Influence of inflation, M1 and GDP on the Eurostoxx50 index

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Abstract

The aim of this study is to investigate the relationship and the impact that changes and shocks in a set of selected macroeconomic variables (Inflation, GDP and M1) have on the Euro stock market returns. The existence of a long-run equilibrium relationship between fundamentals and the stock market index is inquired using the methodological framework of cointegration analysis and a vector error correction model. Moreover, the short-run dynamic dependencies between the variables are examined by performing an impulse response analysis and the empirical question of whether economic variables are useful indicators of future stock market returns is addressed. The empirical results of this study highlights that there are both short run and medium-long run relationship between the variables, showing that, to some degree, innovations in the macroeconomic variables are reflected in stock prices.
Keywords*: vector autoregressive model; cointegration; stationarity test.*

1. Introduction

Relationship between stock returns, inflation and other macroeconomic variables has been the subject of studies of some authors, considerable attention has been placed into US stock market. This paper innovatively studies the relationship between stock prices and a set of macroeconomic variables in the Euro area and in a modern framework. In particular, we want to investigate the casual relationship of monetary policies conducted by the ECB on inflation and stock prices, we are also interested in the effect of shock in the output on stock prices and shocks in the financial markets on all the other variables. The study includes a wide timespan of more than 20 years which covers all the four ECB presidential mandates (Duisenberg, Trichet, Draghi, Lagarde) and comprehends both the global financial crisis, the Euro Debt Sovereign Crisis and the Covid-19 health emergency which leaded to an expansive monetary policy response from the European Central Bank.

Current economic activities are among the determinants of stock market prices and whether they are influential factors in predicting future stock returns is of interest. If stock market returns consistently reflect macroeconomic information, the Euro stock market index should be cointegrated with the set of macroeconomic variables and changes in the latter should contribute significantly to the cointegrating relationship. In economic terms, this would imply that the equity market is sensitive to changes in fundamentals and that future stock prices can be determined, to some degree, by changes in economic factors.

The paper analyses the relationship between this set of variables, given the aforementioned shocks, and propose some policy implications. The rest of this paper proceeds with a literature review in Section 2. Section 3 provides an overview of the econometric methodology. Section 4 presents the empirical findings and discussion. Section 5 presents the concluding remarks and policy implications.

2. Literature review

Existing empirical work (Fama and Schwert, 1977; Fama, 1981) commonly finds a negative relation, at least in the short run, between monetary policy shocks and returns in the stock returns.[2] However, the magnitude of this effect and the precise channel through which monetary policy affects stock prices remains by and large an open question.

Fama (1981, Stock Returns, Real Activity, Inflation and Money) proposes the proxy hypothesis to explain the observed negative stock return–inflation relation. This hypothesis maintains that a positive association between stock returns and real activity, combined with a negative association between inflation and real activity based on a money demand model, leads to spurious negative relations between stock returns and inflation.

The findings of Chen et al. (1986) suggest the possibility that a long-term equilibrium relationship between fundamentals and stock prices existed.

Jeong-Ryeol Kim (2003) confirm the proxy hypothesis of Fama, Gallagher and Taylor (2002) develop a theoretical model for testing the proxy hypothesis and conclude that real stock returns are strongly significantly negatively correlated with inflation purely due to supply innovation exactly as the proxy hypothesis states.

John A. Tatom (2002) analyses the relationship between stock prices, inflation and monetary policy. The paper confirms the presence of cointegration and the negative long-run relationship between stock prices and inflation
Lee (2010) studies the pre- and post-war relation between inflation and stock prices.
Laven and Tong (2012) analyzed global stock price responses to US monetary policy shocks using a dataset of 20,121 firms across 44 countries over the period 1990 to 2008. The finding is that stock prices tend to increase (decrease) following unexpected monetary loosening (tightening).
Cheung and Ng (1998) investigated the long-run relationship between five national stock market indexes and aggregate real economic variables such as real GNP, real oil price, real money supply and real consumption. Using Johansen's like-lihood ratio test for the cointegration rank and an ECM, the authors established that the stock market indexes of Canada, Germany, Italy, Japan and the U.S. are strongly related to changes in real domestic aggregate activity. By employing Johansen's VECM, Mukherjee and Naka (1995) report that the Japanese stock market is cointegrated with a set of domestic macroeconomic variables.

3. Data and Methodology

3.1 Data
The dataset covers a timespan of more than 20 years, from the first quarter of 1997 until the third quarter of 2021, the source of the data is the 'ECB statistical data warehouse'. The variables involved are: Dow Jones Euro Stoxx 50 (monthly data, measured in index points), GDP (quarterly data, measured in in real terms, with base 2015), HICP overall index (monthly data, base 2015 = 100) and monetary aggregate M1 (monthly data, measured in millions of Euro). Since GDP was measured on a quarterly basis and all the other 3 variables were measured monthly, the latter were converted on quarterly frequency.

3.2 Methodology
After exploring the data, all the series have been transformed into log values. The first step of the analysis is stationarity test applying Augmented Dickey-Fuller, DF-GLS.
Structural break tests include: xtbreak, Zivot and Andrews (ZA, 1992) and Clemente et al. (CMR, 1998). The first, xtbreak, implements the tests for and estimation of structural breaks discussed in Bai & Perron (1998, 2003), Karavias, Narayan, Westerlund (2021) and Ditzen, Karavias, Westerlund (2021). Subsequently, we investigated the presence of a long-run relationship between the analyzed series by using Johansen cointegration test and Gregory-Hansen cointegration test with regime shifts.
The model adopted for analyzing both short and medium-long term relationship is the vector error correction model (VECM). After specifying the correct model, some post-estimation tests have been used: stability test, Lagrange multiplier test, normality.
Since a VECM has been employed, it is not possible to use 'vargranger' and, for this reason, a different type of Granger-causality test has been used which analyses causality relationship in the frequency domain. The test adopted is the Spectral Granger causality test, which under the null hypothesis assumes that there is no Granger-causality among variables at time frequency *w*.
Granger causality test does not give the sign of the effect, we do not know if it is positive or negative, and it does not show how long the effect lasts for. For these 2 purposes, we have to analyze the impulse-response function (IRF) and forecast error variance decomposition (FEVD). Finally, we can perform a dynamic forecast.

4. Empirical Results

The empirical analysis is subdivided in 5 sections: descriptive statistics, unit root tests, structural breaks, co-integration, VECM analysis (Causality and IRF and FEVD).

4.1 Exploratory analysis
The mean and median values of each variable are positive and quite similar (Table 1). The variables exhibit a negative skewness (except for logstoxx), which implies the distribution is skewed towards the left, with more observations on the right. the Inter-Quartile Range (IQR) reveals the absence of aberrant observations in our dataset.
Summary statistics. First differences have all zero mean, returns have negative skweness (negative returns).

Table 1

Summary statistics

Variables	Mean	Median	Standard Deviation	Skewness	Kurtosis
Logstoxx	8.068729	8.077968	.2057897	.1373477	2.642417
Lrgdp	4.513527	4.53871	.1117469	-.3039034	1.896484
Loghicp	90.87312	91.84834	10.9413	-.1893685	1.682986
logm1	15.22157	15.27167	.5657428	-.0825048	1.963102
First differences					
Returns	.0073306	.0162849	.0827961	-.8033533	4.283422
Growth	.0038738	.0037231	.0028486	-.9633971	9.336017
Hicprate	.0041238	.0042772	.0034872	.0585521	3.386069
m1growth	.0206224	.0207176	.013255	.218556	3.166143

4.2 Unit root tests

The findings show that the H0 hypothesis of the series not stationary at log-levels cannot be rejected for any of the series (Table 2). Also, DF-GLS confirm these results. Note that logstoxx, although we can reject the null of-non stationarity at 10% according to ADF test, it's not stationary according to DF-GLS.

Table 2

Augmented Dickey Fuller (5 lags) at log-levels

Variables	t-Statistic	p-value for Z(t)	Critical 1%	Critical 5%	Critical 10%
Logstoxx	-2.807	0.0572	-3.518	-2.895	-2.582
Lrgdp	-2.079	0.5577	-4.055	-3.457	-3.154
Loghicp	-1.014	0.7481	-3.518	-2.895	-2.582
logm1	-2.041	0.5789	-4.053	-3.456	-3.154

4.3.1 Structural breaks

When there are structural breaks, the various standard unit root test statistics are biased toward non-rejection of the unit root null, implying that, often, non-stationarity indicative in the data, applying conventional unit root tests, may be invalidated when structural shifts are integrated in the tests. For this reason, we need to test for possible structural break/s in the series.

The empirical evidence suggests that there might be break in the series due to the various perturbances that have occurred during the last 20 years. By running xtbreak we can't conclude that there are structural breaks (Table 3).

The sequential F test for multiple breaks performed by this command indicates that no breaks were found and it's not possible to estimate a single breakpoint, so test statistics are not significant. Although we can get contrasting results by specifying a single or multiple structural break/s in the series, we can observe from the graphs that even if the break/s is/are present then they are temporary and do not affect the series in the long run: lrgdp, loghicp and logm1 seem to maintain their trend; while logstoxx, being the log of a stock index, has its up and down but it seems to be steady around its mean through the time frame analyzed (Graph 1).

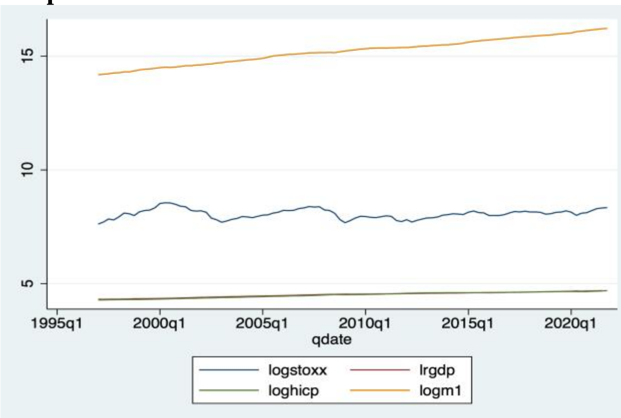
Table 3

Sequential test for multiple breaks at unknown breakpoints (Ditzen, Karavias & Westerlund. 2021)

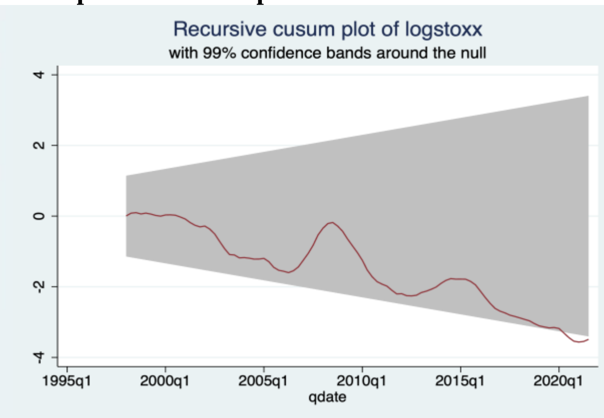
		Bai & Perron Critical Values		
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
F(1/0)	0.55	18.26	13.98	12.08
F(2/1)	0.38	19.77	15.72	13.91
F(3/2)	0.14	20.75	16.83	14.96
F(4/3)	0.11	21.98	17.61	15.68
F(5/4)	0.08	22.46	18.14	16.35
Detected number of breaks		.	.	.

When we fit a time-series regression, we are assuming that the coefficients that are not interacted with time are constant. estat sbcusum tests that assumption and it bases its result on whether the time-series abruptly changes in ways not predicted by your model. So, it tests for structural breaks in the residuals and uses the cumulative sum of recursive residuals or the cumulative sum of OLS residuals to determine whether there is a structural break. Under the null hypothesis, the cumulative sum of residuals will have mean zero. In this case, we can't reject H0 (Graph 2).

Graph 1 – tsline



Graph 2 – cumsum plot



4.3.2 Unit root tests with structural breaks

It is necessary to run the Zivot-Andrews unit root test which allows for one structural break. Under the null hypothesis, the process y_t is a random walk with drift and no structural break occurs, while under the alternative, y_t is trend-stationary with a structural shift happening, in this case we cannot reject H0 for any of the series.

Table 3

Zivot-Andrews unit root test

Variables	t-Statistic	Break date	Critical 1%	Critical 5%	Critical 10%
logstoxx	-3.812	2008q1	-5.34	-4.80	-4.58
lrgdp	-2.598	2001q3	-5.34	-4.80	-4.58
loghicp	-3.646	2014q2	-5.34	-4.80	-4.58
logm1	-4.579	2010q3	-5.34	-4.80	-4.58

4.4 Co-integration tests

It is necessary to test cointegration because it could lead to the wrong assumption that two variables are related, when they do not actually exist based on non-stationary time-series data. The phenomenon is known as the spurious regression, Stock and Watson (2006). The rule of thumb is that if two or more series are non-stationary in themselves, but the linear time series combination is stationary, the series should be cointegrated.

The model specified for Johansen test is the one with intercept (no trend) in CE, no intercept and no trend in VAR, which is the case where there are no linear trends in the data and the first differenced series have zero mean (Table 1). Johansen test for cointegration indicate that there is 1 cointegrated relationship among the variables, while Gregory-Hansen, which test the null hypothesis of no cointegration against the alternative of cointegration with a single shift at an unknown point in time, do not support this thesis. Test results are reported in Table 4.1 & 4.2.

Table 4.1

Johansen test for Cointegration

Max rank	parms	LL	eigenvalue	Trace stat.	5%	1%
0	16	1247.7295		110.6064	53.12	60.16
1	24	1286.8446	0.55358	32.3762 *1*5	34.91	41.07
2	30	1297.751	0.20138	10.5633	19.96	24.60
3	34	1301.6843	0.07790	2.6968	9.42	12.97
4	36	1303.0327	0.02742			

Information Criteria	Maximum rank indicated by the IC
SBIC	1
HQIC	2
AIC	N/A

Table 4.2
Gregory Hansen Cointegration

break	Break date	ADF	Zt	Za	Significance
Trend	2004q2	-4.74	-4.25	-29.19	> 10%
Regime	2009q2	-4.67	-4.65	-34.41	> 10%
Level	2010q2	-4.36	-4.39	-32.47	> 10%

4.5 VECM and Post-estimation

The optimal lag *l* suggested by the information criterion are: 3, 2 and 1. After comparing all the models, it appears that VECM(2) is the best model, but Lagrange-multiplier test indicates that there is autocorrelation at lag order 2, which means that the model could be underspecified, while adopting a VECM(3) there is no evidence of autocorrelation at lag order 3, so we choose the latter model. We can use vecstable to check whether we have correctly specified the number of cointegrating equations. The companion matrix of a VECM with K endogenous variables and r cointegrating equations has $K - r$ unit eigenvalues (4 endogenous variable – 1 cointegrated relation = 3 eigenvalues). If the process is stable, the moduli of the remaining r eigenvalues are strictly less than one. In this case, the model satisfies the stability condition (vecstable).

4.5.1 Causality

Formally, the existence of Granger causality from a variable y_{2t} to another variable y_{1t} entails that, for some forecast horizon h, a better forecast of y_{1t} is achieved by including information about past values of y_{2t} to the set of information about y_{1t}.

In order to study the causal relationship between variables, we employed the test for short-run and long-run causality in frequency-domain proposed by Breitung and Candelon (2006) which, in contrast to the classical time-domain Granger causality, it offers important information of causality between two variables at various ranges of frequencies (w). Frequency domain or spectral analysis aims at decomposing variability in a time series into its periodic components, allowing us to determine relatively more important frequencies that contribute to fluctuations in the variable. Moreover, spectral causality or feedback measures may be very useful if causal links between variables change according to frequency (that is, short run or long run).

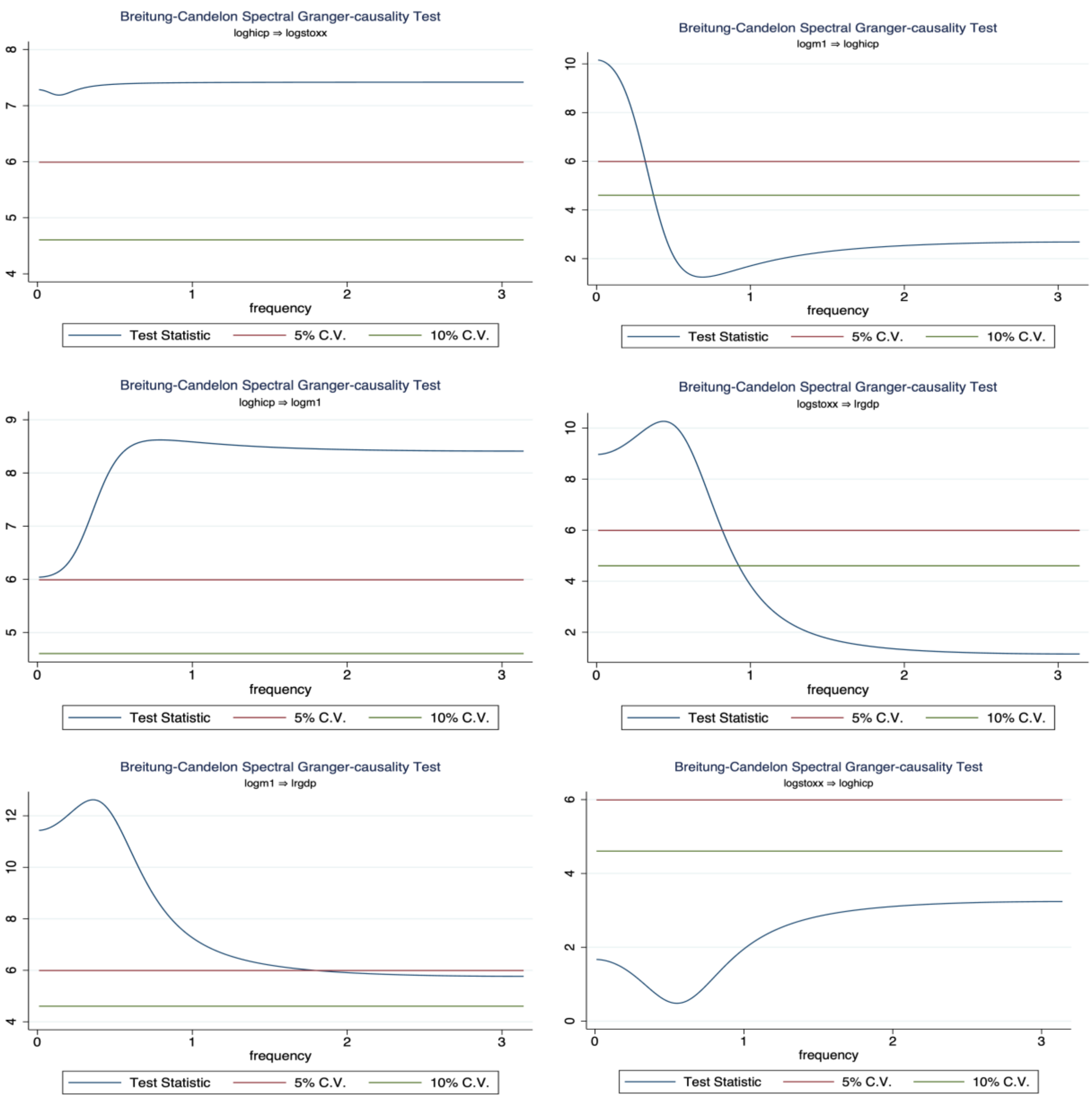
Table 6.2
Spectral Granger causality

w	Effect variable	Cause variable	Conditional variable	Wald test stat.
0.01	logstoxx	loghicp		7.2851 **
3.14	logstoxx	loghicp		7.4186 **
0.01	logstoxx	loghicp	logm1	6.0112 **
0.01	logstoxx	loghicp	lrgdp	9.5138 ***
0.01	loghicp	logm1		10.1580 ***
0.36	loghicp	logm1		4.8505 *
3.14	loghicp	logm1		2.6854
0.01	logm1	loghicp		6.0411 **
3.14	logm1	loghicp		8.4113 **
0.01	logstoxx	logm1		8.4131 **
3.14	logstoxx	logm1		8.4318 **
0.01	logstoxx	logm1	loghicp	7.2718 **
3.14	logstoxx	logm1	loghicp	0.9928
0.01	logstoxx	logm1	lrgdp	13.4446 ***
3.14	logstoxx	logm1	lrgdp	4.7977 *
0.50	lrgdp	logstoxx		10.1273 ***
0.90	lrgdp	logstoxx		4.8841 *

**p < 0.01, **p < 0.05, *p < 0.10.

The results of the test indicate that there is a causal relationship from inflation to eurostoxx50 (both at low and high frequency), this relationship is confirmed also if we assume as conditional variable gdp or M1. The opposite relationship cannot be confirmed, so the relation between the two is unidirectional (no bi-directional feedback effect). On the other hand, eurostoxx50 is also 'Granger-caused' by M1 at 5% level of significance, both at low and high frequency. There is also causal relationship between the other variables, inflation and M1, which present a feedback relationship at low frequencies (0.01; 0.36), while it is unidirectional at high frequencies. We can also observe that there isn't a causality effect from lrgdp to logstoxx, but the opposite causality relation is statistically significant at 10% for the low-frequency range $w \in (0.01;0.92)$.

Graph 3 – Spectral Granger Causality

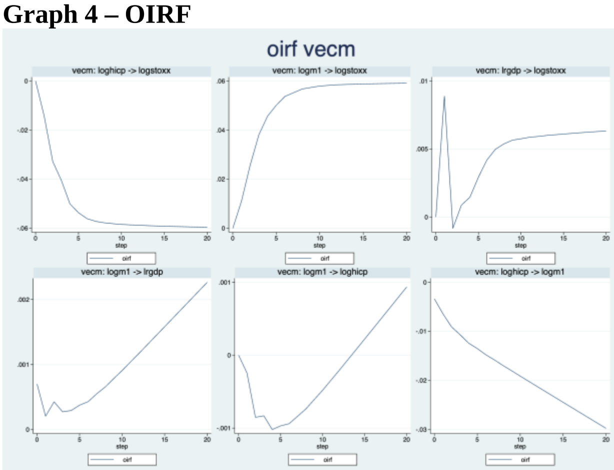


4.5.2 IRF and FEVD

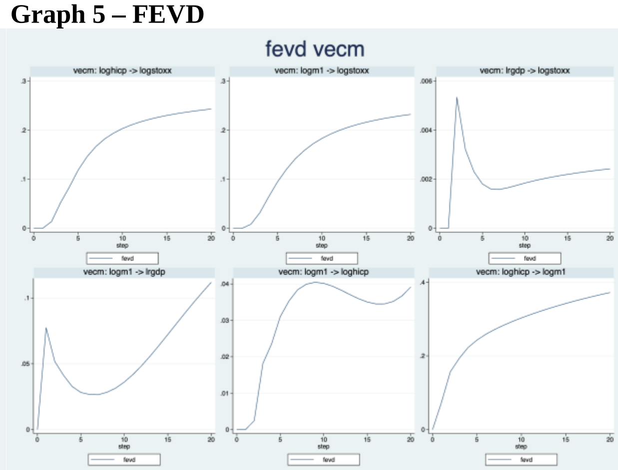
Whereas IRFs from a stationary VAR die out over time, IRFs from a cointegrating VECM do not always die out. Because each variable in a stationary VAR has a time-invariant mean and finite, time-invariant variance, the effect of a shock to any one of these variables must die out so that the variable can revert to its mean. In contrast, the I(1)

variables modeled in a cointegrating VECM are not mean reverting, and the unit moduli in the companion matrix imply that the effects of some shocks will not die out over time.
The forecast-error variance decomposition (FEVD) measures the fraction of the forecast-error variance of an endogenous variable that can be attributed to orthogonalized shocks to itself or to another endogenous variable.
By analyzing the impulse-response function we can state that an orthogonalized shock to inflation has a permanent negative effect on the Eurostoxx50. Moreover, M1 has a positive effect on both GDP and Eurostoxx50, while its impact on inflation is at first negative and after 5 periods positively increasing.
Forecast error variance decomposition graphs indicate the contribution of inflation and M1 to variation in Eurostoxx50 it is quite important.

Graph 4 – OIRF



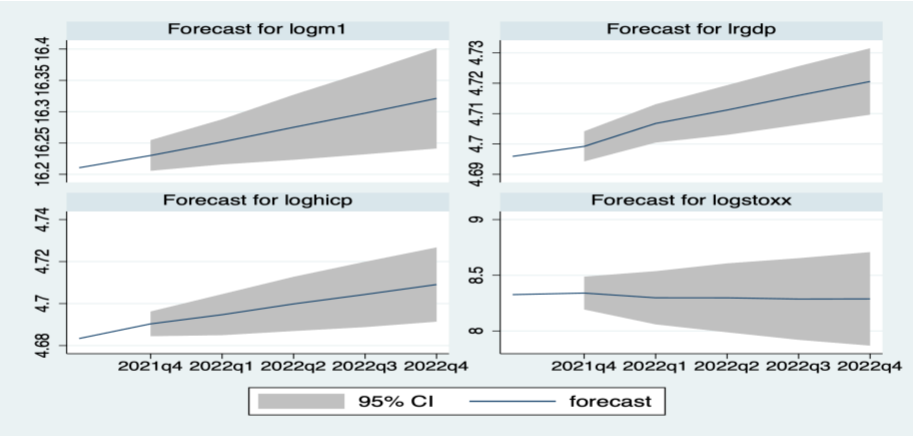
Graph 5 – FEVD



5. Conclusion and Policy implication

Using quarterly data for the Eurozone spanning from 1997 to 2021, this study investigated the relationship between M1, GDP, inflation on the Eurostoxx50. The results for unit root and stationarity tests show that all the variables are non-stationary at levels and cointegration tests reveal the presence of long-run relations.
In the frequency domain we can observe some causal relationship among the variables, in particular between inflation (cause) and eurostoxx50 (effect). Regarding this causality relation, the impulse-response function confirms the literature hypothesis that it consists of a negative relationship. Moreover, FEVD tell us the contribution of the impulse variable to the variation of the response variable, which, in the case of inflation and M1 on the stock index, it's quite relevant. The results highlight also positive causality relationship between M1 and stock prices, meaning that the expansive monetary policy have a positive effect on the financial markets. Although, inflation should follow the money supply we can see that the impact of M1 on inflation it's not so accentuated as we might think. So, although the recent inflation spikes, the stimulus from the PEPP (Pandemic Emergency Purchase Program) should not have an excessive impact on inflation in medium term.

Graph 6 – Forecast



Appendix – IRF and FEVD results

step	(1) oirf	(2) oirf	(3) oirf	(4) oirf	(1) fevd	(2) fevd	(3) fevd	(4) fevd
0	0	0	0	0	0	0	0	0
1	-.014251	.011071	.008888	-.000245	0	0	0	0
2	-.032807	.025733	-.000834	-.000852	.013731	.008288	.005341	.002423
3	-.040462	.038122	.000872	-.000832	.051582	.031639	.003213	.018148
4	-.050031	.045706	.001451	-.00102	.083687	.064217	.002308	.023523
5	-.053658	.050131	.002928	-.000969	.118583	.094677	.001806	.031025
6	-.056057	.053734	.004192	-.00094	.14582	.120189	.001601	.035321
7	-.057148	.055273	.004983	-.000839	.166596	.141641	.001583	.038416
8	-.057747	.056762	.005378	-.000737	.182237	.158388	.001655	.039929
9	-.058105	.057381	.005652	-.000608	.194037	.172125	.001747	.040463
10	-.058393	.057965	.005754	-.00048	.203265	.183137	.001845	.040171
11	-.058587	.058227	.005864	-.000341	.210662	.192243	.00193	.039387
12	-.058766	.058474	.005925	-.000204	.216744	.199773	.002009	.03829
13	-.058897	.0586	.005995	-.000062	.221842	.206124	.002077	.03709
14	-.059019	.058725	.006048	.000079	.226182	.211512	.00214	.035952
15	-.059122	.058805	.006103	.000222	.229926	.216151	.002197	.03504
16	-.059221	.058887	.00615	.000364	.233194	.220175	.00225	.03451
17	-.059314	.05895	.006198	.000507	.236075	.223703	.002298	.034514
18	-.059406	.059016	.006243	.00065	.23864	.22682	.002343	.0352
19	-.059495	.059075	.006288	.000793	.240943	.229596	.002386	.036704
20	-.059585	.059135	.006332	.000935	.243025	.232085	.002426	.039154

(1) irfname = vecm, impulse = loghicp, and response = logstoxx
(2) irfname = vecm, impulse = logm1, and response = logstoxx
(3) irfname = vecm, impulse = lrgdp, and response = logstoxx
(4) irfname = vecm, impulse = logm1, and response = loghicp

General references:

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Note: all the referral links to the literature have been inserted in the paper.