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The effect of investors' confidence on monetary policy transmission mechanism A Multivariate GARCH approach

Chiara Guerello *

Dipartimento di Economia (DIEC), Universita of Genova, via Vivaldi 5, 16126 Genova, Italy
Dipartimento di Economia e Finanza, LUISS Guido Carli, Viale Romania 32, 00197 Roma, Italy

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ABSTRACT

This paper investigates the financial stability's effect on the monetary policy transmission mechanisms. The correlations between investors' confidence in the markets, money growth and economic growth are analyzed along with the correlations within their volatilities. Specifically, the heteroskedasticity of the errors is exploited in a Multivariate GARCH framework to obtain endogenously estimated measures of uncertainty. By a two-step estimator, the indirect interplay of money growth and financial markets is highlighted at different time horizons. The results contrast previous literature supportive of the "Great Moderation" as causing the recent financial crisis. Effectively, by accounting for the breaks in volatility series due to structural shifts in monetary policy, a low period of macroeconomic volatility is found not to drive directly low financial stability.

1. Introduction

The impact of uncertainty on money growth has received greater attention in recent years and it is a crucial issue for Central Banks, particularly for those who focus on monetary policy analysis. In the last decades, a large swath of literature has largely debated whether the behavior of the main Central Banks (FED,[1] ECB,[2] etc.) in the last decades might have contributed to the recent financial turmoil.

* Address: Dipartimento di Economia e Finanza, LUISS Guido Carli, Viale Romania 32, 00197 Roma, Italy.
E-mail address: chiara.guerello86@vodafone.it

[1] US Federal Reserve.
[2] European Central Bank.

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Stylized facts show that, since the 1990s, a passive interest rate rule and, eventually, targeting output stabilization around its long run trend, although subordinated to the primary target of price stability, have generated very low macroeconomics volatility. Since several empirical analysis argued that passive policy and low money's variance lead to high instability in the financial markets, the loosing monetary policy and the consequent high macroeconomic stability observed in the last two decades and called *Great Moderation* might have contributed to the recent financial turmoil. However, in opposition to the main empirical findings, theoretical contributions still argue in favor of both monetary stock and output stabilization.

Since several factors affect the transmission mechanism of the monetary shocks to the financial markets, the problem is more complex and articulated than what appears. Specifically, this paper focus on the interrelations among the uncertainty shocks and tries to shed light on the question with an accurate empirical analysis.

The contribution of the *Great Moderation*, to the extent of a prolonged period of joint low monetary and macroeconomic uncertainty, to the 2008-09 financial crisis is investigated through the analysis of both unconditional and conditional first and second moments of GDP growth, money stock growth and investor's confidence. Eventually, if it is possible to exclude the *Great Moderation* from the causes of recent turmoil, the crisis might been interpreted as unrelated to the last decades Central Banks' behavior, to the extent of high output stabilization. However, if with a different monetary policy the crisis life- cycle would have been smoothed is still an open question.

Several channels, through which the monetary policy affects the financial markets, have been identified in the last decades, but the relation between monetary policy, real economy and financial markets volatility has not been clearly disentangled yet. Even if there are several partial equilibrium models including the three uncertainty measures among the exogenous shocks,[3] the empirical evaluation of the three-side relationship has not caught much the attention and the most influential papers have focus on the second order correlation between monetary policy and economic growth.

Serletis and Rahman (2009) shed light on the controversial impact of monetary policy on the economy during the last decades: they found money growth volatility to have a significant negative effect on the growth rate of real GDP.

Although the early theoretical literature emphasized the interest rate channel as the main transmission mechanism of monetary volatility shocks to the real economy, influential papers as Mascaro and Meltzer (1983) and Evans (1984) argued that, since monetary volatility increases interest rates volatility, it adds to bonds' riskiness as well. Increasing the risk of holding bonds affects the demand for money and, hence, it increases interest rates, leading to a period of a disinvestment and recession.

Recently, Bekaert, Hoerova, and LoDuca (2010) and Jovanovic (2011) have found that the monetary policy directly affects the risk aversion of investors and the latter is linked by a non-linear relation to financial uncertainty.

Finally, recent analysis have revealed a growing interest in the effects of financial stability on macroeconomic activity. Puhan (2011) provides evidence that shifts in the real-economy and in monetary policy related variables help to explain the time varying patterns in assets valuations during the last decades.

The difficulties in measuring uncertainty are at the basis of the small literature over the topic. Endogenously estimated measures of uncertainty have not been largely used for the analysis of the impact of financial markets stability,[4] but previous studies have often employed either "ad hoc" estimates (i.e. Giordani & Söderlind, 2003; Arnold & Vrugt, 2008, 2010; Bachmann, Elstner, & Sims, 2013; Dick, Schmeling, & Schrimpf, 2013, etc.) or sample's measures of volatility.

[3] Among the other Choi and Oh (2003) analyzed the effect of second order shocks in money and output growth in case of both low and high financial market volatility. Bekaert, Engstrom, and Xing (2009) considered also the joint second moments analyzing the relations among financial markets, consumption growth, and dividend yields. A more detailed description of the theoretical literature is provided in Section 2.

[4] Since the work of Elder (2004), an increasing strand of the literature has employed GARCH model to recover endogenous measure of uncertainty but always for bi-variate models (i.e. Serletis & Shahmoradi, 2006; Bekaert et al., 2009; Fountas, Karanasos, & Kim, 2006; Serletis & Rahman, 2009; Cronin, Kelly, & Kennedy, 2011) because stochastic volatility models become computationally expensive as the number of variables increases.

By employing a two-step multivariate GARCH-in-mean estimator, this analysis highlights the relationships that occur among investors' confidence, real money growth, and economic activity. Specifically, a Multivariate GARCH-in-mean model allows for time-varying conditional variances and covariances by means of a martingale process for the error terms and for the estimated variances and covariances in the first moments equations.

By exploiting the properties of this estimator, the contribution of this analysis is twofold: first, by using a multivariate models, the correlations between monetary policy, real economy and financial market, and the correlation between their respective measures of uncertainty are simultaneously estimated thanks to the VAR structure of the model. As the theory states, periods of high/low financial volatility affect the strength of the relationship among either economic or monetary uncertainty and either money or economic growth. Using a multivariate model allows for testing these theories because financial markets effects are accounted while the correlations between money and economic growth are estimated. Second, the use of a volatility models allows for endogenously investigating the problem in terms of uncertainties, with no need to search for an appropriate proxy. Although many disagree about the superiority of GARCH estimates as proxy for uncertainty, since there are not consistent proxies for the variance of the three variables, relying on exogenous variables means that different kinds of uncertainty are jointly employed for investigating the same phenomenon. Using a GARCH model allows for endogenously estimating the uncertainty and, hence, getting measures fully consistent with each other.

Focusing on US economy provides long and rich series (i.e. a period from 1959 to 2011 with different FED chairmen). The main drawback from such length is the presence of possible structural breaks due to institutional changes. The structural shifts in either the conduct of monetary policy or assets market regulation might strongly affect the estimates of the covariance between money stock growth and investors' confidence.

The analysis is based on a two-step estimator of the multivariate GARCH-in-mean model as proposed by Grier and Perry (1998). This technique allows for jointly investigating the relation between the variables in level and their measures of uncertainty. Namely, the variables in level enter each variance equation and the model can be estimated for alternative lags' lengths, accounting for delayed effects.

The paper is organized as follows: Section 2 describes the main findings in the literature and it sketches the model from a theoretical perspective. Section 3 describes the main econometric issues, and Section 4 reports and discusses the results. Section 5 concludes.

2. Theoretical background

Although little has been said about the empirical counter-factual of the theories, the theoretical literature pointed out that, in most cases, an increase in any economic variable volatility leads to an increase in money demand. Furthermore, output uncertainty decreases assets prices and, hence, risk aversion, and financial markets' uncertainty is negatively correlated with consumption.

Over the last decades uncertainty has taken on a more central role in describing the real economy dynamics and the works by Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) have recently theoretically established the relevance of uncertainty shocks in driving the business cycle. Three main channels has been identified that link uncertainty in either assets market or money growth to real economy.

First, as in Boyle (1990) and Boyle and Peterson (1995), an increase in output uncertainty positively affects money demand both by moving the interest rate and by decreasing the assets' rate of return.

Second, as underlined by Choi and Oh (2003), once both money and financial services enter, by assumption, the household's utility function, the uncertainty, due to high volatility in either money growth or output growth, affects both money and financial services' demand by the so called "wealth effect". However, after a second order shock in either money growth or output growth, the final sign of the main real variables response is unpredictable. This ambiguity arises because the wealth effect can be decomposed in two opposite forces:

1. Substitution effect. As the uncertainty related to money growth (output) increases, the households, who dislike risk, substitute consumption with money (money with consumption), because less risky.
2. Precautionary effect. In a situation of high money (output) volatility people prefer to save more (less) and consume less (more), hence there is an increase (decrease) in the demand for money and financial services.

The sign of the volatility indexes coefficients in the money demand and, hence, the prevailing effect depends on both the households' degree of risk aversion and the policy parameters, in particular on the strength of Central Bank's response to output volatility.

Moreover, financial uncertainty, if dominating, may reverse the sign of the substitution effect, because households substitute between more risky assets and money, rather than money with consumption. An increase in uncertainty in the financial markets, in money growth or in output growth, then, always leads to an increase in money demand.

Finally, Bekaert et al. (2009) analyzed the role of financial markets looking at the links between assets price, consumption growth and dividend yields. Since consumption and inflation volatility are the main determinants of output volatility, it is possible to generalize the results about consumption to GDP. Assets valuation is affected by both consumption growth and its volatility. Due to the negative correlation between consumption and its volatility and the positive one between consumption and dividend yields, an increase in output volatility has two opposite effects on assets price: it increases equity price due to the term-structure effect but the latter sums up to a negative cash-flow effect. Furthermore, an adding up in dividends' volatility increases assets market's volatility due to both increasing liquidity costs and to more favorable growth options. Finally, risk aversion and financial markets uncertainty are negatively correlated with consumption.

3. Methodological approach

3.1. Data and variables description

This study using US data analyzes three monthly time-series for, in order, monetary growth, output growth and investors' confidence.[5] The sample spans over a period of more than fifty years, from January 1959 to December 2011. Such a long interval includes several periods of either high or low inflation and different Fed chairmen with alternative approaches to monetary policy. During mid- 1970s, and late 1980s/early 1990s shocks of relatively large magnitude hit inflation, consumption and the whole economic activity. This time-interval includes also the recent financial crisis.

Although, since 1980s, the Fed has used the Funds rate as main policy instrument, this analysis focus on the growth rate of liquid monetary stocks rather than real interest rates. Even if these two measures are strongly correlated and interest rates' movements are able to explain most of money stock volatility, money growth collects additional information about households and firms money holding decisions because its dynamic is generated by both movements in the demand for money and monetary policy decisions. Furthermore, in the last decades the analysis of monetary aggregates has captured the attention of several Central Banks, as Fed and ECB, because money stocks appear strongly correlated with both macroeconomic and financial uncertainty (see Cronin et al., 2011). Finally, although interest rates are typically used as proxy for monetary policy stance, the stronger (at least a *a priori*) correlation with macroeconomic uncertainty and the relation with previous empirical[6] and theoretical[7] literature suggest that the relation between monetary, macroeconomic and financial uncertainty is easier to disentangle and discuss whether a liquid money stock is preferred as a proxy for monetary policy stance. The growth rate real M2 stock is employed, which is calculated as the natural log of nominal M2 less the natural log of the CPI. Data for the monetary stock are collected

[5] Graphical description of the series is reported in Table 1.
[6] See for instance Serletis and Rahman (2009) and Cronin et al. (2011).
[7] See for instance Boyle (1990), Boyle and Peterson (1995) and Choi and Oh (2003).

from the Federal Reserve Economic Database FRED, maintained by the Federal Reserve Bank of St. Louis. Since even the seasonal adjusted series for M2 show a monthly pattern due to the liquidity released by the bank system on a periodic base, the seasonally unadjusted series has been regress on monthly dummies and the residuals taken to jointly account for additive seasonality and the half-yearly peaks.

Reporting the economic situation, it is necessary to rely upon a single variable to capture the whole macroeconomic volatility. The most common variable is the Gross Domestic Product, but monthly series are not available. Overcoming the problem, the GDP series quarterly published by the US bureau of economic analysis (BEA) is interpolated, as proposed by Chow and Lin (1971), with the Main Economic Indicator (MEI), monthly published by OECD. As for the monetary stance proxy, the variable is divided by the CPI and taken in log to consider the growth in real terms and to deal with the unit roots in the series.

A measure of assets risk premium is the best choice to describe the stock market shocks. This measure summarizes the unpredictable movements of the stock market index due to changes in investor's confidence over the market. According with the "Long run risk model" of Bansal and Yaron (2004), the marginal rate of substitution of the representative agent and, hence, the equity risk premium positively co-vary with the price dividend ratio and the ex-post equity return, hence the assets valuation. The most common measures of risk premium are the financial metrics that determine the relative trade-off between the price of a stock, the earnings generated per-share and the company expected growth. Following the idea of Puhan (2011), the Price–Earnings (PE) ratio is a good proxy. The PE ratio is a financial statistic used to detect when a company is over(under)-evaluated, because a decreasing PE ratio implies decreasing investors' confidence in the growth of the companies. However, Price–Earning on Earnings Growth ratio (PEG) might be regarded as a better indicator. This index reflects more the investors' animals spirits by accounting for the companies' growth potentials, because it reckons on several earnings generating factors, such as brand, human capital, expectations, and barriers to entry. In order to compute this index, data of the Price–Earning ratio and the Earnings Growth ratio are collected from the Robert Shiller's database (Shiller, 2000). For stationarity reasons and coherence with the other series employed, the PEG index is considered in first difference.

3.2. An empirical issue: measuring uncertainty

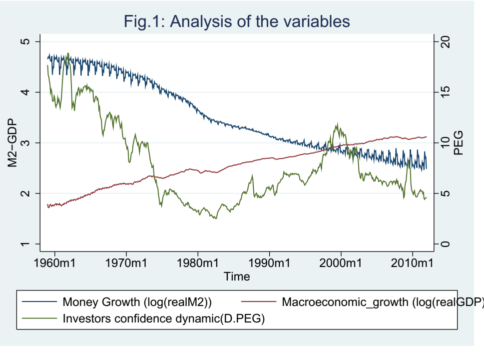
Recently, in the main theoretical literature (e.g. Bloom et al., 2012; Christiano, Motto, & Rostagno, 2010) the theoretical models have often been perturbed with second order shocks to explain the business-cycle fluctuations. In this way, uncertainty is defined as the variance of the stochastic, or unpredictable, component of a variable. However, a large swath of the empirical literature largely employed exogenous proxies to measure uncertainty, typically forecast dispersion from the Philadelphia Fed's Survey of Professional Forecasters (see Giordani & Söderlind, 2003), or measures of implied volatility (see Bloom, 2009).

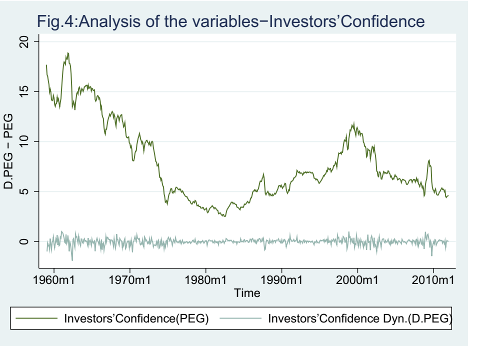
In opposition to the main stream, the premises of this paper are based on Serletis and Shahmoradi (2006) argument, which posits that the relationship occurring among monetary, macroeconomic and financial uncertainty can be more rigorously addressed by using a GARCH-in-mean model. This specification exploits the features of the data, namely the presence of ARCH effect in the series, to produce endogenously estimated time-varying measures of uncertainty.

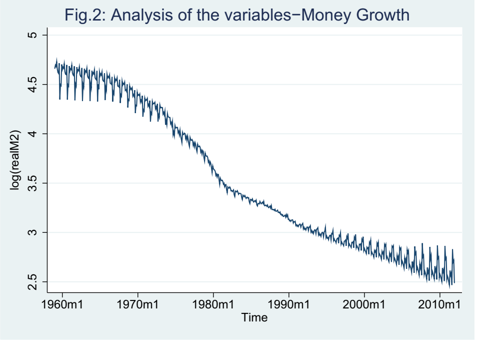
Since the exogenous proxies[8] employed in literature differ among them for the concept of uncertainty approximated, following this alternative approach means that different proxies of uncertainty are inconsistently employed for investigating the same phenomenon. Whereas, volatility models allow for jointly and endogenously estimating uncertainty and, hence, getting measures fully consistent with each other. Second, by employing GARCH models, if the conditional variances are correctly parametrized, it is possible to endogenously get consistent measures of the true levels of uncertainty; while other sample-based measures of uncertainty, like moving averages, provide estimates that are generally inconsistent.

[8] The term *exogenous* is used to the extent of recovered from information other than the series used in the model and does not relates to nature of the items of the underlying economic models. For instance, exogenous proxy might be endogenous simulated series by economic model as firm-level idiosyncratic volatility shifts.

Table 1
Time line graphs of the variables analyzed (Figs. 1–4).







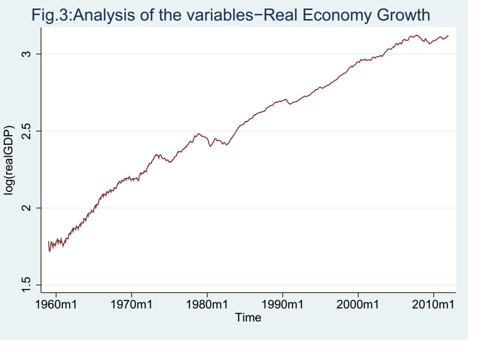


Table 2 compares the estimated measures of uncertainty for real GDP growth and stock market index with some alternative measures.[9] The proxy featuring the highest correlation is the implied volatility index (VIX), as found in Orlik and Veldkamp (2012), but, anyway, the maximum correlation with our uncertainty measures is less than a 60%.

In absence of uncertainty about both the forecasting model and the parameters, uncertainty and volatility are the same concept and alternative proxies of uncertainty do not significantly differ. However, if uncertainty about either the model or the parameters is accounted for, the measures of uncertainty eventually differ because none of them is able to capture the whole uncertainty concept. Specifically, the survey based measures are able to partially capture the uncertainty about the model and parameters but using the range of disagreement among individual forecasts does not give information about each individual's uncertainty regarding their own forecast. Whereas, the endogenously estimated measures of uncertainty approximate just the uncertainty among the own forecast because regards the average forecast.

3.3. Analysis of the individual series

Although for stationarity reasons the series are considered in either growth rates (i.e. money stock and real GDP) or first difference (i.e. PEG), Augmented Dickey–Fuller test in its original formulation,

[9] Specifically as forecast dispersion measures from the SPF: the log difference of the 75th and 25th percentile ratio of either the 1-year-ahead forecast probability of real GDP or the 10-years-ahead forecast probability of the S&P500. In addition, a the price of a volatility option, CBOE Volatility index (VIX).

Table 2
Correlation among different measures of uncertainty.

Endogenous measures	Forecast dispersion*		Implicit volatility
	Real GDP1**	Stock10**	VIX***
h.GDP	0.449819		
h.PEG		0.355696	0.543757

* Forecast dispersion measure are taken from the FED Survey of Professional Forecasters (SPF).
** RealGDP and stock10 = the log difference of the 75th and 25th percentile ratio of respectively the 1-year-ahead forecast probability of real GDP and the 10-years-ahead forecast probability of the S&P500.
*** VIX = the price of a volatility option, CBOE Volatility index (VIX).

with generalized least squared as proposed by Elliot, Rothenberg, and Stock (1996) and the adjusted test proposed by Phillips (1987) and Phillips and Perron (1988) point out PEG to be integrated of order 1 and, hence, its first difference to be integrated of order 0. However, the results for the growth rate of both money stock and real GDP are ambiguous and the tests clearly neither reject nor accept the null hypothesis of unit root in the series. Following the argument of Amado and Teräsvirta (2011), for which in presence of structural breaks the series can be locally stationary, the tests are also performed on sub-samples consistent with the major structural monetary policy shifts, in which the unconditional variance observed is typically constant, and, hence, the tests point out the series to be locally stationary.

Looking at Table 1 and previous literature, all the three series considered seem to suffer of clustered volatility. Table 3 reports the Engle's Lagrange Multiplier (LM) tests for the presence of autoregressive conditional heteroskedasticity over the single series and all of them point out the squared residuals to be auto-correlated. Since in presence of autoregressive residuals volatility the estimates from a simple Vector Auto-regressive (VAR) model would be inconsistent, employing a stochastic volatility estimator is suggested and allows to produce endogenously estimated measures of uncertainty. Table 4 reports the information criteria relative to the ARCH estimator of each individual series.[10] For what concerns money growth, neither Aikaike Information Criterium (AIC) nor Bayesian Information Criterium (BIC) suggest a specification clearly superior to GARCH(1,1). Similarly, looking at the results for PEG, the information criteria are slightly higher for GARCH(2,1), but the second lag of the ARCH component is not significantly different from zero. Finally, according to AIC and BIC, the best specification for real GDP growth is GARCH(2,2). However, although the sum of ARCH and GARCH coefficients is closed to one, which is a sign of instability, it has been decided to use the GARCH(1,1) specification because the results for real GDP are mostly related to the non-stationarity of the series over the whole sample.

3.4. Motivations and choice of the main econometric specification.

Given the strong evidences from previous literature and the descriptive part of this work, it is clear that there are high co-dependencies between all the uncertainty measures. Using a Multivariate GARCH estimator allows for accounting for the time varying nature of variances and covariances matrix, as well as, for investigating the relationship among the fluctuations associated with the volatility of the variables.

Although the uni-variate specifications and properties of the ARCH models are widely known, the multivariate case requires some further specifications for two main reasons:

1. The model has to be flexible enough to represent the dynamics of the conditional variances and covariances. However, since the number of parameters exponentially increases with the dimension of the model, the specification should be detailed enough to allow for both relatively easy estimation of the model and straightforward interpretation of the parameters.

[10] Each individual series is regressed on its own lags and on the lagged values of the other two variables, according with the specification used in the multivariate model.

Table 3
Test for ARCH effects.

	log(realM2)		D.PEG		log(realGDP)	
	Z	*p*-value	*Z*	*p*-value	*Z*	*p*-value
Lags						
1	92.10	(0.000)	33.29	(0.000)	2.69	(0.101)
2	110.68	(0.000)	36.78	(0.000)	1.58	(0.453)
3	113.33	(0.000)	43.62	(0.000)	8.48	(0.037)
4	115.92	(0.000)	44.91	(0.000)	11.20	(0.024)
5	115.77	(0.000)	74.87	(0.000)	16.49	(0.006)
6	116.35	(0.000)	75.11	(0.000)	60.38	(0.000)
7	116.32	(0.000)	78.36	(0.000)	68.00	(0.000)
8	116.44	(0.000)	81.78	(0.000)	36.38	(0.000)
9	116.39	(0.000)	85.70	(0.000)	36.33	(0.000)
10	116.42	(0.000)	90.99	(0.000)	49.92	(0.000)
11	125.23	(0.000)	90.57	(0.000)	50.86	(0.000)
12	160.47	(0.000)	90.79	(0.000)	40.53	(0.000)

Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroskedasticity.

Table 4
Information criteria of alternative specifications of the GARCH process for the univariate series.

	D.PEG			log(realM2)			log(realGDP)		
	(1) GARCH (1,1)	(2) GARCH (2,1)	(3) GARCH (2,2)	(4) GARCH (1,1)	(5) GARCH (2,1)	(6) GARCH (2,2)	(7) GARCH (1,1)	(8) GARCH (2,1)	(9) GARCH (2,2)
ARCH									
L.arch	0.159***	0.159***	0.282***	0.844***	0.469***	0.805***	0.0725***	0.0580	0.0795**
	(0.0254)	(0.0498)	(0.0444)	(0.129)	(0.127)	(0.0975)	(0.0203)	(0.0386)	(0.0313)
L2.arch		0.0000762	0.000920		0.453***	0.800***		0.0186	−0.0739***
		(0.0580)	(0.0355)		(0.134)	(0.0979)		(0.0407)	(0.0261)
L.GARCH	0.839***	0.839***	0.0186	0.00641	0.00346	−1.019***	0.915***	0.910***	1.811***
	(0.0223)	(0.0272)	(0.0461)	(0.0371)	(0.0536)	(0.0329)	(0.0232)	(0.0247)	(0.310)
L2.GARCH			0.704***			−0.0331			−0.818***
			(0.0491)			(0.0343)			(0.288)
Obs.	623	623	623	623	623	623	623	623	623
AIC	26.46	28.46	19.89	−3341.0	−3341.2	−3364.6	−5060.0	−5058.2	−5056.5
HBIC	84.11	90.55	86.41	−3283.4	−3279.1	−3298.0	−4962.5	−4956.2	−4950.0
Likelihood	−0.232	−0.232	5.056	1683.5	1684.6	1697.3	2552.0	2552.1	2552.2

Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2. The positive definiteness of the variance–covariance matrix need to be achieved by constraining the model's parameters.

Although VECH, diagonal VECH, and BEKK being the most common covariances matrix formulations, using a third class of variance–covariance matrix's specification is preferred. Since the assumption that the correlations are null is far away from realty and from what has been observed in the last years, a full correlations matrix is of interest for the research. Once discharged the idea of a diagonal variance–covariance matrix, accounting for the full correlations matrix requires estimating a huge number of parameters.

Due to computation easiness, it is preferred to design the conditional single variance and covariance equations, rather than straightforward modeling the variance–covariance matrix, as generalizations of the Constant Conditional Correlation (CCC) model does.

In this case the variance–covariance matrix is defined as:

$$H_t = D_t P_t D_t \tag{1}$$

$D_t = diag\left(\sqrt{h_{it}}\sqrt{h_{jt}}\rho_{ij}\right)i{\neq}j$ and P_t is the matrix of the correlations.

During the analysis two different models of the Conditional Correlation family are considered: Constant Conditional Correlation model proposed by Bollerslev (1990) and the Dynamic Conditional Correlation model (DCC) proposed by Engle (2002). In both models a GARCH representation is used to estimate the diagonal variance matrix D_t but they differ on the specification of the correlation matrix P_t: the DCC model allows for a dynamic correlation matrix, while the CCC model defines P as constant symmetric positive definite matrix.

In order the MGARCH-in-mean estimator to be consistent, serial correlation of the errors should not arise and, hence, it is chosen a VAR(12) specification for the main equations. However, for real M2 growth and PEG only the number of lags is limited to the 1st, 2nd and 12th lag, because the number of parameters exponentially grows as the numbers of lags increases. The model has the following statistical specification:

$$Y_t = CX_t + \sum_{i=1}^{12} BY_{t-i} + \Gamma H_{t-1} + \epsilon_t \tag{2}$$

$$\epsilon_t = H_t^{-1} z_t \tag{3}$$

$$z_t \approx N(0, D_t P_t D_t) \tag{4}$$

$$D_{i,t}^2 = d(A_{0,i}) + d(A_{1,i}) \circ (z_{t-1} z'_{t-1}) + d(A_{2,i}) \circ D_{t-1}^2 \tag{5}$$

$$P_t = diag\{Q_{t-1}\}^{-1} Q_t diag\{Q_t\}^{-1} \tag{6}$$

$$Q_t = (1 - \lambda_1 - \lambda_2)S + \lambda_1 (D_{t-1}^{-1}\epsilon_{t-1})(D_{t-1}^{-1}\epsilon_{t-1})' + \lambda_2 Q_{t-1} \tag{7}$$

or for CCC

$$P = (\rho_{ij}) \tag{8}$$

$$\rho ij = \frac{\left(exp\left(2\frac{\epsilon_{i,t-1}}{\sqrt{h_{it}}}\frac{\epsilon_{j,t-1}}{\sqrt{h_{jt}}-1}\right)\right)}{\left(exp\left(2\frac{\epsilon_{i,t-1}}{\sqrt{h_{it}}}\frac{\epsilon_{j,t-1}}{\sqrt{h_{jt}}+1}\right)\right)} \tag{9}$$

with X_t the set of time dummies, D_t the estimated variance matrix, P_t the estimated covariance matrix, and S the unconditional correlation matrix. Parametrization of correlations matrix has the same requirements as the variance–covariance matrix. It has to be assured that both the variances and covariances matrices are symmetric and the diagonal of the conditional correlation matrix must be unity. Therefore, the dynamic parameters in the correlation's equations are the same, only the unconditional correlations (constant) varies among the variables and is constrained between zero and one.

Table 6 reports some likelihood ratio tests for the joint significance of either ARCH and GARCH parameters or the dynamic parameters of the correlations equation. Furthermore, Table 5 reports some residuals based diagnostics for the presence of residual correlation in both the error terms and their variance. Looking at Tables 6 and 5, it is clear that a VAR(12)-MGARCH DCC specification of the errors is the best choice possible among those considered.

3.5. Two-step estimator

To disentangle the relationship among the riskiness measures and the variables in level, it has been decided to use a two-step estimator of the multivariate GARCH-in-mean. As proposed by Grier and Perry (1998), a six variables VAR model is estimated for both the levels and variances of the three variables, in which the monetary, macroeconomic and financial uncertainty are measured by the respective estimated conditional variances. The conditional variances and covariances are estimated in the first step, that means by using the GARCH(1,1)-DCC-VAR(12) described above.

Although employing estimated variables causes the t-test to be biased, it is possible to detect the significance of the estimated correlations by Granger causality F-tests, which remain robust. Moreover, the two-step approach has few other advantages:

Table 5
Residuals based diagnostic.

	Ljung-Box Q test for residual autocorr. H0: ϵ are iid Ha: ϵ are AR				Ljung-Box Q test for residual ARCH H0: ϵ^2 are iid Ha: ϵ^2 are AR			
	Lags = 12		Lags = 6		Lags = 12		Lags = 6	
	Z	*p*-value	*Z*	*p*-value	*Z*	*p*-value	*Z*	*p*-value
D.PEG	18.2770	0.0321	9.67650	0.0215	29.5910	0.0005	14.005	0.0026
log(realM2)	210.560	0.0000	157.703	0.0000	77.6983	0.0000	38.8119	0.0000
log(realGDP)	89.9040	0.0000	n.a.	n.a.	47.4855	0.0000	n.a.	n.a.

ϵ are the normalized residuals from the MGARCH used in the analysis.

Table 6
Test for misspecification of the functional form.

	CCC	DCC	
	(1) garch(11)	(2) garch(1 1)	(3) no-arch
Corr(realM2,PEG)	0.0978***	0.114***	0.102***
	(0.0410)	(0.0472)	(0.0492)
Corr(PEG,realGDP)	0.103***	0.133***	0.0649
	(0.0389)	(0.0464)	(0.0496)
Corr(realM2,realGDP)	0.251***	0.281***	0.241***
	(0.0389)	(0.0441)	(0.0528)
Constant variance	Yes	Yes	Yes
ARCH effect	Yes	Yes	No
GARCH effect	Yes	Yes	No
Corr.Dynamics	No	Yes	Yes
VAR(12)	Yes	Yes	Yes
LR test statistic	19.20		747.2
P-value	0.0000		0.0000

Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
LR statistics for joint significance of the dynamic coefficients excluded (λ or ARCH).

- Each conditional variance equation incorporates the lagged values of real money growth, GDP growth and PEG.
- This approach allows to capture the lagged causal effects of the conditional variances on the conditional means, at different lag's lengths. Therefore, it is able to capture the effects of variables, typically the uncertainty measures, that have a delayed impact on the others.
- This approach allows to examine causality on a bidirectional basis between various pairings of variables (Cronin et al., 2011) and, hence, to test for several hypotheses (Fountas & Karanasos, 2007).
- As pointed out by Fountas et al. (2006), this approach minimizes the numbers of parameters to be estimated.

The system of equations estimated in the second step is specified as follows:

$$Y_{i,t} = \sum_{p=1}^{P} B_{1,p}\, Y_{i,t-p} + B_2\, X_t + u_t \quad P = 2, 4, 8, 12 \tag{10}$$

The vector of dependent variables $Y_{i,t}$ is composed by six variables, the conditional mean and variance of investors' confidence, GDP growth and money stock growth, in order: log of real M2 (realM2), log of real GDP (realGDP), D.PEG, variance of real M2 (hrealM2), variance of real GDP (hrealGDP) and variance of PEG (hPEG). On the right hand side, in addition to the lagged value of the dependent variables, there is the matrix of exogenous regressors composed by a constant term, a trend, and the one period lagged estimated conditional covariances from the same GARCH(1,1)-DCC-VAR(12) model used to estimate the variances in the first step. Since the equations are estimated with different lag structures (1, 2, 4, 8, or 12 lags),the size of the endogenous variables' vectors, on the left hand side of the equations, depends on the lags' length. Lags' lengths are consistent with the analysis of the single series, previous literature (Cronin et al., 2011; Fountas et al., 2006; Fountas & Karanasos, 2007), and Friedman's indication that there are long-run varying effects in the impact of money growth on the other economic variables.

3.6. Accounting for structural breaks in the series

The sample spanning from 1959 to 2011 covers several significant periods of both high and low inflation, as well as, of different Fed chairmen with alternative approaches to monetary policy. In particular, the early 1980s shift in the monetary policy towards inflation-oriented conduct and the Fed's change in early 1990s of the primary operating instrument towards the Federal funds rate switch the monetary policy from pro-cyclical to counter-cyclical. As a consequence, since mid 1980s economic volatilities sharply declined for some decades, the so-called *Great Moderation*. In addition, in the late 1970s and early 1980s the inflation rates reached historically high levels.

A variety of recent studies advocates structural breaks in several macroeconomic time series and Puhan (2011) proves the existence of potential breaks in the correlation between the volatilities of inflation and consumption growth, the auto-correlations of the volatilities themselves and the level of inflation.

Since in previous literature and from the graphical analysis of Table 1 and Table 7 there are evidences of structural breaks in all the three time series considered, it is necessary to check the robustness of the results in different sub-sample periods. Specifically, the main shifts in the Fed's conduct are accounted for:

1. May 1971: This date marks the end of Bretton Woods agreements, after which the main target of the FED shifted from the stability of the exchange rate to the stability of the output gap.
2. July 1980: The Depository Institutions Deregulation and Monetary Control Act is the milestone of Volcker's shift in monetary policy towards prices stabilization that becomes the first purpose of the Fed and this starts a periods of financial markets deregulation.
3. April 1989: The Financial Institutions Reform and Recovery Act starts a new period of strong financial markets deregulation, characterized also by a change in the tools used for monetary policy towards the Federal Funds rates.
4. September 2007: Default of Lehman Brothers Investment Bank is used as the starting point of the recent financial turmoil characterized by high financial markets volatility and extraordinary monetary policy measures.

Given the few degrees of freedom left if the sample is reduced to the sub-periods discussed, a preferred solution has been to consider time dummies in both the conditional mean and conditional variance equations. However, to assure the positiveness of the conditional variance matrix, the time dummies enter the variance equations in a multiplicative form. Since the time dummy are designed such that they take value one in the period after the shock, and zero before, it is possible to interpret their coefficients as the causal effects of the structural change in either monetary policy or in the markets regulation.

In agreement with what shown in Table 7, the results in Table 8 report the change in the conditional means of the series considered and their respective variances after the most relevant structural shifts in either monetary policy or market regulation. The results underline the relevance of events as the end of Bretton Woods agreements and the Volcker' shift in monetary policy conduct of early '80. Moving to a flexible exchange rate system, strongly decreased the conditional variances of both GDP growth and investors confidence, whereas the variance of money growth significantly increased. Similarly, the Volcker's shift in the FED policy significantly reduced the variance of GDP growth along with the growth rate of money. Finally, the markets deregulation of early '90s affected just the variance of

Table 7
Estimated conditional variances and covariances (Figs. 5–11).

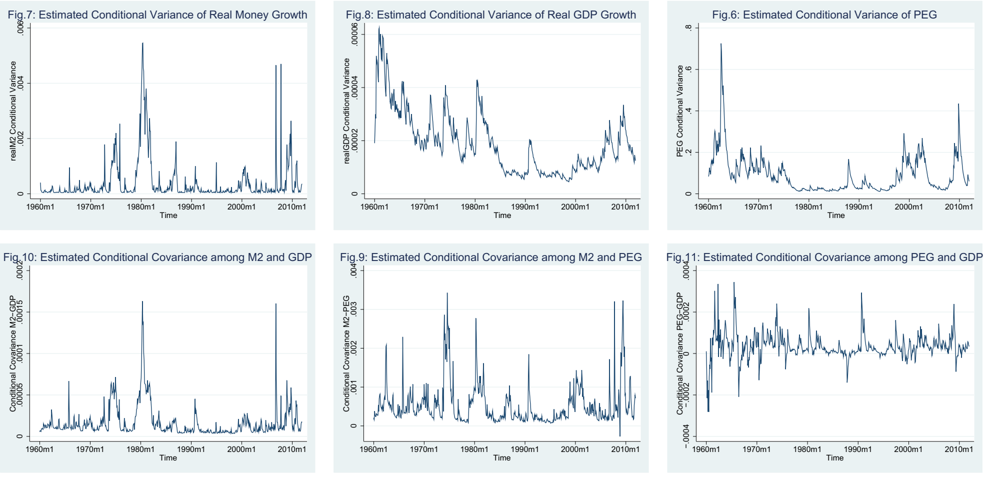


Table 8
Effect of shifts in the monetary policy and financial market regulation.

	Multivariate GARCH DCC with structural breaks					
	PEG		Real M2		Real GDP	
	Mean	Variance	Mean	Variance	Mean	Variance
May 1971	−0.0475	−2.032***	−0.0710***	1.378**	−0.000989	−0.229
	(0.0541)	(0.471)	(0.00266)	(0.678)	(0.000968)	(0.319)
July 1980	−0.0272	−0.167	−0.0238***	−0.533	0.000516	−1.333***
	(0.0591)	(0.502)	(0.00359)	(0.694)	(0.00150)	(0.397)
Apr 1989	−0.0135	0.451	−0.00279	0.728**	−0.000673	0.198
	(0.0339)	(0.438)	(0.00199)	(0.352)	(0.000630)	(0.358)
Sept 2007	−0.0730	1.515***	−0.0159***	0.0314	−0.00255***	1.070***
	(0.0505)	(0.574)	(0.00265)	(0.571)	(0.000835)	(0.362)
LR test statistic	300.3					
P-value	5.28e−49					

Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
The table reports the coefficients of the time dummy in the mean and variance equation. The dummy are constructed to assume value 1 after the date reported and 0 before. The LR test is for the joint significance of the time dummy in all equations.

money growth, whereas the recent financial crisis strongly increased the volatility of PEG index and GDP growth but not money growth volatility.

Additionally to the insights provided on the causal effects of these policies, it is of great interest significance and, hence, the risk of spurious regression bias.

4. Empirical results and further investigations

4.1. First step: variances' estimation

A Multivariate GARCH is estimated to investigate the interrelations among the macroeconomic and monetary uncertainty and to highlight how the financial stability affects both those measures.

Table 9
Conditional covariance estimated from a MGARCH

	Correlations			Dynamics
	PEG-M2	PEG-GDP	GDP-M2	
Constant	0.114** (0.0472)	0.133*** (0.0464)	0.281*** (0.0441)	
lambda1				0.0454** (0.0230)
lambda2				0.664*** (0.127)
Observations				622

Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Estimating the conditional variances and covariances, the very statistical properties of the series, which show time-varying heteroskedasticity, are exploited to obtain the desired measures of uncertainty.

From a preliminary analysis of the results, Table 9 shows that both macroeconomic and monetary uncertainty are positively correlated. This contrasts with the main theoretical models dealing with uncertainty, but it is in line with previous empirical results (for instance, Serletis & Shahmoradi, 2006; Serletis & Rahman, 2009; Cronin et al., 2011). These findings support Friedman's[11] theory, for which in period of high economic uncertainty individuals tend to raise real money holdings, generating an increase in the demand for money. Since it is reasonable to assume that monetary uncertainty has its origins in money growth (Cronin et al., 2011), increasing economic growth uncertainty leads to an adding up in monetary uncertainty.

The results in Table 9 contrast the recent idea that prolonged periods of low money growth volatility may drive periods of large financial instability because of the estimated negative correlations between investors confidence's and money growth volatility. Since both macroeconomic and monetary uncertainty positively co-moves with the financial volatility, the high volatility observed since late 2007 might not be directly imputable to the prolonged period of low monetary and macroeconomic uncertainty, which characterized the last decades of the twenty century and the first decades of 2000's (often called *Great Moderation*). This contrasts partially with the findings in Puhan (2011), which shows inflation and consumption uncertainty (the main determinant of macroeconomics uncertainty) to be negatively correlated with assets valuation and its volatility.

As reported in Table 10, the ARCH and GARCH terms are in general significant for all the variables in the model. Moreover, as in Serletis and Rahman (2009), they sum up to one, suggesting that second order shocks are strongly persistent. Although this is usually a sign of instability of the VAR model, as reported in Table 4, using higher order GARCH models does not improve the conditional variance parameters' estimates and the high persistence of the second order shock remains under alternative specifications of the GARCH model. This might be associated with the local stationarity of the series because few unconditional variances are finite only in shorter periods than the one considered.

As reported in the Table 11, although eventual problems of spurious regressions due to structural breaks in the series, after controlling for the necessary time dummies and, eventually, reducing the sample to the pre-crisis period (i.e. before Sept. 2007), the results are still robust. Although the ARCH and GARCH coefficients are lower in the case inclusive of time dummies in both conditional mean and variance equations, the second order shocks are still estimated to be highly persistent. For what concerns the estimated correlation matrix, the conditional means reported show a small increase if the model is estimated with time dummies in both the mean and variance equations and, hence, the estimated correlation between PEG and M2 is downward biased by the structural changes in monetary policy. The latter result supports several recent theories about the effects of permanent changes in monetary policy over macroeconomic growth and financial stability.

[11] see Friedman (1983) and Friedman (1984).

Table 10
ARCH and GARCH effects estimated from a MGARCH.

	Variance GARCH equations		
	PEG	M2	GDP
L.arch	0.161***	0.861***	0.0856***
	(0.0334)	(0.107)	(0.0254)
L.garch	0.839***	0.118*	0.903***
	(0.0290)	(0.0675)	(0.0278)
Constant	0.00105**	0.0000390***	0.000000227
	(0.000446)	(0.00000772)	(0.000000138)

Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

As highlighted in Papademos (2003), economic cycles are caused by various factors. Monetary policy influences economic cycles by the direct effect on aggregate demand and supply in both goods and financial markets and by affecting expectations and institutions.

Once the effect that permanent changes in monetary policy on expectations and, hence, on investors confidence has been taken out, the correlation among volatilities reflects just the short-run relationship among them. The negative correlation between investors' confidence and real money growth is downward biased by the long-run relationships between the permanent shocks in monetary policy and the investors confidence volatility. Whatever is the effect of a permanent shift in monetary policy on money stock growth volatility, it adds to the investors' confidence's volatility. The modified expectations are negative shocks for the economy and positive second order shocks over the asset markets, affecting both investors' confidence and its stability.

4.2. Second step: Multivariate GARCH-in-mean estimation

A Multivariate GARCH-in-mean model is estimated by a two steps estimator, as proposed by Grier and Perry (1998). In this case, the conditional variances estimated in the first step by a Multivariate GARCH enter the model as dependent variables.

The analysis is based on the Granger-causality tests. A variable Granger-causes another if the former time series is useful to forecast the latter. The test consists in a F-test over the jointly explanatory power of the lagged values of one variable in the equation of another variable. Although simpler correlation tests, as the *t*-test, are the commonly used, the Granger-causality test is preferred because provides indications on the direction of the causality and it is consistent to the use of estimated variables.

Six variables (log(realM2), log(realGDP), D.PEG, hrealM2, hrealGDP and hPEG), along with a constant term, a trend,[12] and the one period lagged estimated conditional covariances from the same GARCH(1,1)-DCC-VAR(12) used to estimate the variances, are included in the equations on which the exclusion tests are undertaken.The equations are estimated with different lag structures (1,2,4,8, or 12 lags). The lags' length is chosen looking at either BIC and AIC criteria or previous literature.

The Chi-squared statistics of Table 12 point out that real GDP growth rate, even in the very short-run, increases after a positive shock to money growth, contrasting the evidence of late response of real economy to monetary policy impulses. Furthermore, the policy response (i.e. an increase in real M2 growth due to the reduction in interest rates) to a negative shock in the real economy has between 8 to 12 months of delay, in the short-run M2 growth and GDP growth positively co-moves. Symmetrically, a similar dynamics is observed for the policy response (i.e. increase of M2 due to the reduction in interest rate) to a positive shock in investors' confidence with at least 12 months of delay. The latter result supports the analysis of Rigobon and Sack (2003), for which the Fed significantly reacts to an

[12] Although the variables considered are either on log or first difference format, it has been necessary to consider a stochastic trend because the log of real GDP shows a stable growing pattern and it is just trend stationary.

Table 11
Multivariate GARCH-VAR(1) with structural breaks.

	No S. Break	With structural break dummies		
	(1) No S.Break	(2) Mean & Var.	(3) Var.	(4) Pre-2008
ARCH_PEG				
L.arch	0.161***	0.151***	0.147***	0.140***
	(0.0334)	(0.0341)	(0.0331)	(0.0330)
L.garch	0.839***	0.804***	0.806***	0.818***
	(0.0290)	(0.0363)	(0.0357)	(0.0369)
Const.	0.001**	−4.356***	−4.352***	−4.445***
	(0.0005)	(0.376)	(0.372)	(0.397)
ARCH_M2				
L.arch	0.861***	1.122***	1.007***	1.150***
	(0.107)	(0.141)	(0.0881)	(0.153)
L.garch	0.118*	0.0350	−0.0223**	0.0453
	(0.0675)	(0.0471)	(0.00945)	(0.0506)
Const.	0.000***	−11.54***	−12.09***	−11.67***
	(0.0000)	(0.423)	(0.416)	(0.492)
ARCH_GDP				
L.arch	0.0856***	0.0617**	0.0765***	0.0601**
	(0.0254)	(0.0243)	(0.0265)	(0.0263)
L.garch	0.903***	0.859***	0.839***	0.872***
	(0.0278)	(0.0477)	(0.0527)	(0.0504)
Const.	0.000	−12.77***	−12.57***	−13.04***
	(0.0000)	(0.500)	(0.514)	(0.564)
Corr(PEG,realM2)				
Const.	0.114**	0.123***	0.109**	0.124**
	(0.0472)	(0.0472)	(0.0480)	(0.0545)
Corr(PEG,realGDP)				
Const.	0.133***	0.132***	0.134***	0.148***
	(0.0464)	(0.0467)	(0.0473)	(0.0548)
Corr(realM2,realGDP)				
Const.	0.281***	0.327***	0.279***	0.315***
	(0.0441)	(0.0450)	(0.0454)	(0.0515)
Corr.Dyn.				
lambda1	0.0454**	0.0363	0.0572**	0.0325*
	(0.0230)	(0.0237)	(0.0251)	(0.0193)
lambda2	0.664***	0.727***	0.650***	0.844***
	(0.127)	(0.204)	(0.127)	(0.0916)
S.Breaks	No	Yes	Yes	Yes
Lags	Yes	Yes	Yes	Yes
N	622	622	622	572

Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
S.Break: Mean and Var = structural break dummy in both mean and variance eq., Var just in variance eq.
Means equations not reported. In all equations there are lags 1,2 and 12 of the 3 series. RealGDP eq. own lags are 1/12.

increase in the S&P500 index by cutting the interest rate, but only to the extent warranted by offsetting the pass-though to aggregate demand.[13]

Both money growth volatility and macroeconomic volatility negatively affect both money and output growth rates in the medium-long run (i.e. after at least 1 year), as it has been found in a large swath of literature (i.e.Fountas et al., 2006; Fountas & Karanasos, 2007; Serletis & Rahman, 2009). Whereas, in the short-run money stock uncertainty does not explain the dynamic of money and output growth, while macroeconomic uncertainty strongly influences the dynamic of those variables.

[13] See Rigobon and Sack (2003) for further considerations on the implicit role of assets price in monetary policy decisions.

Table 12
Granger-causality test.

Excl.	Equation						
	Lags	realM2	realGDP	PEG	hrealM2	hrealGDP	hPEG
RealM2	1		134.22***(+)	1.6372(−)	.1127(+)	2.0231(+)	.41333(+)
	2		134.22***(+)	3.4042(−)	38.839***(−)	2.5319(+)	4.0268(+)
	4		198.19***(+)	4.2613(−)	45.4***(−)	10.813**(+)	16.322***(+)
	8		112.09***(+)	12.071(+)	56.257***(−)	19.266**(+)	28.563***(+)
	12		107.09**(+)	21.353**(+)	59.592***(−)	30.573***(−)	30.078***(+)
RealGDP	1	8.5221***(+)		2.7025*(−)	.27041(−)	26.427***(−)	2.1399(−)
	2	5.0756*(+)		2.0004(−)	12.866***(=)	26.828***(−)	3.2614 (−)
	4	15.632***(+)		1.8204(−)	18.352***(=)	34.805***(−)	5.5512(−)
	8	61.856***(=)		13.284*(−)	25.495***(+)	48.593***(+)	9.6781(−)
	12	426.06***(−)		24.807**(−)	22.332**(+)	55.098***(−)	14.675(−)
PEG	1	2.3347(−)	6.5898***(+)		.23725(−)	.89365(−)	86.077***(−)
	2	2.6711(−)	7.6522**(+)		2.2095(−)	.31927(−)	78.64***(−)
	4	2.0383(−)	6.5383(+)		2.0999(−)	1.525(−)	87.048***(−)
	8	8.6242(−)	10.317(+)		10.327(+)	15.863**(−)	125.95***(−)
	12	77.884***(+)	16.387(+)		15.73(+)	17.426(−)	134.77***(−)
HrealM2	1	.55841(−)	.1983(−)	.67089(−)		6.9649***(+)	1.8065(+)
	2	3.1815(−)	1.339(−)	.70193(−)		8.3186**(+)	6.6863**(+)
	4	2.9321(−)	1.5955(−)	1.156(−)		12.492**(+)	4.0075(+)
	8	7.2226(−)	15.924**(−)	3.7793(−)		16.334**(+)	12.534(+)
	12	31.154***(−)	19.177*(−)	11.306(−)		24.439**(+)	11.264(−)
HrealGDP	1	7.6378***(+)	8.0936***(−)	.001(−)	1.7101(−)		2.4546(+)
	2	6.6915**(+)	11.96***(−)	3.0641(−)	4.9303*(−)		7.1893**(+)
	4	10.315**(+)	20.688***(−)	4.9235(−)	14.249***(−)		11.911***(+)
	8	13.906*(+)	28.07***(−)	13.982*(−)	22.806***(−)		25.867***(+)
	12	170.92*(−)	22.724**(−)	21.159**(−)	29.106***(−)		66.921***(+)
HPEG	1	.27955(+)	.27955(−)	.25111(+)	.31743(−)	1.9787(−)	
	2	.24716(−)	.62112(−)	3.2086(+)	.50134(−)	3.7102(−)	
	4	18.691***(+)	5.1598(−)	3.2961(+)	.88533(−)	5.0664(−)	
	8	22.102***(=)	3.7796(+)	5.6162(−)	7.0391(+)	12.44(−)	
	12	109.73***(+)	7.8141(−)	11.364(−)	11.627(+)	17.796(−)	

Numerical entries are chi2-statistics. The 2nd column gives the # of lags in the causality tests.
+ (−) indicates that the sum of the causing variable is positive (negative). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

However, in the short-run, while the impact on output growth is negative as in the long-run, the impact on money stock growth is reversed and, hence, positive. The positive sign for money growth and the negative one for output growth are in line with the findings of Serletis and Rahman (2009) and support the theory of Choi and Oh (2003), for which output volatility affects money demand, consumption and output mainly through the wealth channel, but the final effect depends on assets' price volatility. Since macroeconomic uncertainty significantly Granger-causes financial stability, with positive co-movements between uncertainty proxies at any lags length considered, and this is not supported for what concerns the effect of money growth volatility, the prevailing pass-through of a second order shock in output growth is the precautionary effects, due to high assets price volatility contemporaneously generated. Indeed, in a environment with high assets volatility, the substitution between risky assets and money overrules the one between money and consumption.

The results partially contrast what found by Mascaro and Meltzer (1983) and Puhan (2011) because only output growth volatility negatively Granger-causes investors' confidence just in the medium-long run and, hence, assets price. Symmetrically, high values for PEG are not able to explain neither output growth nor money growth uncertainty, but only assets price volatility. Furthermore, high money growth, although at the basis of low monetary uncertainty, increases both financial volatility and macroeconomic uncertainty in the medium-long run (i.e. after at least 4 months). These findings contrast with the analysis of Bekaert et al. (2010) and Jovanovic (2011), for which monetary policy influences assets price and its volatility by the direct effect on risk aversion.

In line with the preliminary analysis, which pointed out a positive correlation between real money growth volatility and real GDP growth volatility,the second-step results highlight a reciprocal direct positive causality between these two variables, more than through movements in money growth, as previously found in literature (i.e. Serletis & Rahman, 2009; Cronin et al., 2011). Although the preliminary analysis pointed out the correlation between PEG and GDP growth volatility to be positive, the variability of GDP growth positively Granger-causes the variability of PEG, but the latter does not Granger-causes output uncertainty. However, financial uncertainty affects both monetary and macroeconomic uncertainty just through movements in money growth. Following Bekaert et al. (2009), the positive correlation between dividend volatility and assets market volatility justifies the positive sign of the coefficients of the lagged output volatility in the PEG volatility equation. Whereas, the negative correlation between financial markets uncertainty and consumption, and the positive one of the latter with its volatility can explain the negative sign of lagged PEG uncertainty in both money growth and GDP growth uncertainty equation. However, this latter effect is not statistically significant.

5. Conclusions

This paper investigates how assets valuation affects the relationship among monetary policy and macroeconomic growth. The focus has been on the role of uncertainty. The heteroskedasticity of the employed time series suggests to estimate the uncertainty measures endogenously by a Multivariate GARCH.

Accounting for the main structural shifts in monetary policy and financial markets regulation, the estimates support the strand of literature in favor of a more output stability-oriented monetary policy. After correcting for the main structural breaks in the monetary growth and investors' confidence conditional variance's series, the results challenge the main literature over the topic. Previous analysis show how monetary and macroeconomic growth stability, high correlated among themselves, could eventually lead to high financial instability, as happened during the *Great Moderation*: lowering output volatility reduces both monetary and financial volatility, but the lower monetary uncertainty might increase financial volatility more than the initial drop. On the contrary, this investigation provides evidence that joint stability of money and economic growth eventually drives high stability in the financial markets

The first part of the analysis highlights a positive correlation between money growth's and PEG's volatility and positive co-movements between the proxy for macroeconomic uncertainty with both the proxies for monetary uncertainty and investors' confidence volatility. The second step disentangles the sources of such co-movements by showing that second order shocks on GDP growth directly and positively affect PEG's volatility but the reversal is not true. Whereas, monetary uncertainty affects financial markets volatility indirectly just through the effect on both money growth and assets price. Combining these results, it is possible to state that a prolonged period of low output growth volatility, as the one observed in the US from 1980s after the Volker's shift in the monetary policy (i.e. *Great Moderation*), typically does not drive a period of high financial markets volatility, as the one observed during the last years. This result holds even if the source of the low output growth volatility might be mainly attributed to a period of low money growth volatility (i.e. due to favorable economic environment, low inflation volatility or passive monetary policy) because the indirect effect that money growth uncertainty has on financial stability mainly transmits through macroeconomic uncertainty, assets price and money growth with the former usually prevailing.

These results, jointly with the first step analysis of the estimated correlations matrix, partially contradict the theory that the passive Fed's behavior during the *Great Moderation* period has been among the main causes of the recent financial turmoil. After the initial high financial volatility due to the change in the monetary policy, low macroeconomic uncertainty led to low assets markets volatility without counter-effects due to low monetary growth volatility.

Furthermore, by employing a two-step GARCH-in-mean estimator for the relations between both the conditional means and the conditional variances, this analysis has disentangled the puzzle in a deeper way. Few additional findings of interest are summarized below:

- Supporting the results in Rigobon and Sack (2003), even if the Fed has not explicitly declared to target assets price, PEG and its volatility are able to explain movements in money growth, at least in the medium-long run.
- In line with the analysis of Jovanovic (2011), monetary policy is able to affect directly both investors' confidence and its volatility only in the medium-long run.
- Supportive of the Black's hypothesis discussed and tested in Fountas and Karanasos (2007), the results show both a negative effect of macroeconomic uncertainty on GDP growth and a negative causality between output growth and its volatility.
- High investors' confidence is able to explain high financial stability, while high macroeconomic uncertainty decreases assets price. Although surprising, these results are supportive of the view on investors' responses to uncertainty proposed by Bird and Yeung (2012). They suggested that investors are always avers to uncertainty and this pessimism grows with the level of uncertainty. However, strong investors' sentiments work to weaken the investors' pessimism, which is usually associated with periods of high uncertainty, and, hence, it smooths the overreactions to bad(good) news.

In conclusion, controlling for the assets price to be closed to its fundamentals is beneficial for the economy but not necessary because smoothing the business cycle is enough for granting a stable system. Even if monetary policy can directly control for assets market and its stability, accounting for the strong correlation with GDP and its volatility, output and price stabilization seem to be sufficient targets. Although the results suggest that is enough to smooth the economic cycle to have quite stable financial markets too, the analysis highlights the relevance of monetary developments for monetary policy because of strong negative correlations between money volatility and both macroeconomic and financial stability.

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