International Review of Economics and Finance 51 (2017) 599–620

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Threshold effects of financial stress on monetary policy rules: A panel data analysis☆

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ARTICLE INFO

JEL classification:
E31
E44
E52
E58
C23
C24

Keywords:
Financial stress
Monetary policy
Factor-augmented dynamic panel threshold regression
Cross-sectional dependence

ABSTRACT

This study tests for the state-dependent response of monetary policy to increases in overall financial stress and financial sector-specific stress across a panel of advanced and emerging economy countries. We use a factor-augmented dynamic panel threshold regression model with (estimated) common error components to deal with cross-sectional dependence. We find strong evidence of advanced economy countries' aggressive monetary policy loosening in response to stock market and banking stress but only in times of high financial market volatility. By comparison, evidence of threshold effects of financial stress is generally weak for emerging market countries' interest rate decisions.

1. Motivation

Recent empirical evidence shows that the monetary policy response to episodes of financial turmoil have not been always the same and is generally asymmetric (see Bean, Paustian, Penalver, & Taylor, 2010). The global financial crisis is one such example. The financial crisis of 2007–2008 solicited more aggressive and unprecedented interest rate cuts in advanced economies (AEs) as well as emerging market economies (EMEs) compared to the bursting of the dotcom bubble in 2001 or the Asian financial crisis in 1997. Given that financial stress events occur infrequently and the intensity and sources of these events are not the same, it is thus natural to consider a possible nonlinear relationship between monetary policy and financial stress.

This study tests for a state-dependent monetary policy reaction function of the central bank,–by investigating whether there exists a threshold point for financial stress beyond which monetary policy's response changes significantly, and more specifically, whether there also exists different thresholds for various types of financial sector-specific stress. The conventional view is that monetary policy reacts to movements in and volatility of financial market variables (e.g., exchange rate or stock market volatilities) in a systematic manner through a decrease in interest rates (see Bean et al., 2010; Bernanke & Gertler, 2001). However, the monetary policy-financial stability relationship may exhibit some form of nonlinearity especially when the level of financial stress reaches a certain tipping point, beyond

☆ This article should not be reported as representing the views of the European Central Bank.

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http://dx.doi.org/10.1016/j.iref.2017.07.023
Received 28 April 2016; Received in revised form 26 June 2017; Accepted 12 July 2017
Available online 15 July 2017

which monetary policy may or may not be more aggressive. Existing evidence however, is mostly obtained in the single country case. Panel data methods, by taking into account country-specific characteristics, i.e., political, economic and trade institutions, have the better advantage in addressing the noise coming from individual countries. This allows one to come up with an average (possibly) nonlinear causal relation between monetary policy and financial instability.

Using a unique panel dataset, we estimate the average reaction function of 10 AEs and 11 EMEs between 1994:Q1 and 2013:Q3 and between 1996:Q2 and 2013:Q3 respectively. We employ an off-the-shelf dynamic panel threshold (DPT) regression model to estimate the (possibly) nonlinear impact of financial instability on simple interest rate rules augmented with a financial stress indicator (FSI). In particular, we consider the potential existence of threshold values of the FSI that could account for the time variability of the estimated effects of financial stress (and its subcomponents) on policy interest-rate settings. We relax the assumption of both linearity and the existence of a functional form and allow the interest rate reaction function to switch according to an observable signal in a panel of AE and EMEs.

This paper complements previous studies on the effect of financial variables on the interest rate reaction function of central banks (see Baxa, Horváth, & Vašíček, 2013; Bernanke & Gertler, 2001; Lubik & Schorfheide, 2007; Martin & Milas, 2013) and on papers that employ dynamic panel threshold regressions, an econometric method that has been gaining much attention from applied researchers in recent years (see for example, Chao, Hu, Munir, & Li, 2017; Kremer, Bick, & Nautz, 2013; Kurul, 2017; Proaño, Schoder, & Semmler, 2014). We highlight three main contributions to the literature that are both empirical and methodological. First, we employ the FSI of Dovern and van Roye (2014), as well as its subcomponents, i.e. banking sector, foreign exchange, stock market and government bond market stress for a wider set of countries around the world.[1] To the best of our knowledge, this is the first study to use a comprehensive set of disaggregated financial stress indicators for advanced and emerging market countries in a panel data setup. In addition, we account for the most recent period characterized by unconventional monetary policy measures by employing the shadow policy interest rates of Wu and Xia (2016) and Krippner (2015) for countries that were in the zero lower bound.

Second, we robustify econometric inference by extending the DPT model proposed by Kremer et al. (2013) into a factor-augmented version thereof (FA-DPT). A substantial shortcoming of the dynamic panel threshold regression literature is that error cross-sectional dependencies across countries due from for example, global shocks or global spillovers are largely ignored. Abstracting from these dependencies has grave consequences in terms of the coefficient estimates (Bai, 2009; Pesaran, 2006; Phillips & Sul, 2003). The presence of error cross-sectional dependence may induce biasedness and consistency problems and spurious inference in standard panel data estimators and could minimize the efficiency gains of conducting panel data over single-unit estimation (Phillips & Sul, 2003). In our proposed FA-DPT model, we set up a factor structure of the panel error disturbances. In this way, we account for the potential distortive effects of cross-sectional dependence that could arise due to omitted common effects, which are possibly correlated with the regressors. The common unobserved components that we generate from the regression residuals allow us to capture general forms of unobserved heterogeneity, i.e., global interest rates, global liquidity, cross-country capital flows and commodity price movements. Given that global shocks account for much of the propagation of financial crises across economies, assuming independence in the resultant series could give the illusion of threshold effects or nonlinear effects of financial stress on monetary policy settings.

Third, we lay out the central finding that AE and EME central banks' monetary policy responses to the FSI subcomponents are highly dependent on the state of overall financial market stress.[2] On the one hand, AE central bank interest rate policies most of the time do not respond to stock market and banking sector stress, but react in an aggressively accommodative manner when financial markets are in a state of high volatility. On the other hand, evidence of threshold effects in EMEs are generally weak in the sense that they are not robust to structural change. In particular, EME central banks raise policy interest rates in response to stock market and foreign exchange stress only for levels of the FSI below the threshold, but this evidence does not hold when considering only the post-2000 period. An equally important finding is that when we account for cross-sectional dependence, the size of the interest rate response of AEs and EMEs is generally reduced (or even become statistically insignificant) in some specifications and increased in others.

The paper is organized as follows: Section 2 provides a literature review on previous work done on this subject, Section 3 lays out the econometric methodology employed, Section 4 presents the data, Section 5 discusses the estimation results, and Section 6 concludes.

2. Monetary policy and financial instability: what have we learned so far?

There are more facets to detecting systemic risks as opposed to inflationary risk, which is why financial stability as a monetary policy goal is still widely debated among policymakers and academics. Some advocate a preemptive tightening of monetary policy to address risk-taking behavior in all markets, i.e., the so-called leaning against the wind. Others are cautious about the tradeoffs of using monetary policy to achieve two targets. Indeed, empirical evidence confirms that central banks' interest setting behavior does behave differently in the face of heightened financial stress. Baxa et al. (2013) analyze the interest-rate setting behavior of four major AE central banks in the face of financial stress using time-varying parameter estimations and find a substantial easing of monetary policy settings during periods of "high" financial stress. In the case of the U.K., Martin and Milas (2013) show the tendency of the Bank of England (BoE) to react to financial stress in a nonlinear way. They show that the BoE reacted more strongly to financial stress during the 2007 financial crisis relative to previous financial stress periods. They also find a breakdown of the Taylor (1993) rule starting in 2007. By contrast, Fouejieu (2014) conducts single-unit and panel regressions for EMEs and finds that inflation targeting countries are more responsive to

[1] Balakrishnan, Danninger, Elekdag, and Tytell (2011) and Cardarelli et al. (2011) were the first ones to construct an FSI for a group of AEs and EMEs and FSI subcomponents for AEs, respectively.

[2] Throughout the paper, we will use the terms stress and volatility interchangeably.

financial imbalances through a tightening of monetary policy.

In a recent paper, Milas and Naraidoo (2012) investigate how the European Central Bank (ECB) conducts interest rate policy in the context of both linear and nonlinear policy reaction functions. Their findings reveal that the interest rate response to financial conditions became more symmetric regardless of the state of inflation during the 2007–2008 financial crisis. In more recent years though, a small strand of research has started to focus on threshold effects of financial stress on central bank interest rate decisions. Regressions involving threshold variables are intended to capture the potential state-dependent nature of say, interest rate adjustment. As a result, monetary policy behavior is examined in two or more separate regimes, whose potential nonlinear feature is defined by the state of the threshold variable at each point in time. van Roye (2014) considers a threshold vector autoregression method to analyze the impact of financial stress on the short-term rate and economic activity for Germany. He finds overwhelming evidence of a nonlinear dampening effect of financial stress on economic activity and on the short-term rate only during high stress periods. Vašíček (2012) estimates separate threshold regressions of Taylor (1993) rule fundamentals augmented with financial stress for Hungary, Poland and the Czech Republic. His results reveal that the Czech National Bank and the National Bank of Poland adjust interest rates downwards when financial stress is high, while the Hungarian National Bank raises interest rates when financial stress is above its estimated threshold.

3. Econometric methodology

3.1. The FSI-augmented Taylor rule

The starting point of our analysis is the specification of a linear Taylor (1993) rule equation augmented with an FSI. The Taylor (1993) rule basically captures the reaction function of short-term nominal interest rates against some business cycle indicator and the inflation rate. The inclusion of the lagged value of the short-term nominal interest rate characterizes the interest-rate smoothing feature of monetary policy. We assume a simple, forward-looking rational expectations interest rate rule as in Clarida, Gali, and Gertler (1998, 2000), where we let i_{jt} be the short-term interest rate determined by the following policy rule:[3]

$$i_{j,t} = \alpha_j + \rho_1 i_{j,t-1} + (1-\rho_1)\left[\beta_g g_{j,t+m} + \beta_\pi \pi_{j,t+n} + \beta_\gamma \gamma_{j,t+k}\right] + e_{j,t} \tag{1}$$

for $j = 1, \ldots, N$ and $t = 1, \ldots, T$, where α_j represents unobserved time-invariant country-specific fixed effects. The dependent variable $i_{j,t}$ is the short-term policy interest rate interest rate of country j at time t, and the regressors $g_{j,t}$, and $\pi_{j,t+k}$ are the GDP growth and the inflation rate, respectively. The autoregressive parameter ρ accounts for the observed practice by most central banks of smoothing changes in interest rates, which is characteristic of policy inertia. According to Coibion and Gorodnichenko (2012), interest rate smoothing has the potential benefit of reducing financial sector instability because interest rates would become more predictable. The variable $\gamma_{j,t+k}$ is an overall indicator of financial market uncertainty as measured by the FSI, as uncertainty is the main driving force behind the volatility in financial market indicators (see Cardarelli, Elekdag, & Lall, 2011; Dovern & van Roye, 2014; Illing & Liu, 2006; van Roye, 2014). A number of papers have proposed that the optimal monetary policy augments a simple Taylor (1993) rule with a financial market indicator. Fiore and Tristani (2013) propose a simple extension of the basic new-Keynesian model with financial frictions owing to asymmetric information and default risk, and find that financial frictions do affect macroeconomic aggregates mainly through firms' financing costs. Optimal welfare therefore, entails smoothing the volatility in credit and interest rate spreads. In a similar vein, Curdia and Woodford (2010) characterize optimal monetary policy where financial stability is adopted as a new intermediate target. Disyatat (2010) argues that the optimal interest rate setting at time t is an augmented Taylor (1993) rule with asset prices.

Note that $\gamma_{j,t+k}$ comprise second moments of financial variables, which can be seen as a weighted average of financial market volatility. In our specification, we consider $\gamma_{j,t+k}$ as part of the central bank's standard loss function (enclosed within the square brackets).[4] Due to the forward-looking nature of inflation in our model, $\pi_{j,t+n}$ enters the model endogenously and we set $n = 2$.[5] As we shall see in Section 3.4, our proposed DPT regression framework accounts for the endogeneity inherent in forward-looking monetary policy rules. Meanwhile, we set $m = 0$ due to the backward-looking reaction function of monetary authorities to the growth rate, and $k = 0$, as we assume that the central banks immediately react to financial stress developments within the current month.

3.2. State-dependent impact of financial stress

We now consider asymmetric preferences in the loss function of the central bank. We do that by testing for the potential existence of threshold values of the FSI beyond which monetary policy alters its behavior. We adopt Kremer et al. (2013)'s extension of the threshold methodology of Caner and Hansen (2004) for dynamic models into a panel framework, given that our monetary policy rule reaction function involves a lagged value of the policy interest rate as a regressor. Caner and Hansen (2004) extend Hansen (1999)'s testing and inference techniques for static threshold panel regressions with strictly exogenous covariates. Specifically, they use instrumental variable estimation to allow for endogenous regressors but still require the threshold variable to be exogenous. Thus, Eq. (1) takes the form:

[3] Orphanides (2003) note that forward-looking rules are preferable to backward-looking rules due to lags in monetary transmission.

[4] In other papers, Baxa et al. (2013) treat the FSI indicator as a potential factor in explaining the deviation of central banks from the implied interest rate. Hence, in their case, the FSI is outside the central banks' reaction function.

[5] Batini and Nelson (2001) show from their baseline model that $n = 2$ is the optimal targeting horizon. We nevertheless tested the model for different values of n, but this did not significantly change the results.

$$i_{j,t} = \alpha_j + \rho_1 i_{j,t-1} + (1-\rho_1)\left[\beta_g g_{j,t} + \beta_\pi \pi_{j,t+2} + \beta_\gamma^L \gamma_{j,t} I(\gamma_{j,t} \le \gamma^\star) + \delta_1 I(\gamma_{j,t} \le \gamma^\star) + \beta_\gamma^H \gamma_{j,t} I(\gamma_{j,t} > \gamma^\star)\right] + e_{j,t} \tag{2}$$

where $i_{j,t}$ is a scalar, $I(\cdot)$ is an indicator function, $\gamma_{j,t}$ is the transition variable, γ^* is the threshold variable, and β_γ^L and β_γ^H are heterogeneous threshold parameters associated with "low" and "high" financial stress regimes respectively. The inclusion of a threshold intercept δ minimizes the possibility of biased estimates in both the thresholds and the corresponding marginal impacts (Bick, 2010). We let $E(e_{j,t}) = 0$, which is an i.i.d process, serially uncorrelated and with possibly heteroskedastic error variances. The threshold variable γ^* is assumed to be stationary and exogenous, and uncorrelated with α_j and $e_{j,t}$.

The threshold model described above is basically a statistical technique to endogenously determine the trigger variable that enables potential asymmetries in the conduct of monetary policy. A clear advantage of this method over other existing approaches in modeling nonlinear monetary policy rules (e.g., squared values and spline regressions, among others), is that there is no need to rely on a specific functional form of the nonlinearity aspect of the model as the loss function of monetary authorities is not directly observable. Moreover, given that financial stress events are infrequent and usually have well-identified distinct regimes, i.e., low-stress and high-stress, our preferred method is more appropriate compared to a smooth transition threshold regression approach which uses a continuum of the threshold values.[6]

A remark on the threshold parameters β_γ^L and β_γ^H is in order. Throughout the analysis, we assume that the threshold parameters are the same across countries, albeit they are likely to be heterogeneous. Identifying different threshold coefficients across countries would entail longer time series data on each country, which is not available for most of the EME countries in our data set. Moreover, under the alternative hypothesis, the New Keynesian models of Curdia and Woodford (2010) and Fiore and Tristani (2013) predict certain signs in terms of the optimal monetary policy response to financial stress, such that there actually may not be enough variability in the threshold parameters across countries. Our middle-ground approach is then to estimate regressions in panels grouped according to AEs and EMEs and assume a homogenous γ^* for each panel.

3.3. Common error components

We now entertain the possibility that there exists a cross-sectional dependencies in $e_{j,t}$. Following Pesaran (2006) and Bai (2009), the error term $e_{j,t}$ follows a multifactor error structure

$$e_{j,t} = \boldsymbol{\varphi}_j' \boldsymbol{f}_t + \varepsilon_{j,t}, \tag{3}$$

where $\boldsymbol{f}_t$ and $\boldsymbol{\varphi}_j'$ are a m x 1 vector of common unobserved components and country-specific (unobserved) factor loadings respectively, while $\varepsilon_{j,t}$'s are the idiosyncratic components of $e_{j,t}$, which could be weakly correlated with $\boldsymbol{f}_t$. We further assume that $E(f_t \varepsilon_{j,s}) = 0 \; \forall \; j, t$ and s, where $\boldsymbol{f}_t$ are serially uncorrelated, but any correlation across countries is restricted to the estimated factors only. Intuitively, the factors $\boldsymbol{f}_t$ capture the simultaneous effects of unobserved common shocks affecting all countries at the same time. These common shocks could be in the form of increased synchronization of global interest rates, i.e. the zero lower bound. Increased trade and financial integration especially in EME countries in the last decade also underscores the importance of a common component that generates a joint interest rate response across the countries in our sample. As $\boldsymbol{f}_t$ is unobservable, consistent estimates must therefore be obtained. There are a number of important factor extraction methods that have been proposed in the literature. Pesaran (2006)'s common correlated coefficients (CCE) estimator employs cross-sectional means of the dependent variable and the regressors as proxy variables for $\boldsymbol{f}_t$. Greenaway-McGrevy, Han, and Sul (2012) calculate $\boldsymbol{f}_t$ directly from the dependent variable and the regressors through principal components. Among the methods mentioned, Pesaran (2006)'s CCE is probably the easiest to implement, but requires an *a priori* value of the threshold variable, which would not be suitable in our analysis given that our threshold values are determined endogenously. Gaibulloev, Sandler, and Sul (2014) argue that the factors extracted from the regressors and the regressand may be less efficient than the method of extracting factors from residuals as proposed by Bai (2009). Therefore, we employ Bai (2009)'s proposed method to estimate the unobserved factors by taking principal component estimators from the residuals $e_{j,t}$ from an initial estimation of Eq. (2).

3.4. The factor-augmented dynamic panel threshold regression model

Our main methodological contribution is to augment the DPT model (Eq. (2)) proposed by Kremer et al. (2013) with estimated common components to account for the pervasive problem of cross-sectional dependence in panel data models. Adding (estimated) common components in the regression is particularly important in filtering in the true causal relation between the short-term interest rate and its determinants, and whether this changing relation is due to structural change, nonlinearity or simply the omission of a "global" common factor. Hence, combining Eq. (2) with common error components as shown in Eq. (3) yields:

$$i_{j,t} = \alpha_j + \rho_1 i_{j,t-1} + (1-\rho_1)\left[\beta_g g_{j,t} + \beta_\pi \pi_{j,t+2} + \beta_\gamma^L \gamma_{j,t} I(\gamma_{j,t} \le \gamma^\star) + \delta_1 I(\gamma_{j,t} \le \gamma^\star) + \beta_\gamma^H \gamma_{j,t} I(\gamma_{j,t} > \gamma^\star)\right] + \boldsymbol{\varphi}_j' \boldsymbol{f}_t + \varepsilon_{j,t} \tag{4}$$

[6] The fact that our data is considered relatively of low-frequency makes the regimes well-settled in at observations t+1 when changing some time between t and t+1. To check, we also tried the smooth transition threshold panel regression approach, but find that the transition speed parameter was quite large, making inference from smooth transition models implausible.

We now discuss each step of our estimation strategy in detail, since the estimation of the FA-DPT model in Eq. (4) involves instrumental variables, estimation of threshold parameters, and of common error components to allow for a feasible way of taking cross-sectional dependence into account and occurs in two stages. In the first stage, we ignore cross-sectional dependence and estimate Eq. (2) without common error components. We proceed sequentially as follows:

1. We follow Kremer et al. (2013) by removing the country-specific fixed effects through the use of forward orthogonal deviations transformation of the variables in the model as proposed by Arellano and Bover (1995).[7] Using this method, each variable is transformed by subtracting the average value of future observations. This ensures elimination of the fixed-effects without inducing a Nickell (1981)-type bias.
2. For each t, conduct pooled reduced-form regressions of the endogenous variable $\pi_{j,t+2}$ on a set of instruments, namely higher lags of $\pi_{j,t}$ and $g_{j,t}$.[8]
3. We obtain the fitted values $\widehat{\pi}_{j,t+2}$ and use these values to replace $\pi_{j,t+2}$ in Eq. (2).[9] For different values of the threshold series γ, we repeatedly estimate step 2 via two-stage least squares (2SLS), except for the top and bottom 5 percent of the observations to keep the minimum number of observations in each regime, as recommended by Hansen (1999). Finally, the threshold value $\gamma^\star$ is chosen as the value which best minimizes the sum of squared residuals or in other words, the value which maximizes the best fit of the model. In particular, we choose a $\gamma^\star$ such that $\gamma^\star = \mathit{argmin}\, S(\gamma)$. The function $S(\cdot)$ is employed to obtain the inverted likelihood ratio (LR) statistics, which tests the hypothesis $H_0 : \gamma = \gamma^\star$, and determines whether a given value belongs within the threshold interval (Hansen, 1999; Vašíček, 2012).

$$LR(\gamma) = nT\frac{S(\gamma) - S(\gamma^\star)}{S(\gamma^\star)}$$

4. After choosing our threshold value, we now re-estimate Eq. (2) via Generalized Method of Moments (GMM) with heteroskedastic and autocorrelation-consistent standard errors using the same instruments as in step 2.[10]

The second stage requires the estimation of Eq. (4) this time with augmented common error components. The procedure is as follows: We obtain the residuals $\widehat{e}_{j,t} = i_{j,t} - \widehat{\rho} i_{j,t-1} - \widehat{\beta}_g g_{j,t} - \widehat{\beta}_\pi \pi_{j,t+2} - \widehat{\beta}^L \gamma_{j,t} I(\gamma_{j,t} \leq \gamma^\star) - \widehat{\delta} I(\gamma_{j,t} \leq \gamma^\star) - \widehat{\beta}^H \gamma_{j,t} I(\gamma_{j,t} > \gamma^\star)$ from step 4 in the first stage. We then extract common components $\boldsymbol{f}_t^e$ from $\widehat{e}_{j,t}$ via principal component methods. In determining the number of q factors, we follow Forni and Reichlin (1998)'s rule of thumb in keeping the number q that account for more than a certain fraction of the variance of the panel. We set $q \leq 3$, with the first factor being orthogonal to the second factor and so on.[11] Unlike in Bai (2009) where the fixed effects estimator is used as initial value, we use instead a GMM estimator in the first stage estimation using an appropriate number of period lags of inflation and growth rates as well as the FSI as instruments. This yields consistent residuals, and consequently consistent estimates of the factors in the errors. We also note that in the first stage, GMM already gives us less biased estimators (if at all) as the factors are not serially correlated, so the second stage merely ensures estimation efficiency.

4. Data

We construct a unique and balanced panel database of 21 central banks from AEs and EMEs for the periods 1994:Q1 to 2013:Q3 and 1996:Q2 to 2013:Q3, respectively.[12] The choice of the starting period of the estimation sample was hinged mainly on data availability of the policy variables at a quarterly frequency. The countries in our sample consist of 10 AEs (Australia, Canada, Japan, South Korea, Norway, Sweden, Switzerland, Denmark, the U.S. and the U.K.) and 11 EMEs (Brazil, Colombia, Hungary, Indonesia, Malaysia, Mexico, Peru, Poland, the Philippines, South Africa, and Thailand). In addition, we estimate FA-DPT regressions for a shorter sample, from 2002:Q1-2013:Q3. This would allow us to control for the influence of heterogeneous monetary policy frameworks that characterized most emerging market countries in the early 2000s. Monetary policy in most countries in our sample adopted inflation-targeting as their monetary policy framework, with a low inflation regime in the period starting early 2000s.

Our dependent variable is the end-quarter value of the short-term nominal interest rate, and would typically be an interest rate closely related to the official policy rate. Using end-quarter values of the short-term interest rate ensures that the information coming from the regressors (i.e. inflation, GDP growth and the FSI) were available to the policymakers at the time of the interest rate decision. For countries like the U.S. and the U.K., short-term nominal interest rates were constrained by the zero lower bound starting in 2009:Q1

[7] We thank Alexander Bick for making the MATLAB Code for the panel threshold estimation available online.

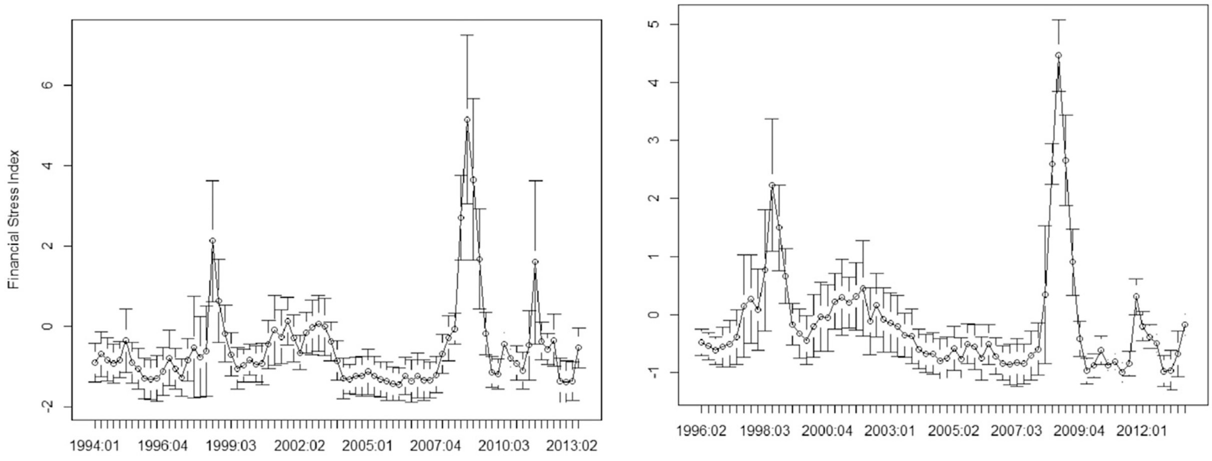
[8] Following Proaño et al. (2014), we employ the maximum number of instruments available for the endogenous regressor, except in the case where the instrument matrix is already close to singular. If so, then we drop an instrument for each regressor one at a time and repeatedly re-estimate the equation until full-rank of the instrument matrix is reached.

[9] We thank an anonymous referee for pointing out the potential problem of generated regressors. Since Eq. (2) is estimated at the first stage via generalized method of moments (GMM) with suitably chosen instruments, endogeneity and biasedness of the resulting coefficients is avoided altogether. Hence, the possibility of potentially running into a generated regressors problem is minimal. We also find comfort in the finding of Bai and Ng (2006) that a generated regressors problem diminishes as $N \to \infty$, such that pooling individual countries actually takes care of this econometric issue.

[10] We choose GMM over 2SLS due to the known fact that GMM provides a more efficient weighting matrix, although Caner and Hansen (2004) noted that the two estimators can be used in place of the other.

[11] The information criteria proposed by Bai and Ng (2006) was also implemented, but similarly this also resulted in the maximum number of factors being selected.

[12] We follow the classification of advanced and emerging economies from the Penn World tables version 7.1.



(a) AE countries (b) EME countries

Fig. 1. FSI in AE and EME countries.

and is therefore not an accurate indication of interest rate policy. Following Nikolsko-Rzhevskyy, Papell, and Prodan (2014), we employ the shadow policy rates of Wu and Xia (2016) from 2009:Q1 to 2013:Q3 for the U.S. and the U.K. Wu and Xia (2016) compute their shadow policy rate time series using a nonlinear term structure model that takes into account the effects of quantitative easing and forward guidance. Hence, the shadow rate is negative throughout the period 2009:Q1 to 2013:Q3.[13] To account for Japan's zero lower bound interest rate policy, we use the estimated shadow policy rate series constructed for Japan by Krippner (2015).[14]

For the explanatory variables, we have the quarterly averages of the inflation rate (measured as the year-on-year change on the CPI) and the GDP growth rate (measured as the year-on-year change on real GDP). We use the growth rate instead of the usual output gap originally specified by Taylor (1993) to keep a consistent and uniform measurement methodology for our heterogeneous sample of 21 countries.[15] As indicator of financial stress, we use the FSI (measured in quarterly averages) of Dovern and van Roye (2014), who developed a single aggregate measure of return volatilities of stocks, bank stocks, foreign exchange money market and government bond market yields as well as simple stock returns. They use these 6 subcomponents for each country in their sample, and the sum of their standardized values make up the single FSI. In this paper, we pick out only 4 FSI subcomponents, namely: banking sector, government bond, foreign exchange and stock market stress due mainly to data availability. We use both the overall index as well as each subcomponent index separately.

Only Colombia, Mexico, Malaysia, Indonesia, Thailand, and South Africa have complete data series for the government bond volatility index starting in 1996. Therefore, in our analysis on government bond volatilities in the EME panel, we run FA-DPT only in these six countries. Additionally, we dropped South Korea in the foreign exchange stress specification in the AE panel, as it did not have a complete foreign exchange stress time series in the sample period.

The FSI subcomponents for each country are calculated as follows:[16]

- *Stock market volatility.* Constructed via a GARCH (1,1) model of month-on-month (m-o-m) aggregate stock market returns
- *Exchange rate volatility.* GARCH (1,1) m-o-m real effective exchange rate returns
- *Government bond market volatility.* GARCH (1,1) model of m-o-m gov't. bond yields
- *Banking sector volatility.* GARCH (1,1) model of m-o-m returns on bank stocks

An advantage of using a continuous-variable, single composite index is that it is able to capture how financial stress evolved in a given review period while quantifying the severity and magnitude of various stress events (Baxa et al., 2013; Cardarelli et al., 2011; Illing & Liu, 2006). This is different from binary variables representing a "stress" or "no stress" event. Upward movements in the FSI and its subcomponents typically signal heightened uncertainty in financial markets, i.e., an increase in the volatility of equity and foreign exchange returns and yields.[17] Fig. 1 verifies that the sharp spikes of this indicator as well as its subcomponents are able to accurately

[13] Although Switzerland and Denmark do not have shadow policy rate series, they have in fact, been targeting negative policy interest rates since 2011 and 2012, respectively. Thus, the negative policy rates also aptly reflect the accommodative monetary policy stance of the Switzerland and Denmark in a zero lower bound environment.

[14] Both Krippner (2015)'s and Wu and Xia (2016)'s shadow policy rates are estimated from term structure models but the latter uses three-factors while the former employs two factors. We thank Cynthia Wu and Leo Krippner for making their shadow policy rates available online.

[15] Coibion and Gorodnichenko (2012) find that policy rates in fact respond more to output growth rather than the output gap, and that this type of responsiveness aids in "restoring determinacy for plausible inflation responses".

[16] See Dovern and van Roye (2014) for a detailed description of the construction of each of the FSI subcomponents.

[17] According to Baxa et al. (2013), the movements in this index should be cautiously interpreted. Variables not included in the FSI but highly correlated with the subcomponents of the FSI causes the indicator to increase.

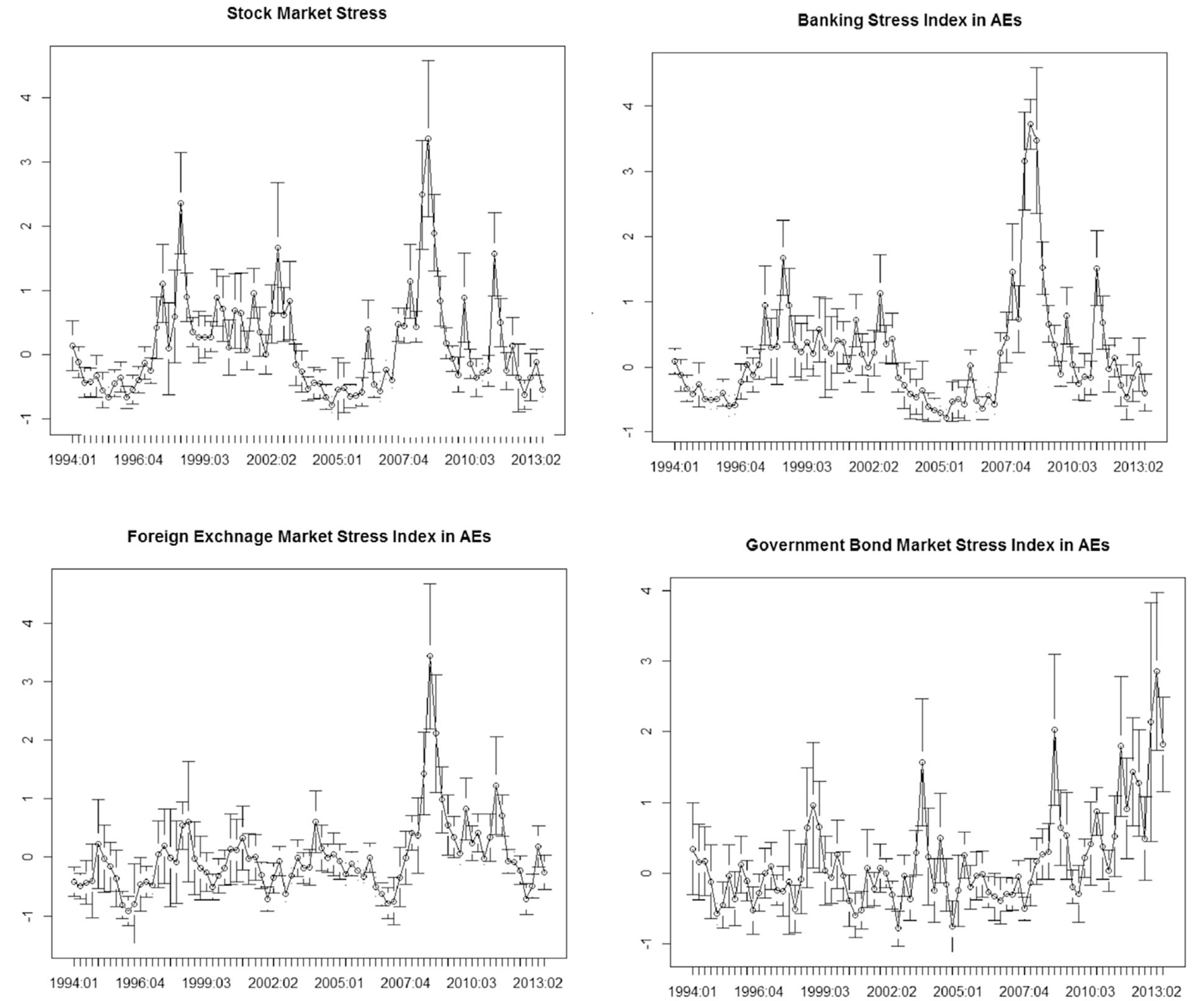


Fig. 2. The FSI subcomponents in AE countries. *Note:* Figs. 1 and 2 plot the mean FSI and FSI subcomponents through time, respectively. The blue vertical lines plot the 95 percent confidence interval around the means.

identify almost all of the documented financial crisis episodes for AEs and EMEs (i.e. banking, stock market, foreign exchange crises).

Breaking down the FSI into its subcomponents, Figs. 2 and 3 confirm contrasting sources of financial market stress during the recent global financial crisis. While stress in the foreign exchange and stock market drove heightened uncertainty in EME financial markets, instability in the banking system was a critical factor in spreading the crisis into the different segments of most AE financial markets.

As the threshold model assumes stationarity of the variables, we employ the stationarity test of Moon and Perron (2004), which allows the panel units to be cross-sectionally dependent. The results in Table 1 lead to us to conclude stationarity in the variables in the panel setup. To highlight the significance of cross-sectional correlation, we conduct Pesaran (2004)'s test for cross-sectional dependence (CD) test and compute the pairwise correlations of the short-term nominal interest rates for both country groups. Table 2 shows that cross-sectional dependence is clearly a problem as evidenced by the highly significant CD statistic, thus supporting the conjecture of augmenting our panel threshold regression model with estimated common components as in Eq. (4).

5. Results

5.1. The FSI as regime-dependent regressor and threshold variable

Table 3 presents the benchmark results of the threshold regression model with and without common components for both country groups. The first row displays the estimated FSI thresholds and the corresponding 95 percent confidence intervals enclosed in brackets. Fig. 4 plots the likelihood ratio (LR) for every γ as well as the critical value for the 95 percent confidence interval, as shown by the horizontal line. Below this line is the no-rejection region, where values falling within this area are the set of all feasible γs for which the

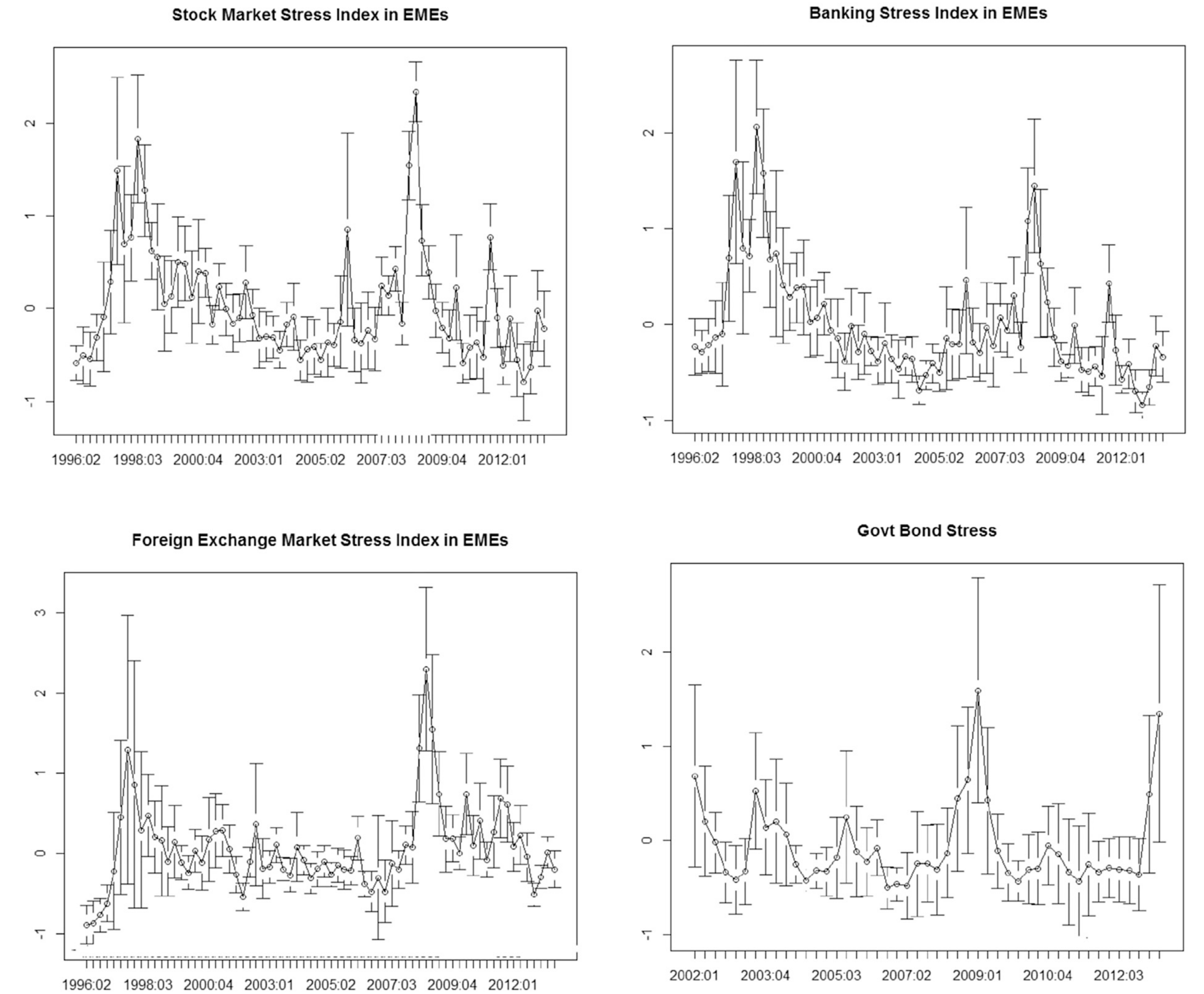


Fig. 3. The FSI subcomponents in EME countries. *Note:* Fig. 3 plots the mean FSI subcomponents through time. The blue vertical lines plot the 95 percent confidence interval around the means.

true threshold value is indeed γ^*. The estimated threshold value is then the point where $LR(\gamma) = 0$, which in the case of the FA-DPT estimator, occurs at $\gamma^* = -1.689$ and $\gamma^* = 1.566$ for AEs and EMEs, respectively. According to Hansen (1999), the shape of the LR line reflects the strength of this threshold effect. A clearly defined V-shaped line means that the threshold effect is strong, which validates sample-splitting and separate estimation for each subsample (Vašíček, 2012). It can be seen from the LR plots in the AE panel that there could be two or more possible minimums: the true threshold could either be -1.689 or 0.750, while for EMEs, all feasible threshold values are included in the set of γs for which the null $H_0: \ \gamma = \gamma^*$ is accepted. Thus, the evidence of a threshold effect is weak for both country groups given the two possible minimums in the AE specification and the wide range of feasible threshold values for which one cannot reject the null in the case of EMEs.

Before looking at the slope parameter estimates, we repeat Pesaran (2004)'s cross-sectional dependence tests this time on the residuals in both the DPT and the FA-DPT regressions. As expected, the null of cross-sectional independence is rejected in the DPT model for both the AEs and the EMEs. Using the FA-DPT thus effectively removes any form of cross-sectional dependence in the EME panel, while it is reduced in the panel of AEs.[18] The residuals of the FA-DPT in the AE panel now exhibit some form of "weak" rather than strong cross-section dependence which, according to Pesaran, Smith, and Yamagata (2013), only affects inference and does not pose serious identification problems. We will thus give more importance to the results obtained from the FA-DPT estimator.

Going back to Table 3, we pay special attention to the FSI coefficients β_γ^L and β_γ^H, which represent the effect of financial stress on

[18] To show the marginal impact of incorporating a factor structure in the regression model, we report Pesaran (2004)'s CD test statistics, where decreases indicate the extent of error cross-sectional dependence that was removed/minimized.

Table 1
Panel unit root test.

	Policy interest rates	GDP Growth	Inflation	FSI	Banking stress	Stock market stress	Foreign exchange stress	Government bond stress
Advanced economies								
MP	−2.02	−3.61	−2.03	−8.95	−9.4	−10.09	−13.6	−13.57
p-value	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Emerging market economies								
MP	−2.80	−3.34	−5.66	−8.02	−17.61	−17.400	−14.05	−14.20
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: MP is the Moon and Perron (2004) panel unit root test which considers a multifactor structure in the errors. The maximum number of factors extracted from the variable is set at four. The lag order is chosen automatically, with a null hypothesis of nonstationarity of all series.

interest-rate settings at the low and high stress regimes, respectively. Given that the LR plot shows more than one possible minimum for the estimated thresholds, we cautiously infer the following: AE as well as EME central banks are concerned with financial stability issues in their mandate of price stability. In particular, AEs implement an accommodative interest rate policy in a high state of financial market uncertainty. By stark comparison, EMEs seem to conduct restrictive monetary policies by raising interest rates in response to financial stress, and only at very high levels of the FSI does the monetary policy response become statistically insignificant. Fouejieu (2014) in both a single-unit and panel context, similarly find that EME central banks tighten the policy stance in response to an increase in his estimated financial conditions index. This tightening response could be attributed to the fact that emerging market crises, particularly those between 1995 and 2001, were often associated with capital outflows which set off massive domestic currency depreciations (Vegh & Vuletin, 2013). Historically, currency depreciations in small open economies have had unpopular inflationary effects on the prices of imported goods as well as the size of foreign currency debt holdings of these countries. This naturally prompted a restrictive policy rate response in order to reign in the contractionary effects of such a currency depreciation.

5.2. The FSI subcomponents as regime-dependent regressors

Now the subcomponents influencing innovations in the FSI level are probably of greater analytic interest. Empirical evidence in the single country case shows that central banks also care about financial sector-specific stress (Baxa et al., 2013; Bernanke & Gertler, 2001; Fouejieu, 2014; Lubik & Schorfheide, 2007). However, their macroeconomic effects vary between AE and EME countries. Cardarelli et al. (2011), for example, find that the growth downturns in AE countries that are associated with banking-related stress are larger than those of stock market or foreign exchange market stress. Ghosh, Ostry, and Chamon (2016) and Mohanty and Klau (2005) on the other hand, find that foreign exchange volatility is a bigger source of output vulnerability for EMEs. We take the existing evidence a step further and investigate whether the relationship between central banks' interest rate setting behavior and the FSI subcomponents is dependent on the overall state of financial markets. To address this question, we condition the FSI subcomponents on the overall level of the FSI. We do that by replacing the FSI variable $\gamma_{j,t}$ in Eq. (4) with each of the 4 subcomponents as the regime-dependent variable $\eta_{j,t}$ one at a time, and keep the FSI as our threshold variable, $\gamma^{\star}$.

$$i_{j,t} = \alpha_j + \rho_1 i_{j,t-1} + (1-\rho_1)\Big[\beta_g g_{j,t} + \beta_\pi \pi_{j,t+2} + \beta_\eta^L \eta_{j,t} I(\gamma_{j,t} \le \gamma^\star) + \delta_1 I(\gamma_{j,t} \le \gamma^\star) \ + \ \beta_\eta^H \eta_{j,t} I(\gamma_{j,t} > \gamma^\star)\Big] + \boldsymbol{\varphi}_j' \boldsymbol{f}_t + \varepsilon_{j,t} \tag{5}$$

where $\eta_{j,t}$ is either the banking, stock market, foreign exchange and government bond market stress indicators. We also consider the possibility that the FSI subcomponents themselves are a source of nonlinearity on the relationship between monetary policy and financial sector-specific stress. Therefore, we compute a separate threshold value for each FSI subcomponent and estimate the following specification:

$$i_{j,t} = \alpha_j + \rho_1 i_{j,t-1} + (1-\rho_1)\Big[\beta_g g_{j,t} + \beta_\pi \pi_{j,t+2} + \beta_\eta^L \eta_{j,t} I(\eta_{j,t} \le \eta^\star) + \delta_1 I(\eta_{j,t} \le \eta^\star) + \beta_\eta^H \eta_{j,t} I(\eta_{j,t} > \eta^\star)\Big] + \boldsymbol{\varphi}_j' \boldsymbol{f}_t + \varepsilon_{j,t} \tag{6}$$

where the variables as well as parameters are defined as in Eq. (5). A low-stress (high-stress) regime in this case denotes a state where the volatility of a given FSI subcomponent is below (above) its estimated threshold level.

5.2.1. The FSI subcomponents in advanced economies

We first tackle the estimation results for Eq. (5) using the FSI as threshold variable. Focusing initially on AEs, Fig. 5 shows that estimates of the FSI threshold are highly significant across specifications using the stock market, banking and foreign exchange stress as regime-dependent regressors. The global minima can be confined within a tighter range, and one clearly defined minimum is evident. The threshold effects of the FSI in the government bond stress specification is rather less clear, as the shape of the LR plots displays three possible minimums, leading us to discard results for government bond stress.

The slope parameter estimates β_η^L and β_η^H in Table 4 suggest that at the low financial stress state where about 85 percent of the observations are typically located, AE central banks do not react to stock market and banking stress while they raise policy rates in the foreign exchange stress specification. Once the FSI threshold is breached however, AE central banks on average care more about addressing volatilities in the stock market and banking sectors, suggesting a "cleaning up" strategy as opposed to a "leaning against the wind" policy stance in response to financial instability. Similar results are found in Baxa et al. (2013)'s single-unit time-varying model.

Table 2
Cross-sectional correlation of short-term nominal interest rates.

	CD-test	p-value	corr
Advanced economies	40.05	0.00	0.672
Emerging market economies	46.85	0.00	0.755

Note: Under the null hypothesis of cross-section independence $CD \sim N(0, 1)$.

Table 3
Factor-augmented dynamic panel threshold regression: The FSI as regime-dependent regressor.

	Advanced economies		Emerging market economies	
	DPT	FA-DPT	DPT	FA-DPT
	(1)	(2)	(3)	(4)
$\gamma^{\star}$	0.299 [-1.689, 1.396]	−1.689 [-1.722, 1.331]	1.566 [-1.372, 1.728]	1.566 [-1.352, 1.673]
β_{γ}^{L}	−0.117*** (0.032)	−0.052 (0.106)	0.375** (0.183)	0.624*** (0.154)
No. of Obs.	674	98	706	706
β_{γ}^{H}	−0.010 (0.039)	−0.087*** (0.023)	0.159 (0.217)	0.331 (0.226)
No. of Obs.	116	692	64	64
ρ	0.945*** (0.012)	0.929*** (0.012)	0.756*** (0.044)	0.703*** (0.034)
β_{π}	0.013 (0.060)	0.050 (0.051)	0.293*** (0.083)	0.302*** (0.063)
β_{g}	0.058*** (0.010)	0.051*** (0.011)	0.001 (0.040)	0.024 (0.033)
δ	0.278*** (0.096)	0.348 (0.249)	1.159 (0.863)	0.792 (0.885)
CD Stat	7.04	−1.36	9.44	−1.40

Notes: Robust standard errors are in parentheses. The symbols $*$, $**$ and $***$ denote significance at the 10, 5 and 1 percent levels, respectively. The dependent variable is the short-term interest rate. Row 1 indicates the threshold estimate with the 95 percent confidence intervals in brackets; Row 2 reports the regime-dependent coefficient estimates for the regime-dependent regressor. Each regime contains at least 5 percent of the observations (Hansen, 1999). CD stat refers to the Pesaran (2004)'s test for cross-sectional dependence; the CD test is normally distributed with a null of cross-sectional independence.

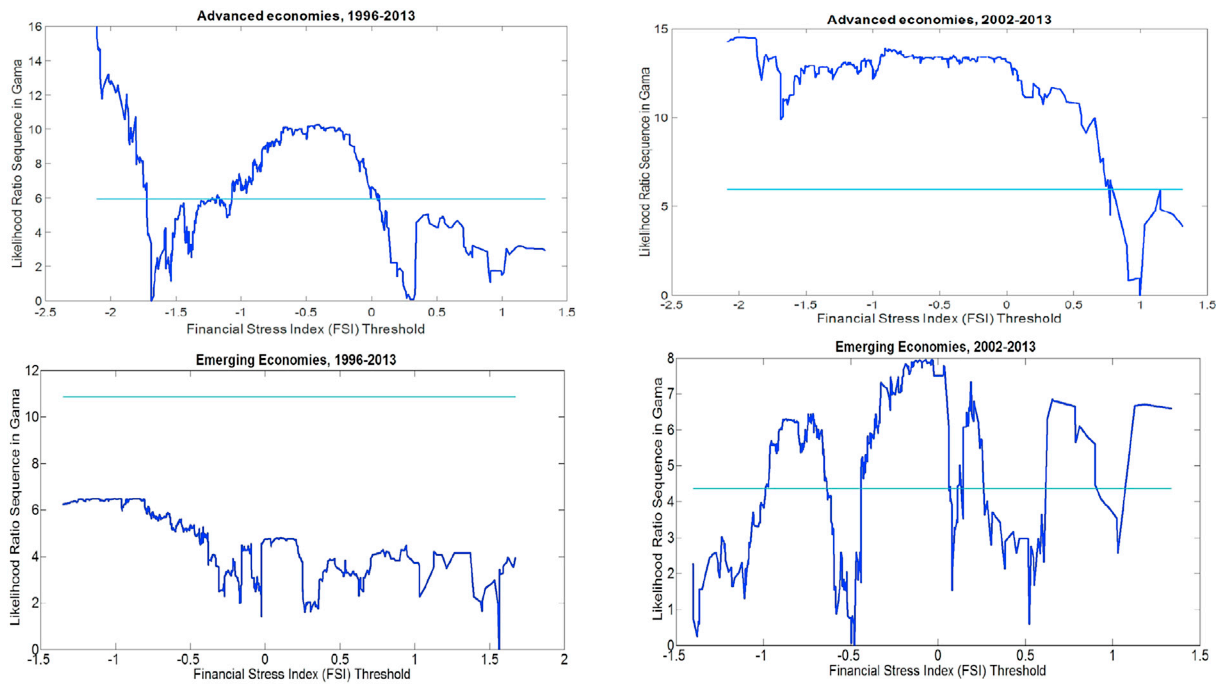


Fig. 4. The likelihood ratio for different FSI threshold values: The FSI as threshold variable and regime-dependent regressor.

They find that the Fed and the Reserve Bank of Australia paid special attention to banking-related stress while the Bank of England was more concerned with stock market stress in times of high financial stress. They also find a significant interest rate reaction in the case of the Bank of Canada and Sveriges Riksbank. An interesting finding is that once we implement the FA-DPT regression, we find that the estimated effect of foreign exchange stress on monetary policy becomes insignificant at the high financial stress regime as compared to the DPT model without factor augmentation.

To put the results into perspective, we identify episodes where the FSI values surpassed its estimated threshold for each of the AEs and consider the nature of threshold effects on the conduct of monetary policy at that point in time. We find five distinct time periods for which $\gamma_{i,t} > \gamma^{*}$: 1998:Q3-1998:Q4, 2001:Q3, 2008:Q1, 2008:Q3-2009:Q2 and 2011:Q3-2011:Q4. Indeed, these identified periods match key financial crisis events (i.e., the Asian financial crisis, the dotcom bubble, the global financial crisis) and the corresponding monetary easing that was often implemented after a financial shock for most of the AEs in our sample.

Next, we analyze the resultant coefficient estimates using each of the FSI subcomponents themselves as threshold variables, as specified in Eq. (6). Focusing on the FA-DPT estimator, we observe in Fig. 6 that bank stress is the only significant threshold estimate. The V-shape feature of the LR line is well-defined and the range of possible thresholds within the no-rejection region is narrow and tight, with only one possible minimum. We discard the models for the stock market and foreign exchange stress due to the weak evidence of a threshold effect. Table 4 (panel B, columns 5 and 6) shows that AE central banks' average policy rate response to bank stress is symmetrically negative and statistically significant in both low and high volatility regimes in the banking sector. Interestingly, the high-stress regime now features more than 20 percent of total observations as compared to 15 percent when the FSI is used as the threshold variable, indicating more equal sample splitting.

5.2.2. *The FSI subcomponents in emerging market economies*

Turning our attention this time to the EME panel, Fig. 7 suggests discarding the threshold specifications involving banking and government stress indices due to the wide confidence intervals and multiple candidate minimums for the feasible FSI threshold. Focusing on the stock market and foreign exchange specifications, the first thing to note is that adding common components results in a tighter confidence interval for the FSI threshold estimate (see Table 5). In addition, the magnitude and significance of the stock market subcomponent coefficient at the high financial stress regime increases. An important message from our findings is that monetary authorities on average react positively to stock market and foreign exchange market stress indicators at the low financial stress regime, but become responsive only to stock market stress in an accommodative manner for FSI levels that go beyond the threshold. To check whether the FSI subcomponent levels could also be a source of nonlinearity, we observe in Fig. 8 that except for foreign exchange stress, the asymptotic confidence intervals for all the other specifications are quite wide, implying a great amount of uncertainty about the regime split. We therefore keep only the foreign exchange stress model. It is worth emphasizing that common components also play a relevant role when foreign exchange markets are in a high volatility state. In particular, the positive and significant foreign exchange stress coefficient using the DPT estimator increases by four times as much in a state of high foreign exchange market volatility when augmenting the regression model with the estimated the common components.

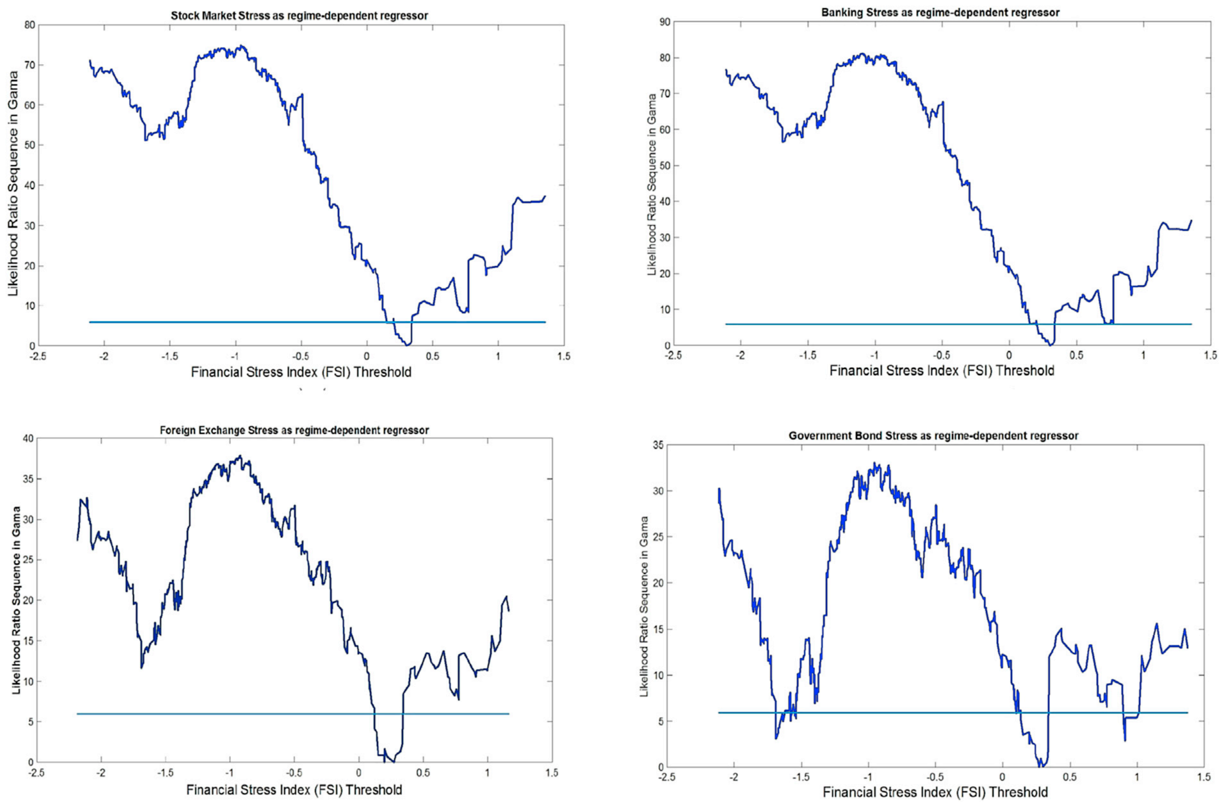


Fig. 5. The likelihood ratio for different FSI threshold values: The FSI subcomponents as regime-dependent regressors in advanced economies, 1994–2013.

Table 4
Factor-augmented dynamic panel threshold regression: FSI subcomponent as regime-dependent regressor in advanced economies, 1994–2013.

	DPT				FA-DPT			
	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: γ^* as Threshold								
γ^*	0.299 [0.150, 0.346]	0.299 [0.136, 0.775]	0.283 [0.121, 0.775]	0.299 [0.150, 0.909]	0.299 [0.150, 0.336]	0.299 [0.198, 0.336]	0.198 [0.121, 0.338]	0.271 [-1.689, 1.013]
β_η^L	0.016 (0.023)	0.001 (0.023)	0.040 (0.036)	−0.010 (0.022)	0.016 (0.022)	−0.013 (0.020)	0.070** (0.030)	−0.002 (0.049)
No. of Obs.	674	674	616	674	674	674	612	672
β_η^H	−0.234*** (0.084)	−0.131* (0.070)	−0.182** (0.086)	0.062 (0.063)	−0.235*** (0.082)	−0.255*** (0.082)	−0.049 (0.069)	0.055 (0.066)
No. of Obs.	116	116	95	116	116	116	99	118
ρ	0.947*** (0.012)	0.946*** (0.013)	0.950*** (0.013)	0.945*** (0.013)	0.952*** (0.012)	0.946*** (0.011)	0.943*** (0.012)	0.943*** (0.012)
β_π	0.034 (0.055)	0.023 (0.061)	−0.082 (0.082)	0.025 (0.063)	0.064 (0.055)	0.069 (0.053)	−0.045 (0.067)	0.088* (0.049)
β_g	0.050*** (0.009)	0.053*** (0.009)	0.073*** (0.012)	0.063*** (0.011)	0.058*** (0.009)	0.066*** (0.009)	0.069*** (0.010)	0.048*** (0.009)
δ	0.205*** (0.075)	0.145** (0.073)	0.335*** (0.078)	0.424*** (0.084)	0.261*** (0.072)	0.263*** (0.069)	0.310*** (0.072)	0.351*** (0.062)
CD Stat	8.95	5.94	6.09	7.13	1.54	1.78	−2.46	−3.60
Panel B: η^* as Threshold								
η^*	1.864 [0.318, 1.864]	0.139 [0.062, 1501]	1.303 [0.150, 1.303]	1.012 [-0.855, 1.739]	0.416 [-0.813, 1.762]	0.116 [0.021, 0.246]	0.150 [-0.823, 1.289]	1.012 [-0.383, 1.170]
β_η^L	−0.029 (0.050)	−0.170** (0.069)	0.010 (0.048)	−0.094 (0.131)	−0.102** (0.044)	−0.171*** (0.058)	−0.064 (0.064)	−0.079* (0.042)
No. of Obs.	737	478	663	673	575	469	504	673
β_η^H	−0.372** (0.174)	−0.170*** (0.054)	−0.402*** (0.150)	−0.021 (0.051)	−0.104** (0.052)	−0.166*** (0.040)	−0.086 (0.060)	−0.031 (0.049)
No. of Obs.	53	312	48	117	215	321	207	117
ρ	0.942*** (0.013)	0.943*** (0.012)	0.944*** (0.013)	0.934*** (0.014)	0.932*** (0.011)	0.934*** (0.011)	0.932*** (0.013)	0.932*** (0.012)
β_π	0.049 (0.057)	0.044 (0.060)	−0.047 (0.078)	0.029 (0.066)	0.058 (0.045)	0.070 (0.051)	−0.020 (0.066)	0.086* (0.046)
β_g	0.074*** (0.010)	0.068*** (0.010)	0.094*** (0.011)	0.083*** (0.011)	0.059*** (0.009)	0.055*** (0.009)	0.088*** (0.011)	0.059*** (0.009)
δ	−0.851* (0.466)	−0.245*** (0.066)	−0.777** (0.302)	−0.062 (0.112)	−0.142* (0.074)	−0.242*** (0.055)	−0.190*** (0.072)	−0.150 (0.102)
CD Stat	6.43	7.60	6.15	8.95	0.57	−1.06	−2.13	−4.37

Note: Refer to Table 3 for details.

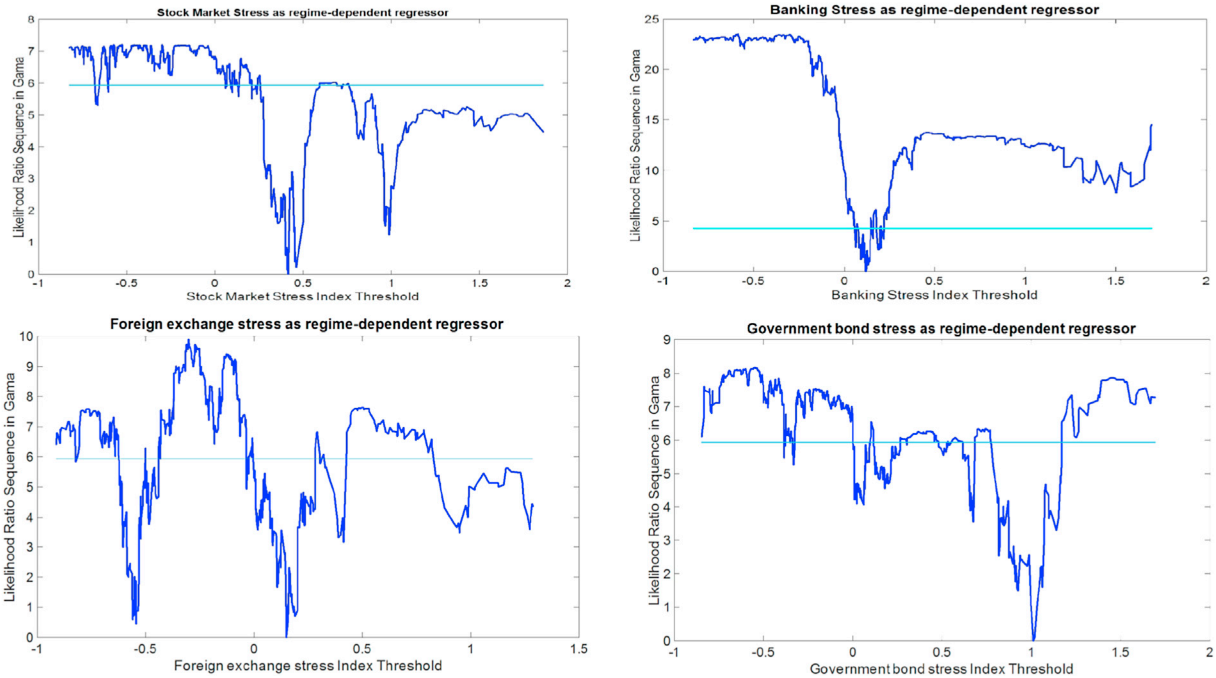


Fig. 6. The likelihood ratio for different FSI subcomponent threshold values: The FSI subcomponents as regime-dependent regressors in advanced economies, 1994–2013.

5.3. Taylor rule policy variables

We now briefly discuss the results for the other Taylor (1993) rule policy variables in the FA-DPT model. We note the large absolute

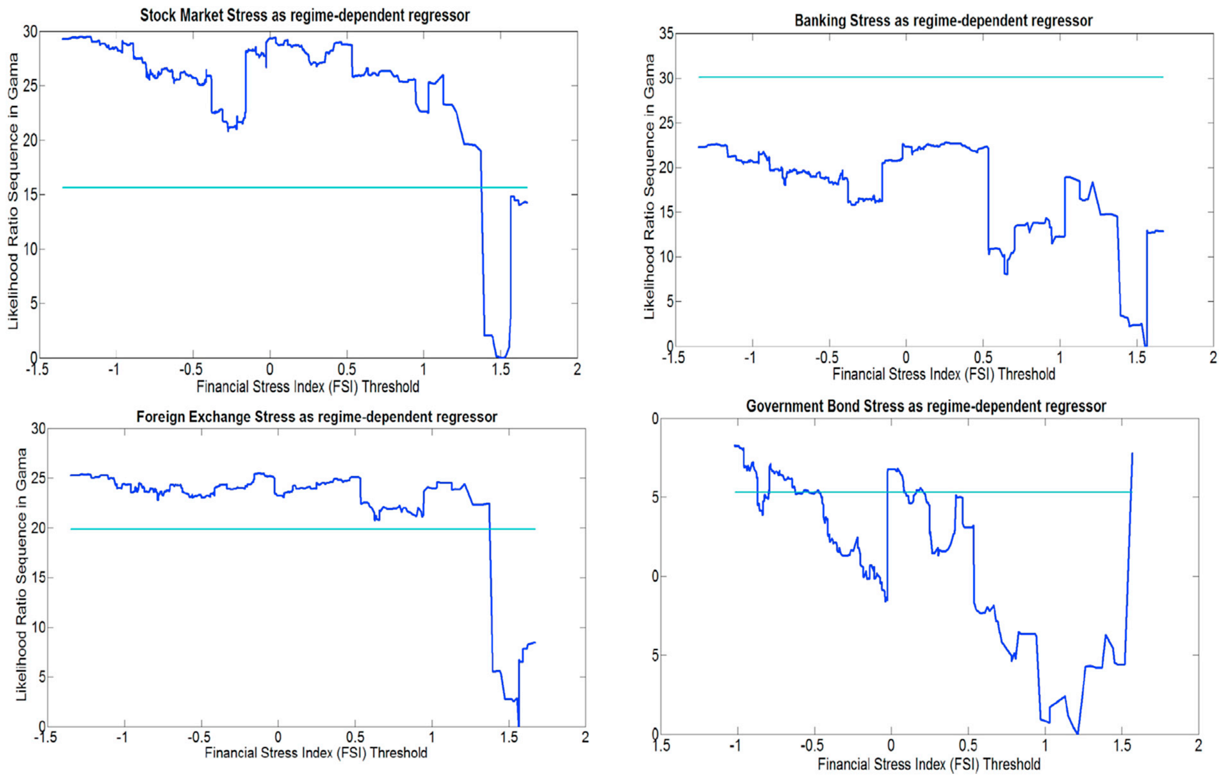


Fig. 7. The likelihood ratio for different FSI threshold values: FSI subcomponents as regime-dependent regressors in emerging market economies, 1996–2013.

Table 5
Factor-Augmented Dynamic Panel Threshold Regression: FSI subcomponent as regime-dependent regressor in emerging market economies, 1996–2013.

	DPT				FA-DPT			
	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: γ^* as Threshold								
γ^*	1.522 [-1.372, 1.728]	1.566 [-1.372,1.728]	1.566 [-1.372, 1.728]	1.214 [-1.022, 1.592]	1.522 [1.397, 1.673]	1.566 [-1.352, 1.673]	1.566 [1.397, 1.673]	1.214 [-1.017, 1.569]
β_η^L	0.648*** (0.221)	0.958*** (0.330)	0.585*** (0.187)	−0.218 (0.287)	0.565*** (0.150)	0.735*** (0.266)	0.699*** (0.159)	−0.361 (0.238)
No. of Obs.	703	706	706	377	703	706	706	377
β_η^H	−0.677 (0.438)	−0.008 (0.415)	−0.054 (0.279)	−1.395** (0.562)	−1.487*** (0.433)	−0.442 (0.328)	−0.352 (0.295)	−1.643*** (0.393)
No. of Obs.	67	64	64	43	67	64	64	43
ρ	0.752*** (0.037)	0.715*** (0.039)	0.760*** (0.044)	0.753*** (0.037)	0.684*** (0.038)	0.635*** (0.037)	0.679*** (0.040)	0.739*** (0.031)
β_π	0.292*** (0.072)	0.328*** (0.075)	0.294*** (0.082)	0.338*** (0.063)	0.327*** (0.062)	0.369*** (0.056)	0.322*** (0.063)	0.296*** (0.051)
β_g	0.003 (0.033)	−0.013 (0.036)	0.011 (0.038)	0.015 (0.033)	0.001 (0.031)	−0.001 (0.034)	0.032 (0.033)	0.062 (0.032)
δ	−0.324 (0.619)	0.569 (0.496)	0.457 (0.495)	−1.356** (0.562)	−0.986* (0.537)	0.402 (0.442)	0.458 (0.469)	−1.573** (0.450)
CD Stat	8.30	5.06	9.22	5.46	0.74	0.31	−1.73	−4.00
Panel B: η^* as Threshold								
η^*	−0.237 [-0.921, 1.567]	1.171 [-0.865, 1.484]	−0.907 [-0.907, 1.133]	0.379 [-0.604, 1.211]	0.737 [-0.917, 1.529]	1.296 [-0.851, 1.434]	1.132 [-0.900, 1.349]	0.376 [0.301, 1.160]
β_η^L	0.242 (0.294)	0.415** (0.186)	8.859*** (3.109)	−0.826*** (0.300)	−0.006 (0.166)	0.753*** (0.239)	0.561 (0.384)	−0.386 (0.268)
No. of Obs.	348	698	42	319	632	709	700	318
β_η^H	0.743*** (0.281)	0.498 (1.474)	0.510*** (0.161)	−1.133* (0.650)	0.205 (0.455)	0.567 (1.434)	1.672*** (0.412)	−1.740** (0.684)
No. of Obs.	422	72	728	101	138	61	70	102
ρ	0.755*** (0.043)	0.724*** (0.048)	0.746*** (0.043)	0.745*** (0.038)	0.712*** (0.034)	0.665*** (0.037)	0.692*** (0.036)	0.710*** (0.032)
β_π	0.287*** (0.081)	0.322*** (0.094)	0.303*** (0.085)	0.355*** (0.058)	0.289*** (0.064)	0.353*** (0.060)	0.301*** (0.065)	0.347*** (0.051)
β_g	0.023 (0.034)	0.029 (0.039)	0.031 (0.038)	−0.028 (0.032)	−0.003 (0.029)	0.003 (0.033)	0.030 (0.031)	0.028 (0.028)
δ	0.424* (0.234)	−0.841 (2.896)	10.733*** (4.161)	−1.343** (0.672)	−0.956 (0.816)	−0.771*** (0.290)	3.035*** (0.965)	−1.781*** (0.681)
CD Stat	7.48	7.17	8.9	6.32	−0.88	−1.49	−2.34	−2.87

Note: Refer to Table 3 for details.

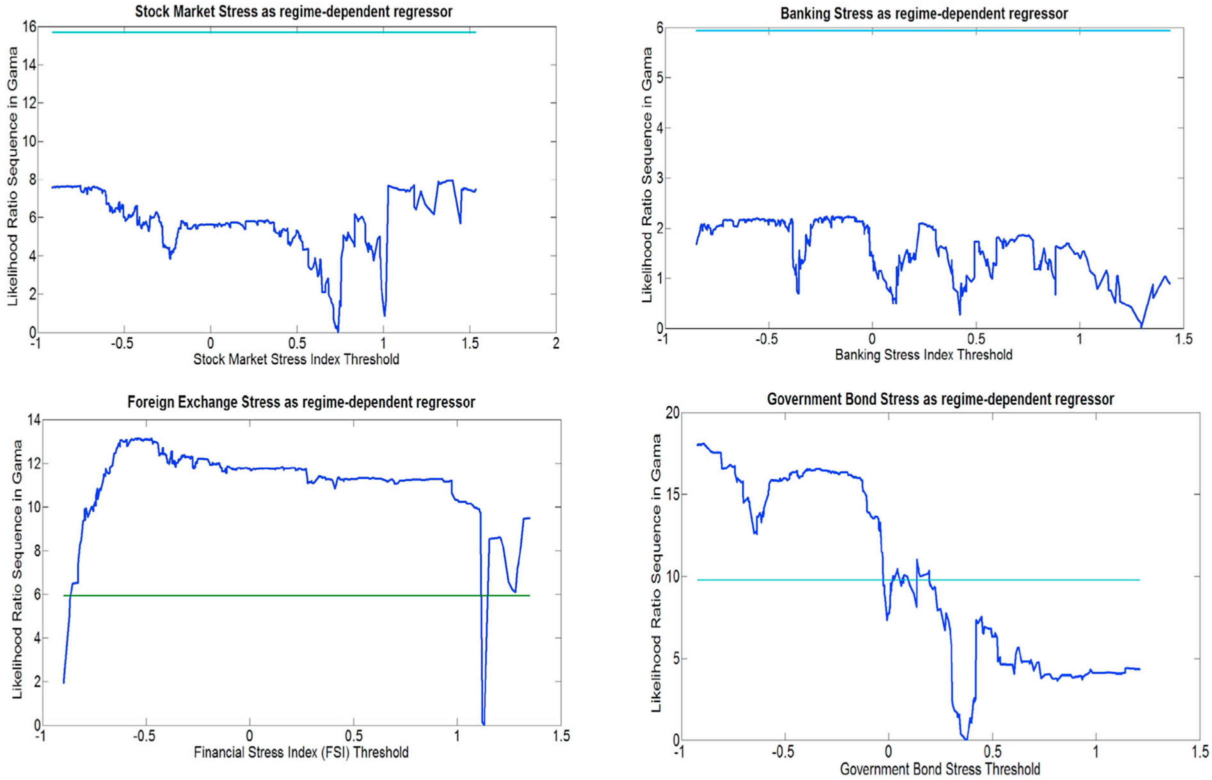


Fig. 8. The likelihood ratio for different FSI subcomponent threshold values: FSI subcomponents as regime-dependent regressors in emerging market economies, 1996–2013.

size of the estimates of the smoothing parameter ρ for the AE panel in both the baseline and FA-DPT specifications, suggesting a relatively greater degree of interest rate smoothing compared to EMEs.[19] This implies that EMEs are much less involved in interest-rate smoothing practices. The mostly insignificant coefficient of growth β_g for EMEs indicates a somewhat procyclical monetary policy of EMEs in response to growth, as confirmed by similar empirical findings by Vegh & Vuletin (2013). The estimated inflation coefficients for the AEs and EMEs both have the correct signs, with the latter exhibiting a statistically significant and much higher degree of monetary policy responsiveness to inflation.

5.4. Sub-sample analyses: post-2000 period

It is essential to test for parameter stability after the post-2000 period as the well-documented structural changes during this time could have an effect on central banks' interest-rate setting behavior. For example, EMEs especially Asian economies, transitioned to low inflation environments and a shift to flexible exchange rates a few years after the Asian financial crisis. Moreover, the period starting from the early 2000s also ushered in increased financial and trade linkages across and within AEs and EMEs (Kose, 2011). This period also coincides with increased synchronization of business cycles among AEs as well as low inflation and low macroeconomic volatility. Fig. 4 (row 1, column 2) this time shows a significant threshold effect of the FSI on the average AE central banks' reaction to overall financial market stress. With a higher estimated threshold value, AE central banks loosen interest rates in the face of financial stress but does not any more react when this estimated threshold is breached (see Table 6). In contrast, we conclude once more the weak threshold effects of the FSI on EME monetary policy settings when the FSI is employed both as the regime-dependent regressor and the threshold variable (see Fig. 4, row 2, column 2).

When the FSI subcomponents are this time allowed to be regime-dependent, significant FSI threshold effects continue to prevail in the AE country group for all subcomponent specifications, with significant dampening effects of stock market and banking stress on interest rates during a high financial stress state (see Fig. 9). It is worth emphasizing that accounting for a "global" common component helps in determining whether structural change or unobserved common shocks account for differences in the variables' explanatory power. In particular, AE central banks only react to banking (foreign exchange) stress at the high financial stress state. However, accounting for unobserved common components reveal that AE central banks' interest rate setting behavior is negative and significant

[19] Baxa et al. (2013) argue that a higher (lower) coefficient value of ϕ and a lower (higher) value of ρ could be interpreted as the central bank adjusting rates substantially (gradually) in response to financial stress due to fears of destabilizing financial markets resulting from sudden changes in interest rates.

Table 6
Factor-augmented dynamic panel threshold regression: The FSI as regime-dependent regressor, 2002–2013.

	Advanced economies		Emerging market economies	
	DPT	FA-DPT	DPT	FA-DPT
	(1)	(2)	(3)	(4)
$\gamma^{\star}$	0.996 [0.774, 1.034]	0.996 [0.774, 1.396]	0.525 [-1.484, 1.185]	−0.477 [-1.476, 1.373]
β_{γ}^{L}	−0.115*** (0.032)	−0.116*** (0.029)	−0.014 (0.080)	0.439*** (0.138)
No. of Obs.	425	425	450	275
β_{γ}^{H}	0.027 (0.046)	0.011 (0.040)	−0.149* (0.087)	0.116** (0.055)
No. of Obs.	45	45	67	242
ρ	0.969*** (0.018)	0.954*** (0.017)	0.867*** (0.030)	0.858*** (0.027)
β_{π}	−0.122 (0.100)	−0.001 (0.087)	0.219*** (0.055)	0.229*** (0.044)
β_{g}	0.0450*** (0.015)	0.035*** (0.013)	0.084*** (0.019)	0.053*** (0.016)
δ	0.706*** (0.261)	0.481*** (0.173)	−0.610** (0.275)	0.475*** (0.140)
CD Stat	10.42	−3.00	5.07	−0.78

Note: Refer to Table 3 for details.

(insignificant) at both regimes (at the high stress regime) (see Table 7). Our analysis identifies that at the same time there is now a significant (insignificant) response to FSI (bank market stress) when it is also employed as the threshold variable, compared with the 1994–2013 sample period (see Fig. 10 and Table 7). Therefore, evidence of state-dependence on the levels of the FSI subcomponents is not robust to structural changes as shown by our sub-sample analysis.

Threshold effects meanwhile, are non-existent in EMEs (see Table 8). With a much lower threshold compared to the full sample, the LR plots of the FSI threshold estimate for all the subcomponent specifications appear to have multiple possible minimums (Figs. 11 and 12). That there is no evidence of threshold effects of the FSI in the post-2000 period suggests that the trajectory of financial stress is not important in EME central banks' monetary policy's responsiveness to financial sector-specific stress. One possible explanation is that the inflation targeting regime, as implemented by EME central banks implies a symmetric policy reaction function as the inflation target is represented by a point value or a band. Combined with the objective to establish credibility, a change in the monetary policy response to financial stress could depend more on inflation and output regimes rather than the state of financial market stress.

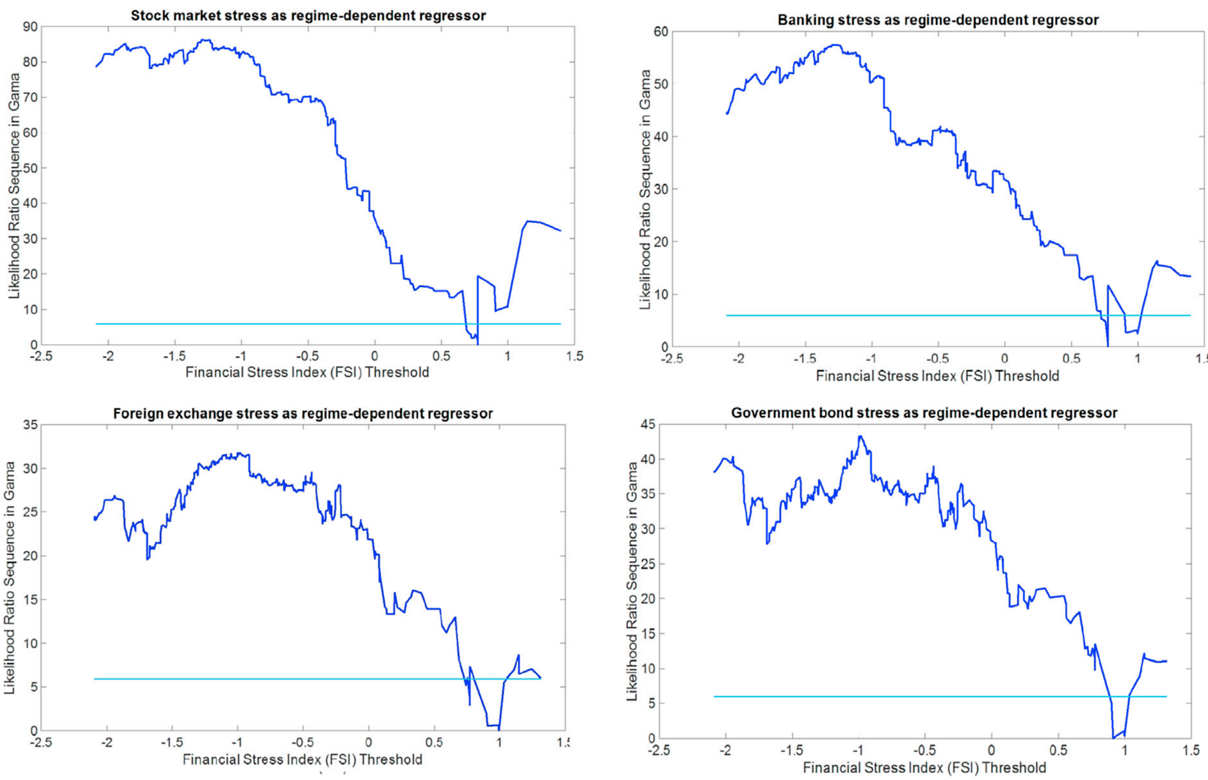


Fig. 9. The likelihood ratio for different FSI threshold values: FSI subcomponents as regime-dependent regressors in advanced economies, 2002–2013.

Table 7
Factor-augmented dynamic panel threshold regression: FSI subcomponent as regime-dependent regressor in advanced economies, 2002–2013.

	DPT				FA-DPT			
	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: γ^* as Threshold								
γ^*	0.775 [0.688, 0.775]	0.775 [0.774, 0.775]	0.775 [0.688, 0.775]	0.996 [0.775, 0.996]	0.775 [0.688, 0.775]	0.775 [0.725, 0.996]	0.908 [0.744, 0.996]	0.909 [0.898, 0.996]
β_η^L	−0.022 (0.026)	−0.025 (0.029)	−0.039 (0.040)	−0.046* (0.027)	−0.030 (0.026)	−0.063*** (0.024)	−0.038 (0.034)	−0.021 (0.020)
No. of Obs.	419	419	376	425	419	419	379	423
β_η^H	−0.281*** (0.101)	−0.213** (0.095)	−0.232** (0.100)	0.158* (0.095)	−0.286*** (0.098)	−0.208*** (0.077)	0.015 (0.084)	0.157* (0.092)
No. of Obs.	51	51	47	45	51	51	44	47
ρ	0.977*** (0.017)	0.975*** (0.018)	0.975*** (0.020)	0.961*** (0.019)	0.965*** (0.019)	0.937*** (0.018)	0.963*** (0.019)	0.957*** (0.017)
β_π	−0.082 (0.090)	−0.104 (0.093)	−0.151 (0.120)	−0.115 (0.110)	−0.012 (0.070)	0.018 (0.075)	0.066 (0.082)	0.055 (0.079)
β_g	0.050*** (0.013)	0.044*** (0.016)	0.052*** (0.013)	0.058*** (0.015)	0.064*** (0.012)	0.048*** (0.018)	0.049*** (0.014)	0.039*** (0.011)
δ	0.249* (0.131)	0.290* (0.153)	0.382*** (0.139)	0.811*** (0.183)	0.337** (0.133)	0.338*** (0.118)	0.454*** (0.105)	0.587*** (0.104)
CD Stat	4.69	7.39	6.71	10.23	0.31	−2.00	−2.15	0.96
Panel B: η^* as Threshold								
η^*	1.012 [0.782, 1.868]	1.372 [0.092, 1.540]	1.019 [0.150, 1.289]	0.529 [-0.053, 2.055]	−0.313 [-0.861, 1.861]	1.373 [0.092, 1.540]	0.150 [-0.806, 1.246]	0.043 [-0.287, 1.958]
β_η^L	−0.065 (0.048)	0.032 (0.069)	−0.083 (0.051)	−0.005 (0.053)	0.213* (0.112)	0.014 (0.042)	−0.144** (0.059)	0.074 (0.081)
No. of Obs.	402	416	377	326	192	416	285	237
β_η^H	−0.349*** (0.123)	−0.137 (0.130)	−0.426*** (0.140)	0.044 (0.040)	−0.041 (0.037)	0.012 (0.090)	−0.166** (0.072)	0.026 (0.027)
No. of Obs.	68	54	46	144	278	54	138	233
ρ	0.971*** (0.018)	0.976*** (0.021)	0.964*** (0.022)	0.964*** (0.022)	0.958*** (0.018)	0.951*** (0.017)	0.965*** (0.018)	0.930*** (0.018)
β_π	−0.029 (0.081)	−0.068 (0.107)	−0.064 (0.119)	−0.180 (0.144)	0.142** (0.057)	0.148** (0.062)	−0.017 (0.098)	0.013 (0.078)
β_g	0.077*** (0.019)	0.070*** (0.020)	0.073*** (0.015)	0.113*** (0.014)	0.062*** (0.015)	0.045*** (0.013)	0.070*** (0.012)	0.090*** (0.014)
δ	−0.517** (0.251)	0.135 (0.132)	−0.567** (0.244)	0.236** (0.095)	0.198** (0.079)	0.328 (0.238)	−0.161* (0.083)	0.150*** (0.057)
CD Stat	7.81	9.00	3.00	9.35	0.470	−1.65	1.23	0.73

Note: Refer to Table 3 for details.

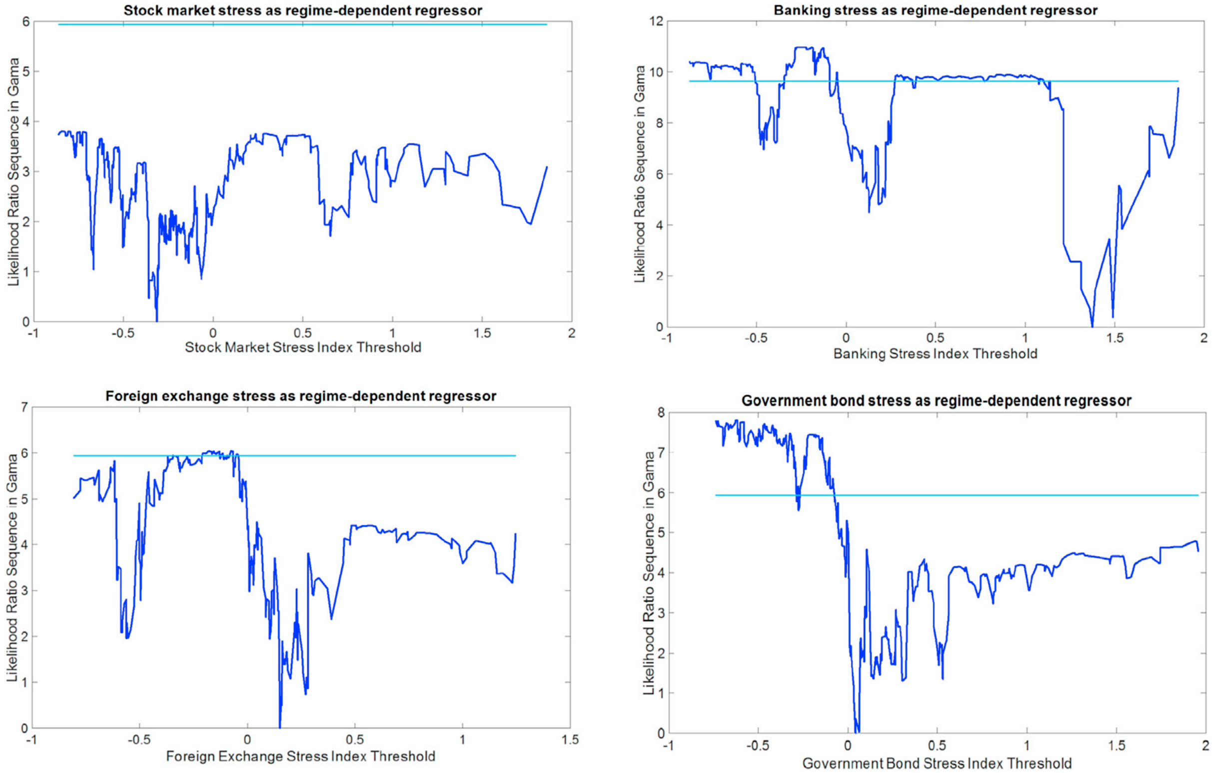


Fig. 10. The likelihood ratio for different FSI subcomponent threshold values: FSI subcomponents as regime-dependent regressors in advanced economies, 2002–2013.

Commenting briefly on the other monetary-policy rule estimates, i.e. growth and inflation, we note an increase in the magnitude of responsiveness (relative to the 1996 to 2013 period) of EME central banks to output growth, which implies a shift to countercyclical behavior post-2001. Our findings are generally in line with the recent work of Vegh & Vuletin (2013), who document an increasingly countercyclical monetary policy in EMEs since the start of 2000s. Meanwhile, the inflation coefficient in the AE panel turned negative but still insignificant. It is reassuring to find that (Baxa et al., 2013; p. 127) provide similar results especially for the U.S. and the U.K in the most recent period. Baxa et al. (2013) attribute the decrease in the inflation response to well-anchored inflation expectations amidst a low-inflation environment. That is, monetary policy is being accommodative in the face of financial stress even if inflation expectations remain anchored.

5.5. Robustness checks

We examine the robustness of our benchmark model to alternative specifications by conducting sensitivity analyses. Our results in Eqs. (4)–(6) are robust to dropping one country at a time. First, we exclude two sets of countries, those with the highest and those with the lowest FSIs over time. Excluding South Korea (highest FSI over time) and the U.S. (lowest FSI over time) one at a time had no significant effect on our baseline results. Next, we excluded the non-inflation targeting countries Hungary and Malaysia. Exclusion of these countries together only marginally changed the coefficients. The results are also robust to the inclusion of additional explanatory variables. In particular, we include dummy variables for the Asian financial crisis and the global financial crisis one at a time and together at the next step. This did not change the sign nor the magnitude of our results across different time periods and specifications. Furthermore, the results remain robust even if we replace the U.S. and U.K. short-term interest rates with the zero lower bound interest rates. In all the specifications (Eqs. (4)–(6)), we assumed a present-looking interest rate reaction function, wherein central banks react immediately to financial stress and its subcomponents. Hence, the FSI and its subcomponents are all set at time t. We employ in addition, a backward-looking model, where we set $k = 1$ we use the first lag of the FSI and subcomponents. We find that the results in the AE panel are robust to the choice of k, while EME central banks react positively to only to foreign exchange stress at the high FSI and foreign exchange stress regime. Similar to the baseline result when $k = 0$, we also did not find significant threshold estimates in the EME panel. Finally, we note that a limitation in our study is that a Taylor rule framework does not capture explicitly the role of other monetary policy instruments. To be specific, instruments such as reserve requirements and other monetary indicators which play an important role in some EMEs as well as balance sheet policies of AE central banks are not taken into account.

Table 8

Factor-augmented dynamic panel threshold regression: FSI subcomponent as regime-dependent regressor in emerging market economies, 2002–2013.

	DPT				FA-DPT			
	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress	Stock market stress	Banking stress	Foreign exchange stress	Government bond stress
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: γ^* as Threshold								
γ^*	−0.440 [-1.485, 1.451]	−0.455 [-0.887, 1.451]	−0.030 [-1.485, 1.451]	0.784 [-1.058, 1.338]	0.081 [-1.403, 1.338]	−0.440 [-0.652, 1.031]	−0.476 [-1.412, 1.373]	0.206 [-1.058, 1.185]
β_η^L	−0.049 (0.073)	−0.105 (0.080)	0.056 (0.055)	−0.034 (0.085)	0.030 (0.067)	−0.065 (0.076)	0.144*** (0.054)	−0.078 (0.080)
No. of Obs.	287	284	388	255	407	287	276	237
β_η^H	0.188*** (0.070)	0.264*** (0.100)	0.283*** (0.100)	0.160 (0.109)	0.090 (0.089)	0.329*** (0.091)	0.318*** (0.092)	0.163 (0.102)
No. of Obs.	230	233	129	27	110	230	241	45
ρ	0.868*** (0.030)	0.868*** (0.030)	0.869*** (0.029)	0.859*** (0.039)	0.856*** (0.027)	0.860*** (0.026)	0.848*** (0.026)	0.85*** (0.039)
β_π	0.233*** (0.054)	0.239*** (0.055)	0.228*** (0.055)	0.252*** (0.062)	0.205*** (0.042)	0.218*** (0.044)	0.261*** (0.034)	0.234*** (0.054)
β_g	0.077*** (0.017)	0.075*** (0.016)	0.084*** (0.018)	0.014 (0.014)	0.077*** (0.015)	0.048*** (0.014)	0.056*** (0.014)	0.038*** (0.014)
δ	0.061 (0.072)	0.016 (0.075)	0.107 (0.105)	0.571** (0.225)	−0.281** (0.129)	0.024 (0.070)	0.189*** (0.067)	0.330* (0.178)
CD Stat	3.83	4.23	3.02	1.8	−1.66	−0.91	−1.59	−0.78
Panel B: η^* as Threshold								
η^*	0.365 [-0.949, 1.008]	0.697 [0.697, 0.697]	0.477 [-0.664, 1.223]	−0.252 [-0.732, −0.198]	0.037 [-0.877, 0.982]	0.754 [0.697,0.754]	−0.331 [-0.649, 1.207]	−0.252 [-0.744, 0.521]
β_η^L	−0.137 (0.105)	−0.177* (0.099)	0.292*** (0.109)	0.356 (0.339)	−0.164 (0.110)	−0.091 (0.100)	−0.369 (0.222)	0.193 (0.321)
No. of Obs.	401	471	419	146	350	472	133	146
β_η^H	−0.049 (0.173)	−0.207 (0.342)	0.322** (0.127)	0.082 (0.081)	−0.048 (0.125)	−0.129 (0.342)	0.243*** (0.073)	0.151* (0.079)
No. of Obs.	116	46	98	136	167	45	384	136
ρ	0.868*** (0.030)	0.868*** (0.029)	0.862*** (0.029)	0.849*** (0.038)	0.853*** (0.027)	0.864*** (0.027)	0.857*** (0.026)	0.849*** (0.036)
β_π	0.247*** (0.055)	0.243*** (0.056)	0.238*** (0.055)	0.240*** (0.063)	0.210*** (0.045)	0.226*** (0.045)	0.215*** (0.046)	0.238*** (0.061)
β_g	0.075*** (0.016)	0.073*** (0.016)	0.081*** (0.016)	0.037*** (0.015)	0.051*** (0.014)	0.056*** (0.014)	0.054*** (0.014)	0.036*** (0.014)
δ	−0.342* (0.187)	−0.810 (0.504)	0.383** (0.182)	0.475** (0.216)	−0.375*** (0.134)	−0.692 (0.526)	0.243*** (0.073)	0.370* (0.206)
CD Stat	4.02	3.74	3.21	1.07	−2.06	2.77	−0.57	−1.04

Note: Refer to Table 3 for details.

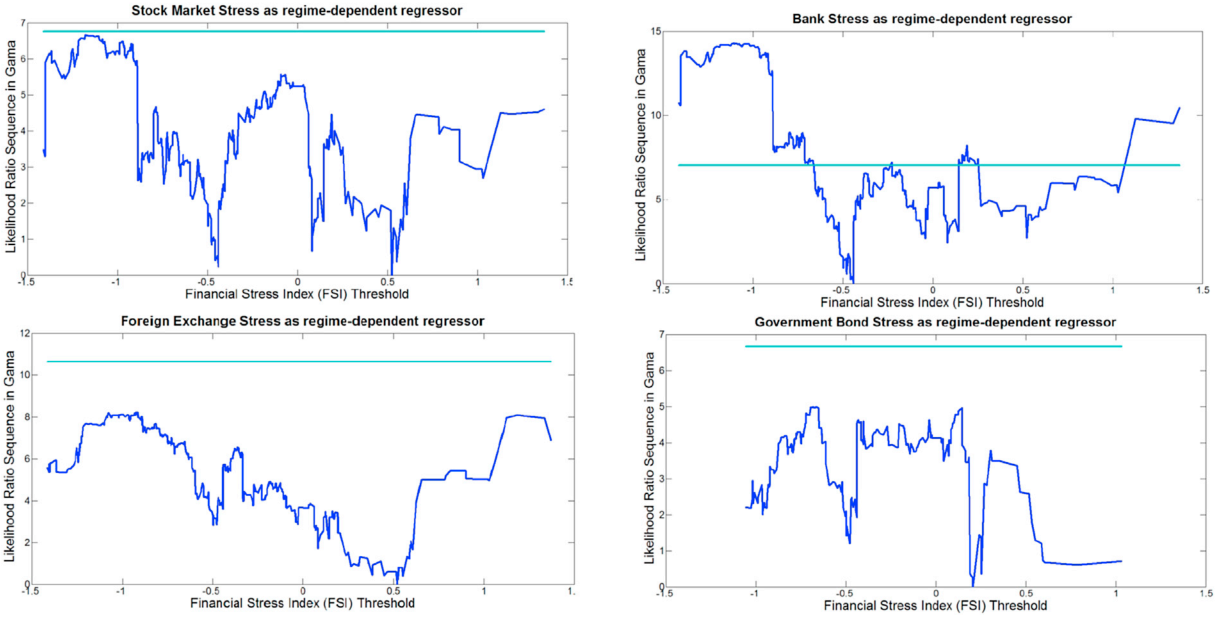


Fig. 11. The likelihood ratio for different FSI threshold values: FSI subcomponents as regime-dependent regressors in emerging market economies, 2002–2013.

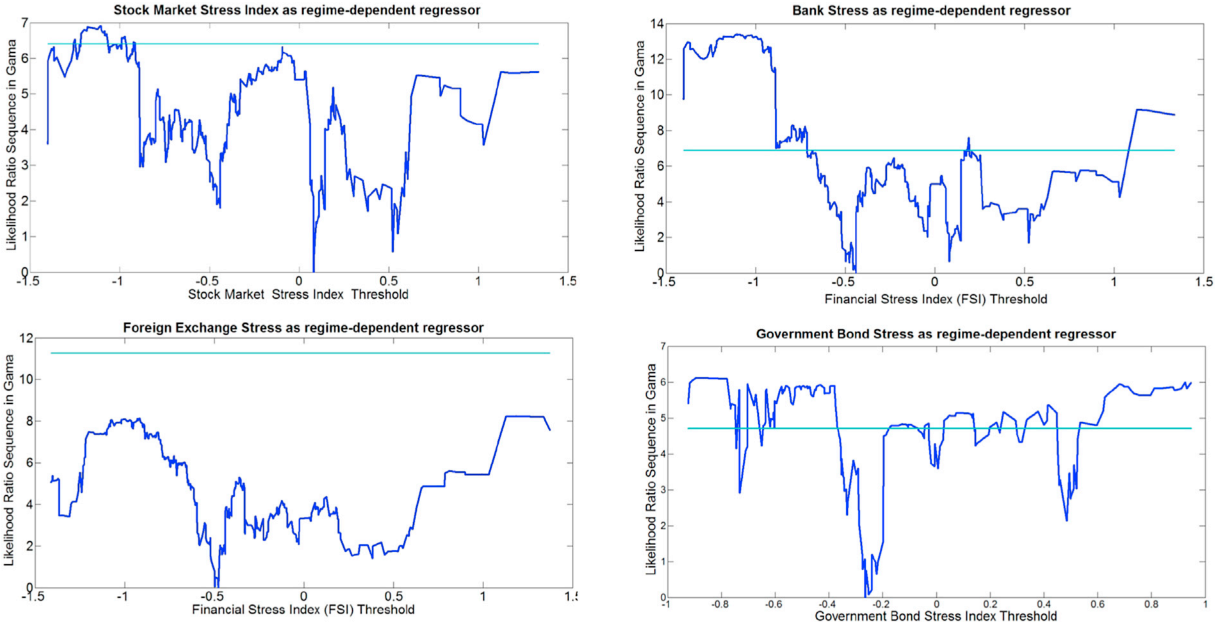


Fig. 12. The likelihood ratio for different FSI subcomponent threshold values: FSI subcomponents as regime-dependent regressors in emerging market economies, 2002–2013.

6. Conclusion

In this study, we investigate state-dependence in the monetary policy reaction function to financial stress and its subcomponents—over and beyond any impact on expected inflation and growth—for a sample of 10 advanced economies and 11 emerging market economies. We do that by employing a nonlinear, dynamic panel threshold regression model originally developed by Kremer et al. (2013) and augment this model with a multifactor structure in the panel residuals to account for unobserved common global shocks. This novel approach allows us to obtain robust statistical inference as well as consistent parameter estimates in the analysis of the heterogeneous impact of financial stress on monetary policy behavior in a panel context.

The analysis in this paper centered on the role that financial instability played in central banks' monetary policy reaction functions in addition to the price stability mandate. Based on our findings taken from a nonlinear model, the degree of financial stress has more consequences on monetary policy settings for AEs than for EMEs. The switch in monetary policy responses to financial sector-specific stress is not triggered by the trajectory in their levels but rather by conditions in financial markets as a whole. In particular, we find a strong negative response of interest rates to stock market and banking stress only when the economy is in a state of high financial stress. On the other hand, we did not find a significant threshold effect of financial stress in the case of EMEs that is robust to structural change.

Overall, the evidence presented in this paper brings to the fore a clearer understanding of the dynamic interest-rate setting process in response to the nonlinear nature of financial stress. By identifying the specific type of stress that drives the monetary policy reaction function of advanced economy and emerging market central banks, the effectiveness of monetary policy coordination between countries could also be further improved going forward. Finally, we contribute to the robustness of the evidence by highlighting the need to account for cross-sectional dependence especially in panel models that deal with financial market data. The implication is that accounting for cross-sectional dependence may yield different dynamic panel results than when simply omitting common components. Therefore, future studies on this subject should consider nonlinear models that consider the modeling of error cross-sectional dependence as an integral part of the model specification.

Acknowledgments

This work was supported by the German Research Foundation grant (grant number DE 1617/4-1). The authors would like to thank the Editor, Kai Carstensen, Matei Demetrescu, Maik H. Wolters and Feng Zhu and three anonymous referees for their comments and suggestions. The authors acknowledge the helpful discussions with the participants of the 2015 DIW Macroeconometrics Workshop, 9th International Conference on Computational Statistics and Econometrics, BIS Asian Research Network Annual Research Conference, and the German Economic Society Annual Conference. Lastly, the authors are grateful to Joselito R. Basilio for his contribution in the earlier versions of this paper.

Appendix A. Descriptions of data

Output growth and price inflation are computed using real GDP data series and monthly year-on-year growth of the consumer price index, respectively, and sourced from the Organization for Economic Cooperation and Development (OECD) database for AEs including South Africa and Brazil, and the International Financial Statistics (IFS) database of the International Monetary Fund (IMF). Short-term policy interest rates were obtained from the IFS as well as central bank websites for the non-OECD countries and EMEs.

Table 9
List of the countries in the sample

Country	Sample Period	Growth/Inflation	Policy Rate
Advanced			
Australia	1994:Q1-2013:Q3	OECD	IFS (STbond, code T60a)
Canada	1994:Q1-2013:Q3	OECD	IFS (disc/bank code T60a)
Denmark	1994:Q1-2013:Q3	OECD	Danmarks Nationalbank
Japan	1994:Q1-2013:Q3	OECD	Krippner (2015)
Korea	1994:Q1-2013:Q3	OECD	IFS (disc, code T60)
Norway	1994:Q1-2013:Q3	OECD	IFS (disc, code T60)
Sweden	1994:Q1-2013:Q3	OECD	IFS (rp, code T60)
Switzerland	1994:Q1-2013:Q3	OECD	IFS (disc/bank, code T60)
UK	1994:Q1-2013:Q3	OECD	Wu and Xia (2016)
US	1994:Q1-2013:Q3	OECD	Wu and Xia (2016)
Emerging			
Brazil	1996:Q2-2013:Q3	IFS	IFS (disc, code T60)
Colombia	1996:Q2-2013:Q3	IFS	IFS (disc, code T60)
Hungary	1996:Q2-2013:Q3	IFS	IFS (disc, code T60)
Indonesia	1996:Q2-2013:Q3	IFS	IFS(disc, code T60)
Malaysia	1996:Q2-2013:Q3	IFS	IFS (mmr, code T60b)
Mexico	1996:Q2-2013:Q3	IFS	IFS (mmr, code T60)
Peru	1996:Q2-2013:Q3	IFS	IFS (mmr, code T60)
Philippines	1996:Q2-2013:Q3	IFS	IFS (disc, code T60)
Poland	1996:Q2-2013:Q3	IFS	IFS (disc, code T60)
South Africa	1996:Q2-2013:Q3	OECD	IFS (disc, code T60)
Thailand	1996:Q2-2013:Q3	IFS	IFS (disc, code T60)

N.B. *disc* = *discount* rate; *mmr* = *money* market rate; *rp* = *repurchase* agreement rate; *st* = *short*-term bond rate; *depo* = *deposit* rate, *bank* = *bank* rate.

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