Good Contagion:
What Do Networks Say about Policy Transmission?

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Abstract

We tend to think of contagion as something bad, as a small initial shock amplifying into a systemic crisis, as a financial distress propagating from one bank to another, or as a spread of infectious disease. This paper focuses on good contagion that can facilitate policy propagation. We develop multi-layer network based *contagion centrality* measures and apply them to analyse the European Central Bank's interest rate policy transmission. Understanding how network contagiousness, and network structure more generally, can influence the policy transmission is useful for this policy's future successful implementations. The findings indicate that policy transmits most efficiently in severe bearish contagion and least efficiently in intense bullish contagion environments. This finding is attributed to the level of attention that markets pay to central bank announcements during turmoil and calm periods. The introduced measures can also be used as indicators of systemic importance and as an early warning system of contagion risk.

1 Introduction

Inflation as well as interest rates have been low during the second decade of the twenty-first. The European Central Bank (ECB), along with other major central banks, has employed both conventional and unconventional measures to bring inflation back to its 2% target. In conjunction with long term refinancing operations (LTRO) and quantitative easing (QE), the ECB has cut the main refinancing rate down to zero in order to loosen the private sector borrowing constraints and stimulate credit growth (Van Riet, 2017), and ultimately drive inflation up. The ECB was also the first central bank to break the zero lower bound of nominal interest rates when it set the deposit facility rate to negative 10 basis points in June 2014 and reduced it further in the following months. This measure aimed to discourage banks from holding too much cash with the ECB, and to encourage lending and investment into the real economy instead. The policy measures undertaken might or might not have always worked as intended or fully transmitted to the economy due to various factors. One of those factors is network structure and the focus of this paper is to study whether and how the network contagiousness can influence the policy transmission.

The Global Financial Crisis 2008 has revealed that not only did we have very limited knowledge of the network structure of the financial system, but also an inadequate comprehension of how exactly that network structure can affect the shock propagation in the system. A question that received particular attention in the literature was whether more connections amplify the initial shock by creating more channels or moderate it by allowing for risk-sharing. This paper's perspective is somewhat opposite to the analysis of crisis propagation where the aim is to make the network *robust*. We analyse the network properties that make the network *prone* and facilitate policy transmission.

Specifically, we consider transmission of ECB's monetary policy into the desired inflation targets in Eurozone countries through the asset prices channel. According to this channel, an expansionary monetary policy, for instance, an interest rate cut, causes an increase in asset prices, for instance, stock prices, which in turn raises the wealth value of the households and enables them to increase their consumption. Higher consumption raises aggregate demand and leads to higher consumer good prices, i.e. to inflation. Putting this into a network context, the monetary policy announcement is an initial shock affecting the asset prices in all network nodes (countries). When contagion level and interconnectedness in the network are high, the direct impact of that initial shock can amplify due to network feedback effects.

The contribution of this paper is three-fold. First, the paper introduces new *contagion centrality* measures which incorporate heavy-tailedness, copula dependence structure and multi-layer network effect. The multi-layer interactions are important and a single layer analysis in isolation might underestimate the overall contagion risk in the system. Indeed, as Buldyrev et al. (2010) demonstrate, the multi-layer network analysis can "destabilize basic assumptions" of (single-layer) network theory. For example, one of the key assumptions in the network theory is that scale-free networks (real-world networks with heavy-tailed degree distribution) are robust to random failures. Their hub-spoke structure guarantees that even if a major hub defaults, the network can still function due to the presence of other hubs. Buldyrev et al. (2010) show that in the multi-layer case, on the contrary, the networks with narrow degree distribution are more resilient to random failures.

The introduced measures have several important uses. The measures can be used for the identification of the systemically important nodes. They can also be applied to analysing the efficiency of policy transmission across the network and thereby identifying the favourable environment for that policy's future implementation. And finally, they can describe the evolution of the dependence and contagion structure of the multi-layer network over time and act as an early warning system of contagion risk. The analysis indicates that the bearish contagion intensifies during turmoil periods, as it did both during the Global Financial Crisis 2008 and the European Debt Crisis 2010. The bullish contagion, on the contrary, escalates in the post-crisis periods as economies recover after the turmoil.

Second, this paper contributes to the literature on monetary policy transmission. Cook and Hahn (1989) empirically test whether changes in federal funds' rates can affect the bond rates. Bernanke and Kuttner (2005) study the effect of the Federal Reserves' monetary policy on the equity prices. More recently, Leombroni et al. (2021) consider the impact of the ECB's communications on the bond yields in Europe. Ozdagli and Weber (2017) and references herein consider the impact of the intersectoral input-output network on the monetary policy transmission into equity prices.

This paper differs from those studies in that it analyses monetary policy transmission into the inflation targets *through* the asset prices network rather than *into* the asset prices themselves. We find that policy transmission is more effective in high bearish and low bullish contagion environments. This finding may have behavioural foundations. In the bearish environment, generally associated with crises, the uncertainty is high and the markets' attention is focused on central bank's policy announcements. In the bullish environment, generally associated with booms, the overoptimism and lack of attention can make the policy transmit slower.

Third, the paper adds to the literature on network origins of tail risk. Gabaix (2011) shows that idiosyncratic shocks to individual firms can contribute to aggregate shocks if the firm-size distribution is heavy-tailed. Acemoglu et al. (2017) address this question in a network setting and demonstrate that the idiosyncratic shocks to the network nodes may lead to aggregate macroeconomic fluctuations given that the nodes' degree distribution is sufficiently heterogeneous. This paper not only studies the propagation of shocks in the network, but also sheds light on the origins of those idiosyncratic shocks in the first place. The results indicate that the network effect captured by *contagion centrality* is indeed a determinant of tail risk that individual network nodes are exposed to.

The rest of the paper is organised as follows. Section 2 describes the methodology and is divided into three parts. First part 2.1 presents the new multi-layer contagion measures. Parts 2.2 and 2.3 describe the methodology of policy efficiency and tail risk analyses, respectively. In Section 3, the data used in the analysis are described. Section 4 discusses the main results. Finally, Section 5 concludes.

2 Methodology

2.1 New Multi-Layer Contagion Measures

In this subsection we introduce the multi-layer contagion centrality, which is an extension of a single-layer contagion centrality introduced in Abduraimova (2019). We start by formally defining the multi-layer network.[1]

Definition 1. *A* ***multi-layer network G*** *(or a graph) is a triplet* $G = (\mathcal{V}, \mathcal{E}, \mathcal{L})$*, consisting*

[1] For a review on multi-layer network theory refer to Boccaletti et al. (2014)

of a set of nodes $\mathcal{V} = \{v_1^\lambda, ...v_N^\lambda\}$ *(consistent in all layers), a set of unordered pairs (edges) of distinct nodes* $\mathcal{E} = \{(v_i^\lambda, v_j^{\tilde{\lambda}})\}$*, where* $i, j \in \{1, ..., N\}$*, and a set of layers* $\mathcal{L}$*, where each layer is denoted by* $\lambda \in \mathcal{L} = \{1, ..., \Lambda\}$*. Nodes* v_i^λ *and* $v_j^{\tilde{\lambda}}$ *are connected if there exists link* $(v_i^\lambda, v_j^{\tilde{\lambda}}) \in \mathcal{E}$ *between them.*

Note that this is a general definition of a multi-layer network, where a link between any nodes in any layers is possible. In this paper we consider a network where any two nodes can connect within the same layer (intra-layer) and each node is connected only with its own counterpart in a different layer (inter-layer) but not with a distinct node. Thus, we define the following three subsets of intra-layer ($\mathcal{E}_\lambda$) and inter-layer ($\mathcal{E}_c$ and $\mathcal{E}_A$) links:

- $\mathcal{E}_\lambda$ - a subset of links between nodes within the same layer λ: $\mathcal{E}_\lambda = \{(v_i^\lambda, v_j^\lambda)\}$, $\mathcal{E}_\lambda \subset \mathcal{E}$, $i \in \{1, ..., N\}$, $j \in \{1, ..., N\}$, $i \neq j$, $\lambda \in \{1, ..., \Lambda\}$;
- $\mathcal{E}_c$ - a subset of links connecting counterparts of the same node in distinct layers: $\mathcal{E}_c = (v_i^\lambda, v_i^{\tilde{\lambda}})$, $\mathcal{E}_c \subset \mathcal{E}$, $i \in \{1, ..., N\}$, $\lambda \in \{1, ..., \Lambda\}$, $\tilde{\lambda} \in \{1, ..., \Lambda\}$, $\lambda \neq \tilde{\lambda}$;
- $\mathcal{E}_A$ - a subset of links between distinct nodes across distinct layers: $\mathcal{E}_A = \{(v_i^\lambda, v_j^{\tilde{\lambda}})\}$, $\mathcal{E}_A \subset \mathcal{E}$, $i \in \{1, ..., N\}$, $j \in \{1, ..., N\}$, $i \neq j$, $\lambda \in \{1, ..., \Lambda\}$, $\tilde{\lambda} \in \{1, ..., \Lambda\}$, $\lambda \neq \tilde{\lambda}$; this is an empty set in this paper setting $\mathcal{E}_A = \varnothing$.

Networks can be generally divided into two types: *Relation-based* networks, where links constitute actual relationships between nodes (for which data are not always publicly available), such as trade volumes between countries, financial bilateral exposures between institutions and so on; and *Similarity-based* networks, where links characterise the extent of co-movement between random variables (usually based on the public market data) associated with the nodes or any other similarity measure, such as correlation. In this paper, the latter network type is considered in a two-layer setting allowing to capture policy transmission during the periods of extreme downward and upward movements in equity index returns and sovereign bond interest rates.

Each node $v_i^\lambda \in \mathcal{V}$ is associated with some risk $r^{i,\lambda}$ in each network layer $\lambda \in \mathcal{L}$. Risk $r^{i,\lambda}$ is a random variable of financial returns, e.g. equity returns, bond rates, exchange rates, etc. Denote the probability of a shock transmission from node i to node j in layer λ by the conditional probability[2]

$$P(r^{j,\lambda} \leq -z | r^{i,\lambda} \leq -z),\ for\, large\, z > 0, \tag{1}$$

and similarly the likelihood of a boom transmission from node i to node j by the conditional probability

$$P(r^{j,\lambda} > z | r^{i,\lambda} > z),\ for\, large\, z > 0. \tag{2}$$

Denote by $C(u^{i,\lambda}, u^{j,\lambda})$, where $u^{i,\lambda}, u^{j,\lambda} \in [0, 1]$, the copula corresponding to the joint cumulative distribution function (cdf) of $r^{i,\lambda}$ and $r^{j,\lambda}$.[3] We assume continuity of cdf's of the considered random variables which implies uniqueness of the corresponding copulas describing their dependence structure. Let $U^{i,\lambda}$ and $U^{j,\lambda}$ stand for uniform (on $[0, 1]$) random

[2] Negative values of $r^{i,\lambda}$ are interpreted as losses, and positive values as gains.

[3] For a review on copula theory refer to Joe (2014), McNeil et al. (2015), Nelsen (2007) and Choroś et al. (2010).

variables with cdf $C(u^{i,\lambda}, u^{j,\lambda}) = P(U^{i,\lambda} \le u^{i,\lambda}, U^{j,\lambda} \le u^{j,\lambda})$. Formally:

$$\begin{aligned} &for\, every\, pair\; r^{i,\lambda}\; and\; r^{j,\lambda}\; there\, exist\;\; U^{i,\lambda}\; and\; U^{j,\lambda}\; uniformly\, distributed\, on\; [0,1] \\ &\qquad\qquad\qquad\qquad such\; that \quad C(u^{i,\lambda}, u^{j,\lambda}) = P(U^{i,\lambda} \le u^{i,\lambda}, U^{j,\lambda} \le u^{j,\lambda}). \end{aligned} \tag{3}$$

Then, for large z's the probabilities in (1) and (2) are close to the lower (4) and upper (5) tail dependence coefficients in the layer λ, respectively:

$$\tau_{ij}^{L,\lambda} = \lim_{z\to+\infty} P(r^{j,\lambda} \le -z | r^{i,\lambda} \le -z) = \lim_{u\to 0} P(U^{j,\lambda} \le u | U^{i,\lambda} \le u) = \lim_{u\to 0} \frac{C(u,u)}{u}, \tag{4}$$

$$\tau_{ij}^{U,\lambda} = \lim_{z\to+\infty} P(r^{j,\lambda} > z | r^{i,\lambda} > z) = \lim_{u\to 1} P(U^{j,\lambda} > u | U^{i,\lambda} > u) = \lim_{u\to 1} \frac{1-2u+C(u,u)}{1-u}. \tag{5}$$

In this paper we focus on the case of a two-layer network with two layers represented by stock market returns and bonds. For convenience and simplicity of notation, the equity returns layer will be denoted by $\lambda = R$ and corresponding risk of node i in that layer by R^i, and the bond interest rates layer will be denoted by $\lambda = B$ and corresponding risk of node i in that layer by B^i.
In sum, the financial network in the current paper is defined as follows:

- *Nodes*: European countries (see Section 3 on the data description for the full list of countries and more details), each of which is characterised by two random variables of financial risks R^i and B^i in layers $\lambda \in \{R, B\}$.

- *Links*: undirected weighted edges $(v_i^\lambda, v_j^{\tilde{\lambda}}) = (v_j^{\tilde{\lambda}}, v_i^\lambda)$ characterised by the tail dependence coefficients $\tau_{ij}^{tail,R}$ and $\tau_{ij}^{tail,B}$ in lower and upper tails ($tail \in \{L, U\}$) of distributions of equity returns R^i and R^j, as well as of bond rates B^i and B^j, respectively.

- *Layers*: equity network layer and bond network layer. Equity network layer is based on the country's stock market index returns and denoted by $\lambda = R$. Bond network layer is based on the 10Y benchmark sovereign bond interest rates and denoted by $\lambda = B$.

The dynamic component is captured by taking snapshots of the network over time. While nodes and layers are constant across time periods, the links (represented by the tail dependence coefficients) are time-varying. The tail dependence coefficient $\tau_{i,j}^{tail,\lambda}(t)$ between nodes v_i^λ and v_j^λ in layer λ at time t is estimated using random variables R^i and R^j in the equity layer and B^i and B^j in the bond layer over the time interval $(t-T^W, t]$, where T^W is a length of the window used for estimation. The choice of the window length is flexible. However, the number of observations should be sufficiently large as estimation is based on the extreme values (tails) only. A window of $T^W = 260$ daily observations (approximately one year) is used in this paper. All variables and notations with parameter (t) correspond to a network realisation at time t.

For financial or economic variables associated with two markets, their tail dependence coefficient represents the conditional probability of (an adverse - crisis, or a positive - economic policy) shock propagation from one market to the other and is a function of their copula. We consider *Symmetrized Joe-Clayton copula* (SJC) to model that dependence. The SJC copula allows for asymmetric dependence in the lower and upper tails of the distribution of the random variables dealt with. We follow Patton (2006) to define Symmetrized Joe-Clayton copula C_{SJC} for each network layer $\lambda = \{R, B\}$:

$$\begin{aligned} C_{SJC}(u^{i,\lambda}, u^{j,\lambda}) = 0.5 \cdot (C_{JC}(u^{i,\lambda}, u^{j,\lambda}) + \\ + C_{JC}(1 - u^{i,\lambda}, 1 - u^{j,\lambda}) + u^{i,\lambda} + u^{j,\lambda} - 1). \end{aligned} \tag{6}$$

In Equation 6 the copula C_{JC} is *Joe-Clayton copula* defined as:

$$\begin{aligned} & C_{JC}(u^{i,\lambda}, u^{j,\lambda}) = \\ & \quad = 1 - (1 - \{[1 - (1 - u^{i,\lambda})^{\kappa}]^{-\gamma} + [1 - (1 - u^{j,\lambda})^{\kappa}]^{-\gamma} - 1\}^{-\frac{1}{\gamma}})^{\frac{1}{\kappa}}, \\ & \quad \textit{where} \quad \kappa = \frac{1}{\log_2(2 - \tau_{ij}^{U,\lambda})} \quad \textit{and} \quad \gamma = -\frac{1}{\log_2(\tau_{ij}^{L,\lambda})}, \end{aligned} \tag{7}$$

and $\tau_{ij}^{L,\lambda} \in (0, 1)$ and $\tau_{ij}^{U,\lambda} \in (0, 1)$ are the tail dependence coefficients as per (4) and (5).

2.1.1 Multi-Layer Contagion Distance and Contagion Centrality

Denote by "market" superscript the market state in which contagion is being analysed. It characterises the nature of contagion. There could potentially be several market states, for instance, *crisis, boom, normal conditions*. In a general case of a network with more than two layers, the number and definition of the states will depend on the number and type of the layers considered. In this paper we define two possible market states for the network with two layers. The first state is the "bullish" market that is associated with higher inflation, policy rate cuts, soaring (or high) equity prices and decreasing bond interest rates. The second state is the "bearish" market that is, on the contrary, associated with lower inflation, policy rate hikes, sinking (or low) equity prices and increasing bond interest rates. Contagion in the "bullish" and "bearish" markets will be referred to as bullish and bearish contagion, respectively (a formal definition follows below).

Definition 2. ***Multi-layer contagion distance*** $d_{cont}^{M,market}(i, j, t)$ *from node* v_i^λ *to node* v_j^λ *of the multi-layer network at time* t *is the distance on the path* $\gamma_{i,j}(t)$ *connecting nodes* v_i^λ *and* v_j^λ *that*
(1) minimises the length $H(\gamma_{i,j}(t))$ *of the path* $\gamma_{i,j}(t)$ *and*
(2) maximises the log probability of shock transmission along the path $\gamma_{i,j}(t)$*:*

$$\min_{\gamma_{i,j}(t)} \left[H(\gamma_{i,j}(t)) - \left(\sum_{(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}} \log \tau_{cc-1}^{market}(t) \right) \right], \tag{8}$$

The length $H(\gamma_{i,j}(t))$ *is the number of links (or steps) on the path* $\gamma_{i,j}(t)$ *and* $\mathcal{E}_{\gamma_{i,j}(t)}$ *is a set of links constituting the path* $\gamma_{i,j}(t)$*. The path* $\gamma_{i,j}(t)$ *consists of nodes* $\mathcal{V}_{\gamma_{i,j}(t)} = \{i = i_{H_\gamma}, ..., i_0 = j\}$ *and links* $\mathcal{E}_{\gamma_{i,j}(t)} = \{(i = i_{H_\gamma}, i_{H_\gamma - 1}), ..., (i_1, i_0 = j)\}$*.*

The shock can travel across the layers tracking the shorter distance: on each step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ of the path $\gamma_{i,j}(t)$, the layer λ with maximum shock transmission probability, i.e. maximum tail dependence coefficient $\tau_{cc_{-1}}^{market}(t)$, is chosen.[4] Formally, $\tau_{cc_{-1}}^{market}(t)$ on each

[4]We remind that links are represented by tail dependence coefficients in this paper. Therefore, τ_{cc-1}^{market} in (8) corresponds to link $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ and the set of all links on the path $\mathcal{E}_{\gamma_{i,j}(t)} = \{\tau_{H_\gamma H_\gamma - 1}^{market}, ..., \tau_{10}^{market}\}$ to $\mathcal{E}_{\gamma_{i,j}(t)} = \{(i = i_{H_\gamma}, i_{H_\gamma - 1}), ..., (i_1, i_0 = j)\}$.

step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ for $market \in \{bullish, bearish\}$ is defined as:

$$\begin{aligned} \tau_{c,c-1}^{bullish}(t) &= \max\{\tau_{cc-1}^{U,R}(t), \tau_{cc-1}^{L,B}(t)\}, \\ \tau_{c,c-1}^{bearish}(t) &= \max\{\tau_{cc-1}^{L,R}(t), \tau_{cc-1}^{U,B}(t)\}, \end{aligned} \tag{9}$$

where $\tau_{cc-1}^{L,R}(t)$, $\tau_{cc-1}^{U,R}(t)$, $\tau_{cc-1}^{L,B}(t)$ and $\tau_{cc-1}^{U,B}(t)$ are the tail dependence coefficients in individual network layers on each step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ on the path $\gamma_{i,j}(t)$ in the network realisation at time t:

$$\begin{aligned} \tau_{cc-1}^{L,R}(t) &= \lim_{z \to +\infty} P(R^j < -z | R^i < -z), \\ \tau_{cc-1}^{U,R}(t) &= \lim_{z \to +\infty} P(R^j > z | R^i > z), \\ \tau_{cc-1}^{L,B}(t) &= \lim_{z \to +\infty} P(B^j < -z | B^i < -z), \\ \tau_{cc-1}^{U,B}(t) &= \lim_{z \to +\infty} P(B^j > z | B^i > z). \end{aligned} \tag{10}$$

Thus, the bullish contagion distance $d_{cont}^{M,bullish}(i,j,t)$ between nodes v_i^λ and v_j^λ is based on the tail dependence coefficients on the path $\gamma_{i,j}(t)$ in the upper tail of the nodes' equity returns distribution $\tau_{cc-1}^{U,R}(t)$ and in the lower tail of the nodes' bond rates distribution $\tau_{cc-1}^{L,B}(t)$, on each step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$. Similarly, the bearish contagion distance $d_{cont}^{M,bearish}(i,j,t)$ between nodes v_i^λ and v_j^λ is based on the tail dependence coefficients on the path $\gamma_{i,j}(t)$ in the lower tail of the nodes' equity returns distribution $\tau_{cc-1}^{L,R}(t)$ and in the upper tail of the nodes' bond rates distribution $\tau_{cc-1}^{U,B}(t)$.
We use the Dijkstra path search algorithm to obtain a $(N-1)$x$(N-1)$ matrix of contagion distances. The matrix is symmetric and each element $d_{cont}^{M,market}(i,j,t)$ represents the contagion distance between node v_i^λ and node v_j^λ at time t in a given market state. The following assumptions are imposed on the path of shock propagation:

- a shock can propagate from node v_i^λ to other nodes v_j^λ in the same network layer λ;
- a shock can propagate from node v_i^λ to its own counterpart node in other layers $v_i^{\tilde{\lambda}}$;
- a shock transition from node v_i^λ to its own counterpart in a different layer $v_i^{\tilde{\lambda}}$ does not count as a step (has zero cost);
- a shock cannot propagate directly from node v_i^λ in layer λ to a different node $v_j^{\tilde{\lambda}}$ in a different layer $\tilde{\lambda}$ (this is only possible through node v_i^λ's counterpart in layer $\tilde{\lambda}$), i.e. through $v_i^{\tilde{\lambda}}$.

Let $\mu_i^{M,bullish}(t)$ and $\mu_i^{M,bearish}(t)$ as well as $\sigma_i^{M,bullish}(t)$ and $\sigma_i^{M,bearish}(t)$ be the sample means and the sample standard deviations of multi-layer contagion distances from node i to the remaining *N-1* nodes at time t in "bullish" and "bearish" markets, respectively:

$$\begin{aligned}
\mu_i^{M,bullish}(t) &= \frac{\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bullish}(i,j,t)}{N-1}, \\
\mu_i^{M,bearish}(t) &= \frac{\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bearish}(i,j,t)}{N-1}, \\
\sigma_i^{M,bullish}(t) &= \sqrt{\frac{\sum_{j=1,j\neq i}^{N-1}(d_{cont}^{M,bullish}(i,j,t)-\mu_i^{M,bullish}(t))^2}{N-2}}, \\
\sigma_i^{M,bearish}(t) &= \sqrt{\frac{\sum_{j=1,j\neq i}^{N-1}(d_{cont}^{M,bearish}(i,j,t)-\mu_i^{M,bearish}(t))^2}{N-2}}.
\end{aligned} \tag{11}$$

We define *Multi-layer Contagion Centrality* as the reciprocal of the concentricity score of multi-layer contagion distances, so that a more important and more central node has a higher value of centrality measure.

Definition 3. ***Multi-layer contagion centrality*** $CC_i^{M,market}$ *of node* v_i *is a network centrality measure based on the multi-layer contagion distances* $d_{cont}^{M,market}(i,j)$ *in* $market = \{bullish, bearish\}$ *and computed as the reciprocal of the concentricity score of those contagion distances:*

$$\begin{aligned}
CC_i^{M,bullish} &= \frac{1}{\sqrt{(\mu_i^{M,bullish})^2+(\sigma_i^{M,bullish})^2}}, \\
CC_i^{M,bearish} &= \frac{1}{\sqrt{(\mu_i^{M,bearish})^2+(\sigma_i^{M,bearish})^2}}.
\end{aligned} \tag{12}$$

Further, denote by $CC^{M,market}$ the contagion centrality of the whole network (note that there is no subscript i as opposed to an individual node i centrality) in $market = \{bullish, bearish\}$. The contagion centrality $CC^{M,market}$ describes the overall contagion level in the network and is defined similar to contagion centrality $CC_i^{M,market}$ of an individual country. However, the sample mean $\mu^{M,market}$ and the sample standard deviation $\sigma^{M,market}$ are estimated using all contagion distances in the network (as opposed to $\mu_i^{M,market}$ and $\sigma_i^{M,market}$, which only use contagion distances from node i):

$$\begin{aligned}
\mu^{M,bullish}(t) &= \frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bullish}(i,j,t)}{N-1}, \\
\mu^{M,bearish}(t) &= \frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bearish}(i,j,t)}{N-1}, \\
\sigma^{M,bullish}(t) &= \sqrt{\frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1}(d_{cont}^{M,bullish}(i,j,t)-\mu^{M,bullish}(t))^2}{N-2}}, \\
\sigma^{M,bearish}(t) &= \sqrt{\frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1}(d_{cont}^{M,bearish}(i,j,t)-\mu^{M,bearish}(t))^2}{N-2}}.
\end{aligned} \tag{13}$$

Definition 4. ***Network contagion centrality*** $CC^{M,market}$ *is a network centrality measure of the whole network based on the multi-layer contagion distances* $d_{cont}^{M,market}(i,j)$ *in* $market = \{bullish, bearish\}$ *and computed as the reciprocal of the network concentricity score of those contagion distances:*

$$\begin{aligned} CC^{M,bullish} &= \frac{1}{\sqrt{(\mu^{M,bullish})^2 + (\sigma^{M,bullish})^2}}, \\ CC^{M,bearish} &= \frac{1}{\sqrt{(\mu^{M,bearish})^2 + (\sigma^{M,bearish})^2}}. \end{aligned} \tag{14}$$

Contagion centrality and distances in Definitions 3 and 4 correspond to a network realisation at time t, while the time scripts (t) are omitted for easier readability.

2.2 Policy Efficiency Analysis

An important aspect in policy efficiency analysis is how the efficiency is defined and measured. In this paper the policy is said to have successfully transmitted if it led to an intended change in the inflation rate within a particular transmission period. Formally, monetary policy transmission indicator $MPsuccess(i,t,\Delta)$ of a policy rate announcement on date t over the transmission period Δ in country i is defined as follows:

$$MPsuccess(i,t,\Delta) = \begin{cases} 1, & \text{if rate change leads to intended inflation change;} \\ 0, & \text{otherwise.} \end{cases} \tag{15}$$

If a policy rate cut (hike) on announcement date t leads to an increase (decrease) in inflation rate in country i by the end of the transmission period, i.e. at time $t+\Delta$, then $MPsuccess(i,t,\Delta)$ equals one. It equals zero otherwise. If the indicator refers to the inflation rate in the Eurozone as a whole, rather than in an individual country, the subscript i is replaced by EZ: $MPsuccess(EZ,t,\Delta)$. We consider six transmission periods: $\Delta = \{3$ months, 6 months, 9 months, 12 months, 18 months, 24 months$\}$. Since the announcement can take place on any day of the month and inflation data are only available on a monthly basis, the transmission period is extended to $\Delta + 1$ for the announcements that were made in the second half of the month to ensure the period is not too short compared to those of the beginning of the month announcements.

The transmission efficiency of ECB's interest rate policy is analysed using a logit regression on two different aggregation levels: network level and individual country level.

Aggregate Network-Level Analysis

The aggregate level analysis is concerned with policy transmission to the whole network and is further divided into two parts.

- ***Aggregate Eurozone logit regression***
  We consider a time series regression, where the contagion centrality $CC_{EZ,t}^{M}$ corresponds to the whole network of the analysed Eurozone countries (Definition 4) and $MPsuccess(EZ,t,\Delta)$ is constructed using the Eurozone composite inflation rate. We

use three models:

$$P\big(MPsuccess(EZ,t,\Delta)=1)|CC^M_{EZ,t}\big) = F(\alpha_1 + \beta_1 CC^M_{EZ,t}) \tag{16}$$

$$P\big(MPsuccess(EZ,t,\Delta)=1)|CC^M_{EZ,t}, CUT_t\big) = F(\alpha_2 + \beta_2 CC^M_{EZ,t} + \gamma_2 CUT_t) \tag{17}$$

$$P\big(MPsuccess(EZ,t,\Delta)=1)|CC^M_{EZ,t}, CUT_t\big) = \\ = F(\alpha_3 + \beta_3 CC^M_{EZ,t} + \gamma_3 CUT_t + \delta_3 CC^M_{EZ,t} \times CUT_t) \tag{18}$$

where $F(X)$ is, hereafter, the cumulative standard logistic distribution function defined in terms of exponential function $F(X) = \frac{1}{1+exp(-X)}$; $t = \{1, ..., 45\}$, and thus there are 45 observations; CUT_t is an indicator variable that is equal to one if the policy rate change at time t was a cut and to zero if it was a hike; $CC^M_{i,t} \times CUT_t$ is an interaction term between contagion centrality and CUT_t indicator variable.

- ***Eurozone countries panel logit regression***
  We also consider an all-country panel regression with time and country fixed effects. Contagion centralities $CC^M_{i,t}$ (Definition 3), as well as policy success indicator $MPsuccess(i,t,\Delta)$, correspond to an individual country i. The regression model is the following:

$$P\big(MPsuccess(i,t,\Delta)) = 1)|CC^M_{i,t}, CUT_t, Controls_i, Controls_p\big) = \\ = F(\alpha_4 + \beta_4 CC^M_{i,t} + \gamma_4 CUT_t + \delta_4 CC^M_{i,t} \times CUT_t + Controls_i + Controls_p) \tag{19}$$

  where $i = \{1, ..., 15\}$, $t = \{1, ..., 45\}$, and thus there are 675 observations; $Controls_i$ are the country fixed effects for 15 countries; $Controls_p$ are the period fixed effects for 5 time periods indicating during which period p the policy announcement t was made. Note that indicator variable for one country and for one period are omitted to avoid dummy variable trap. The exact start and end dates of each period are outlined in Section 4.1.

Country-Level Analysis

The country-level analysis is concerned with the efficiency of policy transmission to the individual countries based on their contagiousness and network position.

- ***Individual country regressions***
  We consider a time series regression for each country i separately. Contagion centralities $CC^M_{i,t}$ (Definition 3) as well as $MPsuccess(i,t,\Delta)$ correspond to an individual country i. We use two models with and without an interaction term:

$$P\big(MPsuccess(i,t,\Delta) = 1)|CC^M_{i,t}, CUT_t\big) = F(\alpha_5 + \beta_5 CC^M_{i,t} + \gamma_5 CUT_t) \tag{20}$$

$$P\big(MPsuccess(i,t,\Delta) = 1)|CC^M_{i,t}, CUT_t\big) = \\ = F(\alpha_6 + \beta_6 CC^M_{i,t} + \gamma_6 CUT_t + \delta_6 CC^M_{i,t} \times CUT_t) \tag{21}$$

  where $t = \{1, ..., 45\}$, and thus there are 45 observations in each regression.

2.3 Contagion and Tail Risk

In this section we focus on the relationship between contagion risk and tail risk in a multi-layer network setting. We follow the instrumental variable (IV) regression approach proposed in Abduraimova (2019) to examine whether multi-layer network contagion can give rise to tail risk in the individual layers of the network. We note that the tail risk is associated with a country in a distinct individual layer. Thus, there is a tail index estimate for each country in the equity returns layer, as well as in the bond interest rates layer.[5] The contagion risk of each country is based on multi-layers, rather than on a single layer. There is a contagion centrality estimate for each country in the bearish market as well as in the bullish market. Ultimately, there are four regression models for each network layer $\lambda \in \{R, B\}$, two for the lower tail index:

$$Tail\,Index_{i,p}^{L,\lambda} = \alpha_1 + \beta_1 CC_i^{M,bullish}(p) + \gamma_1 Eurozone_i + Controls_p + \eta_{i,p} \tag{22}$$

$$Tail\,Index_{i,p}^{L,\lambda} = \alpha_2 + \beta_2 CC_i^{M,bearish}(p) + \gamma_2 Eurozone_i + Controls_p + \epsilon_{i,p} \tag{23}$$

and two for the upper tail index:

$$Tail\,Index_{i,p}^{U,\lambda} = \alpha_3 + \beta_3 CC_i^{M,bullish}(p) + \gamma_3 Eurozone_i + Controls_p + u_{i,p} \tag{24}$$

$$Tail\,Index_{i,p}^{U,\lambda} = \alpha_4 + \beta_4 CC_i^{M,bearish}(p) + \gamma_4 Eurozone_i + Controls_p + e_{i,p} \tag{25}$$

where i corresponds to a country, $i \in \{1, ..., 15\}$, p corresponds to the five periods defined above. $Tail\,Index_{i,p}^{L,\lambda}$ and $Tail\,Index_{i,p}^{U,\lambda}$ are the tail index estimates for country i during period p in the lower and upper tails of layer λ, respectively. $CC_i^{M,bullish}(p)$ and $CC_i^{M,bearish}(p)$ are the bullish and the bearish contagion centralities of country i during period p, respectively. $Eurozone_i$ is an indicator variable that equals one if country i is in the Eurozone and zero, otherwise. $Controls_p$ are fixed effects for time periods.

Contagion centrality and tail index are estimated variables. Moreover, they are both estimated using the same data on equity returns and could be subject to the same estimation noise. This could lead to endogeneity and simultaneity bias. We employ the IV regression approach to address the endogeneity issue and define the instrument for each layer $\lambda \in \{R, B\}$ as the variable's absolute deviation as follows:

$$IV_{i,p}^{R} = \sqrt{\frac{\sum_{t=1}^{T_p} |R_{i,t} - \bar{R}_i|}{T_p - 1}}, \tag{26}$$

$$IV_{i,p}^{B} = \sqrt{\frac{\sum_{t=1}^{T_p} |B_{i,t} - \bar{B}_i|}{T_p - 1}}, \tag{27}$$

where $p \in \{$pre-GFC, GFC, post-GFC, Euro DC, post-Euro DC$\}$,
T_p is the length of period p,
$R_{i,t}$ and $B_{i,t}$ are the return on equity index and sovereign bond rate of country i at time t, respectively, and
$\bar{R}_i$ and $\bar{B}_i$ are the mean return on equity index and mean bond rate of country i over $t \in \{1, ...T_p\}$.

[5] We also differentiate lower and upper tail indices within each network layer.

The first stage regression outcomes hence are:

$$\hat{CC}_i^{M,bullish}(p) = \hat{\rho}_1 + \hat{\phi}_1 IV_{i,p}^{\lambda} \tag{28}$$

for regression models (22) and (24), and

$$\hat{CC}_i^{M,bearish}(p) = \hat{\rho}_2 + \hat{\phi}_2 IV_{i,p}^{\lambda} \tag{29}$$

for regression models (23) and (25). The second stage regressions (22), (23), (24) and (25) are run using the fitted values $\hat{CC}_i^{M,bullish}(p)$ and $\hat{CC}_i^{M,bearish}(p)$.

It is important to note that in addition to potential endogeneity problem, we also face an "error-in-variables" problem that arises due to regressor or regressand (or both as in this paper) being estimated themselves. To tackle this problem we apply a t-statistic robust inference approach developed by Ibragimov and Müller (2010). This approach does not require consistent estimation of coefficient's variance for a statistical inference and, thus, is not subject to the estimation noise in the explained or explanatory variables. It has also been proven to always work for significance levels up to 8.326%. The approach is implemented by partitioning the sample into q not necessarily equal-size groups, estimating the coefficient of interest for each of the groups individually, and conducting a standard t-test based on the q observations. In this paper, we consider $q = 3$ groups: core Eurozone countries (Austria, Belgium, Germany, Finland, France, Netherlands), periphery Eurozone countries (Greece, Ireland, Italy, Portugal, Spain) and the European countries that are not part of the Eurozone (Denmark, Switzerland, Sweden, the UK).

3 Data

We analyse a network of 11 Eurozone (EZ) countries for which consistent data are available over the considered period from January 1, 1998 until May 31, 2019: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain. We also examine a wider network of European states for which data are available throughout the period: (1) European Union (EU) network - EZ countries, Denmark, Sweden, and the UK;[6] (2) EU countries and Switzerland (which is highly integrated with the European economies although is not part of either EU or EZ).

To construct the monetary policy transmission success indicator, the data on inflation rates and on policy rate announcements are required. We use the Harmonised Index of Consumer Prices (HICP) for the inflation rates of 15 countries, as well as of the composite EZ19 (Eurozone 19) and EU28 (European Union 28) from the World Economic Outlook (WEO) database.

The ECB policy rate change announcements are obtained from the ECB statistics portal. There were 47 announcements after the introduction of euro in January 1999, when at least one of the policy rates was changed (main refinancing rate, deposit facility rate or marginal lending facility rate). The main refinancing rate (MRR) is used as a policy rate in the current analysis. It was first amended on the third announcement date on April 9, 1999 to 2.5% down from its initial set level of 3%; this leaves 45 announcements to study. On 4 announcement dates, the MRR was left unchanged. On those occasions, the direction of the

[6]The UK was part of the EU during the analysed period.

previous rate change is carried forward. Of 45 considered announcements, 24 are rate cuts and 21 are rate hikes. Table 1 presents success ratios of policy rate changes over a 12 month transmission period.[7] The success ratio of cuts (hikes) is defined as the ratio of successful cuts (hikes) over the total number of cuts (hikes).

Country	Rate Cuts	Rate Hikes
AUT	0.33	0.43
BEL	0.42	0.52
CHE	0.58	0.71
DEU	0.38	0.24
DNK	0.38	0.76
ESP	0.50	0.52
FIN	0.21	0.43
FRA	0.46	0.48
GBR	0.29	0.48
GRC	0.42	0.48
IRL	0.25	0.57
ITA	0.38	0.38
NLD	0.25	0.29
PRT	0.38	0.48
SWE	0.33	0.24
EZ	0.33	0.52

Table 1. Success Rates of Policy Rate Changes (12 months transmission period)

Daily stock market index returns and 10-year benchmark sovereign bond interest rates used to construct the layers of the network are obtained from Datastream database. The tail dependence coefficient, which is used to construct the links of the network, is estimated daily on a rolling basis with the window of one year. Thus, the starting date of one year before the euro came into existence on January 1, 1999, allows having a first network realisation on the currency launch date.

4 Results

4.1 Global Financial Crisis 2008 and European Debt Crisis 2010

Contagion risk can evolve differently during crises as opposed to more tranquil times. Contagion levels tend to increase during periods of turmoil in both tails of equity returns distribution. Contagion in the lower tail (bear stock markets) is generally higher than in the upper one (bull stock markets). In the current paper we analyse the evolvement of contagion during crises and calm periods using a multi-layer network approach which allows to gain a more holistic view of contagion in bearish and bullish environments beyond stock market contagion as compared to a single-layer network analysis. Two major crises have taken place over the considered period, the Global Financial Crisis 2008 and the European Debt Crisis 2010. The start and end dates of both events and the corresponding five sub-periods are defined as following:

1. Jan 1998 - July 2007, prior to the Global Financial Crisis 2008 (pre-GFC);
2. August 2007 - March 2009, during the Global Financial Crisis 2008 (GFC);
3. April 2009 - September 2009, after the Global Financial Crisis (post-GFC);

[7] Table 11 in Appendix 6.1 shows success ratios for all considered transmission periods.

4. October 2009 - March 2012, during the European Debt Crisis 2010 (Euro DC);
5. April 2012 - May 2019, after the European Debt Crisis 2010 (post-Euro DC).

Table 2 presents contagion risk levels for the whole network of considered countries as well as for sub-networks of countries: (1) GIIPS countries (Greece, Ireland, Italy, Portugal and Spain) which will be referred to as periphery; (2) Core countries (Austria, Belgium, Germany, Finland, France and the Netherlands) which are the non-periphery Eurozone countries; (3) EZ countries which include all Eurozone countries considered (GIIPS and Core); (4) EU countries which include EZ countries and three European Union countries that are not in the Eurozone (Denmark, the UK and Sweden); and (5) All countries considered which include the EU countries and Switzerland.[8]

The bullish contagion is considerably stronger than the bearish contagion as Table 2 shows. This result might be driven by the ECB's policy rates decreasing ever since the Global Financial Crisis. We also observe a clear pattern in both bearish and bullish contagion levels over different time periods for the Eurozone network as well as for the wider European networks (EU and All countries' groups). The bearish contagion environment appears to intensify during the crisis periods compared to the pre- and post-crisis periods. This is an intuitive finding as (1) the stock markets tend to go down synchronously, thereby increasing contagion in the equity layer's lower tail and (2) interest rates might rise as investors move away from stock markets to safer assets like sovereign bonds, thereby increasing contagion in the bond layer's upper tail. The bullish contagion behaves in the opposite manner. It is initially high in the run-up to the Financial Crisis 2008 when stock markets were rallying around the world. During both crises we observe a reduction in bullish contagion levels which are in turn followed by increases post-crises as markets recover.

Period	pre-GFC	GFC	post-GFC	Euro DC	post-Euro DC	Full Period
	Bearish Contagion Centrality					
GIIPS	0.452	0.611	0.587	0.553	0.490	0.503
Core	0.563	0.738	0.666	0.749	0.711	0.650
EZ	0.505	0.674	0.609	0.629	0.571	0.563
EU	0.517	0.688	0.606	0.632	0.565	0.569
All	0.522	0.690	0.607	0.635	0.567	0.573
	Bullish Contagion Centrality					
GIIPS	0.878	0.741	0.882	0.845	0.726	0.730
Core	0.915	0.871	0.834	0.820	0.910	0.926
EZ	0.899	0.743	0.840	0.706	0.787	0.766
EU	0.875	0.746	0.755	0.693	0.791	0.781
All	0.874	0.744	0.756	0.695	0.792	0.787

Table 2. Multi-Layer Contagion Centrality: Sub-Network Analysis

Sub-network analysis of core and periphery shows a certain divergence from the overall network trends. The periphery sub-network (GIIPS) contagion, both bearish and bullish, decreases during the European Debt Crisis and in the following period. Sovereign bond rates are greatly dispersed for the GIIPS countries during these periods and stock markets recovery has been slower than in core countries. The core sub-network shows similar to

[8]The individual country results can be found in Table 10 in the Appendix 6.1.

overall Eurozone trends with the exception of the period between two crises when the bullish contagion level continues its downward course.

4.2 Policy Efficiency Analysis

In this section we analyse the performance of contagion centrality in explaining the successful transmission of the ECB's interest rate policy at an overall network level, as well as at an individual country level. Table 3 presents aggregate Eurozone results for various policy transmission periods as per logit regressions (16) and (17). As the top panel demonstrates, in the bearish contagion environment with plummeting stock markets and high interest rates, the policy transmission is positively related to contagion degree.[9] Thus, the policy is more likely to transmit the higher the bearish contagion levels are. On the contrary, in the bullish contagion environment with rallying stock markets and low interest rates, the policy transmission and contagion levels are negatively related (bottom panel of Table 3). The lower the bullish contagion degree, the better the policy transmits. This essentially means that monetary policy transmits successfully during bearish markets contagion and not very effectively during bullish markets contagion.

Period	9m		12m		18m		24m	
	Bearish Contagion Centrality							
Constant	**-4.946**	**-4.994**	**-2.107**	**-2.297**	**-3.214**	**-3.267**	**-1.642**	**-1.737**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
CC^M	**7.720**	**8.455**	**3.253**	**4.652**	**5.060**	**5.699**	**3.081**	**3.960**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cut_t		**-0.682**		**-1.108**		**-0.565**		**-0.717**
		(0.002)		(0.000)		(0.007)		(0.000)
R^2	0.105	0.122	0.024	0.070	0.053	0.065	0.022	0.042
	Bullish Contagion Centrality							
Constant	1.547	**2.416**	**2.508**	**5.212**	**2.999**	**4.120**	**2.742**	**4.271**
	(0.158)	(0.047)	(0.020)	(0.000)	(0.006)	(0.001)	(0.011)	(0.000)
CC^M	**-2.539**	**-3.340**	**-3.342**	**-5.880**	**-4.037**	**-5.073**	**-3.189**	**-4.575**
	(0.050)	(0.016)	(0.009)	(0.000)	(0.002)	(0.000)	(0.012)	(0.001)
Cut_t		**-0.371**		**-1.102**		**-0.474**		**-0.674**
		(0.079)		(0.000)		(0.023)		(0.001)
R^2	0.007	0.012	0.011	0.056	0.017	0.025	0.010	0.028
Observations	45							

Table 3. Policy Efficiency: Overall Eurozone Regression (p-values in parentheses)

This finding could be attributed to overoptimism and euphoria in markets' behaviour that might prevail during bullish contagion periods. This could in turn destruct the markets from the central bank's policies making the policy transmit slower or not transmit at all. On the contrary, during bearish contagion periods when markets and the wider economy are not doing well, markets are more likely to pay attention to the central bank's policy announcements.

[9]The regression results for very short transmission periods of 3 and 6 months were statistically insignificant or occasionally significant for some countries only. Those periods are probably not sufficiently long for the policy to transmit. Therefore, only results for medium and longer term periods are presented.

The results for an aggregate Eurozone regression model with an interaction term as per Equation (18) are presented in Table 12 in Appendix 6.1.2. With addition of the interaction term the statistical significance decreases, however, economically the results remain similar.

One should note that the p-values of the model parameter estimates reported in Table 3 (and the following tables presenting the results of policy efficiency regressions) are based on the standard errors that are subject to estimation noise in the contagion centrality measures and need to be adjusted. Unfortunately, due to the small number of observations with binary regressand taking on many zero values within q groups, the application of robust t-statistic approaches for inference of logistic regressions appears to be infeasible. In addition, the derivation of the limiting variance of parameter estimators in the model that would account for the error in the estimation of contagion centrality measures appears to be a very difficult problem. It is left for further research. On the other hand, the extremely small p-values based on the unadjusted standard errors obtained for the model in Table 3 suggest that the significance of the coefficients will be also obtained using the standard errors that account for estimation error in contagion centrality.

Contractionary interest rate policy transmission could differ in nature from the expansionary one. Indeed, we observe that the success percentage of the interest rate hikes is generally higher than the success percentage of the interest rate cuts (Table 1).[10] We control for that difference by adding an indicator variable Cut_t and the results remain statistically significant. Furthermore, the sign of the Cut_t regression coefficient estimate is negative (and significant) as expected, confirming that rate cuts tend to transmit less efficiently than rate rises.

	Monetary Policy Transmission	
	Bearish Contagion	Bullish Contagion
Constant	-0.295	**4.858**
	(0.733)	(0.002)
CC_i^M	1.963	**-4.411**
	(0.110)	(0.016)
Cut_t	-0.060	**-8.589**
	(0.950)	(0.001)
$Cut_t \times CC_i^M$	-2.238	**8.588**
	(0.162)	(0.001)
$Controls_i$	Y	Y
$Controls_t$	Y	Y
R^2	0.149	0.161
Observations	675	

Table 4. Policy Efficiency: Panel Regression (p-values in parentheses)

[10]The bank-lending channel (or credit channel more broadly) of monetary policy transmission to real economy (which is not a focus of this paper) can explain the intuition behind the difference between success rates of interest rate hikes and cuts. The bank lending channel is an amplification channel that works beside the main interest rate channel (which is the focus of this paper). According to the credit view, the monetary policy may transmit to the real economy by affecting banks' loans (assets) and deposits (liabilities). Banks could be slower in passing the lower interest rates on to the consumers than the higher rates, due to maturity mismatch between their assets (longer-term generally) and liabilities (shorter-term generally).

We further analyse the transmission of policy to the network by running logit panel regression (19) of country-level observations. As can be seen from Table 4, the findings discussed above are validated for country-level policy transmission as well (p-values of *contagion centrality* coefficient are just above 10% and just above 1% for bearish and bullish contagion, respectively).[11] Thus, contagion centrality can explain the successful transmission of interest rate policy into inflation targets both for the Eurozone as a whole, as well as at a national level.

Finally, we take a closer look at the individual countries' contagiousness focusing on the difference between core and more peripheral countries of the European network. Once again, we confirm the results obtained at the aggregate Eurozone level. Tables 5 and 6 present results for GIIPS countries and for selected core countries, respectively.[12] Core and periphery countries might have different levels of contagiousness and therefore may be located more or less centrally in the contagion network. However, the relationship between contagion centrality and monetary policy transmission efficiency remains consistent. Specifically, the transmission is more successful in a strong bearish contagion environment (implying positive relationship) and less successful during bullish contagion periods (implying negative relationship).
As can be observed from Table 2 in Subsection 4.3, the periphery GIIPS countries generally tend to be less central in the bearish contagion network than the rest of the network. And in the bullish contagion network, the GIIPS countries are relatively comparable with spikes in contagiousness well above the core countries during the Euro Crisis and in the preceding period. Connecting this observation with finding that policy transmission is more efficient for more bear-contagious and for less bull-contagious markets, we conclude that the ECB's interest rate policy transmits more efficiently through the European network core rather than the periphery.

Ireland stands out as an outlier gaining insignificant results for half of the times (Table 5). Ireland has experienced high deflation during the years 2009-2010, reaching the bottom at 6.6% in October of 2009. Those periods' observations are probably distorting the results for this country, as when the inflation rates are in the negative space, monetary policy might not work well or not work as expected.

Another observation that stands out in Table 5 is that the regression coefficient for the Cut_t indicator swaps sign for Greece for transmission periods of 18 and 24 months. This means that interest rate cuts were more successful than interest rate hikes. We attribute this, however, to Greece receiving the emergency financial support in the form of bailouts starting in 2010.
The results also hold for the European countries that do not share the same currency, but are strongly integrated with the Eurozone (Table 6). This could be due to strong economic integration among the countries or equally due to world central banks implementing highly similar policies to address the two major turmoils that happened during the considered 20 year period.

[11] The panel regression results for 12 months transmission periods are presented. Results for 9, 18, 24 months are similar.

[12] The presented results are as per Equation 20. And the regression results for the model equation 21 can be found in Tables 13, 14 and 15 in Appendix 6.1.2. The interaction term itself is mostly not significant and the significance of other coefficients decreases for some of the countries. However, the directions of the coefficient signs generally remain consistent.

	Monetary Policy Transmission								
	Bearish Contagion				Bullish Contagion				
Period	9m	12m	18m	24m	9m	12m	18m	24m	
Constant	**-2.755**	**-2.106**	**-0.578**	**-1.980**	**1.782**	**2.086**	0.781	**1.385**	Greece
CC_i^M	**7.214**	**5.015**	0.725	**3.147**	**-2.140**	**-2.772**	**-1.360**	**-2.660**	
Cut_t	**-1.511**	**-0.498**	**0.767**	**0.927**	**-1.142**	**-0.432**	**0.717**	**0.886**	
R^2	0.170	0.074	0.030	0.074	0.055	0.026	0.034	0.067	
Constant	-0.787	-0.165	**0.938**	-0.648	**1.643**	0.337	**2.713**	**4.546**	Ireland
CC_i^M	1.404	0.921	-0.497	**2.763**	**-2.076**	-0.059	**-2.404**	**-4.573**	
Cut_t	**-1.349**	**-1.458**	**-1.544**	**-1.622**	**-1.366**	**-1.389**	**-1.730**	**-1.696**	
R^2	0.067	0.082	0.105	0.094	0.070	0.081	0.112	0.112	
Constant	**-6.526**	**-3.204**	0.472	**-1.670**	**-3.505**	-0.460	**7.871**	**3.466**	Italy
CC_i^M	**10.334**	**4.726**	-0.324	**3.462**	**3.465**	-0.029	**-8.695**	**-3.648**	
Cut_t	**-0.901**	-0.228	**-0.967**	**-0.975**	-0.244	-0.027	**-1.487**	**-0.988**	
R^2	0.154	0.039	0.042	0.049	0.015	0.000	0.091	0.037	
Constant	**-8.766**	**-5.539**	**-4.909**	**-9.090**	**4.493**	**6.437**	**6.830**	**4.275**	Portugal
CC_i^M	**17.303**	**10.900**	**10.590**	**18.589**	**-5.386**	**-7.668**	**-7.655**	**-4.901**	
Cut_t	**-2.285**	**-1.239**	**-1.289**	**-1.451**	**-1.120**	**-0.866**	**-0.879**	**-0.347**	
R^2	0.282	0.136	0.132	0.302	0.059	0.072	0.074	0.029	
Constant	**-6.582**	**-3.749**	**-1.142**	**-1.741**	**3.399**	**5.778**	**3.374**	0.695	Spain
CC_i^M	**11.498**	**6.623**	**2.816**	**4.238**	**-3.802**	**-6.536**	**-3.321**	-0.002	
Cut_t	**-1.363**	**-0.342**	**-0.937**	**-1.048**	**-0.986**	**-0.400**	**-0.988**	**-0.860**	
R^2	0.184	0.063	0.041	0.058	0.039	0.036	0.039	0.032	
Observations	45								

Table 5. Policy Efficiency: GIIPS Countries Regression (p-values in parentheses)

4.3 Contagion and Tail Risk

Tail index estimation results for full sample period are presented in Table 7.[13] Equity returns tail indices lie in the interval $(2, 3)$, implying that the first and the second moments of those countries' equity returns are finite, while the third and the fourth moments are infinite. Austria and Ireland have tail index estimates below 2 and for these two countries even the variance might be infinite. Moreover, the tail indices in the lower tail appear to be slightly smaller than in the upper tail. This means that the countries considered are slightly more likely to experience tail events in the negative tail of the equity returns (stock market crashes) than in the positive tail (stock market booms).

The results for the bond interest rates layer are strikingly different. Most of the countries appear to have a considerably thin upper tail (with the tail index estimates being above 15) and a profoundly heavy lower tail (with the tail index estimates being below 2). This raises a question of whether power law distributions are a good fit for the bond interest rates in the first place, which is left for the future research.

We now turn to the regression analysis results. Tables 8 and 9 present the estimation results for the instrumental variable (IV) and for the ordinary least squares (OLS) regression

[13]Results for five sub-periods, including crisis and non-crisis periods can be found in Appendix 6.1.3.

	Monetary Policy Transmission					
	Eurozone Countries			non-Eurozone Countries		
	Bearish Contagion	Bullish Contagion		Bearish Contagion	Bullish Contagion	
Constant	**-7.915**	**7.152**	Germany	0.136	**10.163**	Switzerland
	(0.000)	(0.000)		(0.824)	(0.000)	
CC_i^M	**10.993**	**-9.641**		1.365	**-11.074**	
	(0.000)	(0.000)		(0.188)	(0.000)	
Cut_t	0.187	0.275		**-0.623**	**-1.382**	
	(0.419)	(0.228)		(0.002)	(0.000)	
R^2	0.160	0.068		0.017	0.106	
Constant	**-1.235**	0.542	France	**-7.939**	**1.743**	UK
	(0.061)	(0.730)		(0.000)	(0.086)	
CC_i^M	**1.850**	-0.726		**13.020**	**-2.344**	
	(0.077)	(0.684)		(0.000)	(0.067)	
Cut_t	-0.157	-0.098		**-1.463**	**-0.787**	
	(0.423)	(0.625)		(0.000)	(0.000)	
R^2	0.005	0.000		0.22	0.033	
Constant	**-7.903**	**7.392**	Netherlands	**-6.216**	1.062	Sweden
	(0.000)	(0.000)		(0.000)	(0.263)	
CC_i^M	**11.153**	**-9.525**		**8.586**	**-2.725**	
	(0.000)	(0.000)		(0.000)	(0.018)	
Cut_t	**-0.717**	**-0.544**		0.144	**0.380**	
	(0.003)	(0.021)		(0.531)	(0.079)	
R^2	0.114	0.043		0.11	0.02	
Observations	45					

Table 6. Policy Efficiency: Core Countries Regression (p-values in parentheses)

approaches along with t-stat robust inference approach p-values, respectively. We report findings for Hill's estimate tail index (similar conclusions could be drawn using log-log rank-size estimate of the tail index).

Statistically significant regression results for the equity layer in Table 8 confirm that tail risk might indeed arise from network contagion. The first conclusion we draw from these results is that countries that are more contagion-central tend to be more prone to stock market crashes and less so to stock market booms.[14] Thus, network core countries might experience fewer bubbles in their equity markets, however, they are still subject to market meltdowns. Periphery, on the contrary, being located less central in the network, are more prone to tail risk in the upper tail rather than in the lower tail. This does not mean that GIIPS group countries, which are generally referred to as periphery, do not experience bear markets. As Table 2 in Subsection 4.1 shows, the contagiousness of countries varies from period to period and, for instance, during the European Debt Crisis the GIIPS countries have become more central than both the overall Eurozone and the countries that we refer to as core generally. Turning to tail risk in sovereign bond interest rates, more contagion-central countries appear to be less vulnerable to it, both in the upper and lower tails. However, the results are not statistically significant.

[14] Remember that lower tail index means heavier tails and more tail risk.

	Bearish Contagion		Bullish Contagion	
	Equity Index Returns Layer		Bond Interest Rates Layer	
Country	Lower Tail	Upper Tail	Lower Tail	Upper Tail
AUT	1.889	2.495	0.510	19.572
BEL	2.129	2.382	0.645	20.488
CHE	2.141	2.465	1.305	12.766
DEU	2.310	2.425	0.202	21.519
DNK	2.296	2.543	0.213	18.168
ESP	2.345	2.489	1.740	16.045
FIN	2.120	2.090	0.283	20.833
FRA	2.229	2.367	0.622	20.141
GBR	2.124	2.255	1.302	17.210
GRC	2.123	2.286	4.269	1.962
IRL	1.975	2.376	1.488	3.044
ITA	2.391	2.345	2.580	16.953
NLD	2.091	2.189	0.209	19.700
PRT	2.218	2.501	1.251	2.634
SWE	2.264	2.204	0.446	21.527
EU	2.179	2.353	1.126	15.700
EZ	2.165	2.359	1.255	14.808
GIIPS	2.210	2.399	2.266	8.128
ALL	2.176	2.361	1.138	15.504

Hill's tail index estimate, 10% truncation, full sample period results.
The country group (EU, EZ, GIIPS and ALL) values are simply the averages of tail index estimates for countries within the group.

Table 7. Tail Risk: European Countries

	Bearish Contagion		Bullish Contagion	
	Lower Tail	Upper Tail	Lower Tail	Upper Tail
	Equity Index Returns Layer			
Intercept	5.489	**1.332**	**9.459**	-0.240
	(0.331)	(0.013)	(0.070)	(0.407)
CC_i^M	**-5.488**	**2.174**	**-8.981**	**3.558**
	(0.100)	(0.043)	(0.098)	(0.043)
Hausman-Wu p-value	0.002	0.183	0.001	0.265
First Stage F-stat	6.554	6.554	12.130	12.130
Controls	Y			
Observations	75			
	Bond Interest Rates Layer			
Intercept	1.266	-64.731	0.939	-122.160
	(0.975)	(0.497)	(0.979)	(0.500)
CC_i^M	0.731	128.600	0.943	165.790
	(0.987)	(0.505)	(0.987)	(0.505)
Hausman-Wu p-value	0.843	0.054	0.176	0.043
First Stage F-stat	16.740	16.740	11.450	11.450
Controls	Y			
Observations	75			

Hill's estimate tail indices with 10% truncation are used for both equity and bond layers.

Table 8. Contagion and Tail Risk: IV Regression (p-values in parentheses)

	Bearish Contagion		Bullish Contagion	
	Lower Tail	Upper Tail	Lower Tail	Upper Tail
	Equity Index Returns Layer			
Intercept	**3.172**	**2.394**	**3.258**	2.015
	(0.038)	(0.090)	(0.003)	(0.235)
CC_i^M	**-1.467**	0.288	-1.194	0.684
	(0.020)	(0.501)	(0.591)	(0.867)
Controls	Y			
Observations	75			
	Bond Interest Rates Layer			
Intercept	-17.047	-4.437	-92.615	-11.624
	(0.338)	(0.435)	(0.300)	(0.467)
CC_i^M	26.623	26.985	113.344	28.898
	(0.592)	(0.651)	(0.265)	(0.540)
Controls	Y			
Observations	75			

Hill's estimate tail indices with 10% truncation are used for both equity and bond layers.

Table 9. Contagion and Tail Risk: OLS Regression (p-values in parentheses)

OLS results, as can be seen from Table 9, agree with IV results in terms of the directions of regression coefficients' signs, however, they do not gain any statistical significance except for lower tail of equity returns in the bearish contagion environment. This highlights the importance of applying the IV regression approach. As can be seen from Table 8 the instrument relevance condition is satisfied as indicated by significant first stage f-statistics. The f-statistics for equity returns and bond rates layers tail risk are generally above the "rule of thumb" threshold of 10. One exception is equity returns tail risk during the bearish contagion with f-statistic being 6.554, which is still rather large. The instrument exogeneity condition is satisfied for the lower tail of equity layer and for upper tail of bond layer as demonstrated by Hausman-Wu pre-test p-values. Thus, absolute deviation appears to be a valid instrument even though the link between contagion and tail risk is not always observed.

Final important point is that the inference based on OLS standard errors is significant at 10% for both layers in the two-stage regression approach as well as standard one-stage OLS regression approach. Thus, standard techniques can lead to misleading conclusions under the presence of estimation noise and robust approaches such as t-statistic approach should be used instead.

5 Conclusion

We develop contagion centrality measures and apply them to analyse the transmission efficiency of ECB's monetary policy in a multi-layer network setting. The main insight we gain is that monetary policy transmits efficiently during intense bearish contagion times and during weak bullish contagion times. We attribute this to the level of attention that markets pay to the policy announcements in crisis and boom periods.

Furthermore, we analyse the relationship between contagion risk and tail risk. The countries that are more centrally located in the contagion network appear to be less susceptible to tail risk in their bond markets than the periphery countries (GIIPS countries generally). The more central countries also tend to be more resilient to upper tail risk in stock markets (bubbles), however, they are still prone to stock markets crashes.

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6 Appendix

6.1 Tables

6.1.1 Contagion Centrality Estimates

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Bearish Contagion Centrality					
AUT	0.463	0.678	0.657	0.632	0.584	0.557
BEL	0.545	0.699	0.620	0.702	0.642	0.617
CHE	0.563	0.706	0.608	0.654	0.581	0.596
DEU	0.572	0.729	0.651	0.687	0.631	0.619
DNK	0.504	0.695	0.561	0.599	0.518	0.548
ESP	0.569	0.712	0.670	0.643	0.597	0.609
FIN	0.510	0.677	0.529	0.662	0.603	0.566
FRA	0.601	0.752	0.690	0.716	0.647	0.650
GBR	0.579	0.738	0.657	0.681	0.587	0.617
GRC	0.388	0.612	0.447	0.453	0.390	0.420
IRL	0.495	0.604	0.624	0.630	0.559	0.548
ITA	0.562	0.704	0.664	0.673	0.592	0.606
NLD	0.593	0.740	0.695	0.701	0.639	0.637
PRT	0.490	0.655	0.597	0.610	0.551	0.547
SWE	0.551	0.710	0.604	0.659	0.590	0.595
	Bullish Contagion Centrality					
AUT	0.894	0.775	0.780	0.699	0.835	0.833
BEL	0.894	0.793	0.787	0.722	0.826	0.837
CHE	0.867	0.733	0.767	0.700	0.796	0.823
DEU	0.893	0.774	0.724	0.742	0.835	0.830
DNK	0.890	0.772	0.667	0.670	0.824	0.831
ESP	0.894	0.779	0.821	0.713	0.819	0.814
FIN	0.895	0.777	0.816	0.737	0.827	0.830
FRA	0.894	0.801	0.827	0.732	0.836	0.830
GBR	0.768	0.757	0.675	0.709	0.769	0.803
GRC	0.861	0.611	0.742	0.543	0.673	0.561
IRL	0.847	0.636	0.762	0.673	0.820	0.806
ITA	0.892	0.763	0.823	0.736	0.728	0.787
NLD	0.893	0.792	0.822	0.752	0.839	0.832
PRT	0.893	0.748	0.764	0.662	0.715	0.739
SWE	0.871	0.752	0.663	0.716	0.812	0.825

Table 10. Multi-Layer Contagion Centrality: Individual Countries

6.1.2 Monetary Policy Transmission

	Policy Rate Cut Successes						Policy Rate Hike Successes					
Period	3m	6m	9m	12m	18m	24m	3m	6m	9m	12m	18m	24m
AUT	0.17	0.25	0.29	0.33	0.46	0.46	0.38	0.33	0.43	0.43	0.48	0.67
BEL	0.33	0.25	0.29	0.42	0.46	0.54	0.48	0.62	0.62	0.52	0.48	0.62
CHE	0.33	0.42	0.46	0.58	0.63	0.58	0.62	0.67	0.67	0.71	0.67	0.71
DEU	0.29	0.21	0.33	0.38	0.42	0.50	0.48	0.38	0.38	0.24	0.29	0.62
DNK	0.29	0.29	0.33	0.38	0.50	0.33	0.71	0.86	0.90	0.76	0.71	0.71
ESP	0.17	0.25	0.33	0.50	0.42	0.46	0.52	0.48	0.52	0.52	0.62	0.67
FIN	0.25	0.13	0.17	0.21	0.25	0.29	0.38	0.33	0.43	0.43	0.57	0.67
FRA	0.33	0.38	0.38	0.46	0.58	0.50	0.48	0.52	0.43	0.48	0.48	0.57
GBR	0.25	0.13	0.17	0.29	0.25	0.46	0.48	0.43	0.48	0.48	0.29	0.48
GRC	0.38	0.33	0.29	0.42	0.63	0.58	0.57	0.62	0.52	0.48	0.43	0.33
IRL	0.13	0.25	0.21	0.25	0.29	0.33	0.43	0.52	0.48	0.57	0.67	0.67
ITA	0.25	0.21	0.29	0.38	0.33	0.38	0.52	0.43	0.38	0.38	0.57	0.57
NLD	0.25	0.04	0.13	0.25	0.21	0.21	0.52	0.33	0.24	0.29	0.19	0.29
PRT	0.21	0.21	0.29	0.38	0.46	0.50	0.52	0.38	0.48	0.48	0.57	0.52
SWE	0.33	0.21	0.25	0.33	0.42	0.46	0.33	0.33	0.29	0.24	0.29	0.38
EU	0.25	0.17	0.25	0.29	0.38	0.38	0.52	0.43	0.57	0.57	0.62	0.71
EZ	0.25	0.25	0.33	0.33	0.38	0.46	0.48	0.38	0.38	0.52	0.43	0.57

Table 11. Success Rates of Policy Rate Changes by Transmission Period

Period	9m	12m	18m	24m
	Bearish Contagion Centrality			
Constant	**-8.352**	-2.588	-2.530	-1.088
	(0.031)	(0.192)	(0.214)	(0.563)
CC_i^M	**14.378**	5.218	4.307	2.686
	(0.030)	(0.164)	(0.253)	(0.453)
Cut_t	5.848	-0.247	-2.782	-2.550
	(0.221)	(0.943)	(0.468)	(0.447)
$Cut_t \times CC_i^M$	-11.258	-1.533	3.882	3.310
	(0.166)	(0.801)	(0.555)	(0.576)
R^2	0.159	0.071	0.071	0.047
	Bullish Contagion Centrality			
Constant	2.849	**15.941**	12.179	**16.388**
	(0.716)	(0.084)	(0.152)	(0.085)
CC_i^M	-3.838	**-18.178**	-14.364	**-18.427**
	(0.670)	(0.085)	(0.143)	(0.088)
Cut_t	-0.931	-14.641	-10.678	-15.544
	(0.916)	(0.148)	(0.257)	(0.131)
$Cut_t \times CC_i^M$	0.654	15.750	11.916	17.200
	(0.949)	(0.177)	(0.277)	(0.145)
R^2	0.012	0.089	0.046	0.067
Observations	45			

Table 12. Policy Efficiency: Eurozone Regression with Interaction Term (p-values in parentheses)

	Monetary Policy Transmission								
	Bearish Contagion				Bullish Contagion				
Period	9m	12m	18m	24m	9m	12m	18m	24m	
Constant	**-3.604**	**-3.265**	0.322	-0.899	-3.079	-1.679	0.039	0.586	Greece
CC_i^M	**9.389**	**7.889**	-1.536	0.513	4.033	2.009	-0.415	-1.632	
Cut_t	0.432	1.826	-1.233	-1.397	**7.386**	5.676	1.889	2.118	
$Cut_t \times CC_i^M$	-4.438	-5.431	4.774	5.498	**-11.557**	-8.098	-1.532	-1.618	
R^2	0.180	0.093	0.046	0.094	0.135	0.071	0.035	0.069	
Constant	-1.427	-0.699	1.600	-0.047	1.943	0.599	-3.148	-1.300	Ireland
CC_i^M	2.699	2.013	-1.825	1.515	-2.434	-0.372	4.608	2.386	
Cut_t	1.591	0.800	-3.937	-3.959	-1.836	-1.783	6.646	6.611	
$Cut_t \times CC_i^M$	-5.360	-4.138	4.365	4.257	0.578	0.480	-10.307	-10.199	
R^2	0.077	0.088	0.111	0.100	0.070	0.081	0.144	0.142	
Constant	**-13.577**	**-4.923**	2.115	0.049	-9.035	5.053	**57.499**	11.787	Italy
CC_i^M	**21.730**	7.652	-3.200	0.420	9.790	-6.373	**-64.933**	-13.173	
Cut_t	10.486	3.241	-4.758	-5.263	7.096	-7.191	**-58.018**	-11.637	
$Cut_t \times CC_i^M$	-18.172	-5.745	6.359	7.139	-8.513	8.350	**64.721**	12.368	
R^2	0.220	0.052	0.059	0.070	0.024	0.009	0.286	0.056	
Constant	**-18.110**	**-11.868**	**-4.839**	**-18.281**	6.909	**12.002**	**21.147**	5.311	Portugal
CC_i^M	**35.474**	**23.395**	**10.443**	**37.059**	-8.221	**-14.195**	**-24.253**	-6.115	
Cut_t	12.676	**10.125**	-1.456	12.164	-4.472	-8.228	**-18.552**	-1.744	
$Cut_t \times CC_i^M$	**-27.587**	**-21.228**	0.313	-26.269	4.031	8.807	**20.801**	1.664	
R^2	0.357	0.220	0.132	0.366	0.062	0.087	0.137	0.029	
Constant	**-5.921**	-2.618	2.437	1.837	9.240	**24.600**	**63.802**	**25.678**	Spain
CC_i^M	**10.361**	4.674	-3.332	-1.957	-10.514	**-28.106**	**-71.545**	**-28.420**	
Cut_t	-3.285	-3.198	**-10.492**	**-10.441**	-8.280	**-22.848**	**-67.257**	**-30.045**	
$Cut_t \times CC_i^M$	3.089	4.733	**15.672**	**15.502**	8.496	**25.973**	**75.329**	**33.519**	
R^2	0.186	0.070	0.115	0.128	0.049	0.104	0.277	0.135	
Observations	45								

Table 13.
Policy Efficiency: GIIPS Regression with Interaction Term (bold font indicates 10% significance)

	Monetary Policy Transmission								
	9m		12m		18m		24m		
	Bearish Contagion Centrality								
Constant	**-2.571**	-2.259	**-7.915**	**-8.702**	**-4.946**	-5.010	**-2.712**	-0.042	Germany
CC_i^M	**3.556**	3.028	**10.993**	12.213	**6.728**	6.833	**5.570**	0.909	
Cut_t	**-0.430**	-1.215	0.187	1.486	0.240	0.367	**-0.878**	**-8.368**	
$Cut_t \times CC_i^M$		1.250		-1.987		-0.200		**12.095**	
R^2	0.023	0.024	0.160	0.160	0.081	0.081	0.063	0.113	
Constant	**-1.658**	-2.482	**-1.235**	-2.716	**-2.499**	-2.843	-1.040	-2.478	France
CC_i^M	**2.221**	3.551	**1.850**	4.249	**3.898**	4.454	**2.162**	4.512	
Cut_t	-0.327	1.439	-0.157	2.925	0.265	0.985	-0.390	2.590	
$Cut_t \times CC_i^M$		-2.747		-4.817		-1.128		-4.681	
R^2	0.009	0.012	0.005	0.014	0.030	0.031	0.011	0.019	
Constant	**-7.467**	**-12.724**	**-7.903**	**-12.880**	**-9.232**	**-22.286**	**-6.450**	-6.707	Netherlands
CC_i^M	**10.041**	**18.052**	**11.153**	**18.783**	**12.261**	**31.606**	**8.882**	9.286	
Cut_t	**-1.300**	9.362	**-0.717**	7.831	-0.424	17.183	**-0.862**	-0.261	
$Cut_t \times CC_i^M$		-15.911		-12.851		-25.956		-0.904	
R^2	0.108	0.148	0.114	0.141	0.120	0.176	0.083	0.083	
	Bullish Contagion Centrality								
Constant	0.271	3.219	**7.152**	15.312	-0.882	16.213	**3.971**	**23.241**	Germany
CC_i^M	-0.872	-4.272	**-9.641**	-19.228	-0.039	**-19.952**	**-4.009**	**-25.979**	
Cut_t	-0.243	-4.653	0.275	-10.694	**0.578**	**-22.849**	**-0.650**	**-26.745**	
$Cut_t \times CC_i^M$		5.166		13.012		**27.534**		**30.209**	
R^2	0.002	0.006	0.068	0.083	0.014	0.095	0.020	0.113	
Constant	**3.505**	1.886	0.542	13.933	-2.116	14.098	**4.573**	**35.207**	France
CC_i^M	**-4.323**	-2.478	-0.726	-15.980	2.301	-16.167	**-4.879**	**-39.472**	
Cut_t	**-0.384**	1.928	-0.098	-18.639	**0.516**	**-22.399**	**-0.465**	**-38.770**	
$Cut_t \times CC_i^M$		-2.672		21.365		**26.456**		**43.704**	
R^2	0.011	0.012	0.000	0.045	0.011	0.078	0.015	0.136	
Constant	2.507	1.311	**7.392**	-3.371	**3.879**	-1.979	1.161	0.744	Netherlands
CC_i^M	**-4.200**	-2.829	**-9.525**	2.799	**-6.105**	0.607	-2.374	-1.897	
Cut_t	**-0.939**	1.081	**-0.544**	16.276	-0.110	8.142	**-0.502**	0.135	
$Cut_t \times CC_i^M$		-2.365		-19.683		-9.606		-0.740	
R^2	0.031	0.031	0.043	0.080	0.018	0.027	0.010	0.010	
Observations	45								

Table 14. Policy Efficiency: Eurozone Countries Regression with Interaction Term (bold font indicates 10% significance)

	9m		12m		18m		24m		
	Monetary Policy Transmission								
	Bearish Contagion Centrality								
Constant	**-1.806**	0.029	0.136	4.242	**2.038**	**8.949**	-0.174	6.066	Switzerland
CC_i^M	**4.402**	1.160	1.365	-5.677	**-2.327**	**-13.831**	1.911	-8.702	
Cut_t	**-1.031**	-4.753	**-0.623**	**-7.906**	-0.114	**-11.330**	**-0.642**	**-11.766**	
$Cut_t \times CC_i^M$		6.329		**12.339**		**18.655**		**18.769**	
R^2	0.062	0.076	0.017	0.071	0.010	0.115	0.020	0.133	
Constant	**-5.937**	**-10.882**	**-7.939**	**-19.434**	**-6.285**	**-12.473**	**-4.070**	-3.424	UK
CC_i^M	**9.717**	**17.840**	**13.020**	**31.587**	**8.721**	**18.282**	**6.621**	5.548	
Cut_t	**-2.064**	9.027	**-1.463**	**15.974**	**-0.482**	9.499	-0.299	-1.635	
$Cut_t \times CC_i^M$		**-17.451**		**-27.560**		-15.342		2.156	
R^2	0.199	0.269	0.220	0.330	0.097	0.147	0.065	0.066	
Constant	**-6.841**	**-6.779**	**-6.216**	**-11.342**	**-5.079**	**-10.598**	**-7.636**	**-13.538**	Sweden
CC_i^M	**10.075**	9.973	**8.586**	**16.804**	**7.150**	**16.154**	**12.274**	**21.957**	
Cut_t	**-0.667**	-0.800	0.144	7.472	0.323	8.253	-0.137	8.579	
$Cut_t \times CC_i^M$		0.209		-11.679		-12.880		-14.175	
R^2	0.129	0.129	0.110	0.139	0.093	0.134	0.203	0.241	
	Bullish Contagion Centrality								
Constant	**4.459**	0.203	**10.163**	10.514	**9.274**	**13.802**	**4.604**	**21.819**	Switzerland
CC_i^M	**-4.571**	0.600	**-11.074**	-11.487	**-10.323**	**-15.663**	**-4.470**	**-24.619**	
Cut_t	**-1.162**	9.053	**-1.382**	-2.010	**-0.875**	-8.675	**-0.869**	**-26.882**	
$Cut_t \times CC_i^M$		-13.051		0.775		9.605		**31.758**	
R^2	0.051	0.086	0.106	0.106	0.087	0.101	0.033	0.167	
Constant	-0.452	-2.776	**1.743**	3.038	1.044	4.862	**-3.403**	0.435	UK
CC_i^M	0.455	3.414	**-2.344**	-3.997	**-2.508**	-7.448	**4.213**	-0.676	
Cut_t	**-1.517**	3.979	**-0.787**	-3.256	-0.172	-7.034	-0.096	-7.367	
$Cut_t \times CC_i^M$		-7.010		3.147		8.803		9.218	
R^2	0.092	0.103	0.033	0.035	0.008	0.027	0.019	0.040	
Constant	-0.100	0.766	1.062	2.247	0.616	0.870	-0.420	-1.379	Sweden
CC_i^M	-0.994	-2.053	**-2.725**	-4.193	**-1.869**	-2.181	-0.079	1.083	
Cut_t	-0.218	-2.251	**0.380**	-2.105	**0.516**	-0.009	0.316	2.326	
$Cut_t \times CC_i^M$		2.544		3.129		0.657		-2.501	
R^2	0.003	0.005	0.020	0.023	0.019	0.020	0.005	0.007	
Observations	45								

Table 15. Policy Efficiency:
Non-Eurozone Countries Regression with Interaction Term (bold font indicates 10% significance)

6.1.3 Tail Index Estimates

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Equity Returns Layer					
AUT	2.065	2.853	2.265	2.556	2.335	1.889
BEL	2.047	2.408	3.251	2.400	2.276	2.129
CHE	2.031	2.180	2.707	2.142	2.097	2.141
DEU	2.273	1.834	2.257	2.517	2.269	2.310
DNK	2.300	2.168	2.332	2.403	2.119	2.296
ESP	2.381	2.214	2.432	2.612	2.356	2.345
FIN	2.235	2.444	2.520	2.501	2.451	2.120
FRA	2.301	1.886	2.325	2.277	2.338	2.229
GBR	2.256	2.374	1.890	2.485	2.416	2.124
GRC	2.104	2.121	2.991	3.218	2.141	2.123
IRL	2.078	3.148	2.532	2.170	2.245	1.975
ITA	2.208	1.891	2.375	2.312	2.444	2.391
NLD	2.088	1.798	2.902	2.343	2.271	2.091
PRT	2.114	2.030	2.054	2.330	2.438	2.218
SWE	2.407	2.613	3.059	2.066	2.336	2.264
EU	2.204	2.270	2.513	2.442	2.317	2.179
EZ	2.172	2.239	2.537	2.476	2.324	2.165
GIIPS	2.177	2.281	2.477	2.528	2.325	2.210
ALL	2.193	2.264	2.526	2.422	2.302	2.176
	Bond Interest Rates Layer					
AUT	10.941	21.818	73.897	14.351	0.705	0.510
BEL	10.939	23.975	97.691	10.568	0.936	0.645
CHE	7.947	14.135	57.655	5.017	3.547	1.305
DEU	10.377	33.767	17.280	14.068	0.257	0.202
DNK	9.530	22.067	43.725	9.480	0.265	0.213
ESP	9.675	20.821	106.833	42.013	2.496	1.740
FIN	10.169	6.260	92.343	13.234	0.346	0.283
FRA	10.927	21.328	95.888	15.886	0.933	0.622
GBR	12.929	13.842	17.210	15.223	1.798	1.302
GRC	10.766	32.489	60.102	8.478	3.861	4.269
IRL	6.900	55.535	33.065	21.848	2.642	1.488
ITA	11.088	54.533	66.879	24.861	5.028	2.580
NLD	11.351	24.842	64.352	10.987	0.258	0.209
PRT	10.878	18.407	78.984	28.171	1.680	1.251
SWE	8.394	11.071	25.048	13.865	0.601	0.446
EU	10.347	25.768	62.378	17.360	1.558	1.126
EZ	10.365	28.525	71.574	18.588	1.740	1.255
GIIPS	9.861	36.357	69.173	25.074	3.141	2.266
ALL	10.187	24.993	62.063	16.537	1.690	1.138

Table 16. Lower Tail Index: European Countries (Hill's Estimate, 10% trunc.)

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Equity Returns Layer					
AUT	3.016	1.835	3.894	2.667	2.782	2.495
BEL	2.225	2.310	4.642	2.219	2.674	2.382
CHE	2.493	1.841	3.334	2.655	2.570	2.465
DEU	2.498	1.769	3.481	2.500	2.735	2.425
DNK	2.862	2.449	2.942	2.763	2.720	2.543
ESP	2.310	1.907	4.170	2.699	2.456	2.489
FIN	2.205	2.075	2.579	2.351	2.651	2.090
FRA	2.465	1.945	4.029	2.754	2.413	2.367
GBR	2.378	1.834	3.232	2.428	2.465	2.255
GRC	2.074	2.350	3.462	2.614	2.361	2.286
IRL	2.670	2.230	3.859	2.731	3.082	2.376
ITA	2.323	2.051	3.151	2.686	2.336	2.345
NLD	2.073	1.795	2.669	2.809	2.335	2.189
PRT	2.261	2.377	3.756	2.609	2.631	2.501
SWE	2.332	2.232	3.168	2.310	2.707	2.204
EU	2.406	2.083	3.502	2.581	2.596	2.353
EZ	2.374	2.059	3.608	2.604	2.587	2.359
GIIPS	2.327	2.183	3.680	2.668	2.573	2.399
ALL	2.412	2.067	3.491	2.586	2.594	2.361
	Bond Interest Rates Layer					
AUT	36.597	30.540	51.543	49.422	9.601	19.572
BEL	36.931	33.113	54.227	18.217	8.133	20.488
CHE	14.553	26.233	27.806	31.385	10.109	12.766
DEU	41.632	35.018	54.408	55.882	13.845	21.519
DNK	38.368	28.501	102.181	50.959	10.840	18.168
ESP	41.845	34.420	46.137	14.778	7.563	16.045
FIN	43.103	30.664	49.443	51.419	15.122	20.833
FRA	39.653	26.659	50.155	63.872	10.352	20.141
GBR	18.292	55.606	59.870	56.483	22.345	17.210
GRC	6.256	33.089	60.132	18.482	2.484	1.962
IRL	42.726	25.586	74.093	10.547	3.788	3.044
ITA	43.074	31.981	65.379	10.082	6.804	16.953
NLD	41.186	27.083	59.637	55.241	13.616	19.700
PRT	43.116	32.860	123.876	16.592	3.456	2.634
SWE	26.332	62.460	38.963	63.355	11.111	21.527
EU	35.651	34.827	63.575	38.238	9.933	15.700
EZ	37.829	31.001	62.639	33.139	8.615	14.808
GIIPS	35.403	31.587	73.924	14.096	4.819	8.128
ALL	34.244	34.254	61.190	37.781	9.944	15.504

Table 17. Upper Tail Index: European Countries (Hill's Estimate, 10% trunc.)

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Equity Returns Layer					
AUT	0.73%	1.88%	1.64%	1.20%	0.80%	0.92%
BEL	0.79%	1.46%	1.06%	0.98%	0.68%	0.83%
CHE	0.84%	1.34%	0.80%	0.76%	0.62%	0.79%
DEU	1.12%	1.37%	1.23%	1.04%	0.78%	1.02%
DNK	0.83%	1.51%	1.25%	0.91%	0.74%	0.87%
ESP	0.97%	1.48%	1.08%	1.22%	0.89%	1.02%
FIN	1.43%	1.56%	1.42%	1.06%	0.73%	1.16%
FRA	1.00%	1.52%	1.13%	1.13%	0.78%	0.98%
GBR	0.80%	1.45%	0.93%	0.86%	0.60%	0.79%
GRC	1.09%	1.46%	1.39%	1.67%	1.32%	1.27%
IRL	0.76%	1.95%	1.44%	1.09%	0.73%	0.90%
ITA	0.90%	1.45%	1.26%	1.25%	1.02%	1.03%
NLD	1.01%	1.55%	1.14%	0.96%	0.68%	0.94%
PRT	0.71%	1.20%	0.84%	1.01%	0.83%	0.83%
SWE	1.11%	1.65%	1.30%	1.02%	0.73%	1.02%
EU	0.95%	1.53%	1.22%	1.10%	0.81%	0.97%
EZ	0.95%	1.53%	1.24%	1.15%	0.84%	0.99%
GIIPS	0.89%	1.51%	1.20%	1.25%	0.96%	1.01%
ALL	0.94%	1.52%	1.20%	1.08%	0.80%	0.96%
	Bond Interest Rates Layer					
AUT	0.60%	0.19%	0.18%	0.31%	0.62%	1.44%
BEL	0.61%	0.20%	0.13%	0.37%	0.75%	1.38%
CHE	0.45%	0.29%	0.13%	0.38%	0.41%	1.15%
DEU	0.53%	0.39%	0.12%	0.47%	0.52%	1.51%
DNK	0.60%	0.32%	0.10%	0.52%	0.50%	1.57%
ESP	0.61%	0.20%	0.15%	0.65%	1.39%	1.15%
FIN	0.60%	0.26%	0.13%	0.40%	0.55%	1.48%
FRA	0.56%	0.28%	0.11%	0.28%	0.65%	1.34%
GBR	0.37%	0.48%	0.14%	0.54%	0.46%	1.35%
GRC	1.13%	0.36%	0.35%	7.12%	3.56%	3.48%
IRL	0.58%	0.34%	0.26%	2.02%	1.45%	1.55%
ITA	0.57%	0.18%	0.16%	0.71%	1.07%	0.99%
NLD	0.57%	0.24%	0.12%	0.42%	0.60%	1.46%
PRT	0.61%	0.19%	0.22%	3.07%	1.93%	1.50%
SWE	0.62%	0.49%	0.13%	0.51%	0.57%	1.49%
EU	0.61%	0.29%	0.16%	1.24%	1.04%	1.55%
EZ	0.63%	0.26%	0.17%	1.44%	1.19%	1.57%
GIIPS	0.70%	0.25%	0.23%	2.72%	1.88%	1.73%
ALL	0.60%	0.29%	0.16%	1.19%	1.00%	1.52%

Table 18. The Absolute Deviation IV: European Countries