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A single composite financial stress indicator and its real impact in the euro area

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Non-technical summary

In this paper, we construct a single composite financial stress indicator (FSI) which aims to predict developments in the real economy in the euro area. Our FSI contains financial variables that have a causal relationship with the real economy. Therefore, our FSI is able to serve as an early warning indicator for negative impacts of financial stress on the real economy.

The causal relationship between our FSI and the real economy is tested and confirmed by the error-correction models. An empirical analysis reveals that our FSI has more predictive power than the bench-mark normally used for financial markets, especially stock markets, namely the Euro STOXX 50 volatility index for the recent banking crisis and the euro-area sovereign debt crisis. One of the main empirical results is that our FSI shows negative effects from financial markets on the real economy one to four months in advance.

Nicht-technische Zusammenfassung

In der vorliegenden Arbeit wird ein Versuch unternommen, einen Finanzstressindikator (FSI) für den Euro-Raum zu entwickeln. Die Besonderheit dieses FSIs liegt darin, dass er bestimmte Finanzmarktvariablen zusammenfasst, die mit hoher Wahrscheinlichkeit Auswirkungen auf die realwirtschaftliche Entwicklung haben. Damit ist unser FSI in der Lage, vor den negativen realwirtschaftlichen Folgen vergleichsweise früh zu warnen.

Die für die Frühwarnfähigkeit unseres FSIs zugrunde gelegte Kausalität zwischen unserem FSI und der realwirtschaftlichen Entwicklung wurde anhand des sog. Fehlerkorrekturmodells getestet und bestätigt. In einer empirischen Überprüfung mit historischen Daten zeigt sich, dass unser FSI bezüglich der jüngsten Finanz-/Bankenkrise und der Euro-Länderkrise besser abschneidet als der übliche Benchmark für Finanzmarkt-, insbesondere Aktienmarktstress, nämlich die implizierte Euro STOXX 50 Volatilität. Eines der wichtigsten empirischen Ergebnisse ist, dass unser FSI die negativen Folgen des Finanzstresses auf die realwirtschaftliche Entwicklung bis zu vier Monaten voraussagt.

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Abstract

In this paper, we construct a single composite financial stress indicator (FSI) which aims to predict developments in the real economy in the euro area. Our FSI was shown to perform better than the Euro STOXX 50 volatility index for the recent banking crisis and the euro-area sovereign debt crisis and to be able to serve as an early warning indicator for negative impacts of financial stress on the real economy.

Keywords: Financial stress indicator, predictability, financial crisis, real economy

JEL classification: C12, G01

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1 Introduction

Since the financial crisis began in 2007, many authors have considered various indicators for measuring uncertainty or stress in financial markets. The main concern in constructing such financial stress indicators (after the Lehman collapse and the subsequent major global recession) is that the indicators should be able to predict future developments in the real economy, i.e., they should be able to serve as an early warning indicator for slowdowns in the real economy. This is because high financial stress can lead to a reduction in economic activity. See Hakkio and Keeton (2009) and Cardarelli, Elekdag, and Lall (2011) and the references therein on the issue of the impact of financial stress on the real economy.

One widely-used conventional indicator for financial uncertainty is the implied volatility, which is calculated from stock market dynamics. Such implied volatility, however, has been regarded less and less as an optimal indicator for the real economy. There are two reasons for this: the implied volatility from a stock market is usually derived from the stock market dynamics so that it exclusively contains stock market information, which does not necessarily have anything to do with developments in the real economy. In line with this view, Cardarelli et al. (2011) found in their comprehensive empirical work that financial turmoil characterized by banking distress is more likely to be associated with real economic downturns than uncertainty which mainly takes place in securities or foreign exchange markets. The other reason is the direction of causality. The causal direction is reasonably assumed to run from macroeconomics to stock market volatility rather than the other way around,[1] which is confirmed empirically *inter alia* by Beltratti and Morona (2006). Beetsma and Giuliodori (2012) also conclude that the contribution of stock market volatility to the real economy has become negligible in recent years.

In this paper, we construct a single composite (aggregated) indicator[2] of financial stress for the euro area and show the predictive ability of our indicator for the real economy during the recent banking crisis and the euro-area sovereign debt crisis. We also compare the strength of a causal relationship between the real economy and our financial stress indicator (FSI) with that between the real economy and the Euro STOXX 50 volatility index (VSTOXX). It reveals that our FSI performs better than the VSTOXX and shows the negative impacts of financial stress on the real economy with a time lag of three months during the recent financial crisis and the euro-area sovereign debt crisis.

The rest of the paper is structured as follows: in Section 2, we explain how to select economic/financial variables as financial stress indicators and how to construct a single composite financial stress indicator. Section 3 discusses some methods for analyzing the predictive power of our FSI and presents our empirical analysis. Section 4 summarizes the paper with some concluding remarks.

[1] The proxy causality from the stock market to the real economy concerns the stock market *returns*, not its *volatility*, and it results from the expectation of future developments in the real economy as a part of the information for stock markets today; see Kim (2003) on this topic.

[2] There are also in-depth discussions on the advantages/disadvantages of a single composite indicator in comparison with single (sector-specified) indicators; see Gadanecz and Jayaram (1987) for a survey.

2 Framework: a single composite FSI

There are two basic issues to be addressed when constructing a single composite FSI: the choice of variables (as individual components), and the weighting scheme (for their aggregation). The next two subsections deal with these two issues.

2.1 Choice of financial stress indicators

When selecting economic/financial variables, we have taken two criteria into account: high correlation with the real economy, and parsimony. More precisely, we first select some financial variables usually used for constructing FSI in the literature, such as in Nelson and Perli (2006), Illing and Liu (2006) and Holló, Kremer, and Duca (2012). For our FSI, we have determined five market segments (credit, foreign exchange, oil market, stock market and interbank market), which are slightly different from those in Holló et al. (2012). They should also be available daily and appropriate in the context of the euro area. From this set of variables, those variables that are highly correlated with the European real economy, i.e. a correlation of at least 90%-significance level at least one lag between 1 to 6 lags, can be selected into our FSI. Parsimony is maintained by excluding some variables which show a similar financial or economic aspect. This is because the qualitative patterns of many financial variables are similar, such that many measures of volatility and premiums increase during financial crises, as pointed out by Cardarelli et al. (2011). This kind of parsimony also enables us to avoid a possible bias in the weighting for aggregating the various individual components into a single composite FSI.

Despite all the possible criteria and economic backgrounds for selecting variables, the choice of the variables for a FSI remains more or less arbitrary because we usually do not know the complex links between various sectors, above all between the financial systems and the real economy, as pointed out in Geršl and Heřmánek (2006). Therefore, the most interesting concern would be how well an index works in practice, namely its high predictive power for the real economy in our case.[3]

The empirical data contained in our FSI are six daily time series covering the period between January 1, 2007 and April 30, 2013 (1,652 observations). This time period covers both the international banking crisis (marked by the bankruptcy of Lehman Brothers in September 2008) and the European sovereign debt crisis (marked by the clear revelation of Greece's sovereign debt in May 2010, followed by Ireland in September and Portugal in August 2011). All six time series are taken from Bloomberg as follows:

1. CDS spread on iTraxx Europe Crossover (5 years): it captures the default risk of sub-investment grade institutions. The CDS spreads are not only an indicator for default risk but can also easily be transformed into market implied probabilities of default, given

[3] We also investigated other economic/financial variables to check whether another aggregation has higher predictive power and found this 6 variable aggregation has the highest power among those considered.

the recovery rate and time to maturity and under the assumption of risk neutrality of the investor.[4]

2. CDS spread on iTraxx Non-financials (5 years): it measures the default risk of non-financial investment grade institutions. The reason for choosing these two types of institution is that the former has a low credit quality and the latter a high one. Furthermore, they are more closely related to the real economy than pure financial institutions.

3. Implied volatility of the EUR/USD exchange rate (1 month): it shows uncertainty in the foreign exchange market, and, in particular, should reflect the European sovereign debt crisis.

4. Volatility of the future oil price (1 month): it is usually used as an indicator of real economic activity. Because of its role in forming the future price, it can serve as an *early warning* indicator for the business cycle.

5. Earnings-price ratio[5] − 10-year euro interest rate[6]: The difference between the earnings-price ratio and the 10-year interest rate, as is also adopted in Nelson and Perli (2006) for the USA, represents a kind of risk premium (excess return) for the European stock market. The reason for choosing this spread is, as stated in Nelson and Perli (2006), that *the spreads between the yields on riskier and less risky securities widen when investors judge their relative risks to have increased, and also when investors demand a higher premium for a given amount of risk. Thus, these spreads will increase when investor uncertainty increases or financial conditions worsen.*

6. 3-month Euribor − 3-month Euro overnight index average (EONIA): The Euribor/EONIA spread represents the uncertainty in the interbank market. Beirne (2012) discovers that, since the collapse of Lehman Brothers in mid-September 2008, a very large negative spread has been observed between the EONIA and the European Central Bank's policy rate. With large EONIA spreads banks tend to be risk-averse, as credit risk concerns increase, which has a crucial negative impact on the real economy.

One more important choice for the evaluation of our FSI is to determine what is an appropriate measure of activity for the real economy. We take the industrial production (IP) of the euro area as the benchmark for *true stress* in order to assess our FSI. It is a simple sum of the 17 countries in the euro area, and the IP of the 17 countries is taken from Thomson Datastream.

[4] Moreover, as found in Byström (2005), CDS spreads on iTraxx are also significantly positively correlated with stock price volatility, and, therefore, indirectly reflect the uncertainty of the stock market.

[5] 12-month ahead earnings divided by the Eurostoxx

[6] We construct the synthetic 10-year euro interest rate from six stable countries' interest rates by weighting based on their relative nominal GDP. The stable countries are selected when a country has been given at least an A rating by all three biggest rating agencies (Standard & Poor's, Moody's Investor Service, and Fitch Ratings). These are Germany (42%), France (33%), Netherlands (10%), Belgium (6%), Austria (5%), Finland (3%) and Slovakia (1%).

2.2 Construction of the financial stress indicator

The financial stress indicator for the euro area financial system has been constructed as follows. Let $X_{ij}, i = 1, \ldots, 6;\ j = 1, \ldots, 1652$, the time series included in our FSI. The construction of our FSI from the six time series is as follows:

1. In the first step, all time series (including composed time series, e.g. 3-month EURIBOR − 3-month EONIA) are indexed, i.e. for the sake of comparison, each time series is transformed by dividing it by the average value of the first quarter 2010 denoted as $\overline{\text{IQ2010}}$. This is because the first quarter of the year 2010 was a tranquil period.
$$\tilde{X}_{i,j} := X_{i,j}/X_{i,\overline{\text{IQ2010}}}.$$

2. In the second step, all the indexed time series are multiplied by their own inverse variances calculated from the entire sample period.
$$Y_{i,j} := \tilde{X}_{i,j}/\text{VAR}[\tilde{X}_i].$$
The division by its own variance is a standard method and can be interpreted as a risk weight or a variance-equal weight in order to avoid an over weighting of the high volatile variables; see Illing and Liu (2006) and Nelson and Perli (2006) on this issue.

3. In the third step, the individual components have to be re-scaled. In order to ensure that all of the individual components lie between 0 and 1 in the historical data, each of them should be subtracted by its minimum and divided by its maximum over the whole period.
$$\tilde{Y}_{i,j} := (Y_{i,j} - \min_j[Y_{i,j}])/\max_j[Y_{i,j} - \min_j[Y_{i,j}]].$$
In this respect, our construction method differs from the conventional standardization method. Thus, each of our individual components will show 0 for the most tranquil period, and 1 for the period with the most turmoil from the entire sample period. More importantly, this re-scaling enables us to avoid a bias by aggregating the individual components into a single composite index which results from the different scales of the individual components.

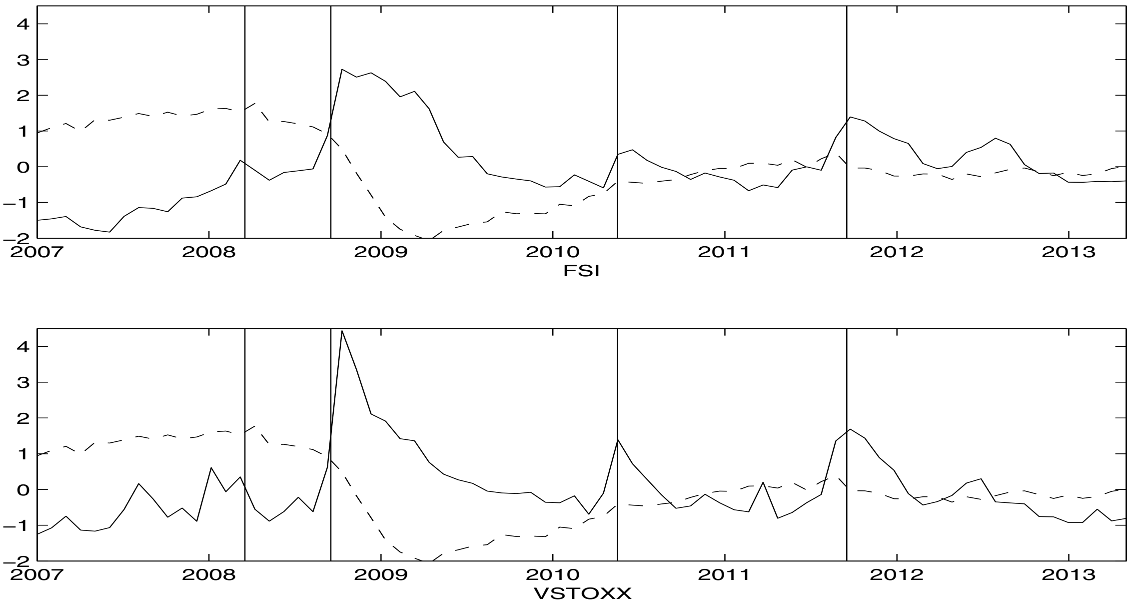
4. In the fourth step, we aggregate all the individual components with an equal weight and the aggregation is again divided by 6 to ensure that the value of our FSI lies between 0 and 1.
$$\text{FSI}_j^{daily} := \sum_{i=1}^{6} \tilde{Y}_{i,j}/6.$$

5. Finally, because the frequency of the IP is monthly, while that of our FSI is daily, we use, for the purpose as an early warning, the maximum value[7] from the daily FSI for each month as the monthly FSI.

$$\text{FSI}_t^{monthly} := \max[\text{FSI}_t^{daily}], \quad t = 1\text{M}2007, \ldots, 4\text{M}2013.$$

The upper panel of Figure 1 shows our monthly FSI (straight line) and the euro-area IP (dashed line) (both standardized) and the lower panel shows the VSTOXX (straight line) and the euro-area IP (dashed line) (both standardized). The vertical lines mark the corresponding financial shocks, such as the collapse of Bear Stearns (March 2008), the collapse of Lehman Brothers (September 2008), the beginning of the sovereign debt crisis in Greece (May 2010) and the worsening of the sovereign debt crisis in Portugal, Spain and Italy. (August 2011).

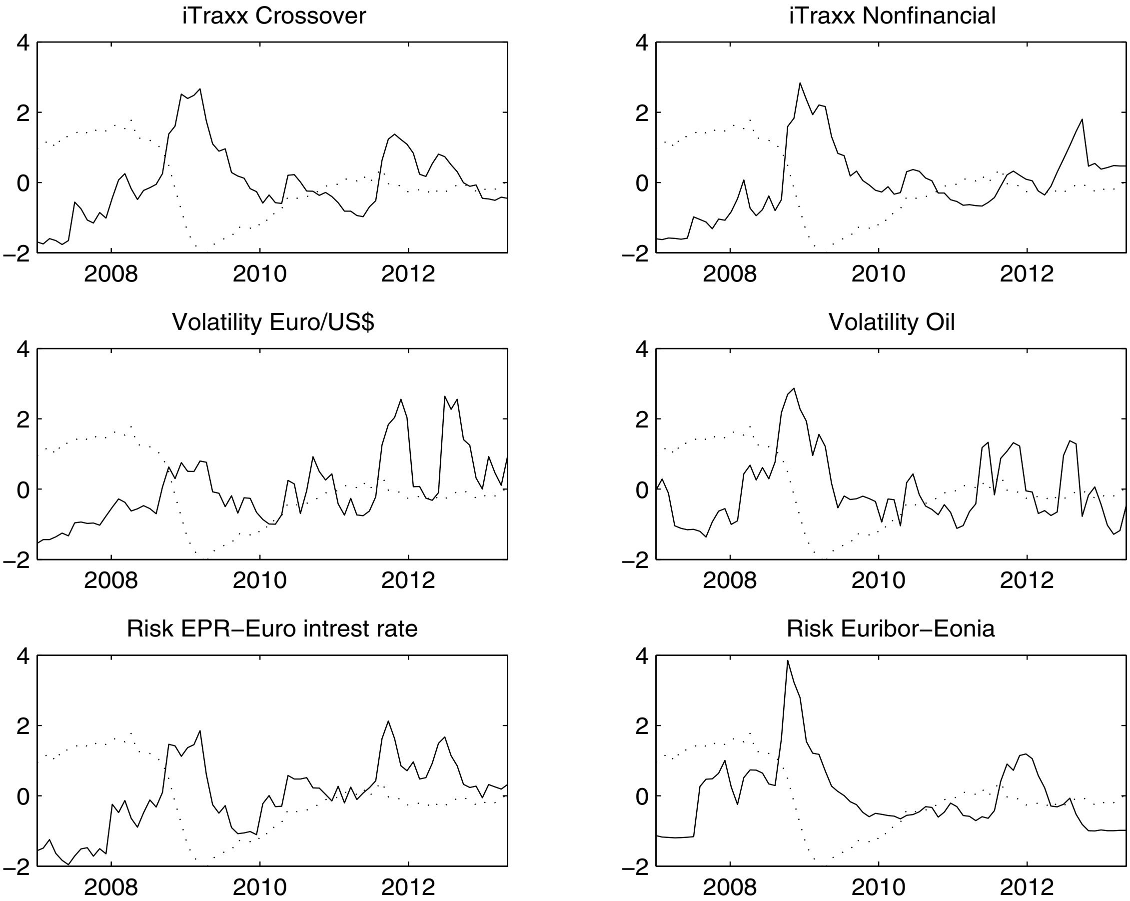
Figure 1: FSI, VSTOXX and the euro-area IP: Jan. 2007 - Apr. 2013 (76 Obs.)



Our FSI shows some predictive properties, i.e. it seems to be (significantly) negatively correlated with the IP some periods ahead. At first glance, the two indices, namely our FSI and the VSTOXX, behave very similarly, but more careful consideration reveals that the VSTOXX was rather volatile and showed some peaks which do not seem to be highly (negatively) correlated with the development of the real economy. As will be shown in the descriptive and the inductive analysis in the next section, this difference is confirmed in favor of our FSI. Figure 2 shows the six individual components (straight line) and the euro-area IP (dashed line).

[7]The main results remain unchanged by the use of the mean and/or median value from the daily data. The results based on the other scale value are available upon request from the authors.

Figure 2: Individual components of the FSI and the euro-area IP



As Figure 2 shows, some individual components (variables 1,2,4 and 6) react relatively more sensitively to stress in the banking sector and some others (variables 3 and 5) react relatively more sensitively to the euro-area sovereign debt crisis. It is worth noting that both types of stress were followed by an economic recession in the euro area.

3 Empirical analysis

In this section, we briefly summarize our method for testing the empirical usefulness of our FSI, namely the causal relationship between our FSI and the real economy. For testing the empirical performance of early warning indicators, the minimizing method of the sum of two types of statistical error is usually employed (see Eichengreen, Rose, and Wyplosz (1996) for example). However, we use the single equation error correction model (SEECM), because the main focus of our FSI is its predictive ability for the real economy and not the financial stress itself.

3.1 Single equation error correction model

The SEECM is designed to capture stable relationships among economic variables, especially non-stationary variables, called co-integration. This co-integration is an expression of a causal relationship due to the representation theorem of Engle and Granger (1987). The SEECM is transformed from the autoregressive model with exogenous variables (ARX), see Banerjee, Galbraith, and Dolado (1990) and Kremers, Ericsson, and Dolado (1992). For our purposes, however, we use a slightly different transformation, as explained below.

Let y_t and x_t be the European real economy (the euro-area IP) and our FSI in time t. Because it is reasonable to assume that uncertainty in the financial markets expressed by the FSI indicates a possible decline in the real economy some periods ahead, we specify the ARX model with lag order of (p, q) as

$$y_t = c + \sum_{i=1}^{p} b_i y_{t-i} + \sum_{j=0}^{q} a_j x_t + u_t, \tag{1}$$

where c is a constant and u_t a usual error term. If both the endogenous and exogenous variables are non-stationary, the ARX model in (1) can be linearly transformed without any change in the residual structures in u_t as

$$\begin{aligned} \Delta y_t \quad = \quad & c + b[y - \beta x]_{t-1} - \sum_{j=2}^{p} b_i \Delta y_{t-1} -, \cdots, -b_p \Delta y_{t-p+1} + \\ & a_0 x_t - \sum_{j=2}^{q} a_j \Delta x_{t-1} -, \cdots, - \sum_{j=q-1}^{q} a_j \Delta x_{t-q+1} + u_t, \end{aligned} \tag{2}$$

with $b = \sum_{i=1}^{p} b_i - 1$ and $\beta = \sum_{j=1}^{q} a_j / (1 - \sum_{i=1}^{p} b_i)$, which is slightly different from the usual transformation; see Banerjee et al. (1990) or Kremers et al. (1992) for the usual transformation. The only difference is that, in our transformation, the exogenous variable in time t remains in level (x_t) and not in difference (Δx_t) as is the case in the usual transformation. The conventional transformation would test whether the *changes* in the FSI have predictive power. The difference in our transformation is that one can test whether the *level* of the FSI has predictive power for changes in the real economy, which makes more sense for an early warning indicator. Furthermore, the SEECM enables us generally to test the causal relationship between the exogenous variable, our FSI, and the endogenous variable, the real economy, called a t_{ECM}-test (see Banerjee, Dolado, and Mestre (1998) for the t_{ECM}-test). This will be the case when the linear combination of the two non-stationary variables becomes stationary, meaning that the t-statistic for the loading parameter of the error correction term, $t_{\hat{b}}$, is (highly) significant. In other words, if a FSI is well constructed, so that it has some predictive power for the development of the real economy, one would expect both of the t-statistics for b and a_0 to be statistically significant in Equation (2).

3.2 Empirical results

Before we present the results of the inductive analysis using the SEECM, we simply calculate the correlations between changes in our FSI and those in the euro-area IP for a rough check for a possible causal structure of our FSI and the euro-area IP. Table 1 summarizes the results.

Table 1: Correlations between the FSI and the euro-area IP^{ab}

Lead Indicator	0	1	2	3	4	5	6
FSI	-0.10	-0.34^{***}	-0.28^{**}	-0.38^{***}	-0.36^{***}	-0.15	-0.15
VSTOXX	0.08	-0.18	-0.22^{*}	-0.24^{**}	-0.31^{***}	-0.05	-0.14

^{a}Correlations between $\text{FSI}_t(\text{VSTOXX}_t)$ and IP_{t+h} for $h = 0, 1, \ldots, 6$. ^{b}$*$,$**$ and $***$ mean significance at the level of 90%-, 95%-, 99%, respectively. According to the analysis of Bartlett (1946), we approximately calculate critical values for the 90%, 95% and 99% significance levels of $1.645/\sqrt{70} = 0.20$, $1.96/\sqrt{70} = 0.23$ and $2.58/\sqrt{70} = 0.31$, respectively.

The results in Table 1 show that our FSI has its significant predictive power for the following four months. The correlations between the VSTOXX and the real economy are, however, weaker than those of the FSI for all significant leads. Including the VSTOXX in our FSI does not improve the predictive power of our FSI for the real economy. This again confirms our view on the relationship between the stock market and the real economy, as discussed earlier. In order to check the leading property of our FSI to the real economy (although it can be clearly seen in Figure 1), we also calculate correlations from the first lag to the fifth lag, i.e., correlations between FSI_{t+h} and IP_t for $h = 1, 2, \ldots, 6$. These are 0.06, 0.13, 0.10, 0.11 and 0.15, which, as expected, are economically meaningless and statistically insignificant.[8]

Before we estimate the SEECM, we test for non-stationarity using the augmented Dickey-Fuller test (ADF, Dickey and Fuller (1979)). The result of the ADF test shows that both of the time series (FSI and euro-area IP) are integrated of order one.[9] In order to specify the model in (1), we again use the two lag specification criteria, namely the Schwarz and Akaike's information criterion. These show their minimum value of 5.15

[8]For a comparison of the correlation structure of the single composite FSI with those of the individual components, we also calculate correlations of the individual components. It reveals that our (composite) FSI shows the highest correlation to the real economy for all significant lags besides the two exceptions (lag one by iTraxx Crossover and lag two by iTraxx Nonfinancial). This conforms the advantage of a single composite index as discussed before. Table 1 in Appendix A summarizes the correlations between the individual components and the real economy.

[9]The estimated ADF test statistic in the test regression with a constant is -2.52 for the FSI and -1.91 for the euro-area IP. In this context, the lag length of the augmented DF regressions was specified using the usual lag specification criteria, i.e., the Schwarz (Schwarz (1978)) and Akaike's information criterion (Akaike (1974)) and the two criteria show their minimum values of -5.47 and -5.53 by lag order of two for our FSI and 0.25 and 0.15 by lag order of three for the IP. According to the 5%(10%) critical value of -2.92(-2.59), the null hypothesis of non-stationarity for the both variables cannot be rejected.

and 5.06; and 5.12 and 5.03, respectively, by $p = 1, q = 1$ for both models (IP/FSI- and IP/VSTOXX-model). Table 2 summarizes the estimation results of the two SEECMs in (2).

Table 2: Estimates for parameter[abc]

Indicator	Parameter			
	c	b	β	a_0
FSI	1.38 (5.26)	-0.09 (-4.62)	-0.18 (-4.82)	-4.05 (-6.16)
VSTOXX	1.69 (4.83)	-0.06 (-3.08)	-0.06 (-2.58)	-2.41 (-5.43)

[a] t-values are reported in parentheses. [b] The critical values of the t_{ECM}-test (based on $t_{\hat{b}}$) tabled in Banerjee et al. (1998) for the significance level of 90%, 95% and 99% are ≈-2.93, ≈-3.28 and ≈-3.94, respectively. [c] The co-integrating parameter, β, is estimated by the two-stage estimation proposed in Engle and Granger (1987).

The co-integrating relationship between our FSI and the euro-area IP is highly significant (at the significance level of 99%) according to the t-value for the loading parameter b (-4.62), while that between the VSTOXX and the euro-area IP is (relatively) weakly significant (at the significance level of 90%) according to the t-value for the loading parameter b (-3.08). This means that, based on the co-integrating causal relationship, our FSI has predictive power for the euro-area IP which is stronger than that of the VSTOXX. The result of the (relatively) weak significance of a co-integrating causal relationship for the VSTOXX is not surprising, because the VSTOXX is calculated using pure stock market dynamics and, hence, represents the uncertainty of the stock markets *only*. Our FSI contains, however, not only financial market variables but also money market variables such as euro area interest rates as well as some indicators connected directly to the real economy such as euro/US$ exchange rates and the volatility of future oil price. Furthermore, the parameter a_0 of the IP/FSI-model, i.e. the relationship of changes between the real economy and our FSI, is also highly significant (-6.16). This means that the level of our FSI has some predictive power for changes in the real economy. The IP/VSTOXX-model shows a similar result in this respect with a t-value of -5.43.

4 Concluding remarks

This paper presents a single composite FSI for the euro area. When constructing our FSI, the focus was placed on the causal relationship between the FSI and the real economy. It revealed that our single composite FSI has more predictive power than any of the individual components included or the Euro STOXX volatility index.

Despite major developments in financial stress/stability indicators in the literature, the shortcoming of such indicators in general, namely some arbitrariness in their choice of variables and their method of construction, still remains. Because this arbitrariness can be only justified through the empirical performance of the indicators, more research on the economic relationships, such as transmission channels between financial sectors and the real economy, will be needed in the future.

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Appendix A

Table 1. Correlation between the individual components of FSI and euro-area IP[a]

Lag	0	1	2	3	4	5	6
iTraxx Crossover	-0.22	-0.38	-0.30	-0.29	-0.33	-0.08	-0.03
iTraxx Nonfinancial	-0.23	-0.26	-0.36	-0.30	-0.28	-0.09	-0.03
Volatility of Euro/US$	-0.03	-0.23	-0.32	-0.34	-0.32	-0.13	-0.17
Volatility of oil	-0.05	-0.13	-0.03	-0.08	-0.24	0.00	-0.04
Risk of EPR-Euro interest	0.03	-0.19	-0.07	-0.21	-0.24	-0.13	-0.08
Risk Euribor-Eonia	-0.04	-0.25	-0.12	-0.17	-0.21	-0.13	-0.09

[a] According to the analysis of Bartlett (1946), we approximately calculate $1.645/\sqrt{70} = 0.20$, $1.96/\sqrt{70} = 0.23$ and $2.58/\sqrt{70} = 0.31$ critical values for the 90%, 95% and 99% significance levels, respectively.