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ORIGINAL ARTICLE



# Real-financial connectedness in the Swiss economy

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**Abstract**

We study macro-financial linkages and their importance within the Swiss economy from a network perspective. First, we investigate the real-financial connectedness in the Swiss economy, using the KOF economic barometer, obtained from real and financial variables, and, the real activity index (RAI), we distilled from a small set of real variables, as two alternative proxies for the real side. Whereas the KOF-barometer-based analysis shows that both sides transmit sizeable shocks to each other without one dominating the other, the RAI-based analysis shows that in the aggregate, the financial side turns out to be the net shock transmitter to the real sector. In the second part, we focus on the relative importance of financial markets as shock propagators using a network centrality measure. We find that 2008–2009 recession in Switzerland and the Swiss National Bank's (SNB) exchange rate policy changes in 2011 and 2015 have significantly altered the way the shocks are transmitted across the two sides of the economy. During 2009–2011, stock, bond, and foreign exchange (FX) markets, in descending order, played important roles as shock propagators. Following the SNB's 2015 policy decision to discontinue the lower bound for the EUR/CHF exchange rate, FX market has become equally important as the stock market but more important than the bond market as a shock propagator.

**Keywords:** Connectedness index, Propagation values, KOF barometer, Volatility, Mixed frequency, Switzerland

**JEL codes:** C38, E44, E37, C32, G10.

## 1 Introduction

As manifested over the recent history, interactions between the real and financial sides of the economy have important repercussions with significant costs of all sorts which cannot be avoided once risks that seemed as tail events are realized. This is a lesson that has only recently been learned on a global scale after the 2008–2009 global financial crisis. In the wake of the global financial crisis, and the global recession, central banks have designed and implemented quantitative easing (QE) policies, not only to contain side effects of the crisis but also to put national economies back on track. These policies were, mostly, executed in the form of bond purchases. As a result, from a policy perspective not only understanding but also tracking the interaction between the real and financial sides of the economy have never been more important. Regardless of this fact, this territory is largely unexplored in the academic literature.

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Using the Diebold-Yilmaz Connectedness Index (DYCI) methodology (see Diebold and Yilmaz (2009); Diebold and Yilmaz (2012); Diebold and Yilmaz (2014)), in Uluceviz and Yilmaz (2018), we recently investigated the joint structure of connnectedness between the real and financial sides of the U.S. economy on a weekly frequency basis.

In this paper, we apply the same analytical framework to Swiss economy on a monthly frequency basis while extending it by quantifying the relative importance of each node as a shock propagator. In this paper, we shift the focus of Uluceviz and Yilmaz (2018). Rather than merely investigating the interaction between the real and financial sides of the Swiss economy, we try to answer the following two interwoven questions in a network-theoretic approach:

Q1: How do the real and the financial sides of the Swiss economy interact; do any of the sides predominantly influence the other?

Q2: Hypothesizing that they influence each other significantly; once hit by a shock, which market has the highest potential to disseminate shocks in the real-financial network?

To elaborate on Q1, we follow a two-step approach. In the first step, we use the KOF economic barometer, a leading composite indicator for the Swiss economy published by KOF Swiss Economic Institute, to represent the real side of the Swiss economy. In addition, we employ return volatilities for the stock, bond, and FX markets to represent the financial side of the Swiss economy. To capture the effects of global shocks on the Swiss economy, we use the U.S. bond market volatility as an exogenous variable. Within the real-financial network setup, we find that real and financial sides do, significantly but not predominantly, influence each other. We question whether this result could be attributed to the use of financial variables in the estimation of the KOF barometer. To examine this, we estimate the real activity index (RAI) solely from real variables with a factor model similar to the one employed to extract KOF barometer. And we find that KOF barometer and RAI move in tandem over the period of our analysis. Interestingly, when we replace the KOF barometer with RAI, the results of the analysis change significantly: the real side of the economy becomes a net connectedness receiver from the financial side.

Our analysis summarized up to now dealt with tracing one-time shocks until they settle in the network and provides a sound answer to Q1 we asked above. However, investigation of the ripple effects of one-time shocks within the network and quantifying the relative importance of nodes as shock propagators takes us to Q2.

To enhance our understanding of Q2, using connectedness tables obtained from the real-financial networks we set up to answer Q1, we compute propagation values as in Schmidbauer et al. (2013); Schmidbauer et al. (2016); Schmidbauer et al. (2017). The approach we follow is simply to compute a certain network centrality measure, a normed left eigenvector, of the network matrices we estimated to answer Q1. It is, in a sense, similar to the approach Google follows to rank its search results based on the importance of the websites it finds.

We find that important turning points, such as recessions and SNB's policies regarding CHF in 2011 and 2015, have important implications over the course of our analysis period. That is to say, the way the real and financial sides of the Swiss economy interact, and the strength of the financial markets as shock propagators, have changed over the periods determined by these dates. Specifically, on average, stock market was the most important financial market as shock propagator followed by the bond and the FX markets over the period defined by the end of 2008–2009 recession in Switzerland and shortly before SNB's minimum EUR/CHF exchange rate policy implemented in September 2011. Following SNB's 2015 policy implementation, i.e., discontinuation of the minimum EUR/CHF exhange rate policy set forth in 2011, both the stock and the FX markets, on average, became the most important nodes as shock propagators followed by the bond market. Supported by empirical evidence, we argue that if a shock hits the USD/CHF exchange rate, some time before SNB's 2011 policy implemented, it would barely have an influence on the real-financial network we investigate. But following SNB's 2015 decision, FX and stock market shocks were, on average, the most important ones followed by the bond market in terms of creating volatility in the real-financial connectedness network we investigated.

Section 2 provides technical details of DYCI methodology insofar as to explain how shocks spread across a system of variables along with quantification of the relative importance of each variable as a shock propagator as well as the details of the data used in the paper.

Section 3 provides connectedness results when KOF barometer is used to represent the real side of the Swiss economy. Section 4 takes a glimpse at the similarities and the differences between the KOF barometer and RAI as alternatives to represent the real side of the Swiss economy. In Section 5, we obtain connectedness results with RAI being used to represent the real side. Section 6 is a look at the net connectedness between the real side of the economy and each financial market, respectively. Section 7 discusses relative importance of nodes as shock propagators, while Section 8 concludes the paper.

## 2 Methodology and data

This section provides a summary of the connectedness index methodology and the details of the data used in this paper. Diebold and Yilmaz (2014) showed that their connectedness index framework was closely linked with the modern network theory and further concluded that the total connectedness, also known as spillover, index measure corresponds to the mean degree of a weighted, directed network where variables represent the nodes of the network.

### 2.1 DYCI methodology: a tool for network analysis

Let $N$ be the number of nodes in the network under scrutiny, and let $(x_t)_{t=1,\ldots,T} \equiv (x_{kt})_{t=1,\ldots,T}$, where $k = 1,\ldots,N$, designate respective $N$ monthly series, e.g., return, volatility, or any other suitable variables of interest. The connectedness matrix for month $t$ is obtained from the series up to, and including, month $t$ (details are explained below). For a given month $t$, the connectedness matrix is a matrix $\mathbf{C} = (c_{ik})_{i,k=1,\ldots,N}$ (we drop the index $t$, for ease of exposition) with row sums equal to one, that is, $\sum_{k=1}^{N} c_{ik} = 1$, where each row $(c_{i1},\ldots,c_{iN})$ provides a breakdown of the forecast error variance of $x_i$ into shares with respect to its origin. In this sense, $c_{ik}$ is the share of variability in $x_i$ due to shocks in $x_k$. For example, in the case of a network with $N = 3$ nodes, i.e., variables of interest[1], a connectedness matrix

$$\mathbf{C} = \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.1 & 0.6 & 0.3 \\ 0.1 & 0.3 & 0.6 \end{pmatrix}, \tag{1}$$

means that 60% (20% each) of forecast error variance of $x_1$ is due to shocks in $x_1$ itself (shocks in $x_2$ and $x_3$, respectively). In other words, 40% of the volatility in node 1 is due to spillovers to node 1 from nodes 2 and 3. Considering the first column of **C**, an "aggregate share" (column sums need not add up to 1) of 0.2 is spilled over from node 1 to nodes 2 and 3, making node 1 a net receiver $(20 - 40\% = -20\% < 0)$. Node 2 is a net transmitter $(50 - 40\% = 10\% > 0)$.

Direct spillovers from node $i$ (or to node $i$) are then given by the column (row, respectively) sums in **C**, excluding the nodes' connectedness to itself:

$$\text{from node } i \text{ to others: } C_{\bullet \leftarrow i} = \sum_{k=1, i \neq k}^{N} c_{ki} \tag{2}$$

$$\text{to node } i \text{ from others: } C_{i \leftarrow \bullet} = \sum_{k=1, k \neq i}^{N} c_{ik} \tag{3}$$

Once shocks, originated from and received by, node $i$ are computed, the difference between the two will yield a measure of net directional connectedness transmitted from node $i$ to all other nodes, denoted by $C_i$:

$$C_i = C_{\bullet \leftarrow i} - C_{i \leftarrow \bullet} \tag{4}$$

Spillovers from node $i$ to others plus spillovers to itself, i.e., respective column sums of **C**, need not sum up to 1.

In the network terminology, with **C** interpreted as adjacency matrix of a weighted directed network of nodes, these aggregates are from-degree of node $i$ (to-degree of node $i$, respectively); see Diebold and Yilmaz (2014).

The Diebold-Yilmaz connectedness methodology is developed on the basis of a vector autoregressive (VAR) model with $N$ variables of interest as components.

Consider a covariance stationary $N$-variable VAR($p$), $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. The moving average (MA) representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N$x$N$, coefficient matrices $A_i$ obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with $A_0$ an $N$x$N$ identity matrix and $A_i = 0$ for $i < 0$. The moving average coefficients (or transformations such as impulse response functions or variance decompositions) are the key to understanding the dynamics. We rely on variance decompositions, which allows us to split the forecast error variances of each variable into parts attributable to the various system shocks. Variance decompositions also allow one to assess the fraction of the $H$-step-ahead error variance in forecasting $x_i$ that is due to shocks to $x_j, \forall i \neq j$, for each $i$.

A study of connectedness is not complete without an analysis of directional connectedness across the nodes. Calculation of variance decompositions requires orthogonal innovations, whereas the VAR innovations are generally correlated. Identification schemes such as that based on Cholesky factorization achieve orthogonality, but the variance decompositions then depend on the ordering of the variables. As a result, it is not possible to use the variance decompositions from the Cholesky factor orthogonalization to study the direction of connectedness. With this understanding, Diebold and Yilmaz (2012) propose to circumvent this problem by exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), which produces variance decompositions invariant to ordering. Instead of attempting to orthogonalize shocks, the generalized approach allows correlated shocks but accounts for them appropriately using the historically observed distribution of the errors. As the shocks to each variable are not orthogonalized, the sum of contributions to the variance of forecast error (that is, the row sum of the elements of the variance decomposition table) is not necessarily equal to one.

Using the VAR framework introduced above, we define *own variance shares* to be the fractions of the $H$-step-ahead error variances in forecasting $x_i$ due to shocks to $x_i$, for $i = 1, 2, .., N$, and *cross variance shares*, or *connectedness*, to be the fractions of the $H$-step-ahead error variances in forecasting $x_i$ due to shocks to $x_j$, for $i, j = 1, 2, .., N$, such that $i \neq j$.

The generalized impulse response and variance decomposition analyses also rely on the MA representation of the $N$-variable VAR($p$) equation above. Pesaran and Shin (1998) show that when the error term $\varepsilon_t$ has a multivariate normal distribution, the $h$-step generalized impulse response function scaled by the variance of the variable is given by:

$$\gamma_j^g(h) = \frac{1}{\sqrt{\sigma_{jj}}} A_h \Sigma \boldsymbol{e}_j, \quad h = 0, 1, 2, ... \tag{5}$$

where $\Sigma$ is the variance matrix for the error vector $\varepsilon$, $\sigma_{jj}$ is the standard deviation of the error term for the $j$th equation, and $\boldsymbol{e}_i$ is the selection vector with one as the $i$th element and zeros otherwise. Node $j$'s contribution to node $i$'s $H$-step-ahead generalized forecast error variance, $\theta_{ij}^g(H)$, for $H = 1, 2, ...$, is defined as:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{6}$$

As explained above, the sum of the elements of each row of the variance decomposition table is not necessarily equal

[1] Throughout the paper, we use the terms "node" and "variable of interest" interchangebly.

to one, i.e., $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. In order to use the information available in the variance decomposition matrix to calculate the connectedness index, Diebold and Yilmaz (2012) normalize each entry of the variance decomposition matrix, Eq. 6, by the row sum as[2]:

$$C_{i\leftarrow j}^{H} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

and $C_{i\leftarrow j}^{H}$, also called pairwise directional connectedness, are summarized in $\mathbf{C}$.

Now, by construction $\sum_{j=1}^{N} C_{i\leftarrow j}^{H} = 1$ and $\sum_{i,j=1}^{N} C_{i\leftarrow j}^{H} = N$. Using the normalized entries of the generalized variance decomposition matrix, Eq. 7, Diebold and Yilmaz (2012) construct the total connectedness index as:

$$C^{H} = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} C_{i\leftarrow j}^{H}}{\sum_{i,j=1}^{N} C_{i\leftarrow j}^{H}} = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} C_{i\leftarrow j}^{H}}{N} \tag{8}$$

A connectedness index $C^{H} = 0$ $\left(C^{H} = 1\right)$ indicates the lowest (highest) level of connectedness: all variability in respective node is due to shocks from within (outside of, respectively) each variable.

Empirically, we fit a standard VARX model of order 1 to $N = 4$ endogenous variables and one exogenous variable, using data from a window of size 36 (that is, months $t-35, \ldots, t$). We follow Diebold and Yilmaz (2012) and use an approach suggested by Pesaran and Shin (1998), namely to identify the impulse response function of a component (here, $x_k$), and give the highest priority to that component; this removes the dependence on an imposed hierarchy of nodes. Forecasting $n$ steps ahead (we use $n = 12$), forecast error variance shares ($c_{i1}, \ldots, c_{iN}$ for $i = 1, \ldots, N$) are summarized in a connectedness matrix $\mathbf{C}$. With $n = 12$, the decomposition of forecast error variance is acceptably settled. This procedure is then applied for every $t$, resulting in a sequence of connectedness matrices.

### 2.2 Propagation values: relative importance of network nodes as shock propagators

The network structure of the spillover matrix with respect to the propagation of shocks lends itself to a broader perspective, as elaborated in Schmidbauer et al. (2013); Schmidbauer et al. (2016); Schmidbauer et al. (2017). Let $\mathbf{C}$ again denote the spillover matrix for month $t$. We assume that $\mathbf{C}$ contains all relevant, and the most recent available, information about the network throughout month $t$. A hypothetical shock ("news", "information") of unit size in node $k$ on month $t$ can be denoted as $n_0 = (0, \ldots, 0, 1, 0, \ldots, 0)'$, where 1 is in the $k$th component of $n_0$. We assume that the propagation of this shock across the nodes of the network within month $t$ will take place in short-time intervals of unspecified length according to

$$\mathbf{n}_{s+1} = \mathbf{C} \cdot \mathbf{n}_s, \quad s = 0, 1, 2, \ldots \tag{9}$$

(where step $s = 0$ initializes the recursion). The index $s$ in Eq. (9) therefore denotes a step in information flow. Moreover, assuming that information flow across variables of interest, and hence nodes of the network, can proceed instantly on month $t$, with spillover conditions (given by $\mathbf{C}$) persisting throughout month $t$, it makes sense to iterate Eq. (9) and investigate steady-state properties (as $s \to \infty$) of the model. In steady-state, this leads to

$$\mathbf{v}' = \mathbf{v}' \cdot \mathbf{C}. \tag{10}$$

When the left eigenvector $\mathbf{v} = (v_1, \ldots, v_N)'$ of $\mathbf{C}$ is normed such that $\sum_{k=1}^{N} v_k = 1$, $v_k$ is called the propagation of node $k$. It renders the value of a shock in variable $k$ as seed for future uncertainty in variables of interest across the network under investigation:

$$v_k = \sum_{i=1}^{N} c_{ik} \cdot v_i \tag{11}$$

For $\mathbf{C}$ as in Eq. (1), $\mathrm{v}' = (0.2, 0.4, 0.4)$, which means that a shock in node 2 is twice as powerful ($0.4/0.2 = 2$) as a shock in node 1 in terms of creating network volatility—a similar concept, eigenvector centrality, is also used in social network analysis; see, for example, Bonacich (1987).

Here, we provide a brief intuitive explanation of what centrality measures quantify in networks. Though they have applications in a diverse set of fields, centrality concepts were first developed in sociological context where researchers aimed to pinpoint the person in the leadership role who typically occupies the most central; thus, the most powerful position in a network of people, i.e., a social network. Later on, applications of technological, biological networks as well as networks of information have emerged. To capture certain aspects of network centrality, various centrality measures such as betweenness, eigenvector, Katz, PageRank, among others, were introduced, see, e.g., Newman (2010) for their definitions, similarities, and differences.

A celebrated centrality measure, which is one of the preeminent methods used by Google to rank webpages in its search results, has the trademark name PageRank. A website is likely to be more important if it receives links from those that are also deemed important. And better search results yield when more important websites are displayed in higher rankings in search results. As put forth by Google founders Brin and Page (1998), "PageRank …corresponds to the principal eigenvector of the normalized link matrix of the Web." In our case, eigenvector centrality measures the importance of a node by its volatility creation capacity which results in Eq. (6).

[2] Alternatively, one can normalize the elements of the variance decomposition matrix with the column sum of these elements and compare the resulting total connectedness index with the one obtained from the normalization with the row sum.

And it also takes into account shock repercussions other than the direct connections, as specified by propagation Eq. (9). Building on this, propagation values obtained from connectedness tables, via computation of normed left eigenvector, can be used to answer Q2 we asked in Section 1: "…which market has the highest potential to disseminate shocks in the real-financial network?"

### 2.3 Data

**Real variables: constituents of RAI**

The real activity index for the Swiss economy is constructed from variables similar (either the same or the equivalents for Switzerland) to the ones used for non-U.S. economies in Scotti (2016). They are the real gross domestic product (GDP), industrial production index (IPI), purchasing managers' index (PMI), total retail trade index, and the unemployment rate[3]. Before proceeding to the model estimation, we suitably transform the data to make them stationary and normalize each series to have zero mean and unit variance. Table 1 provides information about the data used to estimate the model given in Eq. (21) to extract RAI for the time period from January 1991 to March 2017.

**Financial variables: volatilities but not returns**

On the financial side, we use stock, bond, and exchange rate volatilities as endogenous variables. Switzerland, being a small open economy, is susceptible to exogenous global shocks. To be able to capture these shocks, we use the 10-year U.S. government bond price volatility series as an exogenous variable. All volatilities are used in natural logarithms. Relevant information regarding financial variables is given in Table 2. Our financial data set starts in April 1996. All data are retrieved from the Bloomberg terminal.

We base our choice of volatilities, instead of returns, mainly on two grounds: (i) statistical and (ii) empirical. (i) Statistically, asset returns usually exhibit lack of autocorrelation, tend to have fatter tails than the Gaussian and are negatively skewed while volatilities display a strong serial correlation and tend to be distributed asymmetrically, see, e.g., Cont (2001). Besides, approximate normality is often obtained by taking natural logarithms of volatility series, see Diebold and Yilmaz (2014). As pointed out in Section 2.1, we use generalized variance decompositions à la Pesaran and Shin (1998) which assume normality. Therefore, adopting log volatilities is likely to remedy possible statistical complications that may arise due to non-normality of the returns. (ii) On the empirical front, as Diebold and Yilmaz (2015) put it "…volatilities tend to lurch and move together only in crises, whereas returns often move closely together in both crises and upswings." The use of volatilities could also be conducive in identifying aftereffects of periods of "volatility paradox". Volatility paradox refers to excessive risk taking through increased leveraging, as a result of decreased market volatility, see Brunnermeier and Sannikov (2014). Low volatile environment leads to building up of risk, leaving economy exposed to high-volatility events, and their possible social and economic costs. So both from theoretical and empirical perspectives, applying log volatilities is likely to provide more fruitful and useful results than returns which justifies our decision to proceed with volatilities but not returns.

To obtain monthly range volatility measures, following Diebold and Yilmaz (2009), we use a method proposed by Garman and Klass (1980), based on the hypothesis that the stock price process is a geometric Brownian motion.

For the Swiss and the U.S. 10-year government bond markets, we were able to retrieve monthly (opening, high, low, and closing, respectively) yields only. And to obtain volatilities, we first compute corresponding bond prices from the yields ($r_t$) by employing the simple bond pricing formula, $P_t = \frac{100}{(1+r_t)^{10}}$, and plugging these prices into Garman-Klass equation yields monthly bond market volatility series.

**Table 1** Real economic indicators for Swiss RAI

| Series | Description | Freq. | Source |
|---|---|---|---|
| Unemployment | Unemployment rate | M | FRED |
| Trade | Total retail trade index growth | M | FRED |
| PMI | Switzerland procure.ch PMI | M | Bloomberg |
| IPI | Industrial production index growth | Q | OECD |
| GDP | Real GDP growth | Q | FRED |

## 3 Measuring connectedness: KOF barometer as a proxy for the real economic activity

In this section, we examine the real-financial connectedness of the Swiss economy using the KOF economic

**Table 2** Financial market data for connectedness analysis

| Bloomberg ticker | Description | Variable type |
|---|---|---|
| SMI | Switzerland stock market index | Endogenous |
| GSWISS10 | Switzerland gov't bonds 10-year note generic bid yield | Endogenous |
| USDCHF | USD/CHF spot exchange rate | Endogenous |
| USGG10YR | U.S. generic gov't 10-year yield | Exogenous |

[3] As an anonymous reviewer has pointed out: the unemployment rate in Switzerland is calculated with an infrequently adjusted denominator which generates level shifts in the unemployment rate, e.g., in January 2014: -0.1pp, in January 2010: -0.3pp, and in January 2000: -0.2pp.

barometer[4] (further details are given in Section 4) to represent the real side of the Swiss economy. As already noted above, the financial side of the Swiss economy is represented by the stock, bond, and FX market volatilities. Besides, the 10-year U.S. government bond volatility is used as an exogenous variable to proxy global shocks. Due to data availability, the selected VAR(1) model specification and the rolling window size of 36 months, our results span a period from April 1999 to March 2017.

The total connectedness index series (Eq. 8) is given in Fig. 1. As the first sample window includes the East Asian financial crisis of 1997 and the Russian debt crisis of 1998, the total connectedness index starts relatively high at around 25%. However, as the sample window is rolled over it decreases to levels around 13%, a value that is very close to all time minimum of 11.7%. Beginning in early 2000, the index starts to go up again reaching up to 30% in mid-2001. This upward move in the index is likely to be due to the spillover effects of the dot-com bubble burst in the U.S.[5]. Following the U.S. recession of 2001[6], and enroute to and during the 2002–2003 recession[7] in Switzerland, total connectedness index fluctuates within 17–30% band. Throughout the paper, vertical shaded regions in the figures correspond to recession dates in Switzerland. And yet, a stronger upward move in the index follows from 2003 until 2005 that brings total connectedness to a global maximum at 41% (Feb 2005). From 2005 to 2007, there is a decreasing trend in connectedness index which attains an all time minimum of 11.7% in Sep 2006. From 2007 to the beginning of Swiss recession in 2008Q3, index oscillates within a band of 13–20%. With the onset of the Swiss recession which is mainly a consequence of the global financial crisis, connectedness index trends up in two steps. First, from 14 to 24% and second, following the end of the recession, it reaches a local maximum around 35%.

Fluctuations in the total connectedness series persist throughout the European debt crisis of 2010–2012. In September 2011, SNB announced to set a minimum EUR/CHF exchange rate at 1.2 due to "massive overvaluation" of CHF[8] (hereafter, SNB's 2011 decision). This coincided with a period in which connectedness series sharply dropped from a local maximum until it reached a local minimum in Nov 2012. Then, the index started going up in mid-2013 to reach a value close to all time high level for the post recession period (Apr 2009–Mar 2017) in May 2014 (39%). In June 2013, the U.S. financial markets gave a rather adverse reaction to Federal Reserve's announcement that it would start tapering its $85 billion-a-month quantitative easing program before the end of 2013. Swiss real-financial connectedness is likely to be affected from this event, what is now referred to as the "taper tantrum," as its effect was felt through the global financial markets.

From May 2014 to August 2014, connectedness index plunged from 39 to 21%. Further decrease to 16% in December 2014 has come to an end with a rebound in January 2015, with index reaching 35%, when SNB announced that the minimum exchange rate set in September 2011 will be discontinued[9] (hereafter, SNB's 2015 decision). Connectedness index stabilized at around 25% right after SNB's 2015 decision until the end of our analysis period.

Analyzing solely total connectedness index series presents a useful but an incomplete preview of the whole story. To further elaborate on how the real and the financial sides of the Swiss economy interact, we now turn to the analysis of the dynamic total net directional connectedness measures in Fig. 2.

Each panel in Fig. 2 presents the total "net" directional connectedness measure for respective nodes which is obtained from Eq. (4). A negative "net" total directional connectedness value refers to a case where the variable in a question is a net connectedness receiver from the others. That is, shocks transmitted from all other variables to variable $i$, in total, exceeds the shocks that are transmitted from variable $i$ to all others. As they result from the same series of connectedness matrices, all subcharts in the figure are comparable.

An important observation from Fig. 2 is that just before the economy goes into 2002–2003 recession, net real connectedness reaches its global maximum and then it starts to decline and goes into the negative territory (indicating that the real sector becomes a net shock receiver from financial markets) with the onset of the recession (see "KOF" panel in Fig. 2). During the expansion/recovery phase of the business cycle, net connectedness starts to increase again. On the other hand, prior to 2008–2009

[4] We used KOF barometer vintage for June 2017. All monthly vintages (from January 1991 to the most recent month of the year) are available at https://datenservice.kof.ethz.ch/api/v1/public/sets/baro_vintages_monthly?mime=xlsx, accessed 2018-11-23.

[5] "... The technology-heavy NASDAQ reached its pinnacle of 5,048.62 on March 10, [2000]. Then the Internet bubble burst and the index plummeted nearly 40 percent, dropping below 3,000 in December [2000] in it worst annual loss", The New York Times, 2012-03-13; available at http://www.nytimes.com/2012/03/14/business/stocks-rally-to-pre-2008-heights.html, accessed 2018-12-17.

[6] U.S. was in recession from March to November in 2001, see https://nber.org/cycles.html, accessed 2018-12-17.

[7] We refer to (Siliverstovs 2013) for classical business cycle dating in Switzerland. He identifies five business cycles, two of which marked with (*) reside in our connectedness analysis period, i.e., 1981Q2-1982Q2, 1990Q2-1991Q2, 1992Q2-1993Q1, 2002Q1-2003Q1* and 2008Q3-2009Q1*.

[8] "Swiss National Bank sets minimum exchange rate at CHF 1.20." https://www.snb.ch/en/mmr/reference/pre_20110906/source/pre_20110906.en.pdf, accessed 2018-12-04.

[9] "Swiss National Bank discontinues minimum exchange rate and lowers interest rate to − 0.75%". https://www.snb.ch/en/mmr/reference/pre_20150115/source/pre_20150115.en.pdf, accessed 2018-12-04.

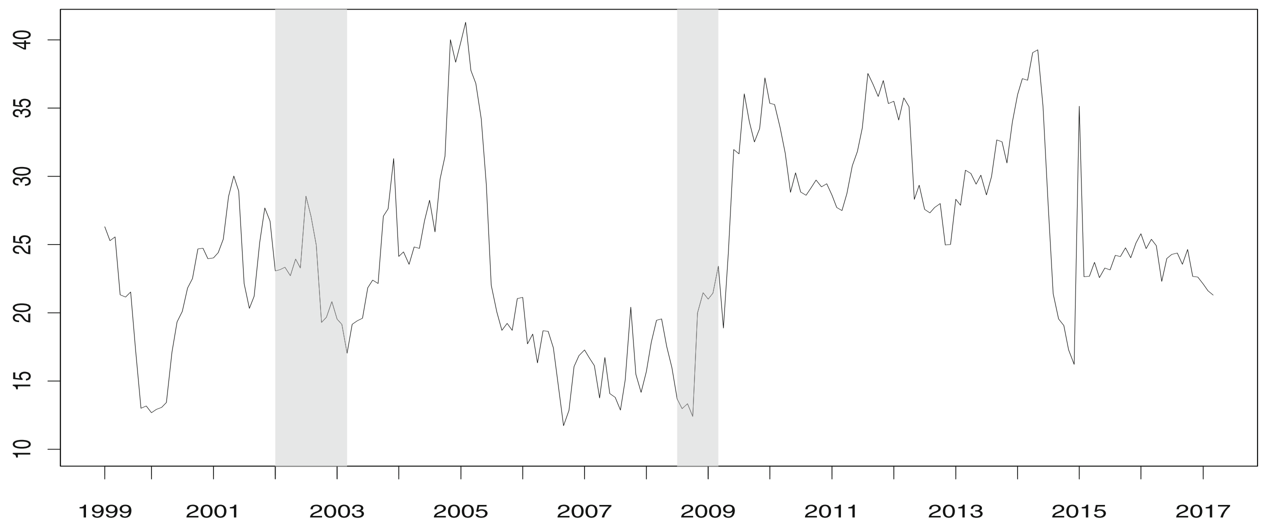


**Fig. 1** Total connectedness index using KOF barometer

recession, net connectedness series drops to negative levels which then recovers and reaches positive levels as the economy recovers. It could be, at least provisionally, argued that prosperity in the real side of the economy also spills over the financial markets as well, as evidenced by increasing net connectedness from the real side of the economy to the financial markets.

Net connectedness pattern for the stock market seems to be portraying the mirror image of what the real economy indicates in net terms, i.e., bulge in one usually become dip in the other, except that 2006–2008 period is much more stable than what we observe for the real economy (see "SMI" panel in Fig. 2). But stock market stays longer on the positive than the negative territory over our

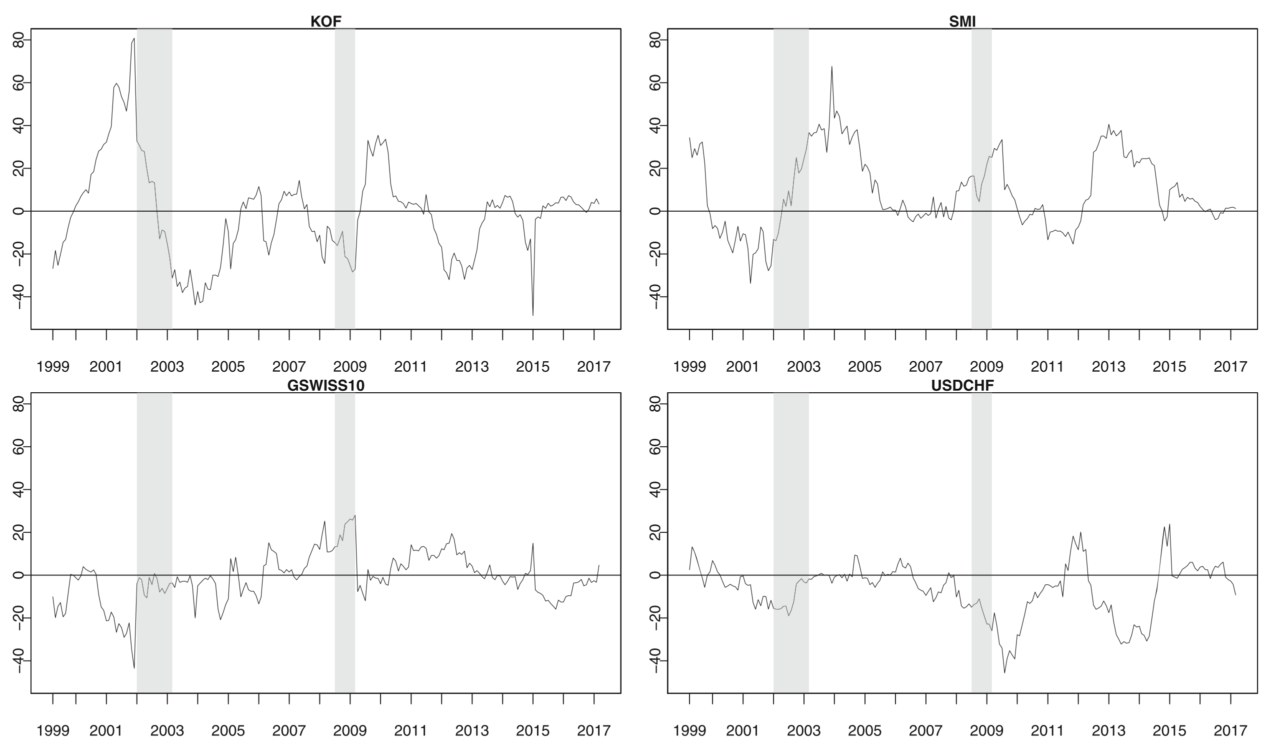


**Fig. 2** Dynamic total net directional connectedness index using KOF barometer

analysis period. 2002–2005 and 2011–2015 periods stand out as periods of positive net connectedness arising from the stock market. To diagnose the direction of this large positive connectedness, we refer to Fig. 9 of Appendix B which plots pairwise connectedness results.

To save space and focus more on our research questions in the main text, we present the pairwise connectedness results and the accompanying analysis in Appendix B. Figure 9 of Appendix B presents almost all relevant connectedness measures; namely, the pairwise directional (the first four rows and the first four columns, see Eq. 7), the total directional (the last row, “to others," see Eq. 2 and the last column, “from others," see Eq. 3), and the total (the single plot located at the bottom row and the last column, see Eq. 8) connectedness measures[10]. As net results of the plots presented in the fifth row and the fifth column of Fig. 9 of Appendix B have already been discussed above using Fig. 2, for discussions on the pairwise connectedness measures (plots in the first four rows and the first four columns), see Appendix B. Each column refers to a variable that transmits the shock while the rows refer to respective variables that receive the transmitted shock. To give an example, the plot in the first row and the fourth column in Fig. 9 of Appendix B presents the time series behavior of the shocks transmitted by the FX market (USDCHF) to the real side of the economy (KOF).

In summary, after controlling for the effects of the global shocks on the Swiss economy through the use of U.S. bond market volatility as an exogenous variable, we find that both the real (as proxied by the KOF barometer) and the financial (as proxied by stock, bond, and FX market volatilities) sides of the Swiss economy have important and significant impacts on the other. This conclusion marks the end of our analysis for the first step towards answering Q1 set forth in Section 1. However, before building further on this finding and computing the relative importance of financial markets as shock propagators, we should ask the following question: How does the financial variables used in the estimation of KOF barometer effect the overall results and conclusions? Inclusion of financial variables in the KOF barometer estimation is sure to prevent strict isolation of the real and the financial sides of the Swiss economy. Shocks in the financial sector would be reflected in the KOF barometer variable which already incorporates the effects of these shocks, making our analysis “less sensitive” to financial shocks as they are already taken into account in the KOF barometer. To fix this issue, we resort to the construction of an alternative real activity index which distills information from real variables only and “purely” represent the real side of the Swiss economy (see Appendix A for technical details). Our rationale to use KOF barometer as a benchmark indicator for the Swiss economy is that it is currently the only publicly available business conditions indicator for the Swiss economy, see Galli (2018). Estimation of a “pure” real activity indicator and its comparison with KOF barometer is the program of the next section.

## 4 RAI vs KOF barometer

Upon estimation of the factor model in Appendix A using real variables only, we are in a position to extract unobserved factor with Kalman Smoother. Extracted factor is used as a proxy for the real activity of the Swiss economy, namely, RAI. Figure 3 plots RAI and KOF barometer together. Both series move closely together over the 1991–2017 period. A certain period over which they do not move so closely requires further explanations. This corresponds to the beginning of the estimation period, i.e., 1991–1995. In RAI, recovery from the 1992Q2–1993Q1 recession was not as strong as KOF barometer estimated. At this point, we should note what (Galli 2018) states: “Note that there is a potential structural break in the GDP series since the ESA2010 benchmark GDP revision was only implemented back to 1995.” As a result, our GDP series is likely to be effected from this as well, whereas variables other than GDP in the KOF barometer estimation could have been instrumental in remedying this side effect. Hence, our results for the pre-1995 period should also be treated with care.

Comparing RAI with KOF barometer for the 2001–2002 period, RAI shows smaller level of contraction in the Swiss economy than KOF barometer anticipates. Accordingly, before the 2002–2003 recession, Swiss economy seems to contract more than RAI anticipates. Beginning with 2005, RAI is mostly in line with what KOF barometer indicates except certain relatively unimportant differences. Besides, our financial data set constrains our analysis over the April 1999–March 2017 period. Consequently, we are on the safe side in carrying out our current connectedness analysis with RAI.

In the following, we outline methodological and empirical similarities and differences between RAI and KOF barometer under four headings: (i) RAI is a small-scale model with five real variables whereas to estimate KOF barometer; analysis starts with 500+ candidate series, including variables from foreign economies and financial variables. The resulting number of selected variables usually exceeds 200, see Abberger et al. (2014) and KOF Swiss Economic Institute website[11]; (ii) in terms of modeling the temporal aggregation of variables, both models use the same Mariano and Murasawa (2003) approach; (iii) both

[10] The only missing set of connectedness measures are the “net connectedness to others" measures that are already presented in Fig. 2.

[11] https://www.kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-economic-barometer.html, accessed 2018-12-09.

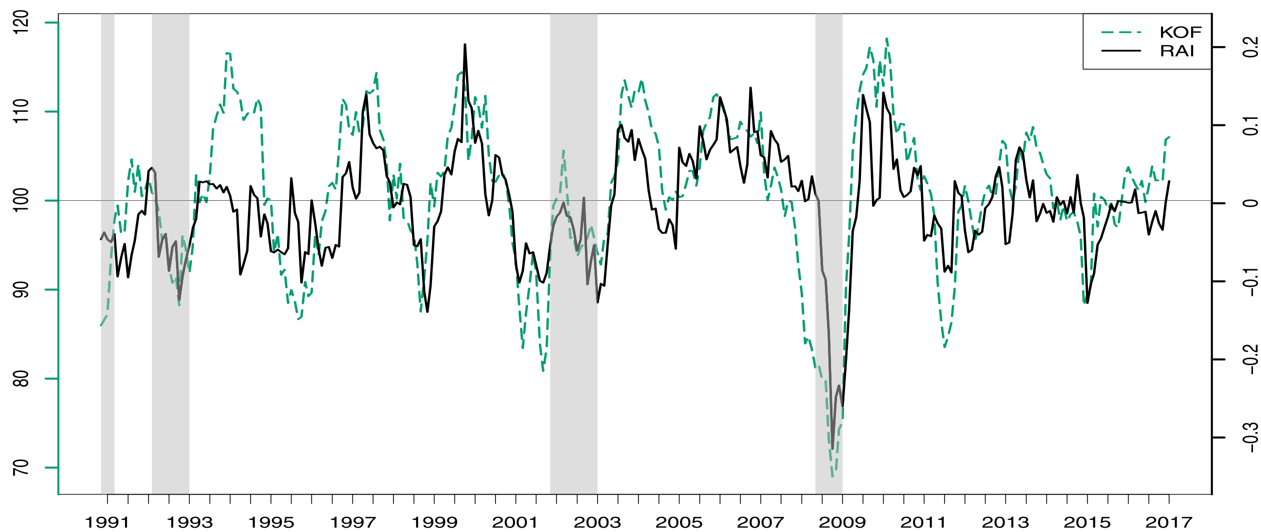

**Fig. 3** Monthly KOF barometer (left scale) vs RAI (right scale)

models use the same number of underlying factors, i.e., one; and (iv) relatively small number of unknowns in RAI makes maximum likelihood estimation (MLE) applicable without usual complications when faced with estimation of large-sized models. We use MLE for RAI estimation. To estimate KOF barometer, expectation maximization (EM) algorithm, which is more suitable for large-sized models, is used, see Abberger et al. (2014).

Based on the above comparison, the sole use of a small number of real variables could be points of criticism directed at our model. But various papers studying Swiss economy find supporting and opposing evidence with respect to these points. A business cycle index distilled from domestic non-financial variables is very similar to the one estimated from variables including financial and foreign variables, see Galli (2018). Large scale factor models are found to beat small scale models in terms of forecasting performance for Switzerland, see Galli et al. (2017). But it has been argued elsewhere that a "... small-scale dynamic factor model for the Swiss economy [performs] as good as that of peers with richer dynamics", see Glocker and Wegmüller (2019).

Given above, we conclude that the close association of RAI and KOF barometer is by no means a surprise and we can safely proceed to our real-financial connectedness analysis using RAI as a proxy to represent the real side of the Swiss economy.

## 5 Measuring connectedness: RAI as a proxy for the real economic activity

Connectedness analysis carried out in Section 3, where KOF barometer represented the real side of the Swiss economy, led us to a certain set of conclusions regarding the interaction between the real and financial sides of the Swiss economy. Nonetheless, as we pointed out, KOF barometer does not exclusively represent the real side of the economy for a legitimate reason. It is ultimately designed to track the performance of the economy as a whole and since it utilizes financial variables, it is directly prone to shocks in the financial markets. This is an important obstacle for our analysis but to overcome this, we computed a real activity index, RAI, which is purely extracted from real variables and shown to move in line with KOF barometer. In this section, we report our connectedness results when KOF barometer in Section 3 is replaced with RAI.

To be able to compare and contrast both analyses, we present total connectedness index series in Fig. 4. When we take a glance at both series, we observe that they behave quite similar over time.

We observe that in both analyses, connectedness index series follow a downward trend after reaching their respective global maxima in 2005. Both series rebound from minimum levels in 2006 enroute to U.S. mortgage crisis (summer 2007). Then, both series trace paths with ups and downs and with the onset of the Swiss recession, they start an upward trend. Turning from their respective local peaks, KOF barometer-based index stabilized at around 30% levels while RAI-based one follows a downward trend until the end of 2014 and SNB's 2015 decision reverses the trend leading to a local maximum in the beginning of 2016.

Investigating the behavior of RAI-based connectedness index is useful but not enough for understanding the interactions between the real and financial sides of the Swiss economy. So, we further look into the dynamic behavior of connectedness across all four variables included in our model.

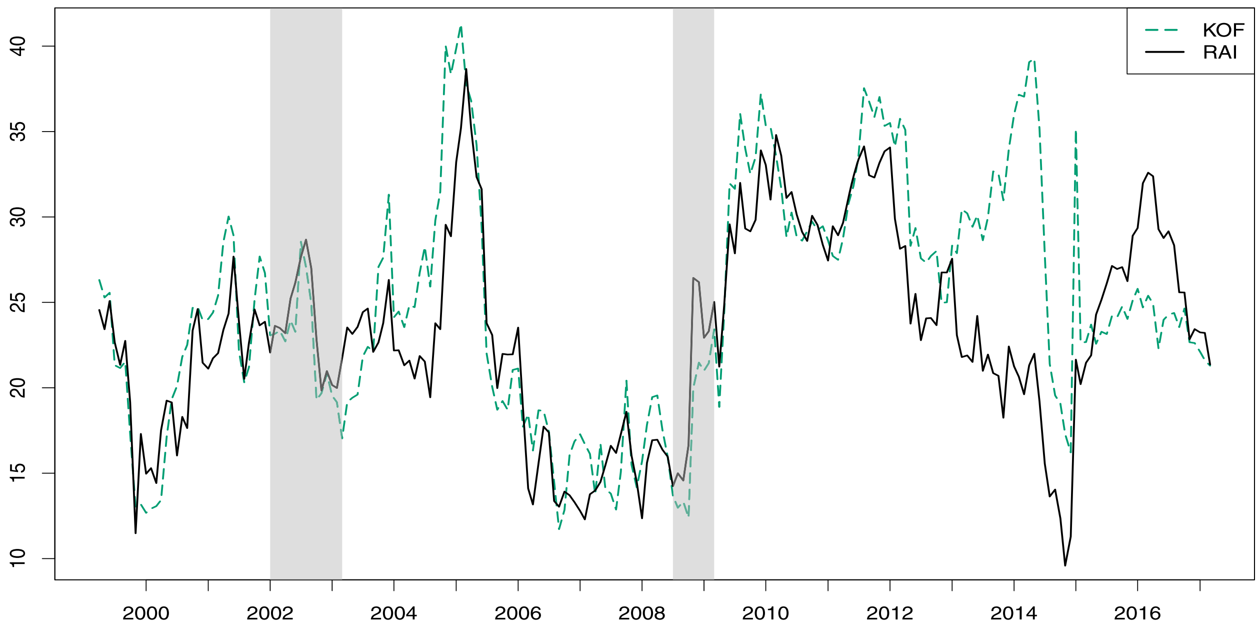

**Fig. 4** Total connectedness index: KOF barometer vs RAI

In Fig. 5, we plot total "net" directional connectedness measures for both the KOF barometer- and RAI-based analysis. We observe that net connectedness for RAI is negative most of the time, indicating a net connectedness receiver behavior (in about 72% of the time over the analysis period; see "REAL Side" panel in Fig. 5).

However, a common characteristics of the periods when it is positive is that they usually precede recession or crisis periods. So, we could, tentatively, argue that if the real side of the economy starts to act as a net connectedness transmitter, this could be taken as an early warning signal for "prospective and detrimental" shocks to the rest of the economy.

Undertaking a similar analysis for the U.S. economy, Uluceviz and Yilmaz (2018) show that a comparable observation holds for the U.S. economy before the 2008–2009 recession. Although net connectedness for weekly RAI was mostly in the negative region, significant amount of net positive connectedness is observed during the 2006–2008 period. With the onset of the global financial crisis and the U.S. recession, net connectedness for RAI peaks. ADS-based results (which is the counterpart for the KOF barometer-based analysis in this paper) also show positive or increasing net connectedness towards the financial markets on or before the recession dates.

In terms of the pairwise directional connectedness, we observe that large levels of connectedness originating from RAI to the financial side variable during mid-2006–2008 period spilled over the financial markets (second, third, and fourth rows, first column of Fig. 6, respectively). When we consider stock market (SMI), we observe that it is a net connectedness transmitter for extended periods (in about 89% of the months net connectedness series is positive, see "SMI" panel in Fig. 5). Sep 2001–Mar 2002 and Jul–Dec 2007 periods are notable exceptions. Beginning with 2008, stock market transmits significant amount of connectedness towards the real economy (first row, second column of Fig. 6) until beginning of 2015. Over this period, it is receiving relatively small amount of connectedness from RAI (except 2007) making stock market a net connectedness transmitter for the real economy.

Real economy is highly sensitive to shocks in the stock market. That is, shocks to stock market result with increased level of volatility in the real economy.

Government bond market behaved as a connectedness transmitter and receiver at moderate levels over the 1999–mid-2007 period (see "GSWISS10" panel in Fig. 5). During the mid-2007–May 2013 period, it acted as a strong net connectedness transmitter which could be attributed to quantitative easing policies, carried out by central banks of major developed economies. In his 19 June 2013 press conference, Fed Chairman Ben Bernanke warned the market participants that the asset purchases might be tapered in 2013 "…if the incoming data are broadly consistent with this forecast, FOMC currently anticipates that it would be appropriate to moderate the monthly pace of purchases later [in 2013]."[12] Consequently, financial markets' overreacted to this prospective plan, and following this development, net connectedness of government bond

[12] https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20130619.pdf, accessed 2018-12-29.

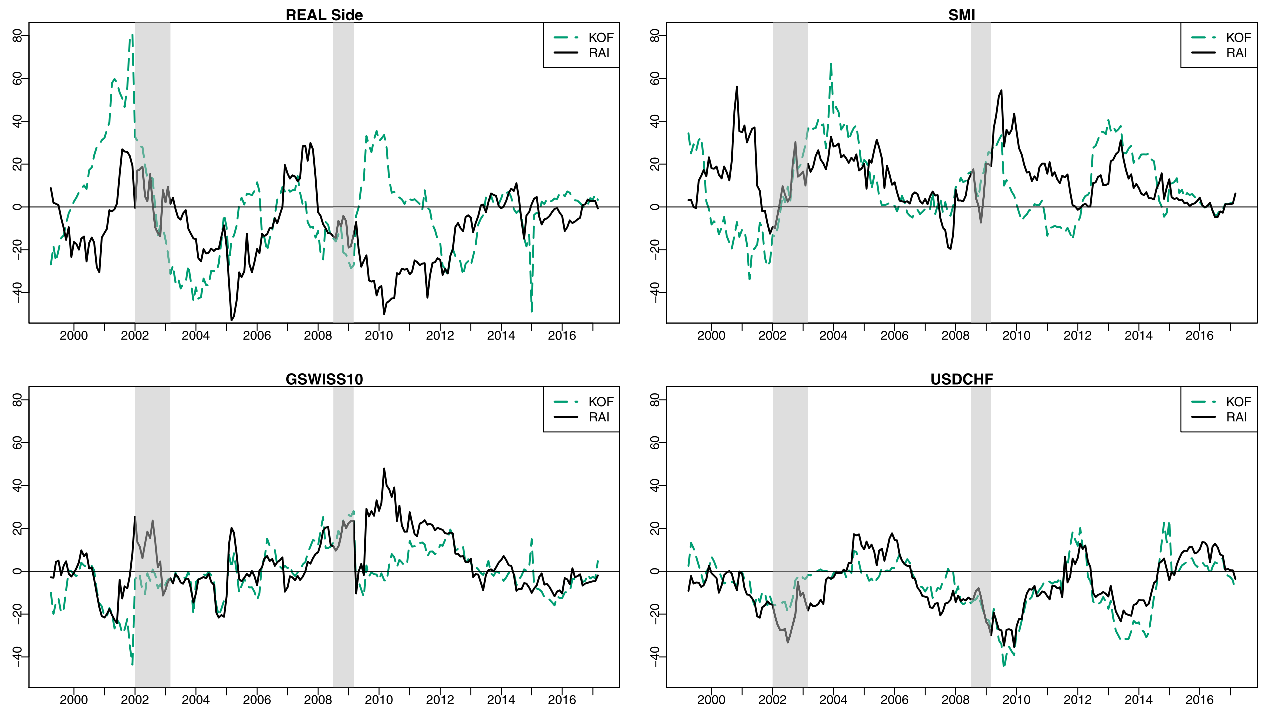


**Fig. 5** Dynamic total net directional connectedness: KOF barometer vs RAI

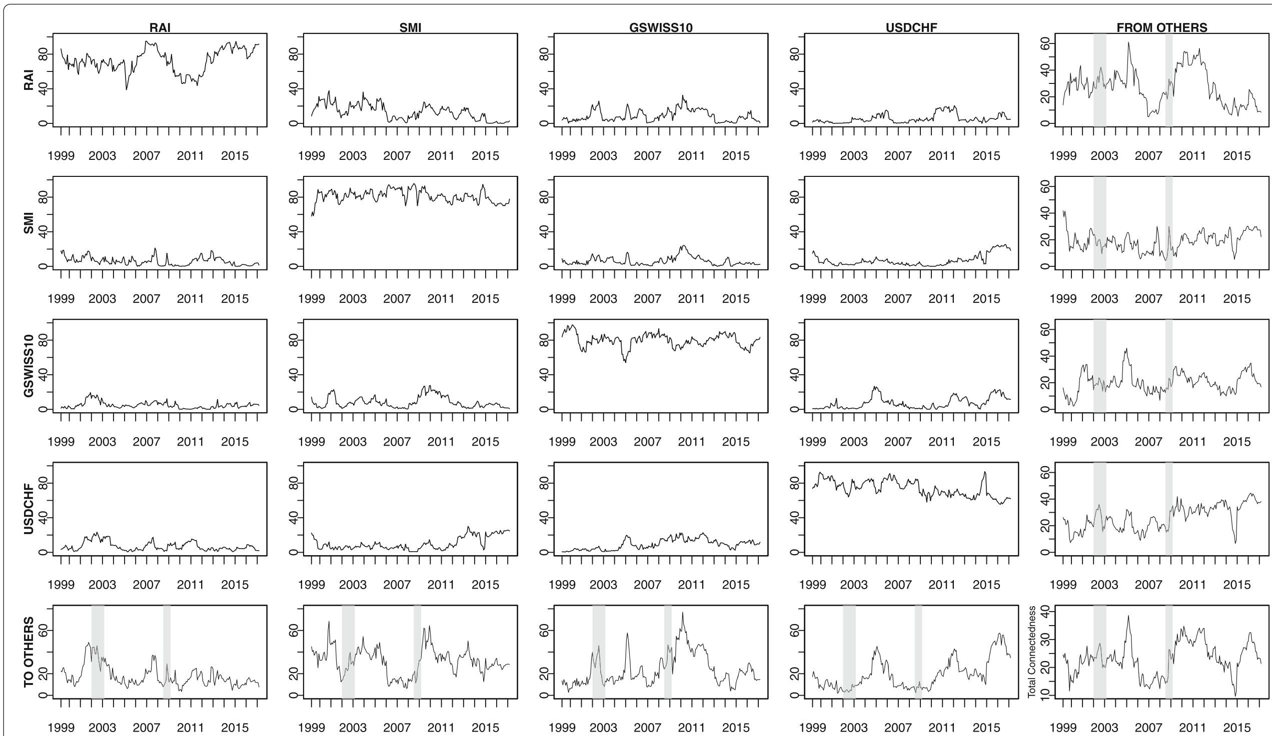


**Fig. 6** Total and pairwise directional connectedness measures using RAI

market became and stayed negative until the end of our analysis period (see "GSWISS10" panel in Fig. 5).

To identify the direction of connectedness originating from the government bond market, we need to focus on Fig. 6. Again, we observe that it transmits large amounts of connectedness towards the real sector, the stock, and the FX markets until mid-2013 (first, second, and fourth rows of third column of Fig. 6, respectively). Its impact towards the real sector diminishes in mid-2013 (first row, third column of Fig. 6). Considering its impact towards the stock market, we observe that just prior to SNB's 2015 decision, pairwise connectedness from the bond market to the stock market first decreased, followed by a temporary increase that stabilized around 5%. Its connectedness impact towards the FX market diminishes around SNB's 2015 decision but then stabilizes around 10–15% levels (fourth row, third column of Fig. 6).

From mid-2006 to beginning 2012, net connectedness of USDCHF is largely negative, while in other periods, it displays both negative and positive levels of net connectedness. Beginning with 2014, the FX market shows positive levels of net connectedness (see panel "USDCHF" in Fig. 5). The connectedness from the FX market towards the real sector is rather limited except for the 2010 to mid-2012 period. On the other hand, especially after 2010, the pairwise connectedness from the FX market to the stock and bond markets are trending up (second and third rows, fourth column of Fig. 6).

The above analysis helps us conclude that interactions between the real and the financial sides of the Swiss economy have a certain pattern, that is, real side of the economy, as proxied by RAI, is a net connectedness receiver from the financial markets. And financial markets' net connectedness transmitter characteristics vary during the course of important episodes in the domestic and global economic conditions, such as recessions, financial market shocks/crises, and SNB's 2011 and 2015 decisions.

Up to now, we have analyzed mostly aggregate values and investigated pairwise relations where we deemed necessary, now we are in a position to diagnose respective interactions between financial markets and the real side of the economy. This is going to be covered in the next section.

## 6 Net connectedness from the real to the financial sector: KOF barometer- vs RAI-based networks

In Sections 3 and 5, we have carried out real-financial connectedness analyses when KOF barometer and RAI, respectively, are used as proxies for the real side of the economy. The results change significantly in the RAI-based connectedness analysis: Most of the time, the real side of the economy acts as a receiver of shocks in net terms. Our analysis was mostly in aggregate terms, as displayed in Figs. 2, and 5, and when needed, we referred to pairwise connectedness results to identify directional relationships explicitly as in Figs. 9 of Appendix B, and 6, respectively. Now, we move on to further investigate net directional connectedness from the real side of the economy to each financial market.

Top panel in Fig. 7 shows net connectedness originating both from KOF barometer and RAI and directed at the stock market. Time net directional connectedness spillover spends in either region (positive in the case of being a net connectedness transmitter and negative, otherwise) are almost the same (negative in 54% of the time for KOF barometer) leading us to no clear conclusion regarding the dominance of the connectedness direction. In a similar vein, middle panel in the same figure, i.e., net connectedness from the real side of the economy directed at government bond market, again, gives mixed results (negative in 40% of the time for KOF barometer) but slightly more on the connectedness transmitter side. For the FX market, we can argue that other than the 2011–2013 period, a period in which SNB heavily intervened the FX market against the international investors, see Auer (2015), real economy is a connectedness transmitter towards the FX market dominantly (overall: positive in 72% of the time for KOF barometer).

In Fig. 7, we observe that the real side of the economy, as represented by RAI, mostly acts as a net connectedness receiver (negative in 71% of the time) from the stock market (top panel), which also holds for the bond market (negative in 65% of the time) as well (middle panel). In both figures, levels when net connectedness become positive are usually not that large and does not last for extended periods. Bottom panel in Fig. 7 shows that the real side of the economy acts both as a connectedness receiver and transmitter vis-à-vis the FX market (negative in 45% of the time). Notable periods during which the real economy, RAI, acts as a connectedness transmitter are, mainly, the recessions and their neighboring periods (such as Oct 2000–Aug 2004, Aug 2006–May 2008, Dec 2008–Nov 2009).

As a last word concerning the interaction between the real and financial sides of the Swiss economy, we have seen that in either case (KOF barometer-based or RAI-based analysis), real side of the economy is effected from shocks that hit financial markets and vice versa, significantly. And this concludes the end of our analysis for Q1 we asked in Section 1, "how do the real and the financial sides of the Swiss economy interact, do any of the sides predominantly influence the other?"

However, there is still one open question that we should answer: Among the financial markets we have analyzed, which one is relatively more important as a shock propagator so that regulators do not risk the introduction of


(a) SMI

(b) GSWISS10

(c) USDCHF

**Fig. 7** Net connectedness from the real sector to each financial market

more volatility into the network owing to a prospective financial market intervention?

As we have outlined in Section 1 and elsewhere, DYCI methodology permits tracing the network consequences of a shock that hit either the real or the financial side of the economy at time $t$ and settle at $t+h$, see, e.g., Schmidbauer et al. (2016) and Section 2.1. Namely, it focuses on one-time spillovers through utilization of raw connectedness tables. Up to now, our analysis was built on this perspective. In the following section, we quantify relative importance of each node as shock propagators. This is attained by investigating the aftermath of one-time shocks and will be explored using propagation values that were defined and derived in Section 2.2. This will provide an answer to the question posed in the previous paragraph and proposed in Section 1 as Q2: "hypothesizing they influence each other significantly; once hit by a shock, which market has the highest potential to disseminate shocks in the real-financial network?"

## 7 Propagation values: KOF barometer- vs RAI-based networks

Applying the methodology of Section 2.2 to series of connectedness tables obtained in Sections 3, and 5, we quantify eigenvector centrality of each node, i.e. propagation values for networks under our scrutiny over time.

Throughout the paper, our interpretation of the spillover tables, mostly, hinged on identifying shock transmitter or receiver nodes of the network in question without further commenting much on how important they are in disseminating shocks. In this section, we will elaborate on the implications of propagation values we obtain from our real-financial networks of interest.

Importance of this effort mainly lies in the fact that financial sector constitutes a relatively large part of the Swiss economy. The country acts as one of the leading financial centers in the world. As of 2017, the contribution of the financial center[13] to Swiss GDP is 9.0% (12.8% and 10.1% in 2007 and 2012, respectively). Accordingly, when a shock hits one of the Swiss financial markets, its impact on the overall economy is likely to be large, making identification of the shock rather difficult when the KOF barometer is used as a proxy for the real sector. On the contrary, a similar shock's implications will be easily traced in the case of RAI-based analysis, as the real and the financial sides of the Swiss economy are precisely disentangled.

In Fig. 8, we plot propagation values for the real side of the economy for both set of results. We observe that whichever real sector proxy is utilized, recession periods are of strict importance. We can, tentatively, argue that when the recession starts to loom on the horizon, real sector becomes more important in the network while financial sector's importance starts declining (as they add up to 1). When compared, in the aftermath of the recession, while KOF barometer-based analysis shows that real sector's relative importance starts to trend up, propagation values for RAI further declines, see Fig. 8.

In a nutshell, RAI-based analysis yields a much more stable relationship between the real and the financial sectors than the KOF barometer-based one. With this observation, we can argue that financial variables used to estimate KOF barometer amplify shocks' impact on the network.

After comparing the real and the financial sectors at aggregate level, we switch to the analysis of relative importance of financial markets in isolation. But this time, we will carry out this exercise by dividing our analysis period into mutually exclusive sub-periods. As we discussed in the preceding paragraphs and in Sections 3 and 5, recession dates and SNB's 2011 and 2015 decisions are of utmost importance for the changing dynamics of the Swiss economy. Accordingly, beginning with our analysis period, we chose the end of recessions to mark the end of and implementation of SNB's 2011 and 2015 decisions as the beginning of new sub-periods. We believe that this selection of sub-periods suitably represents major changes in the Swiss economy throughout our analysis period. For both analyses and each variable, we averaged propagation values over the specified periods, the results are given in Table 3.

Comparing average propagation values, we observe that average values for KOF barometer are, on average, close to RAI in the second (0.17 vs 0.20) and the fourth (0.20 vs 0.22) periods. During the rest of the periods, propagation values for KOF barometer are substantially higher.

It is important to note that these periods are not determined in an ad hoc way, but they are supported by empirical evidence obtained up to now. And further, we have seen that RAI-based analysis provides more reasonable results and in the rest of this section, we will focus on them. Over the whole analysis period, on average, stock market (SMI, 0.36) is found to be the most important market as shock propagator in the RAI-based real-financial network followed by the bond (GSWISS10, 0.27) and the exchange rate (USDCHF, 0.18) markets, respectively (see bottom panel in Table 3). These numbers indicate that if, for example, a hypothetical shock of unit size hits stock market, its power in terms of creating future volatility in the network is, on average, 2.00 $\left(=\frac{0.36}{0.18}\right)$ times of a shock to USD/CHF exchange rate. For each variable, there are relatively small changes in terms of average propagation values over the first and the second periods, i.e., until the end of 2008–2009 recession in Switzerland.

In the aftermath of the global financial crisis, policy makers at the developed economies' central banks intervened and implemented a series of quantitative easing policies which were mostly carried out in the form of bond purchases that were ultimately aiming to stimulate domestic economies. This is reflected in the changing behavior of the bond market's average propagation values during period 3 which spanned a period from the end of 2008–2009 recession until SNB's 2011 decision. Over this period, bond market's average propagation value increased substantially to reach 0.38, all time high value

[13] Key figures Swiss financial center (October 2018), https://www.bundespublikationen.admin.ch/cshop_mimes_bbl/8C/8CDCD4590EE41ED8B082058B7F0FF89D.pdf, accessed 2019-12-23.

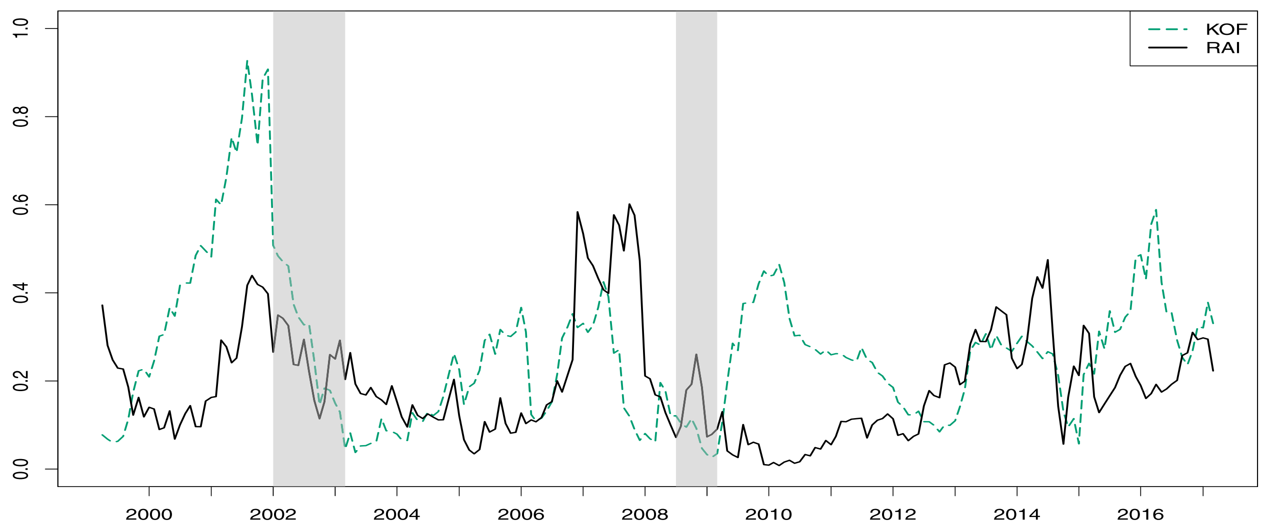


**Fig. 8** Propagation values for the real side of the economy: KOF barometer vs RAI

for the periods under consideration. This occurred at the expense of FX market which bottomed at 0.07. While average propagation values for the stock market increased, to 0.50, RAI's propagation values decreased to 0.05.

Seemingly, SNB's 2011 decision has changed economic fundamentals, i.e., how the real and the financial sides of the Swiss economy interact. Over the period when SNB's 2011 decision was in force (period 4), real sector's (RAI, 0.22) and exchange rate (USDCHF, 0.20) market's average propagation values increased while the stock (SMI, 0.32) and the bond (GSWISS10, 0.25) markets' average relative importance decreased compared to the third period, decrease in stock market being more pronounced (from 0.50 to 0.32).

SNB's 2015 decision seems to have changed average relative propagation values in relatively small amounts (period 5) but not altered the way the real and the financial sides of the economy interact as dramatic as SNB's 2011 decision did. While average propagation values for the foreign exchange market increased, those for the stock and the bond markets have further decreased.

**Table 3** Average propagation values over selected periods

| Period | Dates | End of period | KOF | SMI | GSWISS10 | USDCHF |
|---|---|---|---|---|---|---|
| (a) KOF barometer | | | | | | |
| 1 | Apr 99 - Mar 03 | End of 02-03 recession | 0.39 | 0.25 | 0.19 | 0.17 |
| 2 | Apr 03 - Mar 09 | End of 08-09 recession | 0.17 | 0.35 | 0.28 | 0.20 |
| 3 | Apr 09 - Aug 11 | Shortly before SNB 2011* | 0.31 | 0.29 | 0.27 | 0.13 |
| 4 | Sep 11 - Dec 14 | Shortly before SNB 2015* | 0.20 | 0.36 | 0.23 | 0.21 |
| 5 | Jan 15 - Mar 17 | End of data | 0.34 | 0.26 | 0.17 | 0.23 |
| - | Apr 99 - Mar 17 | End of data | 0.27 | 0.31 | 0.24 | 0.19 |
| (b) RAI | | | | | | |
| Period | Dates | End of period | RAI | SMI | GSWISS10 | USDCHF |
| 1 | Apr 99 - Mar 03 | End of 02-03 recession | 0.23 | 0.36 | 0.28 | 0.13 |
| 2 | Apr 03 - Mar 09 | End of 08-09 recession | 0.20 | 0.36 | 0.24 | 0.19 |
| 3 | Apr 09 - Aug 11 | Shortly before SNB 2011* | 0.05 | 0.50 | 0.38 | 0.07 |
| 4 | Sep 11 - Dec 14 | Shortly before SNB 2015* | 0.22 | 0.32 | 0.25 | 0.20 |
| 5 | Jan 15 - Mar 17 | End of data | 0.22 | 0.29 | 0.20 | 0.29 |
| - | Apr 99 - Mar 17 | End of data | 0.19 | 0.36 | 0.27 | 0.18 |

*SNB 2011 and SNB 2015 refer to SNB's 2011 and 2015 decisions, respectively

To conclude, we have seen that financial markets' relative importance in the Swiss real-financial connectedness framework have switched substantially subject to shocks and/or developments in the financial markets and the real economy. Over our analysis period, on average, stock market is the most important financial market as shock propagator followed by the bond and the FX markets. Real economy is almost as important as the FX market in terms of relative importance as shock propagator. But since Swiss economy's dynamics seem to have altered substantially after SNB's 2011 decision, the order of the relative importance of financial markets as shock propagators has changed. In the period following SNB's 2015 decision, exchange rate (USD-CHF, 0.29) and the stock (SMI, 0.29) markets are the most important markets as shock propagators followed by the bond (GSWISS10, 0.20) market. Real economy's (RAI, 0.22) relative importance as shock propagator has become slightly larger than that of the bond market over this period.

Having determined the relative importance of each node for the real-financial network of the Swiss economy, one might be interested in the potential implications or the usefulness of this information. From the point of view of a policy maker or regulator, it would be extremely useful to identify the market in which a disturbance would introduce excessive uncertainty which translates into future volatility in the network or an adverse affect in the real economy. Knowing which markets matter the most makes it feasible to design intervention policies targeted to the market that is likely to introduce relatively less volatility into the network and still lead to valuable results. For example, from bottom panel in Table 3, we see that a hypothetical shock of unit size that hits the FX market creates, on average, 1.45 $\left(=\frac{0.29}{0.20}\right)$ times of a shock to bond market in period 5, i.e., after SNB's 2015 decision. This number was 0.18 $\left(=\frac{0.07}{0.38}\right)$ in period 3, i.e., after 2008–2009 Swiss recession ended but before SNB's 2011 decision was implemented.

The above numbers suggest that targeting the market that has the lowest potential to distribute shocks in the real-financial network is the right decision (FX market in this case). Leaving all aside, during period 3, FX market was the market with the smallest power to disturb the network and SNB chose to design its policies towards that market. These numbers are averages over extended periods, but they hint us about which markets to oversee with more care. Further research should be carried out in this direction.

## 8 Conclusion

In this paper, we analyze real-financial connectedness and further quantify relative importance of each variable as shock propagators in the Swiss economy.

To that end, we first setup two real-financial networks. In the first setup, to represent real side, we use KOF barometer, a leading composite indicator estimated from a large set of domestic and international real and financial variables. To represent financial side, we use volatilities for stock, bond, and FX markets for Switzerland. To capture global shocks that the Swiss economy is prone to, we use the U.S. bond market volatility as an exogenous variable. Analysis of this network shows us that real side of the economy acts as a net connectedness source for extended periods and with large amount of connectedness at times. In the second setup, we replace the proxy for the real economy, KOF barometer, with a newly estimated real activity index, RAI. We estimate RAI using a small set of real variables only. We repeat the same analysis and find that real side of the economy acts as a net connectedness receiver from the financial markets significantly. In net terms, RAI is mostly a shock receiver from the stock market.

For both networks, we then compute relative importance of each node as shock propagators. In the RAI-based network, we find that, on average, stock market is the most important financial market followed by the bond and the FX markets. Using important episodes (such as recessions and SNB's policies regarding the FX market) in the Swiss economy to determine different periods, we compute average propagation values and find that QE policies carried out globally effected the importance of financial markets and made bond market a very important shock propagator during the period between the end of 2008–2009 recession and the implementation of SNB's minimum EUR/CHF exchange rate policy. Discontinuation of this policy in January 2015 further changed the economic dynamics in the Swiss economy.

Monthly frequency for this type of analysis could be deemed inappropriate since shocks that hit financial markets within a month are usually much more frequent than the ones that hit real sector. One way to remedy this is to carry out this analysis in a weekly frequency, but to accomplish this, we need to extract a weekly RAI. Technically, this is not a very difficult task. Uluceviz and Yilmaz (2018) have extended the current monthly factor model to a weekly one for the U.S. and has shown that weekly RAI for the U.S. move closely with the ADS index of Aruoba et al. (2009) as published by Philadelphia Fed. But empirically, one needs a weekly real economic series to estimate weekly RAI for the Swiss economy. To the best of our knowledge, there is no publicly available weekly real economic series for Switzerland. But as a complement to our analysis, monthly RAI extracted from a large-scale data set constructed from real variables only has the potential to provide interesting results and serve as a crosscheck for the results we obtain in this paper.

## Appendix A: Dynamic factor model: estimation of a real activity index

To construct a real activity index series for the Swiss economy, we use a standard monthly frequency factor model that allows for the analysis of mixed-frequency and missing data situations along with the aggregation of flow variables (the need for estimating a real activity index is made clear in Section 3). Similar models have also been utilized by Banbura et al. (2011), Banbura and Modugno (2014) and Scotti (2016). In this section, we follow modeling conventions similar to that of Scotti (2016).

Accordingly, the unobserved factor follows a process of the form:

$$x_{t+1} = F_1 x_t + u_t, \;\; u_t \sim i.i.d.N\left(0, \sigma_u^2\right) \tag{12}$$

Our model includes monthly $\left(y_t^M\right)$ and quarterly $(y_t^Q)$ variables which have been transformed to be stationary through suitable transformations and then normalized to have zero mean and unit variance (see Section 2.3 for details). Furthermore, monthly and quarterly variables are modeled separately. The dynamics of the monthly variables follow the following factor model representation:

$$y_t^M = Z^M x_t + \epsilon_t^M \tag{13}$$

The idiosyncratic shocks $\left(\epsilon_t^M\right)$ follow an AR(1), process:

$$\epsilon_t^M = \alpha_M \epsilon_{t-1}^M + e_t^M \,, e_t^M \sim i.i.d.N\left(0, \Sigma_{e^M}\right). \tag{14}$$

Quarterly variables are also modeled with a similar factor representation. To model quarterly variables in monthly representation, we use Mariano and Murasawa (2003) approximation, i.e., we assume that log of quarterly variable is observed at the end of each quarter and denoted by $Y_t^Q$; furthermore, it is equal to the average of the log of unobservable monthly components denoted by $Y_t^M, Y_{t-1}^M$, and$Y_{t-2}^M$:

$$Y_t^Q = \frac{1}{3}\left(Y_t^M + Y_{t-1}^M + Y_{t-2}^M\right) \tag{15}$$

Note that Eq. (15) is a geometric mean of the latent monthly variables rather than the usual arithmetic mean of the monthly levels comprising the quarterly variable. This approximation was chosen by Mariano and Murasawa (2003) in order to avoid working with a cumbersome nonlinear state-space model instead of a well-behaving linear model. To obtain growth rate for the quarterly variable in Eq. (15), we define a partially observed monthly series, $y_t^Q$:

$$y_t^Q = \begin{cases} Y_t^Q - Y_{t-3}^Q & \text{, for } t = 3, 6, 9, \ldots \\ N/A & \text{, otherwise} \end{cases} \tag{16}$$

We compute $Y_t^Q - Y_{t-3}^Q$ for the variable defined in (16) in terms of (15) and obtain:

$$Y_t^Q - Y_{t-3}^Q = \frac{1}{3}\left(\underbrace{Y_t^M - Y_{t-3}^M}_{I} + \underbrace{Y_{t-1}^M - Y_{t-4}^M}_{II} + \underbrace{Y_{t-2}^M - Y_{t-5}^M}_{III}\right) \tag{17}$$

$I, II,$ and $III$ in Eq. (17) can be, further, decomposed into

$$\begin{aligned} I: Y_t^M - Y_{t-3}^M &= \underbrace{Y_t^M - Y_{t-1}^M}_{y_t} + \underbrace{Y_{t-1}^M - Y_{t-2}^M}_{y_{t-1}} + \underbrace{Y_{t-2}^M - Y_{t-3}^M}_{y_{t-2}} \\ II: Y_{t-1}^M - Y_{t-4}^M &= \underbrace{Y_{t-1}^M - Y_{t-2}^M}_{y_{t-1}} + \underbrace{Y_{t-2}^M - Y_{t-3}^M}_{y_{t-2}} + \underbrace{Y_{t-3}^M - Y_{t-4}^M}_{y_{t-3}} \\ III: Y_{t-2}^M - Y_{t-5}^M &= \underbrace{Y_{t-2}^M - Y_{t-3}^M}_{y_{t-2}} + \underbrace{Y_{t-3}^M - Y_{t-4}^M}_{y_{t-3}} + \underbrace{Y_{t-4}^W - Y_{t-5}^W}_{y_{t-4}} \end{aligned} \tag{18}$$

Defining $y_t = \triangle Y_t^M$, when we plug in 3 subequations in Eq. (18) into Eq. (17), we obtain observed growth rates, $y_t^Q$, in terms of unobservable monthly growth rates, $y_t$:

$$y_t^Q = Y_t^Q - Y_{t-3}^Q = \frac{1}{3}(y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4}) \tag{19}$$

Then, quarterly variable can be represented in monthly frequency:

$$\begin{aligned} y_t^Q &= Z^Q x_t + \epsilon_t^Q \\ \epsilon_t^Q &= \alpha_q \epsilon_{t-1}^Q + e_t^Q , e_t^Q \sim i.i.d.N\left(0, \sigma_{e^Q}^2\right) \end{aligned} \tag{20}$$

Stacking monthly and quarterly variables in $y_t = \left(y_t^M, y_t^Q\right)'$ vector allows us to cast the above model components into a state-space model of the form:

$$\begin{aligned} y_t &= Z\alpha_t \\ \alpha_t &= T\alpha_{t-1} + \eta_t , \eta_t \sim i.i.d.N\left(0, \Sigma_\eta\right) \end{aligned} \tag{21}$$

State vector, $\alpha_t$, is comprised of the common factor and idiosyncratic shocks to each variable:

$$\alpha_t = \left(x_t, x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, \epsilon_t^M, \epsilon_t^Q, \epsilon_{t-1}^Q \epsilon_{t-2}^Q \epsilon_{t-3}^Q \epsilon_{t-4}^Q\right)' \tag{22}$$

Denoting the number of monthly variables by $n_M$ and quarterly variables by $n_Q$, the state-space representation of the above model becomes:

$$\underbrace{\begin{bmatrix} cy_t^M \\ y_t^Q \end{bmatrix}}_{yt} = \underbrace{\begin{bmatrix} Z^M & 0 & 0 & 0 & 0 & I_{n_M} & 0 & 0 & 0 & 0 & 0 \\ Z^Q & 2Z^Q & 3Z^Q & 2Z^Q & Z^Q & 0 & I_{n_Q} & 2I_{n_Q} & 3I_{n_Q} & 2I_{n_Q} & I_{n_Q} \end{bmatrix}}_{Z} \underbrace{\begin{bmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \\ \epsilon_t^M \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{bmatrix}}_{\alpha_t} \tag{23}$$

$$\begin{bmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \\ \epsilon_t^M \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{bmatrix} = \underbrace{\begin{bmatrix} F_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \alpha_M & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \alpha_Q & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{n_Q} & 0 \end{bmatrix}}_{T} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \\ x_{t-5} \\ \epsilon_{t-1}^M \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \\ \epsilon_{t-5}^Q \end{bmatrix} + \underbrace{\begin{bmatrix} u_t \\ 0 \\ 0 \\ 0 \\ 0 \\ e_t^M \\ e_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}}_{\eta_t}$$

where $\alpha_M = diag(\alpha_1, \ldots, \alpha_{n_M})$.

## Appendix B: Pairwise connectedness for KOF barometer-based analysis

A careful inspection of 2002–2005 and 2011–2015 periods presents us that during these periods, shocks originating from the stock market are mostly directed towards the real sector (first row, second column of Fig. 9 of Appendix B). Similarly, in the 2011–2015 period, we also observe increased levels of connectedness arising from the stock market towards the FX market (fourth row, second column of Fig. 9 of Appendix B). Namely, during the period when minimum EUR/CHF exchange rate was set by SNB, FX market was more prone to shocks from the stock market. SNB's decisions seem to have important consequences on the Swiss economy.

Net connectedness for the government bond market is usually in the negative territory except for several subperiods (see "GSWISS10" panel in Fig. 2). Period from the beginning of 2006 to the end of 2013 is an important exception when government bond market creates significant amount of directional connectedness towards all other nodes, i.e., to the real side and the financial markets, except for certain relatively unimportant short periods where it becomes a net receiver, e.g., during a short period just after the 2008–2009 recession ends. It has been noted that CHF bond market was relatively stable, and over this period, the outstanding volume of CHF bonds was around CHF500 bn[14]. On the other hand, Yesin (2015) finds that "net capital flows have become much more volatile since the [global financial] crisis, suggesting a decoupling of capital inflows and outflows such that they no longer cancel each other out." This finding could be attributed to increased levels of connectedness originating from the bond market. Again we refer to Fig. 9 of Appendix B to identify the direction of this positive connectedness. It shows increased levels of connectedness during the 2006–2013 period with temporary decreases during 2006 (first row, third column of Fig. 9 of Appendix B). This occurs when shocks that hit government bond market spill over the real sector. Mid-2007 to mid-2010 periods are also large relative to other periods (second row, third column of Fig. 9 of Appendix B), that is, large connectedness due to government bond market towards stock market has been observed. Similar observations are also valid for connectedness directed towards the FX market as well (fourth row, third column of Fig. 9 of Appendix B).

Prior to 2008, FX market's role switches between being a net connectedness receiver and transmitter within a narrow band around zero spending more time on the receiver side (see "USDCHF" panel in Fig. 2). Beginning 2008, it behaved as a connectedness receiver predominantly until SNB's 2011 decision. This behavior could be attributed to the overvaluation of CHF over this period reflecting safe haven characteristics of Switzerland that paves the way for SNB's 2011 decision. Figure 9 of Appendix B also shows that during the mid-2010 to mid-2012 period, USD/CHF exchange rate was a transmitter for connectedness towards the real economy, most probably because of the fears of government defaults and of sovereign debt problems in Europe which led to extensive overvaluation of CHF, see Auer (2015). Its behavior as a transmitter, more or less, stabilized with the introduction of the minimum EUR/CHF exchange rate until its discontinuation in 2015 which stabilized after a peak period (first row, fourth column of Fig. 9 of Appendix B). But its impact on the stock (second row, fourth column of Fig. 9 of Appendix B) and government bond (third row, fourth column of Fig. 9 of Appendix B) markets followed an upward trend following SNB's 2011 decision on the EUR/CHF exchange rate. In net terms, following SNB's 2015 decision exchange rate started to behave as a connectedness transmitter with small levels (see "USDCHF" panel in Fig. 2).

[14] "Developments on the Swiss franc capital market and the SNB's monetary policy," https://www.snb.ch/en/mmr/speeches/id/ref_20171116_amr/source/ref_20171116_amr.en.pdf, accessed 2018-12-29.

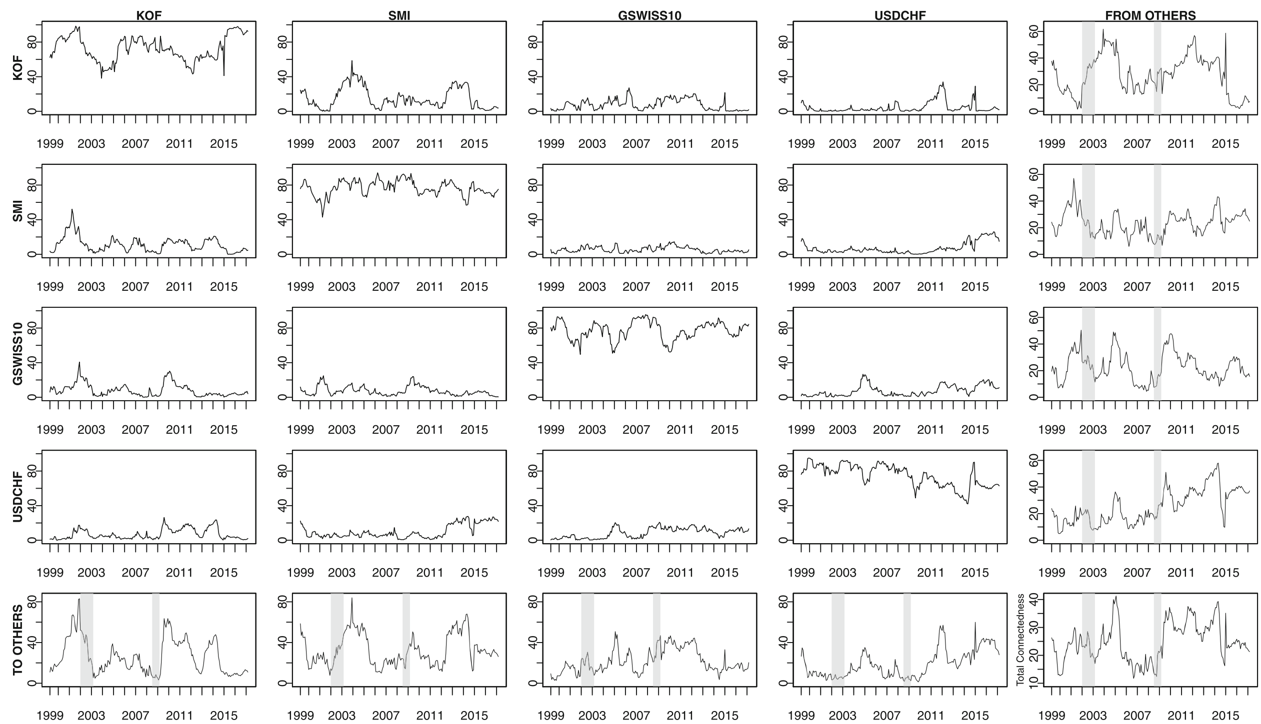


**Fig. 9** Total and pairwise directional connectedness measures using KOF barometer

### Abbreviations

ADS: Aruoba-Diebold-Scotti; DYCI: Diebold-Yilmaz Connectedness Index; EM: Expectation maximization; FOMC: Federal Open Market Committee; FX: Foreign exchange; GDP: Gross domestic product; IPI: Industrial Production Index; MLE: Maximum likelihood estimation; PMI: Purchasing Managers' Index; QE: Quantitative easing; RAI: Real activity index; SNB: Swiss National Bank; U.S.: United States; VAR; Vector autoregressive

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EU analyzed and interpreted the data and the results and was a major contributor in writing the manuscript. KY analyzed and interpreted the data and the results and was a major contributor in writing the manuscript. All authors read and approved the final manuscript.

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