Financial contagion in developed sovereign bond markets

Maastricht University

Norbert Metiu

Financial contagion in developed sovereign bond markets

RM/11/004

METEOR

Maastricht University School of Business and Economics
Maastricht Research School of Economics
of Technology and Organization

P.O. Box 616
NL - 6200 MD Maastricht
The Netherlands

Financial contagion in developed sovereign bond markets☆

Norbert Metiu[1,2]

Department of Economics,
Maastricht University

Abstract

This paper implements a simultaneous equations model to test for international financial contagion among developed sovereign credit markets between May 1, 2000 and September 1, 2010. Two alternative measures are proposed that identify credit crises in the tails of bond yield distributions, which are derived from Extreme Value Theory and Value-at-Risk analysis. The findings show that the large-scale fluctuations in long term sovereign bond yields observed during episodes of financial distress signal a structural shift in cross-market linkages with respect to tranquil periods. All analyzed countries are vulnerable to shift-contagion and the estimated contagion effects are robust across the different measures of credit crises. The empirical results convey the policy implication that a new sovereign debt management mechanism ought to incorporate the risk of financial contagion, as it carries adverse effects on the overall financing constraints in the economy.

JEL classification: C32; G15

Keywords: Contagion; Interdependence; International financial markets; Sovereign risk

☆ *Current version*: January 4, 2011.

[1] *Correspondence*: Address: Tongersestraat 53, 6211 LM Maastricht - P.O. Box 616, 6200 MD Maastricht, Netherlands. Email: n.metiu@maastrichtuniversity.nl.

[2] *Acknowledgements*: I am truly grateful to Bertrand Candelon for his supervision and encouragement. I also wish to thank Helmut Lütkepohl, Massimiliano Marcellino, Michal Markun, Timo Teräsvirta, Jean-Pierre Urbain, Tomasz Woźniak, the participants of the Fourth Methods in International Finance Network Annual Workshop at Shandong University, and the internal seminar at the European University Institute for helpful comments and discussions.

1. Introduction

Developed capital markets have been hit by several waves of financial distress since the outbreak of the global credit crisis in mid-2007. The most recent of these episodes appears to be the turmoil in the European sovereign debt market in spring 2010. The events were triggered by mounting concerns over the fiscal sustainability of the Mediterranean region, which swiftly translated into a surge of government bond yields and an *en masse* flight-to-quality. Prompted by financial market pressures, the governments of Greece, Ireland, Portugal, and Spain have already announced or taken policy measures in order to correct their large imbalances. Nevertheless, since fiscal austerity requires enduring commitments, the future of sovereign debt management remains at the heart of an international policy debate.

In this paper, we investigate whether the recently experienced large-scale fluctuations in sovereign bond yields signal a structural shift in cross-market linkages with respect to tranquil periods. Movements in sovereign bond yields affect the entire risk structure of interest rates, since corporate bonds are priced with a risk premium over benchmark bonds of the same maturity. Hence, spillovers across sovereign credit markets affect government fiscal balances directly, and also convey backlash effects on the fund raising capacity of the corporate sector. Quantifying the exposure of developed countries to such spillovers can help policymakers gain insight into the overall financing constraints, as well as the external risks faced by the economy.

The transmission of financial difficulties from one country to others - across regions and asset classes - characterized the majority of recent large-scale financial crises, including the 1987 U.S. stock market crash, the 1992-1993 exchange rate crisis of the ERM, the 1994 Mexican 'tequila' crisis, the 1997 Asian 'flu', the 1998 Russian bond crisis, the 2001 U.S. 'dot-com' crisis, and the 2007 subprime crisis. Financial shocks are propagated across countries through various transmission channels. Kaminsky and Reinhart (2000) and Van Rijckeghem and Weder (2001) find that financial channels, such as a common bank creditor and cross-market risk hedging are the significant conduits of crises, while Glick and Rose (1999) identify international trade as a potential transmission channel. The strength of trade and financial channels can be exacerbated by institutional links (Allen and Gale, 2000), international portfolio rebalancing (Kodres and Pritsker, 2002), links across multiple asset classes (Pavlova and Rigobon, 2007), or the fragility of the banking sector during a crisis (Bruinshoofd et al., 2010).

Kaminsky and Reinhart (2000) draw a conceptual distinction between the international transmission of financial crises through fundamentals-based channels (finance,

trade, etc.), and 'true' contagion, which arises when all channels of potential interconnection have been controlled for. True contagion is commonly associated with (rational or irrational) investor behavior, such as herding under limited information, index tracking, or bandwagon effects. There is a large body of literature that investigates financial contagion, exhaustive surveys are offered by Claessens and Forbes (2001) and Pericoli and Sbracia (2003). Early contagion studies typically assess changes in cross-correlation coefficients of stock market returns and they interpret a significant increase in cross-correlation after a crisis as evidence for contagion. For instance, in a seminal work, King and Wadhwani (1990) argue that the significant increase in cross-correlations between the United States, the United Kingdom, and Japanese stock markets in the aftermath of the 1987 U.S. market crash was due to contagion. However, Forbes and Rigobon (2002) prove that the tests based on conditional cross-correlation are biased upwards in the presence of heteroskedasticity. Once they control for the bias, they find little evidence for contagion, only cross-market dependence.

Indeed, the last few decades have witnessed a worldwide capital market integration, leading to global interdependence between financial markets. Therefore, the strong cross-country links observed after crises might not be significantly different from those during calm periods. Consequently, Forbes and Rigobon (2001, 2002) distinguish between contagion and interdependence, and introduce the concept of *shift-contagion*, which is defined as "a significant increase in cross-market linkages after a shock to an individual country (or group of countries)" (Forbes and Rigobon, 2001, pp. 13). In this paper, we adopt their definition, as it constitutes a widespread consensus in the literature. Therefore, we do not intend to identify the transmission channel, instead we test for a change in bond yields due to a shift in the transmission mechanism during crisis periods.

A battery of statistical methods have been applied to investigate shift-contagion, a comprehensive review is provided in Dungey et al. (2005). A partial list of methods includes the adjusted correlation test of Forbes and Rigobon (2002), the VAR model of Favero and Giavazzi (2002), the discrete choice models of Eichengreen et al. (1996), and Bae et al. (2003), the coexceedance approach of Hartmann et al. (2004), the common factor models of Corsetti et al. (2005), Bekaert et al. (2005), and Dungey and Martin (2007), the common features test of Candelon et al. (2005), and the copula approach of Rodriguez (2007) and Candelon and Manner (2010). While all of these papers account for strong interdependence, the evidence for shift-contagion appears to be mixed. Nevertheless, most of them agree that shift-contagion has played a role in the propagation of

financial shocks during the crises listed above.[3]

Recently, Pesaran and Pick (2007) have proposed a canonical model which delivers a synthesis of the most imminent econometric issues in the analysis of shift-contagion. The model identifies the contagion effects in the presence of observed financial market interdependence, as well as unobserved cross-sectional dependence between the model residuals. We employ a heteroskedasticity robust version of this canonical model to investigate the cross-country linkages among developed sovereign bond markets, and we propose two credit crisis indicators that are derived from Extreme Value Theory and Value-at-Risk methods. The model is estimated on a sample of long-maturity government bond yields of 18 advanced economies.

The main economic contribution of this paper is to provide statistical evidence that developed countries are subject to a severe risk of contagion whenever a credit crisis is unfolding in another country or a group of countries. In summary, we find that all analyzed countries are vulnerable to shift-contagion and the estimated contagion effects are robust to the different measures of credit crises. Furthermore, the results are robust to a series of diagnostic tests of the model. Our findings convey considerable policy implications in terms of European and global sovereign debt management. The central message is that, at times of stress, governments need to act in concert in order to reassure the markets of their commitment to a balanced fiscal path. Therefore, strong efforts in the supranational coordination of debt policies may be inevitable, of which the first signs are already visible in Europe.

The rest of the paper is structured as follows. In section 2, we formulate the canonical contagion model. Subsequently, the identification strategy of sovereign credit events is described. Section 3 presents the empirical results on contagion among the sovereign bond yields and we provide evidence for the robustness of our findings. Finally, section 4 offers conclusions.

[3] A related strand of the literature investigates international volatility spillovers, for example, Engle et al. (1990), Cheung and Ng (1996), or more recently Diebold and Yilmaz (2009). The typical finding is that financial market volatility can be described as "a *meteor shower* which rains down on the earth as it turns." (Engle et al., 1990, pp. 526). While traditional ARCH and GARCH studies do not explicitly test for a shift in the cross-market volatility linkages, Baele (2005) and Gallo and Otranto (2008) have overcome this deficiency, using nonlinear models. Even though this line of research can offer valuable information for portfolio risk managers, we restrain ourselves to modelling shift-contagion in the first moment of returns, as this approach has been more closely associated with the concept of shift-contagion in the literature.

2. Econometric Methodology

The econometric analysis of contagion generally requires the specification of dynamic multivariate models. Even though there is no scientific consensus on the precise methodology, the formulated model needs to satisfy certain conditions in order to achieve identification of the contagion effects. We briefly review these conditions.

First, in integrated financial markets, equity portfolios are allocated across geographic borders and regions. Consequently, markets are tied together by common factors that are either observed to the econometrician, or latent. These factors give rise to cross-sectional dependence among the time series because they serve as natural conduits to global financial and macroeconomic shocks (for example, commodity price, productivity, or preference shocks, terms-of-trade shocks, or changes in global discount factors). If a model of contagion fails to account for observed as well as unobserved cross-sectional dependence, this could lead to the inconsistent estimation of the contagion effects (see Corsetti et al., 2005 and Pesaran and Pick, 2007 for a detailed discussion). To address this issue, Corsetti et al. (2005), Bekaert et al. (2005), and Dungey and Martin (2007) propose common factor models, in which shift-contagion is captured by the cross-market transmission of an idiosyncratic shock to a particular market. These papers find significant evidence for cross-sectional dependence, as well as shift-contagion in the Asian, European and Latin American region during crises. However, since these models require an *ad hoc* classification of crisis and non-crisis periods, their results are subject to a sample selection bias.

A second consideration concerns that in contrast to the fundamentals-based channels of interdependence which operate at all times, shift-contagion can be viewed as a crisis-contingent transmission mechanism. Thus, during a crisis, it introduces a transitory shift in the process that generates equity returns. At the level of economic theory, such a shift may be associated, for example, with a jump between multiple equilibria due to self-fulfilling expectations (see Masson, 1999), or cross-border portfolio rebalancing under limited information (see Kodres and Pritsker, 2002). This issue suggests the necessity to incorporate nonlinearities in the contagion model. To this end, Bae et al. (2003) and Hartmann et al. (2004) focus on tail correlations in extremal returns, Rodriguez (2007) and Candelon and Manner (2010) employ time-varying copulas, while Ang and Bekaert (2002), Baele (2005), and Gallo and Otranto (2008) formulate time series models with regime-switching dynamics. Nevetheless, in these frameworks it is cumbersome to model latent interdependence. Moreover, regime-switching autoregressions typically overlook the possibility that the transition between regimes in one market may depend on the

other markets and *vice versa*.[4]

Pesaran and Pick (2007) offer a methodological synthesis of these econometric issues in a canonical model of contagion. Their method is closely related to Dungey et al. (2005) and Favero and Giavazzi (2002). In particular, Dungey et al. (2005) propose a multivariate version of the Forbes and Rigobon (2002) test for shift-contagion, and they show that this test can be cast as a Chow structural break test using dummy variables. In a similar framework, Favero and Giavazzi (2002) estimate a structural model with exogenous dummy variables. The main difference between the canonical model of Pesaran and Pick (2007) and the latter approaches is that the crisis dummies are treated as endogenous. Specifically, they formulate a nonlinear simultaneous equations model with endogenous threshold variables accounting for the crisis periods. This canonical model controls for observed common and country-specific factors, as well as for unobserved interdependence. It turns out that if the residuals are cross-sectionally dependent, country-specific regressors are in fact necessary for the identification and consistent estimation of the contagion coefficients.

The residuals in the Pesaran-Pick model are assumed to be homoskedastic, although an increase in volatility in the source country during crisis periods distorts the estimated cross-country financial linkages (see Forbes and Rigobon, 2002), and the unconditional density of financial returns typically exhibits an extremal feature (see Hols and de Vries, 1991). Therefore, we augment the canonical model with two alternative measures of credit crises. We propose a new crisis indicator which is a function of market volatility, and another crisis indicator that exploits the extremal feature of financial returns. Although the estimated contagion effects are remarkably robust across these crisis measures, we favor the volatility-based indicator because it is less subject to sample dependence. The canonical model of contagion is discussed in what follows.

2.1. The Canonical Model of Contagion

Let $\mathbf{y}_t = (y_{1t}, ..., y_{Nt})'$ denote a finite realization of the N-dimensional vector process $\{\mathbf{y}_t\}$, where y_{it} are the changes in sovereign bond yields for country $i = 1, ..., N$ observed over $t = 1, ..., T$ periods ($i \in \mathbb{N}; t \in \mathbb{Z}$). The canonical contagion model for country i is defined as:

$$y_{it} = \boldsymbol{\delta}_i' \mathbf{g}_t + \boldsymbol{\alpha}_i' \mathbf{s}_{it} + \beta_i^+ \mathcal{C}_{it}^+ + \beta_i^- \mathcal{C}_{it}^- + u_{it}, \tag{1}$$

[4]Note, that as a side outcome, regime-shifts present a natural way to overcome the sample selection problem posed by *ad hoc* crisis classifications.

where $\mathbf{g}_t$ is a $(G \times 1)$ vector of global factors that capture observed financial market interdependence ($E(\mathbf{g}_t|u_{it}) = 0$); $\mathbf{s}_{it}$ is a $(S \times 1)$ vector of observed country-specific regressors which may include lagged values of y_{it} ($E(\mathbf{s}_{it}|u_{it}) = 0$); and $\mathcal{C}_{it} = (\mathcal{C}_{it}^{+}, \mathcal{C}_{it}^{-})$ is a credit event indicator which takes the value of unity during a credit event (or crisis), and it is zero otherwise ($E(\mathcal{C}_{it}|u_{it}) \neq 0$). The residuals, u_{it}, are distributed conditional on the $t-1$ information set $\mathcal{F}_{t-1}$ as $u_{it}|\mathcal{F}_{t-1} \sim N(0, \sigma_{it}^2)$. Finally, the unobserved interdependence across countries, which prevails under normal market conditions, is captured by the non-zero contemporaneous correlation coefficient $\text{Corr}(u_{it}, u_{jt}) = \rho_{ij}$ for all $i, j = 1, ..., N$ and $i \neq j$.[5]

The model does not require an *ad hoc* classification of the observations into crisis and non-crisis periods, the indicator $\mathcal{C}_{it}$ is instead derived from the statistical properties of the data. In particular, we consider credit events to be extreme events in the upper and lower tail of bond yield distributions. In case of sovereign entities, a credit event is usually defined *de jure* as an obligation acceleration, moratorium, or restructuring, which we may coin soft forms of default. However, Sy (2004) argues that a definition of sovereign debt crises which relies exclusively on the latter has become obsolete with the emergence of sovereign bond markets in the 1990s. A more accurate definition of debt-servicing difficulties can be obtained in terms of distress in the sovereign bond market, which is said to occur if government bond yields exceed a critical threshold that corresponds to an extreme credit event.

A formulation of the indicator $\mathcal{C}_{it}$ that accounts for extreme bond market dynamics, and which is the most consistent with the conventional definition of a financial crisis in the literature (see, for example, Eichengreen et al., 1996, and Pesaran and Pick, 2007) is given by:

$$\mathcal{C}_{it}^{1+} = \mathrm{I}\left(\sum_{j=1, j\neq i}^{N} \mathrm{I}(y_{jt} - \tau_j > 0)\right), \quad \text{and} \quad \mathcal{C}_{it}^{1-} = \mathrm{I}\left(\sum_{j=1, j\neq i}^{N} \mathrm{I}(-y_{jt} - \tau_j > 0)\right), \qquad (2)$$

where I(.) is an indicator function, and τ_j is a threshold value (where $\tau_j \in \mathcal{F}_{t-1}$). If $|y_{jt}|$ rises above this threshold, then a credit event is said to occur in country j. This crisis indicator accumulates the crisis observations across countries. Thus, under this formulation, whenever at least one of the $N-1$ remaining countries is in crisis, the

[5] With known threshold values the model in eq. (1) is a system of N simultaneous equations that is nonlinear in the endogenous variables (y_{jt}) and linear in the parameters. The primary objective of this paper is the estimation of contagion in international bond markets within this framework. Hence, for the mathematical solution of this system and the possibility of multiple equilibria we refer the reader to Pesaran and Pick (2007), who offer a detailed theoretical exposition of these issues.

turmoil in that credit market (or markets) can potentially spill over to country i.

We also consider the following indicator:

$$\mathcal{C}_{it}^{2+} = \mathrm{I}\left(\sum_{j=1, j\neq i}^{N} \mathrm{I}(y_{jt} - \tau_{jt}(\sigma_{jt}^2) > 0)\right), \tag{3}$$

and

$$\mathcal{C}_{it}^{2-} = \mathrm{I}\left(\sum_{j=1, j\neq i}^{N} \mathrm{I}(-y_{jt} - \tau_{jt}(\sigma_{jt}^2) > 0)\right), \tag{4}$$

which makes the threshold of the jth market a function of the time-varying volatility (σ_{jt}^2) of this market.

The indicators $\mathcal{C}_{it}^{1+}$ and $\mathcal{C}_{it}^{2+}$ correspond to an excessive increase, while $\mathcal{C}_{it}^{1-}$ and $\mathcal{C}_{it}^{2-}$ to an excessive drop in the rate of change of bond yields. Hence, $\mathcal{C}_{it}^{1+}$ or $\mathcal{C}_{it}^{2+}$ type credit events signal upside risks, while $\mathcal{C}_{it}^{1-}$ or $\mathcal{C}_{it}^{2-}$ represent downside risks associated with the underlying bonds. Therefore, we denote them as 'upside-risk' events, and 'downside-risk' events, respectively. Nevertheless, since financial returns typically exhibit persistence in second moments (volatility clustering), the two phenomena are essentially the two sides of the same coin.

In this canonical framework, if the conditions for the identification of the contagion coefficients are met, a test for shift-contagion in country i entails a t-test for the null hypotheses $\beta_i^+ = 0$ and $\beta_i^- = 0$, against the one-sided alternatives, $\beta_i^+ > 0$ and $\beta_i^- < 0$, respectively.

2.2. Identification and Estimation of the Model

Let $\boldsymbol{\theta}_i = (\boldsymbol{\delta}_i', \boldsymbol{\alpha}_i', \beta_i^+, \beta_i^-)'$ denote the vector of parameters. Pesaran and Pick (2007) demonstrate that without imposing further restrictions on the model, the OLS estimator is inconsistent due to the endogeneity of the crisis indicator $\mathcal{C}_{it}$. Furthermore, absent country-specific regressors (that is, if $\boldsymbol{\alpha}_i = 0$) the contagion coefficients (β_i^+ and β_i^-) are not identified. An additional complication is implied by the cross-sectional dependence in the errors. It can be shown that applying, for example, the common correlated effects estimator of Pesaran (2006), which is robust to cross-sectional error-dependence, leads to unidentified contagion coefficients. However, if there are regressors specific to country i that are correlated with $\mathcal{C}_{it}$ and uncorrelated with u_{it}, then the contagion coefficients can be consistently estimated by single-equation instrumental variable methods.

Define the vectors $\mathbf{y}_i = (y_{i1}, ..., y_{iT})'$, $\mathbf{x}_{it} = (\mathbf{g}_t', \mathbf{s}_{it}', \mathcal{C}_{it}')'$, and the matrix $\mathbf{X}_i = (\mathbf{x}_{i1}', ..., \mathbf{x}_{iT}')'$. Further, let $\mathbf{Z}_i = (\mathbf{z}_{i1}', ..., \mathbf{z}_{iT}')'$ represent the matrix of instruments. Pesaran and Pick (2007) apply the following single-equation two-stage least squares (2SLS) estimator:

$$\hat{\boldsymbol{\theta}}_i^{2SLS} = (\mathbf{X}_i'\mathbf{Z}_i\mathbf{W}_i\mathbf{Z}_i'\mathbf{X}_i)^{-1}\mathbf{X}_i'\mathbf{Z}_i\mathbf{W}_i\mathbf{Z}_i'\mathbf{y}_i, \tag{5}$$

where, with *i.i.d.* residuals, the optimal weighting matrix is $\mathbf{W}_i = (\mathbf{Z}_i'\mathbf{Z}_i)^{-1}$. However, if the errors are heteroskedastic or exhibit autocorrelation, then the weighting matrix must be adjusted as $\hat{\mathbf{W}}_i^{H2SLS} = (T^{-1}\sum_{t=1}^{T}\mathbf{z}_{it}'\hat{u}_{it}\hat{u}_{it}'\mathbf{z}_{it})^{-1}$, where $\hat{u}_{it}$ is the residual obtained from the initial consistent estimator in eq. (5), that is, $\hat{u}_{it} = y_{it} - \mathbf{x}_{it}\,\hat{\boldsymbol{\theta}}_i^{2SLS}$. Substituting this weighting matrix into eq. (5), one obtains the heteroskedasticity and autocorrelation consistent (HAC) two-stage least squares (H2SLS) estimator:

$$\hat{\boldsymbol{\theta}}_i^{H2SLS} = (\mathbf{X}_i'\mathbf{Z}_i\hat{\mathbf{W}}_i^{H2SLS}\mathbf{Z}_i'\mathbf{X}_i)^{-1}\mathbf{X}_i'\mathbf{Z}_i\hat{\mathbf{W}}_i^{H2SLS}\mathbf{Z}_i'\mathbf{y}_i. \tag{6}$$

The variance of the latter is estimated as:

$$\hat{V}(\hat{\boldsymbol{\theta}}_i^{H2SLS}) = \left(\mathbf{X}_i'\mathbf{Z}_i\left(\sum_{t=1}^{T}\mathbf{z}_{it}'\hat{\hat{u}}_{it}\hat{\hat{u}}_{it}'\mathbf{z}_{it}\right)^{-1}\mathbf{Z}_i'\mathbf{X}_i\right)^{-1}, \tag{7}$$

where $\hat{\hat{u}}_{it} = y_{it} - \mathbf{x}_{it}\,\hat{\boldsymbol{\theta}}_i^{H2SLS}$. The asymptotic standard errors are obtained as the square roots of the diagonal elements of $\hat{V}(\hat{\boldsymbol{\theta}}_i^{H2SLS})$, and standard inference applies.[6]

We use market-specific regressors of the remaining $N-1$ markets, including lagged dependent variables, to instrument the endogenous credit crisis indicator, $\mathcal{C}_{it}$. Kelejian (1971) suggests that since $\mathcal{C}_{it}$ is a nonlinear function, its approximation can be improved by using a polynomial of degree d in the instruments. Therefore, we consider the following vector of instruments:

$$\mathbf{z}_{it} = \left(\mathbf{s}_{jt}', (\mathbf{s}_{jt}^2)', ..., (\mathbf{s}_{jt}^d)'\right)'. \tag{8}$$

Three features of the model defined in eq. (1) require special attention, as pointed out by Pick (2007) and Dungey et al. (2006). First, the model is incoherent, that is, for certain values of the exogenous regressors and the error term the joint *p.d.f.* of the dependent variables conditional on the exogenous variables does not integrate to unity (in other words, there is no unique mapping from the right-hand-side variables to the left-hand-side variable). This problem does not affect the identification of the parameters of interest, however, it may affect efficiency. Second, the threshold parameter in the indicator function is not identified under the null of no contagion. Third, the model is subject to a problem of weak instruments, as shown by Dungey et al. (2006). These

[6]For a more detailed discussion see Wooldridge (2002), Section 8.3.

issues have been addressed by Pick (2007) via Monte Carlo simulations. He finds, that the effect of incoherence on efficiency is small. Furthermore, exploring different k-class estimators and various methods to choose an optimal instrument set, he concludes that the above described 2SLS estimator with using all possible instruments performs best in terms of empirical size and power. Therefore, we use the H2SLS estimator with all available instruments up to $d = 6$ in our empirical analysis.

2.3. Identification of Credit Events

The choice of the threshold τ_j is crucial for the consistent dating of a credit event, since the faulty identification of crises can result in loss of power, as shown by Dungey et al. (2006). However, the change in bond yields that signals a credit crisis is in general ambiguous.[7] Considering a credit crisis as an extreme event in the sovereign bond market, we compute an unconditional large quantile estimator of τ_j derived from Extreme Value Theory, and a conditional quantile estimator of $\tau_{jt}(\sigma^2_{jt})$ applying Value-at-Risk analysis.

2.3.1. The Extreme Value Theory Threshold

The unconditional $p.d.f.$ of financial returns typically exhibits a heavy tail feature. Extreme Value Theory (EVT) provides an approximation of the asymptotic distribution of extreme returns via the estimation of an extreme-value (or tail) index, α, or its inverse, $\gamma = 1/\alpha$, which represents the degree of probability mass in the tail. Subsequently, the corresponding large quantile can be computed, and this indicates the limit value beyond which a return becomes extreme. EVT has been extensively applied in the analysis of financial returns. For example, Hols and de Vries (1991), Danielsson and de Vries (1997), or more recently Candelon and Straetmans (2006) study extreme exchange rate volatility, whereas Bae et al. (2003), and Hartmann et al. (2004) use EVT to investigate financial crises and contagion.

Several nonparametric estimators are available, which are computed from order statistics of returns, to estimate the tail index and the corresponding unconditional large quantile (see Dekkers and de Haan, 1989, and Hols and de Vries, 1991). We opt for the tail index estimator proposed by Hill (1975) because it performs well in finite samples, as shown by Hols and de Vries (1991), and it has gained strong popularity in the literature. Let $y_{(1)} \leq y_{(2)} \leq ... \leq y_{(T)}$ be the order statistics of the bond yield sample of country i,

[7] Among the various methods to date crises, Pesaran and Pick (2007) set the threshold equal to two standard deviations of y_{jt}, Kaminsky and Reinhart (2000) compute a crisis index based on early warning variables, and Sy (2004) calculates implied probabilities of sovereign default. However, many papers date financial crises *a priori*, relying on anecdotical evidence, see, e.g., King and Wadhwani (1990), Forbes and Rigobon (2002), or Dungey and Martin (2007), to name but a few.

$y_1, ..., y_T$, where we suppress the index i for simplicity. Hill's inverse tail index estimator is defined as:

$$\hat{\gamma}_T(m) \equiv \frac{1}{\hat{\alpha}_T(m)} = \frac{1}{m}\sum_{k=1}^{m}\left(\log(y_{(T+1-k)}) - \log(y_{(T-m)})\right). \tag{9}$$

The estimator is asymptotically distributed as $\hat{\gamma}_T(m) \sim N(0, \gamma^2)$. Once γ is estimated, it can be used to determine which return level τ corresponds to a given low probability p - usually 1% or 5% - of an extreme event. Dekkers and de Haan (1989), and Hols and de Vries (1991) propose the following consistent large quantile estimator:

$$\hat{\tau}(p, T) = \frac{(m/pT)^{\hat{\gamma}_T(m)} - 1}{1 - 2^{-\hat{\gamma}_T(m)}}\left(y_{(T-m/2)} - y_{(T-m)}\right) + y_{(T-m/2)}. \tag{10}$$

The only uncertainty comes from choosing the parameter m corresponding to the mth order statistic $y_{(m)}$. Danielsson et al. (2001) propose a two-step bootstrap procedure to estimate $\hat{m}^{opt}(T)$, the asymptotically optimal cut-off parameter. The method is based on minimizing the asymptotic mean squared error (AMSE) of $\hat{\gamma}_T(m)$, where the AMSE is:

$$\text{AMSE}(T, m) = Asy\text{E}(\gamma_T(m) - \gamma)^2. \tag{11}$$

In brief, the bootstrap algorithm is as follows. Define:

$$\hat{M}_T(m) = \frac{1}{m}\sum_{k=1}^{m}\left(\log(y_{(T+1-k)}) - \log(y_{(T-m)})\right)^2. \tag{12}$$

Let $T_1 < T$, and draw from $y_1, ..., y_T$, B bootstrap samples of size T_1, and obtain the corresponding order statistics, $y^*_{(k)}$, where $k = 1, ..., T_1$. Denote by $\hat{\gamma}^*_{T_1}(m_1)$ the bootstrap Hill statistic computed from $y^*_{(k)}$ as in eq. (9). For a range of different values of m_1, calculate the bootstrap estimate of AMSE(T, m) as:

$$\widehat{\text{AMSE}}(T_1, m_1) = \text{E}\left(\left(\hat{M}^*_{T_1}(m_1) - 2(\hat{\gamma}^*_{T_1}(m_1))^2\right)^2\right). \tag{13}$$

Subsequently, obtain via grid search $\hat{m}_1^{*opt}(T_1) = \arg\min \widehat{\text{AMSE}}(T_1, m_1)$. Repeat this procedure for a resample size $T_2 < T_1$ (e.g., $T_2 = T_1^2/T$), and compute $\hat{m}_2^{*opt}(T_2) = \arg\min \widehat{\text{AMSE}}(T_2, m_2)$. The optimal cut-off parameter $\hat{m}^{opt}(T)$ is then calculated as:

$$\hat{m}^{opt}(T) = \frac{(\hat{m}_1^{*opt}(T_1))^2}{\hat{m}_2^{*opt}(T_2)}\left(\frac{\left(\log\left(\hat{m}_1^{*opt}(T_1)\right)\right)^2}{\left(2\log(T_1) - \log\left(\hat{m}_1^{*opt}(T_1)\right)\right)^2}\right)^{\frac{\log(T_1) - \log\left(\hat{m}_1^{*opt}(T_1)\right)}{\log(T_1)}}. \tag{14}$$

In this procedure T_1 is chosen to minimize $R(T_1) = (\widehat{\text{AMSE}}(T_1, m_1^{*opt}))^2/\widehat{\text{AMSE}}(T_2, m_2^{*opt})$, while in the applications we set the bootstrap sample size to $B = 1000$.

Finally, substituting eq. (14) into eq. (9), the optimal inverse tail index estimator is $\hat{\gamma}_T(\hat{m}^{opt}(T))$, and this is subsequently used to compute the EVT crisis threshold in eq. (10).

The consistency of the Hill estimator for dependent data has been established by Hsing (1991). Furthermore, Danielsson et al. (2001) investigate the finite sample performance of the estimators $\hat{\gamma}_T(m)$ and $\hat{m}^{opt}(T)$ for processes with MA(1) and ARCH(1) dependence, and the estimators perform reasonably well in terms of bias and RMSE, even though the latter are somewhat higher in small samples.

2.3.2. The Value-at-Risk Threshold

The Value-at-Risk (VaR) of an asset portfolio is essentially a p-percent quantile of the conditional distribution of returns earned on this portfolio. VaR analysis has been promoted forcefully by the Bank of International Settlements, and has been adopted by large financial institutions as a standard to evaluate the risks of loss associated with their assets. At the same time, VaR has spurred a large methodological literature (see, for instance, Christoffersen et al., 2001, and Berkowitz and O'Brien, 2002). Without loss of generality, we opt for the most common parametric VaR method.

Let the bond yield process in eq. (1) for country i be expressed as:

$$y_{it} = \mu_{it} + u_{it}, \tag{15}$$

where μ_{it} denotes the conditional mean of this process, and u_{it} is defined as earlier. The VaR for a long position in government bonds over the time horizon t with coverage probability p is defined as the conditional quantile $VaR_{it|t-1}(p)$, where:

$$Pr(y_{it} < VaR_{it|t-1}(p)|\mathcal{F}_{t-1}) = p. \tag{16}$$

We assume that the conditional variance of the bond yield follows a Gaussian GARCH(1,1) process:

$$\sigma_{it}^2 = \omega_i + \gamma_i u_{it-1}^2 + \kappa_i \sigma_{it-1}^2, \tag{17}$$

where $u_{it} = \sigma_{it} v_{it}$ ($v_{it} \sim i.i.d.N(0,1)$), $\omega_i > 0$, $\gamma_i, \kappa_i \geq 0$. The one-step-ahead p percent conditional quantile (i.e., the VaR crisis threshold) is:

$$\tau_{it}(\sigma_{it}^2) \equiv VaR_{it|t-1}(p) = \mu_{it} + \Phi^{-1}(p)\sigma_{it}, \tag{18}$$

where $\Phi^{-1}(p)$ denotes the pth quantile of the standard normal distribution.

Nevertheless, if we assume that the true data generating process is eq. (1) with the endogenous crisis thresholds $\mathcal{C}_{it}^{2+}$ and $\mathcal{C}_{it}^{2-}$, and we attempt to estimate eq. (15) using conventional methods, then, due to the identification problems discussed earlier, the conditional mean equation for μ_{it} will be misspecified. To overcome this difficulty, we follow Lumsdaine and Ng (1999), who propose a robust two-step procedure to tackle the problem of a misspecified mean, which is based on minimizing the bias due to general forms of misspecification.

In the first step, we perform recursive estimation of y_{it} on the observed variables $\mathbf{g}_t$ and $\mathbf{s}_{it}$ from the $(h+1)^{th}$ observation over the remaining $T-h$ observations for some predetermined h, and we obtain the recursive residuals $\hat{\varepsilon}_{it} = y_{it} - (\mathbf{g}_t^{'}, \mathbf{s}_{it}^{'})^{'}\hat{\boldsymbol{\eta}}_{it-1}$. If the mean equation is misspecified, $\hat{\varepsilon}_{it}$ conveys information about the true conditional mean. Therefore, in the second step we estimate:

$$y_{it} = (\mathbf{g}_t^{'}, \mathbf{s}_{it}^{'})^{'}\boldsymbol{\eta}_i + f(\hat{\varepsilon}_{it-1}) + \epsilon_{it}, \tag{19}$$

where, since the crisis indicator is a nonlinear function, we define $f(\hat{\varepsilon}_{it-1}) = \varphi_{i1}\hat{\varepsilon}_{it-1} + \varphi_{i2}\hat{\varepsilon}_{it-1}^2$. The residuals of the latter regression, ϵ_{it}, are robust to misspecification in the conditional mean, and can be used to compute the VaR measure defined earlier.

Notice, that under the VaR formulation of the crisis indicator, the threshold $\tau_{jt}(\sigma_{jt}^2)$ is still conditional on the $t-1$ information set, $\mathcal{F}_{t-1}$. Therefore, the identification and estimation results established in Section 2.2 and in Pesaran and Pick (2007) readily carry over to this specification.

3. Empirical Results

3.1. The Data

In the empirical analysis, we use time series for 18 advanced economies retrieved from Datastream. The data set forms a balanced panel from May 1, 2000 to September 1, 2010. The countries included in the sample are: Australia, Austria, Belgium, Canada, Czech Republic, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, United Kingdom, and the United States. We take the yields on ten-year benchmark government bonds of each country as our dependent variable. The global observed common factors are the U.S. federal funds rate and the yield spread, the latter is calculated as the difference between 3-months yields on Moody's AAA-rated corporate bonds and U.S. Treasury bills. The country specific factors that capture local financial market conditions are the Datastream-calculated price indices of the (total) stock market

of each country expressed in euros, and lagged dependent variables are included to control for country-specific dynamics.

U.S. short-run interest rates are considered as a good candidate to encompass global macroeconomic developments and the associated inflation, liquidity, and credit risks (see, e.g., Forbes and Rigobon, 2002, and Dungey et al., 2005). It is also well-known that leading indicators of the business cycle, such as yield spreads, have some predictive power for financial returns (see, e.g., Fama and French, 1989). Furthermore, the inclusion of country-specific stock market indices can be motivated on two grounds. First, it has been argued in a multitude of papers, including Hartmann et al. (2004), Pavlova and Rigobon (2007), and Dungey et al. (2007), that contagion should not be studied by considering markets in isolation, as there are interaction effects across different asset classes. Second, the typical investment universe of large institutional investors is mainly comprised of stocks and bonds, hence we can control for wealth and substitution effects within such portfolios.

In theory, the U.S. federal funds rate reacts in response to business cycle fluctuations with the aim to smooth the cycle. Its change feeds through the U.S. yield curve to longer maturities, and affects global demand and portfolio decisions (since the USD is the most widely held reserve currency). Thus, an increasing federal funds rate, which signals a monetary tightening in the U.S., should lead to *ceteris paribus* higher long-maturity sovereign bond yields worldwide. Similarly, a widening of the U.S. yield spread, which anticipates a business cycle downturn, should lead to an increase in the perceived riskiness of long term government bonds and a corresponding rise in sovereign bond yields.

The stock market index reflects financial market conditions and general investor sentiment in a particular country. There are various channels of market interaction between stocks and bonds. First, when the expected returns on domestic stocks relative to bonds change, investors may substitute stocks and bonds in their portfolio (domestic substitution effect). Second, in forward-looking financial markets, the evolution of stock prices may be a leading indicator of the business cycle (domestic expectations effect). These two effects suggest a positive relation: higher stock market returns are expected to result in *ceteris paribus* higher long term government bond yields. On the other hand, when the stock market is booming and investors are bullish, the willingness of international risk-taking increases, and if domestic and foreign assets are imperfect substitutes, then international risk-premiums decline along the lines of modern portfolio theory (international substitution effect). Besides, with an increase in the wealth of investors, they may invest in stocks and bonds in similar proportions (international wealth effect). These two effects suggest an inverse relation: a booming stock market should lead to *ceteris paribus*

lower long-maturity yields.

3.2. Preliminary Analysis

Since high-frequency financial data are often subject to market microstructure noise, we compute five-day non-overlapping weekly averages of the daily data.[8]

Figure 1 depicts the 10-year government bond yields of the countries that came under the most severe pressure during the spring 2010 bond market debacle (notably, Greece, Ireland, Italy, Portugal, and Spain), and the yields on the German benchmark bond which usually acts as a safe haven for panicking investors.

[Insert Figure 1 here]

The figure discloses a sharp divergence in bond yield dynamics that began at the height of the global credit crisis in 2008. In particular, the yields on Greek bonds have skyrocketed towards an unusually high peak, followed by the other countries under strains, while there has been a flight-to-quality to the bonds issued by the German government. It can thus be induced that the uncertainties related to the sustainability of government fiscal balance are clearly echoed in the response of sovereign bond markets.

Table 1 presents the contemporaneous correlation matrix of the changes in sovereign bond yields.

[Insert Table 1 here]

The correlations amongst developed sovereign debt markets reveal several patterns. First, the strongest correlations are observed between the core countries of the eurozone. This suggests that the monetary union formed by these countries is grounded on strongly synchronized financial markets. Second, Greece constitutes an exception to these remarkably high figures, which is most likely attributable to the recent divergence of its bond market from the German benchmark (and from the remainder of the core EMU countries), as depicted in Figure 1. Third, the contemporaneous links between all developed countries and the Czech Republic seem to be at best moderate, which may signal a time-varying exchange risk premium demanded by foreign investors in the Czech market. Fourth, and not surprisingly, the correlation pattern for Canada and the U.S. fits in well with the

[8] Another alternative followed by Forbes and Rigobon (2002) and Bekaert et al. (2005) would be to compute two-day rolling returns. However, this filtering is likely to generate artificial serial dependence in the data. On the other hand, we restrain ourselves from using low-frequency data because the EVT and VaR methods described earlier require relatively large T. Moreover, as financial markets typically adjust to shocks upon impact, sampling more sparsely may result in the loss of substantial information because contagion is an inherently high-frequency phenomenon.

core countries of the euro area. Finally, the low cross-correlation of the Japanese bond yields with the remainder of the sample should not come as a surprise since the Japanese economy has undergone a decade of corporate balance-sheet consolidation during which the market was less responsive to financial impulses. To conclude, Table 1 provides evidence for substantial cross-country interdependence, which justifies the relevance of the canonical contagion model.

3.3. Model Specification

Based on conventional unit root tests (omitted here, but available upon request from the author), we cannot reject the hypotheses that the variables in levels have a unit root at the 5% significance level, whereas the changes are covariance-stationary. Therefore, we estimate our model on percentage changes of yields which are computed as $y_{it} = (Y_{it} - Y_{it-1})/Y_{it-1}$, where Y_{it} is the sovereign bond yield of country i in period t. We compute the change of the federal funds rate (g_t^{FFR}) and the U.S. yield spread (g_t^{YSP}) analogously. The returns on the stock market index (s_{it}^{SMI}) are given by the log-difference of the series.

We compute the 5% and 95% unconditional as well as conditional quantile estimators (EVT and VaR thresholds) on the weekly series. To ensure comparability of the results across the models, we perform all estimations from the 2nd week of December, 2001 to the 4th week of August, 2010, thus $N = 18$ and $T = 437$. To establish the robustness of our results to the way credit crises are defined, we present the estimation results with the EVT thresholds, the VaR thresholds, and the thresholds set at two standard deviations of the bond yield changes (in accordance with Pesaran and Pick, 2007). Figures 2-4 provide a visual representation of these three crisis dating methods.

[Insert Figures 2-4 here]

While the VaR thresholds can naturally accommodate volatility clusters, Figures 2-4 reveal the strong sample dependence of the other two methods, which is a clear weakness compared to the VaR method. The EVT and two-standard-deviations thresholds for the full sample are reported in Table 2.

[Insert Table 2 here]

The estimated EVT and two-standard-deviations thresholds closely resemble each other, although the EVT method captures the leverage effect inherent in financial time series, hence the asymmetry of the upside- and downside-risk EVT thresholds.

In order to ensure the exogeneity of the regressors, we estimate the model on the first lag of the change of the federal funds rate, the yield spread, and the stock market returns, and we allow for country-specific lags in the bond yield changes. We select the optimal autoregressive lag for each country based on the conventional Schwarz (SIC), Akaike (AIC), and Hannan-Quinn (HQIC) criteria, the results are given in Table 3.

[Insert Table 3 here]

3.4. Estimation Results

The estimation results with the EVT crisis indicator $\mathcal{C}_{it}^1$, the VaR crisis indicator $\mathcal{C}_{it}^2$, and with the two-standard-deviations indicator are presented in Tables 4-6.[9]

[Insert Tables 4-6 here]

We reject the null hypothesis of 'no shift-contagion' in case of the upside-risk, as well as the downside-risk credit events for all countries at the 5% significance level. This result is crucial, as it signals that even countries with a consolidated fiscal position (among others, Australia or Norway) are exposed to the external risk of contagion during periods of market turbulence. The estimated contagion effects are remarkably robust and differ only marginally across the three definitions of credit crises. Hence, the model appears to capture a fundamental feature present in the data generating process. The message conveyed in this outcome is clear: at times of stress, the cross-country linkages among bond markets change significantly with respect to calm periods due to extraneous factors beyond the fundamental channels of interdependence. Since these changes may be traced back to shifts between multiple equilibria fueled by self-fulfilling beliefs, it is in the individual best interest of each country to act in concert with others in order to reassure international investors of the commitment to a balanced fiscal path.

Most countries respond significantly to changes of the U.S. federal funds rate: rising U.S. short-run interest rates increase bond yields (with the exception of Czech Republic, Norway, and Portugal, depending on the model specification). Similarly, there is a significant and positive response worldwide to the widening of the U.S. yield spread. Local stock market indices have a significant impact on bond markets for most countries, and a surge in stock markets leads consistently to a decline in bond yields. This suggests that the strongest channels of stock and bond market interaction are the international substitution and wealth effects generated by the large fraction of international investors

[9] To preserve a compact representation of the results, we report them only up to the first lag of the dependent variable.

active in the market. In summary, these findings serve as evidence for strong observed macroeconomic interdependence which results from a high degree of developed capital market integration.

We also report the crisis frequencies, which correspond to the ratio between the number of crisis and non-crisis observations for each country.[10] These figures reveal that the EVT and the two-standard-deviations indicators are conservative measures of credit crises. In particular, the EVT indicator appears to be undersized in most cases. We acknowledge that this deficiency may be due to the finite sample performance of the estimators proposed by Danielsson et al. (2001) for our moderate T. In contrast, the VaR indicator attains an empirical size that is close to the 5% nominal size, although in some cases it tends to be oversized because, unlike the EVT indicator, it is not suited for accommodating the asymmetries of the leverage effect.

3.5. Robustness

We perform a series of diagnostic tests to guard against model misspecification, including the Cragg-Donald test statistic for weak instruments (see Cragg and Donald, 1993), residual serial correlation LM tests, and the modified Tsay (1986) test on the residuals for the null of linearity, which has power against a wide range of nonlinearities (see Harvill and Ray, 1999). Furthermore, to assess the structural stability of the canonical model, we split the sample into two periods of equal length at the 3rd week of April, 2006, and perform the estimations on the two sub-samples.

The model diagnostic tests are given in Table 7.

[Insert Table 7 here]

In order to assess the weak instrument problem documented by Dungey et al. (2006) and Pick (2007), Table 7 reports the Cragg-Donald statistic. The null hypothesis of weak instruments cannot be rejected at the 5% level for all countries and model specifications, based on the critical values with two endogenous regressors tabulated by Stock and Yogo (2005). This result indicates that the statistical significance of the contagion coefficients should be regarded with some caution, although it is in accordance with the empirical findings of Pesaran and Pick (2007) and Pick (2007). However, we do not modify our instrument set because all available instruments ensure the best empirical size and power (see Pick, 2007). Upon inspection of the serial correlation LM tests computed with 5 and 10 lags, we find that residual autocorrelation is eliminated with all model specifications in

[10] Note that this ratio does not necessarily coincide with the ratio of ones to zeros in $\mathcal{C}_{it}^1$ and $\mathcal{C}_{it}^2$, since the latter dummies accumulate the number of crises observed across countries.

the majority of the countries, in particular, the VaR model performs best while the two-standard-deviations model performs worst in this respect. This result can be presumably attributed to the low empirical size achieved by the crisis indicators used in the EVT and two-standard-deviations models, and the residual autocorrelation may reflect the omitted crisis periods that were successfully detected with the VaR specification. These results suggest that the use of the HAC estimator is justified.

Turning to the evaluation of structural stability, we cannot reject the null of linearity of the Tsay test at the 5% level for all countries and specifications, which provides strong evidence for residual stability. The sub-sample results are reported in the Appendix, in Tables A1-A3, and the corresponding sub-sample thresholds are given in Table A4. Even though there is some moderate variation of the crisis frequencies as well as the crisis thresholds across the two sub-samples, the estimated coefficients reinforce the evidence on the structural stability of our results across the sub-samples, as they do not show any major discrepancies with the full sample estimates. Moreover, the tables reveal an interesting pattern of the global factors: in the first sub-sample the federal funds rate exerts a strong negative, while in the second a strong positive effect on the bond yields of several countries, including the United Kingdom and the United States. This finding corroborates the idea that the U.S. monetary policy was pro-cyclical in the first half of the decade.

We may conclude that the three crisis indicators perform similarly. However, we favor the volatility-based VaR crisis indicator because it yields independently distributed crisis observations, and it is therefore more reliable in dating credit crises independently of the sample choice (see Figures 2-4). Hence, overall the VaR model specification provides the best model.

Nevertheless, some comments are in order with respect to potentially omitted variables. First, it may be desirable to include macro-fundamentals (e.g., industrial production or inflation) and fiscal variables (for example, debt-to-GDP or deficit-to-GDP ratios, or net interest payments as a percentage of GDP). However, macroeconomic variables are usually observed at low frequencies, and since financial markets are forward-looking and lead the real economy in the short-run, real variables exert their influence on the long-run component of financial market volatility (see Fama and French, 1989, and Engle and Rangel, 2008). Therefore, the potential added value of these variables in our analysis appears to be ambiguous. Second, another set of potentially omitted variables consists of news and announcements related to long-term credit outlook. For example, fiscal policy decisions or credit rating changes. Indeed, a large body of literature has focused on the effects of a sovereign credit rating change of one country on the sovereign credit spreads

of other countries, and typically the effects are asymmetric: rating downgrades can be associated with an increase in spreads, while the effect of upgrades is less pronounced (see Gande and Parsley, 2005).

4. Concluding Remarks

The main contribution of this paper to the growing literature on financial contagion is twofold. First, implementing a heteroskedasticity-robust version of a well-established nonlinear simultaneous equations model of contagion, it provides statistical evidence that developed countries are subject to a severe risk of contagion whenever a credit crisis is unfolding in another country or a group of countries. The message conveyed in this outcome is clear: at times of stress, governments need to act in concert in order to reassure the markets of their commitment to a balanced fiscal path. Second, two new crisis indicators are proposed, one that takes into account extreme features, and another which is a function of the time-varying volatility in the credit market. These indicators are inherited from the Value-at-Risk literature, hence they are easy to implement and their statistical properties are well-established.

The empirical analysis unravels a strong interdependence between developed sovereign credit markets. In advanced economies, the yields on long-maturity government bonds respond overwhelmingly positively to monetary tightening in the U.S., and there are strong contemporaneous links across core euro area bond markets. Furthermore, a booming local stock market typically translates into *ceteris paribus* lower long term yields, which signals that the channels of interaction between stock and bond markets are dominated by international substitution and wealth effects, rather than domestic portfolio-rebalancing or expectations on the country-specific business cycle. In summary, these findings provide evidence for a high degree of developed capital market integration over the analyzed period.

Developed economies are facing complex difficulties, as they have suffered large fiscal costs in the aftermath of the 2007-2009 global financial crisis. Their cyclically adjusted fiscal balances dropped from around zero in 2007 to around minus four percent of GDP by the first half of 2009. Besides, a sharp decline in potential GDP and sizable bank rescue packages are likely to constrain the scope of fiscal consolidation over the coming years. Due to the costs of the welfare state combined with aging populations, developed countries could also be facing increasing risks to long-run debt sustainability if they fail to undertake structural reforms, particularly in their pension and healthcare systems.

Following the Mediterranean credit crisis, an international policy debate has emerged on the future of European fiscal policy, involving the European Central Bank, the Inter-

national Monetary Fund, and the national governments. As a result, several proposals have been advanced on a new mechanism of credit crisis management. A sovereign entity can in principle always alleviate its debt burden by raising taxes, which renders *de facto* sovereign defaults a mere theoretical possibility. In spite of this, our findings convey considerable policy implications in terms of sovereign debt management. The main conclusion is that even countries with a solid fiscal position cannot avoid international bond market contagion. This external risk carries adverse effects on the financing constraints of the public as well as the corporate sector. Therefore, a strong commitment to the supranational coordination of long-term debt policies may be inevitable, and a new regional mechanism for the prevention and resolution of debt crises is expedient in the near future.

References

[1] Allen, F., Gale, D., 2000. Financial contagion. *Journal of Political Economy* 108(1), 1-33.

[2] Ang, A., Bekaert, G., 2002. International asset allocation with regime shifts. *Review of Financial Studies* 15 (4), 1137-1187.

[3] Bae, K.-H., Karolyi, A.G., Stulz, R.M., 2003. A new approach to measuring financial contagion. *Review of Financial Studies* 16(3), 717-763.

[4] Baele, L., 2005. Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis* 40(2), 373-401.

[5] Bekaert, G., Harvey, C.R., Ng, A., 2005. Market integration and contagion. *Journal of Business* 78(1), 39-69.

[6] Berkowitz, J., O'Brien, J., 2002. How accurate are value-at-risk models at commercial banks? *Journal of Finance* 57, 1093-1111.

[7] Cragg, J.G., Donald, S.G., 1993. Testing idendifiability and specification in instrumental variable models, *Econometric Theory* 9(2), 222-240.

[8] Bruinshoofd, A., Candelon, B., Raabe, K. 2010. Banking sector fragility and the transmission of currency crises, *Open Economies Review* 21(2), 364-384.

[9] Candelon, B., Hecq, A., Verschoor, W.F.C., 2005. Measuring common cyclical features during financial turmoil: Evidence of interdependence not contagion. *Journal of International Money and Finance* 24, 1317-1334.

[10] Candelon, B., Manner, H., 2010. Testing for contagion: A new time-varying copula approach. *Pacific Economic Review* 15(3), 364-384.

[11] Candelon, B., Straetmans, S., 2006. Testing for multiple regimes in the tail behavior of emerging currency returns. *Journal of International Money and Finance* 25, 1187-1205.

[12] Cheung, Y.-W., Ng, L. K., 1996. A causality-in-variance test and its application to financial market prices. *Journal of Econometrics* 72, 33-48.

[13] Christoffersen, P., Hahn, J., Inoue, A., 2001. Testing and comparing value-at-risk measures. *Journal of Empirical Finance* 8(3), 325-342.

[14] Claessens S., Forbes, K. (Eds.), 2001, *International financial contagion.* Kluwer Academic Publishers: Boston, MA.

[15] Corsetti, G., Pericoli, M., Sbracia, M., 2005. 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance* 24, 1177-1199.

[16] Danielsson, J., de Vries, C.G., 1997. Tail index and quantile estimation with very high frequency data. *Journal of Empirical Finance* 4 241-257.

[17] Danielsson, J., de Haan, L., Peng, L., de Vries, C.G., 2001. Using a bootstrap method to choose the sample fraction in tail index estimation. *Journal of Multivariate Analysis* 76, 226-248.

[18] Dekkers, A.L.M., de Haan, L., 1989. On the estimation of the extreme-value index and large quantile estimation. *Annals of Statistics*, 17(4), 1795-1832.

[19] Diebold, F. X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119, 158 - 171.

[20] Dungey, M., Fry, R., Gonzalez-Hermosillo, B., Martin V. L., 2005. Empirical modelling of contagion: A review of methodologies. *Quantitative Finance* 5(1), 9-24.

[21] Dungey, M., Fry, R., Gonzalez-Hermosillo, B., Martin V. L., 2006. Sampling Properties of Contagion Tests. Working Paper.

[22] Dungey, M., Martin, V. L., 2007. Unraveling financial market linkages during crises. *Journal of Applied Econometrics* 22, 89-119.

[23] Eichengreen, B., Rose, A., Wyplosz, C., 1996. Contagious currency crises: First tests. *The Scandinavian Journal of Economics* 98(4), 463-484.

[24] Engle, R.F., Ito, T., Lin, W.-L., 1990. Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica* 58(3), 525-542.

[25] Engle, R.F., Rangel, J.G., 2008. The Spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies* 21(3), 1187-1222.

[26] Fama, E. F., French, K. R., 1989. Business cycle conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25, 23-49.

[27] Favero, C. A., Giavazzi, F., 2002. Is the international propagation of financial shocks non-linear? Evidence from the ERM. *Journal of International Economics* 57, 231-246.

[28] Forbes, K. J., Rigobon, R., 2001. Contagion in Latin America: Definitions, measurement, and policy implications. *Economia* 1(2), 1-46.

[29] Forbes, K. J., Rigobon, R., 2002. No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance* 57(5), 2223-2261.

[30] Gallo, G., Otranto, E., 2008. Volatility spillovers, interdependence and comovements: A Markov Switching approach. *Computational Statistics and Data Analysis* 52, 3011-3026.

[31] Gande, A., Parsley, D. C., 2005. News spillovers in the sovereign debt market. *Journal of Financial Economics* 75, 691-734.

[32] Glick, R., Rose, A.K., 1999. Contagion and trade: Why are currency crises regional? *Journal of International Money and Finance* 18(4), 603-617.

[33] Hartmann P., Straetmans S., de Vries C.G., 2004. Asset market linkages in crisis periods. *Review of Economics and Statistics* 86, 313-326.

[34] Harvill, J.L., Ray, B.K., 1999. A note on tests for nonlinearity in a vector time series. *Biometrika* 86(3), 728-734.

[35] Hill, B.M., 1975. A simple general approach to inference about the tail of a distribution. *Annals of Statistics* 3(5), 1163-1174.

[36] Hols, M.C.A.B., de Vries, C.G., 1991. The limiting distribution of extremal exchange rate returns. *Journal of Applied Econometrics* 6, 287-302.

[37] Hsing, T., 1991. On tail index estimation using dependent data. *Annals of Statistics* 19(3) 1547-1569.

[38] Kaminsky, G. L., Reinhart, C.M., 2000. On crises, contagion, and confusion. *Journal of International Economics* 51, 145-168.

[39] Kelejian, H.H., 1971. Two-stage least squares and econometric systems linear in parameters but nonlinear in the endogenous variables. *Journal of the American Statistical Association* 66(334), 373-374.

[40] King, M., Wadhwani, S., 1990. Transmission of volatility between stock markets. *Review of Financial Studies* 3(1), 5-33.

[41] Kodres, L.E., Pritsker, M., 2002. A rational expectations model of financial contagion. *Journal of Finance* 57(2), 769-799.

[42] Lumsdaine, R.L., Ng, S., 1999. Testing for ARCH in the presence of a possibly misspecified conditional mean. *Journal of Econometrics* 93, 257-279.

[43] Masson, P., 1999. Contagion: Macroeconomic models with multiple equilibria. *Journal of International Money and Finance* 18, 587-602.

[44] Pavlova, A., Rigobon, R. 2007. Asset prices and exchange rates. *Review of Financial Studies* 20(4), 1139-1181.

[45] Pericoli, M., Sbracia, M., 2003. A primer on financial contagion. *Journal of Economic Surveys* 17(4), 571-608.

[46] Pesaran, M.H., 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* 74 (4), 967-1012.

[47] Pesaran, M.H., Pick, A., 2007. Econometric issues in the analysis of contagion. *Journal of Economic Dynamics and Control* 31, 1245-1277.

[48] Pick, A., 2007. Financial contagion and tests using instrumental variables. Working Paper No. 139, De Nederlandsche Bank.

[49] Rodriguez, J.C., 2007. Measuring financial contagion: A Copula approach *Journal of Empirical Finance* 14, 401-423.

[50] Stock, J.H., Yogo, M., 2005. Testing for weak instruments in linear IV regressions. In: Andrews, D.W.K., Stock, J.H. (Eds.), *Identification for econometric models: Essays in the honor of Thomas Rothenberg*. Cambridge University Press, Cambridge, 80-108.

[51] Sy, A.N.R., 2004. Rating the rating agencies: Anticipating currency crises or debt crises? *Journal of Banking and Finance* 28, 28452867.

[52] Tsay, R.S., 1986. Nonlinearity tests for time series. *Biometrika* 73, 461-466.

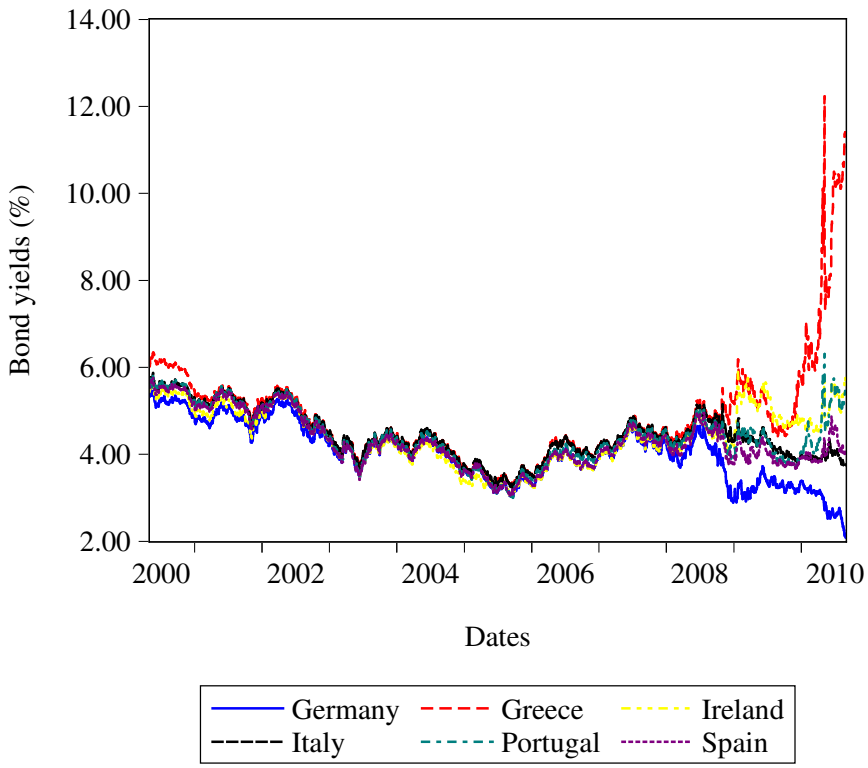
[53] Van Rijckeghem, C., Weder, B., 2001. Sources of contagion: Is it finance or trade? *Journal of International Economics* 54, 293-308.

[54] Wooldridge, J. M., 2002. *Econometric analysis of cross section and panel data*. MIT Press: Cambridge, MA.

Appendix

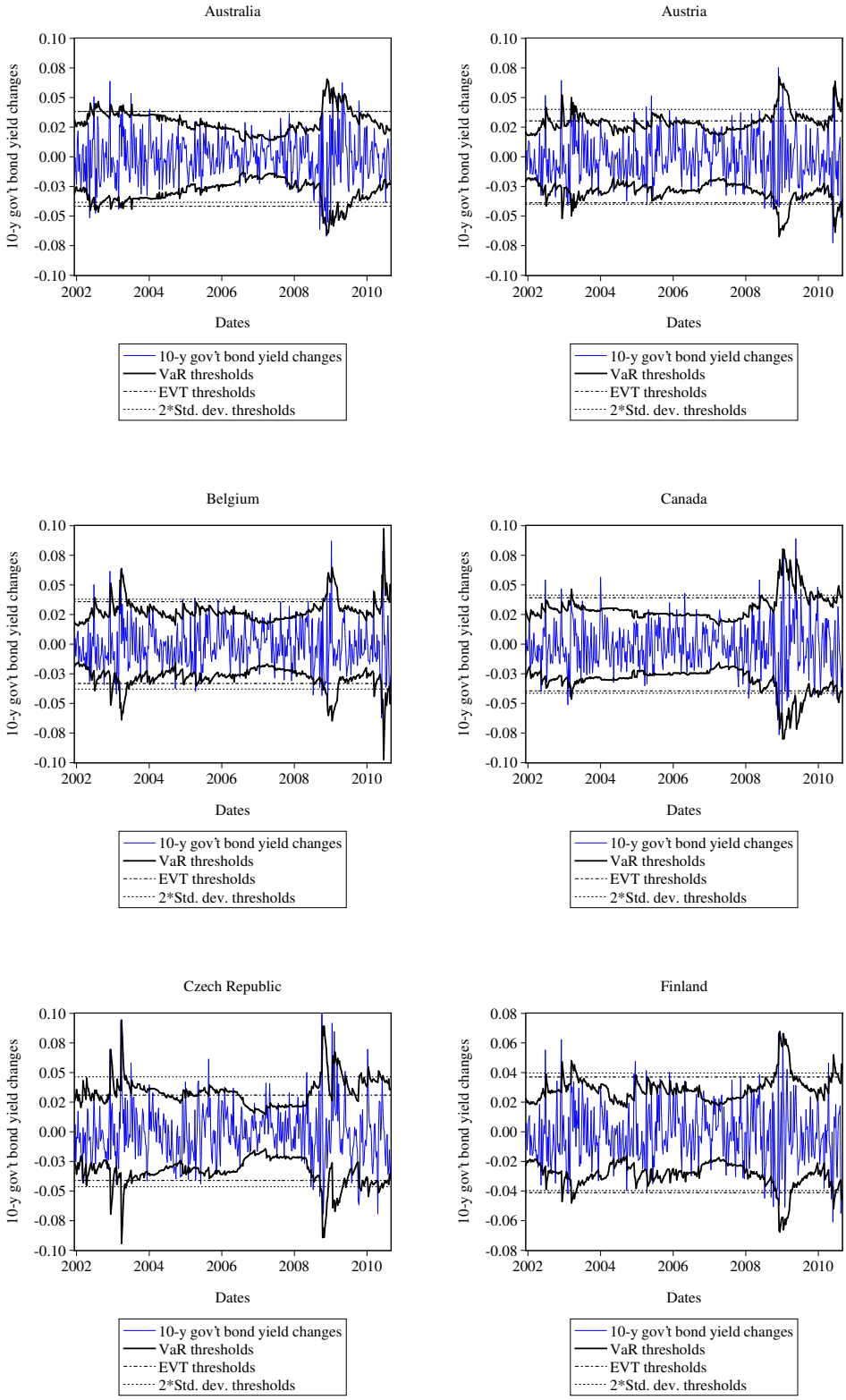
[Insert Tables A1-A4 here]

Figure 1: 10-year government bond yields of selected countries (expressed in %)



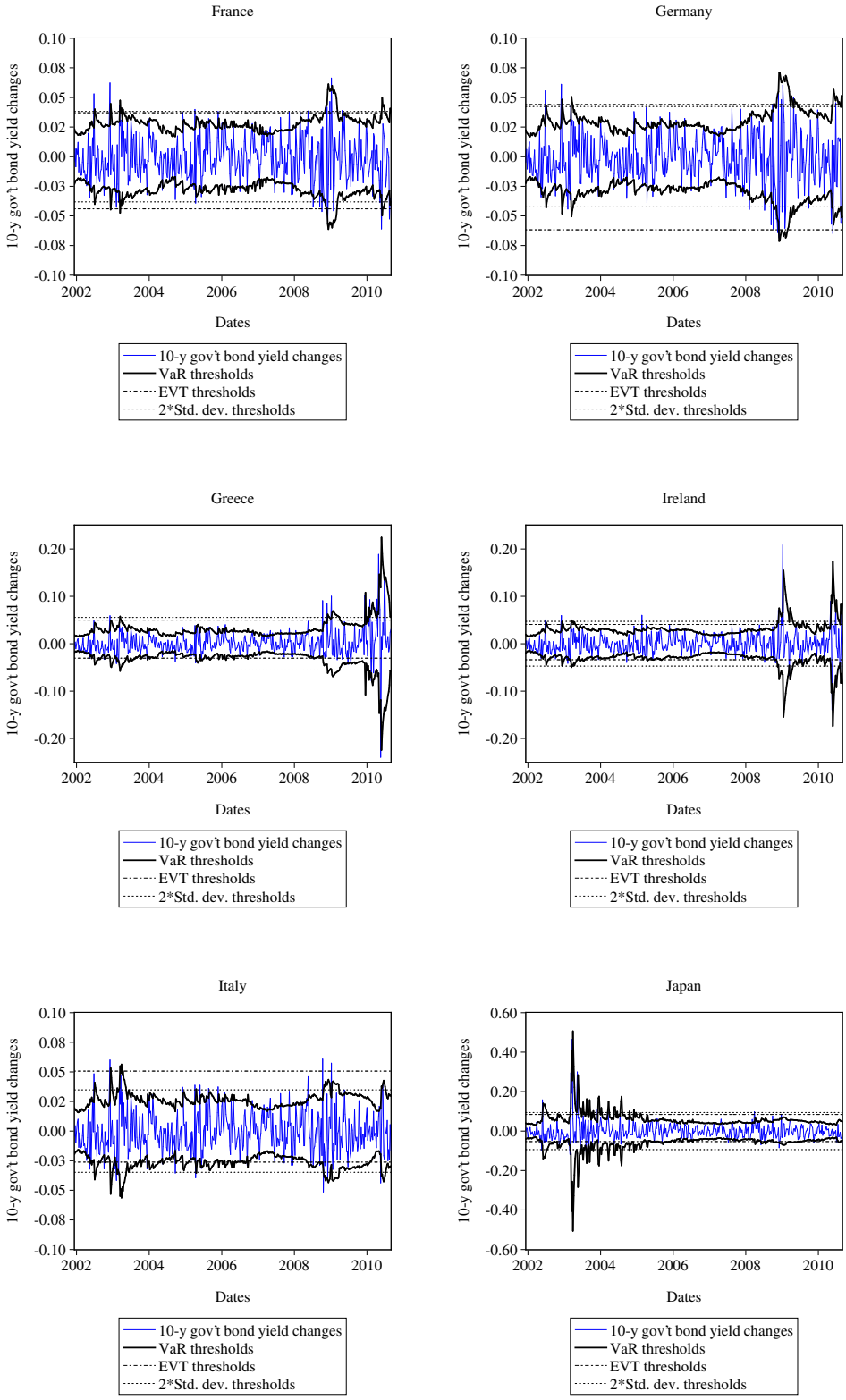
Note: 10-year maturity benchmark government bond yields of selected countries at daily frequency. Sample: May 1, 2000 – September 1, 2010.

Figure 2: Crisis thresholds



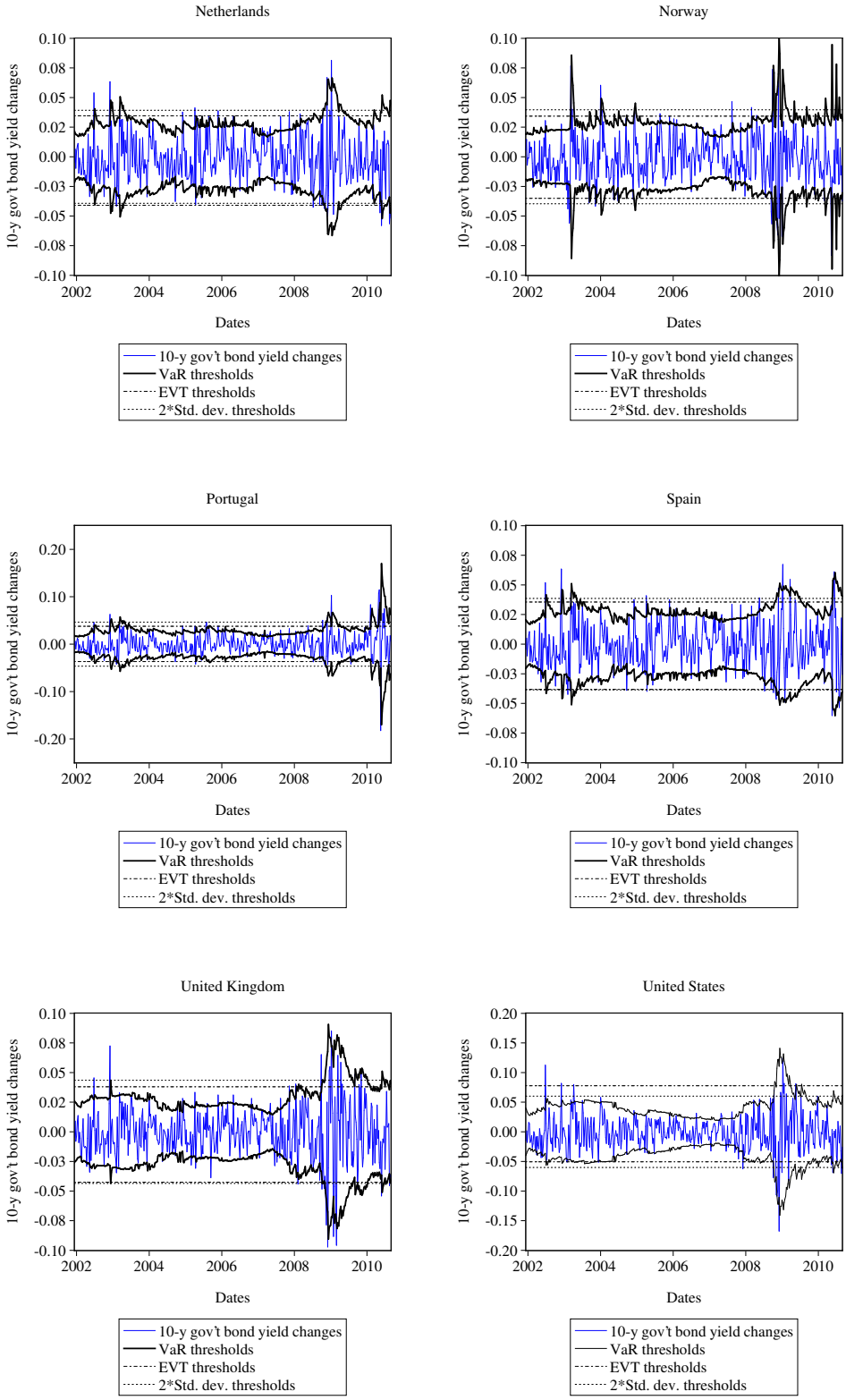
Note: Crisis thresholds computed with the EVT, VaR, and two-standard-deviations methods.

Figure 3: Crisis thresholds - *continued*



Note: Crisis thresholds computed with the EVT, VaR, and two-standard-deviations methods.

Figure 4: Crisis thresholds - *continued*



Note: Crisis thresholds computed with the EVT, VaR, and two-standard-deviations methods.

Table 1: Correlation matrix of sovereign bond yield changes

Countries	Aus	Aut	Bel	Can	CzR	Fin	Fra	Ger	Gre	Ire	Ita	Jap	Net	Nor	Por	Spa	UK	US
Australia	1	0.68	0.67	0.75	0.28	0.72	0.74	0.75	0.36	0.49	0.60	0.34	0.71	0.58	0.50	0.60	0.68	0.75
Austria	–	1	0.92	0.68	0.42	0.92	0.94	0.88	0.53	0.69	0.82	0.37	0.92	0.67	0.68	0.81	0.71	0.72
Belgium	–	–	1	0.67	0.42	0.89	0.94	0.86	0.56	0.75	0.87	0.39	0.93	0.65	0.73	0.83	0.71	0.70
Canada	–	–	–	1	0.27	0.71	0.73	0.75	0.31	0.45	0.59	0.36	0.71	0.56	0.47	0.59	0.71	0.84
Czech Republic	–	–	–	–	1	0.39	0.41	0.36	0.27	0.35	0.46	0.24	0.41	0.35	0.39	0.45	0.28	0.30
Finland	–	–	–	–	–	1	0.96	0.94	0.49	0.67	0.80	0.40	0.95	0.70	0.65	0.78	0.75	0.74
France	–	–	–	–	–	–	1	0.95	0.49	0.70	0.84	0.39	0.96	0.72	0.67	0.82	0.78	0.76
Germany	–	–	–	–	–	–	–	1	0.41	0.60	0.75	0.40	0.94	0.74	0.58	0.76	0.81	0.78
Greece	–	–	–	–	–	–	–	–	1	0.75	0.64	0.17	0.50	0.34	0.85	0.66	0.34	0.32
Ireland	–	–	–	–	–	–	–	–	–	1	0.78	0.26	0.69	0.45	0.87	0.81	0.50	0.50
Italy	–	–	–	–	–	–	–	–	–	–	1	0.35	0.84	0.60	0.78	0.87	0.61	0.63
Japan	–	–	–	–	–	–	–	–	–	–	–	1	0.39	0.37	0.27	0.35	0.34	0.35
Netherlands	–	–	–	–	–	–	–	–	–	–	–	–	1	0.69	0.67	0.82	0.77	0.74
Norway	–	–	–	–	–	–	–	–	–	–	–	–	–	1	0.46	0.58	0.56	0.59
Portugal	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1	0.82	0.50	0.49
Spain	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1	0.67	0.61
United Kingdom	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1	0.73
United States	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1

Note: Contemporaneous correlation matrix of sovereign bond yield changes. The asymptotic standard error is $T^{-1/2} = 437^{-1/2} = 0.0478$.

Table 2: Crisis thresholds

Sample countries	**Estimated thresholds**		
	$\hat{\tau}_i^{EVT+}$	$\hat{\tau}_i^{EVT-}$	$\hat{\tau}_i^{2std}$
Australia	0.0382	0.0418	0.0397
Austria	0.0303	0.0389	0.0386
Belgium	0.0358	0.0333	0.0367
Canada	0.0391	0.0395	0.0414
Czech Republic	0.0310	0.0411	0.0462
Finland	0.0370	0.0410	0.0383
France	0.0371	0.0441	0.0370
Germany	0.0440	0.0618	0.0408
Greece	0.0500	0.0306	0.0526
Ireland	0.0407	0.0338	0.0454
Italy	0.0507	0.0263	0.0338
Japan	0.0841	0.0533	0.0914
Netherlands	0.0346	0.0409	0.0379
Norway	0.0343	0.0351	0.0383
Portugal	0.0377	0.0367	0.0445
Spain	0.0355	0.0382	0.0372
United Kingdom	0.0380	0.0426	0.0425
United States	0.0777	0.0506	0.0589

Note: Columns 2-3 report the estimated thresholds using EVT for the upside- and downside-risk credit events, respectively ($\hat{\tau}_i^{EVT+}$ and $\hat{\tau}_i^{EVT-}$), and column 4 reports 2-times the full-sample standard deviations ($\hat{\tau}_i^{2std}$).

Table 3: Autoregressive lag length selection

Sample countries	**Lag selection criteria**		
	SIC	AIC	HQIC
Australia	-7.83	-7.89	-7.86
AR lags	8	8	8
Austria	-7.90	-7.96	-7.94
AR lags	7	7	7
Belgium	-8.01	-8.08	-8.05
AR lags	1	1	1
Canada	-7.78	-7.85	-7.82
AR lags	6	6	6
Czech Republic	-7.61	-7.67	-7.65
AR lags	3	3	3
Finland	-7.92	-7.98	-7.96
AR lags	1	1	1
France	-7.99	-8.06	-8.03
AR lags	5	5	5
Germany	-7.80	-7.86	-7.83
AR lags	8	8	8
Greece	-7.33	-7.40	-7.37
AR lags	6	6	6
Ireland	-7.60	-7.66	-7.63
AR lags	7	7	7
Italy	-8.16	-8.22	-8.19
AR lags	1	1	1
Japan	-6.26	-6.32	-6.29
AR lags	8	8	8
Netherlands	-7.93	-8.00	-7.97
AR lags	1	1	1
Norway	-7.90	-7.96	-7.94
AR lags	5	5	5
Portugal	-7.66	-7.72	-7.70
AR lags	7	7	7
Spain	-7.99	-8.05	-8.03
AR lags	7	7	7
United Kingdom	-7.73	-7.80	-7.77
AR lags	8	8	8
United States	-7.07	-7.13	-7.11
AR lags	8	8	8

Note: Lag length selection of the lagged dependent variable y_{it-p}. We report the Schwarz, the Akaike, and the Hannan-Quinn information criteria ($SIC = \log \tilde{\sigma}_u^2(p) + ((\log T)/T)p$, $AIC = \log \tilde{\sigma}_u^2(p) + (2/T)p$, and $HQIC = \log \tilde{\sigma}_u^2(p) + (2(\log \log T)/T)p$, where $\tilde{\sigma}_u^2(p) = T^{-1} \sum_{t=1}^{T} u_t^2(p)$), and the corresponding autoregressive lag length (AR lags).

Table 4: Estimation results with EVT crisis indicators

Sample	**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**	
countries	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.
Australia	0.0310*	0.0132	-0.0119	0.1755*	0.0146*	-0.0143*	2.29 %	2.06 %
	(0.0040)	(0.0070)	(0.0194)	(0.0307)	(0.0014)	(0.0009)	–	–
Austria	0.0094	0.0089	-0.0607*	0.0916*	0.0148*	-0.0226*	6.41%	2.52%
	(0.0053)	(0.0094)	(0.0155)	(0.0214)	(0.0014)	(0.0013)	–	–
Belgium	0.0164*	0.0346*	0.0087	0.0736*	0.0154*	-0.0183*	2.97%	4.12%
	(0.0037)	(0.0080)	(0.0066)	(0.0185)	(0.0009)	(0.0009)	–	–
Canada	0.0275*	-0.0029	-0.0456*	0.1763*	0.0127*	-0.0161*	2.75%	3.43%
	(0.0043)	(0.0050)	(0.0170)	(0.0231)	(0.0015)	(0.0011)	–	–
Czech Republic	-0.0088*	0.0373*	-0.1464*	0.0893*	0.0110*	-0.0107*	6.86%	3.20%
	(0.0036)	(0.0120)	(0.0161)	(0.0140)	(0.0015)	(0.0008)	–	–
Finland	0.0182*	0.0297*	-0.0321*	0.0602*	0.0150*	-0.0188*	2.97%	2.75%
	(0.0060)	(0.0062)	(0.0050)	(0.0103)	(0.0012)	(0.0009)	–	–
France	0.0152*	0.0086	-0.0795*	0.1736*	0.0164*	-0.0202*	2.97%	1.37%
	(0.0048)	(0.0090)	(0.0120)	(0.0204)	(0.0012)	(0.0010)	–	–
Germany	0.0190*	0.0091	-0.1002*	0.2703*	0.0135*	-0.0185*	1.83%	0.69%
	(0.0051)	(0.0078)	(0.0172)	(0.0253)	(0.0013)	(0.0011)	–	–
Greece	0.0911*	0.1566*	0.0942*	0.4200*	0.0450*	-0.0225*	3.20%	3.43%
	(0.0010)	(0.0009)	(0.0000)	(0.0040)	(0.0004)	(0.0002)	–	–
Ireland	0.0304*	0.0258*	-0.0028*	0.0594*	0.0199*	-0.0152*	2.75%	2.97%
	(0.0062)	(0.0078)	(0.0112)	(0.0171)	(0.0012)	(0.0010)	–	–
Italy	0.0131*	0.0294*	-0.0466	0.0461*	0.0133*	-0.0139*	0.69%	5.72%
	(0.0060)	(0.0093)	(0.0104)	(0.0153)	(0.0006)	(0.0008)	–	–
Japan	0.0021	0.0568*	0.2355*	0.3893*	0.0145*	-0.0172*	2.29%	5.95%
	(0.0042)	(0.0203)	(0.0471)	(0.0413)	(0.0015)	(0.0015)	–	–
Netherlands	0.0126*	0.0414*	-0.0054	0.0254*	0.0154*	-0.0204*	2.75%	2.52%
	(0.0026)	(0.0072)	(0.0051)	(0.0038)	(0.0010)	(0.0010)	–	–
Norway	-0.0182*	0.0179*	0.0095	0.1755*	0.0115*	-0.0116*	3.20%	3.89%
	(0.0026)	(0.0084)	(0.0141)	(0.0106)	(0.0008)	(0.0008)	–	–
Portugal	0.0693*	0.1892*	-1.6130*	0.4527*	0.0748*	-0.0538*	4.12%	3.20%
	(0.0054)	(0.0054)	(0.0380)	(0.0107)	(0.0009)	(0.0013)	–	–
Spain	-0.0022	0.0210*	-0.0287*	0.0865*	0.0194*	-0.0170*	2.97%	2.97%
	(0.0052)	(0.0086)	(0.0144)	(0.0126)	(0.0009)	(0.0008)	–	–
United Kingdom	0.0388*	0.0136	-0.0033	0.1290*	0.0164*	-0.0174*	3.20%	2.97%
	(0.0030)	(0.0080)	(0.0197)	(0.0216)	(0.0009)	(0.0009)	–	–
United States	0.0286*	-0.0084	-0.0868*	0.2112*	0.0249*	-0.0260*	1.37%	2.97%
	(0.0068)	(0.0090)	(0.0312)	(0.0217)	(0.0013)	(0.0015)	–	–

Note: Estimation results of the canonical contagion model in eq. (1) with the EVT crisis thresholds. g_{t-1}^{FFR} denotes the change of the U.S. federal funds rate, g_{t-1}^{YSP} is the U.S. yield spread, s_{it-1}^{SMI} is the stock market return of country i, y_{it-1} is the first lag of the sovereign bond yield of country i, while $\mathcal{C}_{it}^{+}$ and $\mathcal{C}_{it}^{-}$ are the upside-risk and downside-risk crisis indicators, respectively. The crisis frequencies ('Crisis Freq.') correspond to the ratio between the number of crisis and non-crisis observations for each country. 'Ups.' are upside-, 'Downs.' are downside-risk events. HAC standard errors are reported in brackets, and asterisks (*) denote significance at the 5% level.

Table 5: Estimation results with VaR crisis indicators

Sample countries	**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**	
	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.
Australia	0.0293*	0.0210*	-0.0287	0.1911*	0.0138*	-0.0163*	5.49%	4.81%
	(0.0040)	(0.0073)	(0.0175)	(0.0254)	(0.0009)	(0.0006)	–	–
Austria	0.0078	0.0082	-0.0876*	0.0855*	0.0158*	-0.0235*	7.32%	5.95%
	(0.0055)	(0.0059)	(0.0128)	(0.0232)	(0.0009)	(0.0010)	–	–
Belgium	0.0235*	0.0231*	-0.0398*	0.1057*	0.0143*	-0.0197*	8.01%	6.41%
	(0.0032)	(0.0057)	(0.0130)	(0.0168)	(0.0010)	(0.0008)	–	–
Canada	0.0391*	-0.0040	-0.0657*	0.2346*	0.0151*	-0.0190*	5.03%	5.26%
	(0.0027)	(0,0081)	(0.0089)	(0.0189)	(0.0009)	(0.0011)	–	–
Czech Republic	-0.0055*	0.0362*	-0.1404*	0.0858*	0.0093*	-0.0133*	6.41%	4.58%
	(0.0028)	(0.0083)	(0.0120)	(0.0121)	(0.0007)	(0.0004)	–	–
Finland	0.0207*	0.0380*	-0.0473*	0.0779*	0.0159*	-0.0224*	7.09%	6.64%
	(0.0039)	(0.0058)	(0.0047)	(0.0123)	(0.0009)	(0.0009)	–	–
France	0.0249*	0.0152*	-0.0970*	0.1744*	0.0147*	-0.0211*	6.86%	6.18%
	(0.0031)	(0.0046)	(0.0136)	(0.0159)	(0.0009)	(0.0009)	–	–
Germany	0.0281*	0.0180*	-0.0886*	0.2760*	0.0172*	-0.0218*	6.86%	6.18%
	(0.0057)	(0.0056)	(0.0145)	(0.0235)	(0.0011)	(0.0011)	–	–
Greece	0.0911*	0.1566*	0.0942*	0.4200*	0.0450*	-0.0225*	8.92%	5.95%
	(0.0010)	(0.0009)	(0.0000)	(0.0040)	(0.0004)	(0.0002)	–	–
Ireland	0.0296*	0.0163*	-0.0420*	0.1134*	0.0164*	-0.0166*	7.55%	5.72%
	(0.0071)	(0.0055)	(0.0086)	(0.0194)	(0.0010)	(0.0010)	–	–
Italy	0.0187*	0.0193*	-0.0675*	0.0639*	0.0126*	-0.0151*	6.41%	5.26%
	(0.0021)	(0.0060)	(0.0064)	(0.0099)	(0.0005)	(0.0005)	–	–
Japan	0.0055*	0.0304*	0.2093*	0.4447*	0.0149*	-0.0166*	4.12%	5.72%
	(0.0037)	(0.0146)	(0.0474)	(0.0361)	(0.0018)	(0.0011)	–	–
Netherlands	0.0196*	0.0318*	-0.0149*	0.0332*	0.0162*	-0.0224*	7.09%	6.41%
	(0.0055)	(0.0062)	(0.0070)	(0.0067)	(0.0009)	(0.0005)	–	–
Norway	-0.0208*	0.0075*	0.0111	0.1879*	0.0105*	-0.0174*	6.18%	6.64%
	(0.0035)	(0.0038)	(0.0125)	(0.0188)	(0.0009)	(0.0010)	–	–
Portugal	-0.0408*	0.0086*	0.1515*	0.0707*	0.0241*	-0.0145*	8.01%	7.09%
	(0.0033)	(0.0013)	(0.0094)	(0.0109)	(0.0005)	(0.0003)	–	–
Spain	0.0057*	0.0230*	-0.0428*	0.1003*	0.0165*	-0.0173*	6.64%	7.55%
	(0.0051)	(0.0066)	(0.0124)	(0.0136)	(0.0009)	(0.0010)	–	–
United Kingdom	0.0412	0.0231*	-0.0658*	0.1598*	0.0139*	-0.0175*	5.03%	4.81%
	(0.0038)	(0.0055)	(0.0212)	(0.0229)	(0.0011)	(0.0009)	–	–
United States	0.0404*	0.0115*	-0.0760*	0.1832*	0.0209*	-0.0278*	5.03%	5.49%
	(0.0074)	(0.0016)	(0.0244)	(0.0283)	(0.0012)	(0.0016)	–	–

Note: Estimation results of the canonical contagion model in eq. (1) with the VaR crisis thresholds. g_{t-1}^{FFR} denotes the change of the U.S. federal funds rate, g_{t-1}^{YSP} is the U.S. yield spread, s_{it-1}^{SMI} is the stock market return of country i, y_{it-1} is the first lag of the sovereign bond yield of country i, while $\mathcal{C}_{it}^{+}$ and $\mathcal{C}_{it}^{-}$ are the upside-risk and downside-risk crisis indicators, respectively. The crisis frequencies ('Crisis Freq.') correspond to the ratio between the number of crisis and non-crisis observations for each country. 'Ups.' are upside-, 'Downs.' are downside-risk events. HAC standard errors are reported in brackets, and asterisks (*) denote significance at the 5% level.

Table 6: Estimation results with 2 × std(y_{it}) thresholds

Sample	**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**	
countries	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.
Australia	0.0145*	0.0112	-0.0371*	0.1913*	0.0167*	-0.0217*	2.29%	2.52%
	(0.0043)	(0.0075)	(0.0180)	(0.0277)	(0.0015)	(0.0011)	–	–
Austria	-0.0066	0.0044	-0.0893*	0.1064*	0.0151*	-0.0297*	2.52%	2.29%
	(0.0051)	(0.0096)	(0.0175)	(0.0233)	(0.0015)	(0.0014)	–	–
Belgium	0.0189*	0.0217*	-0.0203*	0.1209*	0.0151*	-0.0224*	2.29%	1.83%
	(0.0059)	(0.0086)	(0.0094)	(0.0194)	(0.0013)	(0.0007)	–	–
Canada	0.0374*	-0.0023	-0.0645*	0.2329*	0.0144*	-0.0264*	2.52%	2.97%
	(0.0036)	(0.0063)	(0.0110)	(0.0143)	(0.0010)	(0.0014)	–	–
Czech Republic	-0.0072	0.0370*	-0.1355*	0.0886*	0.0118*	-0.0098*	2.97%	1.60%
	(0.0040)	(0.0118)	(0.0179)	(0.0110)	(0.0014)	(0.0009)	–	–
Finland	0.0078*	0.0435*	-0.0337*	0.0555*	0.0181*	-0.0306*	2.29%	29.7%
	(0.0037)	(0.0062)	(0.0050)	(0.0100)	(0.0010)	(0.0011)	–	–
France	0.0088	0.0037	-0.1188*	0.2339*	0.0159*	-0.0272*	2.29%	3.43%
	(0.0051)	(0.0088)	(0.0128)	(0.0219)	(0.0011)	(0.0011)	–	–
Germany	0.0090	0.0107	-0.1131*	0.2859*	0.0154*	-0.0313*	2.29%	4.12%
	(0.0072)	(0.0090)	(0.0170)	(0.0248)	(0.0014)	(0.0027)	–	–
Greece	0.2153*	0.1059*	0.3805*	-0.2774*	0.0618*	-0.0440*	2.75%	0.69%
	(0.0034)	(0.0018)	(0.0064)	(0.0084)	(0.0008)	(0.0009)	–	–
Ireland	0.0360*	0.0331*	-0.0062	0.0964*	0.0208*	-0.0159*	2.06%	0.69%
	(0.0064)	(0.0086)	(0.0104)	(0.0197)	(0.0016)	(0.0020)	–	–
Italy	0.0076	0.0290*	-0.0539*	0.0601*	0.0144*	-0.0157*	3.20%	1.60%
	(0.0043)	(0.0082)	(0.0109)	(0.0154)	(0.0005)	(0.0009)	–	–
Japan	0.0034	0.0612*	0.2007*	0.4217*	0.0168*	-0.0266*	2.06%	0.92%
	(0.0060)	(0.0221)	(0.0542)	(0.0524)	(0.0022)	(0.0020)	–	–
Netherlands	0.0152*	0.0435*	-0.0086*	0.0266*	0.0169*	-0.0285*	1.37%	3.20%
	(0.0069)	(0.0069)	(0.0041)	(0.0042)	(0.0012)	(0.0018)	–	–
Norway	-0.0277*	0.0259*	0.0122	0.1807*	0.0127*	-0.0176*	2.06%	2.52%
	(0.0014)	(0.0078)	(0.0104)	(0.0160)	(0.0005)	(0.0008)	–	–
Portugal	-0.0018	0.1341*	-0.5029*	-0.2163*	0.0887*	-0.0790*	2.06%	0.46%
	(0.0024)	0.0025)	(0.0095)	(0.0134)	(0.0003)	(0.0009)	–	–
Spain	0.0026	0.0232*	-0.0300*	0.1176*	0.0180*	-0.0208*	2.29%	2.97%
	(0.0047)	(0.0062)	(0.0147)	(0.0128)	(0.0010)	(0.0014)	–	–
United Kingdom	0.0357*	0.0212	-0.0213	0.1195*	0.0171*	-0.0261*	2.29%	2.97%
	(0.0051)	(0.0110)	(0.0252)	(0.0273)	(0.0013)	(0.0020)	–	–
United States	0.0268*	0.0011	-0.0986*	0.2019*	0.0278*	-0.0379*	2.75%	2.29%
	(0.0075)	(0.0103)	(0.0321)	(0.0231)	(0.0012)	(0.0016)	–	–

Note: Estimation results of the canonical contagion model in eq. (1) with the crisis thresholds set at two standard deviations of the sample. g_{t-1}^{FFR} denotes the change of the U.S. federal funds rate, g_{t-1}^{YSP} is the U.S. yield spread, s_{it-1}^{SMI} is the stock market return of country i, y_{it-1} is the first lag of the sovereign bond yield of country i, while $\mathcal{C}_{it}^{+}$ and $\mathcal{C}_{it}^{-}$ are the upside-risk and downside-risk crisis indicators, respectively. The crisis frequencies ('Crisis Freq.') correspond to the ratio between the number of crisis and non-crisis observations for each country. 'Ups.' are upside-, 'Downs.' are downside-risk events. HAC standard errors are reported in brackets, and asterisks (*) denote significance at the 5% level.

Table 7: Diagnostic tests

Sample	**EVT model**				**VaR model**				**2 × std(y_{it}) model**			
countries	CD	LM(5)	LM(10)	Tsay	CD	LM(5)	LM(10)	Tsay	CD	LM(5)	LM(10)	Tsay
Australia	1.69	3.98	5.22	0.16	1.26	7.27	9.30	0.03	2.37	7.93	16.67	0.50
	–	[0.55]	[0.88]	[0.68]	–	[0.20]	[0.50]	[0.86]	–	[0.16]	[0.08]	[0.48]
Austria	1.57	22.69*	25.38*	0.05	1.14	14.16*	15.01	0.11	2.00	28.58*	30.22*	0.19
	–	[0.00]	[0.00]	[0.82]	–	[0.01]	[0.13]	[0.74]	–	[0.00]	[0.00]	[0.66]
Belgium	1.68	1.42	4.44	0.83	1.18	3.28	8.70	0.39	2.13	7.79	12.05	0.86
	–	[0.92]	[0.93]	[0.36]	–	[0.66]	[0.56]	[0.53]	–	[0.17]	[0.28]	[0.35]
Canada	1.51	12.37*	18.65	0.11	1.26	13.91*	21.99*	0.06	2.21	15.36*	20.11*	0.00
	–	[0.03]	[0.06]	[0.74]	–	[0.02]	[0.02]	[0.80]	–	[0.01]	[0.03]	[0.97]
Czech Republic	1.94	23.61*	27.65*	2.34	1.34	23.49*	28.41*	2.76	2.47	26.27*	30.77*	3.08
	–	[0.00]	[0.00]	[0.13]	–	[0.00]	[0.00]	[0.10]	–	[0.00]	[0.00]	[0.08]
Finland	1.63	11.41*	13.58	1.38	1.18	7.85	10.72	1.62	2.03	16.51*	19.93*	0.37
	–	[0.04]	[0.19]	[0.24]	–	[0.16]	[0.38]	[0.20]	–	[0.01]	[0.03]	[0.54]
France	1.58	3.52	4.15	1.02	1.17	3.30	9.37	1.53	2.15	6.69	9.13	0.34
	–	[0.62]	[0.94]	[0.31]	–	[0.65]	[0.50]	[0.22]	–	[0.24]	[0.52]	[0.56]
Germany	1.62	0.30	2.06	1.16	1.22	2.18	6.01	3.04	2.21	1.87	9.30	0.11
	–	[1.00]	[1.00]	[0.28]	–	[0.82]	[0.81]	[0.08]	–	[0.87]	[0.50]	[0.74]
Greece	0.36	22.48*	26.45*	0.44	0.36	22.48*	26.45*	0.44	0.10	8.23	18.79*	1.80
	–	[0.00]	[0.00]	[0.51]	–	[0.00]	[0.00]	[0.51]	–	[0.14]	[0.05]	[0.18]
Ireland	1.70	7.79	12.40	2.62	1.29	8.27	15.33	1.95	2.28	9.47	14.47	2.62
	–	[0.17]	[0.26]	[0.11]	–	[0.14]	[0.12]	[0.16]	–	[0.09]	[0.15]	[0.11]
Italy	1.77	0.51	3.26	1.48	1.28	0.20	4.08	0.29	2.29	2.34	5.03	1.46
	–	[0.99]	[0.97]	[0.22]	–	[1.00]	[0.94]	[0.59]	–	[0.80]	[0.89]	[0.23]
Japan	1.51	8.54	20.37*	1.35	1.13	8.71	17.82	1.53	2.06	6.95	18.71*	0.91
	–	[0.13]	[0.03]	[0.25]	–	[0.12]	[0.06]	[0.22]	–	[0.22]	[0.04]	[0.34]
Netherlands	1.61	5.19	7.37	1.85	1.12	5.39	8.62	3.91	1.94	15.16*	19.14*	1.12
	–	[0.39]	[0.69]	[0.17]	–	[0.37]	[0.57]	[0.06]	–	[0.01]	[0.04]	[0.29]
Norway	1.81	4.20	8.29	0.14	1.19	5.87	10.15	0.00	2.43	5.52	11.15	0.02
	–	[0.52]	[0.60]	[0.71]	–	[0.32]	[0.43]	[0.98]	–	[0.36]	[0.35]	[0.88]
Portugal	0.17	44.29*	54.41*	0.61	0.21	13.57*	24.35*	0.07	0.11	18.01*	21.56*	1.20
	–	[0.00]	[0.00]	[0.43]	–	[0.02]	[0.01]	[0.79]	–	[0.00]	[0.02]	[0.27]
Spain	1.55	8.15	14.15	0.34	1.26	5.92	8.73	0.07	2.11	11.01*	16.32	0.22
	–	[0.15]	[0.17]	[0.56]	–	[0.31]	[0.56]	[0.79]	–	[0.05]	[0.09]	[0.64]
United Kingdom	1.47	5.03	10.36	0.74	1.17	3.99	7.53	1.07	2.09	7.27	12.56	0.04
	–	[0.41]	[0.41]	[0.39]	–	[0.55]	[0.67]	[0.30]	–	[0.20]	[0.25]	[0.83]
United States	1.62	3.54	7.81	0.04	1.18	6.57	11.94	0.36	2.09	9.24	12.21	0.00
	–	[0.62]	[0.65]	[0.84]	–	[0.25]	[0.29]	[0.55]	–	[0.10]	[0.27]	[0.99]

Note: Model diagnostic tests. In each panel, 'CD' stands for the Cragg-Donald statistic, 'LM(5)' and 'LM(10)' are the residual serial correlation LM tests with 5 and 10 lags (computed with heteroskedasticity-robust standard errors), and 'Tsay' is the Tsay test. Asterisks (*) denote significance at the 5% level and p-values are given in square parentheses. Monte Carlo critical values for the Cragg-Donald statistic are tabulated in Stock and Yogo (2005).

Table A1: Sub-sample estimation results with EVT thresholds

	Sub-sample: 2001W48 - 2006W14								Sub-sample: 2006W15 - 2010W33							
Sample	**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**		**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**	
countries	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.
Australia	-0.0344*	0.0565*	-0.0558*	0.0403*	0.0187*	-0.0187*	5.03%	5.35%	0.0407*	0.0309*	0.0626*	0.1674*	0.0167*	-0.0135*	2.28%	2.74%
	(0.0087)	(0.0047)	(0.0141)	(0.0198)	(0.0005)	(0.0009)	–	–	(0.0020)	(0.0024)	(0.0117)	(0.0137)	(0.0007)	(0.0004)	–	–
Austria	-0.0331*	0.0169*	-0.0306*	0.0642*	0.0227*	-0.0224*	4.09%	3.77%	0.0100*	0.0164*	-0.0473*	0.1657*	0.0184*	-0.0227*	1.37%	3.20%
	(0.0073)	(0.0063)	(0.0081)	(0.0106)	(0.0004)	(0.0006)	–	–	(0.0015)	(0.0024)	(0.0049)	(0.0111)	(0.0005)	(0.0003)	–	–
Belgium	-0.0031	0.0198*	-0.0404*	0.0693*	0.0221*	-0.0217*	5.97%	3.14%	0.0273*	0.0225*	0.0333*	0.0903*	0.0186*	-0.0203*	2.74%	2.28%
	(0.0037)	(0.0052)	(0.0028)	(0.0072)	(0.0005)	(0.0005)	–	–	(0.0012)	(0.0016)	(0.0030)	(0.0045)	(0.0002)	(0.0002)	–	–
Canada	-0.0468*	0.0204*	-0.0549*	0.0892*	0.0171*	-0.0197*	3.46%	3.46%	0.0436	0.0043*	0.0092	0.2421*	0.0174*	-0.0132*	2.28%	6.39%
	(0.0053)	(0.0074)	(0.0122)	(0.0119)	(0.0006)	(0.0004)	–	–	(0.0042)	(0.0033)	(0.0063)	(0.0177)	(0.0007)	(0.0008)	–	–
Czech Republic	-0.0478*	0.0661*	-0.0881*	0.0819*	0.0190*	-0.0150*	3.46%	1.57%	-0.0019	0.0258*	-0.0744*	0.0439*	0.0113*	-0.0097*	5.94%	2.74%
	(0.0067)	(0.0056)	(0.0141)	(0.0130)	(0.0004)	(0.0008)	–	–	(0.0025)	(0.0027)	(0.0104)	(0.0118)	(0.0003)	(0.0005)	–	–
Finland	-0.0027	0.0303*	-0.0142*	0.0283*	0.0214*	-0.0237*	2.20%	3.14%	0.0129*	0.0267*	-0.0572*	0.0412*	0.0164*	-0.0193*	3.65%	2.28%
	(0.0037)	(0.0059)	(0.0043)	(0.0078)	(0.0009)	(0.0002)	–	–	(0.0018)	(0.0032)	(0.0051)	(0.0037)	(0.0005)	(0.0006)	–	–
France	-0.0057	0.0082	-0.0564*	0.1022*	0.0207*	-0.0213*	2.20%	2.83%	0.0301*	0.0138*	-0.0525*	0.2140*	0.0209*	-0.0229*	3.20%	3.65%
	(0.0070)	(0.0066)	(0.0090)	(0.0110)	(0.0005)	(0.0006)	–	–	(0.0033)	(0.0033)	(0.0100)	(0.0123)	(0.0005)	(0.0004)	–	–
Germany	-0.0074	0.0269*	-0.0444*	0.0726*	0.0201*	-0.0221*	2.20%	3.14%	0.0259*	0.0138*	-0.0127*	0.2874*	0.0202*	-0.0205*	3.20%	2.28%
	(0.0049)	(0.0051)	(0.0057)	(0.0117)	(0.0002)	(0.0005)	–	–	(0.0040)	(0.0025)	(0.0112)	(0.0163)	(0.0007)	(0.0008)	–	–
Greece	-0.0003	0.0358*	-0.0396*	0.1264*	0.0167*	-0.0174*	1.89%	3.46%	-0.0768*	0.3201*	0.4236*	-0.3299*	-0.0101*	-0.0397*	0.91%	3.65%
	(0.0051)	(0.0101)	(0.0094)	(0.0122)	(0.0007)	(0.0004)	–	–	(0.0064)	(0.0125)	(0.0000)	(0.0620)	(0.0009)	(0.0012)	–	–
Ireland	0.0223*	0.0146	-0.0881*	0.0632*	0.0199*	-0.0234*	3.14%	1.89%	0.0421*	0.0206*	0.0404*	0.1080*	0.0214*	-0.0136*	2.74%	9.13%
	(0.0044)	(0.0081)	(0.0100)	(0.0120)	(0.0005)	(0.0004)	–	–	(0.0031)	(0.0025)	(0.0062)	(0.0093)	(0.0005)	(0.0006)	–	–
Italy	-0.0070	0.0126*	-0.0944*	0.0569*	0.0205*	-0.0213*	3.46%	1.57%	0.0138*	0.0217*	-0.0619*	0.0372*	0.0129*	-0.0153*	3.20%	9.59%
	(0.0051)	(0.0050)	(0.0123)	(0.0052)	(0.0003)	(0.0004)	–	–	(0.0019)	(0.0050)	(0.0055)	(0.0119)	(0.0002)	(0.0002)	–	–
Japan	0.0630*	0.1207*	0.3655*	0.3863*	0.0431*	-0.0183*	3.14%	1.57%	0.0135*	-0.0106	0.0176	0.3855*	0.0177*	-0.0166*	4.11%	2.28%
	(0.0147)	(0.0217)	(0.0166)	(0.0338)	(0.0013)	(0.0014)	–	–	(0.0027)	(0.0061)	(0.0250)	(0.0345)	(0.0008)	(0.0009)	–	–
Netherlands	-0.0021	0.0168*	-0.0087	0.0041	0.0242*	-0.0236*	1.57%	3.77%	0.0200*	0.0235*	0.0198*	0.0400*	0.0192*	-0.0214*	2.74%	2.74%
	(0.0066)	(0.0038)	(0.0047)	(0.0027)	(0.0004)	(0.0003)	–	–	(0.0033)	(0.0013)	(0.0034)	(0.0024)	(0.0004)	(0.0004)	–	–
Norway	0.0434*	0.0769*	-0.0454*	0.0941*	0.0166*	-0.0152*	2.20%	2.83%	-0.0182*	0.0065	0.0334*	0.1921*	0.0140*	-0.0122*	3.65%	2.74%
	(0.0045)	(0.0080)	(0.0114)	(0.0211)	(0.0004)	(0.0009)	–	–	(0.0022)	(0.0037)	(0.0073)	(0.0165)	(0.0005)	(0.0005)	–	–
Portugal	0.0158*	0.0224*	0.0206	0.0391	0.0211*	-0.0222*	4.09%	2.83%	0.1316*	-0.3952*	-0.7536*	1.3747*	0.0060*	-0.0199*	3.65%	2.74%
	(0.0051)	(0.0086)	(0.0166)	(0.0221)	(0.0008)	(0.0006)	–	–	(0.0045)	(0.0112)	(0.0230)	(0.0406)	(0.0015)	(0.0015)	–	–
Spain	0.0068	0.0319*	-0.0326*	0.0623*	0.0184*	-0.0223*	2.20%	3.46%	0.0109*	0.0139*	-0.0269*	0.0684*	0.0203*	-0.0175*	3.20%	4.57%
	(0.0053)	(0.0044)	(0.0103)	(0.0130)	(0.0005)	(0.0007)	–	–	(0.0023)	(0.0044)	(0.0110)	(0.0095)	(0.0008)	(0.0004)	–	–
United Kingdom	-0.0283*	0.0394*	0.0167	-0.0021	0.0147*	-0.0188*	8.49%	1.57%	0.0391*	0.0202*	0.0015	0.2017*	0.0190*	-0.0191*	3.65	1.83
	(0.0032)	(0.0066)	(0.0098)	(0.0183)	(0.0004)	(0.0004)	–	–	(0.0012)	(0.0022)	(0.0112)	(0.0137)	(0.0007)	(0.0005)	–	–
United States	-0.0648*	0.0340*	0.0551*	0.0058	0.0263*	-0.0285*	2.52%	3.77%	0.0371*	0.0090*	-0.0799*	0.1902*	0.0265*	-0.0255*	5.94%	1.83%
	(0.0071)	(0.0110)	(0.0097)	(0.0224)	(0.0006)	(0.0006)	–	–	(0.0032)	(0.0032)	(0.0164)	(0.0173)	(0.0010)	(0.0007)	–	–

Note: See Table 4.

Table A2: Sub-sample estimation results with VaR thresholds

	Sub-sample: 2001W48 - 2006W14								Sub-sample: 2006W15 - 2010W33							
Sample	**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**		**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**	
countries	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.
Australia	-0.0370*	0.0910*	-0.0702*	0.0905*	0.0210*	-0.0159*	5.05%	4.13%	0.0407*	0.0336*	0.0308*	0.1522*	0.0116*	-0.0145*	5.93%	5.4795
	(0.0091)	(0.0087)	(0.0156)	(0.0173)	(0.0004)	(0.0007)	–	–	(0.0025)	(0.0017)	(0.0067)	(0.0115)	(0.0006)	(0.0003)	–	–
Austria	-0.0065	0.0368*	-0.1074*	0.1019*	0.0204*	-0.0187*	7.33%	5.96%	0.0122*	0.0271*	-0.0769*	0.0920*	0.0153*	-0.0219*	7.30%	5.93%
	(0.0081)	(0.0114)	(0.0125)	(0.0131)	(0.0008)	(0.0005)	–	–	(0.0029)	(0.0030)	(0.0068)	(0.0196)	(0.0005)	(0.0008)	–	–
Belgium	-0.0016	0.0321*	-0.1079*	0.1816*	0.0213*	-0.0182*	6.88%	6.42%	0.0210*	0.0287*	0.0067*	0.0662*	0.0152*	-0.0181*	9.13%	6.39%
	(0.0036)	(0.0088)	(0.0084)	(0.0157)	(0.0004)	(0.0006)	–	–	(0.0025)	(0.0026)	(0.0065)	(0.0090)	(0.0005)	(0.0003)	–	–
Canada	-0.0448*	0.0398*	-0.1111*	0.1885*	0.0144*	-0.0149*	3.66%	4.12%	0.0342*	0.0135*	-0.0273*	0.2220*	0.0162*	-0.0183*	6.39%	6.39%
	(0.0047)	(0.0112)	(0.0075)	(0.0146)	(0.0010)	(0.0004)	–	–	(0.0043)	(0.0023)	(0.0077)	(0.0175)	(0.0005)	(0.0005)	–	–
Czech Republic	-0.0322*	0.1146*	-0.0980*	0.1175*	0.0196*	-0.0119*	5.04%	5.04%	-0.0022*	0.0273*	-0.1160*	0.0703*	0.0067*	-0.0120*	7.76%	4.10%
	(0.0058)	(0.0064)	(0.0135)	(0.0201)	(0.0006)	(0.0005)	–	–	(0.0011)	(0.0023)	(0.0071)	(0.0094)	(0.0005)	(0.0005)	–	–
Finland	0.0018	0.0410*	-0.0533*	0.1174*	0.0216*	-0.0202*	6.88%	6.42%	0.0162*	0.0335*	-0.0711*	0.0716*	0.0137*	-0.0214*	7.30%	6.84%
	(0.0052)	(0.0052)	(0.0025)	(0.0098)	(0.0009)	(0.0005)	–	–	(0.0048)	(0.0025)	(0.0103)	(0.0058)	(0.0003)	(0.0003)	–	–
France	-0.0040	0.0110*	-0.1178*	0.2084*	0.0192*	-0.0179*	7.79%	5.96%	0.0255*	0.0197*	-0.0764*	0.2044*	0.0151*	-0.0212*	5.93%	6.39%
	(0.0048)	(0.0044)	(0.0037)	(0.0088)	(0.0003)	(0.0002)	–	–	(0.0018)	(0.0020)	(0.0117)	(0.0139)	(0.0002)	(0.0004)	–	–
Germany	-0.0100	0.0323*	-0.1151*	0.1835*	0.0203*	-0.0187*	7.33%	5.96%	0.0238*	0.0222*	-0.0616*	0.2813*	0.0147*	-0.0228*	6.39%	6.39%
	(0.0067)	(0.0097)	(0.0083)	(0.0130)	(0.0011)	(0.0004)	–	–	(0.0029)	(0.0010)	(0.0091)	(0.0125)	(0.0003)	(0.0007)	–	–
Greece	-0.0003	0.0358*	-0.0396*	0.1264*	0.0167*	-0.0174*	6.42%	7.33%	0.0096*	0.0007	-0.1606*	0.1778*	0.0232*	-0.0124*	11.41%	4.56%
	(0.0051)	(0.0101)	(0.0094)	(0.0122)	(0.0007)	(0.0004)	–	–	(0.0025)	(0.0010)	(0.0127)	(0.0099)	(0.0003)	(0.0008)	–	–
Ireland	0.0165*	0.0276*	-0.1036*	0.1725*	0.0192*	-0.0187*	5.96%	5.04%	0.0366*	0.0235*	-0.0068	0.0850*	0.0172*	-0.0130*	9.13%	6.39%
	(0.0042)	(0.0067)	(0.0050)	(0.0114)	(0.0008)	(0.0004)	–	–	(0.0037)	(0.0019)	(0.0048)	(0.0133)	(0.0004)	(0.0006)	–	–
Italy	0.0084	0.0069	-0.1594*	0.1763*	0.0189*	-0.0181*	6.42%	6.42%	0.0181*	0.0196*	-0.0740*	0.0199	0.0114*	-0.0120*	4.10%	6.84%
	(0.0049)	(0.0048)	(0.0030)	(0.0120)	(0.0002)	(0.0002)	–	–	(0.0023)	(0.0035)	(0.0081)	(0.0111)	(0.0003)	(0.0003)	–	–
Japan	0.0313*	0.2138*	0.4165*	0.4578*	0.0449*	-0.0135*	4.12%	4.58%	0.0154*	-0.0006	-0.0149	0.3387*	0.0152*	-0.0204*	8.21%	6.39%
	(0.0148)	(0.0192)	(0.0262)	(0.0285)	(0.0008)	(0.0009)	–	–	(0.0015)	(0.0034)	(0.0174)	(0.0232)	(0.0006)	(0.0008)	–	–
Netherlands	0.0109*	0.0647*	-0.0224*	0.0238*	0.0205*	-0.0196*	5.96%	6.42%	0.0162*	0.0278*	-0.0161*	0.0576*	0.0156*	-0.0213*	7.76%	6.84%
	(0.0049)	(0.0033)	(0.0015)	(0.0022)	(0.0006)	(0.0004)	–	–	(0.0023)	(0.0010)	(0.0067)	(0.0046)	(0.0003)	(0.0005)	–	–
Norway	0.0405*	0.0939*	-0.0311*	0.1227*	0.0170*	-0.0131*	4.58%	6.42%	-0.0168*	0.0137*	0.0278*	0.1525*	0.0096*	-0.0158*	6.39%	4.10%
	(0.0038)	(0.0063)	(0.0076)	(0.0072)	(0.0003)	(0.0002)	–	–	(0.0021)	(0.0023)	(0.0065)	(0.0126)	(0.0003)	(0.0005)	–	–
Portugal	0.0053	0.0465*	-0.0310*	0.0913*	0.0189*	-0.0194*	6.42%	7.79%	0.0166*	0.0068*	-0.0533*	0.1331*	0.0216*	-0.0178*	9.58%	6.39%
	(0.0066)	(0.0065)	(0.0101)	(0.0171)	(0.0006)	(0.0004)	–	–	(0.0032)	(0.0018)	(0.0156)	(0.0109)	(0.0005)	(0.0008)	–	–
Spain	0.0060	0.0347*	-0.0750	0.1705*	0.0181*	-0.0175*	6.42%	8.25%	-0.0015	0.0193*	-0.0461*	0.0793*	0.0174*	-0.0140*	6.84%	6.84%
	(0.0053)	(0.0075)	(0.0057)	(0.0135)	(0.0006)	(0.0005)	–	–	(0.0035)	(0.0034)	(0.0091)	(0.0110)	(0.0005)	(0.0004)	–	–
United Kingdom	-0.0200*	0.0424*	-0.0663*	0.1120*	0.0166*	-0.0154*	5.50%	4.58%	0.0401*	0.0218*	-0.0465*	0.2382*	0.0138*	-0.0179*	4.56%	5.02%
	(0.0050)	(0.0080)	(0.0135)	(0.0143)	(0.0007)	(0.0004)	–	–	(0.0031)	(0.0018)	(0.0107)	(0.0106)	(0.0005)	(0.0006)	–	–
United States	-0.0372*	0.0685*	0.0114*	0.1413*	0.0247*	-0.0199*	4.12%	3.66%	0.0353*	0.0178*	-0.1042*	0.1892*	0.0205*	-0.0280*	5.93%	7.30%
	(0.0081)	(0.0046)	(0.0133)	(0.0199)	(0.0006)	(0.0009)	–	–	(0.0019)	(0.0030)	(0.0121)	(0.0131)	(0.0005)	(0.0006)	–	–

Note: See Table 5.

Table A3: Sub-sample estimation results with 2 × std(y_{it}) thresholds

	Sub-sample: 2001W48 - 2006W14								Sub-sample: 2006W15 - 2010W33							
Sample	**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**		**Observed regressors**				**Shift-Contagion**		**Crisis Freq.**	
countries	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.	g_{t-1}^{FFR}	g_{t-1}^{YSP}	s_{it-1}^{SMI}	y_{it-1}	$\mathcal{C}_{it}^{+}$	$\mathcal{C}_{it}^{-}$	Ups.	Downs.
Australia	-0.0418*	0.0650*	-0.0880*	0.0445*	0.0211*	-0.0195*	2.83%	1.26%	0.0332*	0.0354*	0.0185*	0.1504*	0.0116*	-0.0174*	2.28%	3.20%
	(0.0099)	(0.0070)	(0.0104)	(0.0158)	(0.0009)	(0.0009)	–	–	(0.0032)	(0.0030)	(0.0095)	(0.0130)	(0.0009)	(0.0005)	–	–
Austria	-0.0264*	0.0311*	-0.0312*	0.0396*	0.0235*	-0.0243*	3.46%	2.52%	0.0007	0.0237*	-0.0421*	0.0855*	0.0144*	-0.0268*	1.37%	2.28%
	(0.0073)	(0.0074)	(0.0116)	(0.0118)	(0.0010)	(0.0005)	–	–	(0.0033)	(0.0025)	(0.0083)	(0.0183)	(0.0009)	(0.0012)	–	–
Belgium	-0.0063	0.0120*	-0.0672*	0.1082*	0.0213*	-0.0250*	3.14%	2.52%	0.0207*	0.0246*	-0.0122*	0.0947*	0.0139*	-0.0226*	2.28%	2.28%
	(0.0070)	(0.0055)	(0.0089)	(0.0122)	(0.0006)	(0.0005)	–	–	(0.0033)	(0.0029)	(0.0057)	(0.0128)	(0.0010)	(0.0003)	–	–
Canada	-0.0496*	0.0249*	-0.1055*	0.1214*	0.0192*	-0.0203*	3.14%	1.89%	0.0397*	0.0109*	-0.0116	0.2208*	0.0139*	-0.0214*	2.74%	2.28%
	(0.0042)	(0.0080)	(0.0074)	(0.0140)	(0.0006)	(0.0008)	–	–	(0.0047)	(0.0029)	(0.0082)	(0.0162)	(0.0008)	(0.0009)	–	–
Czech Republic	-0.0508*	0.0789*	-0.0970*	0.1076*	0.0176*	-0.0176*	2.52%	1.57%	-0.0012	0.0247*	-0.0951*	0.0708*	0.0071*	-0.0075*	3.65%	2.28%
	(0.0085)	(0.0106)	(0.0152)	(0.0089)	(0.0007)	(0.0011)	–	–	(0.0007)	(0.0025)	(0.0081)	(0.0094)	(0.0005)	(0.0020)	–	–
Finland	-0.0042	0.0173*	-0.0285*	0.0775*	0.0230*	-0.0258*	3.14%	2.52%	0.0101*	0.0336*	-0.0501*	0.0597*	0.0141*	-0.0251*	1.83%	4.57%
	(0.0059)	(0.0062)	(0.0045)	(0.0087)	(0.0009)	(0.0002)	–	–	(0.0029)	(0.0023)	(0.0068)	(0.0088)	(0.0011)	(0.0008)	–	–
France	-0.0097	0.0045	-0.0893*	0.1392*	0.0204*	-0.0233*	2.20%	2.20%	0.0213*	0.0200*	-0.0829*	0.2360*	0.0146*	-0.0263*	1.37%	3.65%
	(0.0070)	(0.0041)	(0.0095)	(0.0069)	(0.0006)	(0.0006)	–	–	(0.0041)	(0.0032)	(0.0109)	(0.0144)	(0.0006)	(0.0005)	–	–
Germany	-0.0047	0.0093	-0.0544*	0.1187*	0.0205*	-0.0249*	2.52%	2.52%	0.0307*	0.0202*	-0.0667*	0.3036*	0.0144*	-0.0296*	1.37%	5.48%
	(0.0051)	(0.0053)	(0.0105)	(0.0129)	(0.0006)	(0.0009)	–	–	(0.0052)	(0.0039)	(0.0198)	(0.0197)	(0.0008)	(0.0024)	–	–
Greece	0.0082	0.0392*	-0.0404*	0.0242*	0.0192*	-0.0206*	3.77%	2.83%	-0.0419*	-0.0599*	-0.4604*	-0.2880*	0.0431*	-0.0522*	5.02%	0.91%
	(0.0061)	(0.0082)	(0.0082)	(0.0122)	(0.0006)	(0.0004)	–	–	(0.0060)	(0.0085)	(0.0187)	(0.0260)	(0.0014)	(0.0013)	–	–
Ireland	0.0167*	0.0098	-0.1020*	0.1138*	0.0198*	-0.0254*	2.83%	1.57%	0.0426*	0.0240*	0.0176*	0.0376*	0.0222*	-0.0081*	2.74%	1.37%
	(0.0051)	(0.0054)	(0.0112)	(0.0072)	(0.0007)	(0.0011)	–	–	(0.0037)	(0.0025)	(0.0070)	(0.0131)	(0.0012)	(0.0012)	–	–
Italy	0.0024	0.0072*	-0.1455	0.1194*	0.0192*	-0.0240*	3.77%	1.89%	0.0182*	0.0260*	-0.0845*	0.0068*	0.0116*	-0.0141*	2.74%	1.37%
	(0.0061)	(0.0072)	(0.0206)	(0.0173)	(0.0006)	(0.0007)	–	–	(0.0033)	(0.0031)	(0.0060)	(0.0087)	(0.0003)	(0.0009)	–	–
Japan	0.0221*	0.1010*	0.3642*	0.4300*	0.0498*	-0.0341*	2.83%	0.31%	0.0109*	-0.0052	-0.0254	0.3782*	0.0139*	-0.0220*	2.74%	2.28%
	(0.0114)	(0.0192)	(0.0165)	(0.0228)	(0.0016)	(0.0023)	–	–	(0.0014)	(0.0054)	(0.0142)	(0.0211)	(0.0008)	(0.0008)	–	–
Netherlands	0.0051	0.0259*	-0.0175*	0.0041	0.0226*	-0.0273*	2.83%	2.83%	0.0172*	0.0300*	-0.0284*	0.0662*	0.0150*	-0.0242*	0.91%	4.57%
	(0.0078)	(0.0049)	(0.0023)	(0.0030)	(0.0008)	(0.0008)	–	–	(0.0038)	(0.0008)	(0.0048)	(0.0065)	(0.0007)	(0.0011)	–	–
Norway	0.0377*	0.0732*	-0.0386*	0.1207*	0.0175*	-0.0175*	2.52%	2.52%	-0.0191*	0.0139	0.0230*	0.1600*	0.0112*	-0.0194*	2.28%	3.20%
	(0.0086)	(0.0076)	(0.0076)	(0.0139)	(0.0007)	(0.0011)	–	–	(0.0020)	(0.0031)	(0.0075)	(0.0111)	(0.0004)	(0.0004)	–	–
Portugal	0.0115	0.0210*	0.0518*	0.0670*	0.0212*	-0.0270*	3.77%	2.52%	0.1879*	0.1743*	-0.1149*	-0.2821*	0.0007*	-0.0064*	3.20%	0.91%
	(0.0066)	(0.0080)	(0.0106)	(0.0180)	(0.0008)	(0.0009)	–	–	(0.0072)	(0.0031)	(0.0099)	(0.0074)	(0.0007)	(0.0010)	–	–
Spain	0.0096*	0.0207*	-0.0407*	0.1260*	0.0184*	-0.0239*	3.14%	2.52%	0.0005	0.0193*	-0.0698*	0.0463*	0.0195*	-0.0176*	1.83%	2.28%
	(0.0044)	(0.0047)	(0.0083)	(0.0124)	(0.0005)	(0.0004)	–	–	(0.0033)	(0.0049)	(0.0103)	(0.0134)	(0.0007)	(0.0022)	–	–
United Kingdom	-0.0195*	0.0364*	-0.0341*	0.0496*	0.0137*	-0.0203*	1.89%	1.57%	0.0365*	0.0263*	-0.0031	0.1900*	0.0145*	-0.0257*	2.28%	2.74%
	(0.0041)	(0.0086)	(0.0110)	(0.0186)	(0.0005)	(0.0005)	–	–	(0.0017)	(0.0027)	(0.0090)	(0.0081)	(0.0004)	(0.0010)	–	–
United States	-0.0629*	0.0530*	0.0098	0.0918*	0.0277*	-0.0281*	3.46%	1.26%	0.0387*	0.0203*	-0.1336*	0.1947*	0.0213*	-0.0323*	1.83%	3.65%
	(0.0074)	(0.0126)	(0.0092)	(0.0303)	(0.0009)	(0.0015)	–	–	(0.0034)	(0.0039)	(0.0163)	(0.0166)	(0.0010)	(0.0009)	–	–

Note: See Table 6.

Table A4: Sub-sample crisis thresholds

	2001W48 - 2006W14			**2006W15 - 2010W33**		
Sample	**Estimated thresholds**					
countries	$\hat{\tau}_i^{EVT+}$	$\hat{\tau}_i^{EVT-}$	$\hat{\tau}_i^{2std}$	$\hat{\tau}_i^{EVT+}$	$\hat{\tau}_i^{EVT-}$	$\hat{\tau}_i^{2std}$
Australia	0.0319	0.0287	0.0382	0.0429	0.0414	0.0402
Austria	0.0319	0.0287	0.0337	0.0429	0.0414	0.0430
Belgium	0.0278	0.0318	0.0328	0.0356	0.0386	0.0397
Canada	0.0306	0.0304	0.0347	0.0500	0.0364	0.0476
Czech Republic	0.0396	0.0429	0.0423	0.0367	0.0489	0.0491
Finland	0.0401	0.0312	0.0341	0.0337	0.0488	0.0420
France	0.0355	0.0319	0.0330	0.0381	0.0412	0.0407
Germany	0.0370	0.0301	0.0331	0.0421	0.0576	0.0483
Greece	0.0371	0.0270	0.0313	0.1213	0.0307	0.0701
Ireland	0.0329	0.0333	0.0335	0.0463	0.0278	0.0561
Italy	0.0328	0.0336	0.0321	0.0326	0.0235	0.0345
Japan	0.1025	0.0863	0.1059	0.0473	0.0552	0.0579
Netherlands	0.0402	0.0294	0.0335	0.0354	0.0459	0.0421
Norway	0.0358	0.0320	0.0343	0.0335	0.0470	0.0416
Portugal	0.0315	0.0302	0.0331	0.0431	0.0404	0.0548
Spain	0.0363	0.0308	0.0326	0.0357	0.0368	0.0413
United Kingdom	0.0211	0.0327	0.0316	0.0476	0.0636	0.0530
United States	0.0513	0.0429	0.0481	0.0564	0.0830	0.0688

Note: See Table 2.