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The effects of QE and monetary policy on implied stock market volatility: a VAR approach

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[1] The thesis contains 16424 words

Executive summary

This thesis aims to investigate the relationships between monetary policy and implied stock market volatility in the euro area. Both types of monetary policies (conventional and unconventional monetary policies) are considered though we put a particular highlight on QE when it comes to explore unconventional effects.

Our work aims to contribute to the growing literature which identifies structural monetary policy shocks from (intra-daily) financial market reactions to central bank announcements. We postulate, as do Jarociński and Karadi (2020), that monetary policy announcements simultaneously disseminate information on monetary policy and the central bank's assessment of the economic outlook. Based on this assumption, we capture and distinguish the respective effects of monetary policy (conventional and unconventional) separately from this information shock by imposing sign restrictions on these reactions of financial variables to the ECB's monetary policy decisions. In addition to this, we refine and distinguish conventional and unconventional monetary policy by imposing sign restrictions on the slope as Goodhead (2019) does. The responses to each shock on implied stock market volatility are then analysed through a VAR model which contains different interest rates measures (short and long), macroeconomic indicators and related stock market variables (Vstoxx and Euro Stoxx 50).

Although our results depend on the specification of the VAR and on the selection of variables, we can suggest from them that implied stock market volatility is particularly affected by the information that investors might receive from a central bank when it motivates its monetary policy decisions. In addition, our results tend to show some degree of pass-through where implied stock market volatility can notably be affected by stock prices and the level of interest rates. These results, although promising, should be taken with caution notably due to the low number of observations we have, their sensitivity to model specification and a possible misidentification of the structural shocks previously mentioned.

Preface

Before beginning this thesis, I would like to make a few preliminary remarks about the research topic developed in this work.

First, as a master student with an orientation in "Macroeconomics and Finance", I wanted to choose a topic in line with the courses I have followed throughout this master's degree. I wanted to find a topic which could in a certain extent make the bridge between my macroeconomics courses (e.g. the "monetary economics" course of Mr. Lejeune but also the macroeconomics courses of Mr. Artige) and financial courses (e.g. the "Financial Derivatives" course of Mr. Hambuckers).

In addition, it was important for me to use and extend some of the econometric skills I had previously acquired in another context, in particular the techniques related to VAR models seen with Mr. Lejeune. Therefore, the techniques and methods developed in this work are in a way a continuation of what I have learned.

Finally, I wanted to provide some precisions concerning the statistical software used for this work. According to the different stages of this thesis and for practical reasons, I decided to use Matlab, Stata and Gretl.

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List of abbreviations

AIC - Akaike Information Criteria

APP – Asset Purchase Program

CLT – Central Limit Theorem

CTM – Closest-to-median

ECB – European Central Bank

EME – Emerging Market Economy

ETF – Exchange Traded Funds

EU – European Union

HICP – Harmonised Index of Consumer Prices

IRF – Impulse response function

MP (shock) – Conventional monetary policy (shock)

OIS – Overnigh Indexed Swap

OLS – Ordinary Least Squares

QE – Quantitative Easing

UK – United Kingdom

UMP (shock) – Unconventional monetary policy (shock)

US – United States

VAR – Vector Autoregression

ZLB – Zero Lower Bound

1. Introduction

In recent years, monetary policy has continuously evolved. Since the episode of the financial crisis in 2008, we have seen the emergence of new unconventional measures with QE at the forefront. The introduction of those unconventional measures has been motivated by the apparition of the "zero lower bound" limit, a situation where central banks have seen their reliance on their policy rates and conventional tools reduced.

It is well known that monetary policy has several roles to play in the financial system and more generally in the economy. One of them is that monetary policy has the power to guide people's expectations and to restore confidence about future economic and financial developments. If we focus on financial markets, it is important as a policymaker to control or monitor investor sentiment and expectations.

First, we know that stock market developments are particularly influenced by investors' expectations about it, which means that a policymaker, since a central bank can influence these expectations, can prevent possible situations of imbalances in the financial system and financial instabilities. This could happen if, for example, investors are overconfident about the real health of the stock market based on economic fundamentals pushing stock prices to an abnormally high level. Besides these stability reasons, looking at stock market sentiment and expectations can be interesting for the effectiveness of the transmission of monetary policy, since stock markets play a role in the monetary policy pass-through.

The literature has so far put in evidence the effects of monetary policy mainly on interest rates or on real macroeconomic variables (e.g. Beyer and al., 2017; Altavilla and al., 2015), highlighting in particular the presence of several monetary transmission mechanisms. While some authors (e.g. Bernanke & Kuttner, 2005; Bomfim, 2003) have considered and explored the link between monetary policy and the stock market, studies focusing on the link between implied stock market volatility (expected volatility) and monetary policy are less extensive. This measure reflects investor sentiment and expectations regarding the future development of stock prices. Since we know that monetary policy can affect stock markets and other macroeconomic indicators notably through interest rates and other transmission mechanisms, it could be interesting to explore possible links between monetary policy and this last metric.

For these reasons, this work aims to contribute to this field of research present in the literature. We will explore the eventual relationships between conventional and unconventional (in particular QE) policies on implied stock market volatility.

How and why does the stock market react to new monetary policy developments? Is it because of the expected consequences that a monetary policy may entail or because monetary policy decisions convey other sources of information about future economic prospects? What are the drivers of these implied volatility responses and market anticipations? Are there differences between conventional and unconventional monetary policies? These types of issues will be addressed in our analysis.

Our work will be detailed as follows. First, we will review some theoretical concepts by describing the main transmission channels of monetary policy for each type of policy in order to get a first idea of how and why implied stock market volatility can be related to monetary policy innovations. As this thesis also focuses on QE when considering non-conventional measures, a brief summary about its implementation in Europe will be added. The following section will be devoted to a review of the empirical literature with the objective of highlighting the two main existing methodologies when it comes to analyse the impacts of a monetary policy. Next, we will describe our methodology and the data used to perform our analysis. After presenting the baseline results, we will perform some robustness diagnostics to check the consistency of our results. Finally, we will devote a section to some of the monetary policy implications of our results.

2. Background and theoretical foundations

To begin this thesis, it is important to have a better understanding of the different types of monetary policies (conventional vs unconventional) and the reasons why an unconventional monetary like QE has been implemented by the ECB. In order to do so, I have decided to devote this section to laying some theoretical foundations and providing some background on conventional and non-conventional measures. Because this thesis focuses particularly on QE when talking about unconventional monetary policy, a brief summary regarding its implementation will also be added.

Many questions will be treated: How QE has been materialized in Europe? Why central banks decided to implement QE and unconventional measures? What are the main transmission channels of unconventional monetary policy and QE? Are they different from other types of monetary policies?

Answering these questions is crucial to perform our further VAR analysis. The methodology and the role of the VAR will be discussed in a further section. However, this introduction will help us to choose correctly the relevant variables in order to:

- properly identify "QE" and more generally unconventional shocks in the data from other sources of shocks (mainly conventional ones);
- select the relevant period for this analysis when it comes to "target" QE;
- have a first guess of how monetary policy and implied stock market volatility can be linked.

2.1 How and why QE was implemented in Europe?

Quantitative Easing has been implemented in Europe but also in US, England and Japan. However, there exist some differences in the way this monetary policy has been conducted by those central banks. Table 1 gives more insight regarding this.

Table 1: The different mandates of some major central banks

Central bank	Source	Mandate
US Federal Reserve	Federal Reserve Act 1977	'The Board of Governors of the Federal Reserve System and the Federal Open Market Committee shall maintain long run growth of the monetary and credit aggregates commensurate with the economy's long run potential to increase production, so as to promote effectively the goals of maximum employment, stable prices and moderate long-term interest rates.'
Bank of England	Bank of England Charter 1998	'In relation to monetary policy, the objectives of the Bank of England shall be – (a) to maintain price stability, and (b) subject to that, to support the economic policy of Her Majesty's Government, including its objectives for growth and employment.'
European Central Bank	Lisbon Treaty 2009	'The primary objective of the European System of Central Banks ... shall be to maintain price stability. Without prejudice to the objective of price stability, the ESCB shall support the general economic policies in the Union ... The ESCB shall act in accordance with the principle of an open market economy with free competition, favouring an efficient allocation of resources.'

Sources: Federal Reserve, Bank of England, European Commission.

Source: Oxenford, 2016.

As we can see on the table, the mandate of each central bank is different meaning that their monetary policy strategy and their expected objectives are different. For example, if we put the focus on the ECB and the Fed, we can see that even though both central banks share a common objective of price stability, the Fed also pays particular attention to the level of employment and economic activity when conducting its monetary policy.

It is in 2015 and well after the crisis that we have seen for the first time the apparition of QE in Europe. QE is often assimilated and confused with the "Outright Monetary Transaction Program" (OMT) implemented in 2012. These programs are genuinely similar as they both consist in purchasing series of public bonds. Nevertheless, the OMT was designed to face the eurozone sovereign debt crisis (Botta, 2019).

Before what we call "QE", the ECB had already started to implement other types of unconventional programs[2]. These programs were pursued in response to the European sovereign debt crisis and to support countries that seemed to be dysfunctional in their monetary transmission mechanism (Gern and al., 2015).

[2] For more information on unconventional measures implemented by the ECB : https://www.ecb.europa.eu/press/key/date/2017/html/ecb.sp170912.en.html

Among these programs, we can cite:

- The Securities Markets Program (SMP)
- Covered bond purchases
- 12-month and 36-month LTROs

However, these measures are not qualify as QE because as Gern and al. (2015) said: "*the scope and size of the interventions were not pre-announced and the asset purchases were sterilised so that the monetary base would not increase as a result and the overall monetary stance would not be affected*".

The main reason why QE has been implemented in Europe on the 22nd January 2015 was to avoid any eventual risk of deflation or a too low HICP level for a long period (Gambetti and Musso, 2017).

The ECB started to implement QE under the influence of the Bank of Japan[3] and the Fed[4].
The APP of the ECB can be summarized as follows[5]:

- Launch in March 2015 with the purchase of 60 billion per month of public debt securities of euro area's countries;
- April 2016: the volume of asset purchases increased until reaching a level of 80 billion euros per month. Moreover, debt securities of private companies were included in the purchases;
- Progressive "tapering"[6]: the volume of purchases went down gradually (60 billion euros per month, then 30 billion euros per month and finally 15 billion euros per month at the end of 2018).

The total amount of the different APP between 2015 and 2018 was 2562 billion euros. Let's also note that the Greek debt was not part of the program and that the distribution of purchased assets among euro area countries was proportional to their level of economic activity within the union.

[3] Japan introduced QE in 2001.
[4] The Fed introduced QE in 2008.
[5] https://www.lesechos.fr/finance-marches/marches-financiers/le-qe-de-la-bce-resume-en-5-graphiques-238570
[6] Tapering means that a quantitative easing program begins to gradually decrease in intensity : https://www.investopedia.com/terms/t/tapering.asp

At the end of Mario Draghi's mandate, the ECB reintroduced once again a QE policy. The ECB announced that starting from November 2019, a new series of assets purchases would begin for a level of 20 billion euros per month and for an undetermined period.

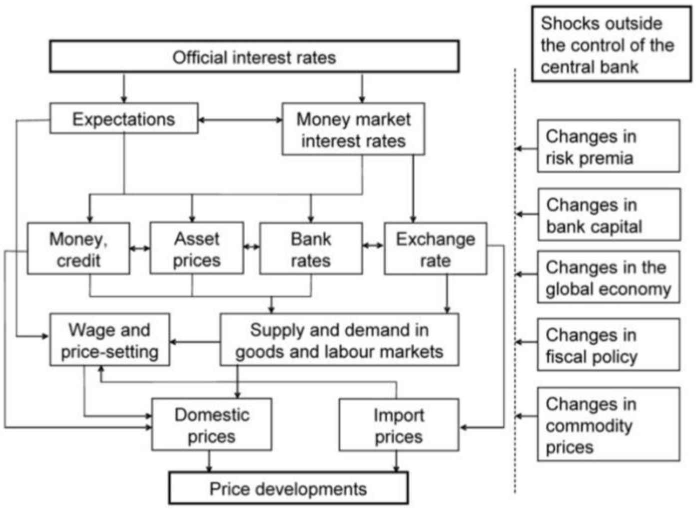
2.2 What are the main transmission channels of monetary policy?

The monetary transmission mechanism

The transmission mechanism of monetary policy describes how a monetary tool can influence indirectly and through several specific channels some real economic variables. It is important to note that conventional tools require different channels from unconventional ones.

The figure 1 is a synthetic representation of how central banks can attain their mandate objectives trough the monetary transmission mechanism. As we can see on the figure, this process is quite complex, long and involves a lot of variables.

Figure 1: A synthetic monetary transmission mechanism



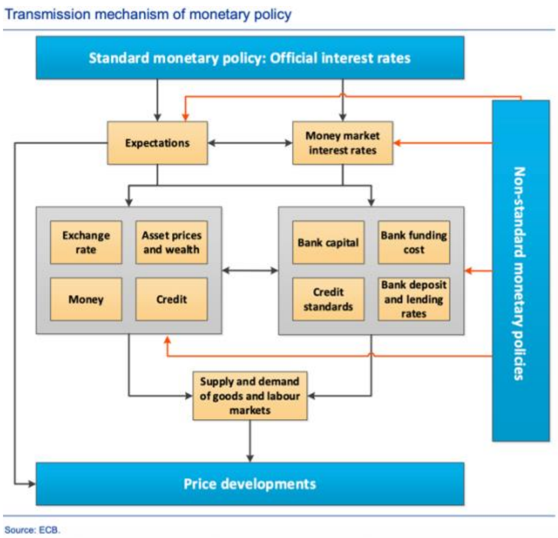
Source: ECB[7]

[7] https://www.ecb.europa.eu/home/html/index.en.html

However, if we have a look at figure 2, we can spot the major differences in the monetary transmission mechanism between conventional and unconventional measures. The black arrows show the transmission channels of conventional monetary policies and the red ones show those of unconventional measures. These channels involve plenty of changes in:

- Official interest rates
- Expectations
- Financial market and banking system conditions
- Etc.

Figure 2: Channels of unconventional vs conventional measures



Source: Beyer and al. (2017)

The different transmission channels

All of these changes and channels are expected to have an impact on economic activity and hence on inflation over time. Beyer and al. (2017) cite the main monetary transmission channels, which are grouped in Table 2.

Table 2: The major transmission channels

Transmission channels

Transmission Channels	Description
Interest rate	Policy measures have an impact on money market rates, bank funding costs and saving and borrowing costs
Money	Changes in money supply affect liquidity conditions in the economy which may affect spending
Exchange rate	Affects price of imports and competitiveness
Asset price and wealth	Asset prices react to policy changes with implications for wealth due to valuation effects
Balance sheet and profitability	Changes in policy affect private sector balance sheets, net worth and collateral value
Bank funding and lending	Changes in policy affect bank lending supply and demand
Bank capital	Changes in policy have implications for bank capital and profitability
Risk-taking	Search for yield and lending behaviour. Accommodative policy for too long a period can create incentives for more risk-taking
Expectations	Influence private sector long-term expectations including by signalling the future policy course

Source: ECB.

Source: Beyer and al. (2017)

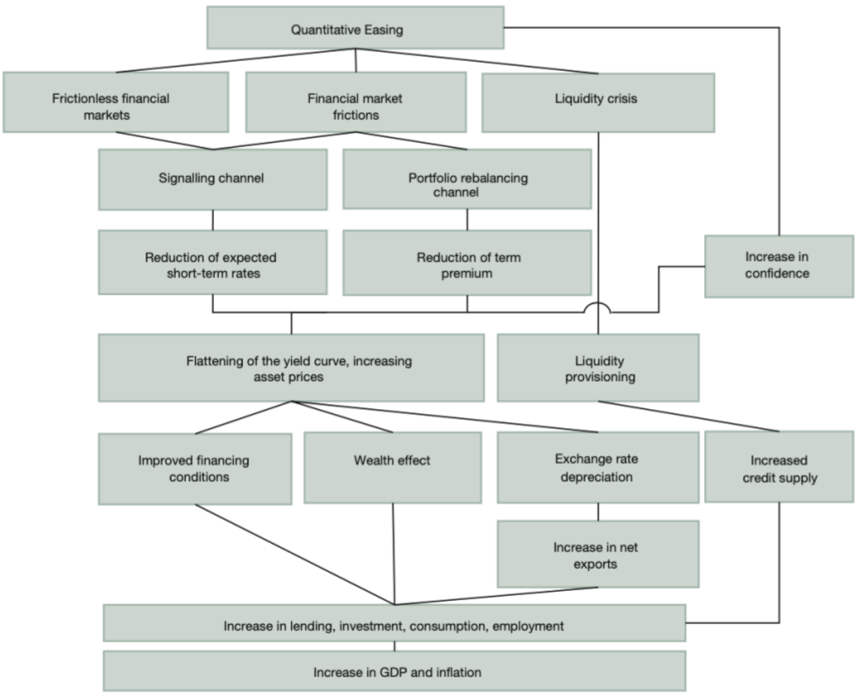
At first glance, these channels appear to be different in terms of their respective effects and their function in the monetary transmission mechanism. However, it is really difficult to untangle these channels because they are actually interconnected and they can affect some common economic variables. Among all these different channels, we can highlight one in particular: the interest rate channel.

This channel is often discussed when we talk about the transmission of conventional monetary policy. This is often included in the standard courses of monetary economics. This channel can be defined in the next way (Beyer and al., 2017): when central banks decide to change the level of their policy rates, this has an effect on money market rates. Since banks use the money market as a benchmark for setting their deposit and lending rates, the lending and deposit rates offered to customers are indirectly influenced by changes in short-term interest rates (money market rates). In addition, long-term yields could react to changes in short-term yields due to the expectations hypothesis of the term structure of interest rates. If for example short term interest rates decline due to an expansionary policy, agents could believe that this change will persist in the future and by consequent the level of long-term interest rates will also decline. These nominal interest rates changes will have an impact on real interest rates in the short run due to the presence of a certain prices rigidity. Consequently, economic agents see their borrowing conditions revised and this affects their consumption and investment decisions. At the end, all of this should support aggregate demand, economic activity and alter the prices dynamics. However, in the low interest rates context we face today, policy makers can’t expect too much from this channel and therefore they have to find other ways to attain their mandate's economic objectives. This explains why central banks have introduced progressively unconventional tools.

The channels specific to QE

As we can see on figure 3, the transmission of QE involves also a lot of intermediaries and variables. Among the different QE transmission channels often discussed in the literature, two main channels dominate (Gambetti and Musso, 2017): the portfolio rebalancing channel and the signalling channel.

Figure 3: The transmission channels of QE



Source: Gern and al. (2015)

<u>The portfolio rebalancing channel</u>

Let's begin with the portfolio rebalancing channel. When a central bank decides to buy massively specific assets like for example T-bonds with new money, the prices of those securities increase and their yields decline. Let's note that contrarily to the signalling channel which we'll discuss later, the portfolio rebalancing channel requires the presence of financial market frictions to be effective. Indeed, the latter is only effective if financial assets are not perfectly substitutable. In this situation, changes in relative supply between long-term and short-term bonds can have an impact on the yield curve. By consequent, when a central bank decides to buy long-term bonds, the supply of long-term bonds increases relatively to short-term bonds causing a lowering in the longer maturity bonds term premium (Gern and al., 2015).

Consequently, investors decide to rebalance their portfolio (e.g. because the duration of those securities has changed, because they find other assets with better risk adjusted returns, etc.) towards riskier securities (the risk-taking channel) like equities or other bonds (Gambetti and Musso, 2017). By arbitrage, a large range of financial assets see their prices increase and their yields decrease. These developments (asset price increase, compression of the yield curve, etc.) have consequences notably on households, companies and banks.

Assets price movements create some wealth effects for households. Then, households might choose to consume or invest more because of their larger financial wealth (Beyer and al., 2017). We might wonder why that would happen. In classical economic theory, the decisions of economic agents about consuming and investing can be derived by a utility maximizing problem under constraints. The presence of wealth effects relaxes some of these constraints (budget constraints) and consequently, agents decide to consume more in order to have a greater utility.

Companies are able to finance their investments at lower cost (because of the reduction of long-term yields) and therefore a lot of investments opportunities emerge because they have now a positive "Net Present Value". Moreover, due to the rise in asset prices, companies have a greater amount to pledge as collateral when they borrow from banks. In general, financing conditions are favourable to support investments for companies (Beyer and al., 2017).

Because long term yields are lower, banks can finance their volume of credits at lower costs not only thanks to deposits but also by borrowing on financial markets. In addition, rising asset prices facilitate access to funding for banks because their collateral assets have now a higher value. As we can see, the effects of the portfolio rebalancing channel on banks can be connected with the ones of the broad credit channel present in the literature. According to Gambetti and

Musso (2017), the increase in lending supply resulting from asset purchases is caused indirectly by the induced effects of the portfolio rebalancing channel. Therefore, this channel comes after in the "transmission chain" and can be included in the more general class "portfolio rebalancing channel". However, the direct pass-through channel between APP and bank lending can exist in a lower extent if for instance the asset purchases concern asset-backed-securities. In this case, the price of those targeted assets would increase, encouraging banks to increase the amount of securitized loans which would lead to lower lending rates.

When considering the transmission channel between QE policies and financial markets, there is an evidence that the portfolio rebalancing channel is one of the most important channels (Gambetti and Musso, 2017). This is supported by Altavilla and al. (2015) for the euro area; Joyce and al. (2011) for the UK; and Gagnon and al. (2011) and D'Amico and al. (2012) for the US.

The signalling channel

The other major channel of transmission concerning QE is the signalling channel.

The signalling channel relates central banks actions to expectations about inflation and output. Conventional tools (interest rate cuts) or unconventional ones (APP, NIRP, etc.) can be considered in reality as signals or messages sent by a central bank about its ambition and ability to maintain inflation and output in its mandate's objectives. On the other side, economic agents interpret this signal and consequently revise their future expectations about inflation and output following this monetary policy decision. As we have seen in Figure 1 above, expectations are also important concerning the monetary transmission mechanism effectiveness.

Furthermore, the importance of the expectations can also be seen in the "Basic New Keynesian model" proposed by Gali (2015) in which he shows the links between business cycles (output gap), inflation dynamics and monetary policy responses.

The link between monetary developments and inflation expectations that we have explained so far can be related to what we call the inflation re-anchoring channel. This channel can be included in the signalling channel category (Gambetti and Musso, 2017).

In the case of QE, the signalling channel can be taken into account since the APP can signal a central bank's commitment to pursue an accommodative policy in the future in order to achieve its price stability objectives. The signalling channel is also particularly present under forward guidance policy which is another unconventional monetary tool from the toolbox. The primary purpose of this policy is to guide the expectations of economic agents by communicating on central bank's future intentions regarding its monetary policy decisions. For this policy to be effective, it is essential that the central bank be credible in what it announces to the public. This underscores how QE and forward guidance are linked. APP can be considered as a way for central banks to reinforce their credibility when they decide to implement forward guidance. After receiving this "message", agents should revise their expectations concerning the future path of inflation and the future conduct of monetary policy, this affecting a large variety of long-term interest rates we can find on financial markets. This will in turn as we have seen above stimulate other channels and help the monetary policy transmission.

Other effects

As we can see on Figure 3, QE can also have an effect on exchange rate depreciation, as a result of the portfolio rebalancing channel. Indeed, when a large variety of domestic asset prices increases resulting from the portfolio rebalancing channel, this can lead to an increase demand for external assets by domestic residents or a return of funds from non-residents (Gambetti and Musso, 2017). All of these flows of funds lead to exchange rate depreciation.

By depreciating its currency, a central bank can make exports relatively cheaper and imports relatively more expensive from an international perspective. This should help to increase a country's trade balance and support aggregate domestic demand.

2.3 Why monetary policy can be linked to implied stock market volatility?

Before going deeper into our thinking and analysis, it is important to first ask why and how implied stock market volatility may react to monetary policy.

Implied volatility has not to be confused with realized (past) volatility. From a financial point of view, (realized) volatility is sometimes associated to big and frequent variations in asset prices and can be considered as a risk measure for an asset. In contrast implied volatility doesn’t tell us how markets reacted yesterday and today but how they might react in the future. We attribute the name “implied” to volatility because this measure is derived from option prices. Therefore, this measure has the power to reflect investor expectations and their future sentiment about financial markets and economic outlook.

We have seen in particular through the signalling channel and through the synthetic monetary transmission mechanism that monetary policy influences notably expectations. In addition, we know that monetary policy and QE affect financial markets directly or indirectly through the monetary transmission mechanism. Consequently, we may wonder if there is a direct link between monetary policy and this implied volatility measure.

However, a fundamental question for this analysis is still outstanding. What does affect the financial markets the most? Is it the effect of the policy announcement or its implementation? Which effect can be considered as a surprise for financial markets? These questions are important because they will help us to identify properly monetary policy innovations in the data.

Let’s remind that we are interested in studying the impacts of a shock, something that from a statistical point of view is purely stochastic and not anticipated. Financial markets are more likely to be "surprised" after an announcement of a QE policy or a cut in policy rates than when a central bank actually buys certain bonds and increases its balance sheet, although this surprise effect may disappear with repeated episodes. In order to study proper causal effects, a policy must not be endogenous to other economic variables entering in a statistical regression. With central bank announcements, identification problems can be mitigated because we can isolate unexpected variation in monetary policy and by consequent, we are more entitled to interpret causality (Jarociński & Karadi, 2020).

If we focus on QE in particular and its two main channels, we can claim several things. The portfolio rebalancing channel and the signalling channel can be considered once a QE episode is announced. As we have seen, the signalling channel is a transmission particularly active under forward guidance policy. Therefore, its effects can be considered more significant after an APP announcement than after its implementation. The reaction of financial markets to a "QE signal" depends on how they interpret it. QE can be viewed positively because it signals an expansionary policy and can, to some extent, restore some confidence, thereby reducing uncertainty about future monetary and macroeconomic developments. By consequent, stock markets can be enthusiastic about the prospects ahead. In addition, financial market professionals anticipate future monetary and macroeconomic developments when managing their positions and asset portfolios. A lot of their decisions are taken according to their expectations on the market. Even though the effects of the portfolio rebalancing channel are at first glance the result of a QE implementation, we can suppose that investors start rebalancing their portfolio already after a QE policy announcement.

Unlike other studies, the main objective of this work is not really to analyse the impacts of monetary policy on real economic variables such as the level of employment or GDP growth. The emphasis is placed on studying financial markets developments and especially its nervousness through volatility indexes.

For all these reasons, we will consider for this work that the effects of monetary policy on financial markets come into play as soon as it is announced and not after its implementation. The identification of QE policies (unconventional monetary policies) from other types of monetary policies in the data will be done in this spirit.

3. Related empirical literature

This section provides a brief overview of common practices for identifying and assessing the impacts of a monetary shock. When it comes to study empirically the impacts of a monetary shock on certain variables, two major trends emerge in the literature (Potters & Smets, 2019) and (Balatti and al., 2016).

The first one is the use of VAR-type models. A VAR model is an econometric method used to relate a set of endogenous variables to each other and that allows to study the dynamics of these variables following an exogenous shock (e.g. a monetary policy shock) through impulse responses. Further explanations and theoretical concepts about VAR models will be presented in a further section. This approach is really flexible and can be used to study the effects and transmission channels of an (un)conventional monetary policy shock.

Although this type of literature was already well established before the financial crisis and the introduction of unconventional measures (notably with Bernanke and al., 2005; Thorbecke, 1997; Bjørnland & Leitemo, 2005), this method has been used to a greater extent to study the effects of unconventional tools like QE in a ZLB environment. This explains why the literature review below enumerates mainly studies focusing particularly on QE and unconventional policies.

These authors used VAR models as a practical way to identify (conventional) monetary policy shocks and to study their effects on different variables of interest. Moreover, Bjørnland & Leitemo (2005) and Thorbecke (1997) have research questions that are to some extent close to our own, since they focus their analysis on equity markets and the effects of monetary policy on them.

This approach despite being used for a variety of specific reasons by researchers has not really been used specifically to study the effects of monetary policy on stock market stress or implied stock market volatility. As an exception we can cite Bekaert and al. (2013) who investigate the monetary policy effects on the VIX[8] index through a VAR approach. After decomposing the

[8] The VIX index is an implied volatility index established by the Chicago Board Options Exchange (CBOE). This index is calculated from the option prices on S&P 500 index.

VIX into two components, they conclude that monetary policy can impact this metric through two main factors: risk aversion and uncertainty. Their results show that an expansionary monetary policy reduces particularly risk aversion but also uncertainty. By consequent this "uncertainty" and "risk aversion" measure can in a certain extent be associated respectively with the signalling channel and the portfolio rebalancing channel we exposed so far supporting our early insights on how monetary policy can affect stock market and investor behaviour. This view is also supported by Nave & Ruiz (2015), who found that Europeans' risk aversion is reduced after an easing of monetary policy.

Among researchers who focused on the effects of QE and unconventional monetary policies particularly under the VAR approach, we can cite Gambetti & Musso (2017), Balatti and al. (2016), Belke and al. (2017), Gambacorta and al. (2014), Schenkelberg & Watzka (2013), Bhattarai and al. (2015), Tillmann (2016), Meinusch & Tillmann (2016).

Belke and al. (2017) analyse the effects of Federal Reserve's QE on international interest rates differentials. In their paper they show that long-term interest rates followed a global downward trend before the financial crisis and the introduction of unconventional measures. Moreover, according to them, bonds purchases made by the FED didn't alter this global downward pattern.

VAR models have not only been used to study interest rate dynamics. Tilmann (2016) and Bhattarai et al. (2015) studied the potential international spillovers that US QE can generate. Tilmann decided to integrate a "Qual VAR" which gives a binary information of QE announcements into a standard VAR as a way to identify QE shocks and to resolve endogeneity problems. His low-frequency VAR (standard VAR) includes U.S. and emerging market economic variables. The results of his study suggest that QE has impacted the financial conditions of emerging market economies and has played a role in explaining capital inflows, equity prices and exchange rates. Bhattarai and al. (2015) contrary to Tilmann didn't identify QE shocks from the announcement dates. Indeed, they first identified US QE shock by using a Bayesian VAR including macroeconomic and financial variables. Once this shock identified, they integrated this one into another (Bayesian) VAR model containing emerging market economies in order to capture any potential spillovers. Their study suggests that the U.S. QE

(https://financial-dictionary.thefreedictionary.com/VIX+Index) had impacts on financial variables in EMEs, such as a reduction in their long-term bond yields, an increase in their stock prices and an increase in capital inflows to these countries.

Gambetti & Musso (2017), Balatti and al. (2016), Schenkelberg & Watzka (2013), Meinusch & Tillmann (2016), Gambacorta and al. (2014) used VAR models to study QE real macroeconomic effects respectively for EU, UK, Japan, US and a panel of countries. Although these authors differ in their approach and in the identification of QE shocks, all these studies support the fact that QE has had real effects in supporting economic activity and inflation.

The other major empirical alternative is the event study approach. This method consists in analysing high frequency data movements taken for a short time window in which a particular event takes place (e.g a monetary policy announcement). In contrast to VAR models which identify monetary shocks from a system of variables following an autoregressive model, the event study approach consists in analysing data movements at the time where an exogenous (i.e. unexpected) shock is supposed to take place. However, some criticisms can be made about this method. Event studies are based on the idea that all asset price changes observed during the window of the event are only caused by the announcements, which could be questionable if central banks were to announce a different set of measures at the same time. Moreover, the observed market reaction could be motivated by other factors such as a reassessment of the macroeconomic outlook by market participants after the publication of the central bank opinions and not by the monetary shock itself (e.g. a cut in a policy rate).

Unlike VAR models, event studies are less appropriate for studying the presence and magnitude of different transmission channels to real economic variables because it is a "micro" rather than a "macro" type of analysis. Event studies based on QE have been used to study asset prices and interest rates variations in UK and in the US notably with Joyce and al. (2011), Steeley (2015) and D'Amico & King (2013). If we focus not only on unconventional monetary policies, we can cite Rigobon & Sack (2004), Bernanke & Kuttner (2005) who employed an event-study approach to analyse the effects of conventional monetary policy on asset prices.

Joyce and al. (2011) performed an analysis of UK asset prices reaction to Bank of England's QE. On the basis of this analysis, they infer that the £200 billion APP of February 2010 made in UK could have decreased long-term government bonds yields by 100 basis points, with portfolio rebalancing effect as the major impact. Steeley (2015) explored also the behaviour of

UK government bonds before, during and after some QE episodes. In this paper, Steeley also highlights the potential side effects of QE for financial markets. Indeed, he found evidence that investors could still have obtained an abnormal rate of return after deduction of relative costs and expenses during the asset purchase periods. This last point also calls into question the efficiency of financial markets.

D'Amico and King performed a similar analysis by exploring US Treasury Securities after the $300 billion Fed's asset purchases in 2009. In this paper, they conducted an analysis of the price elasticities of those securities as a function of their maturity.

In another spirit, Wongswan (2009) studied the response of global equity indexes to US monetary policy announcements. He found the evidence that foreign equity indexes responded significantly to US monetary surprises in the short run. On average, an unanticipated 25-basis-point cut in Fed's funds rate is accompanied by an increase in foreign equity indexes between 0.5 and 2.5%. This work follows the spirit of Rigobon & Sack (2004) and Bernanke & Kuttner (2005) who demonstrated the existence of a certain link between monetary policy and equity prices. These authors used unexpected changes in futures data to capture monetary policy exogenously[9].

This study confirms also the findings of Bomfim (2003) which stated that surprises in monetary policy decisions tended to increase stock market volatility in the short-term. Moreover, there is an asymmetry in the responses following a monetary surprise: values of federal funds rate higher than previously anticipated have higher incidence on stock market volatility.

To conclude this literature review, I will mention two works which can to a certain extent be characterized as a "hybrid methodology" between the VAR approach and the event study approach. These two works, like most of event-studies, use high-frequency data on financial variables around policy announcements as a way to capture the effect of surprise in the data. However, the identification of shocks is even more precise. Indeed, by using a (Bayesian) structural[10] VAR, they are able to control eventual endogeneity problems and to disentangle pure monetary policy shocks from other innovations that may act at the same time on these

[9] Rigobon and Sack (2002) used the eurodollar futures rate while Bernanke & Kuttner (2005) used federal funds futures data.
[10] The structural approach in VAR models will be discussed in more details in a further section.

same high-frequency data. These papers are the one of Jarociński and Karadi (2020) and Goodhead (2019).

Jarociński and Karadi (2020) claim that central bank's announcements give information about both monetary policy and central bank's sentiment regarding the economic outlook. In this paper, they measured the impact of the monetary policy shocks and of the central bank information shocks using a Bayesian structural vector autoregression (VAR) for both US and EU economy.

The inclusion of high frequency financial market surprise variables completes a set of monthly variables including interest rates, price level, economic activity and other financial indicators. These high frequency variables include variations in interest rate derivatives and stock market indexes for both US and EU. The inclusion of high-frequency data is relevant for the identification of the two types of structural shocks they want to focus on. Indeed, it is from these high-frequency surprises that they decided to apply certain sign restrictions on the orthogonal impulse responses[11]. These steps were done with the intention of isolating two types of structural shocks: information shock and monetary policy shock. These two types of shocks are identified by using high frequency co-movement in interest rates and stock prices around policy announcements: a positive monetary surprise (a surprise tightening policy) raises interest rates and decreases stock prices while a positive "information" shock raises both.

Their sign restriction to identify monetary shock is motivated by the fact that a tightening in interest rates decreases stock prices. The present value of these securities decreases due to two main reasons. The discount rate is now higher since both real interest rates and risk premia increase. In addition, the present value can decline as investors anticipate an eventual decline in their payoffs due to the deteriorating economic outlook following a restrictive monetary policy.

Their results suggest that the dynamics of macroeconomic variables is sensitively different according to a response to either the "information shock" or either to a "monetary policy shock". A positive monetary shock (i.e. an increase in interest rates accompanied by a decline in stock prices) tends to contract significantly output and to tighten financial conditions. On the other hand, a positive information shock (i.e. a positive co-movement between asset prices and

[11] These impulse responses are generated through a variance decomposition method called "QR" decomposition.

interest rates) is followed by an increase in short-term interest rates, an increase in the level of price and output and also better financial conditions. In addition, Jarociński and Karadi put into evidence the importance to take into account this "information shock" when it comes to properly identify a monetary shock. Indeed, the identification problems often mentioned in the literature [12]seem to be in part resolved because the price level falls more rapidly and the impacts on financial conditions are stronger when one considers the responses to a "monetary policy shock" purged of the "information shock".

Goodhead (2019) followed the spirit of Jarociński and Karadi (2020) in his methodology. He also identified structural shocks from sign restrictions applied on high-frequency financial market movements around policy announcements for the euro area. However, unlike Jarociński and Karadi (2020), Goodhead didn't identify explicitly the "information shock" as a separate shock from monetary policy shocks but he decomposed monetary policy shocks into unconventional and conventional monetary policy shocks. This decomposition is somewhat interesting to do because, as we saw earlier, the effects and transmission mechanisms are different according to the type of monetary policy and also because both types of policy can be announced in a central bank press release time window. Goodhead proposes to distinguish conventional and unconventional monetary policy shocks using sign restrictions[13]. Among the various sign restrictions, the one which really makes a clear distinction between the two types of shocks is the one relative to the slope of the yield curve. Indeed, Goodhead assumes that an expansionary conventional monetary policy tends to make the slope of the yield curve steeper, while an expansionary unconventional monetary policy tends to flatten it. Once these structural shocks "candidates" were identified, he incorporated them as a vector of exogenous variables in a standard VAR model, more precisely called a VAR-X, containing certain macroeconomic and financial variables such as an industrial production index, the unemployment rate, an inflation level (HICP) for the macroeconomic variables and German bond yields, exchange rates and a stock market index (Euro stoxx50) for the financial variables. The macroeconomic effects showed by the different impulse responses tend to go in the same direction independently of the type of shocks. Despite the fact that the dynamics of the macroeconomic variables are similar in their direction, Goodhead (2019) raises the fact that the macroeconomic

[12] The literature evoques often the presence of certain problem when it comes to identify a monetary policy shock through the use of a VAR. We observe strange responses of price level indicator after constructing a VAR model and identifying a monetary policy shock. This problem is called the "price puzzle problem" which indicates thee presence of a possible bad monetary policy shock identification.

[13] Goodhead uses like Jarociński and Karadi (2020) QR variance decomposition and sign restrictions to identify strucutral shocks.

effects following an unconventional monetary shock are higher in magnitude than conventional ones.

4. Data and Methodology

The methodology we decided to implement is inspired by the one of Goodhead (2019) and Jarociński and Karadi (2020). Like them, we will try to identify the different types of structural shocks that they mentioned in their work: the information shock of Jarociński and Karadi (2020) and both the conventional and unconventional shock of Goodhead (2019).

The first step consists in separating these shocks by using high-frequency (intra-daily) financial market movements around ECB monetary policy announcements. The identification of structural shocks will be done through sign restrictions and a QR variance decomposition inspired by the algorithm of Breitenlechner and al. (2019). This algorithm is derived from the one of Rubio-Ramírez and al. (2010) when it comes to identify structural shocks only with pure sign restrictions. Once these shocks identified, we will examine their impact on the implied financial volatility of equity markets using a VAR system[14] containing certain control variables such as interest rates measures (short and long), macroeconomic indicators and finally a stock market index.

The identification of structural shocks will be carried out on the basis of the euro area database of Altavilla and al (2019). This database contains series of unexpected movements in financial variables calculated from high-frequency movements in a time window that captures the ECB's monetary policy announcements. Unlike these papers which make the use of Bayesian estimation methods to estimate their VAR models, we will not follow this method in our analysis for reasons of simplicity. The VAR model will be estimated by OLS.

4.1 Motivation for the choice of this methodology

The reason we decided to use this "hybrid methodology" is that it combines the advantages of both the event study and the VAR approach that dominate the empirical literature we reviewed.

[14] The specification of our VAR system will be done in the same spirit as Goodhead (2019), putting structural shocks identified as exogenous regressors.

Measuring the causal effect of a policy requires monitoring changes in the economic fundamentals to which the policy responds endogenously. Since surprises are based on high-frequency data movements, we are sure to identify the surprise effect from the different policy announcements. Moreover, we are convinced that these recorded variations are caused only by these monetary policy announcement phenomena. Moreover, by using sign restrictions and by making a "QR" variance decomposition of these intra-daily surprises, we can go further because we are able to "refine" these shocks into several types. The use of QR decomposition and sign restrictions is intended to correctly identify a more causal relationship. Indeed, even within a short time window, these intra-daily variations may be caused by other types of surprises than monetary policy effects.

Finally, measuring and analysing the effects of these shocks through a VAR impulse response is something important and interesting. First, when studying the effects of a monetary policy shock on a particular variable over time, it is necessary to take into account any other fundamental economic factors that could also have an impact on that variable. For example, in this analysis, implied stock market volatility may not only be influenced by the series of structural shocks that we will identify, but may also depend on other factors such as, for example, the levels of stock market indices, the levels of inflation and economic activity or interest rate. The VAR approach allows us to control these effects. The second argument in favour of using a VAR model is that we can better understand how our variable of interest, in this case implied volatility, is affected. In other words, we can explore the effects in a dynamic way, thus identifying the main intermediaries to the responses.

4.2 Foundation of Vector Autoregressive models

Since their introduction by Sims (1980), VAR models have become a reference tool in macroeconomic modelling and for studying macroeconomic dynamics. VAR models are frequently used for macroeconomic analysis, forecasting and as a complement or alternative to theoretically based dynamic stochastic general equilibrium (DSGE) models (Danne, 2015; Breitenlechner and al., 2019).

So far, we have discussed on many occasions the importance of identifying structural shocks for this analysis. The section below explains why and is based on the works of Danne (2015) and Breitenlechner and al. (2019).

In order to understand the intuition of SVAR models, let's consider a set of n endogenous variables following a VAR (1) model of the type:

$$y_t = Ay_{t-1} + \varepsilon_t \qquad (1)$$

where y_t is a $n \times 1$ vector of endogenous variables, A is a $n \times n$ matrix of coefficients, and ε_t corresponds to the error term which is a $n \times 1$ vector of stochastic components with zero mean, zero autocorrelation, and constant variance.

The variance-covariance matrix of the error-term is:

$$\sum = E\,[\varepsilon_t \varepsilon_t{}'] \qquad (2)$$

The above representation corresponds to the reduced form representation of a VAR model.
In this representation, all variables are endogenous and dependent on each other.
However, this representation has a drawback: we are still not able to explain how endogenous variables react to each other in the system. In other words, we are still unable to identify a causal relationship between the variables. To interpret causal dynamics, we need to have orthogonal shocks ε_t between the equations of the system. This may not be the case, as the reduced-form shocks are probably still correlated between the equations. Therefore, ε_t has no economic interpretation unless the variance covariance matrix of the residuals is diagonal i.e. $\sum_{\varepsilon} = E\,[\varepsilon_t \varepsilon_t{}'] = I$.

It is clear that macroeconomic and financial variables are inherently endogenous between them. Nevertheless, this representation does not allow us to model the contemporary relationships between the endogenous variables of the system. This therefore motivates the use of a structural VAR framework (SVAR).

Let's now consider ε_t as linear combinations of i.i.d innovations μ_t:

$$\varepsilon_t = B_0\, \mu_t:$$

where B_0 corresponds to a $n \times n$ matrix of structural parameters and $\mu_t \sim N(0,1)$ are the structural shocks of the model we want to identify.

The structural form of this VAR (1) model can be rewritten as:

$$Yt = B_0 Y_t + B_1 Y_{t-1} + \mu_t$$

To estimate this equation, we need to get rid of the contemporaneous endogenous variables Yt on the right-hand side. By consequent, we need the reduced-form representation to infer the structural one.

Reduced form and structural form can be retrieved by following these operations:

$$(I - B_0 Y_t) = AY_{t-1} + \mu_t$$
$$B_0^* Y_t = AY_{t-1} + \mu_t \qquad \text{where } B_0{}^* = I - B_0$$
$$Y_t = B_0^{*-1} AY_{t-1} + B_0^{*-1} \varepsilon_t$$

From (2) we can rewrite the variance-covariance matrix as:

$$\sum_\varepsilon = E\,[\varepsilon_t \varepsilon_t{}'] = B_0^* B_0^{*\prime}$$

There is, however, one outstanding issue. How to identify structural shocks μ_t?

From the reduced form of the VAR, we have already an estimate of $\sum_\varepsilon$ thanks to the residuals of the model and an estimate of the matrix A. The identification of structural shocks requires the identification of the matrix B_0^* which is the only unknown. How to resolve this identification problem? By construction, the matrix B_0^* contains n^2 unknowns. The identification of these unknown elements therefore requires at least n(n-1)/2 restrictions to solve this problem.

A popular and a standard method to identify structural shocks is the "Cholesky identification". According to the Cholesky decomposition, for any positive-definite matrix X, we have a unique decomposition $X = PP'$ where P is a lower triangular matrix. In our case, the matrix X will be $\sum_\varepsilon$ and the decomposition of the variance will be such that $\sum_\varepsilon = PP'$.

Once P obtained, we have an estimate of the matrix B_0^*. We can infer the structural shocks we want to identify by denoting μ_t, the structural shocks candidates such as:

$$\mu_t = P^{-1} \varepsilon_t$$

Contrary to ε_t , μ_t are orthogonal because these innovations are uncorrelated both over time and across equations:

$$E\,(\mu_t \mu_t{}') = I$$

Identification under Cholesky allows us to obtain relevant impulse responses to study a causal dynamic between the variables of the VAR. Although this approach is, at first glance, easy to implement, we can make some criticisms. The Cholesky identification is one way among many others to obtain orthogonal impulse responses. In addition, using P which is a lower triangular matrix as an estimate of the B_0^* matrix has implications on how structural shocks affect the variables in the system. As an example, for a VAR containing output and interest rates (y_t and i_t) as endogenous variables, we have the following estimate of the matrix B_0^*:

$$\mathrm{P} = \begin{bmatrix} p_{11} & 0 \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} \hat{b}_{11} & \hat{b}_{12} \\ \hat{b}_{21} & \hat{b}_{22} \end{bmatrix}$$

This structure imposes that $\hat{b}_{12}$ = 0 which means that output and interest rates are affected contemporaneously by structural shocks as follows:

$$\begin{bmatrix} \hat{\varepsilon}_{y_t} \\ \hat{\varepsilon}_{i_t} \end{bmatrix} = \begin{bmatrix} \hat{b}_{11} & 0 \\ \hat{b}_{21} & \hat{b}_{22} \end{bmatrix} \begin{bmatrix} \hat{\mu}_{y_t} \\ \hat{\mu}_{i_t} \end{bmatrix}$$

From this, we understand that $\hat{\mu}_{i_t}$affects contemporaneously interest rates through $\hat{\varepsilon}_{i_t}$but affects only output with a lag. Moreover, interest rates react contemporaneously to both shocks $\hat{\mu}_{y_t}$and $\hat{\mu}_{i_t}$. According to economic theory, $\hat{\mu}_{i_t}$can be considered as a structural monetary policy shock candidate but its identification requires a predefined chain of causation between the variables and is sensitive to the ordering of the variables.

So, we understand that $\hat{\mu}_{i_t}$simultaneously affects interest rates through $\hat{\varepsilon}_{i_t}$, but that it only affects production with a certain lag. Moreover, interest rates respond simultaneously to both shocks $\hat{\mu}_{y_t}$and $\hat{\mu}_{i_t}$. According to economic theory, $\hat{\mu}_{i_t}$can be regarded as a structural monetary policy shock candidate, its identification requires however a predefined chain of causation between the variables and is consequently sensitive to the order of the variables entering in the system (Danne, 2015 ; Breitenlechner and al., 2019).

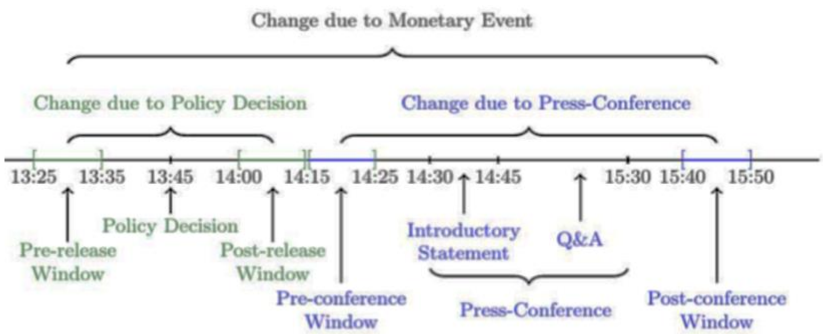
Unlike Cholesky, our method, which uses both QR variance decomposition and sign restrictions, allows us to be much more flexible and accurate in identifying structural shocks. Further explanations on how we implemented this method (QR decomposition) to identify our structural shocks can be found in the Appendix.

4.3 Shocks identification based on high-frequency financial data movements and sign restrictions

Discussion on the selection of data to identify structural shocks

The identification of our structural shocks begins by selecting some relevant time series surprises from the database of Altavilla and al. (2019). The database specifies different event windows when recording intra-daily financial surprises around policy announcements. Indeed, this one distinguishes the policy announcement time window into a press release window and a press conference window. Figure 5 below gives more details about this distinction. We decided to choose what Altavilla and al. (2019) called the “monetary event window” which records changes in the median quote from the window 13:25-13:35 before the press release to the median quote in the window 15:40-15:50 after the press conference. This event window’s choice is the same as Goodhead (2019).

Figure 4: The "monetary event window"



Source: Altavilla and al. (2019)

This dataset has the advantage of being large enough to both identify the information shock mentioned by Jarociński and Karadi (2020) and various monetary policy shocks mentioned by

Goodhead (2019). This dataset includes monetary policy announcements from January 1999 to January 2020[15].

The time series necessary to identify the different shocks are: Euro Stoxx 50, OIS 3-month[16] and a measure of the slope of the yield curve (10-year minus 2-year German sovereign yield). The reasons why we chose these variables follow.

Jarociński and Karadi (2018) used interest rate swaps (3-month Eonia OIS) and a stock index (Euro Stoxx 50) to identify their information shock for the euro area[17]. By consequent, since our study is also based on the euro area, it seems logical to use the same variables. In particular, these data will be used to replicate the information shock of Jarociński and Karadi (2020). Like them, we will identify this information shock by imposing positive co-movements between the stock index and interest rates.

The stock index variable will also be useful for identifying monetary policy shocks. Indeed, Goodhead decided to include this variable in his sign-restrictions. Goodhead's sign restrictions are detailed in Table 3.

Table 3: Goodhead's sign restrictions

	Conventional Policy	Unconventional Policy
2Y DE Yield	↓	↓
10Y - 2Y DE Yield	↑	↓
Stocks	↑	↑

Source: Goodhead (2019)

As we can see, the sign restriction that differentiates conventional from unconventional shocks is the one related to the slope of the yield curve (10Y – 2Y German sovereign yield). However,

[15] The data set begins before the crisis of 2008 and before the introduction of UMP policies. Nevertheless, we decided to take a larger sample of data for better identifcation purposes. UMP policies can be considered to have taken place after 2008 and after 2014 for the so-called QE in Europe.
[16] OIS means Overnight Index Swap.
For more information : https://www.investopedia.com/terms/o/overnightindexswap.asp
[17] In fact, Jarociński and Karadi used OIS 3-month based on Eonia for their euro area analysis instead of using interest rate futures. This choice is motivated by the fact that euro area swap market is more liquid and has a longer history than the futures market for interest rates.

we can wonder if these sign-restrictions are pertinent to identify the different types of monetary policy shocks. Goodhead (2019) justifies this sign restriction as follows:

- A conventional shock is temporary by nature. By consequent, its effect should dissipate with the time horizon;
- Long-term interest rates contain a “term-premium” which is not hardly impacted by temporary movements in short-term interest rates. In addition, unconventional monetary shocks are, for the most part, surprises arising from purchases of long-term assets. This will therefore tend to lower the term-premia at the end of the yield curve, in particular through the portfolio rebalancing channel explained above.

These distinctions can be discussed if we believe that monetary policy primarily affects the level of the term structure and not its slope. In this case, only interest rates taken at different maturities (short and long) could be used to distinguish the type of monetary policies. The problem with this way of thinking is to know from which maturity an interest rate can be considered "short" or "long". Imagine that the effects of the portfolio rebalancing channel (characteristic of an unconventional monetary policy) go beyond the scope of long-term rates and reach medium-term rates. If the limit we have placed to distinguish binary short and long-term interest rates has a higher maturity than these medium-term rates, we will include "non-conventional effects "as "conventional ones". By taking the slope, we avoid this problem.

Imposing a sign restriction on the slope of the yield curve is not a bad idea if we believe that conventional monetary policy affects mainly short-term interest rates. We saw earlier when we explained the monetary transmission mechanism that conventional monetary policy affects short-term money market rates by setting the level of official interest rates. While these changes may alter people's expectations and, hence, the level of long-term interest rates, we can assume that the decline in long-term interest rates is smaller than the decline in short-term interest rates after a conventional monetary policy. By consequent, this should raise the slope.

In addition, we explained that unconventional monetary policies were implemented in particular after the introduction of the ZLB, which is a situation in which precisely the conventional monetary transmission mechanism is less effective. This means that the transmission of short-term rates movements towards long-term rates is even more restrained in this situation. This also supports the first argument that long-term rates respond relatively less than short-term rates after a conventional monetary policy.

Finally, we have seen that unconventional monetary policies and QE in particular have affected long-term interest rates through the activation of other channels. Therefore, we can assume that long-term rates react relatively more than short-term rates in response to an unconventional measure which thereby tends to lower the slope of the yield curve.

All these reasons explain why the slope can be a way to differentiate monetary policy types. However, even if the idea of slope can be accepted, the choice of the variable associated with this slope (German yield) can be discussed. The German bond can sometimes be considered the safest asset in its class. This particular status can eventually explain variations in the data which are not the cause of the shocks we mentioned. This could be controlled with another time series, but the German yield series has the advantage of containing much more data than the other yield series present in our database. The number of data is an important factor to identify precisely structural shocks and this is the reason why we decided to keep the German yield.

Sign restrictions

After this reflection, I decided to impose some sign restrictions on the impulse responses of surprises (the three "surprises" variables described above) as a way to capture the structural shocks. The set of sign restrictions follows in Table 4.

Table 4: Sign restrictions

	Euro Stoxx 50	Slope (10Y-2Y German government bond yields)	OIS 3month
Information shock	(+)	•	(+)
UMP ("QE") shock	(+)	(-)	(-)
MP shock	(+)	(+)	(-)

* (•) means that no particular sign restrictions have been made.

This step is crucial in our analysis because a bad shocks identification could lead to misleading results. Of course, the choice of both variables and sign restrictions can be challenged and discussed and there is not only one possibility to identify those shocks. These sign restrictions can to some extent be considered as a synthesis of those made by Goodhead (2019) and Jaroncinski & Karadi (2020), authors that can be regarded as our reference.

The 3-month OIS is useful to distinguish information shocks from monetary policy shocks. A positive information shock (good news perceived by financial markets) is accompanied by a rise in equity prices and a rise in yields quoted on the market. Why? When a central bank communicates on its monetary policy, the positive information perceived by the market on financial and macroeconomic fundamentals should lead investors to be more confident in investing in equities and a rise in stock market indices should follow. Economic and financial conditions better than previously expected contribute to support inflation in the future. Since markets act by expectations, they will anticipate this future inflation, and this will be reflected in yields quotations.

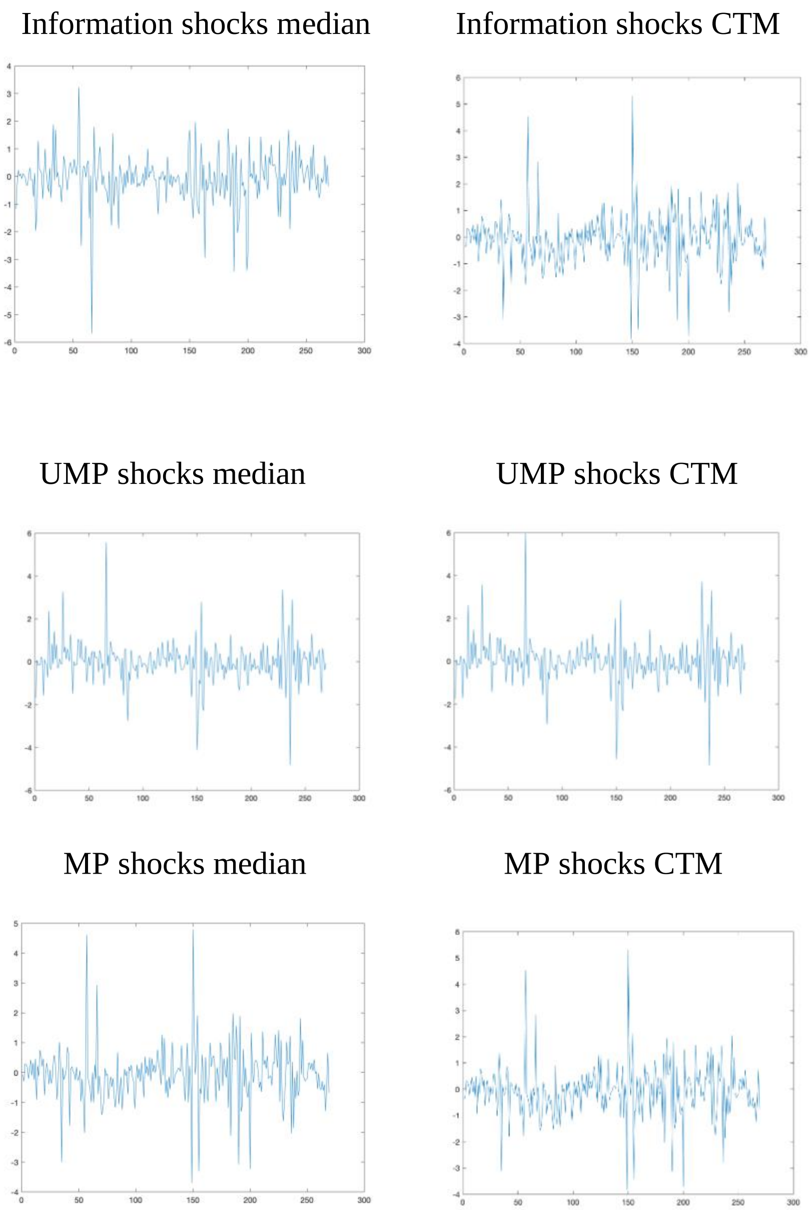
On the other hand, the slope is useful to distinguish UMP and MP shocks. An expansionary monetary policy shock, either conventional or unconventional is accompanied by a rise in stock prices and a decline in interest rates (OIS month) for the reasons explained earlier. Although interest rates decline after an expansionary shock, conventional shocks might affect short-term interest rates more than long-term ones explaining the rise in the slope of the yield curve. Non-conventional shocks have opposite effects on the yield curve according to the same reasoning. An UMP shock is accompanied by a negative change in the slope of the yield curve.

Remarks on structural shocks

The figures below summarize the relative structural shocks after the execution of the QR decomposition and the sign restrictions. Among 2000 iterations, the code returns 837 models matching the imposed sign restrictions.

As we can see in Figure 6 below, these series behave approximately like a “White noise” (i.i.d observations) at the exception that these series might present some heteroskedasticity.

Figure 5: Structural shocks series identified after sign restrictions and QR decomposition

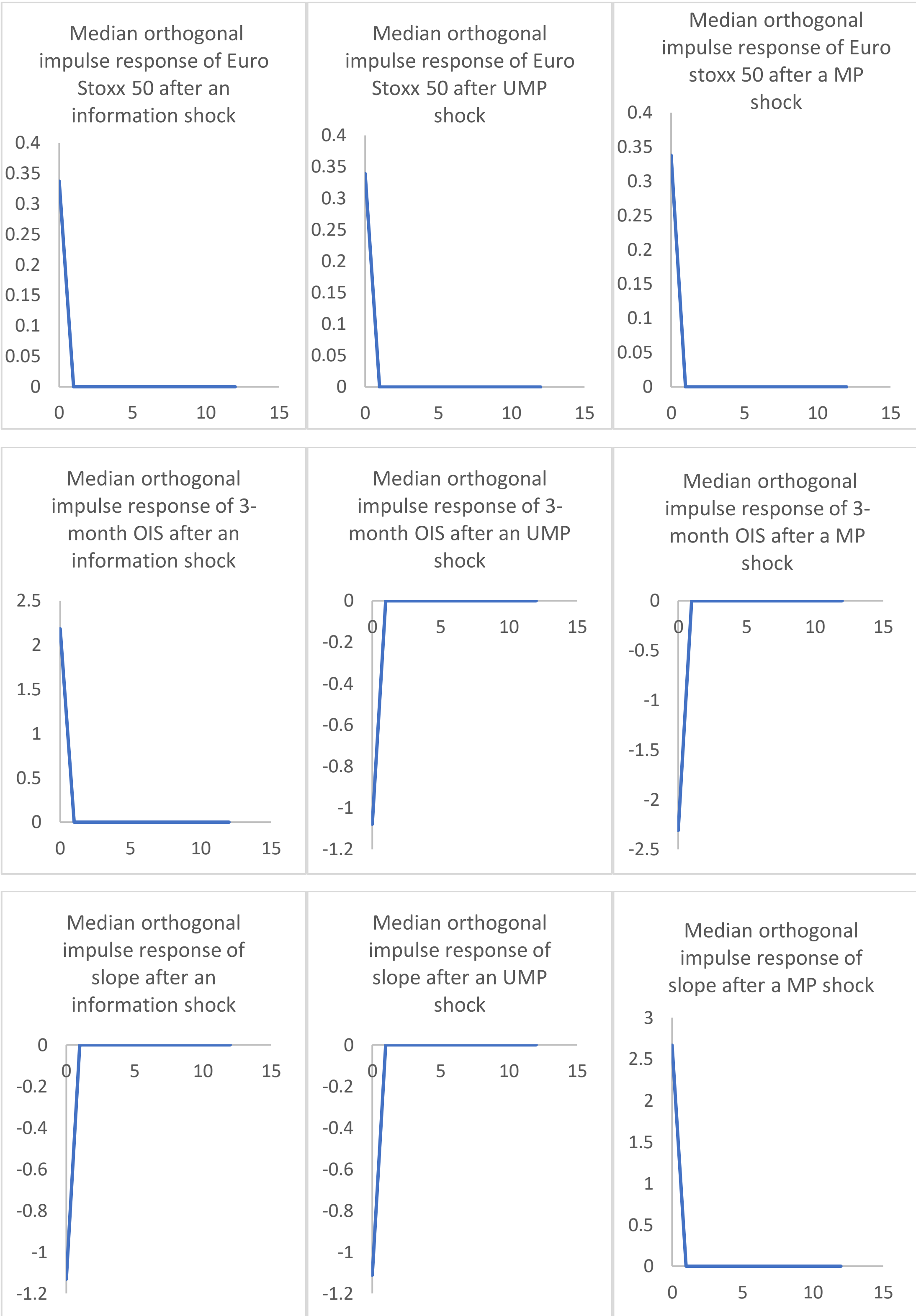


Source: Altavilla and al. (2019) - Own calculations (Matlab)

At first glance, these graphs tend to prove that the series of structural shocks follows a stationary process. Stationarity is an important concept in time series econometrics because it facilitates CLT, the fundamental theorem on which statistical inference can be made. Moreover, by looking hereafter at median orthogonal impulse responses of the “surprises variables” following these different shocks, we can deduce that the time dependence of these series (both the structural shock series and the intraday surprise series) is almost zero. All the impulse responses plot a value of zero for a horizon of t+1. The responses on the shocks are contemporaneous.

Figure 7 below illustrates the responses of the “surprise” variables after identifying the three types of shocks.

Figure 6: Impulse responses of "surprise" variables after shock identification



Source: Altavilla and al. (2019) – Own calculations (Excel)

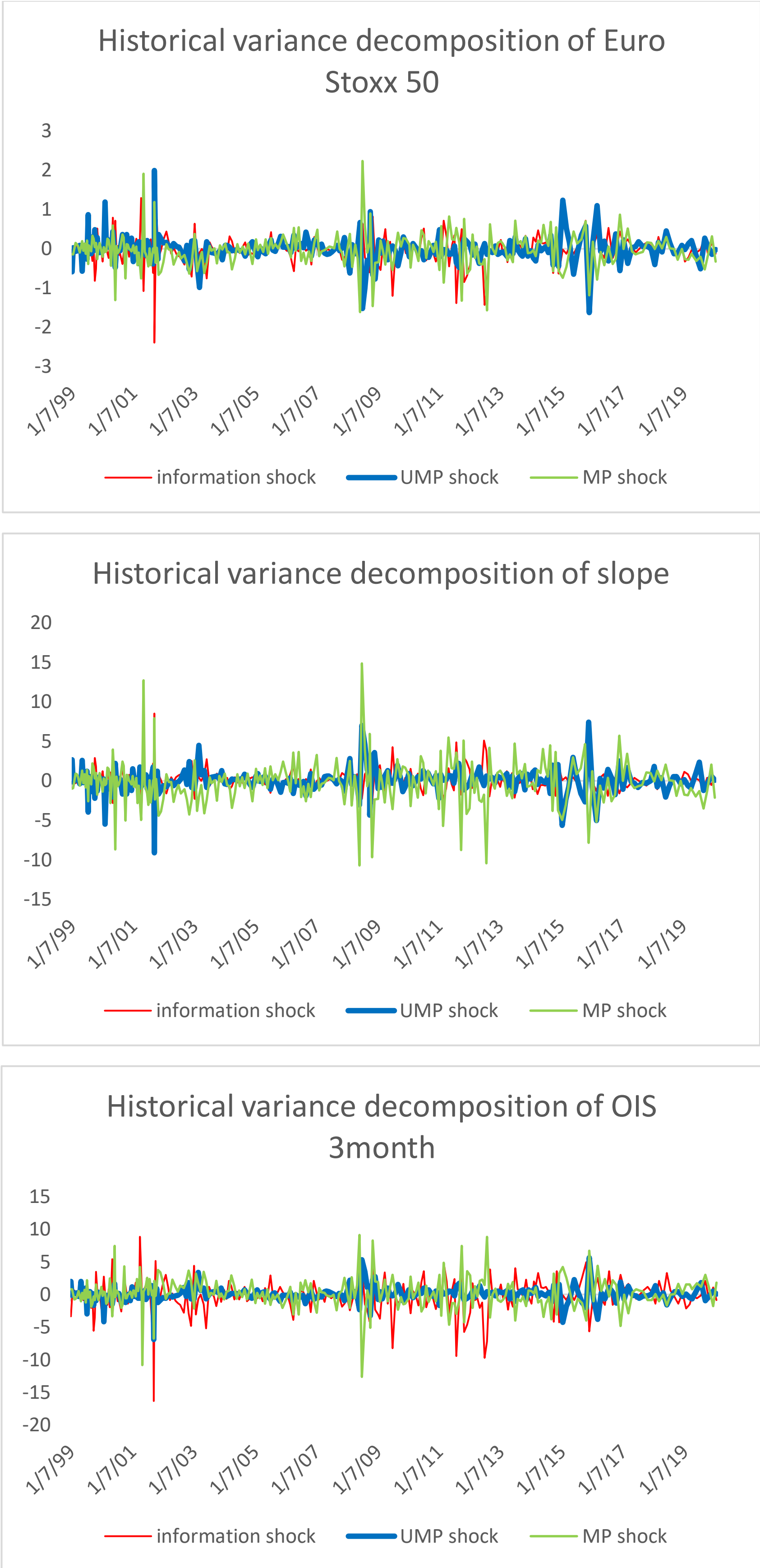
The magnitude of the median impulse response for the Euro Stoxx 50 seems to be equal for all shocks. However, the responses of both the slope and OIS 3 month are a bit different. The IRF for the slope is relatively more sensitive to the conventional monetary policy shock compared to the information and UMP shock. These remarks on median IRFs can be extended to the CTM IRFs which are plotted in Appendix.

By looking at the historical variance decomposition[18] of the intra-daily surprises in the Figure 8 just below, we can see that:

- the magnitude of the various shocks on the variables seems to be greater in the case of particular stress events. Indeed, we can observe higher peaks during the financial crisis of 2008 and its aftermath, in the early 2000s corresponding to the introduction of the euro and during the dates corresponding to the various episodes of quantitative easing.
- UMP shocks seem to contribute relatively more to the historical variance of Euro Stoxx 50 surprises than other types of shocks. On the other hand, the contribution of UMP shocks to the change in the slope is smaller than that of MP and information shocks. Concerning information shocks, they seem to contribute relatively more to the variation in the slope and the 3-month OIS than to the variation in the Euro Stoxx 50 surprises.

[18] Other graphs plotting the historical variance dcomposition for each individual shock can be found in the Appendix.

- *Figure 7: Historical variance decomposition*



Source: Altavilla and al. (2019) – Own calculations (Excel)

4.4 Baseline VAR model

Our baseline VAR model contains a mix of euro area macro and financial time series. These data were taken from January 1999 to January 2020 at a monthly frequency which constitutes a sample of 253 observations. Concerning the "macro" and interest rate time series[19], I recorded the HICP for all items in the euro area, total industry euro area production index (a proxy for GDP) excluding construction, 90 days interbank rates (a short-term measure of euro area interest rates) and 10-year euro area Government bond yields (a long-term measure of interest rates). Financial market variables[20] will be captured by including the Euro Stoxx 50 price index and its corresponding implied volatility index, the Vstoxx. Finally, I decided to specify all the variables in logarithms at the exception of the interest rate series.

Treatment of the data

Important concepts in time series econometrics are (weak) stationarity and weakly dependent conditions. Indeed, these conditions are necessary to satisfy asymptotic least squares properties (Wooldridge, 2016).

As a reminder, a stochastic process X_t is said to be weakly stationary if:

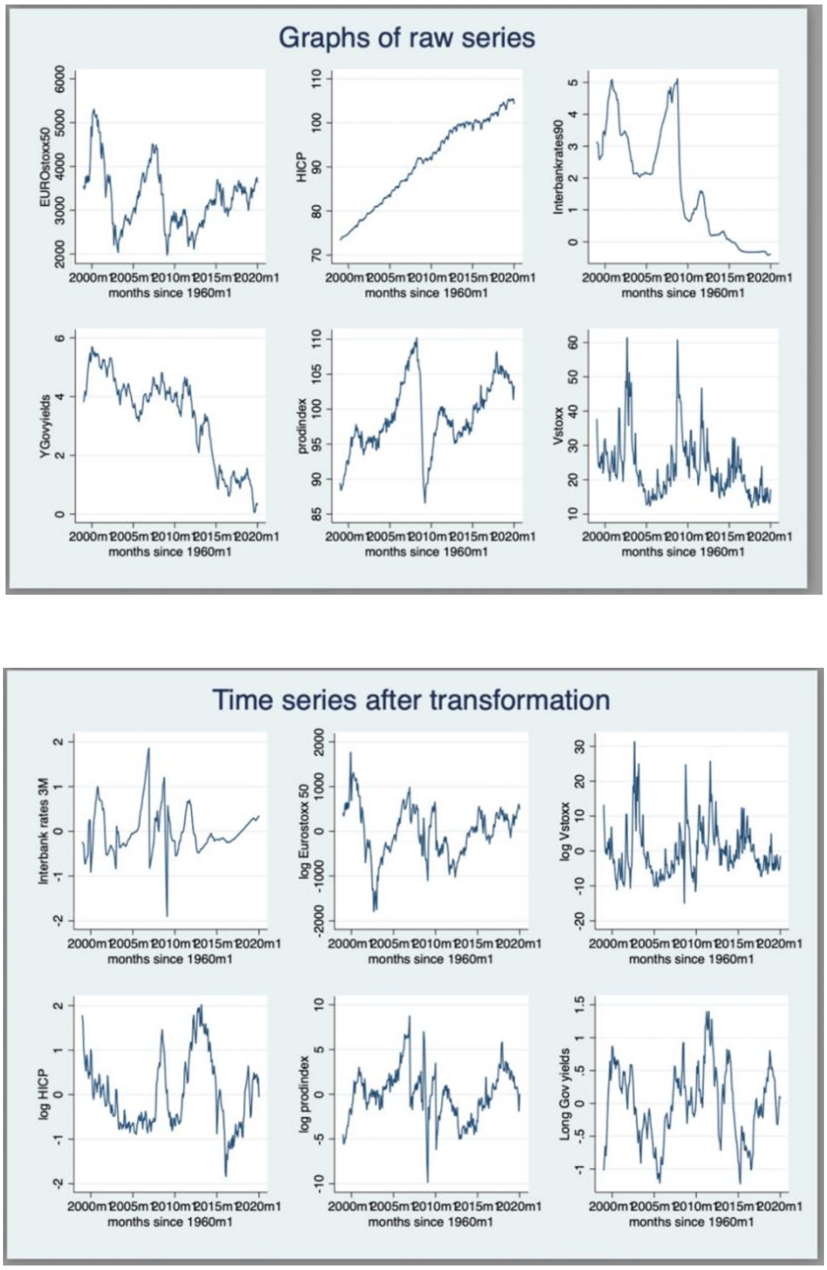
1) E(X_t) $= \mu$ (the unconditional mean is a constant and does not depends on time)
2) Var(X_t) = σ^2(the unconditional variance is constant over time)
3) Cov(X_{t}, X_{t+h}) = f(h) = γ_h (the covariance is a function of the number of lags but not of time)

This process is also said to be weakly dependent if Corr(X_{t}, X_{t+h}) tends to 0 as h tends to infinity. These conditions replace one of the Gauss-Markov conditions which stipulates that the data are i.i.d in an asymptotic context. To deal with this problem, I performed some regressions on the variables to eliminate possible deterministic effects (trends, seasonal effects) of the variables as well as possible structural breaks such as the 2008 financial crisis. The results of these preliminary regressions can be found in Appendix.

The Figure 4 below shows the behaviour of the series before and after the data treatment.

[19] Retrieved from "FRED"database, Federal Reserve Bank of St. Louis : https://fred.stlouisfed.org
[20] Retrived from "Refinitiv Eikon" database : https://eikon.thomsonreuters.com/index.html

Figure 8: Time series before and after data treatment



Sources: FRED (2020); Eikon (2020) – Own calculations (Stata)

In addition to these transformations, I performed some Dickey-Fuller (1979) tests reported in Appendix. By looking at the results of these tests, we conclude that the series don't follow a unit root at both 90 % and 95% confidence level.

Finally, I decided to specify the variables in levels. The reasons that pushed me to make this choice are the same as those given by Sims (2011). Indeed, we are not sure at one hundred percent that the series are I(0) as the specification of the Dickey-fuller might give conflicting results. Therefore, in this case, cointegration between series can exist and differencing the variables is not appropriate as it will create misspecification errors in the model. By consequent, the “safest” procedure recommended by Sims (2011) is to specify the model in levels as long as we include enough lags.

VAR lags selection

Selecting the right number of lags in a VAR model is an empirical problem. A model with too few lags can suffer from omitted variables biases and serial correlation in residuals. On the other hand, a model with too many lags decreases the number of degrees of freedom. Therefore, the specification of our VAR model has to meet a certain compromise. On the one hand, we need enough lags to capture the dependence of our time series, and on the other hand, we need to be parsimonious about the number of degrees of freedom remaining.

The number of lags depends on the frequency of observations in the sample. Sims (2011) recommends choosing a lag order equivalent to one year’s worth lag. He also recommends the use of certain information criteria such as the AIC. The advantage of this information criteria is that it already takes this "trade-off" into account since it includes a penalty function that depends on the number of delays included in the model.

Concerning Jaronciski & Karadi, they specified their model with 12 lags, the same order as Goodhead. As previously mentioned, these models are in a way our reference and include more or less the same number of variables as our baseline model. However, these models are estimated using Bayesian methods that are different from the OLS estimation performed in this work.

For the specification of this baseline model, I decided to go first for a model in accordance with some information criteria. The table 5 below reports the right number of lags according to different information criteria. All these information criteria tend to report 1 or 2 lags as the optimal lag order. According to AIC previously mentioned, the optimal lag order is 2. The baseline model will therefore be specified with this lag order. Then, the specification of the baseline model with 12 lags will be considered in the robustness part.

Table 5: Information criteria

Selection-order criteria
Sample: **2000m1 - 2020m1** Number of obs = **241**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**-3645.33**				**642962**	**30.4011**	**30.506**	**30.6614**
1	**-2497.28**	**2296.1**	**36**	**0.000**	**63.143**	**21.1725**	**21.487***	**21.9533***
2	**-2455**	**84.57**	**36**	**0.000**	**59.9795***	**21.1203***	**21.6446**	**22.4217**
3	**-2435.29**	**39.415**	**36**	**0.320**	**68.7791**	**21.2555**	**21.9895**	**23.0774**
4	**-2408.03**	**54.508**	**36**	**0.025**	**74.1798**	**21.3281**	**22.2718**	**23.6706**
5	**-2369.77**	**76.537**	**36**	**0.000**	**73.1407**	**21.3093**	**22.4627**	**24.1723**
6	**-2345.43**	**48.672**	**36**	**0.077**	**81.1271**	**21.4061**	**22.7692**	**24.7896**
7	**-2312.51**	**65.85**	**36**	**0.002**	**84.0081**	**21.4316**	**23.0045**	**25.3357**
8	**-2283.74**	**57.532**	**36**	**0.013**	**90.3153**	**21.4916**	**23.2742**	**25.9163**
9	**-2255.75**	**55.986**	**36**	**0.018**	**98.0588**	**21.5581**	**23.5504**	**26.5033**
10	**-2232.6**	**46.301**	**36**	**0.117**	**111.271**	**21.6647**	**23.8668**	**27.1305**
11	**-2208.11**	**48.966**	**36**	**0.073**	**125.435**	**21.7603**	**24.1721**	**27.7466**
12	**-2179.11**	**58.001***	**36**	**0.012**	**136.891**	**21.8184**	**24.4399**	**28.3252**

Endogenous: logprodindex logVstoxx logEurostoxx ShortIR logHICP LTyields
Exogenous: Infoshocks UMPshocks MPshocks

Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

5. Impulse responses of the baseline model

To get an idea of the dynamics of causal impacts within our VAR system, let us examine the impulse responses after a unit change in the series of structural shocks. As a reminder, the unit of measurement for the series of structural shocks is in base points because they were constructed from the various "surprises", all entered in base points. The results of the baseline VAR for each equation can be found in Appendix. The following figures summarize the different responses of the endogenous variables after a unit change in an exogeneous regressor (here the structural shocks series). The impulse responses below are related to an expansionary shock (i.e. increase in one unit in the structural shocks series).

5.1 Impulse responses to a conventional monetary policy shock

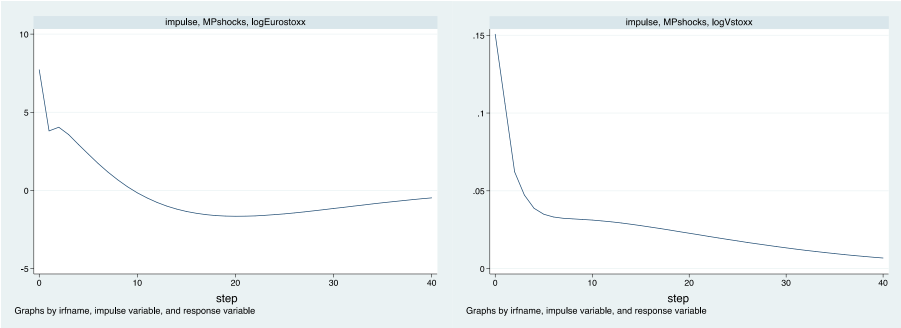
There are several remarks to make when analysing and interpreting those graphs: the direction of the responses and the magnitude of the responses.

Firstly, if we look at the responses of the "financial variables" in the Figure 9 below (i.e. log Euro Stoxx 50 and log Vstoxx), we can see that they both increase on impact before gradually decreasing in the medium to long term. Implied stock market volatility rises by 0.15% (15 basis points) after an unexpected 0.01% drop of central bank's policy rates (or equivalently after a 0.01% increase in the "MP shocks" variable). Concerning the stock market index, at the moment of the impact, it increases quite considerably (more or less + 7%) and then starts to decrease until becoming negative after 10 months. After 20 months, we see that the stock index gradually rises again. Let's remark that the magnitude of this response seems to indicate a potential problem in this model[21]. Due to the quite big contemporaneous impact on Euro Stoxx 50, we can suspect that this model suffers from omitted variables bias. In other words, the model may not capture enough lags, either for endogenous variables or exogenous regressors. By

[21] In this study, we will pay less attention to the magnitude of the responses than to their dynamics. This is because the command (*"var"*) of the statistical software (*Stata*) used to generate these responses provides responses with confidence intervals that are not robust to heteroskedasticity and autocorrelation. Since we suspect autocorrelation in the residuals and we have heteroskedastic errors, classical asymptotic inference procedures are no longer valid in this context. For these reasons, responses will be reported without confidence intervals.

hypothesis, the structural shock variables behave like random noise since they correspond to unexpected surprises, so we'll not consider a possible time dependency for these variables.

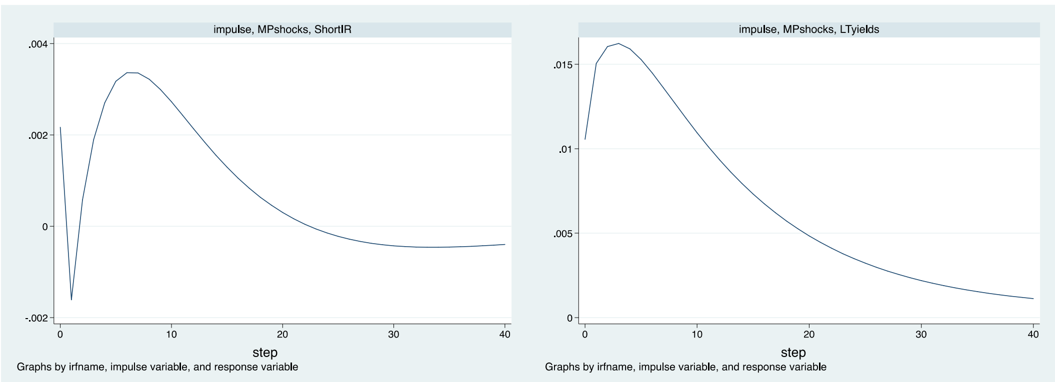
Figure 9: Responses of Euro Stoxx 50 (log) and Vstoxx (log) to a MP shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

Secondly, by examining the interest rate series in the Figure 10 below, we can see that the sign restrictions applied to the slope are consistent since long rates have approximately a peak of 0.017 and short rates have approximately a peak of 0.003. As a result, the slope of the yield curve increases. Despite the fact that both yields series exhibit the expected diminishing behaviour after some lags, we observe first an increase in yields. The reaction of interbank rates seems a little confusing because there is a break after one month, then a recovery and finally a long-term decline. The long-term yields don't have a break, but they show a similar pattern. This strange behaviour in interest rate responses can be linked to the remarks made by Goodhead. He explains this (a priori) unexpected rise in interest rates as follows. He argues that interest rates can rise because a monetary policy shock can potentially induce a central bank to raise rates if the latter policy provides sufficient stimulus to inflation and economic activity.

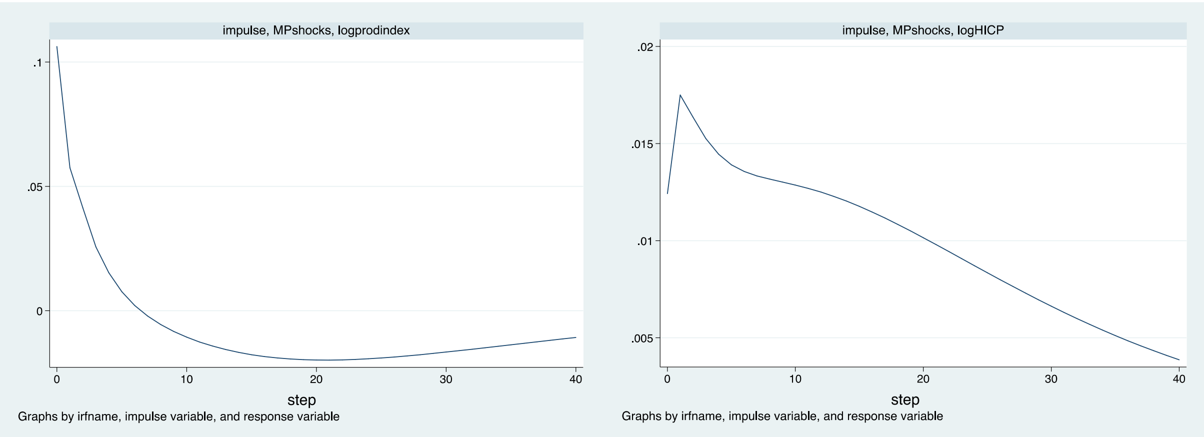
Figure 10: Responses of interest rates to a MP shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

The Figure 11 below corresponds to the responses of “macro” variables. We can see that the direction of the responses is coherent with economic theory because we observe a positive increase in the production index and the HICP index. The responses of the macro variables then show a downward pattern as yields increase. This can be consistent with the interest rate channel example explained earlier.

Figure 11: Responses of "macro" variables to a MP shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

5.2 Impulse responses to an information shock

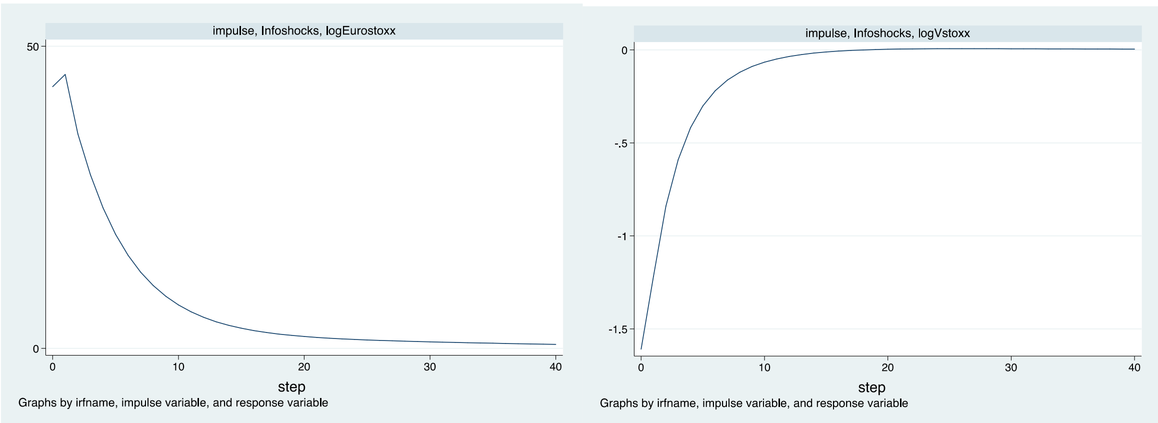
We can see on the Figure 12 below that a “positive” information shock is accompanied by a big rise in the stock index. The coefficient at impact is extremely high and should alert us. I've formulated some hypotheses to explain this strange behaviour.

One explanation for this could be a hypothetical overreaction of the stock market when unexpected positive information arrives. On the basis of behavioural finance theory, we know that financial markets experience short-term overreactions to the arrival of new information. This concept is notably illustrated by M. De Bondt & Thaler (1985). Therefore, the magnitude of the Euro Stoxx 50 responses could possibly be explained by this phenomenon.

However, caution must be exercised in interpreting this coefficient because, as noted above, this model may suffer from omitted lags. In a lower extent, the other hypothesis concerns the choice of the Euro Stoxx 50 in itself. This stock index[22] is not representative of the stock market as a whole because its composition includes only fifty stocks considered as the most liquid and the most important in terms of market capitalization. Furthermore, this index is heavily traded on the market as it constitutes benchmarks for other financial products such as ETFs and derivatives. Because of these peculiarities, this index may therefore possibly overreact to arrival of information.

Unlike an accommodative conventional monetary policy, the implied volatility index decreases a bit more than 1.5% at impact. The magnitude of this response is also much higher than previously.

Figure 12: Responses of Euro Stoxx 50 (log) to an information shock

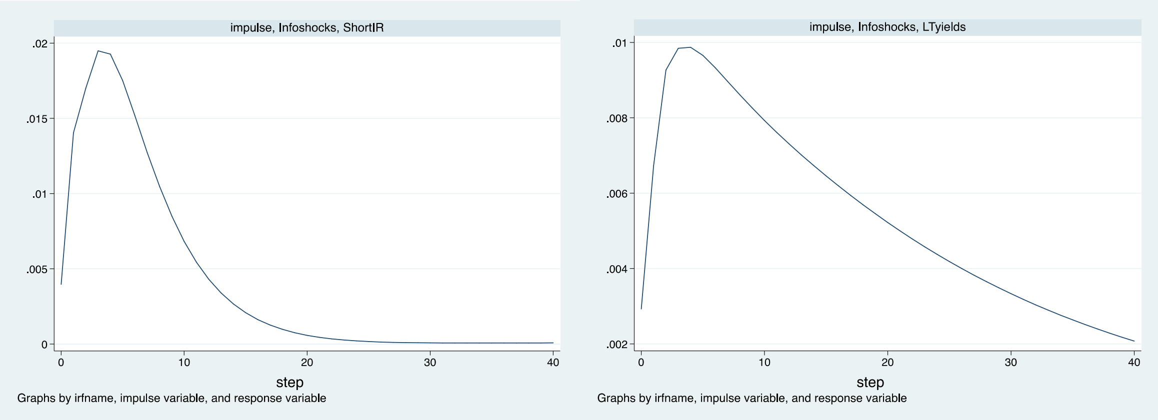


Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

Responses to information shock for short and long rates are pictured in Figure 13. The responses of interbank rates after an information shock are consistent with the sign restrictions previously discussed. The peak of the response comes after 3 months with an increase of 0.019 % (1.9 basis point). Long-term yields show a similar response to short-term yields, as they initially increase before this effect gradually vanishes over time. However, they take more time to return back to their starting level.

[22] For more information on the composition of this index : https://www.stoxx.com/index-details?symbol=SX5E

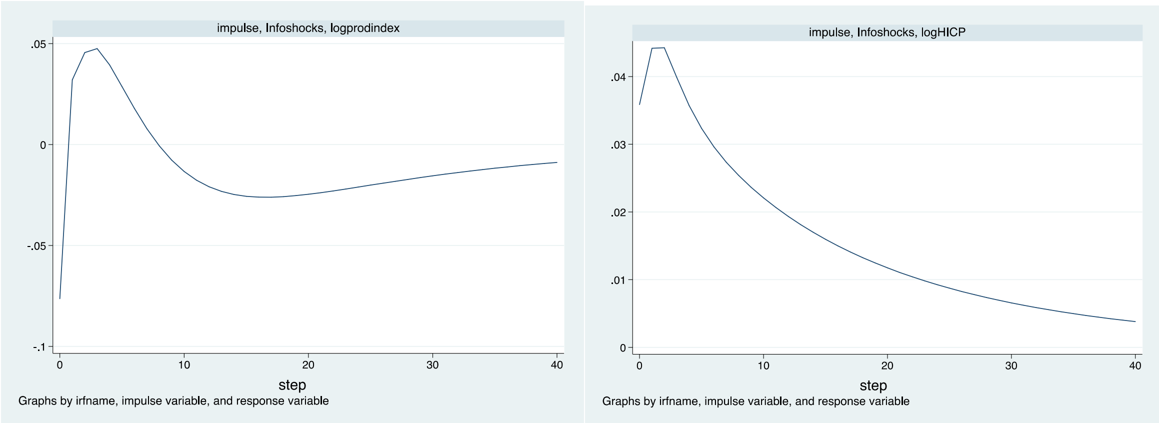
Figure 13: Responses of interest rates to an information shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

As we can see on the Figure 14 below, the responses of the macro variables after an information shock are a bit different. Indeed, the response of the production index is negative at impact but rises after some months attaining a peak of 0.05 % (5 basis points) to return back below zero after 10 months. The price index seems to react positively to a positive information shock. This is in line with the signalling (expectations) channel we explained earlier. Let us imagine that a central bank decides to cut its rates lower than expected. This can be seen as a restrictive decision on the part of the central bank. However, beyond these purely "monetary" effects, economic agents may interpret this monetary decision positively because it means that the economic situation is behaving better than expected. Consequently, agents should revise their expectations as a result of this information, which prompts them to adjust their decisions today. This would give them an incentive to consume and invest more today, pushing an upward pressure on aggregate demand and price level. Moreover, as they are more confident for the future, their behaviour relative to savings might be altered. One decision attributable to saving is the degree of risk aversion: the more we are risk averse, the more we save. Consequently, economic agents can decide to save less as they are relatively less risk averse (more confident) regarding the future.

Figure 14: Responses of "macro" variables to an information shock

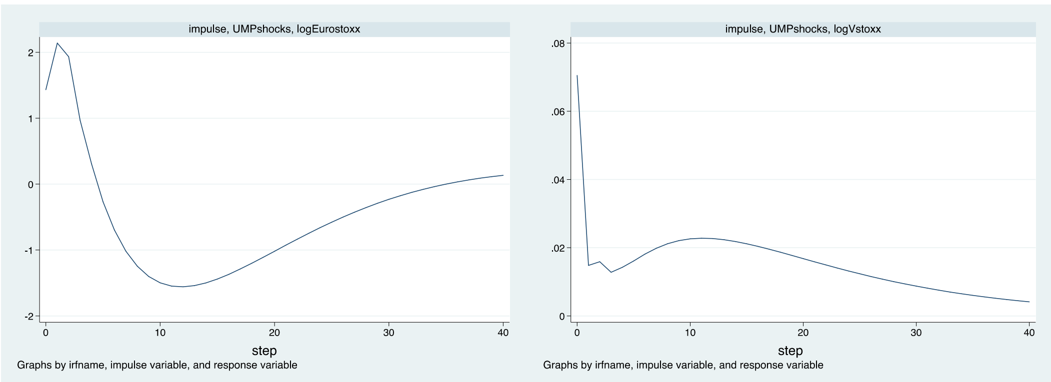


Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

5.3 Impulse responses to an unconventional monetary policy shock

Figure 15 shows the responses of the Vstoxx and the stock index after an unconventional monetary policy shock. The response of the Euro Stoxx 50 after this shock seems similar to the previous monetary shock. There is a positive reaction at the impact, a medium-term decline and then a long-term recovery. However, it should be noted that this recovery starts earlier and is faster than in the previous case. As for the magnitude of the stock market index response, it peaked at 2%, which is well below the response to the conventional shock. For the Vstoxx, we observe a positive reaction to impact (7 basis points) which is in turn lower than for the conventional case.

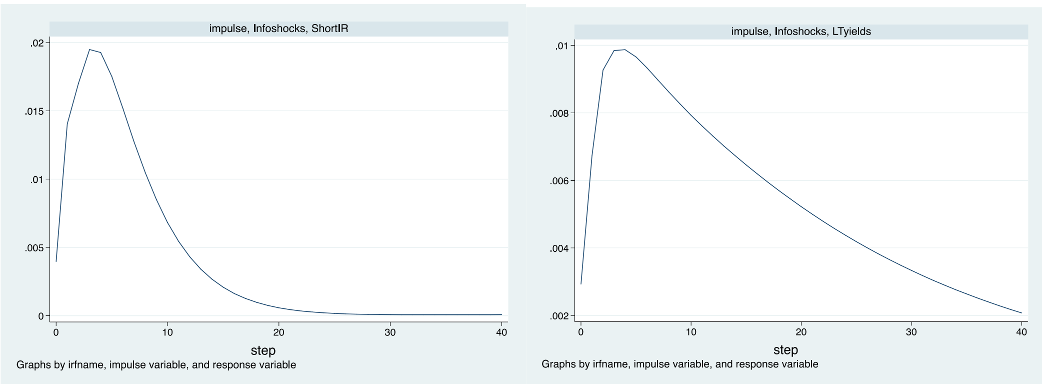
Figure 15: Responses of Euro Stoxx 50 (log) and Vstoxx (log) to an UMP shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

Figure 16 below shows the responses of interest rates. By looking at the magnitude of the responses for both short and long yields at impact and in the short run, we deduce that long-term interest rates increase less than short-term rates which tends to support the previous sign restriction posed on the slope. The remarks made previously concerning the interest rate responses in the conventional case can be extended here. Indeed, we observe as previously a decline after some months in the medium-term for both series. It should also be noted that this decline is slower for long-term rates than for short-term rates.

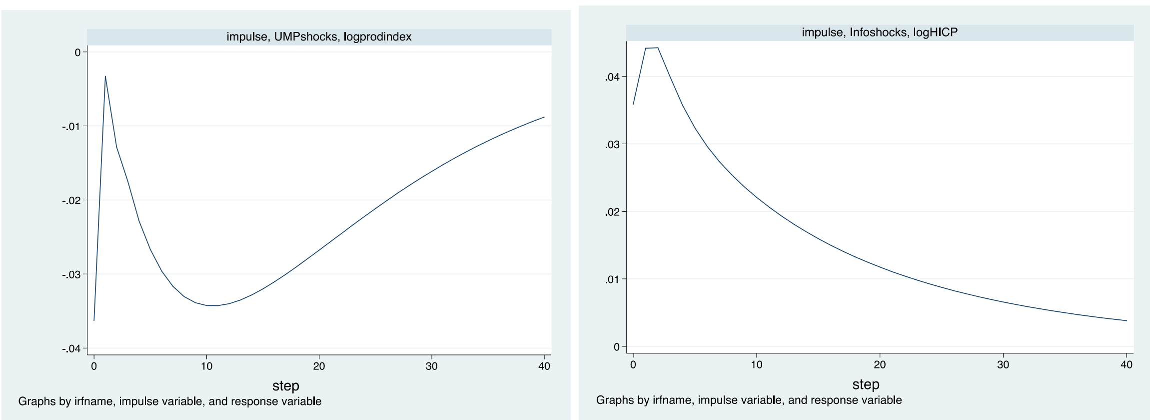
Figure 16: Responses of interest rates to an UMP shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

On Figure 17, we can see the responses of macro variables. The response of the price index shows a dynamic similar to the one of the conventional monetary impulse. We remark that unlike in the conventional case, the production index behaves a bit differently because it reacts negatively at impact. However, as yields start to decline, we see a recovery after 10 months.

Figure 17: Responses of macro-variables to an UMP shock



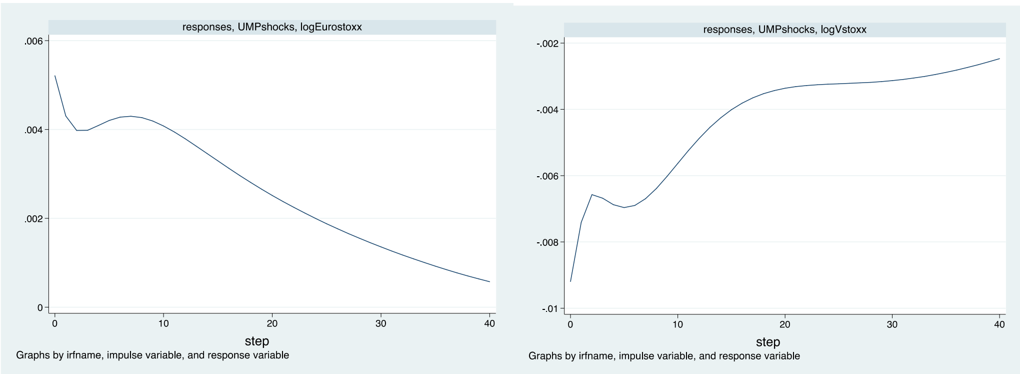
Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

5.4 Impulse responses after resampling to capture "QE"

The dataset used to obtain these responses contains observations prior to 2008. We saw earlier that unconventional monetary policies, and in particular QE, began to be implemented after the aftermath of the 2008 financial crisis[23]. In order to better capture the QE in our database, it is useful to re-sample and then look at the responses to unconventional shocks. The new sample starts from January 2010.

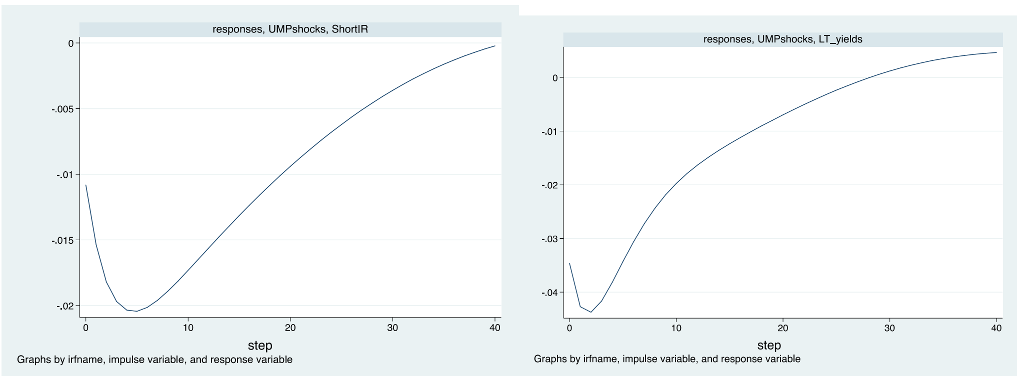
Figures 18-19-20 show the responses of financial variables, interest rates, and macroeconomic variables.

Figure 18: Responses of Euro Stoxx 50 (log) and Vstoxx (log) to a "QE" shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

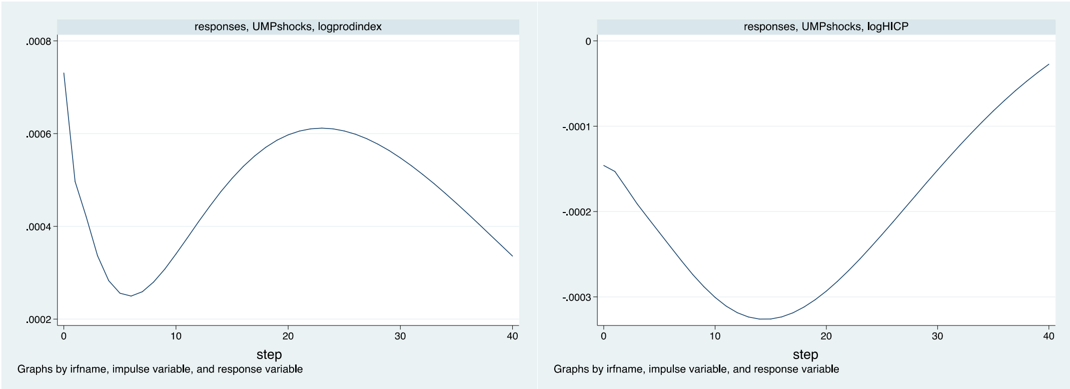
Figure 19: Responses of interest rates to a "QE" shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

[23] To be exact, according to the appelation of the ECB, the term "QE" has been announced for the first time from 2014 onwards in Europe. However, we consider that the previous asset purchases (OMT program) can be included in the overall term "QE". Even if the names of the two programs are different, they both represent basically the same thing: bonds purchases on the financial markets. This choice is motivated by the need to obtain sufficient data for the estimation of the VAR.

Figure 20: Responses of macro variables to a "QE" shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

We can see that the dynamics of these graphs are considerably different when we proceed to the resampling.

First, the reaction of the interest rates variables to impact are consistent with what we expected because interest rates drop at impact and in the short run. After a few months, both interest rate series show an upward trend although it doesn't start at the same time. Long-term yields decrease more (3.5 basis points) than interbank rates (1 basis point) supporting the hypothesis that QE affects principally yields with a higher maturity and has a negative effect on the slope.

Secondly, the response of the Euro Stoxx 50 is positive at impact as before but its magnitude is now much lower (0.5 basis point). On the other hand, the response of the implied volatility index is now negative at impact. However, as the stock index begins to drop and yields to rise, the implied volatility index increases. According to Bekaert and al. (2013) there are two major reasons to explain that dynamic. Indeed, we can consider like them that the Vstoxx is composed by a risk-aversion factor and an uncertainty factor. The decline in the stock index and the rise in interest rates can therefore be interpreted as a rise in uncertainty perceived by the market explaining the rise in the Vstoxx. The other explanation is based on risk aversion. When interest rates increase, investors have incentive to invest more in safer asset classes (they rebalance their portfolio) because the risk-adjusted returns of those securities are higher. Differently said, investors are no longer constrained to search yields towards riskier securities (i.e. being less risk averse). By consequent, they expect future price developments (future volatility) on the stock market.

Finally, let’s note that the responses of the macro variables are a bit different than previously. The response of the production index doesn’t present a sudden rise anymore. In addition, we observe a recovery in the medium term and a decline once again in the long run. On the other hand, the response of the HICP index is different. We observe a decline at impact but followed by a recovery beginning after 15 months. To conclude with the macro variables, it has to be said that the variations at impact are extremely low.

6. Robustness of the responses

In this section, we will consider different model specifications to test the robustness of the baseline model. We will start by specifying the basic model with 12 lags in order to control for possible errors in model specification and biases resulting from omitted lags[24]. We'll report the responses for each variable in the model.

Since we have highlighted a hypothetical overreaction of the Euro Stoxx 50 to the information shock, we will also include a broader index, the Stoxx Europe 600 index[25], to check and discuss whether the reaction to information shock is sensitively different from the Euro Stoxx 50.[26]

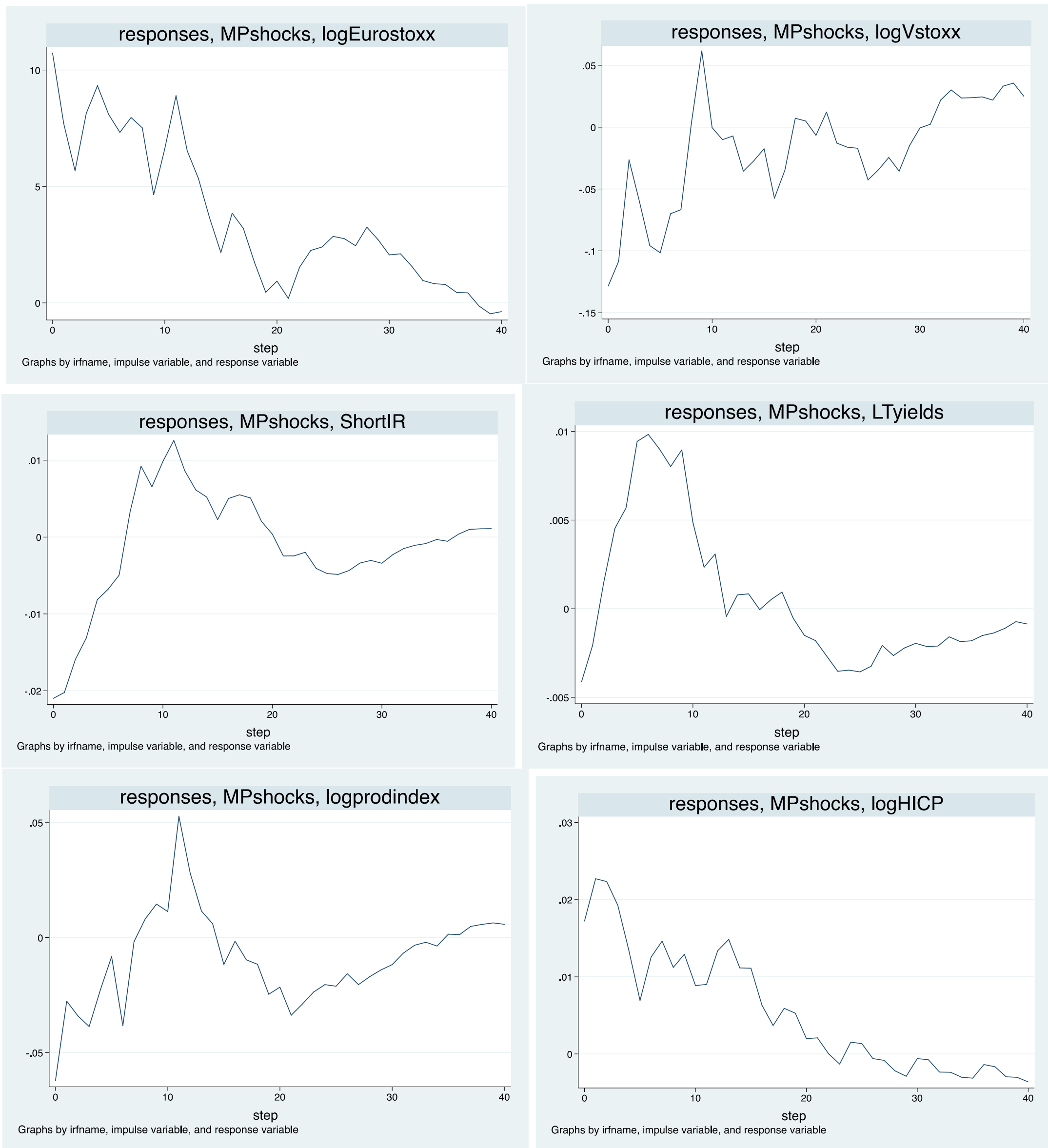
To conclude with this robustness analysis, we'll also include different implied stock market volatility according to their maturity. Recall that this index is derived from Euro Stoxx 50 options prices and as options can be sorted according to their maturity, we can deduce different implied volatility parameters from the price of these options and construct different implied volatility indices. It might be useful to compare the reaction of several volatility indices as this would allow us to understand how stock markets anticipate the effects of each shock and to know whether the indices react rather for short, medium and long-term levels. If the index reacts more in the short term than in the long term after a particular shock, it means that investors expect the financial and economic evolution of that shock to occur in the short term.

6.1 Baseline model extended to more lags

The figure 21 below shows the responses of the extended baseline model to a conventional monetary policy shock.

[24] When it will come to study the responses of unconventional monetary (QE) shocks, we'll proceed with the same resampling as before.
[25] Retrived from "Refinitiv Eikon" database : https://eikon.thomsonreuters.com/index.html
[26] This check will be done in a VAR model with 2 lags like the original baseline model

Figure 21: Extended baseline model responses to a MP shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

As we can see, changing the model's specification has an incidence on the responses. Adding more lags doesn't change the problem we had with the magnitude at impact of the Euro Stoxx 50, we observe still a quite high response of the index in the short run. Contrary to before, the response at impact of the Vstoxx is now negative (13 basis points). One thing that is particularly striking about the dynamics of these graphs is the evolution of the Vstoxx in relation to the other variables, in particular the Euro Stoxx 50 and the interest rate series. First, we notice that implied stock market volatility depends logically on the Euro Stoxx 50 level. By looking at the two graphs, we notice that the decline in the stock market index is associated with a rise in implied volatility. This negative relation seems logical because as the stock market goes down, the level of uncertainty perceived by investors increases for the future. Therefore, markets expect future movements in asset prices explaining the increase in the level of implied stock market volatility.

In addition, we can consider that the increase in implied stock market volatility can also be linked to some extent to rising interest rates for the same reasons mentioned above. However, although it is possible to assume a direct relationship between interest rate variables and implied volatility, the transmission of this monetary shock to the Vstoxx appears to be via the Euro Stoxx 50. As short-term and long-term rates start to rise, we observe a decline in the value of the stock index. This can be explained notably by the fact that the expected value of future cash flows decreases as the level of interest rates increases. Moreover, the portfolio rebalancing[27] channel can also explain the decline in the stock index. When the rates on long-term government bonds increase, the price of those bonds decreases pushing investors to invest in those securities instead of holding equities.

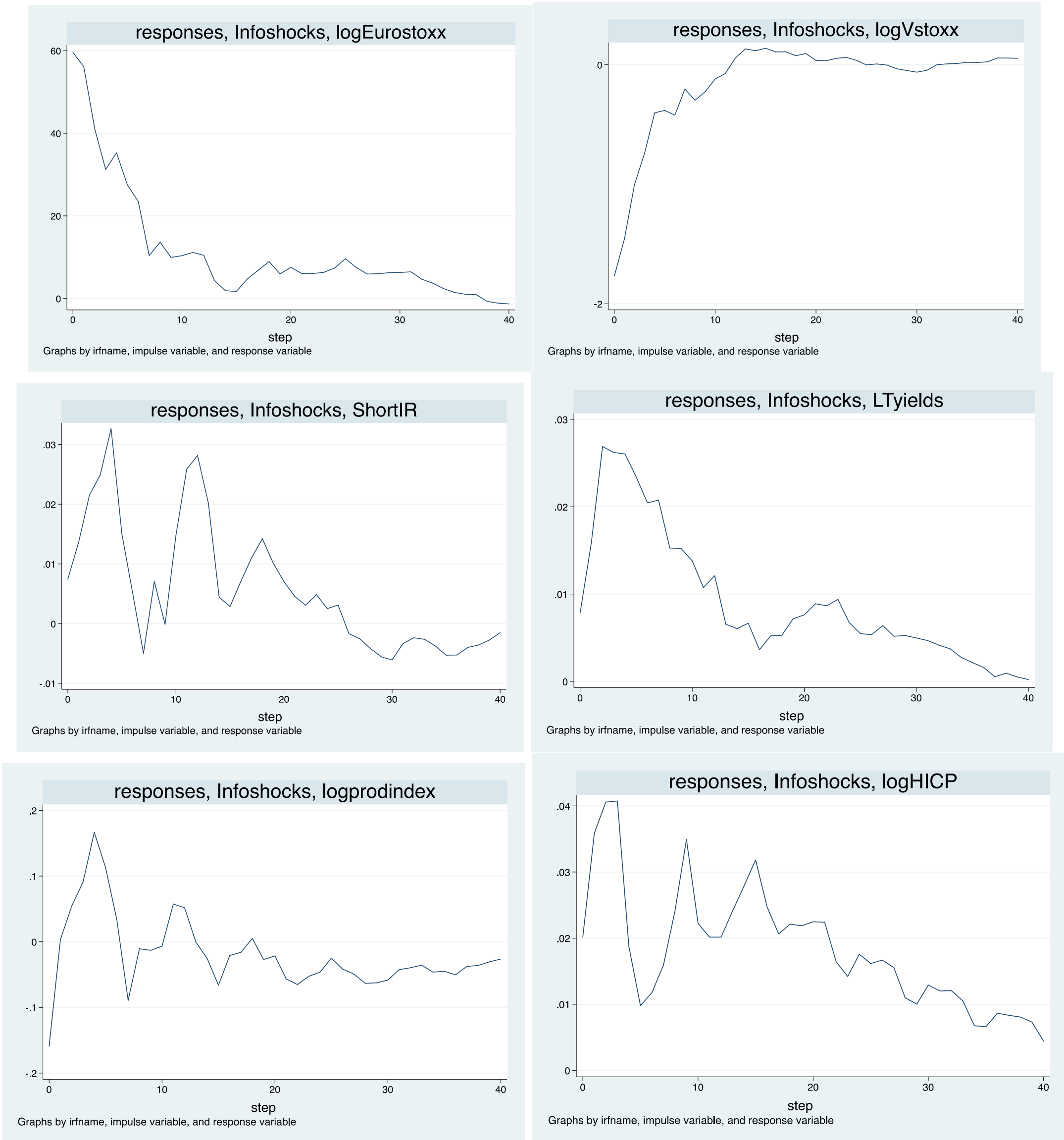
Concerning the interest rates variables, the responses are negative at impact which is consistent with what we expected. In addition, the responses at impact seem to validate the hypothesis we have made on the slope since short rates decrease more than long-term ones. On the other hand, there is an increase in short-term interest rates accompanied by a decrease in the medium term and a stabilisation in the long term. This dynamic is consistent with Goodhead's, although the magnitude of the response is different[28].

Finally, the reaction of the price index shows a similar trend to that observed previously. However, the response to the impact appears to be slightly higher (0.02%) than before. Moreover, the evolution of the price index is consistent with the decline in yields. On the other hand, the response to the impact of the output index is no longer positive (0.06%) and there is a peak in the medium term (12 months). It should be noted that we don’t see a clear transmission mechanism for macroeconomic variables, in contrast to the transmission mechanism between interest rates and the Euro Stoxx 50.

[27] Note that the portfolio rebalancing channel is often associated with unconventional monetary policies such as QE. However, this channel can, to some extent, also be considered in the context of conventional monetary policies.
[28] Recall that Goodhead uses 2-year German bond yields as a measure of short rates and Bayesian estimations which can explain the differences in the magnitudes of his responses.

The responses after an information shock are summarized in Figure 22.

Figure 22: Extended baseline model responses to an information shock

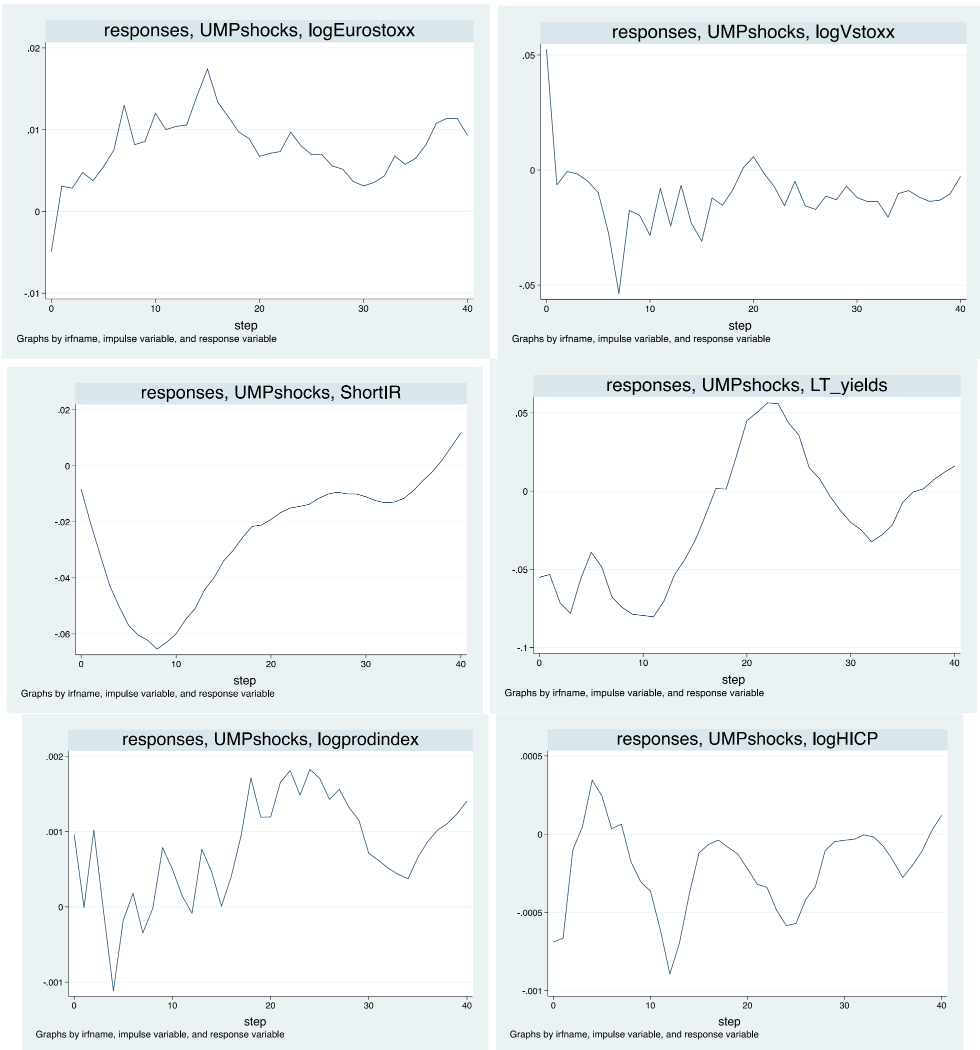


Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

Regarding the stock index's response, adding more lags doesn't solve the problem and it is even worse because the magnitude at impact is higher than before. Although the magnitude at impact is different, the response dynamics for the Euro Stoxx 50 and the Vstoxx are similar. The stock market index reacts strongly to the impact and then declines as rates rise. Implied volatility, on the contrary, is reduced following the information shock (1.8 %). However, it rises as the stock market index declines and rates rise. The responses of the interest rate variables seem to behave as before, except for their magnitude. We observe a positive reaction at impact followed by an increase in the short run[29] and a further decline in the long run. Interbank rates respond positively to the impact, which is consistent with previous sign restrictions. From the responses of the macro variables, we don't see a clear pattern of transmission as both the production index and the price index are oscillating. Changes in the direction of the responses might coincide with the behaviour of interbank rates.

Let's conclude this section by looking at the responses after an unconventional monetary policy shock illustrated in Figure 23.

Figure 23: Extended baseline model responses to an UMP shock



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

[29] It has to be noted that the rise in short-term interbank rates is less obvious.

We notice from the above figures that interest rates react negatively to the impact. In addition, long rates fall more than short rates, which supports the assumption made about the slope of the yield curve. It has to be noted that in contrast to the information shock, we observe a lower magnitude in the responses of the financial variables (-0.5 basis point for the Euro Stoxx 50 and +0.5 basis point for the Vstoxx). As before, the responses for the macroeconomic variables are quite low. Moreover, the dynamics of the responses are not as obvious to interpret as the other variables in the model, indicating some lack of evidence of the monetary transmission mechanism to the macroeconomic variables.

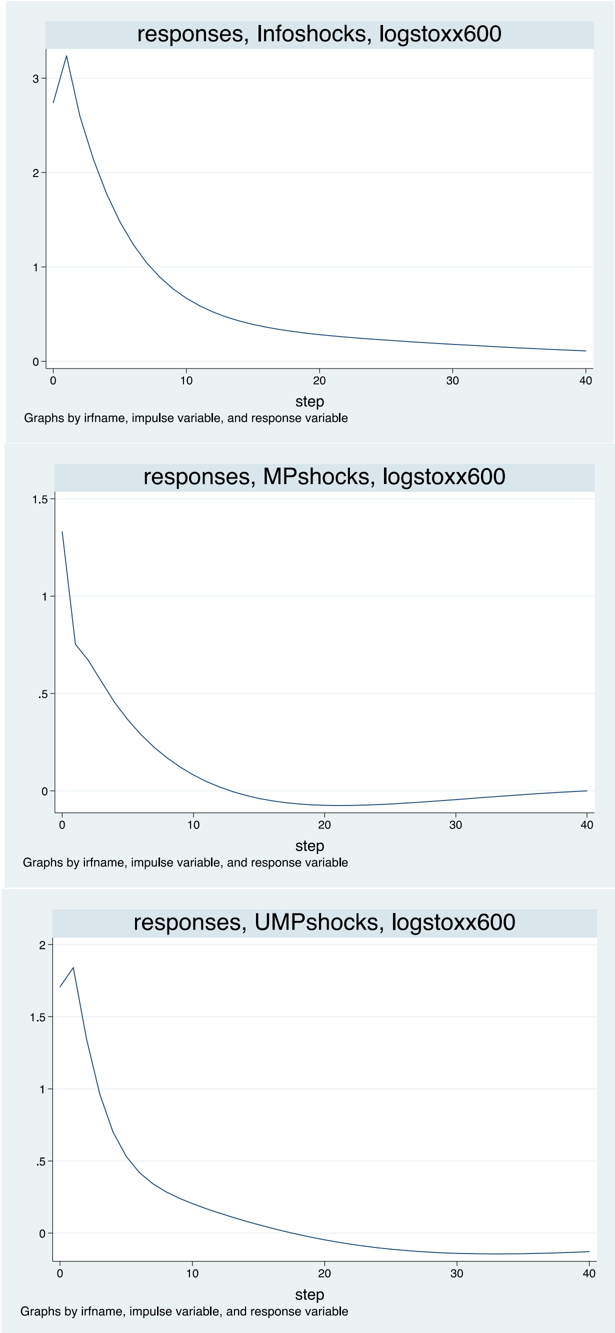
Nevertheless, we observe a certain relationship in the dynamic of the responses and a presence of transmission mechanism between interest rates, the stock index and implied stock market volatility. As interest rates drop, financial conditions are less tightened causing a rise in the stock index. As a result, while returns are declining and the stock market appears to be performing well, investors' expectations regarding the future development of the financial economy are good which tends to lower the level of the implied volatility index.

6.2 Responses with a broader stock market index

The figure 24 below shows the responses of the Stoxx Europe 600 index[30] after each type of impulse to shocks in the first baseline configuration (with two lags).

[30] We applied the same preliminary regressions as for the Euro Stoxx 50 to avoid non-stationarity problems as much as possible.

Figure 24: Responses of the Stoxx Europe 600 (log) to shocks



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

By examining the response of the new index to the information shock, we conclude that the change in the index has a significant impact on the magnitude of the response. The response to the impact is now more realistic at around 3% compared to the previous situation with the Euro Stoxx 50. The shape of the responses is quite similar as previously with the other stock index measure. However, the magnitude at the time of the impact of a conventional monetary policy shock is now around 1.3 % which is less than before. On the other hand, if we have a look at the response to a non-conventional monetary policy shock, the magnitude at impact (1.75%) is approximately the same as before in the very first small baseline model[31].

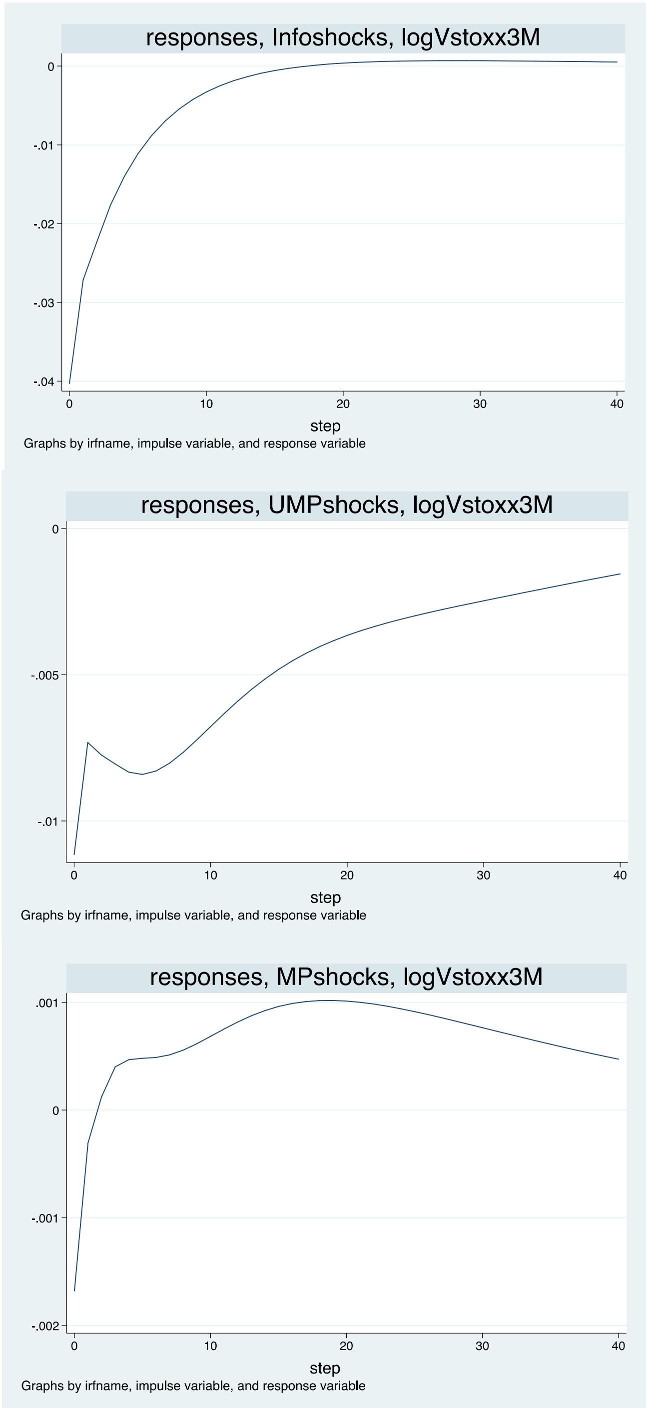
It can be concluded that the hypothesis we have made about the Euro Stoxx 50 and its specificities seems, to a certain extent, not to be invalidated. There is a kind of over-reaction of the Euro Stoxx 50 index which does not seem to appear in the case of the Stoxx Europe 600 index. This hypothetical overreaction can be explained by the atypical nature of this index.

6.3 Analysis of implied volatility responses for different levels of maturities

Figures 25-26-27 show the Vstoxx responses at the 3-month, 12-month, and 24-month maturity levels, respectively, for each type of shock. In this section, we'll put the emphasis on the magnitude of the responses to impact and less on the dynamic of the responses. This analysis will be based on responses generated from a VAR model with 2 lags. Although these responses may be less interpretable since they come from a model specification[32] which may be too light, it is possible to obtain some information on the basis of the different responses to the shocks.

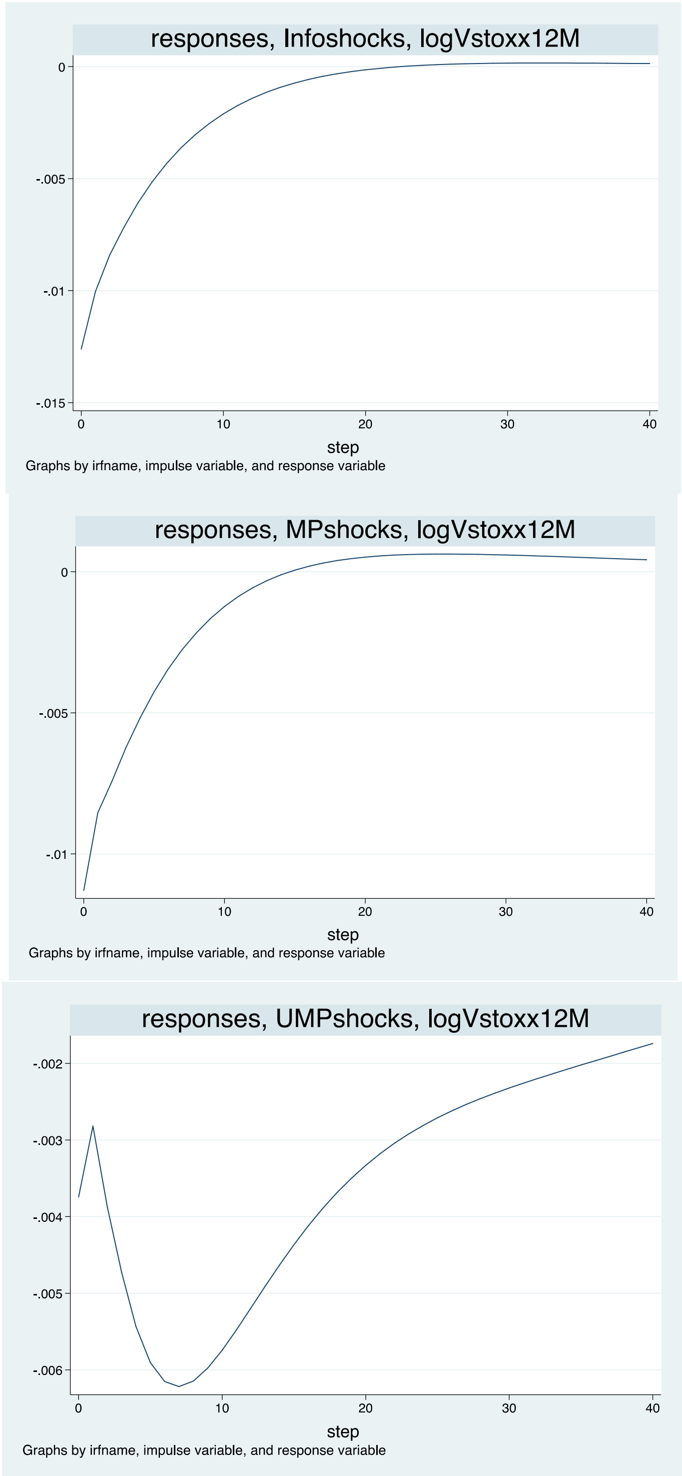
[31] The model with two lags and without resampling.
[32] Responses are generated from the basic specification (2 lags). In addition, responses after an unconventional shock were obtained from the same subsample as before.

Figure 25: Responses of log Vstoxx (3-month)



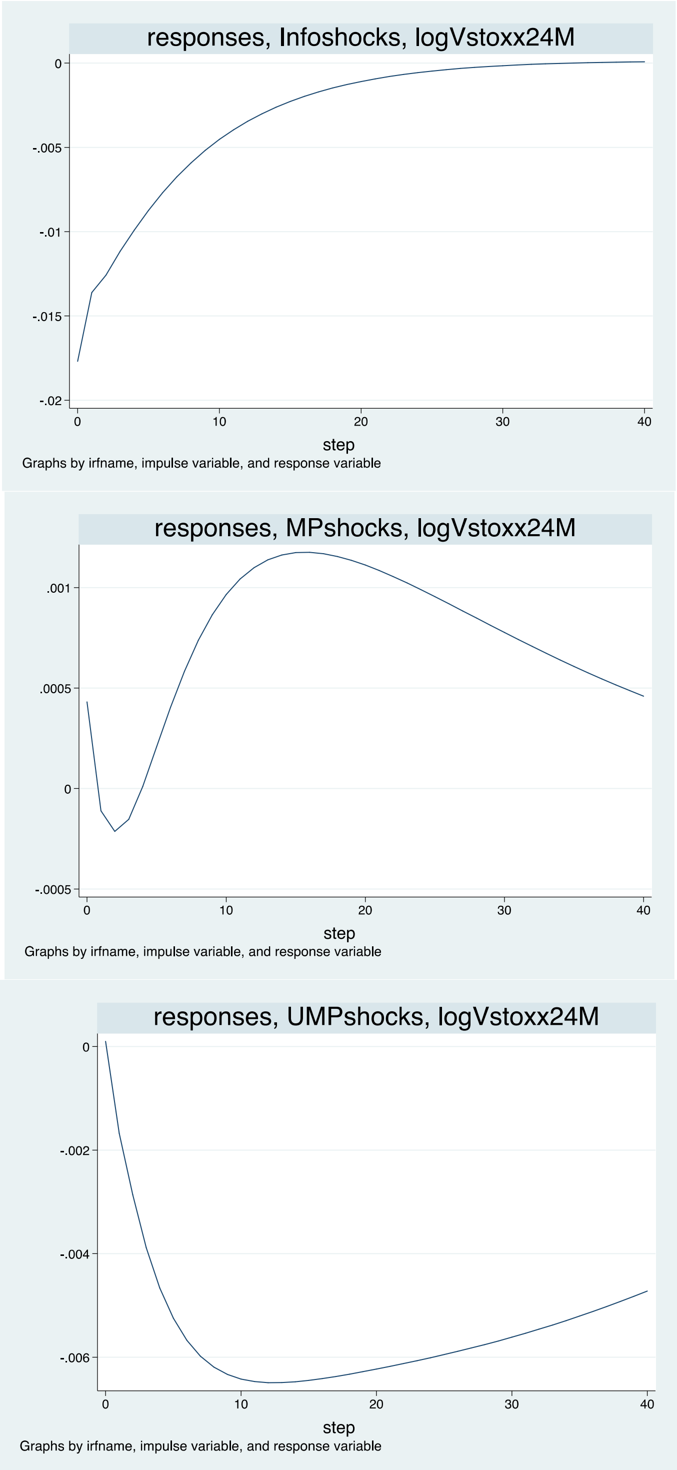
Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

Figure 26: Responses of log Vstoxx (12-month)



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

Figure 27: Responses of log Vstoxx (24-month)



Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Stata)

What can we learn from those responses? First, by looking at the different responses following the information shock, we can see that the biggest impact is for the 3-month Vstoxx (4 basis points). The response to the impact is negative, which makes sense when considering a positive information shock. In addition, it is logical to observe this because financial markets are less susceptible to react to a source of information after 12 or 24 months. Therefore, when a central bank positively informs the market regarding its monetary policy and its own perception of the economic outlook, investors expect the effects generated by this information to occur in the short term rather than in the long term. However, this type of pattern cannot be extended to monetary policy shocks.

When we examine the responses to a conventional monetary policy shock, we first find that the responses of the Vstoxx at 3 and 12 months are quite similar to those of the information shock. We observe a clear decline in implied stock market volatility for a maturity level of 3 and 12 months. In contrast to the information shock, the largest magnitude response occurs for the 12-month implied volatility index. It is not surprising to observe this because as we have seen in the previous section dedicated to the monetary transmission mechanism, it may take time for observing financial markets developments after a monetary policy decision.

Finally, when we compare the impact responses between conventional and unconventional monetary policy shocks, we find that the latter seems to affect in a lower extent implied volatility indexes, with the exception of the 3-month Vstoxx which shows a reaction of -1.2 basis points after a one basis point increase in the impulse variable. It should also be noted that the response of this index is again weaker than that of the information shock. This suggests that financial markets expect unconventional effects to occur in the shorter term than those that occur after a conventional monetary policy. Here again, we can rely on the monetary transmission mechanism. We have seen that unconventional monetary policies are a more direct way for policymakers to achieve macroeconomic objectives because they can bypass traditional channels by using channels specific to unconventional tools. If we take the QE as an example, it is easier and faster to reach long-term yields and people's long-term expectations in this way than by using "conventional" short-term policy rates.

7. Monetary policy implications

It is difficult to express clear and unanimous conclusions regarding our results as the impulse responses depend considerably on factors like the number of observations and the model specification (choice of the variables and number of lags). In addition, the following interpretations need to be tempered as we have pointed out potential problems and anomalies throughout our analysis. In spite of this, we can still try to draw some observations and conclusions that may be useful for policy purposes.

First and foremost, we have seen through the different responses the presence of a certain dynamic linking interest rates, the stock market and implied stock market volatility. As interest rates increase, we observe a decline in the level of stock prices accompanied by an increase in the Vstoxx. By consequent, monetary policy has a role to play in the level of uncertainty perceived by investors. This type of scheme cannot be extended to the other variables in the model because the dynamics of the macro variables are a bit more confused, which leads us to say that the transmission to these variables is unclear or at least less relevant.

In addition, we can discuss whether implied stock market volatility is particularly affected by QE. Looking at the responses after resampling, we can deduce that implied stock market volatility appears to respond less to the impact of a QE shock than in other cases. Implied stock market volatility reacts relatively more to conventional monetary policy than unconventional monetary policy such as QE. Besides, although the implied volatility responses follow a dynamic consistent with the evolution of interest rates and the stock market index[33], the direction of the implied volatility response is initially positive to the impact when considering both the extended and the normal baseline specification. However, we should be cautious because although the sign restrictions we imposed might in a certain extent capture QE[34], we could have added more restrictions when identifying QE. For example, some authors (Bhattarai and Neely, 2016; Rossi, 2018) suggest that QE has had significant effects on exchange rates and that the exchange rate channel is particularly important in explaining the real effects that QE policies can cause. That being said, we could possibly have been more restrictive in

[33] As a reminder, we observed a decline in the level of implied stock market volatility when interest rates (especially interbank rates) were falling and the stock index was increasing.
[34] We know already from Bhattarai and al. (2015) that QE affects stock prices positvely and negatively long-term yields (reduce the slope in our case).

identifying unconventional monetary policy and QE shocks by adding sign restrictions on a series of exchange rate "surprises" from the Altavilla (2019) database.

To conclude this section, we can make an important observation concerning the responses after a positive information shock. Regardless of the specification of the VAR model that we impose, the behavior of responses following this shock suggests that European stock markets seem to react especially to the information that they could infer from central bank decisions. It is therefore important for a policymaker like the ECB to pay attention to the way in which economic agents interpret its decisions. If market expectations about future economic and financial outlooks do not match with the expectations of the central bank on which its monetary decisions are based, a central bank monetary policy announcement may involuntarily transmit a positive or a negative information shock to financial markets, an information shock which may have quite important impacts on some stock markets metrics[35]. This may explain why central banks are now increasingly relying on forward guidance policies and this is in accordance with the views of Blinder and al. (2008), in which they underline the importance of communication in the conduct of monetary policy. Besides, this highlights the importance for central banks to use surveys as a way to obtain information about expectations regarding inflation and financial conditions and also about business sentiment (Van den Bergh, 2009).

[35] In particular the Euro Stoxx 50.

8. Conclusion

Throughout this thesis, we aimed to investigate the relationships between monetary policy types and implied stock market volatility. After exposing the two major types of monetary policies (conventional vs unconventional) and their different channels, we have been able to identify a series of structural shocks by using sign restrictions on financial market responses to central bank announcements, a method used by a growing part of the literature. Taking Jaroncinski & Karadi (2020) and Goodhead (2019) as reference, we infer from ECB's policy decisions announcements three structural shock candidates: an information shock, a conventional monetary policy shock and an unconventional monetary policy shock. Then, we explored the effects and the dynamics of each shock on implied stock market volatility through a medium-scale VAR-X model containing interest rates measures and macroeconomic indicators.

Among the "unconventional" category of shocks identified, we put a particular emphasis on QE. We first imposed sign restrictions that we considered to be consistent with the literature and economic theory, and then resampled our dataset to examine and capture only its actual implementation period in the euro area. We found that QE per se had little or no contemporaneous impact on implied stock market volatility relative to the other types of shocks considered. However, we should be cautious regarding this because we can consider that the number of observations after resampling is relatively small (120 observations) and because the sign restrictions we imposed might not be sufficiently restrictive to capture precisely QE shocks in the data.

From the responses analyzed after the different shocks, we can make several remarks. Firstly, we noticed the presence of a certain interrelation between interest rates, stock market and implied stock market volatility whatever the number of lags we included in the VAR. As interest rates rise, we observe that the Euro Stoxx 50 declines and implied stock market volatility increases. In the spirit of Beckeart and al. (2013), two reasons can be given to explain this situation. As interest rates rise and stock returns decline, the level of uncertainty perceived by investors may increase which tends to rise the Vstoxx level. Moreover, the main other factor influencing implied stock market volatility according to Beckeart and al. (2013) is the degree of risk aversion. When interest rates are higher and stock market starts to become more bearish, investors might be tempted to revise their optimal asset allocations (i.e. they rebalance their portfolio). Indeed, it is no longer necessary for them to invest in riskier securities as before, as they can now find less risky assets offering similar returns. This means that their risk aversion increases when it comes to make investment decisions. Secondly, we saw that including the information shock apart from the monetary shock can be useful as it is in reality the shock which affects the most the financial market variables. This tends to support Jaronciski and Karadi (2020) who claim that it is important to consider this shock separately when identifying structural monetary policy shocks because otherwise we could obtain misleading results and overestimate the effects of monetary policy shocks on some variables. Nevertheless, we should be prudent when claiming a possible considerable impact of this shock on financial variables (especially the Euro Stoxx 50). We have seen that the shock reaction on the stock market is quite sensitive to the choice of the stock index which might indicate a possible bias or overreaction coming in particular from the choice of the Euro Stoxx 50. Another possibility that could explain this is a possible misidentification of structural shocks when establishing our sign restrictions. The sign restrictions we have imposed could be such that the so-called information shocks identified actually capture some of the shocks attributable to (non-) conventional monetary policy shocks.

Since the methodology we followed for retrieving and identifying structural shocks is quite different from standard identification procedures used in the literature (e.g. Cholesky identification based on traditional time series data) and can still be considered in its "experimental" phase, it may be interesting to explore these outstanding issues in greater depth for future research, for example with different sign restrictions and with more and different data.

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Appendices

A1. Identification of structural shocks through QR decomposition and sign restrictions

This section explains in more details how I decided to implement sign restrictions for identifying the three structural shocks. This approach, in contrast to Cholesky identification, is an identification scheme that doesn't need a predefined causal sequence in the model.

The variance decomposition of the reduced form residuals is not the same as Cholesky where the matrix P is by definition a lower triangular matrix. This method enables all variables to respond simultaneously to the different identified shocks. The idea behind sign restrictions for structural shocks identification is to explore all possible "structural" decompositions of the variance of $\hat{\varepsilon}_t$ but only keeping $\hat{\mu}_t$ so that impulse responses are consistent with the set of sign restrictions. These restrictions are usually specified to obtain impulse responses that are "economically acceptable".

To illustrate this identification method, let's rewrite the reduced form of the VAR (1) in an equivalent moving average form:

$$Y_t = \sum_{i=0}^{\infty} \phi_i \, \varepsilon_{t-i} \qquad (1)$$

In this representation, ϕ summarize the impulse responses of the reduced form where ϕ_0=I and ϕ_i= $\sum_{j=1}^{i} \phi_{i-j} \, A_j$.

Under Cholesky, we have $\sum_{\varepsilon}$= PP' and $Y_t = \sum_{i=0}^{\infty} \phi_i \, PP^{-1} \varepsilon_{t-i}$.
Hence, the structural variance-covariance can be written as:

$$\sum_{\mu} = P^{-1} E(\varepsilon_t \varepsilon_t{}') \, P^{-1\,\prime} = P^{-1} \sum_{\varepsilon} P^{-1\prime} = P^{-1} PP' P^{-1\prime} = I$$

and the structural impulse responses are summarized by $\gamma_i = \phi_i \, P$

The identification of structural shocks is accomplished by setting restrictions on the signs of γ_i. The objective is to obtain different orthogonalizations of the reduced form model which satisfy the imposed sign restrictions on the structural impulse responses. One way to obtain an orthogonal representation of the impulse responses in Equation (1), we can multiply $\gamma_i = \phi_i P$ by a random matrix Q such as $QQ'=I$ so that:

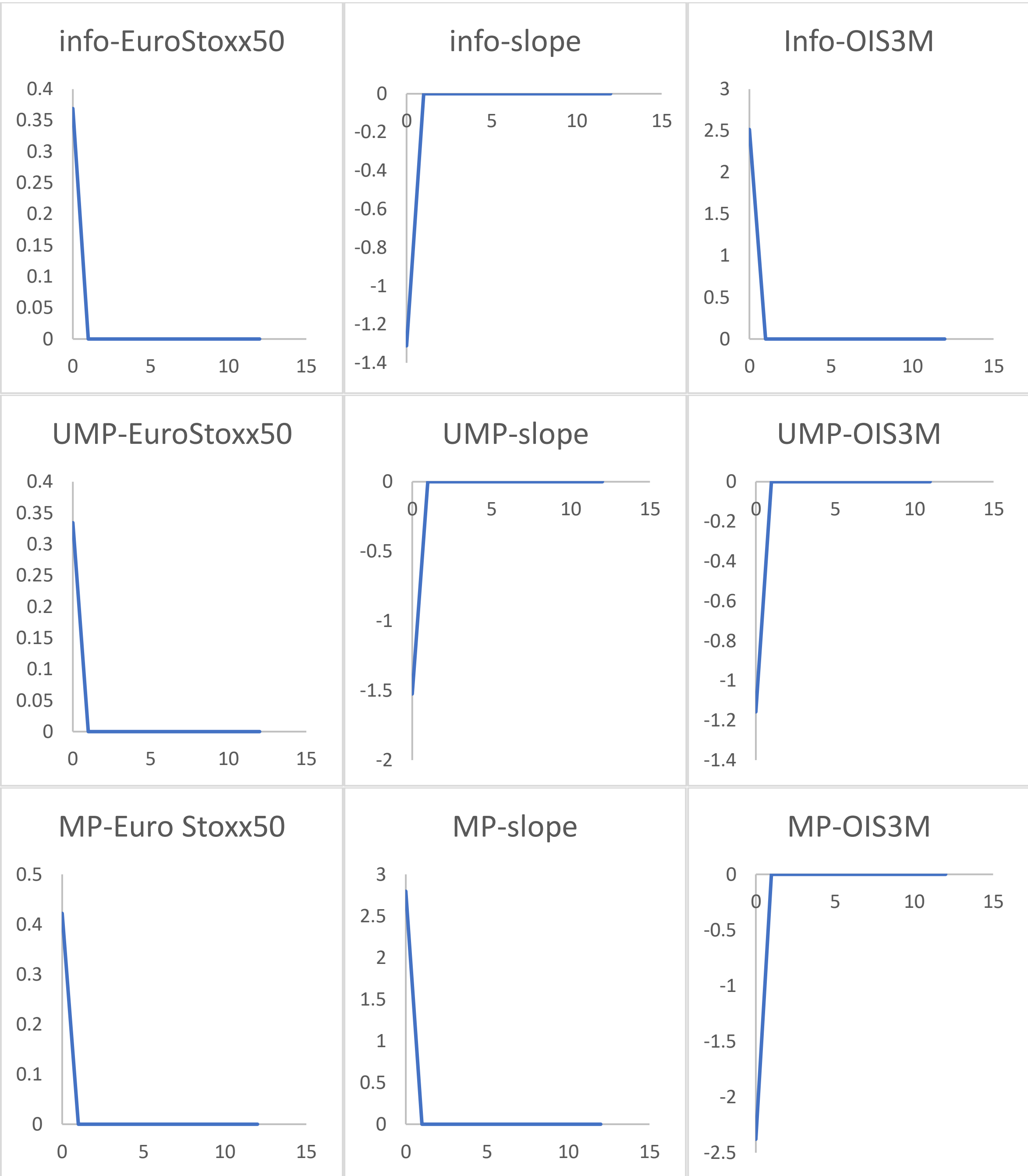
$$\Sigma_\mu = E(Q'P^{-1}\varepsilon_t\varepsilon_t'P^{-1}Q)=I$$

Therefore, the identification algorithm of Breitenlechner and al. (2019) follows these steps:

1) Estimate a reduced form of the VAR. Here, because the variables are composed of intra-daily surprises, these data should not be autocorrelated. By consequent, I just took these variables as a vector and specified a VAR containing 0 lags and a constant. By doing so, I obtained demeaned equations and remove the eventual constant component in the series.
2) Multiply ϕ_i by the lower triangular Cholesky matrix P and Q in order to obtain orthogonal impulse responses. These matrices come respectively from the decomposition of the reduced form variance-covariance matrix Σ_ε = PP' and a random orthonormal matrix Q which satisfies $Q'Q = I$.
3) Verify whether the orthogonal impulse responses satisfy the sign restrictions
4) If yes, we considered that the orthogonal impulse responses have a structural interpretation and are consequently saved.
5) If not, we disregard these orthogonal impulse responses and repeat step 2 and 3.

A2. More on structural shocks series

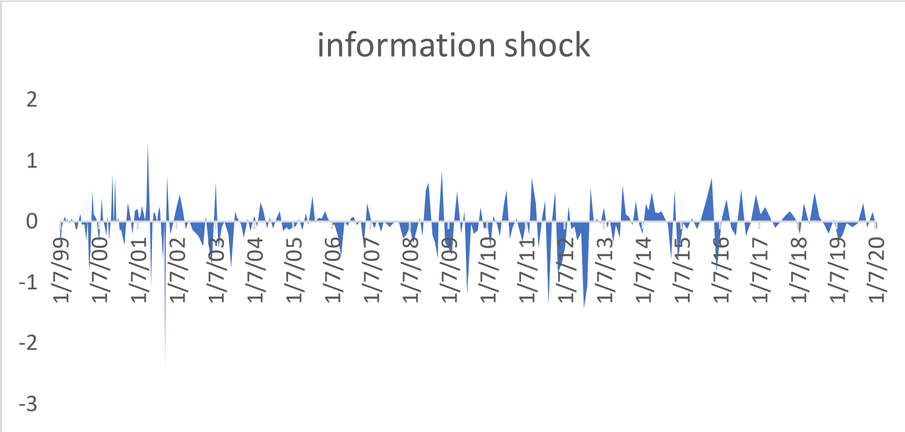
A2.1 CTM impulse responses

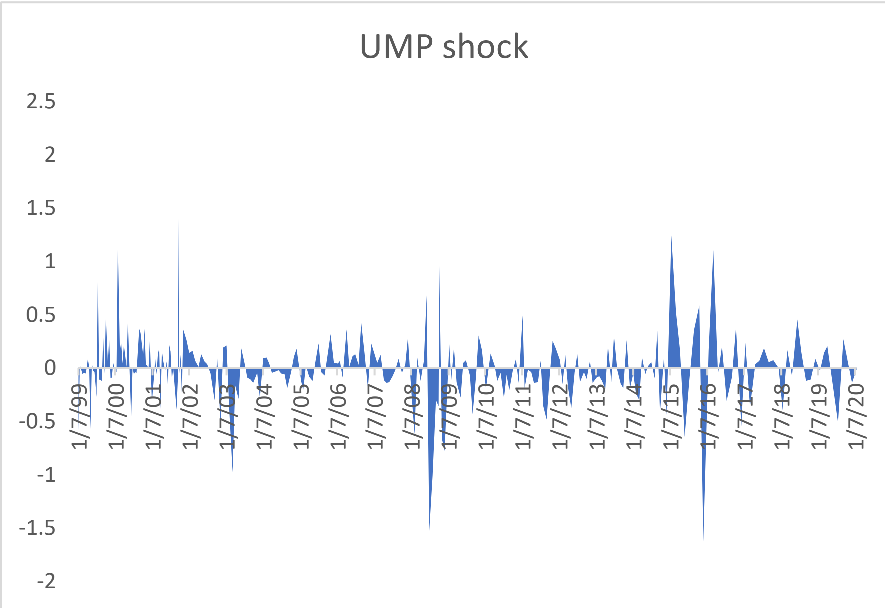


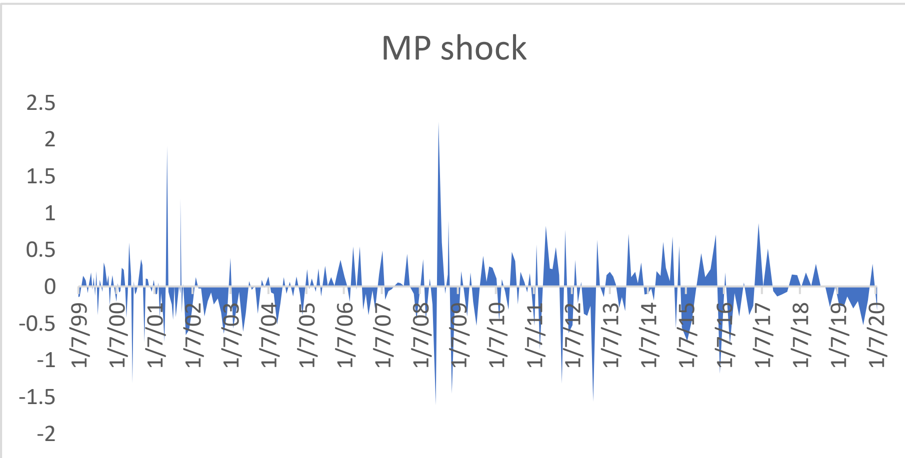
Source: Altavilla and al. (2019) – Own calculations (Excel)

A2.2 Variance decomposition of the "surprise" variables according to each structural shock

1) *Euro stoxx 50*

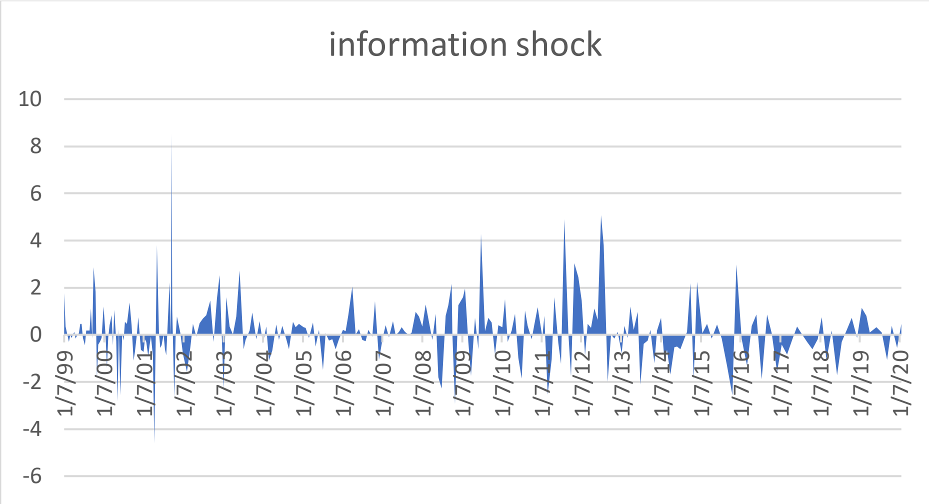


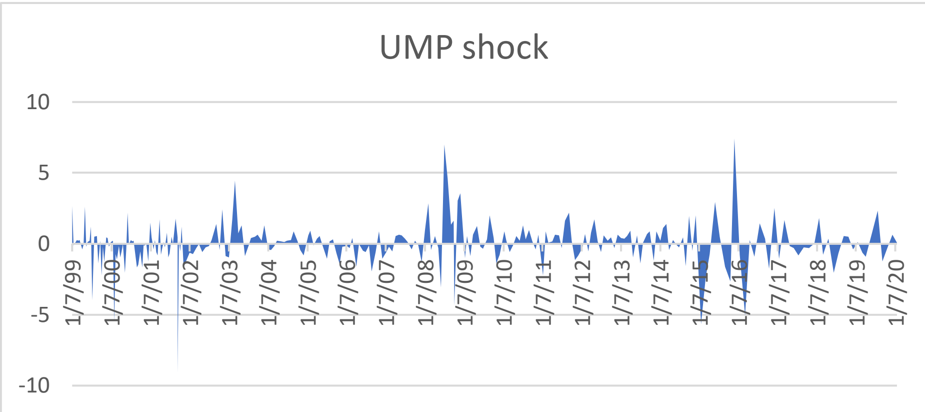


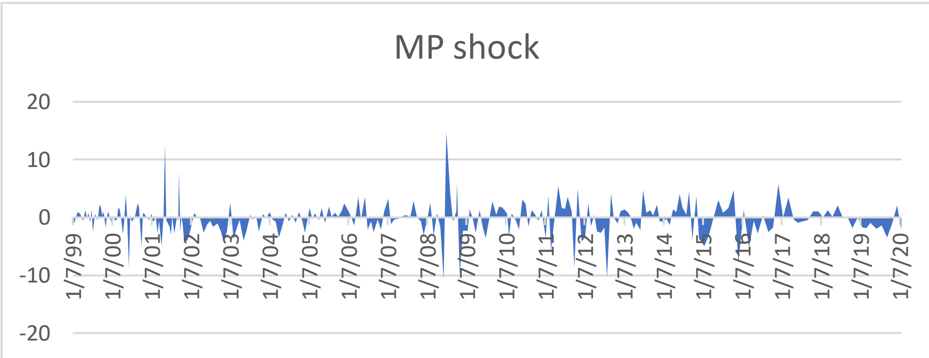


Source: Altavilla and al. (2019) – Own calculations (Excel)

2) Slope (10Y- 2Y)

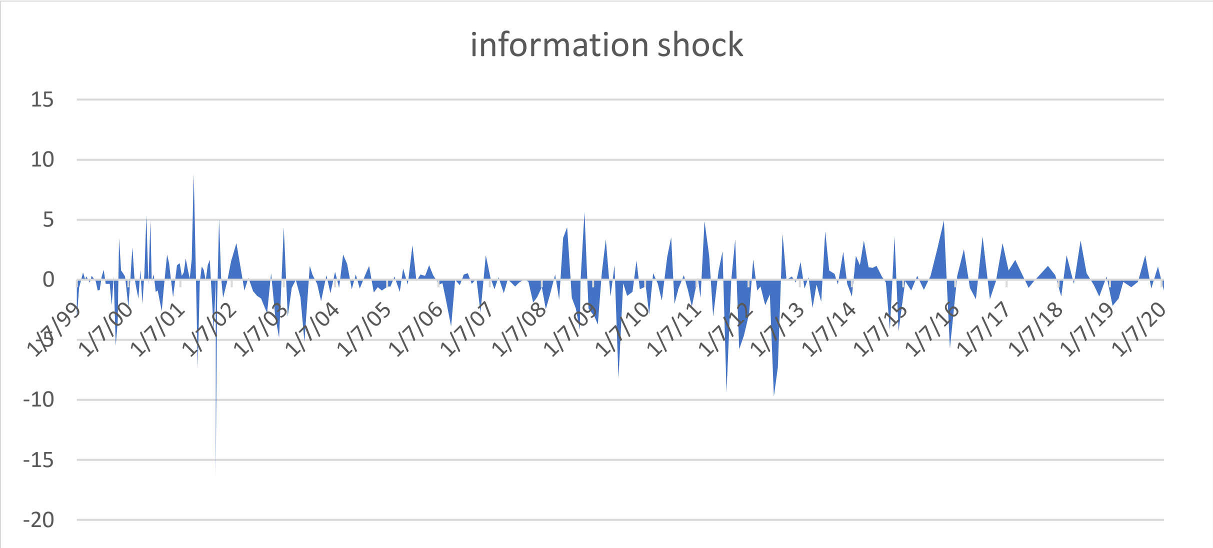


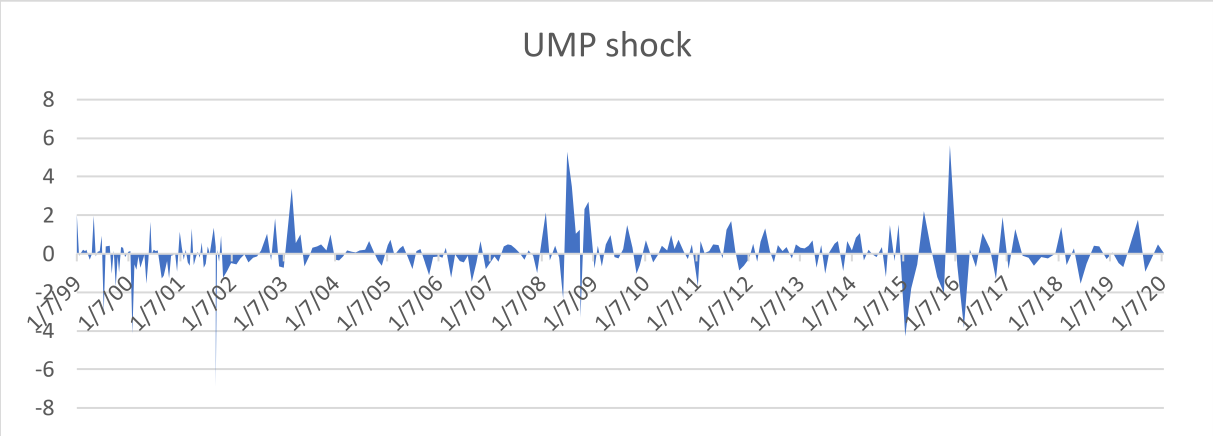


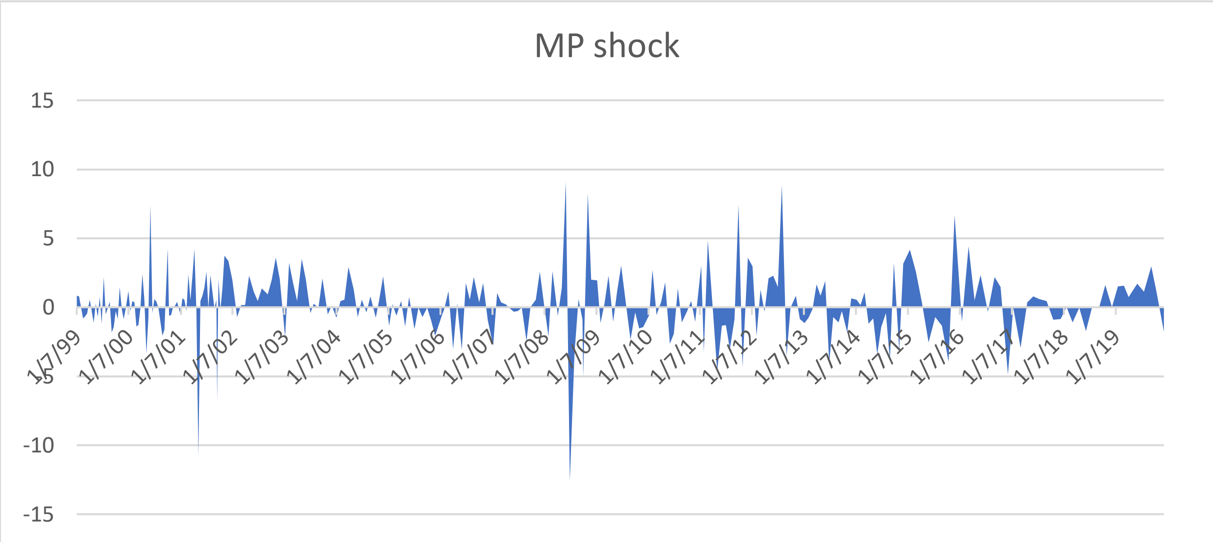


Source: Altavilla and al. (2019) – Own calculations (Excel)

3) OIS 3 month

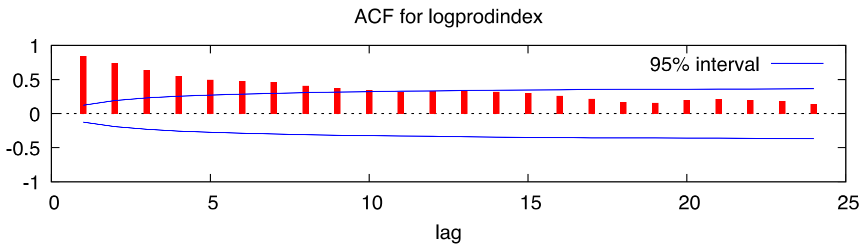


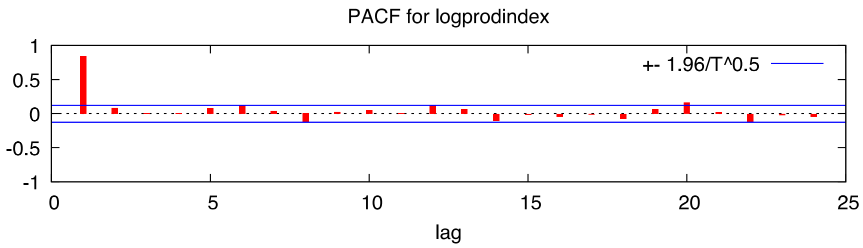


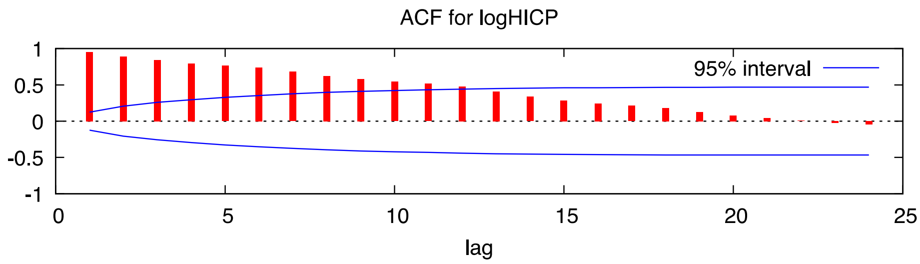


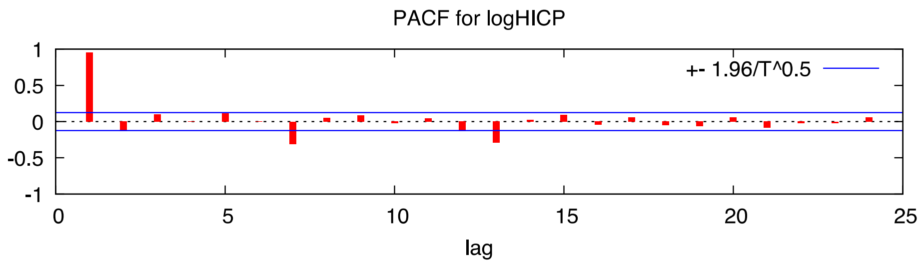
Source: Altavilla and al. (2019) – Own calculations (Excel)

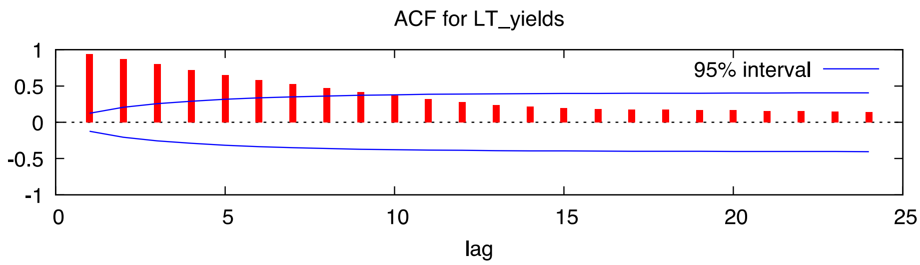
A3. ACF and PACF of the series entering in the VAR

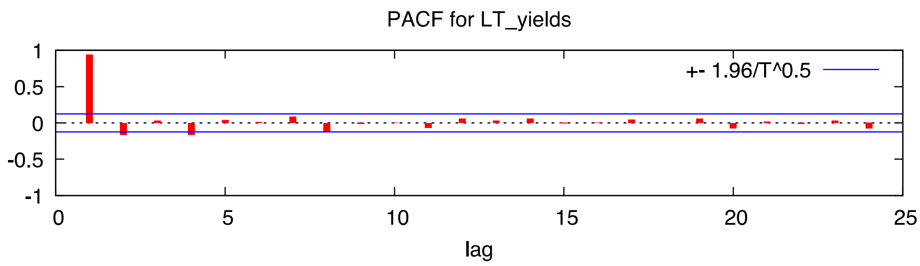




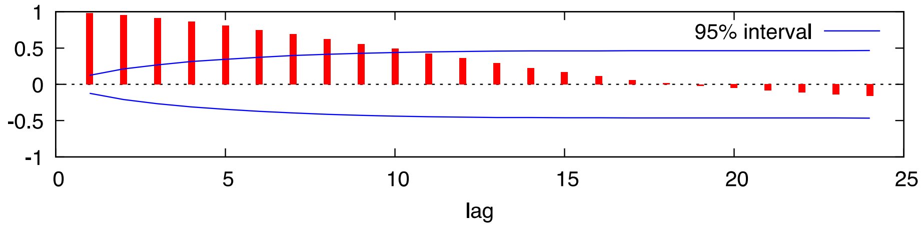




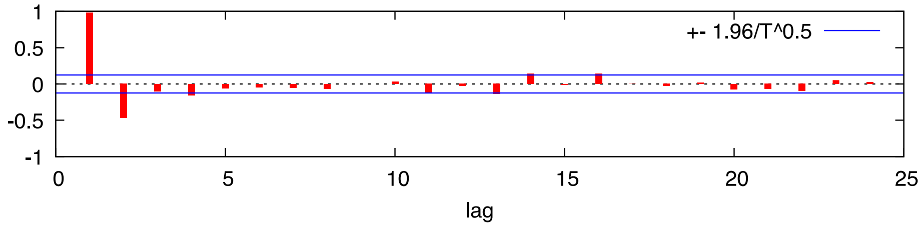




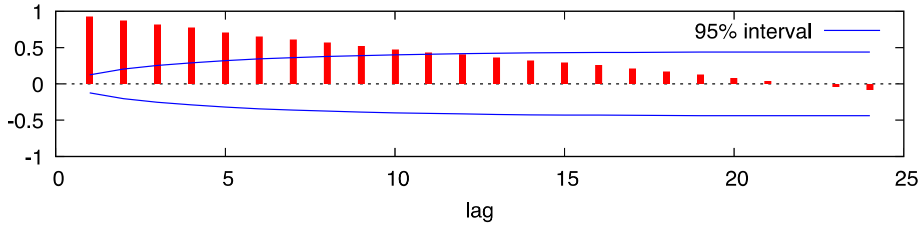
ACF for Interbankrates



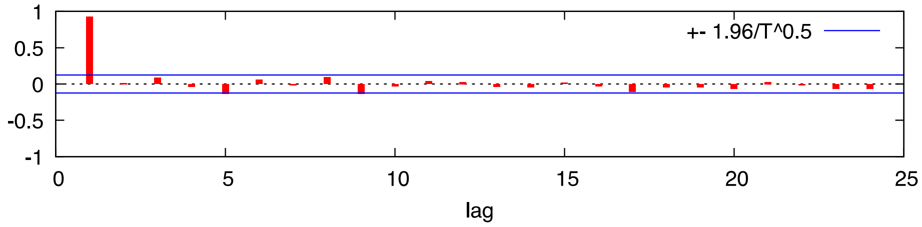
PACF for Interbankrates



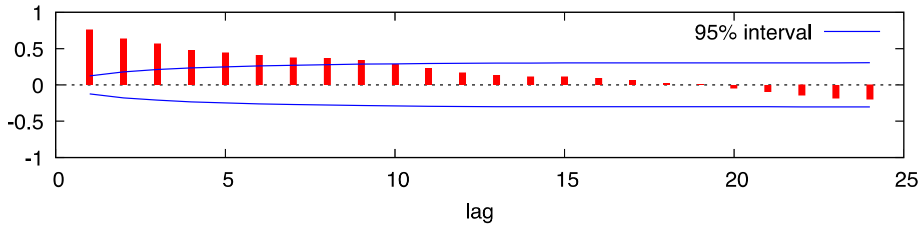
ACF for logEurostoxx



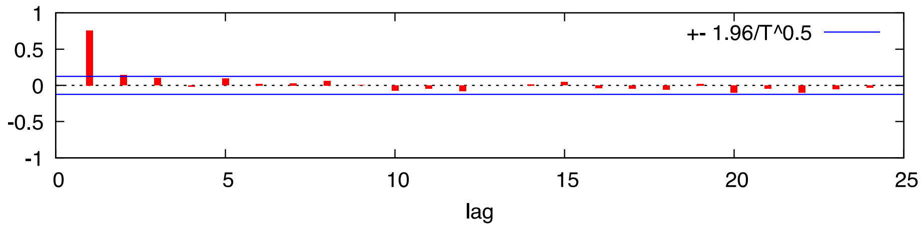
PACF for logEurostoxx



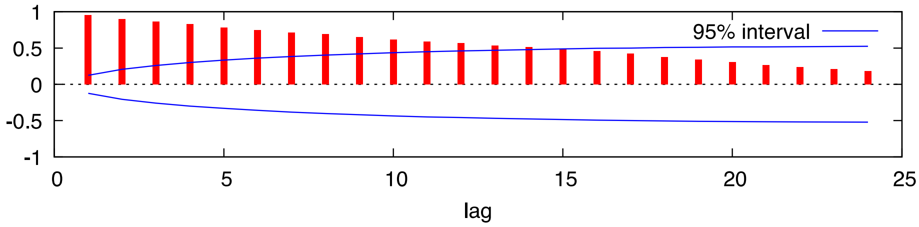
ACF for logVstoxx



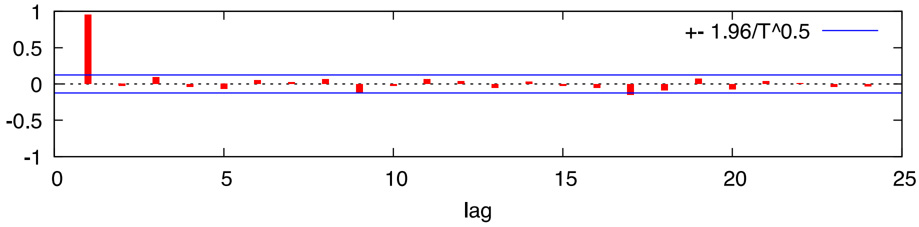
PACF for logVstoxx



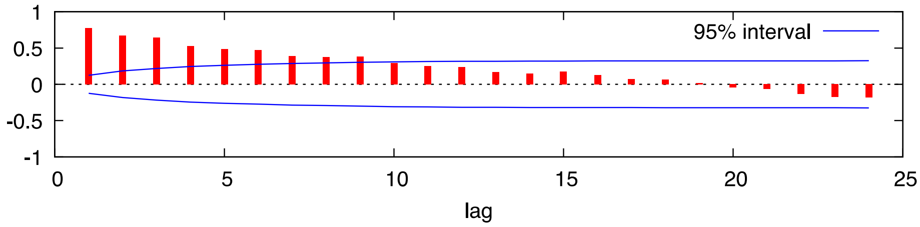
ACF for LogStoxx600



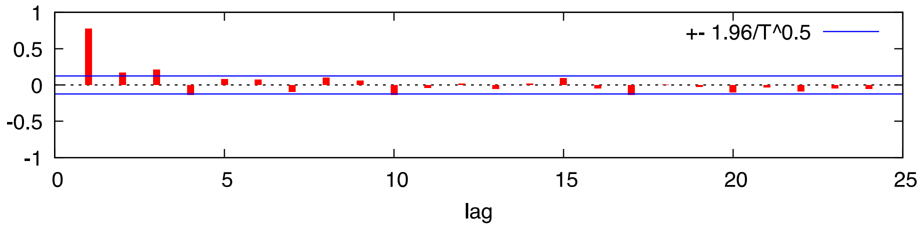
PACF for LogStoxx600



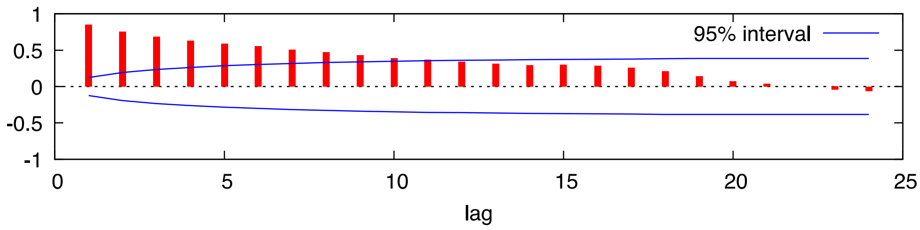
ACF for logVstoxx3M



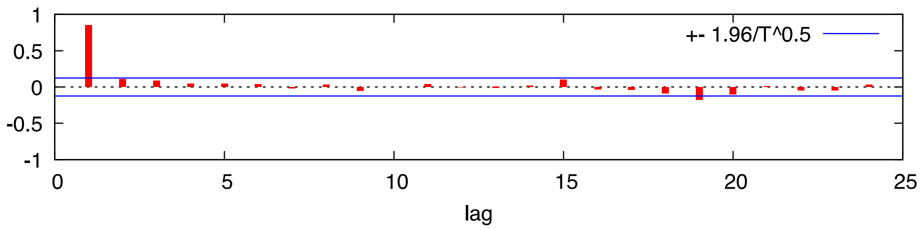
PACF for logVstoxx3M

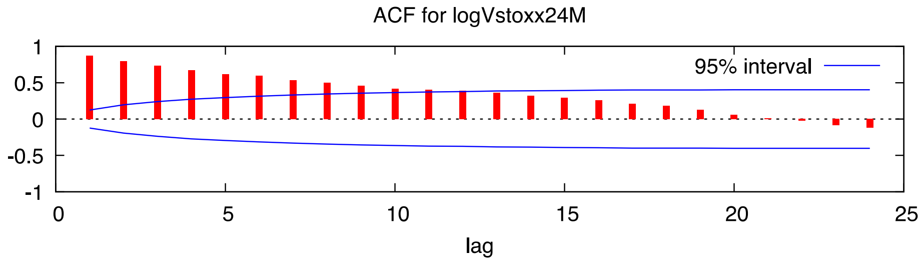


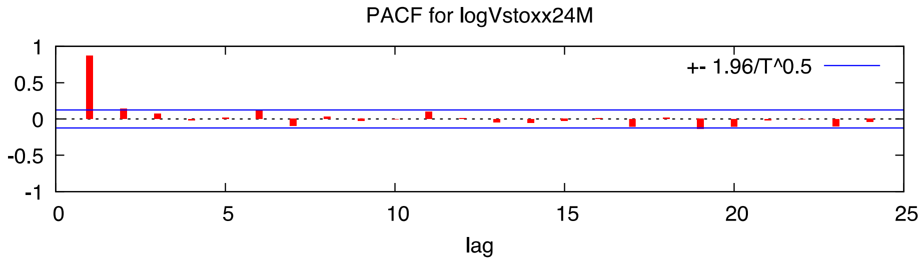
ACF for logVstoxx12M



PACF for logVstoxx12M







Sources: FRED (2020); Eikon (2020) – Own calculations (Gretl)

A4. Preliminary regressions to make time series stationary

```
Model 1: OLS, using observations 1999:01-2020:01 (T = 253)
Dependent variable: l_prodindex
HAC standard errors, bandwidth 4 (Bartlett kernel)

             coefficient    std. error    t-ratio   p-value
  ----------------------------------------------------------
  const       4.54224       0.00742553    611.7     0.0000    ***
  GFC         0.0951783     0.00754216     12.62    1.48e-28 ***
  time        0.000377929   4.62858e-05     8.165   1.61e-14 ***
  GFCbis     -0.0938134     0.0146271      -6.414   7.09e-10 ***

Mean dependent var    4.593340   S.D. dependent var    0.050188
Sum squared resid     0.205029   S.E. of regression    0.028695
R-squared             0.676986   Adjusted R-squared    0.673094
F(3, 249)             159.6358   P-value(F)            1.02e-57
Log-likelihood        541.4345   Akaike criterion     -1074.869
Schwarz criterion    -1060.735   Hannan-Quinn         -1069.183
rho                   0.842043   Durbin-Watson         0.303926

Model 2: OLS, using observations 1999:01-2020:01 (T = 253)
Dependent variable: l_HICP
HAC standard errors, bandwidth 4 (Bartlett kernel)

             coefficient    std. error    t-ratio     p-value
  ------------------------------------------------------------
  const       4.27725       0.00312084    1371        0.0000     ***
  time        0.00230927    5.36167e-05     43.07     1.26e-114  ***
  sq_time    -3.37666e-06   1.98728e-07    -16.99     5.42e-43   ***
  dm2         0.00169946    0.00121798       1.395    0.1642
  dm3         0.00854690    0.00180261       4.741    3.65e-06   ***
  dm4         0.0110633     0.00206712       5.352    2.04e-07   ***
  dm5         0.0114339     0.00226776       5.042    9.11e-07   ***
  dm6         0.0110091     0.00246663       4.463    1.24e-05   ***
  dm7         0.00636556    0.00246461       2.583    0.0104     **
  dm8         0.00622876    0.00243628       2.557    0.0112     **
  dm9         0.00808500    0.00239001       3.383    0.0008     ***
```

```
  dm10        0.00835125    0.00216814       3.852   0.0002    ***
  dm11        0.00597319    0.00186092       3.210   0.0015    ***
  dm12        0.00756330    0.00148749       5.085   7.44e-07  ***

Mean dependent var   4.505217   S.D. dependent var   0.107804
Sum squared resid    0.015969   S.E. of regression   0.008174
R-squared            0.994547   Adjusted R-squared   0.994251
F(13, 239)           1045.198   P-value(F)           2.5e-202
Log-likelihood       864.3290   Akaike criterion    −1700.658
Schwarz criterion   −1651.191   Hannan-Quinn        −1680.756
rho                  0.949861   Durbin-Watson        0.082738
```

```
Model 3: OLS, using observations 1999:01-2020:01 (T = 253)
Dependent variable: Long-term yields
HAC standard errors, bandwidth 4 (Bartlett kernel)

             coefficient    std. error    t-ratio   p-value
  ---------------------------------------------------------
  const      −227.918       75.2027       −3.031    0.0027  ***
  time          4.31808      1.96960       2.192    0.0293  **
  sq_time       0.0154188    0.00783646    1.968    0.0502  *

Mean dependent var   651.4117   S.D. dependent var   657.3140
Sum squared resid    16005960   S.E. of regression   253.0293
R-squared            0.852994   Adjusted R-squared   0.851818
F(2, 250)            327.6814   P-value(F)           1.38e-70
Log-likelihood      −1757.459   Akaike criterion     3520.919
Schwarz criterion    3531.519   Hannan-Quinn         3525.184
rho                  0.968459   Durbin-Watson        0.063996

Test for addition of variables -
  Null hypothesis: parameters are zero for the variables
    sq_time
  Test statistic: F(1, 250) = 3.87133
  with p-value = P(F(1, 250) > 3.87133) = 0.050223
```

```
Model 4: OLS, using observations 1999:01-2020:01 (T = 253)
Dependent variable: Short-term interest rates
HAC standard errors, bandwidth 4 (Bartlett kernel)

                       coefficient  std. error  t-ratio   p-value
  ---------------------------------------------------------------
  const                 3.98967     0.357587     11.16    1.04e-23 ***
  time                 −0.0185979   0.00165457  −11.24    5.58e-24 ***
  GFCbis                0.439569    0.681200      0.6453  0.5193
  Structural_break~     0.546253    0.356929      1.530   0.1272

Mean dependent var   1.738897   S.D. dependent var   1.747750
Sum squared resid    218.6979   S.E. of regression   0.937179
R-squared            0.715891   Adjusted R-squared   0.712468
F(3, 249)            149.2267   P-value(F)           2.37e-55
Log-likelihood      −340.5607   Akaike criterion     689.1213
Schwarz criterion    703.2549   Hannan-Quinn         694.8077
rho                  0.983964   Durbin-Watson        0.029319

Test for omission of variables -
  Null hypothesis: parameters are zero for the variables
    GFCbis
    Structural_break_2000_2003
  Test statistic: F(2, 249) = 1.28082
  with p-value = P(F(2, 249) > 1.28082) = 0.279634
```

```
Model 5: OLS, using observations 1999:01-2020:01 (T = 253)
Dependent variable: log Euro stoxx 50
HAC standard errors, bandwidth 4 (Bartlett kernel)

                      coefficient  std. error  t-ratio  p-value
  --------------------------------------------------------------
  const                8.03966    0.0242633   331.4    0.0000   ***
  GFC                  0.216430   0.0525810     4.116  5.24e-05 ***
  GFCbis              -0.265805   0.0768379    -3.459  0.0006   ***
  Structural_break~    0.220777   0.0897107     2.461  0.0145   **

Mean dependent var   8.075274   S.D. dependent var   0.208213
Sum squared resid    7.758094   S.E. of regression   0.176513
R-squared            0.289866   Adjusted R-squared   0.281310
F(3, 249)            11.90517   P-value(F)           2.60e-07
Log-likelihood       81.81714   Akaike criterion    -155.6343
Schwarz criterion   -141.5007   Hannan-Quinn        -149.9479
rho                  0.932968   Durbin-Watson        0.134610

Model 6: OLS, using observations 1999:01-2020:01 (T = 253)
Dependent variable: l_Vstoxx
HAC standard errors, bandwidth 4 (Bartlett kernel)

                      coefficient  std. error   t-ratio   p-value
  ----------------------------------------------------------------
  const               3.16352     0.0862514    36.68     2.23e-102 ***
  time               -0.00106026  0.000484079  -2.190    0.0294    **
  GFCbis              0.508896    0.107396      4.738    3.62e-06  ***
  Structural_break~   0.236403    0.113305      2.086    0.0380    **

Mean dependent var   3.099650   S.D. dependent var   0.335496
Sum squared resid    19.55632   S.E. of regression   0.280249
R-squared            0.310534   Adjusted R-squared   0.302227
F(3, 249)            14.12600   P-value(F)           1.56e-08
Log-likelihood      -35.13997   Akaike criterion     78.27994
Schwarz criterion    92.41349   Hannan-Quinn         83.96634
rho                  0.759986   Durbin-Watson        0.469051
```

Sources: FRED (2020); Eikon (2020) – Own calculations (Gretl)

A5. Dickey-Fuller tests to check for stationarity

```
Augmented Dickey-Fuller test for log prod index
testing down from 15 lags, criterion AIC
sample size 251
unit-root null hypothesis: a = 1

  test without constant
  including one lag of (1-L)log prod index
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.147242
  test statistic: tau_nc(1) = -4.25147
  asymptotic p-value 2.252e-05
  1st-order autocorrelation coeff. for e: -0.003
```

```
Augmented Dickey-Fuller test for log HICP
testing down from 15 lags, criterion AIC
sample size 238
unit-root null hypothesis: a = 1

  test without constant
  including 14 lags of (1-L)log HICP
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.055096
  test statistic: tau_nc(1) = -2.85323
  asymptotic p-value 0.004211
  1st-order autocorrelation coeff. for e: 0.002

Augmented Dickey-Fuller test for Long-term yields
testing down from 15 lags, criterion AIC
sample size 249
unit-root null hypothesis: a = 1

  test without constant
  including 3 lags of (1-L)Long-term yields
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.0741041
  test statistic: tau_nc(1) = -3.61542
  asymptotic p-value 0.0002968
  1st-order autocorrelation coeff. for e: 0.008

Augmented Dickey-Fuller test for Short-term interest rates
testing down from 15 lags, criterion AIC
sample size 247
unit-root null hypothesis: a = 1

  test without constant
  including 5 lags of (1-L)Interbankrates
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.0322923
  test statistic: tau_nc(1) = -3.30925
  asymptotic p-value 0.0009155
  1st-order autocorrelation coeff. for e: -0.004

Augmented Dickey-Fuller test for log Euro stoxx 50
testing down from 15 lags, criterion AIC
sample size 252
unit-root null hypothesis: a = 1

  test without constant
  including 0 lags of (1-L)log Eurostoxx
  model: (1-L)y = (a-1)*y(-1) + e
  estimated value of (a - 1): -0.0670317
  test statistic: tau_nc(1) = -2.93904
  p-value 0.003378
  1st-order autocorrelation coeff. for e: -0.019

Augmented Dickey-Fuller test for log Vstoxx
testing down from 15 lags, criterion AIC
sample size 250
unit-root null hypothesis: a = 1

  test without constant
  including 2 lags of (1-L)log Vstoxx
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.18205
  test statistic: tau_nc(1) = -4.05953
  asymptotic p-value 5.064e-05
  1st-order autocorrelation coeff. for e: -0.001
```

```
Augmented Dickey-Fuller test for log Vstoxx 3M
testing down from 15 lags, criterion AIC
sample size 249
unit-root null hypothesis: a = 1

  test without constant
  including 3 lags of (1-L)log Vstoxx 3M
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.15998
  test statistic: tau_nc(1) = -3.73698
  asymptotic p-value 0.0001856
  1st-order autocorrelation coeff. for e: -0.000

Augmented Dickey-Fuller test for log Vstoxx 12M
testing down from 15 lags, criterion AIC
sample size 251
unit-root null hypothesis: a = 1

  test without constant
  including one lag of (1-L)log Vstoxx 12M
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.129982
  test statistic: tau_nc(1) = -3.8925
  asymptotic p-value 0.0001
  1st-order autocorrelation coeff. for e: -0.019

Augmented Dickey-Fuller test for log Vstoxx 24M
testing down from 15 lags, criterion AIC
sample size 251
unit-root null hypothesis: a = 1

  test without constant
  including one lag of (1-L)logVstoxx24M
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.102779
  test statistic: tau_nc(1) = -3.29431
  asymptotic p-value 0.0009654
  1st-order autocorrelation coeff. for e: -0.011
```

Sources: FRED (2020); Eikon (2020) – Own calculations (Gretl)

A6. VAR results

A6.1 Baseline model (with 2 lags)

```
VAR system, lag order 2
OLS estimates, observations 1999:03-2020:01 (T = 251)
Log-likelihood = 2706.7593
Determinant of covariance matrix = 1.7313139e-17
AIC = -20.8507
BIC = -19.5866
HQC = -20.3420

Equation 1: logprodindex
HAC standard errors, bandwidth 4 (Bartlett kernel)

coefficient   std. error   t-ratio  p-value
-------------------------------------------------------------
logprodindex_1     0.655796     0.0687472     9.539   1.89e-18 ***
logprodindex_2     0.0719784    0.0848136     0.8487  0.3969
logHICP_1          0.674410     0.428363      1.574   0.1167
logHICP_2          1.10971      0.419079      2.648   0.0086   ***
LT_yields_1        0.00253818   0.00484134    0.5243  0.6006
LT_yields_2        0.00338517   0.00458986    0.7375  0.4615
Interbankrates_1   0.0164372    0.00876598    1.875   0.0620   *
Interbankrates_2   0.0151063    0.00881234    1.714   0.0878   *
logEurostoxx_1     0.00606297   0.0252833     0.2398  0.8107
logEurostoxx_2     0.00937296   0.0252166     0.3717  0.7105
logVstoxx_1        0.00729028   0.00647543    1.126   0.2614
logVstoxx_2        0.00224338   0.00478937    0.4684  0.6399
Infoshocks         0.000724332  0.000882818   0.8205  0.4128
UMPshocks          0.000207467  0.000967311   0.2145  0.8304
MPshocks           0.000992098  0.00105633    0.9392  0.3486
```

```
Mean dependent var   0.000441   S.D. dependent var   0.028198
Sum squared resid    0.050241   S.E. of regression   0.014591
R-squared            0.747313   Adjusted R-squared   0.732323
F(15, 236)           46.53074   P-value(F)           9.41e-62
rho                  0.012655   Durbin-Watson        2.022699
Equation 2: logHICP
HAC standard errors, bandwidth 4 (Bartlett kernel)

coefficient   std. error   t-ratio   p-value
---------------------------------------------------------------
logprodindex_1     0.00618752   0.00813262    0.7608   0.4475
logprodindex_2     0.00669814   0.00982938    0.6814   0.4963
logHICP_1          1.05695      0.0566544     18.66    2.45e-48 ***
logHICP_2          0.134816     0.0588343     2.291    0.0228   **
LT_yields_1        0.00137210   0.000825823   1.661    0.0979   *
LT_yields_2        0.000742448  0.000816756   0.9090   0.3643
Interbankrates_1   0.000809055  0.000863100   0.9374   0.3495
Interbankrates_2   0.000491577  0.000894624   0.5495   0.5832
logEurostoxx_1     0.00511199   0.00372321    1.373    0.1711
logEurostoxx_2     0.00703831   0.00355526    1.980    0.0489   **
logVstoxx_1        8.97060e-05  0.00114850    0.07811  0.9378
logVstoxx_2        0.000203632  0.00111988    0.1818   0.8559
Infoshocks         0.000299824  0.000141571   2.118    0.0352   **
UMPshocks          0.000248820  0.000204441   1.217    0.2248
MPshocks           0.000144199  0.000145534   0.9908   0.3228

Mean dependent var   0.000128   S.D. dependent var   0.007860
Sum squared resid    0.001147   S.E. of regression   0.002204
R-squared            0.925784   Adjusted R-squared   0.921381
F(15, 236)           196.2603   P-value(F)           6.1e-124
rho                  0.010038   Durbin-Watson        2.003734
Equation 3: LT_yields
HAC standard errors, bandwidth 4 (Bartlett kernel)

coefficient   std. error   t-ratio   p-value
----------------------------------------------------------------
logprodindex_1      0.879348     0.577415      1.523    0.1291
logprodindex_2      0.736117     0.711415      1.035    0.3019
logHICP_1           5.86211      3.84240       1.526    0.1284
logHICP_2           4.32997      3.76942       1.149    0.2518
LT_yields_1         1.11802      0.0561629     19.91    2.05e-52 ***
LT_yields_2         0.190317     0.0590630     3.222    0.0015   ***
Interbankrates_1    0.0556883    0.0703104     0.7920   0.4291
Interbankrates_2    0.0577900    0.0646076     0.8945   0.3720
logEurostoxx_1      0.643028     0.211993      3.033    0.0027   ***
logEurostoxx_2      0.454491     0.202961      2.239    0.0261   **
logVstoxx_1         0.113896     0.0820993     1.387    0.1667
logVstoxx_2         0.0641074    0.0745650     0.8598   0.3908
Infoshocks          0.00454819   0.0149493     0.3042   0.7612
UMPshocks           0.00622706   0.0135083     0.4610   0.6452
MPshocks            0.0137000    0.0142591     0.9608   0.3376

Mean dependent var   0.007802   S.D. dependent var   0.562969
Sum squared resid    7.308035   S.E. of regression   0.175972
R-squared            0.907784   Adjusted R-squared   0.902313
F(15, 236)           154.8798   P-value(F)           7.2e-113
rho                  0.001624   Durbin-Watson        2.001984


Equation 4: Interbankrates
HAC standard errors, bandwidth 4 (Bartlett kernel)

coefficient   std. error   t-ratio   p-value
----------------------------------------------------------------
logprodindex_1      2.74280      0.953905      2.875    0.0044   ***
logprodindex_2     ,àí2.78770      1.00866      ,àí2.764    0.0062   ***
logHICP_1           9.23083      4.14842       2.225    0.0270   **
logHICP_2           9.56664      4.46844       2.141    0.0333   **
LT_yields_1         0.0197305    0.0311979     0.6324   0.5277
LT_yields_2         0.0230774    0.0306637     0.7526   0.4524
Interbankrates_1    1.46066      0.0666687     21.91    8.39e-59 ***
Interbankrates_2    0.484159     0.0662755     7.305    4.24e-12 ***
logEurostoxx_1      0.530742     0.373817      1.420    0.1570
logEurostoxx_2      0.584773     0.350144      1.670    0.0962   *
logVstoxx_1         0.142252     0.0927911     1.533    0.1266
logVstoxx_2         0.0868313    0.0835411     1.039    0.2997
Infoshocks          0.00572317   0.0177673     0.3221   0.7476
UMPshocks           0.0257711    0.0168733     1.527    0.1280
MPshocks            0.00843362   0.0160333     0.5260   0.5994

Mean dependent var   0.006765   S.D. dependent var   0.932190
Sum squared resid    3.717650   S.E. of regression   0.125510
R-squared            0.982888   Adjusted R-squared   0.981873
F(15, 236)           903.7081   P-value(F)           5.8e-199
rho                 ,àí0.040223   Durbin-Watson        2.079764

Equation 5: logEurostoxx
HAC standard errors, bandwidth 4 (Bartlett kernel)

coefficient   std. error  t-ratio   p-value
-------------------------------------------------------------
logprodindex_1     0.0411777    0.337099     0.1222   0.9029
logprodindex_2     0.361874     0.390922     0.9257   0.3556
logHICP_1          1.45775      1.67528      0.8702   0.3851
logHICP_2          1.78009      1.62913      1.093    0.2757
```

```
LT_yields_1        0.0167906    0.0212044    0.7918   0.4292
LT_yields_2        0.00431143   0.0202200    0.2132   0.8313
Interbankrates_1   0.0254701    0.0263133    0.9680   0.3341
Interbankrates_2   0.0257147    0.0252349    1.019    0.3092
logEurostoxx_1     0.826238     0.128092     6.450    6.26e-10 ***
logEurostoxx_2     0.119454     0.126168     0.9468   0.3447
logVstoxx_1        0.0393128    0.0375181    1.048    0.2958
logVstoxx_2        0.0493488    0.0349231    1.413    0.1590
Infoshocks         0.0148941    0.00591638   2.517    0.0125   **
UMPshocks          0.000475451  0.00525876   0.09041  0.9280
MPshocks           0.000960082  0.00528573   0.1816   0.8560

Mean dependent var   0.000998 S.D. dependent var   0.175799
Sum squared resid    0.908001   S.E. of regression   0.062028
R-squared            0.882483   Adjusted R-squared   0.875511
F(15, 236)           118.1477   P-value(F)           1.6e-100
rho                  0.012390   Durbin-Watson        2.024625

Equation 6: logVstoxx
HAC standard errors, bandwidth 4 (Bartlett kernel)

coefficient   std. error   t-ratio    p-value
-----------------------------------------------------------------
logprodindex_1      0.791498     0.920183      0.8602    0.3906
logprodindex_2      1.54947      0.817839      1.895     0.0594   *
logHICP_1           0.0733279    5.38953       0.01361   0.9892
logHICP_2           0.761926     5.57951       0.1366    0.8915
LT_yields_1         0.0303847    0.0588501     0.5163    0.6061
LT_yields_2         0.0548383    0.0577554     0.9495    0.3433
Interbankrates_1    0.0664471    0.0621590     1.069     0.2862
Interbankrates_2    0.0528243    0.0596814     0.8851    0.3770
logEurostoxx_1      0.374530     0.227899      1.643     0.1016
logEurostoxx_2      0.291710     0.237481      1.228     0.2205
logVstoxx_1         0.588375     0.0764331     7.698     3.77e-13 ***
logVstoxx_2         0.121040     0.0836426     1.447     0.1492
Infoshocks          0.0499881    0.0116164     4.303     2.47e-05 ***
UMPshocks           0.00195946   0.0146713     0.1336    0.8939
MPshocks            0.00642041   0.0103704     0.6191    0.5364

Mean dependent var   0.002912   S.D. dependent var   0.277614
Sum squared resid    7.176870   S.E. of regression   0.174386
R-squared            0.627552   Adjusted R-squared   0.605457
F(15, 236)           26.50969   P-value(F)           2.33e-42
rho                  0.050712   Durbin-Watson        2.096415
```

Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Gretl)

A6.2 Baseline with resampling

```
VAR system, lag order 2
OLS estimates, observations 2010:01-2020:01 (T = 121)
Log-likelihood = 1526.311
Determinant of covariance matrix = 4.4529771e-19
AIC = -23.7407
BIC = -21.6612
HQC = -22.8961

Equation 1: logprodindex
HAC standard errors, bandwidth 3 (Bartlett kernel)

                    coefficient   std. error   t-ratio  p-value
  --------------------------------------------------------------
  logprodindex_1     0.515649     0.0982097     5.250   7.86e-07 ***
  logprodindex_2     0.178817     0.0752093     2.378   0.0192   **
  logHICP_1          0.0540970    0.406064      0.1332  0.8943
  logHICP_2          0.589054     0.397777      1.481   0.1416
  LT_yields_1        0.00177644   0.00520273    0.3414  0.7334
  LT_yields_2        0.00166249   0.00426270    0.3900  0.6973
  Interbankrates_1   0.0301406    0.0279427     1.079   0.2832
  Interbankrates_2   0.0177315    0.0224569     0.7896  0.4315
  logEurostoxx_1     0.0747680    0.0533830     1.401   0.1643
  logEurostoxx_2     0.0793800    0.0609646     1.302   0.1957
  logVstoxx_1        0.00710415   0.0107526     0.6607  0.5102
  logVstoxx_2        0.0117770    0.00968502    1.216   0.2267
  Infoshocks         0.000314211  0.00123416    0.2546  0.7995
  UMPshocks          0.000176594  0.000883875   0.1998  0.8420
  MPshocks           0.000693243  0.000991395   0.6993  0.4859

Mean dependent var   0.006914   S.D. dependent var   0.025174
Sum squared resid    0.014235   S.E. of regression   0.011588
R-squared            0.826047   Adjusted R-squared   0.803072
F(15, 106)           33.55735   P-value(F)           2.20e-33
rho                  0.071656   Durbin-Watson        2.067602
```

Equation 2: logHICP
HAC standard errors, bandwidth 3 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
logprodindex_1	0.0177407	0.0142562	1.244	0.2161	
logprodindex_2	0.0334092	0.0178640	1.870	0.0642	*
logHICP_1	0.984140	0.0812131	12.12	9.85e-22	***
logHICP_2	0.0722999	0.0774038	0.9341	0.3524	
LT_yields_1	0.00107776	0.00100409	1.073	0.2855	
LT_yields_2	0.000589149	0.000981916	0.6000	0.5498	
Interbankrates_1	0.00219834	0.00375367	0.5857	0.5594	
Interbankrates_2	0.00212539	0.00363022	0.5855	0.5595	
logEurostoxx_1	0.00199261	0.00849541	0.2346	0.8150	
logEurostoxx_2	0.00979982	0.00923445	1.061	0.2910	
logVstoxx_1	0.000854426	0.00209388	0.4081	0.6841	
logVstoxx_2	0.000727141	0.00228893	0.3177	0.7514	
Infoshocks	0.000470104	0.000265235	1.772	0.0792	*
UMPshocks	0.000130369	0.000278396	0.4683	0.6405	
MPshocks	1.91902e-05	0.000229517	0.08361	0.9335	

Mean dependent var	0.001220	S.D. dependent var	0.009433
Sum squared resid	0.000580	S.E. of regression	0.002339
R-squared	0.946591	Adjusted R-squared	0.939537
F(15, 106)	125.2463	P-value(F)	3.46e-60
rho	0.002053	Durbin-Watson	1.980887

Equation 3: LT_yields
HAC standard errors, bandwidth 3 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
logprodindex_1	2.05540	1.47973	1.389	0.1677	
logprodindex_2	1.31983	1.82612	0.7228	0.4714	
logHICP_1	7.88917	6.03218	1.308	0.1938	
logHICP_2	3.09467	5.14927	0.6010	0.5491	
LT_yields_1	0.959120	0.0820300	11.69	8.74e-21	***
LT_yields_2	0.108469	0.0804259	1.349	0.1803	
Interbankrates_1	0.974733	0.382315	2.550	0.0122	**
Interbankrates_2	1.02531	0.341331	3.004	0.0033	***
logEurostoxx_1	0.892348	0.562413	1.587	0.1156	
logEurostoxx_2	1.25414	0.606053	2.069	0.0409	**
logVstoxx_1	0.186550	0.154719	1.206	0.2306	
logVstoxx_2	0.210724	0.124870	1.688	0.0944	*
Infoshocks	0.0101743	0.0261712	0.3888	0.6982	
UMPshocks	0.0327889	0.0130304	2.516	0.0134	**
MPshocks	0.0179998	0.0226789	0.7937	0.4292	

Mean dependent var	0.060270	S.D. dependent var	0.599317
Sum squared resid	3.949541	S.E. of regression	0.193028
R-squared	0.909292	Adjusted R-squared	0.897312
F(15, 106)	70.83895	P-value(F)	4.16e-48
rho	0.049353	Durbin-Watson	2.089035

Equation 4: Interbankrates
HAC standard errors, bandwidth 3 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
logprodindex_1	1.72596	0.733395	2.353	0.0204	**
logprodindex_2	1.19880	0.513492	2.335	0.0214	**
logHICP_1	0.302275	1.86196	0.1623	0.8713	
logHICP_2	0.00495135	1.88965	0.002620	0.9979	
LT_yields_1	0.0431844	0.0242193	1.783	0.0774	*
LT_yields_2	0.0206026	0.0212404	0.9700	0.3343	
Interbankrates_1	1.35310	0.160536	8.429	1.88e-13	***
Interbankrates_2	0.422049	0.139392	3.028	0.0031	***
logEurostoxx_1	0.0717385	0.160920	0.4458	0.6566	
logEurostoxx_2	0.0228352	0.185043	0.1234	0.9020	
logVstoxx_1	0.000186146	0.0317467	0.005863	0.9953	
logVstoxx_2	0.00142469	0.0276707	0.05149	0.9590	
Infoshocks	0.0176972	0.00679518	2.604	0.0105	**
UMPshocks	0.00691476	0.00448210	1.543	0.1259	
MPshocks	0.0104679	0.00541951	1.932	0.0561	*

Mean dependent var	0.217240	S.D. dependent var	0.323453
Sum squared resid	0.265336	S.E. of regression	0.050032
R-squared	0.985473	Adjusted R-squared	0.983554
F(15, 106)	479.3830	P-value(F)	4.81e-90
rho	0.162395	Durbin-Watson	2.244203

Equation 5: logEurostoxx
HAC standard errors, bandwidth 3 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
logprodindex_1	0.0464428	0.482191	0.09632	0.9235	
logprodindex_2	0.0968424	0.379926	0.2549	0.7993	
logHICP_1	0.177215	1.88293	0.09412	0.9252	
logHICP_2	0.415530	1.89173	0.2197	0.8266	
LT_yields_1	0.0176795	0.0242365	0.7295	0.4673	
LT_yields_2	0.00990134	0.0203833	0.4858	0.6281	
Interbankrates_1	0.220211	0.129877	1.696	0.0929	*
Interbankrates_2	0.185993	0.114552	1.624	0.1074	
logEurostoxx_1	1.09862	0.116899	9.398	1.27e-15	***
logEurostoxx_2	0.252661	0.136931	1.845	0.0678	*
logVstoxx_1	0.0432714	0.0288459	1.500	0.1366	
logVstoxx_2	0.0331443	0.0298352	1.111	0.2691	
Infoshocks	0.0223588	0.00681263	3.282	0.0014	***
UMPshocks	0.00302828	0.00407889	0.7424	0.4595	
MPshocks	0.00327578	0.00544744	0.6013	0.5489	

Mean dependent var	0.019418	S.D. dependent var	0.138589
Sum squared resid	0.226609	S.E. of regression	0.046237
R-squared	0.903589	Adjusted R-squared	0.890855
F(15, 106)	66.23054	P-value(F)	1.01e-46
rho	0.010185	Durbin-Watson	2.017418

Equation 6: logVstoxx
HAC standard errors, bandwidth 3 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
logprodindex_1	1.17228	1.36209	0.8607	0.3914	
logprodindex_2	1.19490	1.56804	0.7620	0.4477	
logHICP_1	3.46242	7.62621	0.4540	0.6507	
logHICP_2	7.41804	7.42941	0.9985	0.3203	
LT_yields_1	0.0222741	0.0708798	0.3143	0.7539	
LT_yields_2	0.0298191	0.0743219	0.4012	0.6891	
Interbankrates_1	0.359614	0.310380	1.159	0.2492	
Interbankrates_2	0.349106	0.290022	1.204	0.2314	
logEurostoxx_1	0.868877	0.482117	1.802	0.0744	*
logEurostoxx_2	1.08815	0.523270	2.080	0.0400	**
logVstoxx_1	0.364489	0.120495	3.025	0.0031	***
logVstoxx_2	0.359367	0.143240	2.509	0.0136	**
Infoshocks	0.0706354	0.0134785	5.241	8.21e-07	***
UMPshocks	0.00597973	0.0139156	0.4297	0.6683	
MPshocks	0.00527220	0.0118100	0.4464	0.6562	

Mean dependent var	0.051387	S.D. dependent var	0.257049
Sum squared resid	2.953301	S.E. of regression	0.166917
R-squared	0.641957	Adjusted R-squared	0.594668
F(15, 106)	12.67024	P-value(F)	1.84e-17
rho	0.063555	Durbin-Watson	2.120516

Sources: Altavilla and al. (2019) ; FRED (2020); Eikon (2020) – Own calculations (Gretl)

A6.3 Results of the log Stoxx Europe 600 equation (Robustness part)

Equation 6: Log Stoxx Europe 600
HAC standard errors, bandwidth 4 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
logprodindex_1	−0.432312	0.333231	−1.297	0.1958	
logprodindex_2	0.0709010	0.345512	0.2052	0.8376	
logHICP_1	0.968456	1.45867	0.6639	0.5074	
logHICP_2	−1.13481	1.46691	−0.7736	0.4399	
LT_yields_1	−0.0177201	0.0193963	−0.9136	0.3619	
LT_yields_2	0.00837233	0.0169964	0.4926	0.6228	
Interbankrates_1	0.0345875	0.0242852	1.424	0.1557	
Interbankrates_2	−0.0331240	0.0211763	−1.564	0.1191	
logVstoxx_1	0.00455253	0.0254351	0.1790	0.8581	
logVstoxx_2	0.0100521	0.0214770	0.4680	0.6402	
LogStoxx600_1	1.04344	0.0858601	12.15	1.03e-26	***
LogStoxx600_2	−0.0757324	0.0850086	−0.8909	0.3739	
Infoshocks	0.0105399	0.00529386	1.991	0.0476	**
UMPshocks	0.000420260	0.00531716	0.07904	0.9371	
MPshocks	0.00521086	0.00480738	1.084	0.2795	

Mean dependent var	0.000480	S.D. dependent var	0.190366
Sum squared resid	0.699710	S.E. of regression	0.054451
R-squared	0.922768	Adjusted R-squared	0.918186
F(15, 236)	187.9817	P-value(F)	6.6e-122
rho	−0.019932	Durbin-Watson	2.039744

Sources: Altavilla and al. (2019) ; FRED (2020); Eikon (2020) – Own calculations (Gretl)

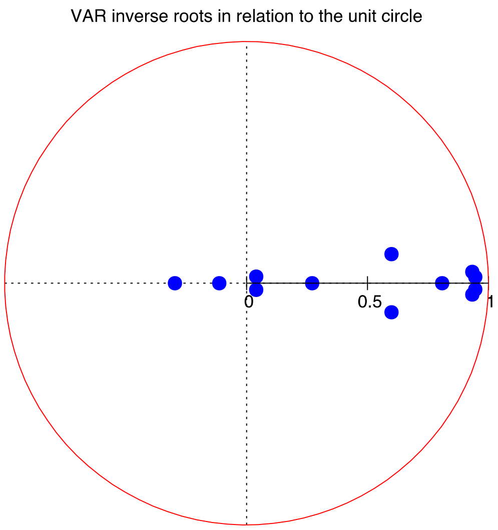
A6.4 Results of the different implied volatility indexes (Robustness part)

```
VAR system, lag order 2
OLS estimates, observations 1999:03-2020:01 (T = 251)
Log-likelihood = 2714.8847
Determinant of covariance matrix = 1.622773e-17
AIC = -20.9154
BIC = -19.6513
HQC = -20.4067
Equation 6: log Vstoxx 3M
HAC standard errors, bandwidth 4 (Bartlett kernel)

                     coefficient   std. error   t-ratio   p-value
  -------------------------------------------------------------
  logprodindex_1      1.02682      0.744651      1.379    0.1692
  logprodindex_2     -1.72988      0.627654     -2.756    0.0063   ***
  logHICP_1          -2.77548      4.54041      -0.6113   0.5416
  logHICP_2           1.56167      4.78943       0.3261   0.7447
  LT_yields_1        -0.0342080    0.0548997    -0.6231   0.5338
  LT_yields_2         0.0587928    0.0551438     1.066    0.2874
  Interbankrates_1    0.142687     0.0678720     2.102    0.0366   **
  Interbankrates_2   -0.127023     0.0630706    -2.014    0.0451   **
  logEurostoxx_1     -0.660326     0.219539     -3.008    0.0029   ***
  logEurostoxx_2      0.498324     0.237180      2.101    0.0367   **
  logVstoxx3M_1       0.504595     0.0768033     6.570    3.18e-10 ***
  logVstoxx3M_2       0.201779     0.0742121     2.719    0.0070   ***
  Infoshocks         -0.0396077    0.0102317    -3.871    0.0001   ***
  UMPshocks           0.00139754   0.0129669     0.1078   0.9143
  MPshocks           -0.00408393   0.00936721   -0.4360   0.6632

Mean dependent var  -0.001572   S.D. dependent var   0.265593
Sum squared resid    6.090872   S.E. of regression   0.160651
R-squared            0.654624   Adjusted R-squared   0.634136
F(15, 236)           29.82093   P-value(F)           4.15e-46
rho                 -0.081184   Durbin-Watson        2.157495

Equation 6: log Vstoxx 12M
HAC standard errors, bandwidth 4 (Bartlett kernel)

                     coefficient    std. error   t-ratio   p-value
  --------------------------------------------------------------
  logprodindex_1      0.610469      0.442089      1.381    0.1686
  logprodindex_2     -0.902089      0.422956     -2.133    0.0340   **
  logHICP_1          -3.33747       2.48577      -1.343    0.1807
  logHICP_2           1.50719       3.04601       0.4948   0.6212
  LT_yields_1         0.0225380     0.0330279     0.6824   0.4957
  LT_yields_2         0.0146292     0.0319005     0.4586   0.6470
  Interbankrates_1   -0.00861594    0.0322510    -0.2672   0.7896
  Interbankrates_2    0.0112649     0.0308229     0.3655   0.7151
  logEurostoxx_1     -0.395993      0.130350     -3.038    0.0026   ***
  logEurostoxx_2      0.330710      0.120390      2.747    0.0065   ***
  logVstoxx12M_1      0.649252      0.0710066     9.144    2.89e-17 ***
  logVstoxx12M_2      0.137482      0.0870854     1.579    0.1157
  Infoshocks         -0.0146564     0.00811525   -1.806    0.0722   *
  UMPshocks          -0.000888709   0.00814402   -0.1091   0.9132
  MPshocks           -0.0116435     0.00711750   -1.636    0.1032

Mean dependent var  -0.002866   S.D. dependent var   0.211247
Sum squared resid    2.645856   S.E. of regression   0.105883
R-squared            0.762883   Adjusted R-squared   0.748816
F(15, 236)           50.61919   P-value(F)           5.92e-65
rho                 -0.019721   Durbin-Watson        1.962045

Equation 6: log Vstoxx 24M
HAC standard errors, bandwidth 4 (Bartlett kernel)

                    coefficient   std. error  t-ratio   p-value
  -----------------------------------------------------------
  logprodindex_1      0.155584     0.322747     0.4821   0.6302
  logprodindex_2    -0.295613     0.290186    -1.019    0.3094
  logHICP_1         -3.13565      2.17978     -1.439    0.1516
  logHICP_2          2.28250      2.36253      0.9661   0.3350
  LT_yields_1        0.0343179    0.0331024    1.037    0.3009
  LT_yields_2       -0.0140278    0.0300176   -0.4673   0.6407
  Interbankrates_1  -0.0205396    0.0282402   -0.7273   0.4678
  Interbankrates_2   0.0238002    0.0268616    0.8860   0.3765
  logEurostoxx_1    -0.338761     0.103180    -3.283    0.0012   ***
  logEurostoxx_2     0.255039     0.113931     2.239    0.0261   **
  logVstoxx24M_1     0.631619     0.0844762    7.477    1.49e-12 ***
  logVstoxx24M_2     0.178948     0.0784581    2.281    0.0235   **
  Infoshocks        -0.0188674    0.00575437  -3.279    0.0012   ***
  UMPshocks          0.00582854   0.00718531   0.8112   0.4181
  MPshocks          -0.000560641  0.00626062  -0.08955  0.9287

Mean dependent var  -0.000840   S.D. dependent var   0.183701
Sum squared resid    1.714892   S.E. of regression   0.085244
R-squared            0.796733   Adjusted R-squared   0.784675
F(15, 236)           61.66901   P-value(F)           9.99e-73
rho                 -0.044019   Durbin-Watson        2.086115
```

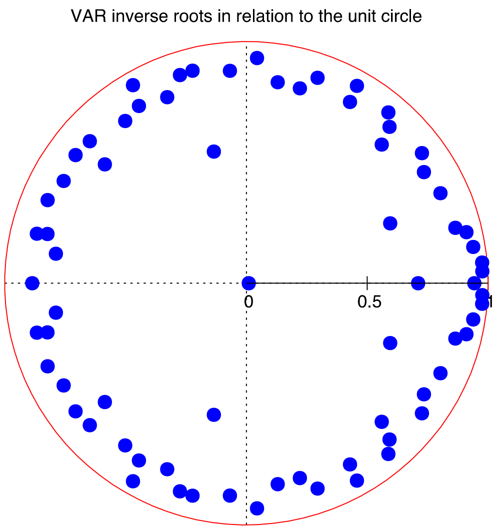
Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Gretl)

A7. VARs stability conditions

A7.1 Baseline (2 lags)



A7.2 Baseline (12 lags)

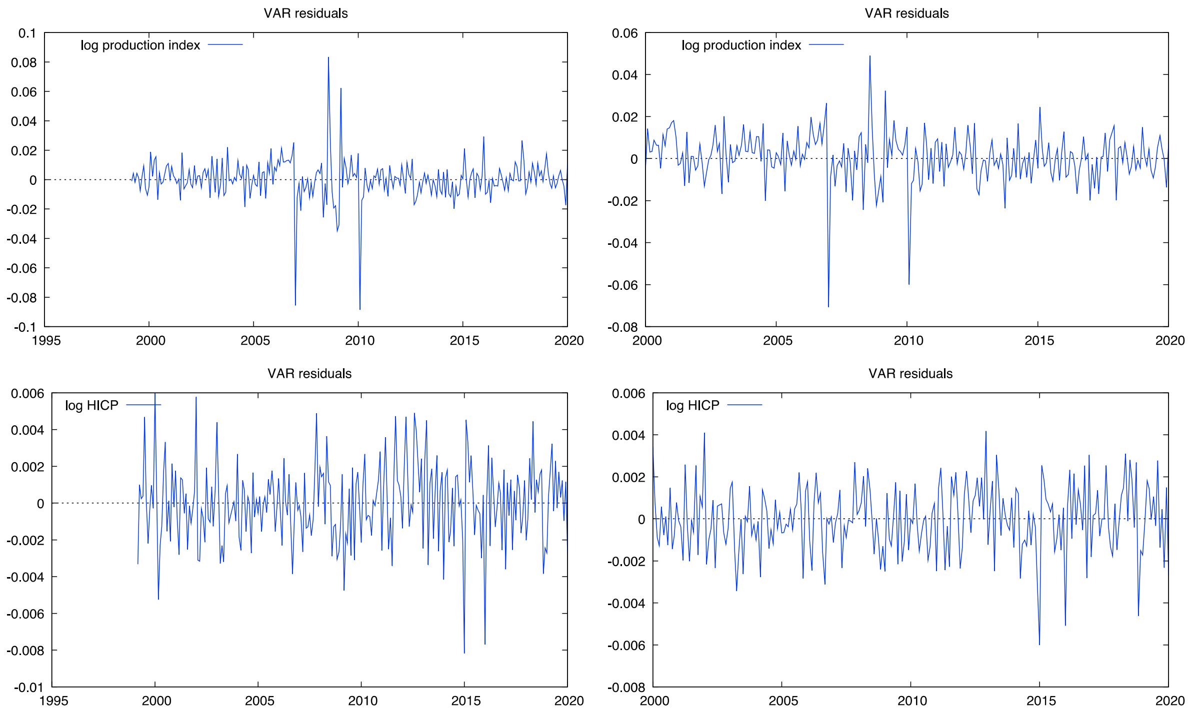


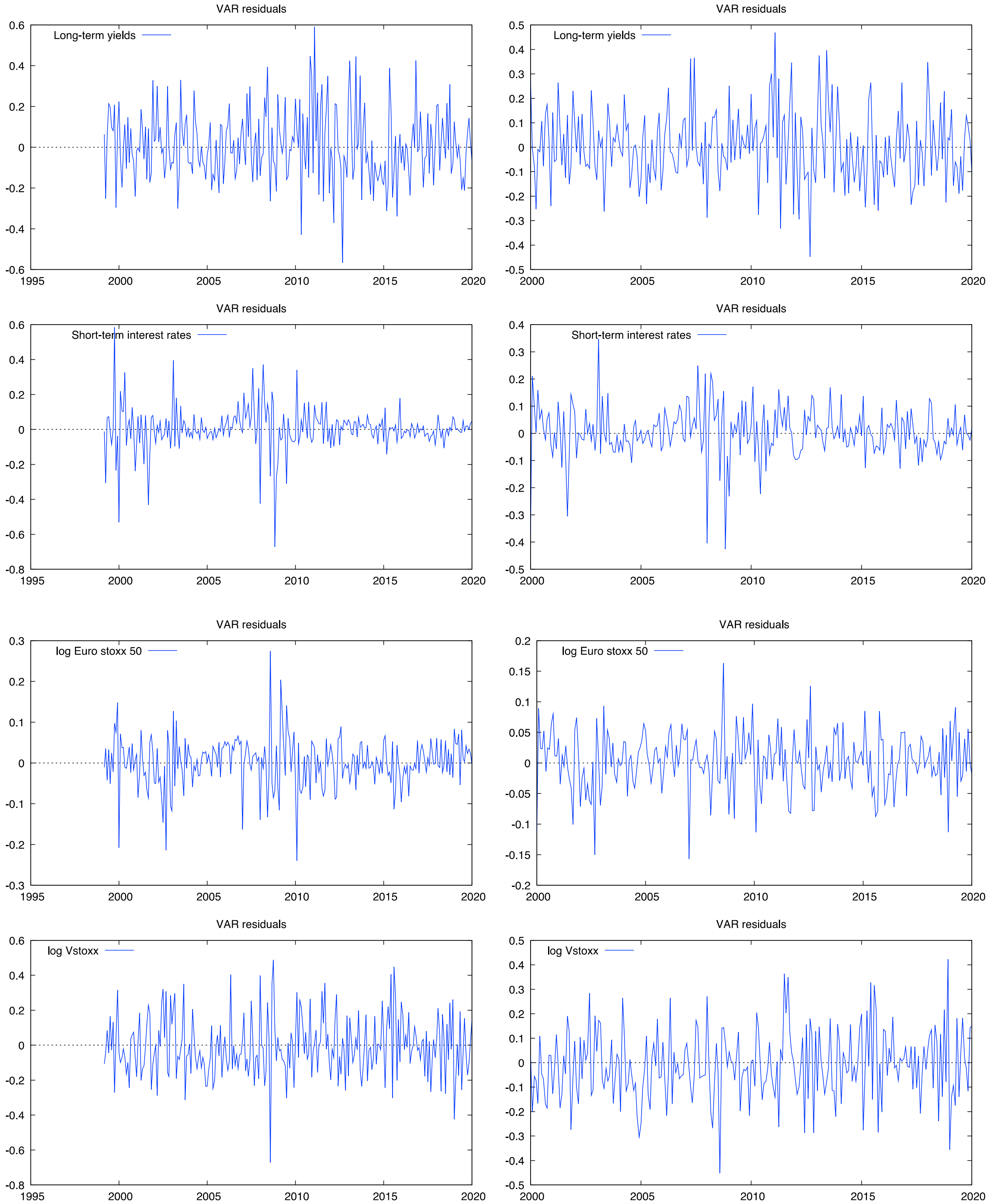
Sources: Altavilla and al. (2019); FRED (2020); Eikon (2020) – Own calculations (Gretl)

A8. VARs residuals analysis

A8.1 Graphs of residuals

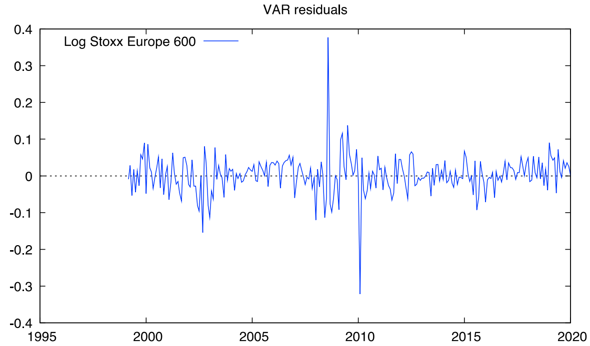
A8.1.1 Baseline (2 lags) vs extended baseline (12 lags)





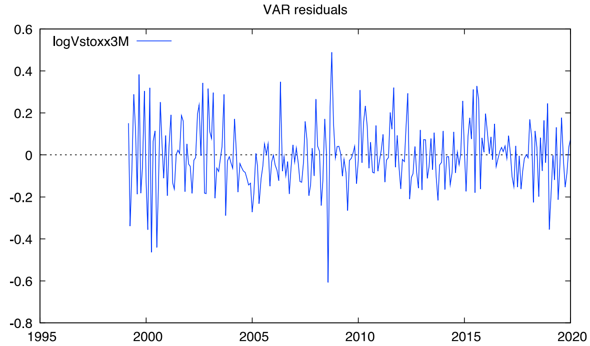
Sources: FRED (2020); Eikon (2020) – Own calculations (Gretl)

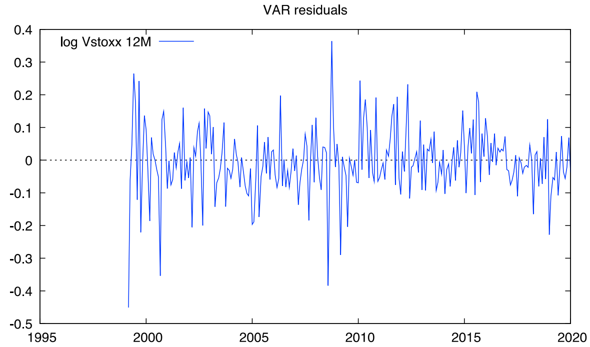
A8.1.2 Log Stoxx Europe 600 index

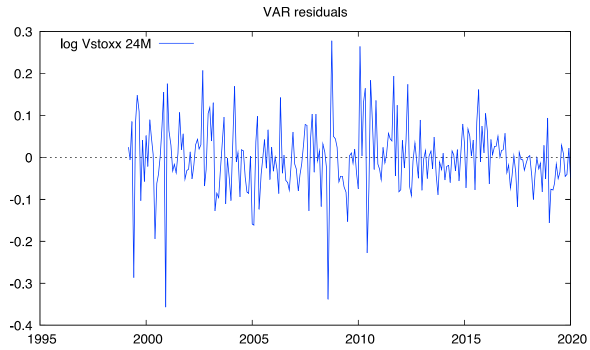


Sources: FRED (2020); Eikon (2020) – Own calculations (Gretl)

A8.1.3 Residuals of the different implied volatility indexes (3-month, 12-month, 24-month)







Sources: FRED (2020); Eikon (2020) – Own calculations (Gretl)

A8.2 Ljung-Box White noise tests on residuals

A8.2.1 Baseline vs extended baseline

Variables	Baseline with 2 lags	Baseline with 12 lags
log prod index	Portmanteau (Q) statistic = 54.1612 Prob > chi2(40) = 0.0668	Portmanteau (Q) statistic = 40.1525 Prob > chi2(40) = 0.4635
log HICP	Portmanteau (Q) statistic = 245.5800 Prob > chi2(40) = 0.0000	Portmanteau (Q) statistic = 57.8218 Prob > chi2(40) = 0.0338
long-term yields	Portmanteau (Q) statistic = 36.0596 Prob > chi2(40) = 0.6483	Portmanteau (Q) statistic = 22.9564 Prob > chi2(40) = 0.9859
short-term interet rates	Portmanteau (Q) statistic = 45.1174 Prob > chi2(40) = 0.2666	Portmanteau (Q) statistic = 37.7856 Prob > chi2(40) = 0.5704
log Euro stoxx 50	Portmanteau (Q) statistic = 40.5311 Prob > chi2(40) = 0.4468	Portmanteau (Q) statistic = 36.5139 Prob > chi2(40) = 0.6280
log Vstoxx	Portmanteau (Q) statistic = 30.7315 Prob > chi2(40) = 0.8538	Portmanteau (Q) statistic = 40.8192 Prob > chi2(40) = 0.4343

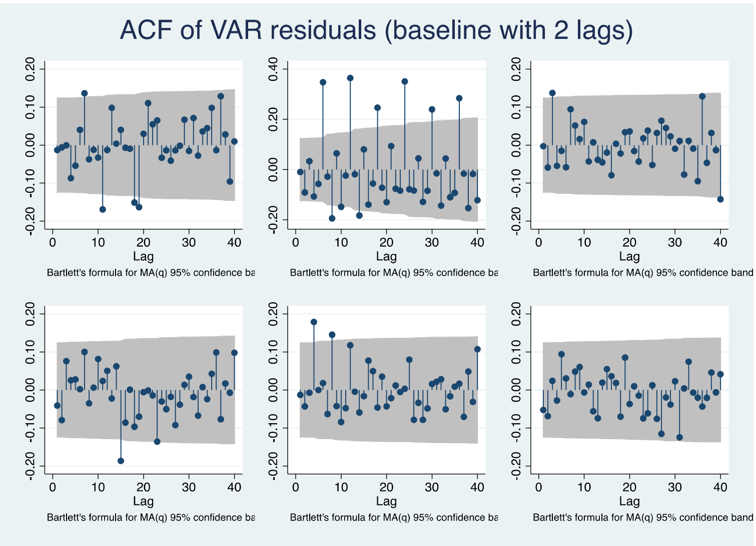
Sources: FRED (2020); Eikon (2020) – Own calculations (Stata)

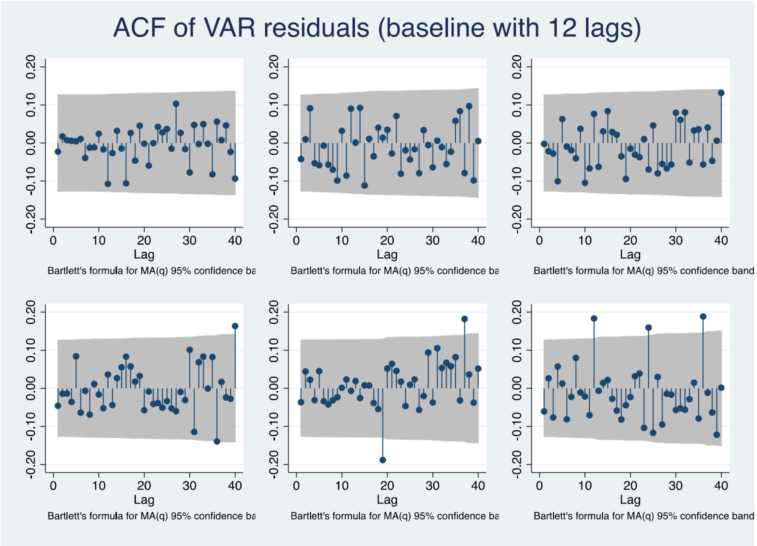
A8.2.2 Robustness part

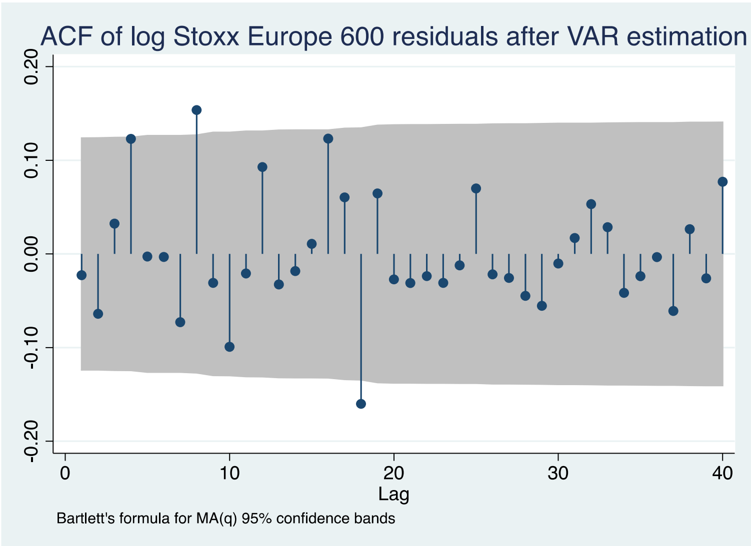
Variables	Statistics
log Stoxx Europe 600	Portmanteau (Q) statistic = 40.9790 Prob > chi2(40) = 0.4274
log Vstoxx 3M	Portmanteau (Q) statistic = 80.6227 Prob > chi2(40) = 0.0001
log Vstoxx 12M	Portmanteau (Q) statistic = 23.5450 Prob > chi2(40) = 0.9822
log Vstoxx 24M	Portmanteau (Q) statistic = 41.2184 Prob > chi2(40) = 0.4171

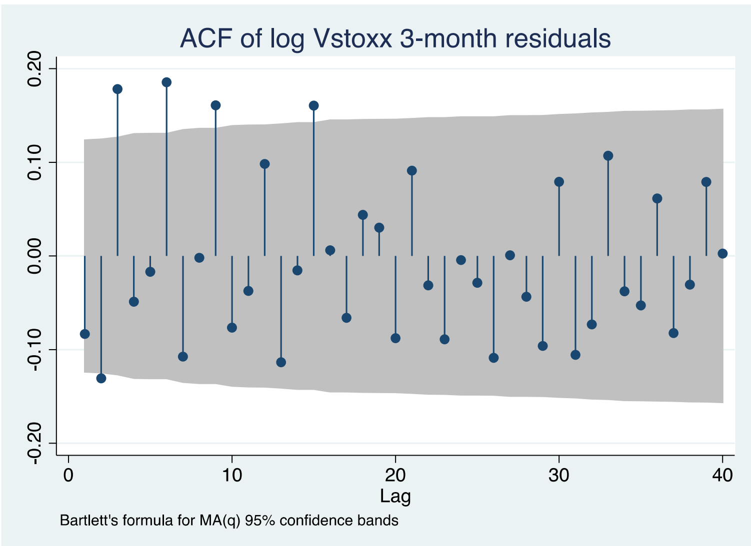
Sources: FRED (2020); Eikon (2020) – Own calculations (Stata)

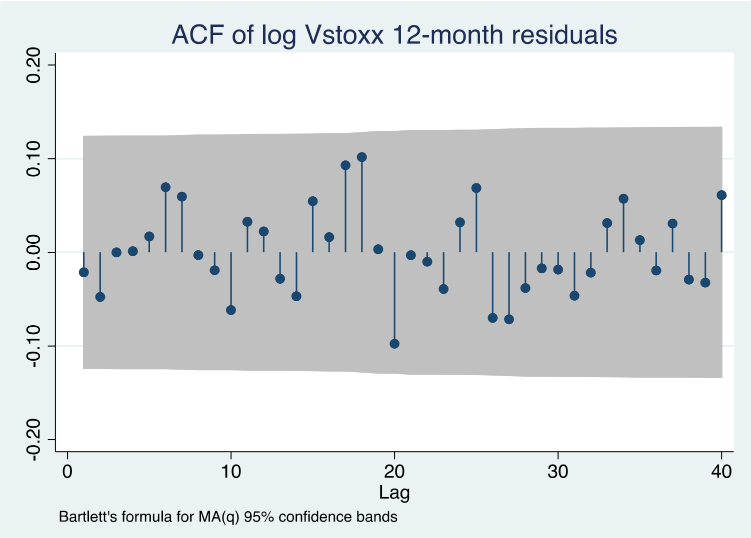
A8.3 ACF of residuals

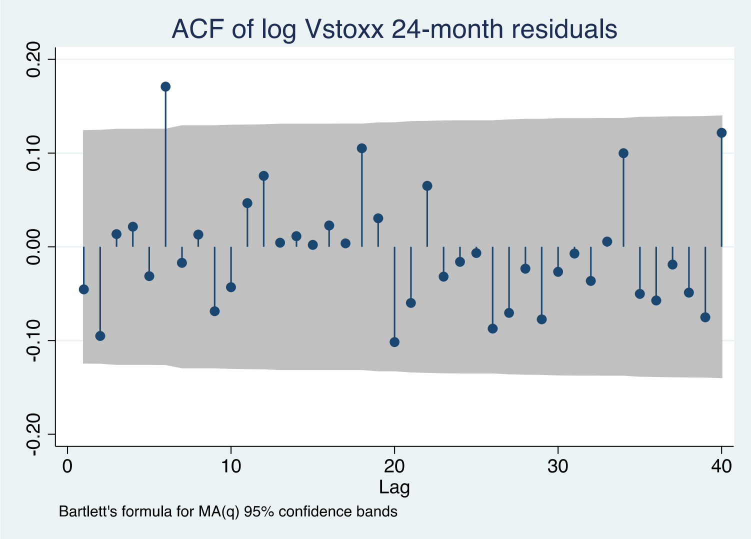



ACF of VAR residuals (baseline with 12 lags)
Lag
Bartlett's formula for MA(q) 95% confidence bands


ACF of log Stoxx Europe 600 residuals after VAR estimation
Lag
Bartlett's formula for MA(q) 95% confidence bands


ACF of log Vstoxx 3-month residuals
Lag
Bartlett's formula for MA(q) 95% confidence bands





Sources: FRED (2020); Eikon (2020) – Own calculations (Stata)