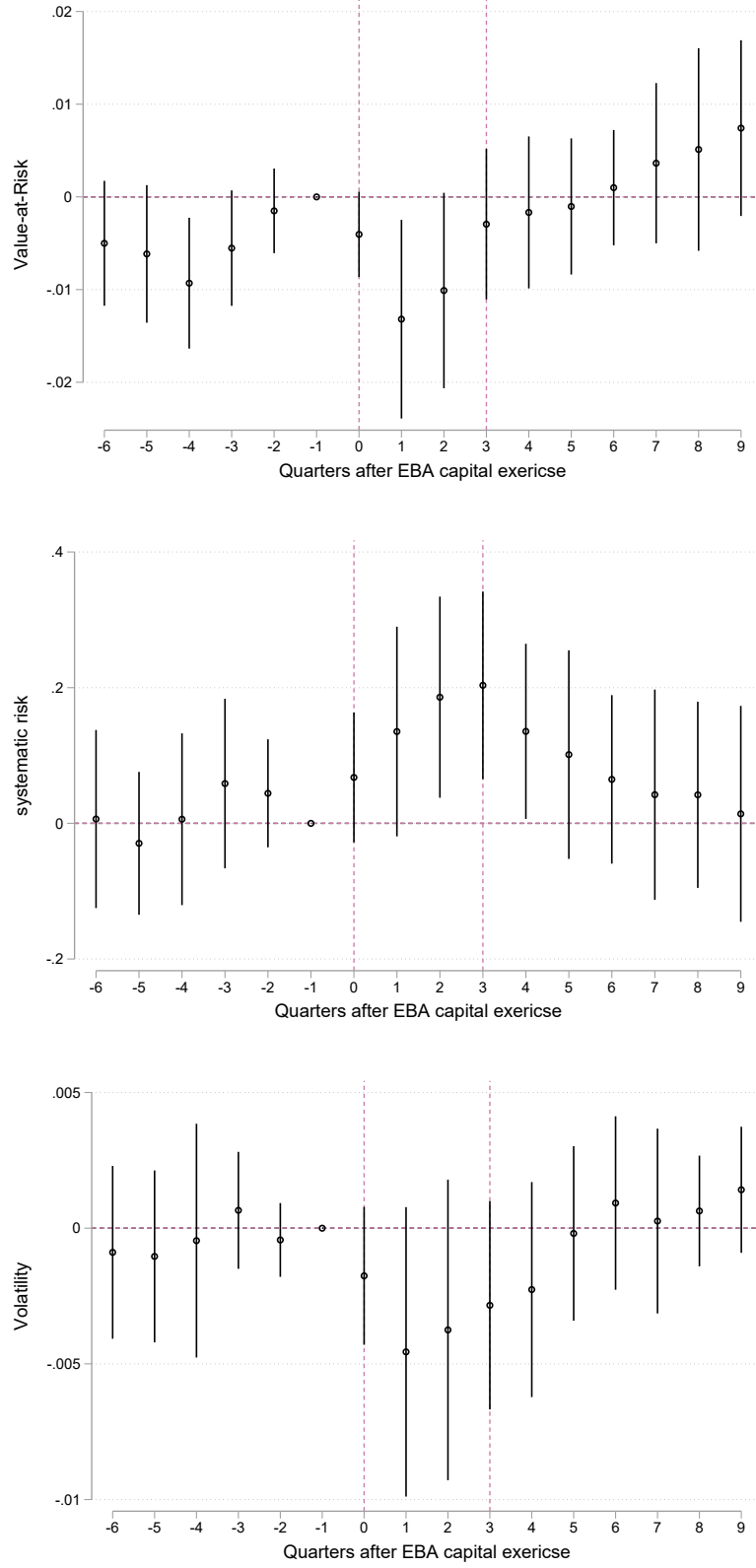


Figure 8: This figure shows the evolution of VaR, systematic risk (beta), and stock return volatility. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

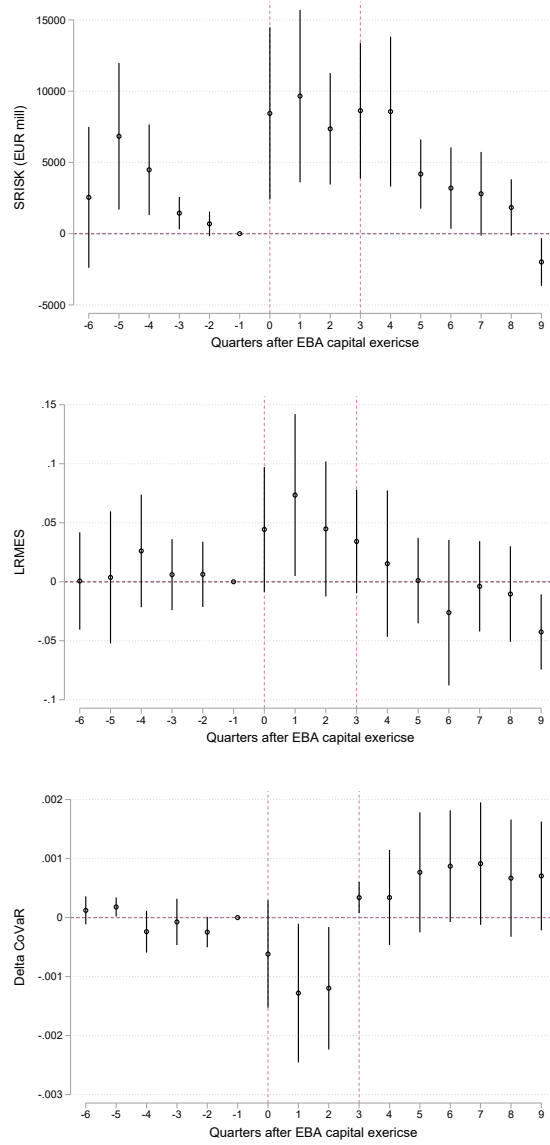


Figure 9: This figure shows the evolution of SRISK, LRMES, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

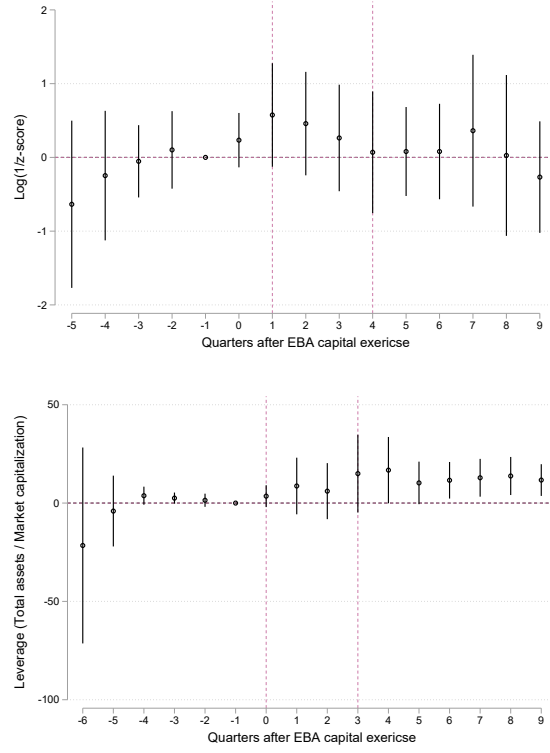


Figure 10: This figure shows the evolution of z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

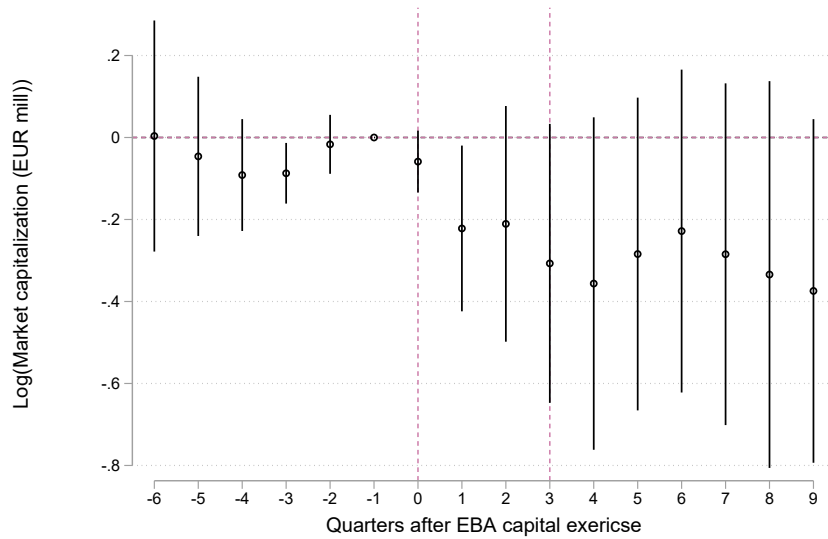


Figure 11: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (1) using the log of market capitalization as outcome variable. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.4 Extended sample

In this section, we show that our results are not sensitive to the various filters we apply in the main part of the paper. Specifically, we redo the exercise on the initial sample of banks, before we apply our specific filters. The results remain qualitatively and quantitatively similar to the results in the main text.

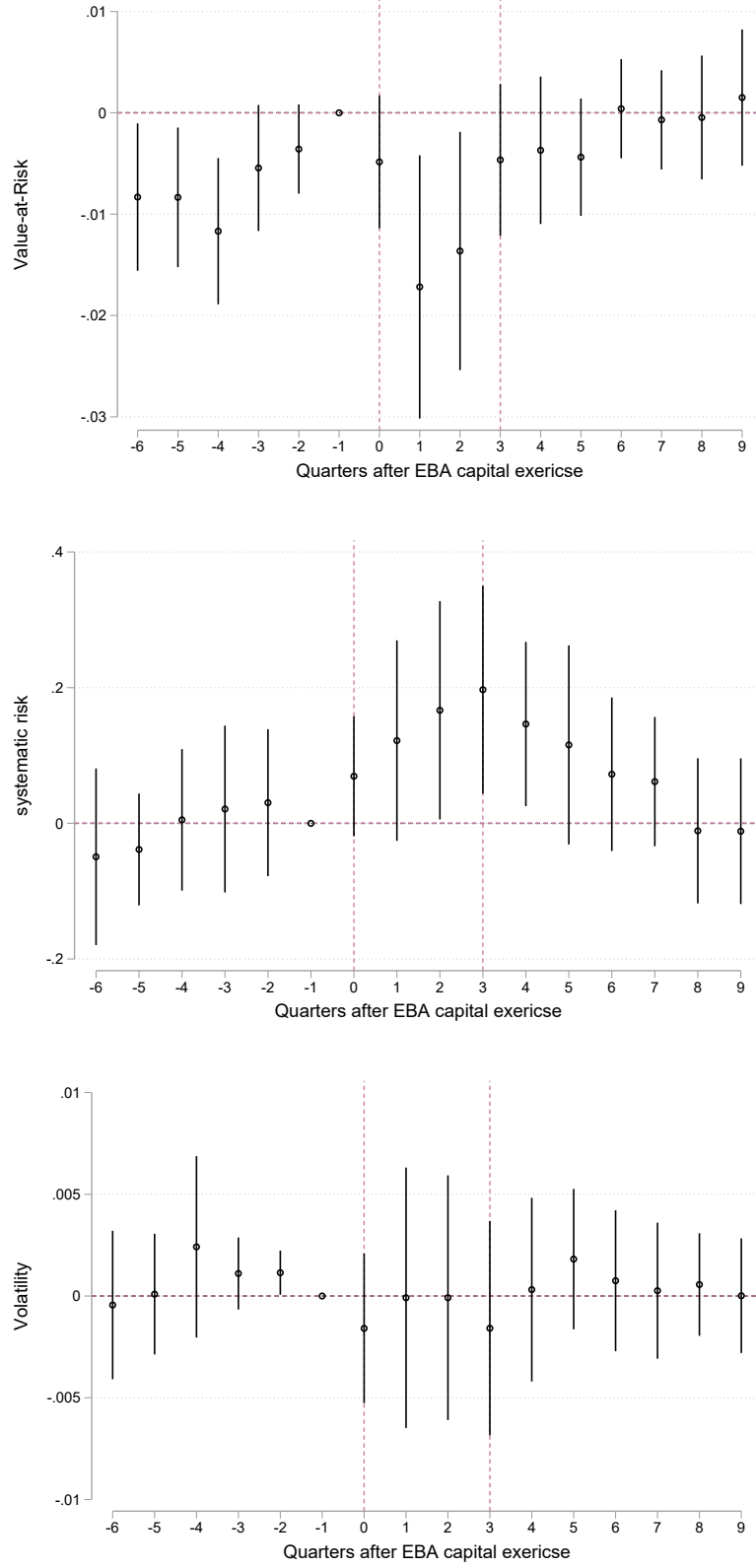


Figure 12: This figure shows the evolution of VaR, systematic risk (beta), and stock return volatility. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

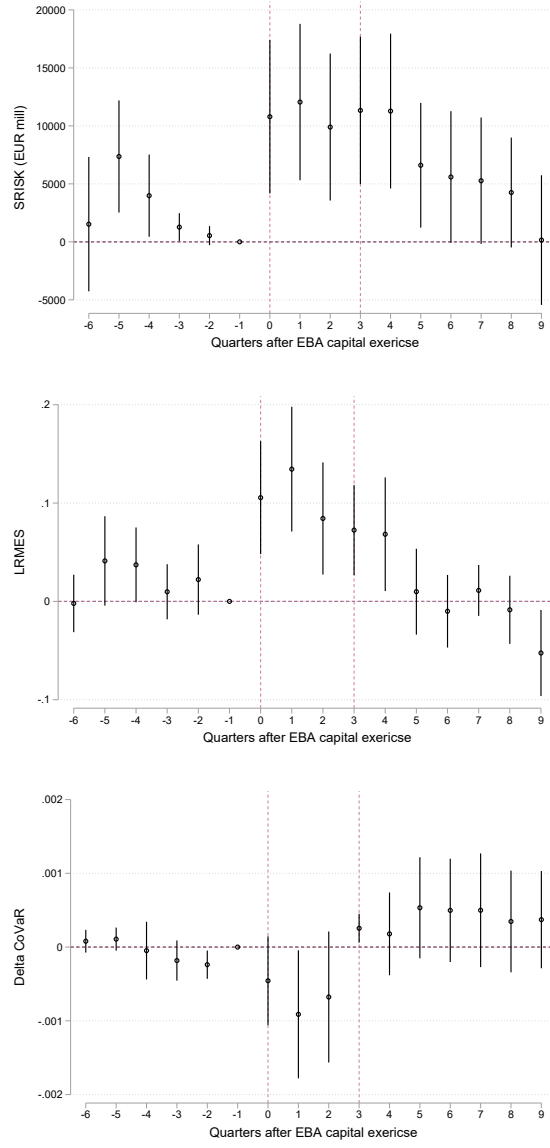


Figure 13: This figure shows the evolution of SRISK, LRMES, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

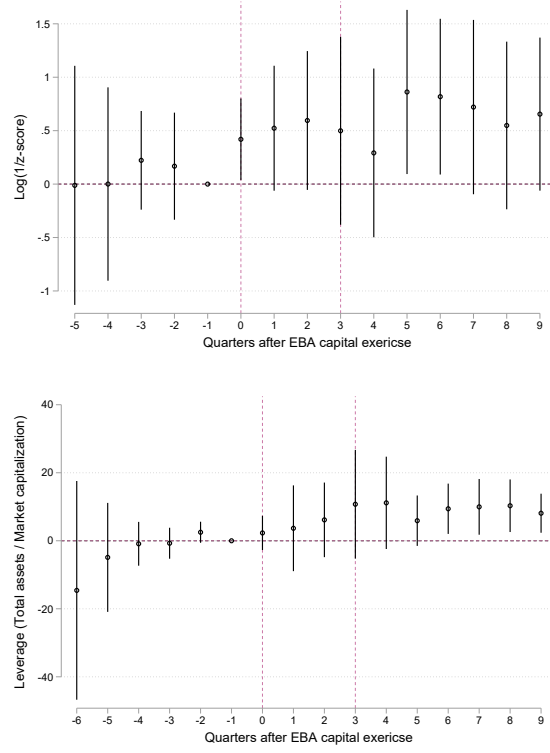


Figure 14: This figure shows the evolution of (inverse) z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

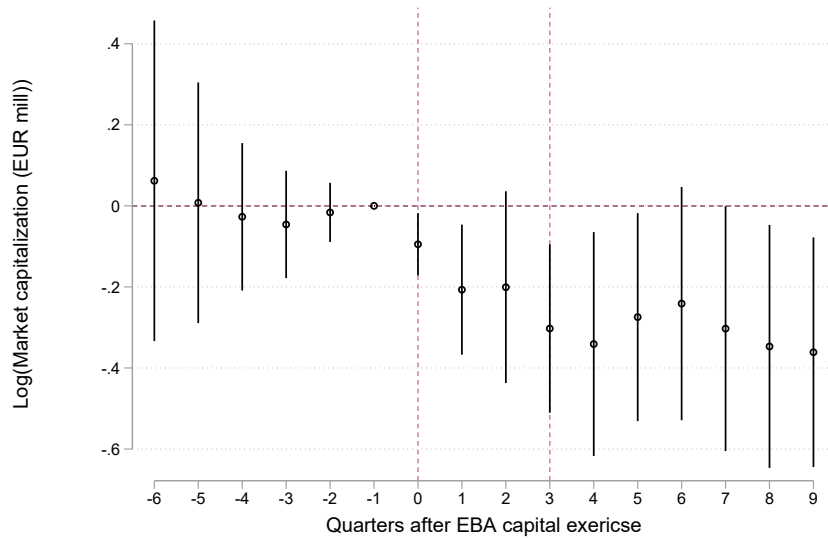


Figure 15: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (1) using the log of market capitalization as outcome variable. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.5 Matching estimator

In this section, we show the estimated effect of the EBA capital exercise on our outcome variables replacing our original control group with a matched control group. We adopt three different matching strategies: size (market capitalization, SRISK and total assets), business model (deposit ratio, net interest margin, loan ratio and RoA), and capitalization (Tier 1 ratio and market leverage). Matching is done based on end-of 2010 values of the respective matching covariates.

A.5.1 Matching on size

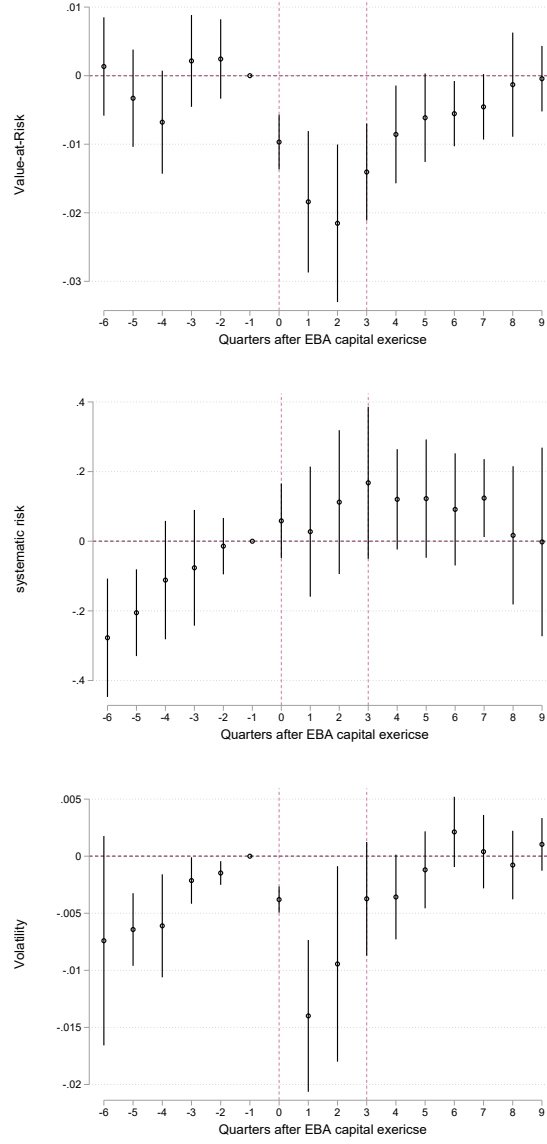


Figure 16: This figure shows the evolution of $VaR_{5\%}$, systematic risk (beta), and stock return volatility. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on three size variables (market capitalization, SRISK and total assets). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

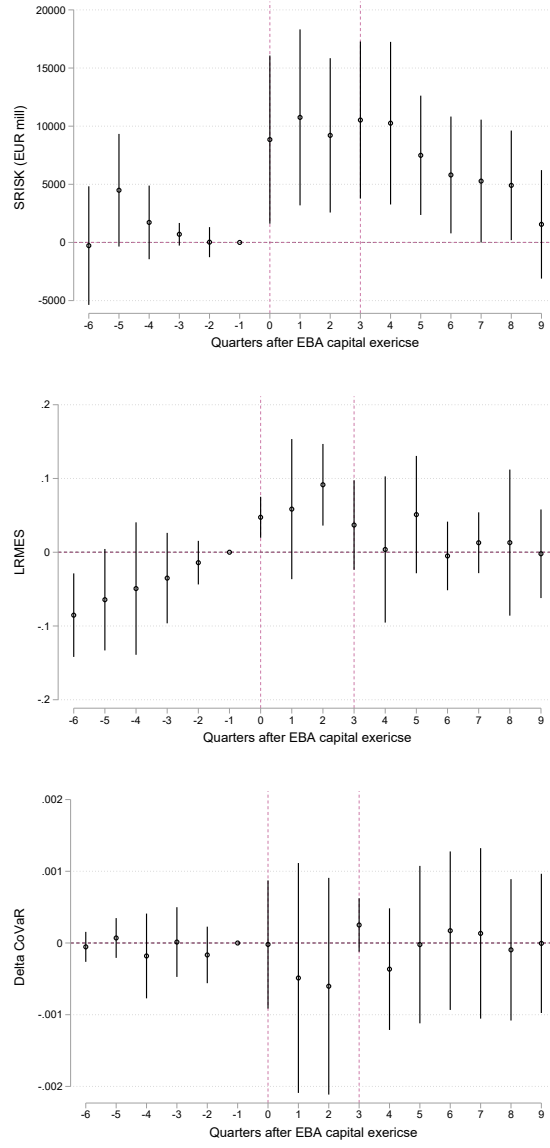


Figure 17: This figure shows the evolution of SRISK, LRMS, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on three size variables (market capitalization, SRISK and total assets). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

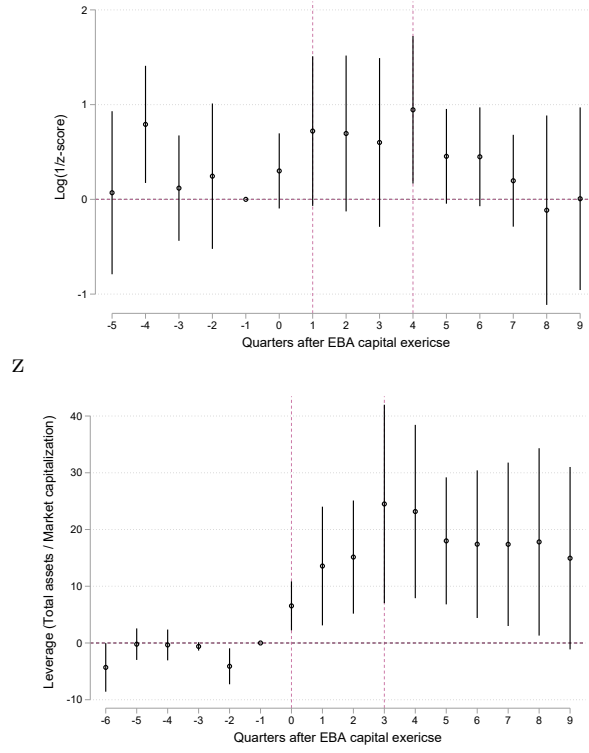


Figure 18: This figure shows the evolution of the (inverse) z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on three size variables (market capitalization, SRISK and total assets). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

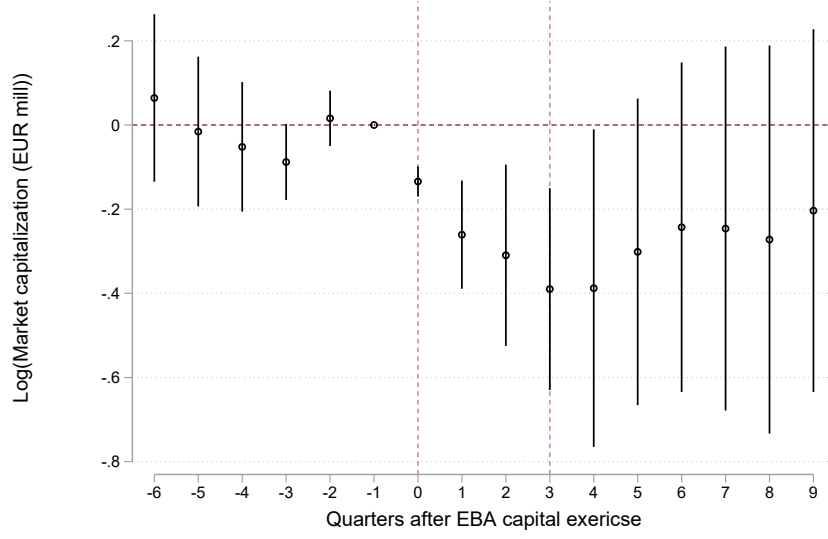


Figure 19: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (1) using the log of market capitalization as outcome variable and considering a matched sample of banks. Matching is done based on three size variables (market capitalization, SRISK and total assets). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.5.2 Matching on business model

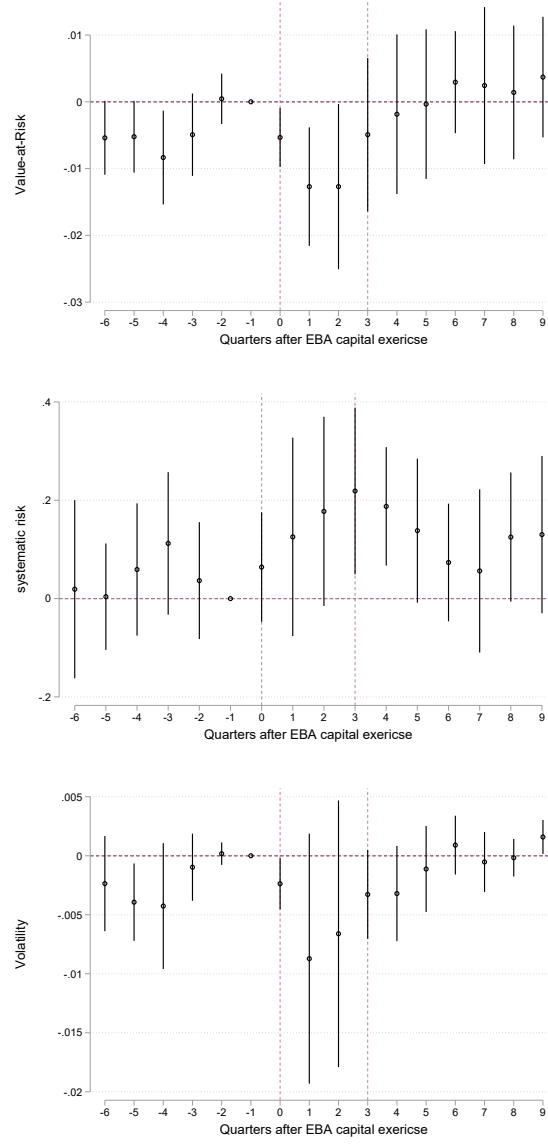


Figure 20: This figure shows the evolution of $Var_{5\%}$, systematic risk (beta), and stock return volatility. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on four business model variables (deposit ratio, net interest margin, loan ratio and RoA). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

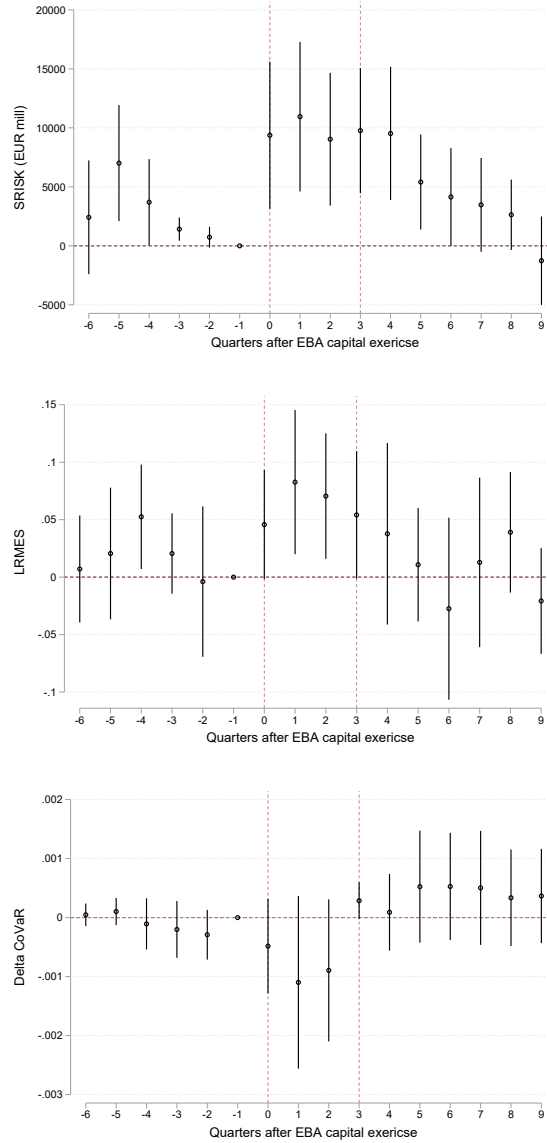


Figure 21: This figure shows the evolution of SRISK, LRMEs, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on four business model variables (deposit ratio, net interest margin, loan ratio and RoA). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

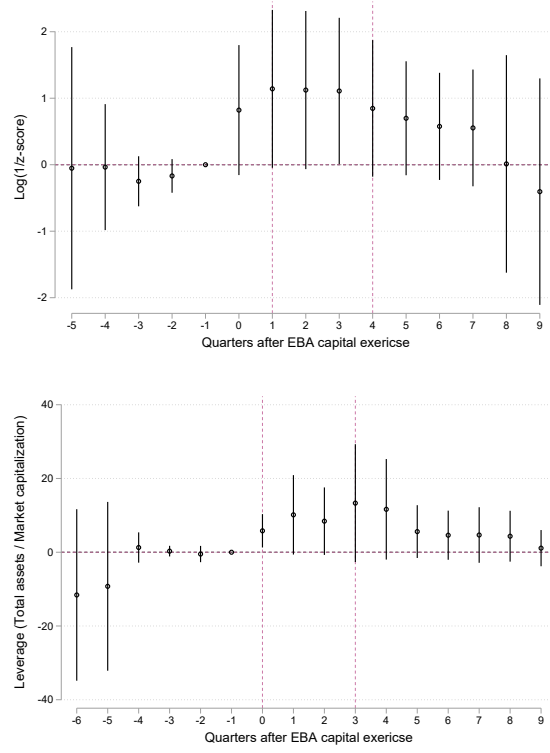


Figure 22: This figure shows the evolution of the (inverse) z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on four business model variables (deposit ratio, net interest margin, loan ratio and RoA). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

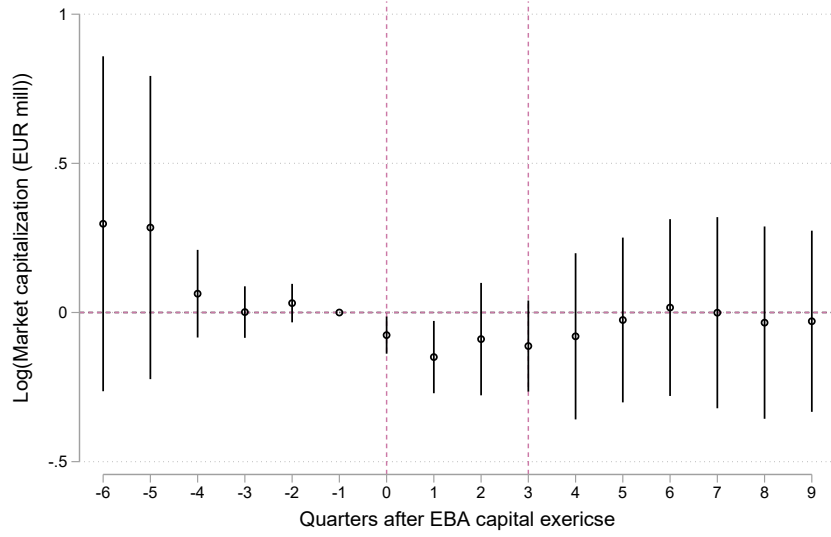


Figure 23: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (1) using the log of market capitalization as outcome variable and considering a matched sample of banks. Matching is done based on four business model variables (deposit ratio, net interest margin, loan ratio and RoA). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.5.3 Matching on capitalization

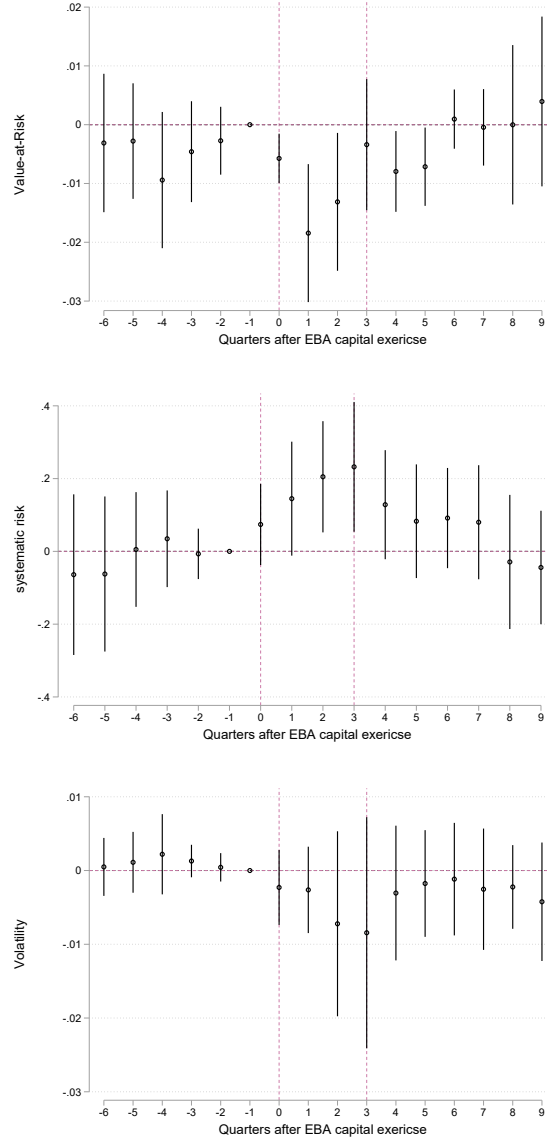


Figure 24: This figure shows the evolution of $Var_{5\%}$, systematic risk (beta), and stock return volatility. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on four business model variables (deposit ratio, net interest margin, loan ratio and RoA). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

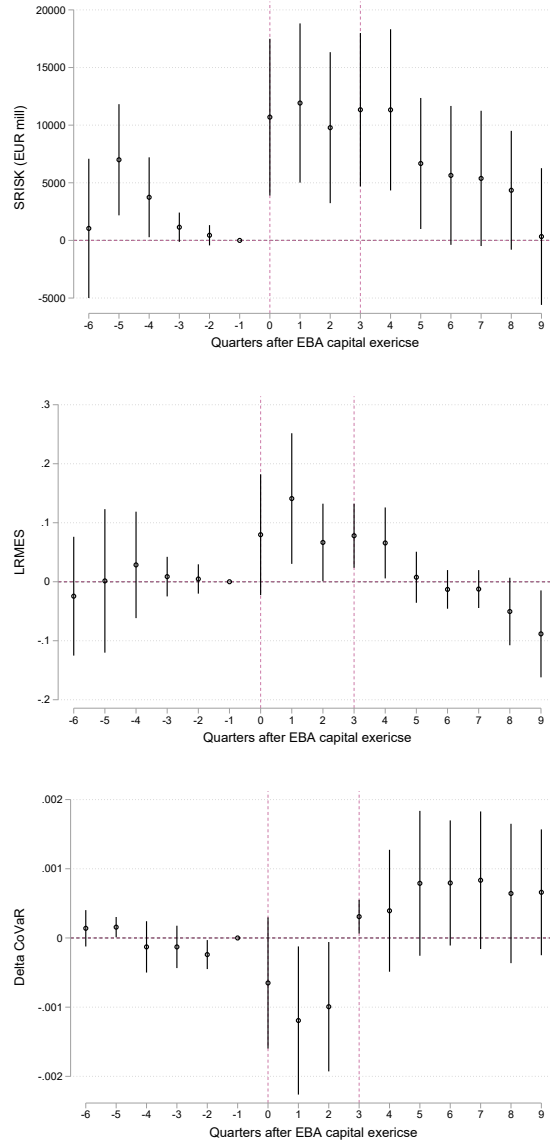


Figure 25: This figure shows the evolution of SRISK, LRMS, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on two capitalization variables (Tier 1 ratio and market leverage). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

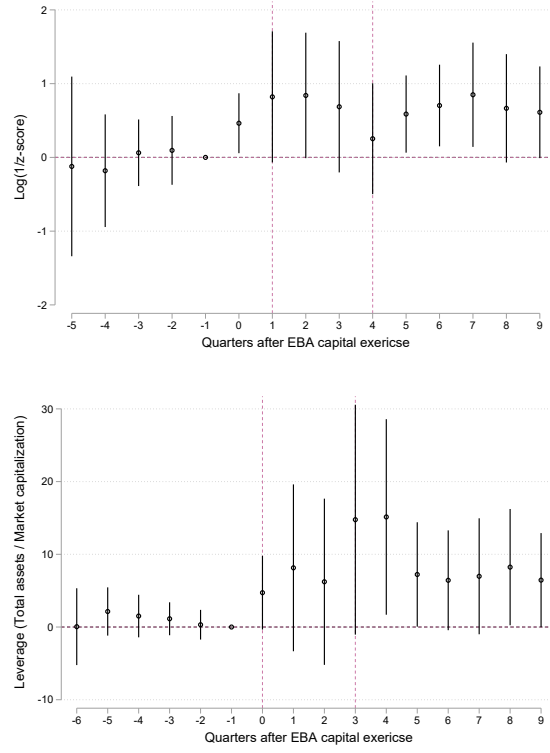


Figure 26: This figure shows the evolution of the (inverse) z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1), where we consider a matched sample of banks. Matching is done based on two capitalization variables (Tier 1 ratio and market leverage). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

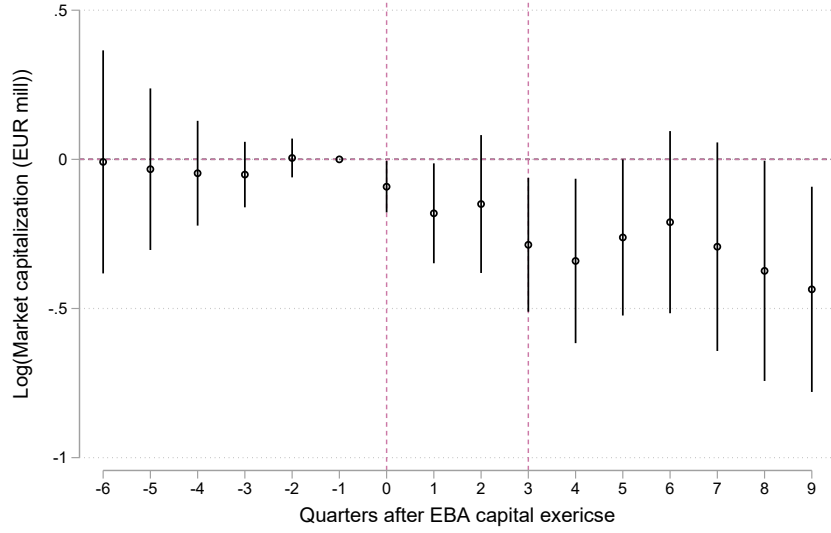


Figure 27: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (1) using the log of market capitalization as outcome variable and considering a matched sample of banks. Matching is done based on four business model variables (deposit ratio, net interest margin, loan ratio and RoA). Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.6 Within-country variation

In this section, we saturate our main specification in equation (1) with country \times year-quarter fixed effects. This effectively ensures that identification comes from comparing the evolution of risk-metrics for EBA versus non-EBA banks within a given country \times year-quarter. The results are shown in Figures 28, 29 and 30 and are largely consistent with the results reported in the main text. The only exception is stock return volatility, which under this approach declines significantly in contrast to the results presented in the main text.

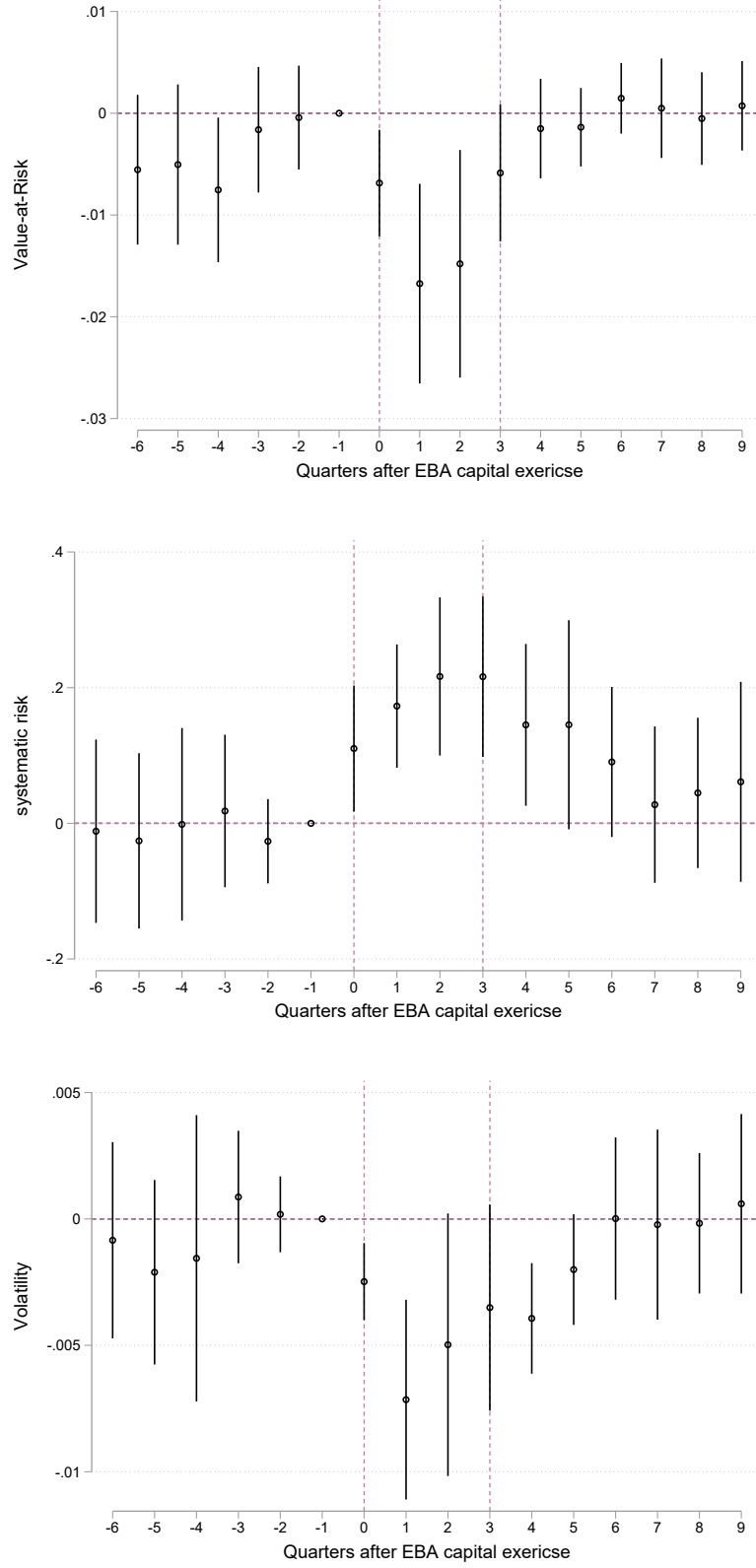


Figure 28: This figure shows the evolution of VaR, systematic risk (beta), and stock return volatility. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1) with country \times year-quarter fixed effects. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

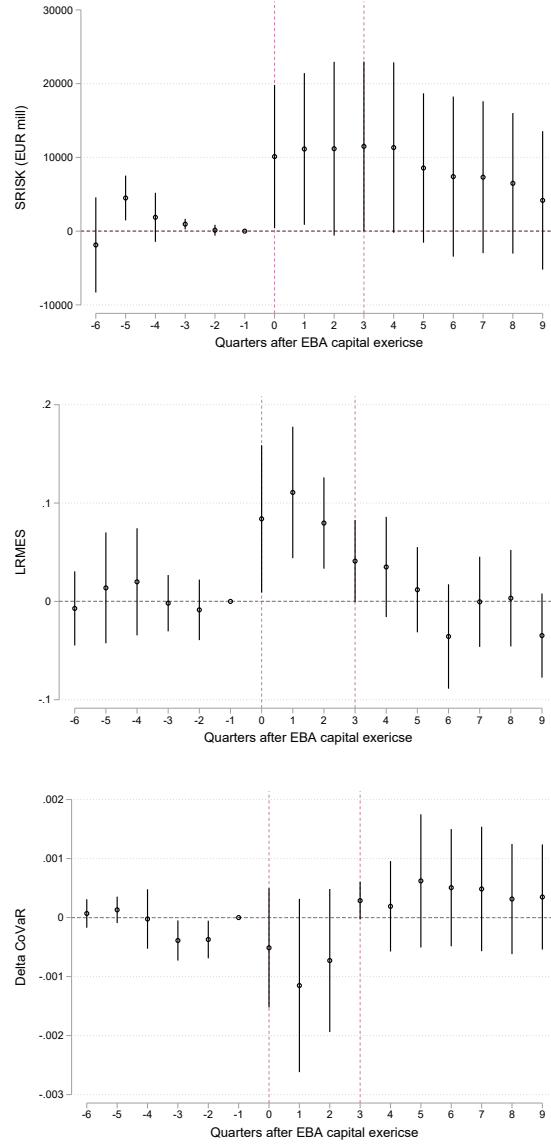


Figure 29: This figure shows the evolution of SRISK, LRMS, and ΔCoVaR . In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1) with country \times year-quarter fixed effects. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

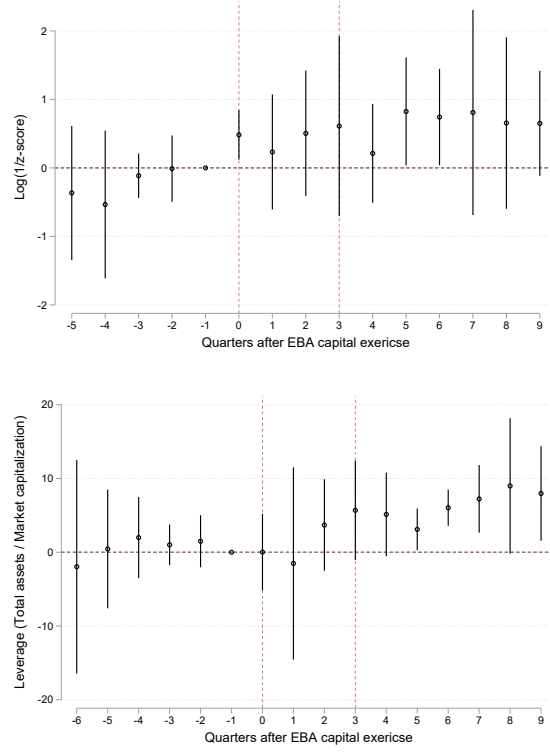


Figure 30: This figure shows the evolution of the (inverse) z-score and market leverage. In all panels, we plot the sequence of estimated $\{\gamma_k\}$ from equation (1) with country \times year-quarter fixed effects. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

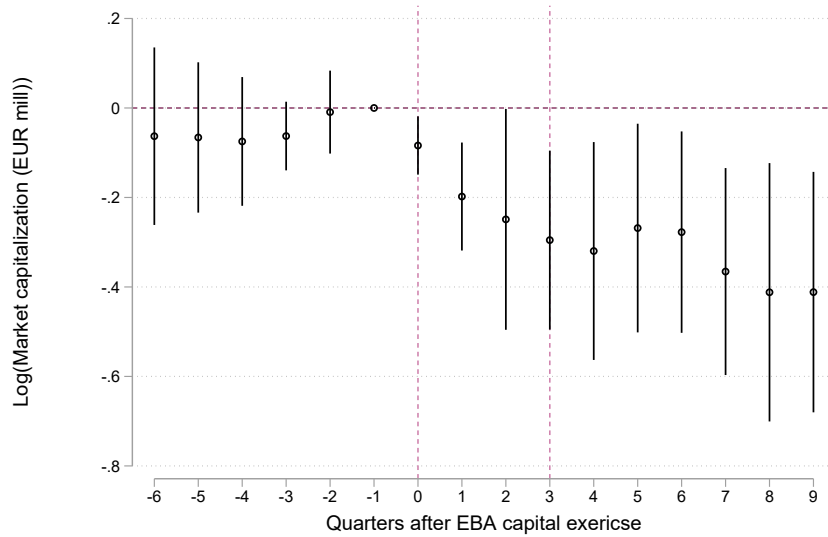


Figure 31: This figure shows the sequence of estimated $\{\gamma_k\}$ from equation (1) with country \times year-quarter fixed effects using the log of market capitalization as outcome variable. Vertical bars correspond to 95% confidence intervals. Standard errors are clustered at the country level.

A.7 Absolute levels

Our main empirical approach is to investigate parametrically whether the difference-in-differences between EBA and non-EBA banks for the outcomes considered is statistically different from zero after the EBA capital exercise. A drawback of this approach is that it is uninformative about the evolution of the *level* of the various outcomes. For instance, an increase in the difference-in-differences can arise if risk falls for both types of banks, but more for the control group. To shed further light on how risk evolves, we here plot the absolute value of the various risk-metrics considered. A key take-away is that - in general - the increase in relative risk is driven by risk increasing more for EBA banks compared to non-EBA banks, rather than a smaller decline.

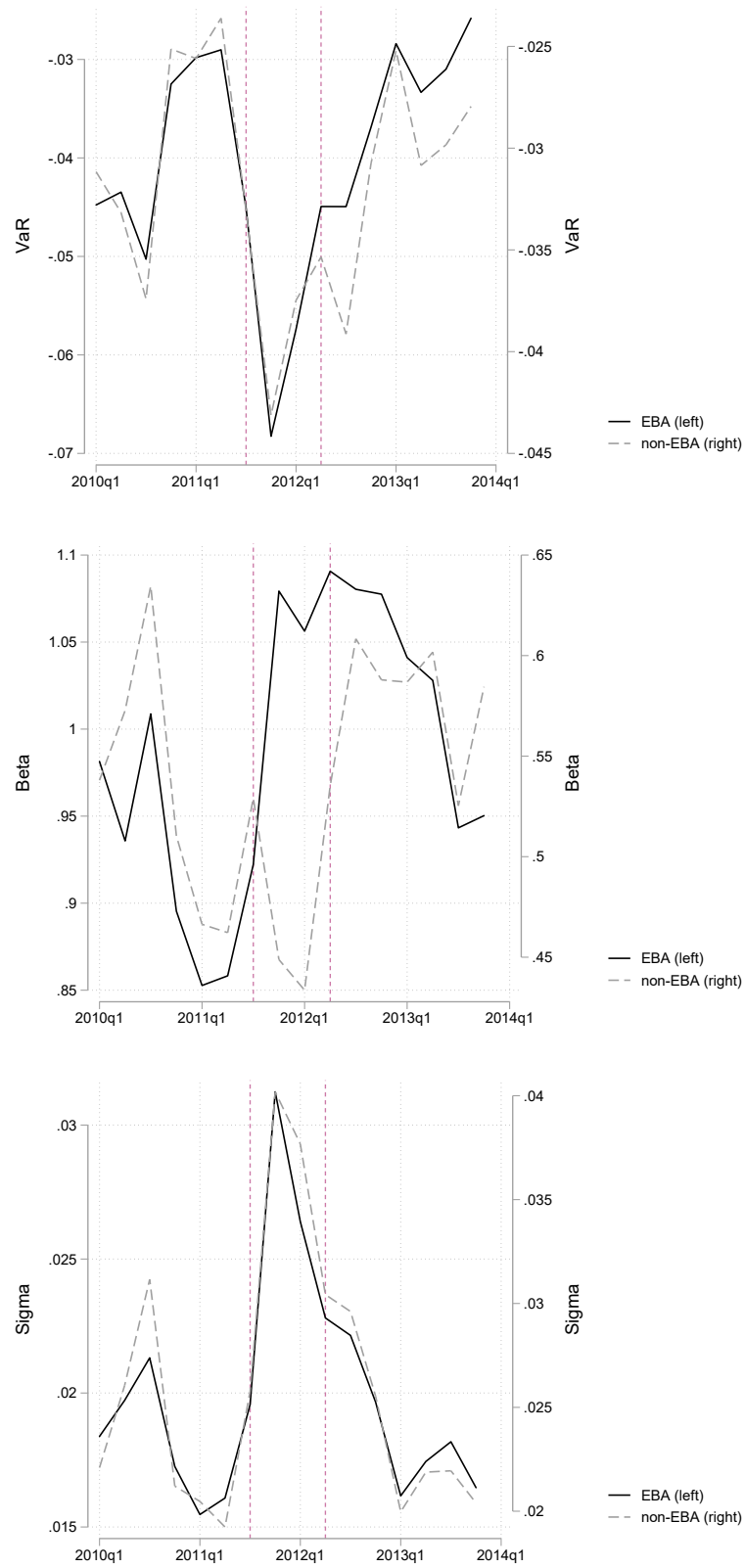


Figure 32: This figure shows the evolution of VaR, systematic risk (beta), and stock return volatility.

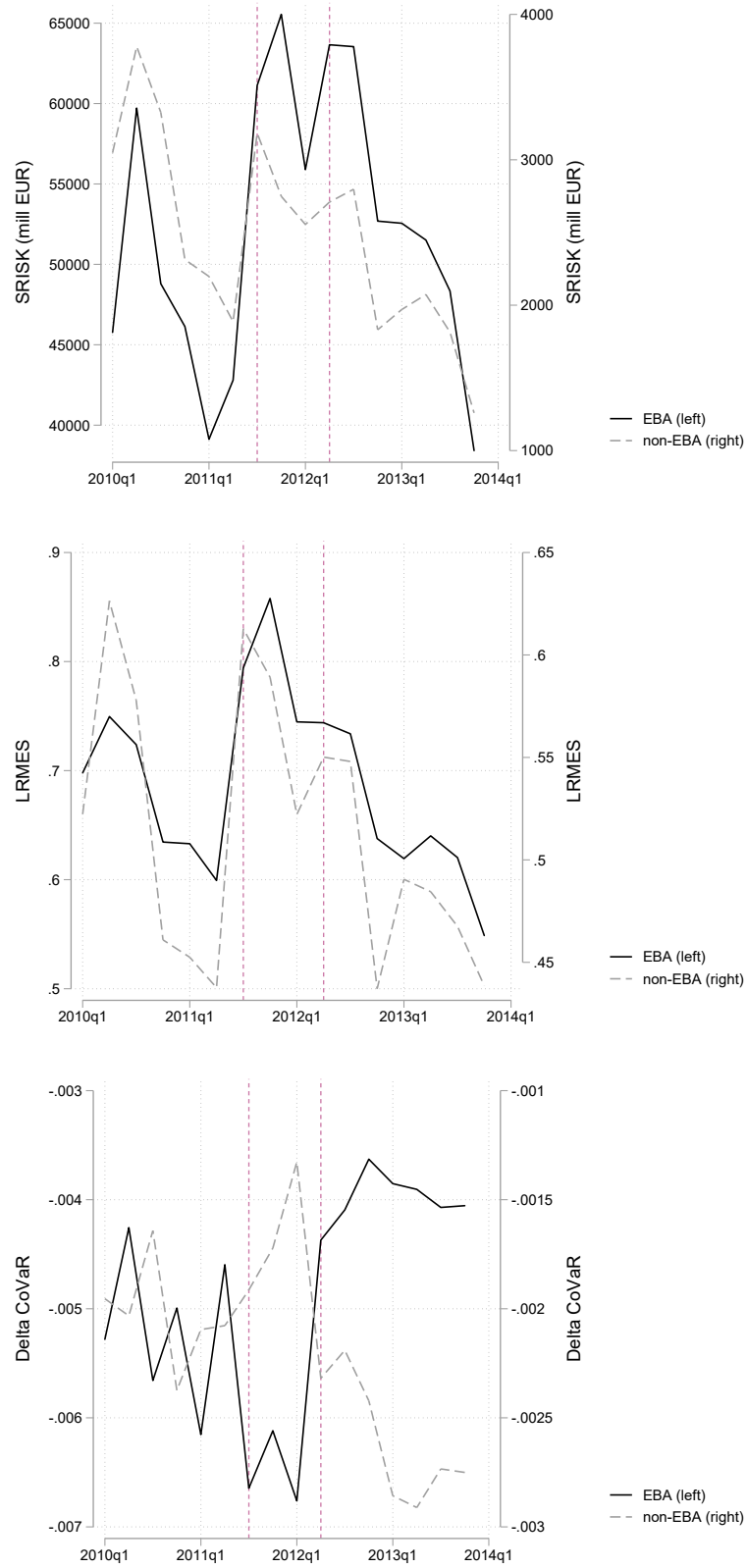


Figure 33: This figure shows the evolution of SRISK, LRMES, and ΔCoVaR .

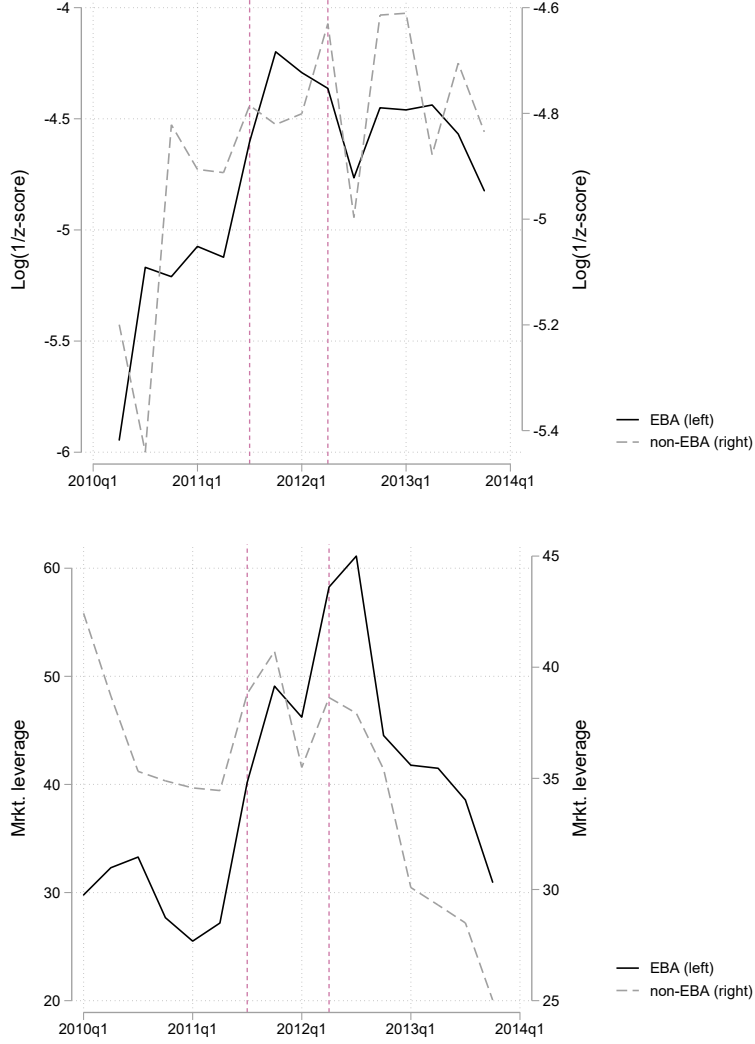


Figure 34: This figure shows the evolution of the (inverse) z-score and market leverage.

A.8 Alternative measure of TBTF-subsidies

As an alternative approach to measuring TBTF-subsidies via support ratings, we follow [Kelly et al. \(2016\)](#) and consider bank-level put option price spreads as an indicator of implicit TBTF-guarantees. Put options serve as insurance against stock price crashes and thus, are costlier when the likelihood of such a crashes is higher. In the context of TBTF, the spread between observed put prices and model-implied put prices should be narrower for those banks receiving implicit guarantees.

We follow [Kelly et al. \(2016\)](#) obtain daily, standardized data on put options (with 365 days maturity and a delta of -25) from the OptionMetrics Volatility Surface file. We are able to collect daily put option data during the sample period from Q1:2010 to Q4:2013 for 15 EBA banks and 6 non EBA banks and calculate model-implied put prices using the Black-Scholes formula. The

evolution of the average put option spread and the coefficient estimate from (1) using the put option spread as dependent variable is shown in Figure 35.

If the capital exercise takes away some of those implicit/explicit TBTF guarantees for affected banks, we would expect the spread for EBA banks to widen relative to non-EBA banks. This is not the case. None of the coefficient estimates after the exercise are significant at statistically relevant levels. Also, we find that the coefficients are and remain exclusively negative after two quarters after the exercise. Overall, the spread between observed put price and model implied put price becomes, if anything, narrower for EBA banks relative to non-EBA banks which would, if anything, result in more guarantees (but not less). This is consistent with the evidence from bank support ratings presented in the main text.

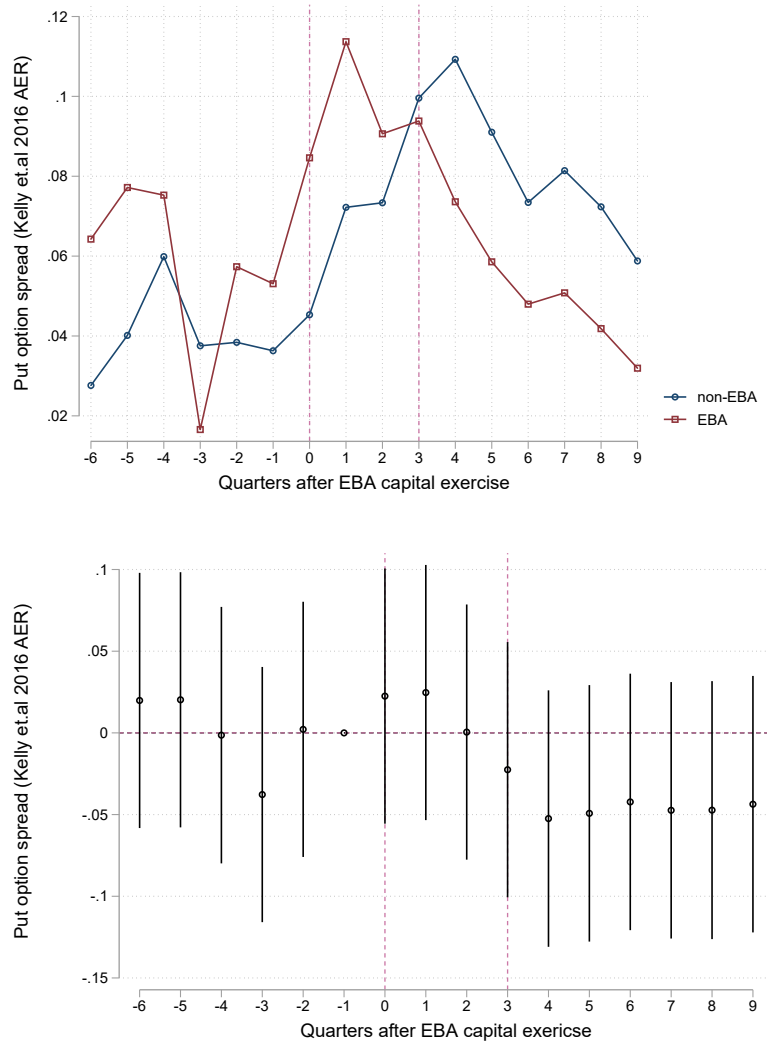


Figure 35: This figure shows the evolution of the average put options spread as calculated in Kelly et al. (2016) (top) and the sequence of estimated $\{\gamma_k\}$ from equation (1) using the put option spread (as a fraction of the underlying equity price) as dependent variable and dropping fixed effects (bottom). Vertical bars correspond to 95% confidence intervals.

B Appendix: Systemic risk measures

B.1 ΔCoVaR

The estimations of the conditional CoVaR, i.e., CoVaR_t and VaR_t are time-varying. We estimate the time variation conditional on a vector of lagged state variables M_{t-1} . They can be interpreted as conditioning variables shifting the conditional mean and the conditional volatility of the risk measures. The previous quantile regression is now performed using weekly data with

$$\begin{aligned} R_{i,t} &= \alpha^i + \gamma^i M_{t-1} + \epsilon_t^i, \\ R_{system,t} &= \alpha^{system|i} + \beta^{system|i} R_{i,t} + \gamma^{system|i} M_{t-1} + \epsilon^{system|i}_t. \end{aligned}$$

The predicted values of VaR and CoVaR are given by

$$\begin{aligned} \text{VaR}_t^i(q) &= \hat{\alpha}^i + \hat{\gamma}^i M_{t-1}, \\ \text{CoVaR}_t^i(q) &= \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} \text{VaR}_t^i(q) + \hat{\gamma}^{system|i} M_{t-1}. \end{aligned}$$

Here the predicted values from the regressions of $R_{i,t}$ and $R_{system,t}$ are used. In the end, ΔCoVaR_t^i for each institution is calculated by

$$\begin{aligned} \Delta\text{CoVaR}_t^i(q) &= \text{CoVaR}_t^i(q) - \text{CoVaR}_t^i(50\%), \\ &= \hat{\beta}^{system|i} (\text{VaR}_t^i(q) - \text{VaR}_t^i(50\%)). \end{aligned}$$

As we focus on the European banking market, we do not use the state variables based on U.S.-level data as proposed by [Adrian and Brunnermeier \(2016\)](#) to estimate ΔCoVaR . Instead, we consider appropriate European state variables, i.e., the change in the Euro yield curve, the change between the ten-year Euro area yield rate and the three-month Euro interest rate, the Euro Stoxx 50 return, real estate returns in excess of the Euro Stoxx 50 equity market, the short-term Treasury Bill Eurodollar spread and the change in the credit spread VSTOXX to estimate the conditional CoVaR.

B.2 Dynamic Marginal Expected Shortfall

Addressing concerns that the static definition of the MES proposed by [Acharya et al. \(2017\)](#) cannot adequately capture the time variation in a bank's exposure to systemic risk, [Brownlees and Engle \(2017\)](#) propose a dynamic specification that builds on well-known time series techniques. Therefore, let $R_{j,t}$ and $R_{M,t}$ be the j^{th} bank's and the market log return on day t , respectively.

The bivariate process of the daily bank and market returns is then given by

$$\begin{aligned} R_{M,t} &= \sigma_{M,t} \epsilon_{M,t}^1 \\ R_{j,t} &= \sigma_{j,t} \rho_{j,t} \epsilon_{M,t}^2 + \sigma_{M,t} \sqrt{1 - (\rho_{j,t})^2} \epsilon_{j,t}^2 \\ (\epsilon_{M,t}^1, \epsilon_{j,t}^2) &\sim H, \end{aligned}$$

where $\sigma_{i,t}$ is the conditional volatility of the market return ($i = m$) or bank j 's return ($i = j$), $\rho_{j,t}$ is the conditional market/bank correlation and $(\epsilon_{M,t}^1, \epsilon_{j,t}^2)$ are i.i.d. innovations with $\mathbb{E}(\epsilon_{i,t}^j) = 0$, $Var(\epsilon_{i,t}^j) = 1$ for $n = \{1, 2\}$ and $i = \{j, M\}$ and zero covariance (although they are not necessarily independent of each other).

The one-period-ahead MES for a systemic event S is denoted by

$$\begin{aligned} MES_{j,t-1}^1 &= \mathbb{E}_{t-1}(R_{j,t} \mid R_{M,t} < S) \\ &= \sigma_{j,t} \mathbb{E}_{t-1} \left(\rho_{j,t} \epsilon_{M,t}^1 + \sqrt{1 - (\rho_{j,t})^2} \epsilon_{j,t}^2 \mid S/\sigma_{M,t} \right) \\ &= \sigma_{j,t} \rho_{j,t} \mathbb{E}_{t-1}(\epsilon_{M,t}^1 \mid S/\sigma_{M,t}) + \sigma_{j,t} \sqrt{1 - (\rho_{j,t})^2} \mathbb{E}_{t-1}(\epsilon_{j,t}^2 \mid S/\sigma_{M,t}). \end{aligned}$$

Furthermore, the conditional probability of the systemic event is given by

$$Pr_{S,t}^1(S) = Pr_{t-1}(r_{M,t} < S) = Pr(\epsilon_{M,t}^1 < S/\sigma_{M,t}).$$

In contrast to the one-period-ahead MES, the multi-period-ahead MES is estimated by a simulation procedure to construct forecasts. First, K return paths of length h for $k = 1, \dots, K$ are simulated on day $t - 1$

$$\left\{ \begin{array}{c} R_{M,t+\delta-1}^k \\ R_{j,t+\delta-1}^k \end{array} \right\}_{\delta=1}^h.$$

Next, pseudo-innovations are drawn from the innovation distribution H yielding

$$\left(\epsilon_{M,t+\delta-1}^{1,k}, \epsilon_{M,t+\delta-1}^{2,k} \right)_{\delta=1}^h \sim H.$$

Using the pseudo-innovations in the Dynamic Conditional Correlation (DCC) and GARCH models with the current levels of volatility and correlation as starting conditions, we obtain the simulated return paths. The MES is then estimated as the Monte Carlo average of the simulated paths

$$MES_{j,t-1}^h(S) = \frac{\sum_{k=1}^K R_{j,t:t+h-1}^k I\{R_{M,t:t+h-1}^k < S\}}{\sum_{k=1}^K I\{R_{M,t:t+h-1}^k < S\}},$$

where $R_{i,t:t+h-1}^k$ is the k^{th} simulated cumulative return of bank j or of the market from period t to period $t + h - 1$, i.e.,

$$R_{j,t:t+h-1}^k = \exp \left\{ \sum_{\delta=1}^h r_{j,t:t+h-1}^k \right\} - 1.$$

Finally, the multi-period probability of a crisis is then given by

$$Pr_{S,t}^1(S) = Pr_{t-1}(R_{M,t:t+h-1}^k < S) = \frac{1}{K} \sum_{k=1}^K I\{R_{M,t:t+h-1}^k < S\}.$$

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