Herding to comply: Systemic risk consequences of capital policy actions in Europe

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Abstract

In this paper, we contribute to the ongoing policy debate on the resilience of financial institutions by assessing whether capital policy actions in Europe contribute to systemic risk. Using a flexible Bayesian framework, we estimate systemic risk and assess the multilevel effects of capital policy actions across Europe. The framework produces a hierarchy of systemic risk implications of capital policy actions for each of the 21 European countries. We focus specifically on tightening, loosening, and ambiguous policy actions in the data. Our results reveal that the accumulation of tightening policy actions have the unintended consequence of increasing system risk by between 1 and 10 quarterly percentage points at the bank level. When evaluating the intra-national posterior probability of the 'random effects', banks in Greece, Ireland and the United Kingdom seem to be driving this result. Our results suggest capital adequacy regulation can have the unintended consequence of increasing systemic risk. This involuntary association may result from several systemically unimportant institutions becoming 'systemic as a herd' when investing in the same asset classes to comply with capital rules.

Introduction

Not since the Great Depression-era reforms has there been such sweeping re-regulation of financial institutions and markets. Following the global financial crisis of 2007-09, national regulators and international bodies have promoted a series of reforms to foster economic stability. Ten years on from the problem, regulators, policymakers and industry participants are trying to assess the outcomes of such reforms and the interplay of regulation, supervision and financial stability. One of the key concerns is that individually prudent behaviour of banks could amplify systemic risk. In particular, regulators worry that reforms that aimed to restrict total balance sheet risks, such as higher capital requirements and the introduction of leverage ratio requirements under Basle III, could result in banks becoming increasingly similar. Precisely due to prudential rules encouraging an expansion into specific areas and individual assets. As a result, while banks might be safer individually, they might also have become "systemic as a herd", that is, susceptible to the same shocks, which could, in turn, increase systemic risk. Despite its importance, work on this topic is at a relatively early stage.

In this paper, we contribute to this debate by evaluating how European banks' systemic risk contributions are affected by the build-up of capital policy actions. We source the data on policy actions from the *Ma*cro*P*rudential *P*olicy *E*valuation *D*atabase (MaPPED)[1] introduced by Budnik and Kleibl (2018). The MaPPED data captures the "*life-cycle*" of policy instruments expected to impact the whole banking system significantly. The database categorises instruments into either genuinely macroprudential or essentially microprudential. It tracks events of the evolution of eleven categories and 53 subcategories of instruments.

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MaPPED uses a carefully designed questionnaire in cooperation with experts from national central banks and supervisory authorities of all EU member states. Nevertheless, survey information only reflects whether laws are on the books, not to what extent they affect the network-wide risk in practice.

Building on the $\Delta CoVaR$ methods (Adrian and Brunnermeier 2016; Brunnermeier, Rother, and Schnabel 2020), which allows us to study banks as systemic *risk inducers*, we employ a flexible two-stage Bayesian empirical design. In stage one, we capture the complete posterior distribution of extreme event risk by extended the methods of Bernardi, Gayraud, and Petrella (2013). Specifically, to improve accuracy, we use a Bayesian adaptive LASSO technique to regularise the set of time-varying covariates that adjust for macro-level dynamics in tail risk. Unlikely a standard LASSO, this model adapts each predictor separately in terms of the optimal regularisation to improve accuracy and stabilise predictions(Li, Xi, and Lin 2010; Gelman, Hill, and Vehtari 2020). In stage two, we use a Bayesian hierarchical regression model to disentangle policy action effects. This multilevel framework exploits the natural nested structure of the data (repeated observations of banks within countries), allowing different intercepts and slopes to varying across countries and over time. When the number of banks per country is small, only including group indicators in a least-squares regression gives unacceptably noisy estimates. Our bayesian multilevel regression, via a partial pooling approach, uses the variation in the data to estimate prior distribution on the deviation of the intercepts and slopes (Gelman, Hill, and Vehtari 2020). The procedure is especially appropriate when the critical variable of interest is at the country level and where some groupings (countries) have only a few publicly listed banks.

Our baseline results point to a positive link between the build-up of tightening policy actions and systemic risk contribution one quarter on. Our hierarchical model disentangles this effect and finds that banks in Greece, Ireland and the UK seem to be driving this risk inducing behaviour. Overall, the influence of policy actions on individual system risk is weak, with banks in many countries showing little impact from policy actions one quarter. Interestingly, our models allow us to compare effect sizes and loosening policy actions have the strongish relative impact[2]. However, the estimate is quite noisy, with a 95% credibility interval of [-0.139,0.141].

This finding supports the fallacy of composition hypothesis (Embrechts et al. 2001): capital regulation - based on a bank's own risk - can unintentionally exacerbate systemic risk (Acharya 2009; Danielsson, Shin, and Zigrand 2012; Embrechts et al. 2001; Gehrig and Iannino 2017). As banks comply with minimum capital standards, they invest (herd) in similar securities that are more likely to be associated with common factors, especially in crisis time (Danielsson, Shin, and Zigrand 2012).

There is a body of theoretical research that has investigated why banks herd. One hypothesis posits that banks seek safety in similarity; that is, as banks become concerned about regulatory bailouts, they have incentives to copy each other's behaviour as they seek to exploit the "too many to fail" guarantee (Acharya and Yorulmazer 2007; Vives 2014). Another strand of the literature argues that banks herd through investment choices. As individual banks diversify, their asset portfolios may increase, increasing the linkages between financial institutions and ultimately increasing systemic risk. Allen, Babus, and Carletti (2012) present a model in which asset commonality and short-term bank debt interact to generate systemic risk.

Herding behaviour has also been studied on the liabilities side (Farhi and Tirole 2012; Horváth and Wagner 2017; Segura and Suarez 2011; Stein 2012). Vives (2014) argues that well-intentioned regulation and supervision can lead to unexpected risk enhancing consequences through strategic complementarity. The empirical literature has also investigated banks herding behaviour through the diversification channel (Hirakata, Kido, and Thum 2017; Nijskens and Wagner 2011).

Our study also contributes to the literature on bank risk-taking and the quality of regulation and supervision. Studies using the World Bank surveys on bank regulations and oversight find laws that empower remote monitoring, promote information disclosure, and create incentives for private sector corporate control advocate sustainable banks' performance and encourage stability(Barth, Caprio, and Levine 2001, 2004, 2006, 2008, 2012). Further work focusing on bank risk-taking finds mixed results. Agoraki, Delis, and Pasiouras (2011) find that the direct effect of market power reduces risk-taking in banks in Central and Eastern Europe. However, risk-taking is decreased only when banks with weak (strong) market power are exposed to more

[2]Typically they have a 13 basis point reduction in average quarter systemic risk for a one standard deviation move in the predictor

stringent capital (activity restrictions) regulation. They find that official supervisory authority has only a direct effect on bank risk. Klomp and Haan (2012) construct multidimensional bank risk measures distilling 25 risk indicators into two common factors. They see the relationship between bank risk, regulation, and supervision depending on size, ownership structure, and riskiness level. A few studies consider regulation, supervision and system-wide risk. Demirgüç-Kunt and Detragiache (2011) find that BCP compliance is not robustly associated with bank soundness, estimated by a system-wide z-score. One shortcoming of this study is that the authors' risk measure fails to capture systemic contribution at the bank level, which in turn would not provide disaggregated information on individual bank strategies (Delis and Staikouras 2011). Gehrig and Iannino (2017) assess the Basel process of capital regulation's financial stability using two risk measures that capture a bank's contribution and exposure to systemic risk. Surprisingly, they find evidence that the adoption of internal models of credit risk is enhancing systemic risk. This effect is more pronounced in large systemically critical European banks. Their results extended the finding of unintended risk consequences of internal model-based regulation in the German banking system (Behn, Haselmann, and Vig 2016). They provided empirical evidence for Basel II endogenous systemic risk warnings of (Embrechts et al. 2001).

The remainder of this paper is structured as follows. Section II presents the data collection process. Section III offers a practical design and estimation process. Section IV provides a discussion of the essential findings, and Section V concludes.

Data

We start with daily equity and macroeconomic state variable data from Refinitiv Datastream for the four ICB financial sector industries, banks, investment banks and brokerage, insurance and real estate for 21 European countries. Compustat Global provides quarterly balance sheet data used to create bank-level predictors. The quarterly data only include observations with a price to book ratio and leverage values in the interval $[0, 100]$. We further apply truncation to the maturity mismatch variable at the 1st and 99th percentile. Finally, to ensure meaningful risk estimation, only those institutions which have at least two years of equity data are included in the sample. After data cleansing, we have a total of 724 financial institutions in our (116 commercial banks, 238 investment banks, 284 real estate companies, and 66 are insurance firms). The sample period for the systemic risk estimation is 1995:I-2015:IV. The central part of the estimation uses daily data.

We source the data on policy actions from the *Ma*cro*P*rudential *P*olicy *E*valuation *D*atabase (MaPPED)[3] introduced by Budnik and Kleibl (2018). The data tracks events of the evolution of eleven categories and 53 subcategories of instruments] MaPPED was compiled using a carefully designed questionnaire, in cooperation with experts from national central banks and supervisory authorities of all EU member states. We focus on the minimum capital requirements (hereafter MCR) policy actions in this database. To investigate their relationship to systemic risk, we create a quarterly sum of these policy actions categorised by their intended impact. There are three categories of impact:

1. Policy loosening
2. Policy tightening
3. Other and ambiguous impact

In line with Cerutti, Claessens, and Laeven (2017), we create a lagged cumulative count of actions to capture the overall policy stance of the regulators. This sum increases when the policy instrument is activated, or there is a change in scope and decreases when they are deactivated. Unlike previous studies, we do not impose a prior assumption on the impact of the three categories. This numeration places a prior belief on the expected sign of the action[4] which could like to bias regression inference. Precisely, we capture the accumulated effect of each policy action using a cumulative sum and hypothesis that:

1. An increasing number of tightening actions will reduce systemic risk
2. An increasing number of policy loosening actions will not affect systemic risk

[3]https://www.ecb.europa.eu/pub/research/working-papers/html/mapped.en.html

[4]Previous studies have signed policy actions in terms of their intended consequence. In this way, they construct a result rather than allow the data to provide evidence of any risk effect (Akinci and Olmstead-Rumsey 2017, @Cerutti2016, @Meuleman2019)

3. We have no a priori hypothesis on an increasing number of ambiguous actions.

Table 1: Summary of minimum capital requirement actions

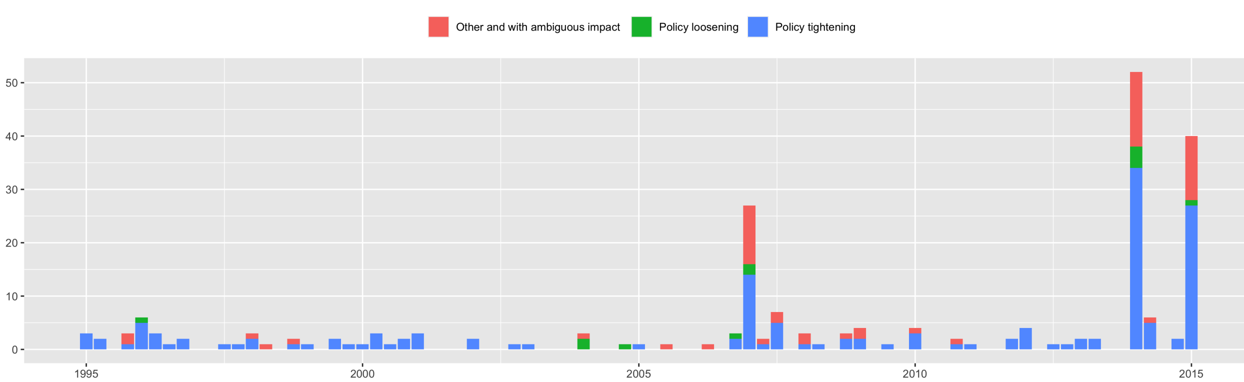
Intended Impact	Count	Percentage
Ambiguous	56	25
Loosening	12	5
Tightening	155	70

Table 1 shows the quarterly frequency of minimum capital requirement policy actions by the national central bank's intended impact. Policy tightening is the dominant intention over the sample period, with 70% of the total actions, while actions which loosen policy are the least frequent.

Table 2: Type of action of policy tool

Activation of a new tool	Change in the level of an existing tool	Change in the scope of an existing tool	Deactivation of an existing tool	Maintaining the existing level and scope of a tool	Intended Impact
4	2	46		4	Ambiguous
1	8	1	2		Loosening
68	29	56		2	Tightening

Table 2 we can further disentangle the three categories in terms of the scope of the action. Of the 56 MCR actions categorised as ambiguous, most are changes in the scope of an existing tool. Again, policy tightening actions dominate, with the majority of actions being the activation of a policy tool, then a change in scope, and finally a change in the level of an existing policy. When disentangling the specific descriptions of the 29 changes in the level of existing policy tightening actions, the textual sentiment increases level tightness. This latter observation indicates the extent of the aggressive attempts to curb excessive risk-taking in European banking. Our fundamental research question is to assess whether this ramping up of actions had any unintended network consequences.



Strengthening/Loosening	qtr	n
Policy tightening	2014 Q1	34
Policy tightening	2015 Q1	27
Other and with ambiguous impact	2014 Q1	14
Policy tightening	2007 Q1	14
Other and with ambiguous impact	2015 Q1	12
Other and with ambiguous impact	2007 Q1	11

Figure 1: Count of minimum capital requirements policy actions

Figure 1 describes the evolution of the MCR policy actions over the sample period. The bottom panel indicates some spikes in activity, notably in 2007 Q1, 2014 Q1, and 2015 Q1. These activity spikes are unsurprising given intital reactions to the crisis and the wave of regulatory reform which swept through Europe in this period.

Methodology

We use a Bayesian inference framework to estimate systemic risk and investigate the impact of policy actions. In a dynamic setting, this offers some benefits compared to classical panel estimators. In contrast to traditional approaches, which treat group-levels parameters as nuisance parameter to be removed, Bayesian methods allow group-level estimates regularised to only include information that adds explanatory power. Furthermore, they can be used to likely attenuation bias that is known to be associated with policy action count data Akinci and Olmstead-Rumsey (2017). Finally, they can include a noise component with incorporates the panel structure of the data.

Systemic risk measurement

We use the $CoVaR$ approach to systemic risk contribution estimation, which extends the Value at Risk (VaR) concept to the system. CoVaR can be thought of as the VaR of the whole system conditional on institution i being in a certain state. Systemic risk is approximated using $\Delta CoVaR$; the difference between the $CoVaR$ conditional on the distress of an institution and the CoVaR conditional on the median state of that institution. $\Delta CoVaR$ is best thought of as a reduced form statistical tool which captures tail codependency or the part of systemic risk that co-moves with the distress of an institution. $\Delta CoVaR$ frames a bank as a *risk inducer*, quantifying the contribution of a financial institution to the system's level of systemic risk. This is achieved by estimating the additional value at risk of the entire financial system associated with this institution experiencing distress (Brunnermeier, Rother, and Schnabel 2020).

Formally, Let $(Y_1, \ldots, Y_d)$ be a d-dimensional random vector where each Y_j is expressed through some covariates $X = (X_1, X_2, ..., X_M)$. In the systemic risk context, Y_j denotes the behaviour of either an institutions or the whole system. Without loss of generality, thereafter, we fix $\tau \in (0, 1)$ and suppose that we are interested in institutions j within system k. The Value-at-Risk, $VaR_j^{\mathbf{X},\text{ø}}$ of institution j is the τ-th level conditional quantile of the random variable $Y_j|\mathbf{X} = \mathbf{x}$:

$$\mathbb{P}(Y_j \leq VaR_j^{\mathbf{X},\text{ø}} | \mathbf{X} = \mathbf{x}) = \text{ø} \tag{1}$$

.The Conditional Value-at-Risk $\left(CoVaR^{\mathbf{X},\text{ø}}_{system=k|j}\right)$is the Value-at-Risk of system k conditional on $Y_j = VaR_j^{\mathbf{X}\text{ø}}$ at the level τ which satisfies:

$$\mathbb{P}\left(Y_{system=k} \leq CoVaR^{\mathbf{X},\text{ø}}_{system=k|j} | \mathbf{X} = \mathbf{x}, \mathbf{Y_j} = \mathbf{VaR_j^{X,\text{ø}}}\right) = \tau \tag{2}$$

Using Bayesian inference, equation 2 implies that CoVaR corresponds to the τ-th percentile of the conditional distribution (For a detailed exposition see Bernardi, Gayraud, and Petrella 2013)

Bayesian regularised time-varying $\Delta CoVaR$ estimation

To capture all forms of risk including volatility feedback, adverse asset price movements and funding liquidity risk, we estimate $\Delta CoVaR$ using daily return losses from 1995:I to 2018:IV for a sample of European commercial banks, investment banks, insurance companies and real estate companies. Return losses Y_{it} are measured using market equity ME of the publicly traded institution,

$$Y_{i,t+1} = -log(ME_{i,t+1}/ME_{i,t}) \tag{3}$$

We extend the work of Bernardi, Gayraud, and Petrella (2013) by using an Bayesian adaptive LASSO quantile regression to evaluate daily time varying $\Delta CoVaR$. Regularisation techniques, such as the LASSO, have been shown to improve predictive accuracy of quantile regression by only include information which adds to the predictive power of the explanatory variable set (Li, Xi, and Lin 2010). Regularisation techniques employed with Bayesian inference are increasing common in financial econometric (See for example Tibshirani 2011; Mogliani and Simoni 2020; Fan, Ke, and Wang 2020). The adaptive LASSO is especially useful when estimated time-varying $\Delta CoVaR$, given the set of state variables used to adjust for macro-level risk dynamics (See Table A.1 for full list). Finally, in the context of systemic risk, Bayesian methods are highly flexible and are extreme useful in the context of the analysis of interdependence effects of extreme market events. Using data and prior information they provide the complete posterior distribution of the parameters of interest. Since the quantities of interest in this paper are risk measures, learning about the whole distribution becomes more relevant due to the interpretation of $CoVaR$ as financial losses (Bernardi, Gayraud, and Petrella 2013)

Formally, the Bayesian Adaptive Lasso regression is a hierarchical model which exploits a skewed Laplace distribution[5] to estimated $VaR_j^{\mathbf{X,ø}}$ and $\left(CoVaR^{\mathbf{X,ø}}_{system=k|j}\right)$ as follows:

$$Y_{jt} = \beta_{0,j} + \mathbf{M}^{'}_{\mathbf{i,t-1}}\mathbf{\text{fi}_j} + \mathbf{\text{`}_j z_j} + \mathbf{\text{Œ¸}_j}\sqrt{\mathbf{\text{œ}^{-1} z_j}} \tag{4}$$

$$Y_{kt} = \beta_{0k} + \mathbf{M}^{'}_{\mathbf{i,t-1}}\mathbf{\text{fi}_k} + \mathbf{\text{ffi}Y_{jt}} + \mathbf{\text{`}z_j} + \mathbf{\text{Œ¸}_k}\sqrt{\mathbf{\text{œ}^{-1} z_k}} \tag{5}$$

where M is a set of European financial and macroeconomic variables detailed in Table A.1 in the appendix.

VaR and CoVaR posterior estimation

In the Bayesian inference, we capture the more intuitive probability of the parameter estimates learned from the data[6]. Conventionally, posterior probabilities using a maximum of the posterior density (Maximum a Posteriori or MaP)[7] as a summary. We assume an asymmetric Laplace distribution for the error terms and weakly informative priors on the regressor parameters[8]. From all the MaP parameters involved in the marginal and conditional quantiles the estimates of $VaR_j^{\mathbf{X,ø}}$ and $\left(CoVaR^{\mathbf{X,ø}}_{system=k|j}\right)$ are derived as follows:

$$(VaR_j^{X,\tau})^{MaP} = X^{'}\beta_j^{MaP} \tag{6}$$

$$(CoVaR^{X^{'},\tau}_{system=k|j})^{MaP} = X^{'}\beta^{MaP}_{system=k} + \delta^{MaP}(VaR_j^{\mathbf{X,ø}})^{MaP} \tag{7}$$

Figure 2 visualised the Bayesian quantile adaptive $L1$ regularised estimate for a selection of banks. In each plot the credibility set is represented by the shaded area and represents the uncertainty in each MaP estimate. The x-axis is a daily time indicator for the sample period. The plots summarise of these MaP estimates and their 99% credible sets for a number of the banks in the sample. The shaded grey area characterises the uncertainty around the MaP estimate. While the time patterns are similar in each plot with a spike at the height of the European crisis, both KBC group and National Bank of Greece stand out for their significantly higher systemic risk inducing behaviour.

[5]which has the attractive property of being represented as a scale mixture of normal distributions (Tsionas 2003)

[6]There is no free lunch, and bayesian inference comes at the cost of some additional assumptions, named priors. Our analysis interrogated these assumptions using prior predictive checks. Given that Bayesian models are generative, prior predictive checks allow the use of a range of informative and non-informative priors to generate simulated data that can be checked against the actual data. This process is robust and is not subject to information leakage as in certain data dredging frequentist practices

[7]MaPs are mathematically equivalent to the minimisation problem in the frequentist context (Lin and Chang 2012)

[8]Prior predictive checks show that the size of the dataset quick dominants any undue influence of these priors and is available upon request from the author

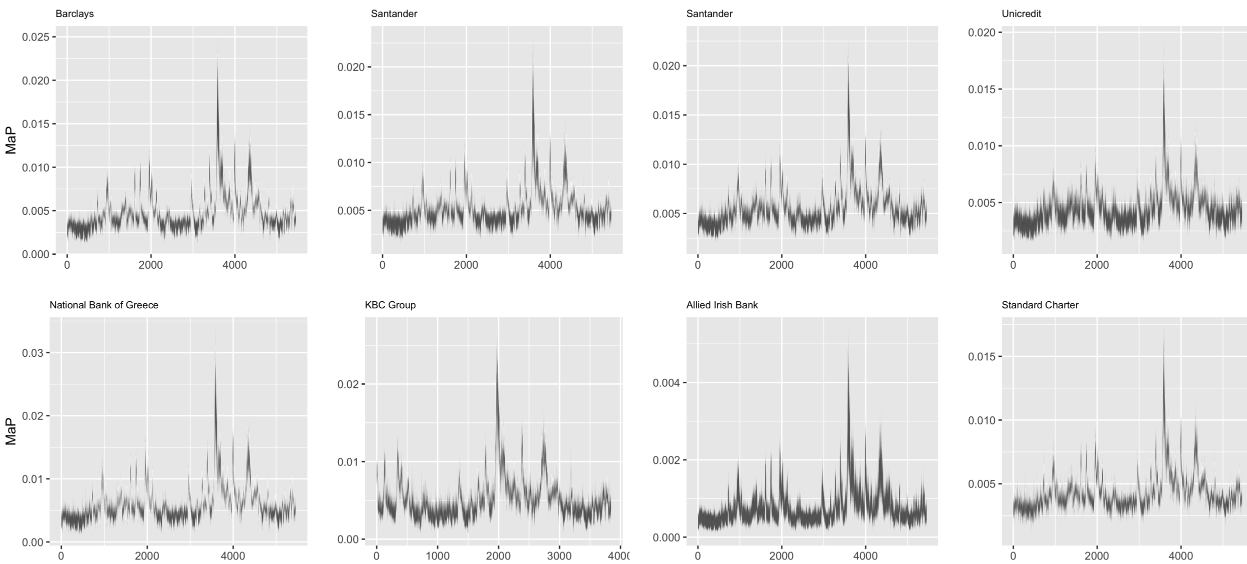


Figure 2: Posterior probability credible set MaP CoVaR estimates

Bayesian Hierarchical Model

This section will lay out the Bayesian hierarchical model to investigate systemic risk implications of capital actions in Europe. Bayesian hierarchical or multilevel models exploit a data structure with several levels that are either nested or non-nested. The key to identifying a variable as a level is that its units are a random sample from a wider population. In this instance, we have a three-level nested data structure of repeat observations within banks within European countries. The banks are a random sample from a broader population of banks; likewise, the countries are a random sample from many countries. In general, multilevel models are helpful where relationships vary across higher-level units[9]. This is in stark contrast to classical least squares regression models where group effects are typically binary indicators, so-called *fixed effects* models. Typically, a *fixed effects* model cannot discriminate between observed and unobserved group characteristic effects (for example, a policy action applied by the national regulator).[10] What results from a fixed effect model is, at best, a partial estimate of the ground truth. To date, there are some notable exceptions in panel data econometrics to this (see, for example, Wooldridge (2019)). There is no such issue with a multilevel model, where full effects at many levels can be simultaneously estimated.

Multilevels $\Delta CoVaR$ Regressions

The regression models use MaP estimates of $\Delta CoVaR$ for the 116 commercial banks as the dependent variable. Our hierarchical regression model aims to extract meaningful effects of country-level policy actions on bank-level system risk levels. Our strategy allows for (bank-level) coefficients on the policy action variables to vary by country and quarter, in addition to being 'fixed'. We can think of these then as our three *random effects*. Denoting $y_{c,t[i]}$ as the $\widehat{CoVaR_{c,t[i]}}$ estimate of firm i in-country in time t, we set up two specifications. A baseline where we assume that policy action effect across countries is constant. Then we relax this assumption allowing banks in each country to experience their effect, which is then regularised, via partial pooling, by the global mean effect. Equation 8 describes our baseline model (regression 1), while 9 describes the more country-level *random effects* model (regression 2).

$$y_{c,t[i]} = (\alpha + \alpha_{c,t}) + \beta^L loose_{c,t} + \beta^T tight_{c,t} + \beta^A ambig_{c,t} + Bank_A djustments_{c,t[i]} + M_{c,t} + \epsilon_{c,t[i]} \tag{8}$$

[9] As a rule of thumb, the highest level should have at least 20 units to be suitable for this type of analysis (http://www.bristol.ac.uk/cmm/learning/multilevel-models/data-structures.html)

[10] Econometrically, there is a confounding effect of the group level dummies on the group-level predictors

$$y_{c,t[i]} = (\alpha + \alpha_{c,t}) + (\beta^L + \beta^L_{c,t}) loose_{c,t} + (\beta^T + \beta^T_{c,t}) tight_{c,t} + (\beta^A + \beta^A_{c,t}) ambig_{c,t} + +Bank_A djustments_{c,t[i]} + M_{c,t} + \epsilon \quad (9)$$

α, β^L, β^T and β_A are the 'fixed' effect population coefficients that represent the global 'average' intercept and globe slope coefficients our policy actions variables for a total pooled sample. $\beta^L_{c,t}, \beta^T_{c,t}, \beta^A_{c,t}$ are the 'random' effects counterparts and represent the slope coefficients for each of the 22 countries c and 83 quarters t. The "random" policy effect coefficient estimates, for each country or year, deviates from the population average; such that $\beta^T_{c,t}$ describes how the systemic risk impact of tightening policy actions in the country c or year t deviates from the average impact across taken all countries and quarters. Following Brunnermeier, Rother, and Schnabel (2020), we use a concise set of bank-level and macro-level adjustments[11]. The bank-level variables include (i) leverage, measured as the ratio of total assets to common equity; (ii) maturity mismatch, measured as short-term borrowings to total assets; (iii) size, measured as the log of market equity, (iv) loan growth measures as the percentage change in gross loans, and (v) an asset price boom indicator, which is the number of consecutive quarters of being in the top decile of the price to book ratio across all firms. The macro-level variable set M is the same as that used in the time-varying systemic risk estimation. Finally, we include an AR(1) error process to adjust for the panel nature of our data, which are excluded from the already crowded specification above.

Robustness checks

By its theoretical nature systemic risk, and its joint distribution with policy actions is a tail risk phenomenon, and capturing this feature in the conditional distribution of our hierarchical regression may require more nuance distributional assumes than normality. To this end, we consider three alternative probability distributions, skewed-normal, t-distribution and log-normal. Widely accepted information criteria suggest that the t-distribution is the most appropriate among these alternatives, which conforms with expert advice for modelling extreme events in hierarchical models (Gelman et al. (2019)). The reported results are those based on a t-distribution. Furthermore, attenuation bias is a known issue when assessing the impact of country-level policy actions on individual banks (Akinci and Olmstead-Rumsey 2017). The flexibility of our Bayesian framework allows us to adjust for this measurement error using a latent variable set up. The results using a measurement error model are qualitatively similar to the reported estimates and are available upon request.

[11]The common practice use of *control* when describing the adjudicating variables in a regression implies overconfidence in the analyst's ability and is sloppy statistical language. The true meaning of a *control* variables is when we can intervene and change the variable by a certain amount, which is clearly not possible in any observational studies. We, therefore, prefer the more modest and realistic *adjusting* description

Results

Table 3: Summary of Baseline Model Regression Results

Variable	Estimate	l-95 CI	u-95 CI
Fixed Effects			
α	12.851	8.949	16.932
β^A	0.007	-0.079	0.096
β^L	-0.130	-0.399	0.143
β^T	0.058	0.011	0.105
Random Intercepts			
σ_{α_c}	8.697	6.068	12.553
σ_{α_t}	0.904	0.765	1.074
Student-t Parameters			
σ	0.707	0.692	0.722
ν	1.001	1.000	1.004

[a] Results for regression model 1, which excludes random effects of the policy actions at the country level.For each coefficient, the mean(Estimate), 5% and 95% percentiles (l-95% CI and U-95% CI) of the posterior distribution is reported. The latter two percentile ranges represent the 90% credible/uncertainty interval.Adjusting macro economic parameter estmates are excluded for brevity

Table 4: Summary of Hierarchical Model Regression Results

	Estimate	Est.Error	l-95 CI	u-95 CI	R_hat
Fixed Effects					
Intercept	13.146	2.005	9.154	17.214	1.005
B_{Size}	0.114	0.012	0.031	0.164	1.000
$B_{Leverage}$	0.511	0.112	0.110	0.810	1.000
$B_{MaturityMismatch}$	-0.221	0.012	0.201	0.251	1.000
$B_{loanGrowth}$	0.012	0.005	0.000	0.002	1.000
B_{Boom}	0.810	0.120	0.410	0.551	1.000
Country Random Effects					
sd(Intercept)	8.687	1.620	6.006	12.325	1.015
sd(tightSum)	0.079	0.052	0.005	0.201	1.006
sd(looseSum)	0.044	0.058	0.001	0.189	1.000
sd(ambigSum)	0.060	0.042	0.002	0.159	1.003
Quarter Random Intercepts					
sd(Intercept)	0.912	0.084	0.767	1.094	1.001
Student-t Parameters					
sigma	0.707	0.008	0.692	0.722	1.003
nu	1.001	0.001	1.000	1.004	1.000

[a] Results for regression model 2, which includes random effects of the policy actions at the country level.For each coefficient, the mean(Estimate), 5% and 95% percentiles (l-95% CI and U-95% CI) of the posterior distribution is reported. The latter two percentile ranges represent the 90% credible/uncertainty interval. R_hat is the convergence metric and close to one when the MCMC chains are well-mixed and converged. Note that the 'total' estimated coefficient for a given country or year is the sum of the population fixed effect coefficient and the rand effect coefficient particular to that country or year. We do not report the estimated correlations between coefficients within each group-level regression, which our LKJ prior estimates, as their estimated error is too large. Adjusting macro economic parameter estimates are excluded for brevity

Table 3 and 4 present regression results for our baseline and multilevel models. The baseline model assumes policy actions effects are constant over time and across the country. Predictors are standardised. For brevity, Bank-level covariate posterior probability not shown in the baseline model. In both instances, the Bayesian R^2 indicates the model *fit*[12] is very good. For the baseline model Bayesian R^2 lies between $[0.781, 0, 793]$ and for the multilevel model lies between $[0.885, 0.891]$ for the 95% credible interval. Both models allow the effects to be correlated, but we have not reported them in this table as they are not significant. The results are stable to the use of different priors and likelihoods.[13].

Several initial findings are noteworthy. There is a statistically credible positive link between the build-up of tightening policy actions and systemic risk one quarter on. Specifically our baseline model estimates a global random effect of 0.058 with a 95% posterior credible interval of [0.011,0.105]. The estimates of equation 8 provide a more complex set of outputs (this model has 473 parameters) which are best-summarised visually[14]

[12]We follow the procedure outline in Gelman et al. (2019), which calculates the Bayesian Bayesian R^2 as the variance of the predicted values divided by the variance of the predicted values plus the expected variance of the errors

[13]Fixed effect coefficients are almost identical, while some non-critical variation in the random effects occurs. The Bayesian R^2 for the normal likelihood is smaller than the student-t by around 9%-13%

[14]The direct frequentist counterpart to this model is a mixed effect model estimated by maximising a multivariate normal likelihood. Technically, these models treat group-level parameter estimates as a random variable that marginalises out to become part of the error term. Traditional "fixed-effects" panel data analytics perform a similar operation to remove group-level parameters. However, the group-level effects cannot be recovered, meaning the model coefficient represent a partial effect that ignores group-level covariance.

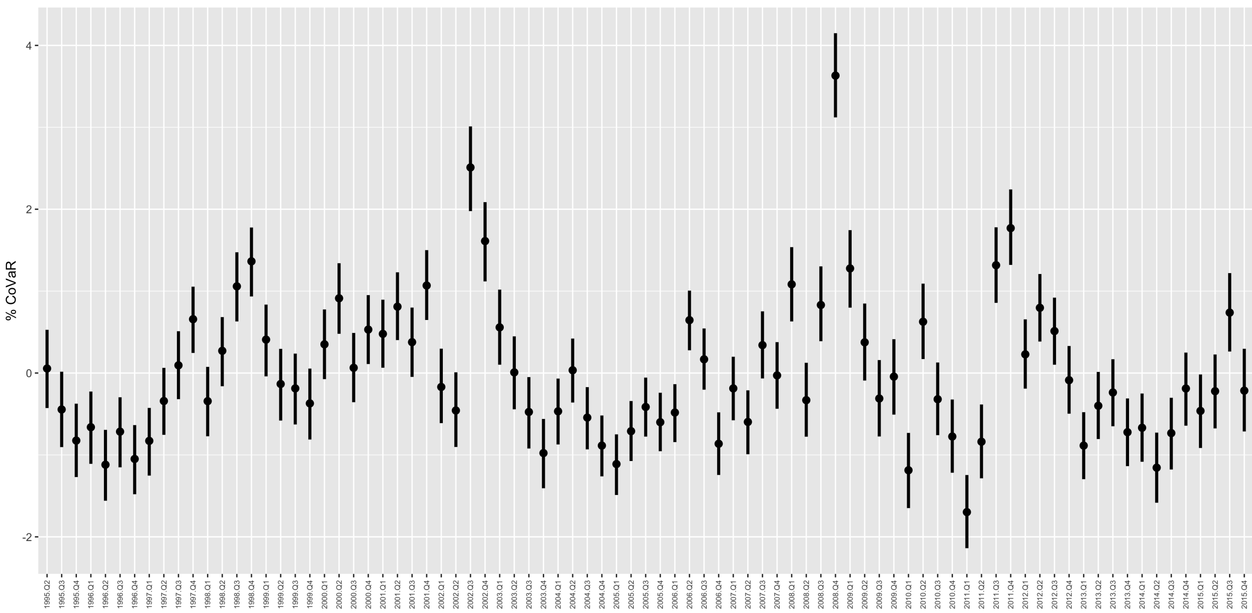


Figure 3: Posterior probability distributions for quarter random intercepts

Figure 3 provides *random* effects and their 99% *plausibility* intervals for the quarterly intercept parameters for the $CoVaR_{it}^{99}$ regressions. The estimate shows a clear risk pattern which peaks in 2008:Q4, the epicentre of the recent financial crisis in Europe.

Figure 4 illustrates country-level random intercepts and show that banks in each country are experiencing meaningful different systemic risk contributions hold all else equal.

Figures 5-7 disentangle the pooled effects of the baseline model into random effects at the country level. Specifically, they capture the systemic risk implications one quarter on the build-up of policy tightening, loosening and ambiguous actions, respectively. The tightening policy actions effects for individual nations reveal that Greek, Irish, and UK banks appear to be the driving force. The 99% credible intervals in each of these countries are statistically meaningful. More generally, the effect of MCR policy actions on individual system risk is weak, with banks in many countries showing little impact from policy actions one quarter on. Interestingly, our models allow us to compare effect sizes and loosening policy actions have the strongish relative impact (-0.13 average reduction on quarterly systemic risk for a one standard deviation move in the predictor). However, the estimate is quite noisy with a credibility interval of [-0.139,0.141].

Conclusion

The global financial crisis highlighted how losses at individual financial institutions could spread across the financial system, giving rise to systemic risk, and underscored the importance of regulation and supervision to a well-functioning banking system. This paper assesses the contribution of European capital adequacy policy actions to a bank's system-wide risk. We focus on the MaPPED database of European policy actions. The sample offers a detailed overview of the "life-cycle" of policy instruments that are either genuinely macroprudential or essentially microprudential but likely to impact the whole banking system significantly. To hone in on our hypothesis question, we consider the subcategory of minimum capital requirement policy actions and use a flexible Bayesian hierarchical model to identify precise effects of these policy actions on systemic risk measured using Bayesian $\Delta CoVaR$. The MaP estimates from the posterior probabilities are then used in the hierarchical regressions to investigate the capital policy action impact.

Overall, our results point to a positive link between the build-up of tightening policy actions and systemic

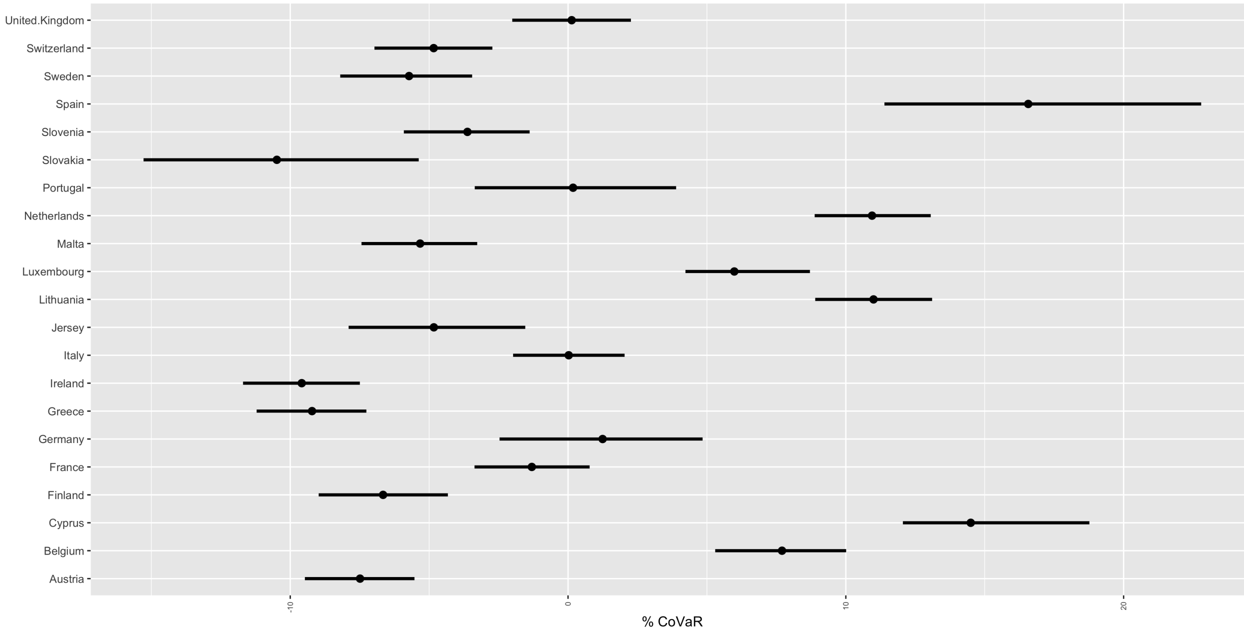


Figure 4: Posterior probability distributions for country random intercepts

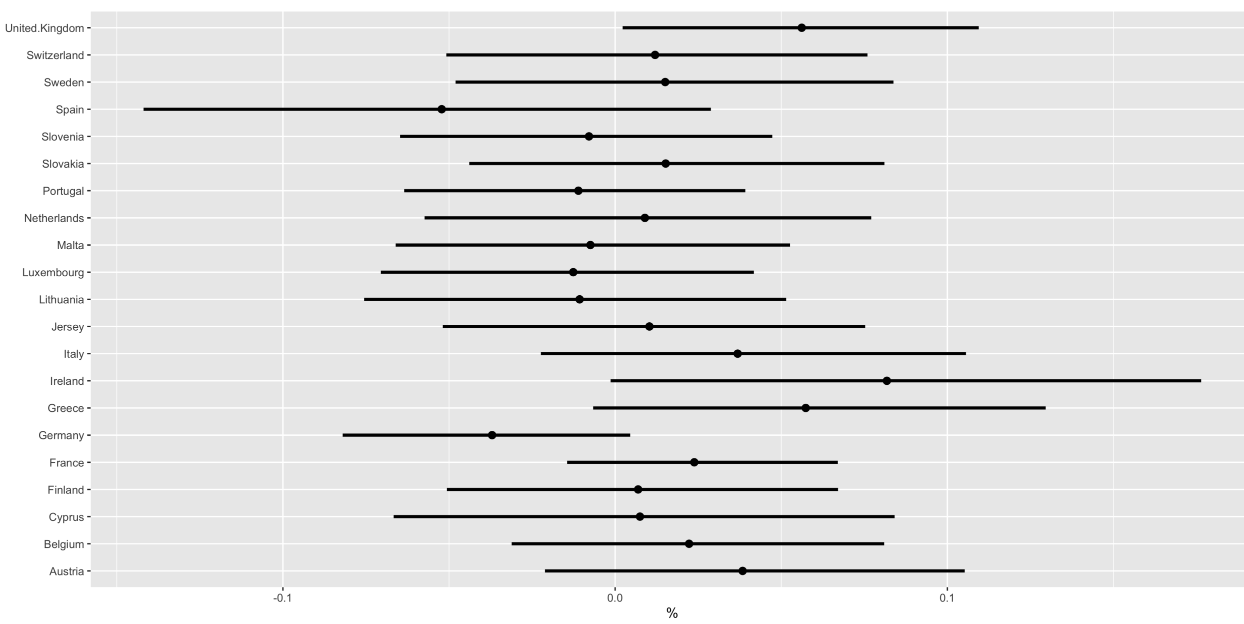


Figure 5: Posterior probability distributions for country level random effects of tightening policy actions

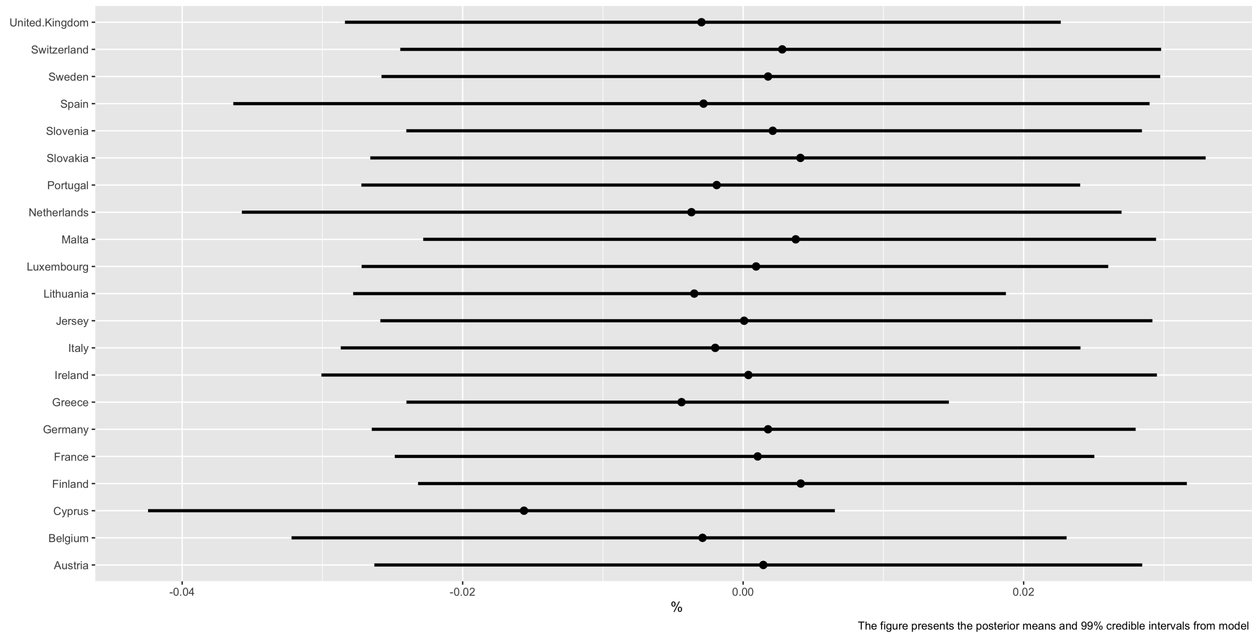


Figure 6: Posterior probability distributions of country level random effects of loosening policy actions

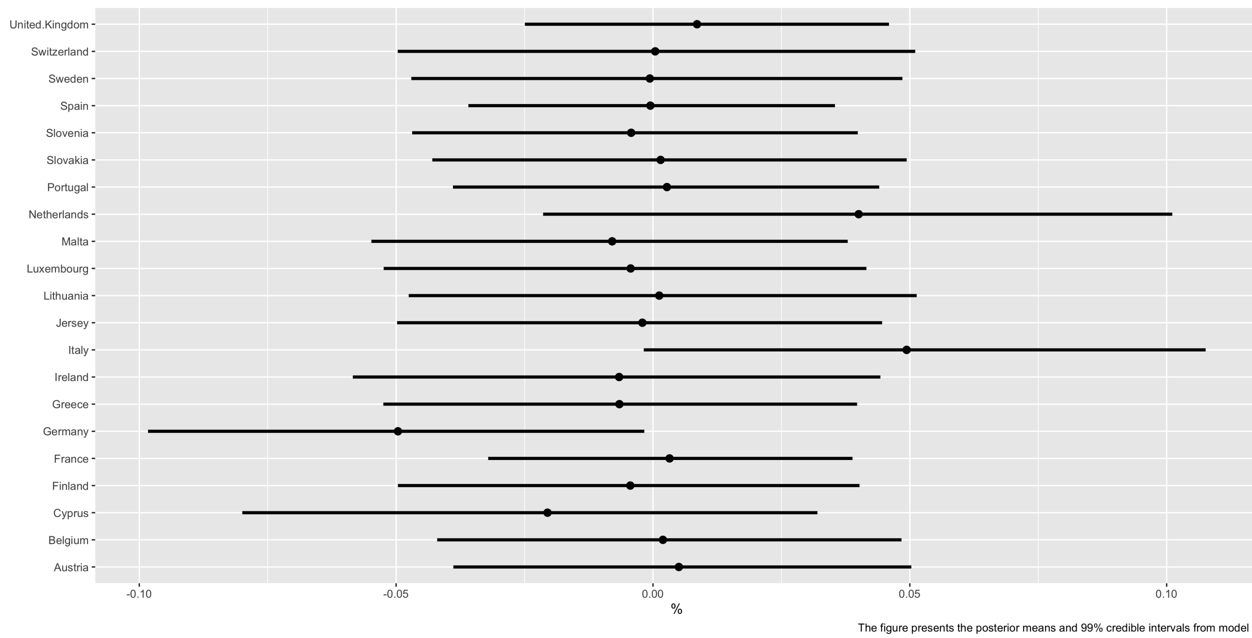


Figure 7: Posterior probability distributions for country level random effects of ambiguous policy actions

risk one quarter on. Specifically our baseline model estimates a global random effect of 0.058 with a 95% posterior credible interval of [0.011,0.105]. Our hierarchical model disentangles this result, suggesting that banks in Greece, Ireland and the UK seem to be driving this effect. Overall, the MCR policy actions have a weak effect on systemic risk, with banks in many countries showing little impact from policy actions one quarter. Interestingly, our models allow us to compare effect sizes and loosening policy actions have the strongish relative impact (-0.13 reduction in average quarter systemic risk for a one standard deviation move in the predictor). However, the estimate is quite noisy with a credibility interval of [-0.139,0.141].

Systemic risk can emanate from large institutions which are highly interconnected, but importantly, several smaller institutions may be systemic as a herd. We argue that banks tend to choose correlated risks during periods of increasing regulatory pressure and compliance constraints and invest in correlated assets. This choice could increase 'herding" as bank managers must benchmark themselves to regulatory imposed industry standards. This type of market inefficiency could increase rather than decrease systemic risk.

Appendix

Table A.1

Variable	Description	Frequency
Change in the three-month yield	Measured as the Change in the three-month Bund rate	
Change in the slope of the yield	Measured as the Change in the spread between the long-term composite bond and the three-month Treasury bill rate.	
TED spread	Measured as the difference between the three-month EURIBOR rate and the three-month secondary market bund rate.	Refinitiv
Change in the credit spread	Measured as the Change in the spread between the 10-year BAA rated bonds and the 10-year Treasury bonds.	Refinitiv
Europe market returns	Daily	Refinitiv
Daily housing sector excess returns	Daily	Refinitiv
Equity volatility	Which is computed as the 22-day rolling standard deviation of daily equity market returns	Daily

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