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A structural approach to identify financial transmission in distinguished scenarios of crises

by Helmut Herwartz and Jan Roestel

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A structural approach to identify financial transmission in distinguished scenarios of crises

Helmut Herwartz ^{*} Jan Roestel [†]

Abstract

This paper investigates the propagation of instability through key asset markets of the US financial system - equity, real estate, banking and treasury - between 1/3/2000 and 12/26/2014. For this purpose, we develop an identification method to uncover characteristic financial market interrelations under distinguished scenarios of crises. It refers to the logic behind narrative sign restrictions and allows to extract time varying contemporaneous effects and volatility transmission from conventional reduced form volatility models with dynamic correlations. We find the market value of banking institutions to be highly sensitive to news originating in other markets, with those originating in the real estate market being most important. Under stress, in turn, the banking sector tends to dominate financial market (co)variation, where it exhibits a marked feedback relation with both the real estate and the equity market.

Keywords: Identification, Contemporaneous effects, Causality, Impulse response analysis, GARCH, Volatility transmission, Financial crises.

JEL Classification: C39, C32, E44, G01

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1 Introduction

Since the beginning of the new millennium, the US financial system has witnessed distinguished episodes of common turmoil and potential instability that originated from distinct parts of the financial market. Some shocks, for instance, those associated with the early millennium burst of the equity bubble had limited systemic effects (Mishkin and White, 2002; Reinhart and Rogoff, 2008; Aoki and Nikolov, 2015). Other ones, such as those implied by the unwinding of financial imbalances in the supprime mortgage market after January 2007, triggered self enforcing feedback mechanisms with other market constituents that almost led to a meltdown of the US financial system (Ait-Sahalia et al., 2012; Hellwig, 2009).

The understanding of the characteristic transmission and amplification mechanisms behind distinguished scenarios of financial turmoil is a core issue of research.¹ Empirically disentangling such mechanisms from the data, however, is difficult, especially when interest lies on their *economic* identification. Given that financial systems exhibit strong contemporaneous interdependence and structural change, finding uncontroversial ‘conventional’ economic restrictions appears hardly feasible.

In light of numerous empirical applications (e.g. Chan, Karolyi, and Stulz, 1992; Bekaert and Harvey, 1995; Baele, 2005), reduced form multivariate GARCH (MGARCH) representations such as the distinct BEKK forms or the DCC (see Bauwens et al., 2006, for a review) have proven successful in describing both conditional joint financial market comovement and volatility dynamics. Structural interpretations of MGARCH-type models are typically based upon ad-hoc decompositions of conditional covariance matrices (e.g. Hafner and Herwartz 2006; Henry et al. 2010; Jin et al. 2012), or data driven methods that require the system to obey a particular ad-hoc dynamic structure (Rigobon and Sack, 2003; Caporale, Cipollini, and Spagnolo, 2005; Weber, 2010; Dungey, Milunovich, and Thorp, 2010). Economic inter-

¹See e.g. Mishkin and White (2002); Allen and Gale (2004); Caporale, Cipollini, and Spagnolo (2005); Reinhart and Rogoff (2008); Shin (2008); Aikman et al. (2009); Brunnermeier and Pedersen (2008); Niinimäki (2009); Koetter and Poghosyan (2010); Gai and Kapadia (2010); Dimitriou, Kenourgios, and Simos (2013); Bekaert, Ehrmann, Fratzscher, and Mehl (2014); Aoki and Nikolov (2015); Hau and Lai (2017).

pretation of the derived relations can be obtained ex post via innovation accounting (Dungey, Milunovich, and Thorp, 2010). Ideally, however, one would like to study the effect of those shocks that, by identification, have a particular economic meaning, as it is done in SVAR analysis (Sims, 1980; Bernanke, 1986; Sims, 1986; Blanchard and Quah, 1989; Faust, 1998; Uhlig, 2005; Antolin-Diaz and Rubio Ramírez, 2017).²

In this study, we shed new light on the distinct financial transmission mechanisms that have characterized the main episodes of US financial market turmoil between 1/3/2000 and 12/26/2014. For this purpose, we suggest an identification method which allows to extract time varying contemporaneous relations and variance transmission dynamics from any reduced form multivariate volatility model with time varying correlations. Our method is mainly related to the ‘identification via heteroscedasticity’ (IVH) approach in Rigobon (2003), Rigobon and Sack (2003) and further developments on structural MGARCH models such as Caporale, Cipollini, and Spagnolo (2005), Weber (2010) or Dungey, Milunovich, and Thorp (2010). As a particular feature, it draws upon the logic behind narrative sign restrictions in SVAR analysis recently introduced in Antolin-Diaz and Rubio Ramírez (2017). One main type of such restrictions establishes that the model implied variance decompositions conform with a consensual economic narrative on a handful of characteristic periods. Exploiting that the squared entries of conditional correlation matrix decompositions reflect transient, i.e. time local, one step ahead return variance decompositions, the global identification criterion is based upon spillover indices in the spirit of Diebold and Yilmaz (2009). These indices summarize the extent to which news originating in given markets explain the variance of the remaining markets’ returns. By identification, model implied time varying patterns of market ‘dominance’ are jointly matched to conform with the sample’s characteristic crisis episodes and their predominant market origins as well as possible. A market is considered as locally dominant whenever it has the tendency to induce stronger overall

²In a related field of research, Diebold and Yilmaz (2009) use the structural VAR model toolkit to analyze the transmission of realized volatilities, referring to standard (ad hoc) decomposition schemes.

spillovers than any other market within a given time period.

While the aforementioned data driven approaches are based upon a similar intuition, several differences are noteworthy. In our case, both the identification of market specific innovations and their labelling are explicitly guided by normative (time) local economic properties. In contrast to Rigobon and Sack (2003), contemporaneous effects are not restricted to remain invariant over heterogeneous scenarios of volatility and crises. Moreover, no further ad-hoc restrictions on structural dynamics are necessary to enable identification of regime specific contemporaneous effects such as in Caporale, Cipollini, and Spagnolo (2005) or Dungey, Milunovich, and Thorp (2010). Our identification scheme is not restricted to a particular volatility model and can be easily applied to more sophisticated ones that allow for cross equation variance dynamics. In this context, we discuss the implementation of local variance impulse response functions (VIRFs, hereafter, Hafner and Herwartz, 2006) in our framework. Drawing upon both local samples of (i) identified conditional covariance decompositions, and (ii) identified structural shocks, these VIRFs allow to illustrate typical volatility transmission dynamics associated with characteristic scenarios of interest.

To summarize some core findings of our empirical analysis, the market value of banking institutions seems generally sensitive to shocks originating in other markets, but especially to those originating in the real estate market. Under stress, in turn, banking institutions tend to dominate financial (co)variation and exhibit a marked feedback relation with both the real estate and the equity market. In addition to direct interbank counterparty risk (Allen and Gale, 2000), therefore, indirect linkages operating via fire sales and balance sheet effects (Shin 2008, Gai and Kapadia 2010, Aikman et al. 2009) might contribute to the spread of bank default risks quite substantially.³ The treasury market induces only minor spillovers, though being of some importance for the real estate market. Alternative identification approaches do not provide uncontroversial model implications.

³Of course, a rigorous comparison of direct vs. indirect effects requires an explicit consideration of intra-banking dynamics in our model (and for its identification). This is an issue of future research.

Subsequently, we introduce our approach to contemporaneous modeling to which we refer as ‘Market Dominance Targeting’ (MDT, henceforth). Moreover, identified local VIRFs are developed within this framework. In Section 3, we analyze (time) local transmission among US key financial markets between 2000 and 2015, and discuss the performance of our method in comparison with other approaches. Section 4 concludes. In Appendices A, B and C, we provide details on episode selection, reduced form model estimates and structural stability, respectively.

2 Analyzing financial transmission

Starting from a contemporaneous model nesting the one of Rigobon and Sack (2003) we introduce our approach to contemporaneous financial return modelling. Moreover, we discuss how episode specific average VIRFs can be derived from the structural model.

2.1 A local model for mean zero asset returns

To establish the link between MDT identification and IVH, consider the following contemporaneous model for an N -dimensional vector of zero-mean asset returns e_t ,

$$\Lambda_t e_t = \Psi_t^{1/2} u_t, \quad u_t \sim N(0, I_N), \quad t = 1, \dots, T, \quad (1)$$

where the matrix $\Psi_t^{1/2} = \text{diag}(\psi_{11t}, \dots, \psi_{NNt})$ contains the conditional standard deviations of uncorrelated innovations u_t originating in markets $i = 1, \dots, N$. The matrix Λ_t captures the time varying contemporaneous effects among observed returns with a main diagonal normalized to unity. By assuming time invariance of contemporaneous transmission, i.e. $\Lambda_t = \Lambda$, and GARCH- or regime switching-type behavior for Ψ_t , model (1) nests Rigobon and Sack (2003) and Rigobon (2003) as special cases. We will subsequently consider an

equivalent so-called ‘B-model’ representation of the unrestricted model in (1),

$$e_t = G_t u_t, \quad (2)$$

where $G_t \stackrel{!}{=} \Lambda_t^{-1} \Psi_t^{1/2}$ summarizes the conditional ‘importance’ of market specific ‘news’, u_t , for the interrelated price adjustments among distinct (classes of) financial assets in e_t . Put differently, the stylized model (2) provides a flexible framework to analyze time varying news effects shaping interdependent and heteroscedastic financial systems. Specifying such news effects, consider the following representation of (2)

$$e_t = \Gamma_t \Sigma_t^{1/2} u_t, \quad (3)$$

where the diagonal matrix $\Sigma_t^{1/2} = \text{diag}(g_{11t}, \dots, g_{NNt})$ comprises the standard deviations of the system at time t . Hence, $\Sigma_t^{1/2} u_t$ collects the market specific ‘own’ parts of variation in e_{it} and Γ_t quantifies their systemic transmission, with a main diagonal normalized to unity. Apparently, G_t in (2) is of key importance for the analysis of time varying interdependence. If G_t could be identified, one could directly solve for the time varying parameters in (normalized) Γ_t and the structural standard deviations $\Sigma_t^{1/2}$ in (3) or, in analogy, for Λ_t and $\Psi_t^{1/2}$ in (1).⁴ While G_t cannot be estimated directly, its square, $G_t G_t' = E(e_t e_t')$, can be assessed by means of any suitable reduced form multivariate volatility model. For instance, if the observed mean-zero returns exhibit MGARCH-type behaviour, one might consider a BEKK-MGARCH model (Engle and Kroner, 1995):

$$H_t = G_t G_t' \quad (4)$$

$$= CC' + A' e_{t-1} e_{t-1}' A + B' H_{t-1} B. \quad (5)$$

⁴With normalized Γ_t (or Λ_t), $G_t = \Gamma_t \Sigma_t^{1/2}$ (or $G_t = \Lambda_t^{-1} \Psi_t^{1/2}$) have N^2 equations and N^2 unknowns.

In (4) and (5), $H_t = E(e_t e_t' | \mathcal{F}_{t-1})$ is the conditional (i.e. measurable with respect to the process history \mathcal{F}_{t-1}) covariance of e_t , where coefficient matrices C , A and B are of dimension $N \times N$, and C is lower triangular. Associated estimates can be obtained by means of QML.⁵

Without external information, however, conditional covariance estimates H_t are hardly useful for inference on the structural model (2). With R denoting a time invariant rotation matrix such that $RR' = I_N$ and $R \neq I_N$, it follows from (4),

$$H_t = G_t G_t' = G_t R R' G_t = \tilde{G}_t \tilde{G}_t', \quad (6)$$

highlighting that any rotation $G_t R$ preserves the (observable/estimated) local covariance structure in (4), but implies distinct local news effects in (2). Under the Gaussian assumption, rotations of G_t are observationally equivalent since the normal distribution is fully specified in terms of first and second order moments.

2.2 Identification of time varying instantaneous effects

To uncover the linear linkages among structural and reduced form innovations in systems of financial returns, most of the available approaches have particular drawbacks. For instance, available economic (theory guided) identification approaches (Sims, 1980; Bernanke, 1986; Sims, 1986; Blanchard and Quah, 1989; Faust, 1998; Uhlig, 2005) might not be suitable, since they throughout refer to first order models with time invariant innovation covariance structure. While, in principle, the Diebold and Yilmaz (2009) approach allows for an economic identification in the class of VAR-based volatility models, a sufficient number of economic restrictions is typically not available for higher dimensional systems or highly interdependent macroeconomic/financial systems. For this reason, Diebold and Yilmaz (2009) employ ad-

⁵For a thorough discussion of conditions establishing consistency and asymptotic normality of the QML estimator in MGARCH models see Jeantheau (2000), Comte and Lieberman (2003) and Hafner and Preminger (2009).

hoc Choleski decompositions for a small number of alternative variable orderings,⁶ but their choice is not guided by economic reasoning. A further strand of literature to the SVAR (and also MGARCH) field opts for data driven approaches to model identification (e.g. Rigobon, 2003; Rigobon and Sack, 2003; Weber, 2010; Dungey, Milunovich, and Thorp, 2010). These do not identify shocks according to normative economic properties, but require the system to obey a particular ad-hoc structure. Rigobon (2003), for instance, stresses that time varying correlations indicate changes in the relative importance of financial market shocks. Accordingly, he proposes an identification scheme exploiting nonproportional switches of variances in the (diagonal) matrix Ψ_t in (1) over distinct regimes, while assuming time invariance of contemporaneous interactions $\Lambda_t = \Lambda$. Rather than considering regime specific heteroscedasticity, Rigobon and Sack (2003) derive a structural MGARCH model grounding on GARCH type volatility of implied structural shocks. Recently, narrative sign restrictions (Antolin-Diaz and Rubio Ramírez, 2017) have been proposed to improve standard economic VAR identification approaches. In Antolin-Diaz and Rubio Ramírez (2017), the narrative sign restriction No.2, for instance, requires the absolute contribution of oil supply shocks to unexpected movements in oil price growth to be larger than the absolute value of the contribution of any other structural shock during local episodes of war escalation in oil producing economies. Against this background, we next propose a novel identification scheme for financial return processes that exploits such a reasoning in the context of MGARCH-type modelling.

A stylized fact of financial market returns is that conditional (co)volatilities tend to increase markedly during scenarios of crises. This is often attributed to the strong impact of particular types of shocks that characterize such transitory episodes. A suitable model should establish that, under an increased interest in the state of a struggling market i , associated news u_{it} trigger relatively ‘strong’ effects across the financial system. At the same time, the

⁶Studying all possible variable orderings for the Diebold and Yilmaz (2009) case, Klößner and Wagner (2013) show that the associated inferential conclusions differ substantially.

impact of similar sized news u_{jt} that originate in other markets $j \neq i$ should be ‘weaker’ in comparison. Given that the representation in (2) formalizes these conditional news impacts explicitly, alternative ‘parameterizations’ $\{\tilde{G}_t\}_{t=1}^T$ in (2) could be evaluated according to their (historical) economic credibility.

Based upon this intuition, MDT relies on the attribution of distinguished non-overlapping episodes of common turmoil to a specific market as a time local, dominant source of general financial (co)variation. For each of $i = 1, \dots, N$ markets under consideration, assume that a sufficiently large set of characteristic time instances (‘episodes’) is available for which news originating in market i was the most important (dominant) source of general financial variation.⁷ Henceforth, these non-overlapping episodes are denoted as $\Omega_1, \Omega_2, \dots, \Omega_N$. For instance, for a sample comprising US asset returns on stocks, real estate trusts, banks and treasury bonds, one might distinguish (i) the early millennium burst of the equity bubble, (ii) the real estate crisis (first part of the great financial crisis), (iii) the banking crisis (second part of the great financial crisis), and (iv) the period of debt ceiling disputes as such episodes. Intuitively, the attribution of systemic turmoil to originate in particular markets should provide information i) for the identification of contemporaneous effects of market specific shocks, and ii) characteristic ‘baseline’ scenarios of volatility transmission.⁸ All other time instances that cannot be assigned to one of the ‘informative’ episodes $\Omega_1, \Omega_2, \dots, \Omega_N$ comprise Ω_0 , the set of time instances characterized by ‘non-informative’ market conditions. A set of time instances is considered as being not ‘non-informative’ if there exists no compelling argument in favor of the relative dominance of one particular financial market constituent. The core idea of MDT is to select the (full sample) decomposition sequence $\{\tilde{G}_t\}_{t=1}^T$ as defined in (6) from a huge set of alternative candidate sequences. The MDT based decomposition scheme, denoted $\{\hat{G}_t\}_{t=1}^T$, is chosen to match as close as possible all assumptions on market dominance

⁷The assumption that the number of episodes equals the system dimension is made for convenience in this study. Applying the MDT approach, an analyst might focus on specific markets being agnostic with respect to eventual dominance exhibited by other parts of a system of interest.

⁸See Sections 2.2 and 2.3 for a more detailed discussion of these issues.

during the selected characteristic turmoil episodes $\Omega_s, s = 1, \dots, N$, jointly. Hence, while economic identification in first order homoscedastic systems is mostly achieved by imposing global restrictions on instantaneous effects, economic identification in MGARCH-type models (formalizing changing market conditions) is guided by local restrictions on such effects applying in selected situations (subperiods). Clearly, this flexibility facilitates to put forth credible identifying restrictions in highly interdependent financial systems.

Since $G_t G_t' = \sum_{i=1}^N g_t(\cdot, i) g_t(\cdot, i)'$, where $g_t(\cdot, i)$ is the i -th column of G_t , any identified matrix G_t in (2) is ‘unique’ except for the column signs and the ordering of the columns. To establish ‘sign uniqueness’ we follow the convention to assume that the diagonal elements of G_t are positive.⁹ Turning to the column ordering, we assume without loss of generality that the elements in the i -th column of G_t , denoted $g_t(\cdot, i)$, quantify the conditional effect of news originating in market i (news u_{it} , henceforth) on market returns e_{jt} , $j = 1, \dots, N$, in time t . It is important to emphasize that, by this assumption, the diagonal elements of G_t are considered as market specific effects of news u_{it} on their ‘own’ reduced form counterparts e_{it} . The MDT implied sequence $\{\widehat{G}_t\}_{t=1}^T$ shall imply that, within each turmoil episode Ω_s , the impact of news u_{it} originating in market $i = s$ tends to be more important for the remaining markets’ return variations than it is the case for the impact of news u_{jt} , $j \neq i$. Subsequently, we derive a scale free summary measure of local market importance to formalize such comparisons.

Consider an equivalent representation of (2),

$$e_t = V_t^{1/2} Q_t u_t, \quad (7)$$

where V_t is a diagonal matrix comprising the diagonal entries in estimated/observable H_t such that $V_t^{-1/2} H_t V_t^{-1/2}$ is the reduced form conditional correlation matrix. Hence, $Q_t = V_t^{-1/2} G_t$

⁹In the SVAR literature, the positivity of diagonal elements of covariance decomposition matrices has been established by noticing that respective impulse response functions trace the effects of positive (rather than negative) isolated unit shocks (see Lütkepohl, 2007, Chap. 9).

is a decomposition of the correlation matrix. The identification problem reads as

$$H_t = G_t G_t' = V_t^{1/2} Q_t Q_t' V_t^{1/2} = V_t^{1/2} Q_t R R' Q_t' V_t^{1/2} = V_t^{1/2} \tilde{Q}_t \tilde{Q}_t' V_t^{1/2} = \tilde{G}_t \tilde{G}_t'. \quad (8)$$

For given reduced form conditional variance estimates, hence, identification of G_t might refer to conditional correlation decompositions without loss of generality.

Noting that (7) implies $V_t^{-1/2} e_t = Q_t u_t$, typical elements $Q_t(i, j)$ measure the impact of news u_{jt} on conditionally standardized returns of market i . More importantly, $(Q_t(i, j))^2$ can be shown to be equal to the relative share of $E_{t-1}[e_{it}^2]$ that can be traced back to news u_{jt} , where $i, j = 1, \dots, N$.¹⁰ Hence, for any given G_t , the squared entries of the associated Q_t quantify the associated ‘importance’ of identified news u_{jt} for the joint variation of observed financial returns e_t in terms of local one step-ahead variance shares. Thus, if investors’ decisions are predominantly influenced by news originating in market i during Ω_s , $s = i$, one would expect the sum of the squared elements in the i th column of Q_t , denoted as $q_t(\cdot, i)$, to be relatively large in magnitude for all $t \in \Omega_i$. The full sample MDT implied sequence $\{\hat{Q}_t\}_{t=1}^T$ (and, thus, $\{\hat{G}_t\}_{t=1}^T$) shall imply that, within each turmoil episode Ω_s , the impact of news originating in market $i = s$ tends to be more important for the remaining markets’ return variations than it is the case for the impact of news originating from other markets j , $j \neq i$. Put differently, the sum of the squared off-diagonal elements contained in the i -th column of Q_t should tend to be larger than the sum of the squared off-diagonal elements in the j -th column. Noteworthy, Diebold and Yilmaz (2009) use ‘off-diagonal’ sums of forecast error decompositions to summarize market specific spillover magnitudes.

To establish MDT as an identification criterion requires i) a parametric description of a suitable and numerically tractable space of alternative decomposition schemes, and ii) a criterion to assess local dominance of market i for the variation in the returns of other

¹⁰Referring to (2), $G_t(i, j)^2 / \sum_{k=1}^4 G_t(i, k)^2$ is the share of $E_{t-1}[e_{it}^2]$ attributed to news originating in market j . As a consequence, $G_t(i, j)^2 / \sum_{k=1}^4 G_t(i, k)^2 = \frac{G_t(i, j)^2 / V_t(i, i)^2}{(1/V_t(i, i))^2 \sum_{k=1}^4 G_t(i, k)^2} = Q_t(i, j)^2$.

markets $j, j \neq i$. Next, we describe how these issues are addressed. For convenience, we will throughout refer to correlation decompositions Q_t . Hence, we implicitly determine associated covariance decompositions G_t and their implied one-step ahead forecast error variance shares.

(i) Decomposition space

Let \tilde{Q}_t denote a factor such that $V_t^{-1/2}H_tV_t^{-1/2} = \tilde{Q}_t\tilde{Q}_t'$.¹¹ Then, a space of candidate decompositions obtains as $\mathcal{Q} = \{ \{ \{ \tilde{Q}_t R_\theta P_\phi \}_\theta \}_\phi \}_{t=1}^T = \{ \{ \tilde{Q}_{t,m} \}_{m=1}^M \}_{t=1}^T$, where R_θ and P_ϕ denote rotation and permutation matrices, respectively.¹² Rotation matrices R_θ are determined in a systematic way by means of the product of distinct forms of Givens rotation matrices. For the exemplary case of $N = 4$ a representative rotation matrix would read as

$$R_\theta = \begin{pmatrix} \cos \theta_1 & -\sin \theta_1 & 0 & 0 \\ \sin \theta_1 & \cos \theta_1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos \theta_2 & -\sin \theta_2 & 0 \\ 0 & \sin \theta_2 & \cos \theta_2 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \cos \theta_3 & 0 & -\sin \theta_3 & 0 \\ 0 & 1 & 0 & 0 \\ \sin \theta_3 & 0 & \cos \theta_3 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \\ \times \begin{pmatrix} \cos \theta_4 & 0 & 0 & -\sin \theta_4 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ \sin \theta_4 & 0 & 0 & \cos \theta_4 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos \theta_5 & 0 & -\sin \theta_5 \\ 0 & 0 & 1 & 0 \\ 0 & \sin \theta_5 & 0 & \cos \theta_5 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \cos \theta_6 & -\sin \theta_6 \\ 0 & 0 & \sin \theta_6 & \cos \theta_6 \end{pmatrix}.$$

The angles θ_l collected in $\theta = (\theta_1, \dots, \theta_6)'$, $0 \leq \theta_l < \pi/2$, are varied along K equidistant grid points, obtaining K^6 distinct decomposition matrices $\tilde{Q}_t R_\theta$. To enhance the set of candidate decompositions, note that the columns of each candidate matrix $\tilde{Q}_t R_\theta$ allow $N! = 24$ distinct permutations. Indexing the set of column permutation matrices P_ϕ , $\phi = 1, 2, \dots, 24$, we combine each rotation $\tilde{Q}_t R_\theta$ with each permutation P_ϕ to define

¹¹ \tilde{Q}_t has to be chosen by the analyst. Without loss of generality, we use the eigenvalue decomposition of the correlation matrices $V_t^{-1/2}H_tV_t^{-1/2}$.

¹²Though permutations are also rotations, we opt for a different notation to enable a more ‘parsimonious’ structuring of the decomposition space \mathcal{Q} . Hence, rather than choosing a grid between 0 and 2π , we choose a grid between 0 and $\pi/2$ and apply permutation matrices. To establish sign uniqueness, columns of particular rotations of \tilde{Q}_t are multiplied with minus unity if their respective diagonal element is negative.

\mathcal{Q} . Let $m = 1, 2, \dots, M$ index the set of all combinations of θ and ϕ .¹³ Then, candidate decompositions of $V_t^{-1/2} H_t V_t^{-1/2}$ read as $\tilde{Q}_{t,m}$ with typical elements $\tilde{Q}_{t,m}(i, j)$.

(ii) Quantifying instantaneous transmission

Assume that in period t market i is considered as a dominant determinant of financial market (co)movements. To decide if this fact is covered by a specific decomposition scheme $\{\tilde{Q}_{t,m}\}_{t=1}^T$ consider the indicator

$$d_{i,t,m} = I \left(\sum_{k=1, k \neq i}^N \tilde{Q}_{t,m}(k, i)^2 > \sum_{k=1, k \neq j}^N \tilde{Q}_{t,m}(k, j)^2, \forall j = 1, \dots, N, j \neq i \right). \quad (9)$$

Accordingly, dominance of market i is indicated if the associated ‘spillover index’ (Diebold and Yilmaz, 2009) of market i , i.e. the off-diagonal sum of the squared values in the i -th column of $\tilde{Q}_{t,m}$, exceeds respective indices of the remaining markets $j, j \neq i$. Note that, by this definition, an indication of dominance does not exclude other markets to be influential sources of financial volatility.

By assumption, Ω_s is the set of calendar dates (the time series support) for which news originating in market s have played a dominant role for investors’ decisions. Henceforth, the size of this set is denoted ω_s .¹⁴ A candidate sequence of decomposition matrices, $\{\tilde{Q}_{t,m}\}_{t=1}^T$, can be characterized in terms of frequency estimates attributing market dominance to partitions of sample information. Define

$$d_{is}(m) = \frac{1}{\omega_s} \sum_{t \in \Omega_s}^T d_{i,t,m}, \quad i = 1, \dots, N, s = 0, 1, \dots, N, \quad (10)$$

to measure the frequency of dominance of market i attributed to time instances in Ω_s . Notice that in (10) the division by ω_s accounts for the (likely) scenario that periods of market turmoil (Ω_s) differ in length. A unique decomposition scheme for the full

¹³In total, therefore, $M = 24 \cdot K^6$ alternative decomposition sequences are available.

¹⁴In analogy, regular market conditions prevail in the set of time instances Ω_0 having size ω_0 .

sample is obtained by selecting the particular \widehat{m} (i.e. the specific combination of R_θ and P_ϕ) such that

$$\{\widehat{Q}_t\}_{t=1}^T = \{\widetilde{Q}_{t,\widehat{m}}\}_{t=1}^T, \text{ where } \widehat{m} = \max_m S = \prod_{i=1}^N d_{ii}(m). \quad (11)$$

As outlined, MDT builds upon frequency estimates $d_{ii}(m)$, $i = 1, \dots, N$, to evaluate dominance of market i in times of turmoil Ω_s , $s = i$.¹⁵ As such, the criterion in (11) is agnostic with regard to other frequency characteristics as, e.g., d_{is} , $i \neq s$, or d_{i0} which are also implied by $\{\widehat{Q}_t\}_{t=1}^T$. While the former statistics might quantify, e.g., the incidence of dominance of the banking market during the real estate crisis, the latter type of statistics describe the incidence of banking market dominance during normal times. If additional (more specific) economic information on such local transmission characteristics is available, respective frequencies might further be considered as arguments to enter the criterion in (11). All frequencies that are left agnostically unspecified, however, provide important additional information for both model evaluation and economic inference.

For identification, we have put a particular emphasis on aspects of cross market news effect *transmission*. In this context, uncontroversial local economic restrictions can be formulated most straightforwardly. However, a sequence of decompositions could also be evaluated in terms of its implied reception patterns. The intensity of cross market news *exposure* experienced by market i in time t is quantified by the off-diagonal elements entailed in the i -th row of matrices \widehat{Q}_t (or \widehat{G}_t). Against this background, it is worth to note the specific characteristics of (ad-hoc) decompositions commonly applied to obtain structural interpretations of the MGARCH model.¹⁶ For instance, the symmetric eigenvalue decomposition implies time local symmetry of transmission and reception. Such a symmetry condition might lack

¹⁵The MDT criterion has a multiplicative rather than an additive form to penalize models with very heterogeneous (i.e. polar) frequencies being either close to one or zero.

¹⁶See e.g. Spargoli and Zagaglia (2008), Jin, Lin, and Tamvakis (2012), Henry, Olekalns, and Shields (2010), Rahman and Serletis (2011), Olson, Vivian, and Wohar (2014)

economic support, if it is possible to highlight particular markets as intense transmitters or receivers of news effects during distinct time episodes. In turn, triangular decomposition schemes imply that a particular market is a-priori considered to be a mere transmitter (recipient) of volatility with no volatility reception from (transmission to) other markets, irrespective of the changing market conditions and shifting correlations. In contrast, rotations according to the criterion in (11) allow to conform the structural model features with available historical economic information on local market conditions.

2.3 Local average variance impulse response analysis

VIRFs are conveniently derived from the vec-form of the BEKK model in (5):

$$\text{vec}(H_t) = \tilde{\mathcal{C}} + \tilde{\mathcal{A}}\text{vec}(e_{t-1}e'_{t-1}) + \tilde{\mathcal{B}}\text{vec}(H_{t-1}), \quad (12)$$

$$\text{where } \tilde{\mathcal{C}} = (C \otimes C)\text{vec}(I_N), \tilde{\mathcal{A}} = (A \otimes A)', \tilde{\mathcal{B}} = (B \otimes B)'.$$

Concentrating on the distinct moments in $\text{vec}(H_t)$, the half-vec analog of (12) is

$$\text{vech}(H_t) = \mathcal{C} + \mathcal{A}\text{vech}(e_{t-1}e'_{t-1}) + \mathcal{B}\text{vech}(H_{t-1}), \quad (13)$$

where $\mathcal{A} = L_N \tilde{\mathcal{A}} L'_N$ and $\mathcal{B} = L_N \tilde{\mathcal{B}} L'_N$ and L_N is the so-called elimination matrix.¹⁷ As formalized in (2) and (4)-(5), the elements in $h_t = \text{vech}(H_t)$ depend on the structural innovations u_{t-1} , and the covariance state H_{t-1} . For purposes of impulse response analysis it has become a convention to depict the time paths of effects of isolated shocks occurring in one variable and instance of time on a system's dynamic patterns (see Lütkepohl, 2007,

¹⁷To describe the link between the vec- and the half-vec model, and for the derivation of VIRFs, some elementary matrices turn out to be useful: The elimination matrix L_N , the duplication matrix D_N and its generalized inverse D_N^+ . Let $N^* = N(N+1)/2$. With reference to a symmetric square $N \times N$ matrix Z , the $N^* \times N^2$ ($N^2 \times N^*$) elimination (duplication) matrix L_N (D_N) is defined by the property $\text{vech}(Z) = L_N \text{vec}(Z)$ ($\text{vec}(Z) = D_N \text{vech}(Z)$). Since $D'_N D_N$ is nonsingular, the Moore-Penrose inverse or generalized inverse of D_N is $D_N^+ = (D'_N D_N)^{-1} D'_N$. See Lütkepohl (1996).

Chap. 9). To derive VIRFs from MGARCH processes, it is natural to assume that such shocks occur in the innovation vector u_{t-1} (Hafner and Herwartz, 2006). Referring to model parameters in (13) and time specific MDT-implied conditional variance decompositions (2), VIRFs are determined recursively as

$$\mathcal{V}_{t+\nu}(u_{t-1}^*, \widehat{G}_{t-1}) = (\mathcal{A} + \mathcal{B})^\nu \mathcal{A} D_N^+ (\widehat{G}_{t-1} \otimes \widehat{G}_{t-1}) D_N \text{vech}(u_{t-1}^* u_{t-1}^{*\prime} - I_N), \quad (14)$$

for $\nu = 0, 1, \dots$, where D_N is the duplication matrix and D_N^+ denotes its generalized (Moore-Penrose) inverse. Hence, VIRFs are defined as the path of volatilities that is expected in the sequel of an artificial shock u_{t-1}^* in comparison with a hypothetical benchmark ‘steady state’ path of volatilities. For both paths, subsequent innovations u_t^*, u_{t+1}^*, \dots are set to zero according to their unconditional expectations. It is a particular feature of VIRFs that they are derived conditional on the covariance state in the time of shock generation, H_{t-1} (and, hence, \widehat{G}_{t-1}). Moreover, shock selection is highly arbitrary since no ‘natural’ specification of an isolated stylized unit shock affecting a system of variances exists.¹⁸ To address these problems, we next discuss a simulation-based approach to assess ‘mean’ (co)variance responses to market specific innovations within characteristic episodes Ω_s , $s = 0, \dots, N$.

As a starting point, we define potential choices of u_{t-1}^* that might be suitable for studying effects of market specific shocks on system (co)variances for a given instance of time. To potentially (govern the) increase (of) the conditional variances across financial markets, the market specific element of the shock vector, u_{it-1}^* , has to be of sufficient magnitude. With regard to (co)volatility generation, moreover, negative shocks are of more interest by assumption. Concerning the shock u_{t-1}^* , we obtain a representative set of suitable candidates by means of resampling from a censored empirical distribution of MDT-implied empirical shocks. Formally, let $\{u_r^{(i)*}\}_{r=1}^R$ denote a set of R draws with replacement from the set

¹⁸Note that zero elements in the innovation vector might be seen as additional ‘negative’ shocks to the considered system of variances.

$\{\hat{u}_t \in \{\hat{u}_t\}_{t=1}^T | \hat{u}_{it} < \kappa\}$, where κ is the empirical $\alpha\%$ quantile of the empirical structural shocks \hat{u}_{it} (here: $\alpha = 10\%$). Based on a sample of R (here: $R = 500$) variance shocks, we obtain R distinct (shock specific) VIRFs conditional on the covariance structure in $t - 1$.

For studying variance responses to such shocks under distinct ‘characteristic’ scenarios, all conditional covariances H_t (and thus, MDT-implied decompositions \hat{G}_{t-1}) collected in respective episodes $\Omega_0 \dots, \Omega_N$ are potentially informative. For instance, referring to the subset of model implied conditional covariance matrix estimates from the burst of the equity bubble is likely most informative for depicting news responses of financial (co)volatilities applying under stress in the equity sector. Accordingly, we determine scenario specific VIRFs by averaging over all VIRFs derived from combining all selected shocks and scenario specific covariance decompositions. Formally, we consider the following local statistics of volatility transmission originating in market i and period Ω_s

$$\bar{\mathcal{V}}_{t+\nu}^{(is)} = \frac{1}{\omega_s R} \sum_{t-1 \in \Omega_s} \sum_{r=1}^R \mathcal{V}_{t+\nu}(u_r^{(i)*}, \hat{G}_{t-1}), \quad i = 1, \dots, N, \quad s = 0, \dots, N. \quad (15)$$

3 A structural view at financial turmoil in the US

Subsequently, we provide a structural analysis of scenarios of US financial turmoil between 2000 and 2015. Firstly, we define historical (characteristic) episodes $\Omega_0, \dots, \Omega_K$ and discuss stylized properties of the data. Secondly, we provide BEKK estimates, some reduced form model diagnostics and identification details. In the third place, we provide a comprehensive analysis of the characteristic dependence patterns among equity, real estate, banking and treasury markets by referring to instantaneous effects, respective one-step-ahead forecast error variance decompositions and volatility transmission dynamics. In this context, we also discuss how these characteristic patterns have changed over distinguished scenarios of US financial turmoil between 2000 and 2015. Finally, we compare the economic implications of MDT identification to those of alternative approaches.

3.1 Data

Table 1 and Figure 1 provide descriptive information on the returns of the Dow Jones Industrial Average, the Wilshire US REIT, the Datastream Americas Banks and the Datastream US benchmark 10 year government bond indices between 1/3/2000 and 12/26/2014. All indices are obtained from Datastream.¹⁹ For the analysis, all returns are mean adjusted and standardized to have unit unconditional variance.²⁰ Figure 1 and Table 1 illustrate that, in

Table 1: Descriptive statistics of returns, reduced form and structural innovations.

i	Mean	Min/Max	Covariance				Skew.	Kurt.	JB
Raw returns (r_{it})									
1	0.01	-8.20/10.51	1.39				-0.07	11.43	11567*
2	0.03	-22.02/17.38	1.53	3.86			-0.24	22.31	60167*
3	0.01	-14.43/14.60	1.69	2.49	3.10		0.01	15.22	24347*
4	0.00	-1.98/2.134	-0.12	-0.12	-0.17	0.09	-0.06	5.76	1037*
Reduced form model disturbances (e_{it})									
1	0.00	-6.98/ 8.92	1						
2	0.00	-11.22/ 8.83	0.66	1					
3	0.00	-8.20/ 8.29	0.82	0.72	1				
4	0.00	-5.92/ 8.31	-0.35	-0.21	-0.32	1			
Structural form model innovations based on MDT (u_{it})									
1	-0.01	-5.28/7.14	1.00				0.09	4.86	571*
2	0.02	-5.14/5.50	0.01	1.02			-0.00	4.71	477*
3	-0.00	-8.22/5.25	-0.01	-0.01	1.02		-0.20	4.73	518*
4	0.00	-4.18/4.45	0.00	-0.00	0.01	0.99	-0.07	3.78	104*

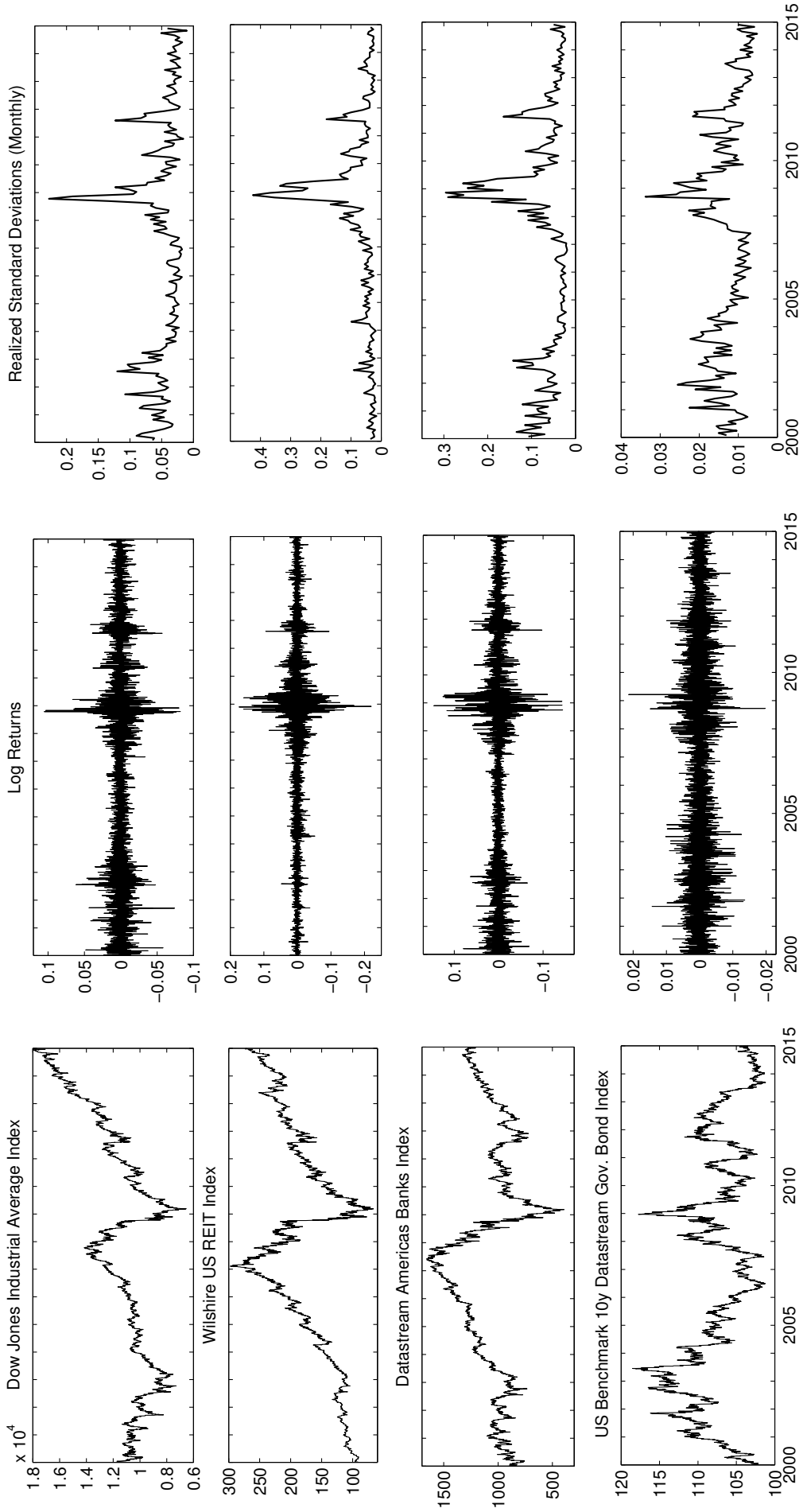
Descriptive statistics for raw returns r_{it} , reduced form model disturbances e_{it} (i.e. unconditionally standardized raw returns) and structural form model innovations u_{it} obtained by means of the MDT identification scheme. JB is short for the Jarque-Bera test and the asterisk denotes significance of the corresponding test statistic at the 1% level.

comparison with returns on equity, the return variation in the real estate and the banking market is rather large. In comparison, the variation of treasury market returns is small in general, but shows a considerable persistence. Apart from pronounced patterns of heteroscedasticity, the data is characterized by its non-normality in general and excess kurtosis in particular. Moreover, we observe strong positive correlations among equity-, real estate-

¹⁹The corresponding codes are: DJINDUS, WILDJRT, BANKSAM, BMUS10Y.

²⁰Considering unconditionally standardized returns facilitates the comparison of VIRF dynamics.

Figure 1: Daily Indices, respective log returns and monthly realized standard deviations



and banking index returns (0.66 – 0.82). In contrast, government bond index returns exhibit moderate, negative correlations with the remaining index returns (–0.21 to – 0.35).

3.2 Selected episodes of market dominance

We subsequently summarize our stylized assumptions on local market dominance. A detailed justification of these assumptions is provided in Appendix A. Four disjoint subperiods of US financial market turmoil are of particular interest, namely (i) the early millennium burst of the equity bubble, (ii) the real estate crisis (first part of the great financial crisis), (iii) the banking crisis (second part of the great financial crisis), and (iv) the period of debt ceiling disputes. We assume that news originating in the equity market (and, hence, the firm sector) dominate investors’ decisions between 3/1/2000 until 4/1/2003. The set of all time instances within this period is denoted Ω_1 . Moreover, we assume that during the period from 2/1/2007 until 3/14/2008 (from 3/15/2008 until 6/1/2009), news originating in the real estate (banking) sector have dominated the (co)variations in the financial system (Ω_2 and Ω_3 , henceforth). News on the treasury market are assumed to have played a dominant role on financial (co)variations between 3/1/2011 – 1/1/2012 and 5/1/2013 – 11/1/2013, defined as episode Ω_4 . To complete the structuring of the sample, all time instances between 3/1/2000-12/26/2014 that are not included in one of these ‘informative’ (and non-overlapping) episodes comprise Ω_0 , the set of time instances characterized by regular or normal market conditions.

3.3 BEKK estimates, identification details and evaluation

Full sample QML estimates of the BEKK model in (5), and a residual based check for structural invariance are given in Appendices B and C.²¹ Selected out of a huge set of decomposition processes \mathcal{Q} and based upon a grid with $K = 11$ equidistant points,²² the

²¹Optimization is based on a procedure which iterates the Quasi-Newton, Nelder-Mead and Trust-region algorithms (as implemented in Matlab 2011a) until they jointly fulfill the convergence criteria.

²²Given the computational resources, $K > 11$ required a disproportional amount of computing time. Results from finer resolutions are expected to be qualitatively identical.

sequence of correlation decompositions $\{\widehat{Q}_t\}_{t=1}^T$ that optimizes the MDT criterion in (11) is based upon initial eigenvalue decompositions rotated by means of the matrix

$$R_{\hat{\theta}}P_{\hat{\phi}} = \begin{pmatrix} .4935 & -.0581 & -.8627 & .0932 \\ -.5133 & .4044 & -.3909 & -.6482 \\ .4918 & .8412 & .2246 & .0000 \\ -.5011 & .3540 & -.2289 & .7556 \end{pmatrix}. \quad (16)$$

The decomposition scheme implied by the rotation in (16) is of central importance for the structural analysis, since it determines the interpretation of full sample reduced form conditional covariance estimates. Hence, one should reassure that the local dominance assumptions have been met successfully. The upper part of Table 2 provides diagnostics $d_{is}(\widehat{m})$ on the success ($i = s$) and failure ($i \neq s$) of $\{\widehat{Q}_t\}_{t=1}^T$ in attributing dominance of news originating in market i , $i = 1, \dots, 4$, to the associated turmoil episodes Ω_s .

By construction, rotating the initial eigenvalue decompositions towards $\{\widehat{Q}_t\}_{t=1}^T$ achieves a concentration of dominance indications for markets $i = 1, \dots, 4$ during the associated turmoil episodes Ω_s , $s = i$. Respective frequencies range from $d_{44}(\widehat{m})=25\%$ (treasury market dominance during the debt ceiling disputes Ω_4) to $d_{33}(\widehat{m})=67\%$ (banking market dominance during the banking crisis Ω_3). On average, these frequencies are both large in magnitude ($\overline{d_{ii}}(\widehat{m})=50.17\%$) and sizeable in comparison with relative frequencies attributed to other, non-dominant markets ($\overline{d_{is}}(\widehat{m})=16\%$, $i \neq s$, $s \neq 0$). Moreover, the model implied agnostic dominance indications provide economic support for the identification scheme. We obtain frequent indications of banking dominance during the real estate crisis Ω_2 ($d_{32}(\widehat{m}) = 25\%$), as well as of real estate dominance under turmoil in the banking market Ω_3 ($d_{23}(\widehat{m}) = 16\%$). During the period of treasury market dominance, Ω_4 , the banking sector remained an influential source of financial variation ($d_{34}(\widehat{m}) = 48\%$). Consider next the (relative) importance of the examined financial markets under ‘regular conditions’ (Ω_0). The housing sector seems to

Table 2: Identification details

Identification ($\{Q_t\}_{t=1}^T$)	i	d_{i1}	d_{i2}	d_{i3}	d_{i4}	d_{i0}
Rotated eigenvalue decomposition, \widehat{Q}_t	1	.5031	.0925	.0095	.0695	.2614
	2	.3702	.5788	.1646	.1964	.4268
	3	.1193	.2466	.6741	.4843	.2845
	4	.0075	.0822	.1519	.2508	.0273
Unrotated eigenvalue decomposition, \widetilde{Q}_t	1	.6584	.4966	.5570	.7372	.6882
	2	0	0	.0759	.0544	.0152
	3	.3416	.5034	.3671	.2085	.2965
	4	0	0	0	0	0
Lower triangular Cholesky factor, Q_t^∇	1	1	1	1	1	1
	2	0	0	0	0	0
	3	0	0	0	0	0
	4	0	0	0	0	0
Rigobon and Sack implied factor, Q_t^*	1	.5826	.0479	.0633	.0393	.0642
	2	0	.1849	.3481	.0060	.0282
	3	.2000	.0582	.3291	.0181	.0129
	4	.2174	.7089	.2595	.9366	.8947

Relative frequencies d_{is} of time instances where, according to the selected decomposition of correlation matrices, the distinguished market sectors $i = 1, 2, 3, 4$ show strongest on impact volatility transmission during (turmoil) periods $\Omega_s, s = 1, \dots, 4$, according to (9). Ω_0 corresponds to the set of time instances that are not attributed to episodes of market turmoil. In the upper block, frequencies in bold are those that enter and maximize the MDT criterion in (11). The remaining frequencies d_{is} in the upper block are left agnostic by the MDT criterion (see (10) for a definition). Q_t^* is defined as $Q_t^* = V_t^{*-0.5} G_t^*$, where $G_t^* = \Lambda^{-1} \text{diag}(\psi_{1t}, \dots, \psi_{Nt})$.

be of general importance, since it often appears to dominate other markets' behaviour during these time periods ($d_{20}(\widehat{m}) = 43\%$). Meanwhile, the treasury sector has rarely been a dominating factor of financial market volatility during calm periods ($d_{40}(\widehat{m}) = 3\%$). Summarizing, we conclude that the achieved identification appears economically reasonable according to the considered criterion of market dominance.

3.4 Transmission characteristics among key financial markets

We subsequently discuss the characteristic roles of key financial markets for the financial transmission mechanism. To analyse contemporaneous effects, firstly, we refer to scenario

specific averages of matrices Γ_t and $\Sigma_t^{1/2}$ in (3), i.e.

$$\bar{\Gamma}_s = \frac{1}{\omega_s} \sum_{t \in \Omega_s} \Gamma_t; \quad \bar{\Sigma}_s^{1/2} = \left(\frac{1}{\omega_s} \sum_{t \in \Omega_s} \Sigma_t \right)^{1/2}, \quad (17)$$

which are documented in Table 3. To assess their economic importance, secondly, we consider one-step ahead forecast error variance decompositions,

$$\lambda_{ijs} = \frac{1}{\omega_s} \sum_{t \in \Omega_s} \lambda_{ijt}, \quad \text{with} \quad \lambda_{ijt} = \frac{G_t(i, j)^2}{\sum_{k=1}^4 G_t(i, k)^2} = Q_t(i, j)^2, \quad (18)$$

measuring the scenario specific average fraction of market i 's variation attributed to market j , and documented in Table 4. To illustrate variance transmission, lastly, Figure 2 displays scenario specific average VIRFs conditional on sizeable negative innovations u_t^* originating in distinct markets.²³

3.4.1 Equity market

Results documented in the left hand side panel of Table 3 (upper row in each block) indicate that equity market returns positively respond to banking and real estate market news, while the influence of treasury market news is negative. In comparison to the treasury or real estate market, the equity market appears to be quite sensitive to news originating in other markets (left hand side panel of Table 4), where especially the banking market seems important. Depending on the scenario, up to 50.0% of equity return variation is associated with banking market news, whereas e.g. only $\leq 15.4\%$ ($\leq 11.4\%$) of equity return variation is associated with real estate (treasury) market news. VIRFS shown in the first column of Figure 2 further underpin that the equity markets' sensitivity to adverse 'large' banking market news had been especially pronounced during the banking crisis, and, to a somewhat weaker extent, during the burst of the equity bubble. The strong and positive dependence of stock returns

²³Respective covariance responses are available upon request but not discussed here.

Table 3: Average instantaneous effects $\bar{\Gamma}_s$ and standard deviations $\bar{\Sigma}^{1/2}$

$\bar{\Gamma}_s$	eq.	$\bar{\Gamma}_{\bullet 1}$	$\bar{\Gamma}_{\bullet 2}$	$\bar{\Gamma}_{\bullet 3}$	$\bar{\Gamma}_{\bullet 4}$	σ_i	$\bar{\Gamma}_{\bullet 1}$	$\bar{\Gamma}_{\bullet 2}$	$\bar{\Gamma}_{\bullet 3}$	$\bar{\Gamma}_{\bullet 4}$	$\tilde{\sigma}_i$	$\bar{\Gamma}_{\bullet 1}^*$	$\bar{\Gamma}_{\bullet 2}^*$	$\bar{\Gamma}_{\bullet 3}^*$	$\bar{\Gamma}_{\bullet 4}^*$	σ_i^*
Equity bubble (Ω_1)	e_1	1.000	1.825	3.889	-0.242	0.6986	1.000	0.306	0.581	-0.159	1.020	1.000	0.316	0.371	-0.306	1.072
	e_2	-0.183	1.000	1.051	-0.377	0.2352	0.113	1.000	0.127	-0.019	0.393	0.269	1.000	0.255	-0.201	0.486
	e_3	0.836	3.333	1.000	-0.223	0.2423	0.449	0.258	1.000	-0.099	0.833	0.334	0.263	1.000	-0.253	0.852
	e_4	-0.861	1.202	0.639	1.000	0.7268	-0.147	-0.050	-0.119	1.000	0.930	-0.173	-0.133	-0.163	1.000	1.003
Real est. crisis (Ω_2)	e_1	1.000	0.645	2.721	-0.300	0.4688	1.000	0.340	0.586	-0.170	0.693	1.000	0.316	0.371	-0.306	0.628
	e_2	-0.210	1.000	2.151	-0.766	0.5492	0.379	1.000	0.435	-0.084	0.789	0.269	1.000	0.255	-0.201	0.803
	e_3	0.833	1.115	1.000	-0.305	0.2478	0.497	0.345	1.000	-0.121	0.636	0.334	0.263	1.000	-0.253	0.615
	e_4	-1.159	0.410	0.400	1.000	0.6915	-0.208	-0.096	-0.158	1.000	0.868	-0.173	-0.133	-0.163	1.000	0.921
Banking crisis (Ω_3)	e_1	1.000	0.537	2.004	-0.466	0.9282	1.000	0.408	0.439	-0.201	1.469	1.000	0.316	0.371	-0.306	1.308
	e_2	0.139	1.000	1.943	-1.107	1.5490	0.587	1.000	0.516	-0.182	2.244	0.269	1.000	0.255	-0.201	2.309
	e_3	1.293	1.272	1.000	-0.653	0.7112	0.612	0.503	1.000	-0.243	1.921	0.334	0.263	1.000	-0.253	1.922
	e_4	-1.176	0.168	0.057	1.000	1.2386	-0.247	-0.160	-0.205	1.000	1.465	-0.173	-0.133	-0.163	1.000	1.479
Debt ceiling (Ω_4)	e_1	1.000	0.743	3.474	-0.360	0.3734	1.000	0.465	0.562	-0.194	0.614	1.000	0.316	0.371	-0.306	0.579
	e_2	-0.166	1.000	2.385	-0.548	0.3824	0.406	1.000	0.396	-0.034	0.547	0.269	1.000	0.255	-0.201	0.603
	e_3	0.879	1.264	1.000	-0.328	0.1522	0.481	0.392	1.000	-0.159	0.489	0.334	0.263	1.000	-0.253	0.478
	e_4	-1.548	0.525	0.672	1.000	0.6883	-0.255	-0.044	-0.230	1.000	0.972	-0.173	-0.133	-0.163	1.000	1.073
Regular times (Ω_0)	e_1	1.000	0.881	3.804	-0.210	0.3876	1.000	0.332	0.575	-0.126	0.596	1.000	0.316	0.371	-0.306	0.590
	e_2	-0.288	1.000	2.282	-0.495	0.3602	0.283	1.000	0.283	-0.019	0.559	0.269	1.000	0.255	-0.201	0.583
	e_3	0.817	1.451	1.000	-0.174	0.1648	0.436	0.261	1.000	-0.082	0.515	0.334	0.263	1.000	-0.253	0.509
	e_4	-1.440	0.846	0.894	1.000	0.6983	-0.186	-0.031	-0.135	1.000	0.905	-0.173	-0.133	-0.163	1.000	0.956

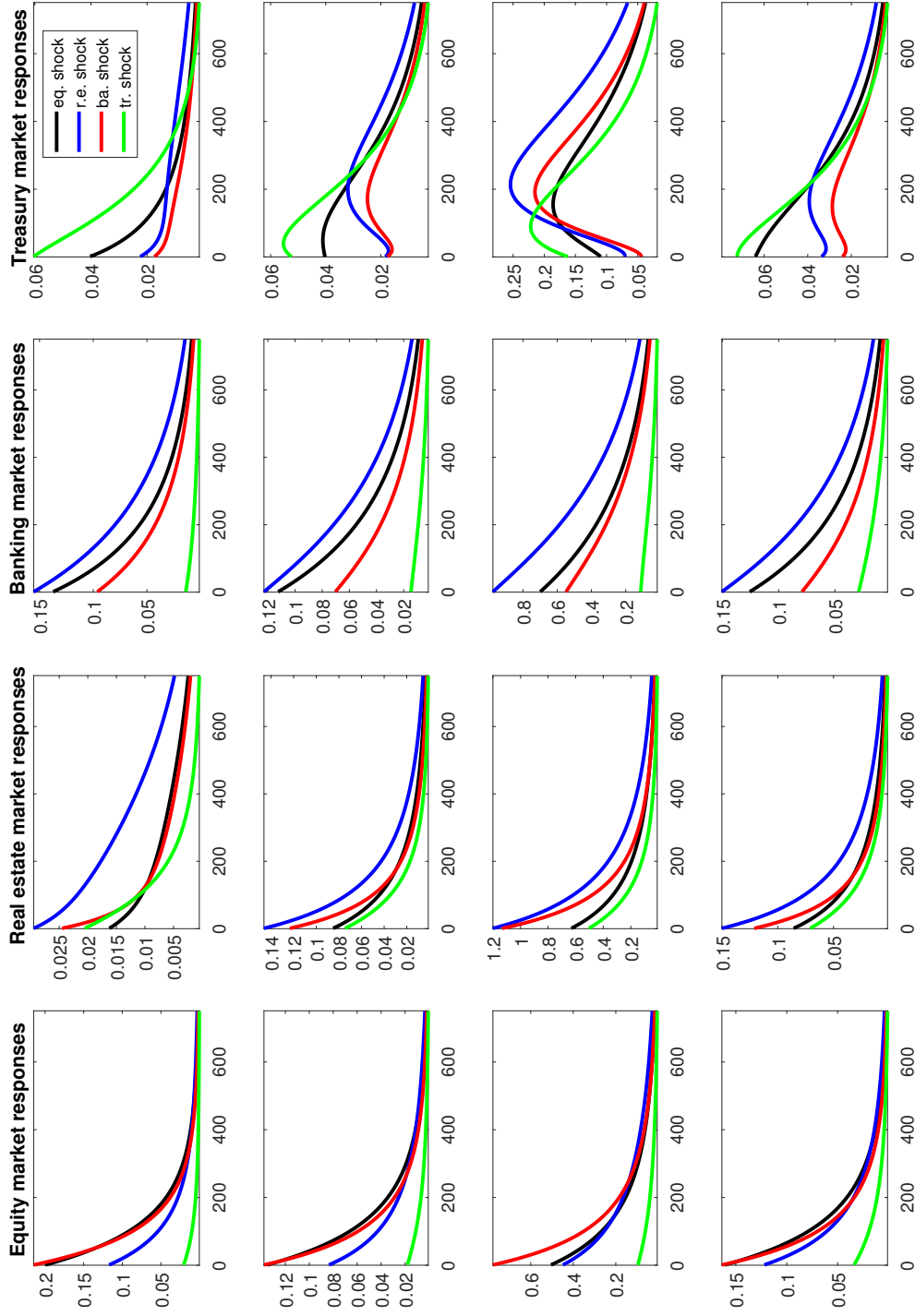
Averages of contemporaneous effects $\bar{\Gamma}_t$ and structural standard deviations $\bar{\Sigma}_t^{1/2}$ during scenario Ω_s . To emphasize those contemporaneous effects which are of particular economic importance, estimates are given in bold whenever respective forecast error variance decompositions in Table 4 exceed 0.25. The left, medium and right hand side panel refers to average contemporaneous effects and structural standard deviations implied by rotated unrotated eigenvalue decompositions $\{\hat{G}_t\}_{t=1}^T$ ($\tilde{G}_t\}_{t=1}^T$), and the factorization implied by the model in Rigobon and Sack (2003), respectively).

Table 4: Local market specific exposure to shocks in financial markets

$i \leftarrow j$	$\widehat{G}_t; \lambda_{ij}^s$				$\sum_{i \neq j}$	$\widehat{G}_t; \lambda_{ij}^s$				$\sum_{i \neq j}$	$G_t^*; \lambda_{ij}^s$				$\sum_{i \neq j}$
	1	2	3	4		1	2	3	4		1	2	3	4	
Ω_1	.3692	.1214	.4766	.0328	.6308	.7400	.0435	.1902	.0263	.2600	.8196	.0192	.0780	.0832	.1804
1	.0885	.2730	.2382	.4003	.7270	.0435	.9075	.0423	.0067	.0925	.1995	.5734	.1135	.1136	.4266
2	.3504	.5564	.0573	.0359	.9427	.1902	.0423	.7481	.0194	.2519	.1563	.0209	.7300	.0928	.2700
3	.3424	.0747	.0195	.5634	.4366	.0263	.0067	.0194	.9476	.0524	.0339	.0044	.0208	.9408	.0591
4	.7813	.7526	.7343	.4690	-	.2600	.0925	.2519	.0524	-	.3897	.0445	.2123	.2896	-
$\sum_{i \neq j}$.3062	.1524	.4748	.0667	.6938	.6759	.0926	.1971	.0344	.3241	.6744	.1084	.0816	.1355	.3255
Ω_2	.0281	.3434	.2626	.3658	.6566	.0926	.7783	.1144	.0147	.2217	.0447	.8710	.0339	.0504	.1290
1	.2658	.5618	.0913	.0811	.9087	.1971	.1144	.6665	.0220	.3335	.1009	.0962	.6829	.1199	.3170
2	.3417	.0600	.0136	.5847	.4153	.0344	.0147	.0220	.9289	.0711	.0149	.0134	.0114	.9603	.0397
3	.6356	.7741	.7510	.5136	-	.3241	.2217	.3335	.0711	-	.1605	.2180	.1269	.3058	-
4	.2436	.1544	.4877	.1143	.7564	.6263	.1576	.1725	.0437	.3738	.5057	.1744	.2121	.1078	.4943
$\sum_{i \neq j}$.0057	.3432	.2869	.3642	.6568	.1576	.6582	.1589	.0253	.3418	.0293	.8709	.0627	.0370	.1290
Ω_3	.2384	.5412	.0863	.1342	.9137	.1725	.1589	.6287	.0399	.3713	.0449	.0741	.8309	.0500	.1690
1	.3484	.0195	.0047	.6274	.3726	.0437	.0253	.0399	.8912	.1089	.0179	.0328	.0404	.9089	.0911
2	.5925	.7151	.7793	.6127	-	.3738	.3418	.3713	.1089	-	.0921	.2813	.3152	.1948	-
3	.2680	.1461	.4863	.0997	.7320	.6521	.1283	.1750	.0446	.3479	.6729	.0696	.0762	.1813	.3271
4	.0396	.3475	.3130	.2999	.6525	.1283	.7349	.1142	.0226	.2651	.0626	.7983	.0456	.0935	.2017
$\sum_{i \neq j}$.2753	.5460	.0754	.1032	.9246	.1750	.1142	.6731	.0377	.3269	.1014	.0636	.6692	.1658	.3308
Ω_4	.4017	.0630	.0214	.5140	.4860	.0446	.0226	.0377	.8951	.1049	.0119	.0068	.0087	.9726	.0274
1	.7166	.7550	.8206	.5028	-	.3479	.2651	.3269	.1049	-	.1759	.1400	.1305	.4406	-
2	.3159	.1363	.5002	.0476	.6841	.7171	.0760	.1821	.0249	.2830	.6885	.0671	.0653	.1791	.3115
3	.0617	.3116	.2798	.3468	.6884	.0760	.8462	.0676	.0102	.1538	.0793	.7650	.0437	.1120	.2350
4	.3067	.5782	.0655	.0497	.9345	.1821	.0676	.7286	.0217	.2714	.1254	.0670	.6225	.1851	.3775
$\sum_{i \neq j}$.3525	.0870	.0195	.5409	.4591	.0249	.0102	.0217	.9432	.0568	.0124	.0065	.0072	.9739	.0261
Ω_0	.7209	.8015	.7995	.4442	-	.2830	.1538	.2714	.0568	-	.2171	.1406	.1162	0.4762	-

Average shares λ_{ij}^s of market i 's fraction of volatility that can be traced back to shocks originating in market j during scenario Ω_s . The left, medium and right hand side panel refers to average shares implied by rotated unrotated eigenvalue decompositions $\{\widehat{G}_t\}_{t=1}^T \equiv \{V_t^{-1/2} \widehat{Q}_t\}_{t=1}^T$ ($\{\widehat{G}_t\}_{t=1}^T$, and the factorization implied by the model in Rigobon and Sack (2003), respectively).

Figure 2: Variance responses under distinct scenarios of financial stress



The graphs in the first, second, third and fourth row (column) refer to turmoil scenario Ω_s , $s = 1, \dots, 4$ (Variance responses of market i , $i = 1, \dots, 4$). Black, blue, red and green VIRFs are conditional on shocks originating in the equity, real estate, banking and treasury market, respectively. For instance, the red VIRF in the lower left subplot refers to the equity market's average variance response (left column) to banking shocks (red) during the debt ceiling crisis Ω_4 (fourth row).

to banking market news likely reflects that the expected performance of the private sector is strongly subject to the capitalization and liquidity (and, hence, also the lending behavior) of financial institutions.

3.4.2 Real estate sector

Further results shown in Table 3 (left hand side panel, second rows in each block) show that real estate sector returns tend to negatively respond to equity market news (except during the banking crisis) and treasury market news, while the influence of banking market news is positive. In comparison with the banking or equity market, the real estate market appears less sensitive to news originating in other markets (see Table 4). Especially the treasury market (30.0 - 40.0%) and the banking sector (23.8 - 31.3%) are important external determinants of real estate market returns on a day-to-day basis. Referring to the effects of sizeable adverse news, VIRFs given in the second column of Figure 2 highlight that the banking market is the strongest external source of real estate market turmoil.²⁴ During the banking crisis, the effects of own shocks and banking market shocks are extremely strong and of similar magnitude. Apparently, news on the state of the capitalization and liquidity of the banking sector (also governing its lending behavior) are important for the expected performance of the real estate market. Moreover, banks hold real estate as collateral and might be forced to sell it in case of adverse events (Shin 2008, Gai and Kapadia 2010, Aikman et al. 2009). Regarding the sizeable influence of treasury market news on REITs, one might consider a substitution relation dominated by the performance of treasury bonds. Accordingly, treasury bonds would be substituted for REITs in response to adverse treasury market news.

²⁴Remember that variance decompositions are derived from all observations within Ω_i , while VIRFs are based upon observations falling below the 10% quantile of empirical shocks within Ω_i .

3.4.3 Banking sector

The banking market (see Table 3, left hand side, third rows in each block) positively responds to news originating in the real estate and the equity market, and negatively to treasury market news. First of all, banking sector variation appears highly sensitive to real estate sector news (54.1 - 57.8%), while it further responds to equity market news quite strongly (23.8 - 35.0%). This, in turn, implies a weak impact of own news, at least on a day-to-day basis ($\leq 9.1\%$). VIRFs shown in the third column of Figure 2 emphasize these marked dependence characteristics, but further highlight a sizeable influence of ‘large’ own shocks. Hence, the banking sector appears as a central catalyst of financial turmoil. Its market capitalization strongly responds to real estate market news (as implied by the collateral value hypothesis, Niinimäki 2009; Koetter and Poghosyan 2010) and, to a somewhat weaker extent, to equity market news (associated with borrower net worth). As discussed before, it is further diagnosed as a central determinant of equity and real estate market performance. Hence, we find strong evidence for a financial amplification mechanism characterized by falling asset prices to undermine banks, and struggling banks to induce plunging asset markets (Krishnamurthy, 2010). Moreover, we find that, in addition to direct dependencies within the banking system due to interbank claims (Allen and Gale, 2000), indirect linkages operating via fire sales and balance sheet effects (Shin 2008, Gai and Kapadia 2010, Aikman et al. 2009) might substantially contribute to the spread of bank default risks. Furthermore, model estimates underpin why (in contrast to the burst of the equity market bubble during Ω_1), the unwinding of imbalances in the real estate sector during Ω_2 led to a systemic crisis. Though the banking sector had been subject to equity market shocks during Ω_1 , the variation in the real estate sector remained almost unaffected (in absolute terms) by the adverse developments in both markets (see Figure 2). During Ω_2 , in contrast, both real estate markets and equity markets show an increased sensitivity to adverse banking market news. This, in turn, implies a strengthening of the feedback mechanism.

3.4.4 Treasury market

According to the results documented in Table 3 (left hand side, fourth rows in each block), the treasury market positively reacts to banking and real estate market news, but negatively to equity market news. Treasury market volatility mainly reflects own news (51.4 - 62.7%) and equity market news (34.2 - 40.2%), which is also confirmed by VIRFs shown in the fourth column of Figure 2. The negative dependence of treasury returns on equity market news should reflect the ‘flight to quality’ phenomenon, where investors substitute safe assets for risky ones (risky assets for safe assets) in response to increasing (decreasing) risk.

4 Implications of alternative approaches

Subsequently, we will discuss in how far structural evidence based upon ad-hoc decompositions (unrotated eigenvalue decomposition (\tilde{G}_t), lower Cholesky factors (G_t^∇)) and the model of Rigobon and Sack (2003) (G_t^*) conforms with the stylized crisis chronology. The lower panels of Table 2 provide respective dominance frequencies. In addition, Table 4 shows average one-step ahead forecast error variance decompositions (λ_{ijs}) obtained by means of i) unrotated eigenvalue decompositions $\{\tilde{Q}_t\}_{t=1}^T$ and ii) the approach of Rigobon and Sack (2003). To economize on the discussion, we will focus on dominance frequencies and forecast error variance decompositions. Instantaneous effects $\bar{\Gamma}_s$ and associated volatilities are sketched in the center and right hand side panel of Table 3 for completeness.

Results shown in Table 2 underpin that, by construction, triangular decompositions favour/exclude particular patterns of market dominance. For instance, with lower triangularity no market except the equity market shows up as a dominating market according to the criterion in (9). As a consequence, one can hardly discriminate among volatility transmitters over distinct periods of market turmoil by means of Cholesky factors, irrespective of the ordering of variables. For space considerations, we do not provide further diagnostics on

triangular decomposition schemes.

In contrast, the structural model based on the sequence of (unrotated) eigenvalue decompositions, $\{Q_t\}_{t=1}^T$ appears less restrictive in terms of the causality structure. With regard to our empirical example, however, eigenvalue based decompositions $\{Q_t\}_{t=1}^T$ often appear controversial economically. For instance, real estate market dominance is never indicated during the first part of the financial crisis ($d_{22}(\widehat{m}) = 0$), while both the equity and banking sector appear as dominant markets ($d_{12}(\widehat{m}) \approx d_{32}(\widehat{m}) \approx 50\%$). Moreover, the banking crisis is predominantly associated with equity market dominance ($d_{13}(\widehat{m}) = 55.7\%$). According to forecast error variance decompositions in Table 4, market specific volatility is mainly traced back to own shocks (62.6 - 94.7%). Hence, the observed variation in standardized returns of sector i reflects structural shocks hitting sector i almost in a one-to-one manner. Consequently, instantaneous transmission and reception, identical by construction, are rather weak. For instance, news on events in the banking sector would have explained only 0.4-17.3% percent of variation in other markets during the banking crisis Ω_3 . Moreover, the exposure of the banking sector to the real estate sector during the first part of the great crisis (Ω_2) would be diagnosed surprisingly small (11.4%). In general, instantaneous features of the banking and the equity sector appear almost identical over time which is economically counterintuitive in light of their distinct roles within the financial system. In summary, it appears that (symmetric) eigenvalue decompositions are characterized by a fundamental weakness in separating particular effects of interest.

Finally, we consider patterns of market importance implied by QML-estimates of the structural MGARCH model in Rigobon and Sack (2003). At first sight, respective forecast error variance decompositions in the right hand side of Table 4 appear intuitive. Own news effects of markets $i = 1, \dots, 4$ tend to be strongest during associated dominance episodes Ω_s , $i = s$, while the local total spillovers of market i tend to be stronger in Ω_s , $s = i$ comparison with those during Ω_s , $s \neq i$. However, the structural model of Rigobon and Sack (2003)

also bears some controversial economic implications. For instance, news originating in the treasury market exert very strong cross market impacts. Especially during the real estate crisis and normal times, cross market impacts of news originating in the treasury sector throughout exceed respective cross market effects triggered by all other markets. Moreover, central aspects of the great financial crisis lack indication. With regard to the real estate crisis, for instance, the IVH approach predicts that only 9% (10%) of the variation in the banking sector (equity market) is associated with news originating in the real estate market. At the same time, only 3% of real estate variation is accounted to news in the banking sector. During the banking crisis, moreover, only 7% of the variation in the banking market is traced back to news originating in the real estate sector. Moreover, the variation in the real estate sector is hardly affected by the news on struggling banking institutions and associated fire sales (6%). Consequently, some dominance frequencies in Table 2 appear at odds with economic intuition. The real estate crisis, for instance, is strongly characterized by market dominance of the treasury sector (71%), rather than by real estate or banking sector dominance (18% and 6%). Under regular market conditions, the IVH model attributes market dominance to the treasury sector in 89% of all time instances which casts some doubts on the model outcome and/or its interpretation.

5 Conclusions

We introduce a new structural view on MGARCH modelling to investigate contemporaneous interaction and variance transmission dynamics among the US equity, real estate, banking and treasury market during 1/3/2000 and 12/26/2014. Drawing upon recent contributions to identification via heteroscedasticity and structural VAR analysis, the novel identification scheme - market dominance targeting (MDT) - formalizes transmission in a way that a structural MGARCH model is best in line with narrative economic information on historic episodes of financial market turbulence and its presumed origin. MDT is a coherent

framework i) to uncover the economic structure underlying financial transmission, and ii) to illustrate the implied model dynamics by means of identified volatility impulse response functions (VIRFs). In comparison to alternative approaches to structural MGARCH modeling (ad-hoc decompositions, and the structural MGARCH model of Rigobon and Sack 2003), the MDT identified model offers very intuitive model implications and allows insights on time varying patterns of instantaneous interactions and volatility transmission during the era of financial market fragility. The structural BEKK model provides various insights into the interplay of financial markets, illustrating the key importance of the banking sector for financial stability. It is the most sensitive market with regard to shocks originating in other markets in general and to shocks originating in the real estate sector in particular. In turn, it is the dominant source of general (co)variation in the financial sector if it comes under stress. The real estate market is the most important trigger of banking market volatility, while being also strongly exposed to shocks originating in the banking market. The equity market is of moderate importance for generating financial turmoil, while its impact under stress in the banking sector still seems quite strong. The treasury sector is neither a dominant transmitter nor a core recipient of volatility in comparison with the other markets. However, it exerts some influence on real estate market volatilities. Though our evidence points at a strong relevance of indirect linkages with regard to the spread of bank defaults, a rigorous comparison of direct vs. indirect effects would require an explicit consideration of intra banking sector linkages. Apparently, this would enlarge the cross section and might require the combining of MDT with event based identification techniques. We regard this as an issue of future research.

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Appendix A: Episode selection

As proposed in this work, the identification of instantaneous transmission among distinct financial markets relies on the attribution of distinguished periods of common turmoil to a specific market as a time local, dominant source of general (co)variation. In this section, we summarize some consensual facts on the local dominance²⁵ of particular markets as sources of general financial (co)volatility during 2000/1 and 2014/12.²⁶ Four disjoint subperiods of US financial market fragility are of particular interest, (i) the early millennium burst of the equity bubble, (ii) the real estate crisis (first part of the great financial crisis), (iii) the banking crisis (second part of the great financial crisis), and (iv) the period of debt ceiling disputes. To support the discussion, Figure 1 shows the time paths of index quotes, log returns and monthly realized volatilities for the Dow Jones Industrial Average, the Wilshire US REIT, the Datastream Americas Banks and the Datastream US benchmark 10 year government bond indices.

The burst of the equity bubble (episode Ω_1): After years of growth in equity value reflecting the uprise of the so-called new economy (e.g. the internet or biotech sectors), US stock markets faced a period of increased turmoil between 3/15/2000 and 4/1/2003.²⁷ The 9/11 terrorist attacks spurred equity devaluation. After recovering from lows reached after the 9/11 attacks, the so-called ‘stock market downturn’ of 2002 constituted another characteristic part of this episode. Especially during 7/5/2002 and 10/9/2002, US stock markets dropped strongly in value. For instance, from 7/5/2002 to 7/23/2002 (8/22/2002 to 10/9/2002) the Dow Jones dropped from 9379 to 7702 (9053 to 7286) points. Until 3/31/2003 the Dow Jones had recovered to about 9000 points, and market volatility declined in the af-

²⁵The term ‘dominance’ is meant in a comparative sense. Hence, other markets might also exert an important (though not dominant) impact on financial volatility.

²⁶See, e.g., the home page of the Federal Reserve Bank of St. Louis for a chronology of crisis related events (<https://www.stlouisfed.org/financial-crisis/full-timeline>).

²⁷The peak of the Nasdaq 500 index on 3/10/2000 is often seen as the beginning of this development.

termath. Hence, during the first episode of (relatively) high conditional (co)variances within the US financial system displayed in Figure 1, risk relevant news originating in the equity market should have been more important for investors' decisions in comparison with news originating in other markets. We therefore consider the period of equity market dominance to prevail from 3/1/2000 until 4/1/2003. Subsequently, the set of all time instances within this period is denoted Ω_1 .

The great financial crisis (Ω_2 and Ω_3): The great financial crisis, which took its course between 8/1/2007 and 6/1/2009 (Hellwig, 2009; Ait-Sahalia et al. 2012), covers the burst of the US real estate market bubble and a subsequent banking crisis with global effects. This time period is characterized by the second sizeable volatility cluster displayed in Figure 1. After a period of sustained US house price inflation, excessive subprime lending, and mispricing of risks inherent in mortgage backed securities and collateralized debt obligations until early 2006 (Nadauld and Sherlund, 2009), a strong deceleration of home prices initiated the real estate market crisis in the beginning of 2007. This decline triggered mortgage delinquencies and foreclosures, further amplifying the implosion of house prices and associated asset backed securities. The strong increase of short term interest rates after August 8, 2007 made the financial crisis apparent (Taylor, 2009). For a period ending with the collapse of the US financial institution Bear Stearns, and its distress sale to JPMorgan Chase (3/16/2008), one might presume that risk factors stemming from the real estate sector have been a primer source of the volatility in other parts of the financial system. For instance, financial system (co)variation could have been driven by influential events such as the first major subprime related loss reported by HSBC in February 2007, the largest US house builder DR Horton's warning of huge losses in March 2007, or Bear Stearns' announcement of the collapse of two of its hedge funds in July 2007.

The more the banking sector was adversely affected by the implosion of the real estate market, the stronger became its own impact on systemic risk and volatility. To maintain

solvency, struggling banking institutions had to liquidate their financial assets, thereby amplifying the decline in house and stock prices. With the collapse of major financial institutions such as Bear Stearns (3/16/2008), IndyMac (7/11/2008), Fannie Mae and Freddie Mac (9/7/2008), or Lehman Brothers (9/15/2008), risk factors stemming from the banking sector might have come into a primary focus. For instance, owing to their important role in the mortgage market, the takeover of Fannie Mae and Freddie Mac caused a market panic.²⁸ Since the Lehman default, moreover, it has become apparent that the US government might refuse to bail out banking institutions heading for insolvency. According to Aït-Sahalia et al. (2012), the government's ad-hoc decisions to bail out particular banks, or to accept their failure, were accompanied by a significant increase in interbank risk premia.

We therefore distinguish two further subperiods of relative market dominance. In the first (second) time period, 2/1/2007 until 3/14/2008 (3/15/2008 until 6/1/2009), risk factors stemming from the real estate (banking) sector are considered to dominate the (co)variations in the financial system.²⁹ Subsequently, we denote the sets of time instances within these periods as Ω_2 (real estate market dominance) and Ω_3 (banking market dominance), respectively.

The debt ceiling disputes (episode Ω_4): During the periods of debt ceiling disputes, risks originating from the treasury market gave rise to considerable financial market volatility (McCarthy, 2012; Baker et al., 2013). Fostered by huge spendings on banking bailout programs the US federal government reached the debt ceiling in March 2011. The dispute on raising the debt ceiling to prevent either a partial government shutdown or a default on the debt continued through the first half of 2011 until the Budget Control Act was implemented on 8/2/2011. After 7 decades of highest possible rating, Standard & Poor's downgraded the

²⁸<http://www.nytimes.com/2008/07/11/business/11ripple.html?ex=1373515200&en=8ad220403fcfd6e&ei=5124&partner=permalink&exprod=permalink>

²⁹Targeting at a distinction between the 'local' US subprime crisis and the 'global crisis', Aït-Sahalia et al. (2012) split the crisis period into two similar sub-periods: 7/1/2007 to 9/14/2008 and 9/15/2008 to 3/31/2009.

federal government’s credit rating from AAA to AA+ on 8/5/2011. The rating agencies Fitch and Moody’s, moreover, changed their outlook to ‘negative’ on 7/2/2011 and 11/28/2011, respectively. One might conjecture that these developments also contributed to the drop of the Dow Jones Industrial Average by almost 2,000 points (-15%) in late July and August 2011. For instance, after the downgrade on 8/5/2011, the Dow Jones dropped by about 635 points (-5%) on 8/8/2011. As illustrated in Figure 1, the time period 3/1/2011 – 1/1/2012 is also characterized by local peaks in realized monthly standard deviations of government bond index returns. The debt ceiling was reached on 12/31/2012 again, and extraordinary measures had to be taken. The government’s need to relax this limit gave rise to intense debates in Congress in the mid of 2013. The debates ended in October 2013 when Republicans backed down one day before the legal default as announced by the treasury department.³⁰ Realized monthly standard deviations of government bond index returns increased markedly during the period from 5/1/2013 until 11/1/2013 (see Figure 1). Hence, an increased focus could have been put on the risks originating from the treasury market during the periods 3/1/2011 – 1/1/2012 and 5/1/2013 – 11/1/2013. Henceforth, the set of time instances within these periods is denoted as Ω_4 .

Regular market conditions (Ω_0): Representing distinct scenarios of financial fragility each of the outlined turmoil episodes Ω_s , $s = 1, \dots, 4$, is associated with risks stemming from one particular market. These episodes should provide information i) for the identification of contemporaneous effects of sizeable market specific shocks, and ii) for characteristic scenarios under which sector specific volatility transmission takes place.³¹ To complete the structuring of the era of financial fragility, all time instances between 3/1/2000-12/26/2014 that are not included in one of these ‘informative’ (and non-overlapping) episodes comprise Ω_0 , the set of time instances characterized by regular or normal market conditions. Due to the lack of

³⁰http://www.nytimes.com/2013/10/17/us/congress-budget-debate.html?_r=0

³¹See Sections 2.2 and 2.3 for further discussion of these issues.

economic arguments, eventual patterns of dominance characterizing Ω_0 are left agnostically unspecified. Hence, model implied patterns of market dominance during Ω_0 can be used to evaluate if the model accords with economic intuition.

Appendix B: BEKK estimates

$$\begin{aligned}
 C &= \begin{pmatrix} 0.0825 & - & - & - \\ (63.45) & & & \\ 0.0347 & 0.0538 & - & - \\ (32.09) & (41.51) & & \\ 0.0423 & -0.0021 & -0.0272 & - \\ (41.26) & (-3.23) & (-23.22) & \\ -0.0102 & 0.0381 & 0.0003 & 0.0675 \\ (-9.24) & (39.55) & (0.28) & (41.80) \end{pmatrix}, \\
 A &= \begin{pmatrix} 0.2299 & 0.0220 & 0.0035 & -0.0030 \\ (19.66) & (1.8628) & (0.2537) & (-0.4233) \\ -0.0023 & 0.2700 & 0.0141 & -0.0005 \\ (-0.22) & (27.1906) & (1.2982) & (-0.0837) \\ 0.0142 & 0.0095 & 0.2228 & 0.0012 \\ (1.41) & (0.9082) & (21.3066) & (0.2084) \\ -0.0070 & 0.0060 & -0.0022 & 0.1513 \\ (-0.51) & (0.4748) & (-0.1448) & (20.6453) \end{pmatrix}, \\
 B &= \begin{pmatrix} 0.9675 & -0.0057 & 0.0006 & -0.0005 \\ (295.88) & (-1.64) & (0.19) & (-0.29) \\ -0.0015 & 0.9572 & -0.0008 & -0.0014 \\ (-0.50) & (330.80) & (-0.27) & (-0.96) \\ -0.0043 & -0.0014 & 0.9734 & -0.0001 \\ (-1.51) & (-0.50) & (359.93) & (-0.08) \\ 0.0007 & -0.0072 & 0.0008 & 0.9843 \\ (0.20) & (-2.26) & (0.24) & (601.97) \end{pmatrix}.
 \end{aligned}$$

Appendix C: Structural homogeneity

The structural MGARCH model relies on an iid assumption for underlying model innovations u_t . Moreover, we determine VIRFs from averaging the effects of sizeable shocks and covariance states that characterize distinguished periods of market turmoil. To underpin structural stability, and to motivate the empirical approach to shock selection, it is worthwhile to diagnose that the respective shocks are drawn from a homogeneous distribution across distinct episodes of market turmoil and regular market conditions. Full sample and subsample diagnostics on the homogeneity of innovation distributions during the era of fragility are documented in Table 5.

The estimated BEKK model captures the covariance dynamics of market returns conveniently over distinguished periods of market turmoil. Episode specific structural shocks have means and correlation matrices close to zero and the identity matrix, respectively. Subsample specific standard deviations of model innovations are somewhat larger during crisis episodes ($\Omega_1, \dots, \Omega_4$) in comparison with tranquil periods (Ω_0). Among the former, the extreme turmoil during the second part of the financial crisis (Ω_3) reveals some unmodelled return variation with standard errors of innovations up to 1.2. More importantly, however, the identified BEKK specification is rather convenient to model market comovements under turmoil. Among 24 (six correlation statistics for each of four subsamples) measures of innovation correlation only 2 are nonzero with 5% significance.

Addressing distributional homogeneity of identified innovations, Table 5 further documents Kolmogorov-Smirnov statistics (Massey, 1951), measuring the distance between market specific marginal innovation distributions under turmoil (Ω_i) and during tranquil periods (Ω_0). While some distributional heterogeneity is already reflected by heterogeneous standard deviations, the KS test signifies such heterogeneity for only one market (real estate)

with 1% significance. Assessing the heterogeneity of market specific innovations between normal times and turmoil, respective p -values for the remaining markets are 4% (equity), 14% (banking) and 58% (treasury).

Having diagnosed that the identified BEKK specification obtains contemporaneously uncorrelated and (almost) homogeneously distributed structural innovations, one might ask if rival identification schemes, $(\{\tilde{Q}_t, Q_t^\nabla, Q_t^\Delta\}_{t=1}^T)$, perform similarly. Evaluating KS statistics for innovations retrieved from ad-hoc decompositions shows that (i) applying unrotated eigenvalue decompositions obtains evidence for innovation heterogeneity for three markets with 5% significance; (ii) applying a lower triangular Cholesky factor obtains significant distributional heterogeneity for the equity and the real estate sector; and (iii) applying an upper triangular Cholesky factor shifts innovation heterogeneity to shocks originating in the treasury market (with 5% significance).

Table 5: Residual diagnostics

	mean		corr/std dev.				mean		corr/std dev.		
All	-0.010	0.999				Ω_2	-0.023	1.083			
	0.014	0.015	1.013				-0.113	0.058	1.130		
	0.001	-0.011	-0.005	0.013			0.063	0.018	0.005	1.022	
	-0.010	0.003	-0.002	0.011	0.996		0.084	-0.024	-0.047	-0.058	1.079
	0.008	0.951					Ω_3	-0.020	1.136		
0.055	-0.027	0.956			-0.061	-0.004		1.202			
0.013	-0.027	0.021	0.952		-0.088	-0.083		-0.042	1.189		
-0.033	0.024	-0.001	0.008	0.962	-0.019	0.144*		-0.017	0.032	1.104	
-0.034	1.023				Ω_4	-0.020		1.024			
0.023	0.099*	1.004				-0.061	0.009	1.056			
-0.055	0.070	-0.065	1.086			-0.088	-0.066	0.033	1.019		
0.001	-0.054	0.053	0.062	1.007		-0.019	-0.078	-0.037	-0.049	0.997	
s	0	1	2	3	4		0	1	2	3	4
KS		MDT					Eigenvalue decomposition				
	\hat{Q}_t	0.058	0.149	0.070	0.041	\tilde{Q}_t	0.088	0.104	0.083	0.034	
	(0.04)	(0.00)	(0.14)	(0.58)		(0.00)	(0.01)	(0.05)	(0.82)		
		Lower Choleski					Upper Choleski				
	Q_t^∇	0.098	0.133	0.047	0.034	Q_t^Δ	0.056	0.067	0.063	0.075	
	(0.00)	(0.00)	(0.58)	(0.81)		(0.05)	(0.18)	(0.23)	(0.04)		

Means, standard deviations and correlation coefficients for structural shocks for distinct episodes are given in the upper panel. Asterisks ‘*’ indicate significance of correlation coefficients at the 5% level, according to the rule-of-thumb threshold $2/\sqrt{\omega_i}$ for correlations in (sub)samples Ω_s , $s = 0, \dots, 4$. In the lower panels, Kolmogorov-Smirnov test statistics on the hypothesis $F(u_{it}|u_{it} \in \Omega_0) = F(u_{it}|u_{it} \in \Omega_s)$ $s = 1, \dots, 4$ are provided (p -values).