Factors of Contagion for the G7 countries during the Global Financial Crisis and the European Sovereign Debt Crisis

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Abstract: This paper employs newly developed time-varying parameters structural vector autoregression (TVP-VAR) model with stochastic volatility (Nakajima, 2011) to study the role that tightening in liquidity conditions and the collapse in risk appetite played for the transmission of the Global Financial Crisis and the European Sovereign Debt Crisis for the G7 countries. In order to improve the estimation performance, we make the assumption of stochastic volatility with the application of multi move sampler. Using weekly data from early 2005 to the end of 2012, we focus on three shocks during the crisis: BNP Paribas' freezing (BNP) on three investment funds on August 9th 2007, Lehman Brothers bankruptcy (LBB) on September 15th 2008 and Greek debt crisis (GDC) on May 8th 2010. Our results show that channels of transmission of contagion changed between crises. Liquidity shocks were first transmitted through monetary markets during BNP and LBB and then through stock markets during the GDC; with a very fast and strong reaction for all countries. Risk aversion shocks were transmitted through stock markets rather than through monetary markets, which was not the case for liquidity shocks. Moreover, monetary markets take more time to adjust to liquidity shocks than stock markets to risk aversion shocks.

Keywords : Liquidity, risk, Global Financial Crisis, European Sovereign Debt Crisis, Time-Varying Parameters VAR, stochastic volatility, Bayesian inference, shock, G7 countries.

JEL classification: C11, C15, G01, G15.

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1. Introduction and questions

Global financial crisis which originated in the U.S. in 2007, spread all over the world[2]. The global transmission of this crisis raises questions about the channels through which it propagated. In this paper, we study the liquidity and the risk channels during the global financial crisis (henceforth, GFC) as well as during the European sovereign debt crisis (henceforth, ESDC)[3]. As stated by Chudik and Fratzscher (2010), Adrian and Shin (2010) and Sugihara (2010), on the one hand, liquidity risk is a distinguished feature of the GFC and could explain why the crisis has become truly global. On the other hand, change in risk appetite is an important feature of this crisis. They explain the two channels by the following arguments. First, the role of large financial institutions in various financial markets (mortgages, credit derivatives, corporate loans, commodities all over the world) and the way they transfer risk through the "originate and distribute" model could have lead large losses from an asset to fire sales of other assets independent of their fundamental values. Second, the highly leveraged and interconnected financial institutions could have lead market participants more uncertain about future asset prices and increase their expectation for future volatility. The first hypothesis of liquidity risk implies that credit markets, in particular interbank markets, became highly illiquid leading to the collapse or near-collapse of numerous financial institutions (Adrian and Shin, 2010, Brunnermeier and Pederson, 2008). In addition, the liquidity channel of financial transmission implies that funding liquidity shocks were propagated to bank lending and the real economy (BCBS, 2011). The second hypothesis, repricing of risk, leads investors to become more risk adverse and ask for a higher remuneration. We adopt a financial market perspective to measure these two shocks. Shock to liquidity is measured with the U.S.TED spread between U.S short-term money market rates and U.S. treasuries and shock to risk appetite, with the U.S. VIX index of implied volatility of the S&P 500. Even though the global crisis dynamics was more complex than these two factors, our analysis captures the main feature of the crisis. The two shocks are U.S. specific by nature, i.e. originated from the U.S.

This paper sets out to explore the role of these two different mechanisms in spreading the crisis to G7 countries (Germany, U.S., United Kingdom, France, Italy, Canada and Japan) over the period 2006-2012. We address the following three questions: first, which factor (liquidity or risk) played an increasing role in the transmission of the global financial crisis, indeed what was the main cause of contagion, and why. Secondly, was the amplitude of the channels of transmission of financial contagion changed or did they remain constant during these two crises. Third, was the magnitude of the impact of crisis the same or different across all countries during the GFC and the ESDC? Or in other words, which countries were the most or the least affected by the crisis?

[2] See for instance J.-C. Trichet'speech at the Foreign Correspondents' Club of Japan, Tokyo, April 18th, 2009.
[3] Even thought, there is no consensus about the official time periods of the two crises, we consider that the global financial crisis reached its peak with Lehman Brothers bankruptcy on September 2008 while for the European sovereign debt crisis; it was the Greek debt crisis on May 2010.

In this paper, we adopt a macroeconomic approach to study the main factors during the two major last crises. Contrary to previous chapters of the thesis about banking contagion with data on individual banks, we use global data on financial markets and money markets. Our paper is related to the literature from three approaches. First, our question of international financial markets transmission of crisis has been addressed mainly by the literature, but this latter focused mainly in the equity market (Sugihara (2010), Hasbah and Zarour (2010), Morales and Andreosso-O'Callaghan (2009)). On top of that, this large literature focuses mainly on transmission of contagion during past crises (Forbes and Rigobon, 2002). Our approach is different in the sense where we are interested in the international transmission of the global financial crisis and the European sovereign debt crisis in equity markets as well as monetary markets. Second, our econometric methodology of VAR models has been largely used since Sims (1980)[4], but with different specifications. Among them, we use TVP-VAR model which became popular in economic literature since Cogley and Sargent (2005), Primiceri (2005) and Nakajima (2011). However, the limitation of the Cogley and Sargent (2005) model is the constant volatility assumption. This could neglect possible heteroskedasticity of shocks and any nonlinearities in the relations among the variables of the model (such as a gradual change or a structural break into the data). Tor reconcile this issue, Primiceri (2005) takes into account the time variation in the variance-covariance matrix of innovations and estimates the TVP-VAR model with stochastic volatility. While this model was used for policy analysis, we suggest applying this model for channels of contagion during the GFC and ESDC. Third, as far the results of factors of contagion, we refer to Chudik and Fratzscher (2010) who show the transmission of contagion during the global financial crisis of the factor liquidity and risk aversion on advanced and emerging markets. Indeed, we study the same factors; however our analysis focus on individual countries of the G7 by measuring the impact with impulse response functions.

The objective of this paper is to give some insight about the channels of contagion (liquidity and risk) during the two last major crises on G7 countries, with a particular focus on their dynamics over time. As we are interested in capturing interdependencies among multiple time series, we consider a Vector AutoRegression (VAR) framework. In addition, it seems not realistic to suppose that liquidity or risk aversion shocks on stock and monetary markets do not change over time, notably due to highly volatile markets. More generally, it has been recognized that the structure and functioning of the economy changes over time, and so there is a need to account for that evolution in the estimation procedure as well (Koop et al. 2009). That is why we consider a time-varying parameters vector autoregressive (TVP-VAR) model. Finally, since we are adopting a financial market perspective and a well-known fact about financial time series models is that their residuals often vary in time (heteroskedasticity of shocks), we consider a TVP-VAR model with stochastic volatility (Nakajima,

[4] VAR models are used for describing the dynamic behavior of economic and financial time series; therefore they are commonly used in structural inference and policy analysis.

2011)[5]. Thus, the TVP VAR model enables to capture the potential time-varying nature of the underlying structure in the economy in a more robust manner.

Our results show (i) that both types of shocks played a role in the global transmission of the crisis, however, shock to liquidity have been relatively more important on monetary markets and shock to risk aversion on stock markets, (ii) the amplitude of the channels of contagion changed during the two crises. Liquidity shocks were transmitted through monetary markets during BNP and LBB, and then during the GDC it was through the stock markets with a very fast and strong reaction for all countries. The risk aversion shock was transmitted through the stock markets. And (iii) the magnitude of the impact of shocks was different across countries. U.S. was clearly more sensitive during Lehman Brothers' bankruptcy and Greek debt crisis, while European countries had a higher sensitivity during BNP event.

We adopt the following plan for the paper. In second section, we focus on the literature review on financial contagion using different VAR approaches. In third section, we outline the data used in the study and give details about our estimation process. The fourth section allows us to present the TVP-VAR methodology. Section five presents results. Finally, section six presents concluding remarks and extension of the current study.

2. Literature review

In the literature review, we develop studies on transmission of shocks with VAR models (table 1 in the appendix). We adopt the following plan for the literature review: firstly, we focus on studies on monetary policy shocks, and secondly on studies about financial shocks. Thirdly, we develop the measures of financial shocks. Fourthly, we focus on VAR model and lastly on TVP-VAR model. Typically, VAR models introduced by Sims (1980) are used to examine the interactions of various economic and financial variables[6]. At the beginning and still now, they were greatly used in macroeconomic models to study the impact of monetary policy shocks (Kazi et al. (2011), Mumtaz et al. (2011) and Darvas (2009)). The econometric methodologies differ from FAVAR (Factor Augmented VAR), Time-Varying Parameters (TVP) VAR and TVP-FAVAR (Time-Varying Parameters - Factor Augmented VAR). Kazi et al. (2011) study the transmission of U.S. monetary shocks on OECD economies. They construct a large dataset of variables for the 14 major OECD countries. They find that the negative U.S. monetary shocks could have a positive or negative impact on the OECD economies depending on the country. Mumtaz et al. (2011) investigate evolving dynamics in the real exchange rate for United Kingdom, Euro zone and Canada. By applying TVP-VAR methodology from Cogley and Sargent (2005), and using long time series, they find that the real exchange rate dynamics have changed over time. Darvas (2009) study the transmission of monetary

[5] The idea of stochastic volatility originally introduced by Black (1976) is frequently introduced into the analysis of financial econometrics (Sheppard, 2005).
[6] The impulse response functions measure the reactions of a set of variables to specific shock.

policy in three new member states of the E.U. (Czech, Hungary and Poland). With the TVP-VAR model from Cogley and Sargent (2005), he shows that the monetary transmission changed before and after the entrance of these three new members.

However, few studies comparatively investigate exclusively the transmission of financial shocks (e.g. Sugihara (2010), Galesi et al. (2009), and Eickmeier et al. (2011)). Galesi et al. (2009) study the international transmission of financial shock across borders from U.S. to European countries with the global VAR (GVAR) model from Pesaran, Schuermann and Weiner (2004). They show that asset prices are the main channel of contagion in the short run, however cost and quantity of credit matter in the long run. Besides, Eickmeier, Lemke and Marcellino (2011) look at the temporal evolution in the dynamic transmission of U.S. financial shock (identified as unexpected changes in a Financial Conditions Index published by Hatzius et al. (2010)) to major advanced economies with TVP-Factor Augmented VAR (FAVAR) model. Using quarterly data from 1971 to 2009, they focus on the G7 countries, plus Spain and Austria. They find that positive U.S. financial shocks have a positive impact on the other countries (and vice versa for negative shocks). Moreover, U.S. positive financial shock is transmitted through trade and financial markets.

As we are studying the financial transmission of contagion during the global financial crisis and the European sovereign debt crisis, our question is related to the literature on financial shocks. This literature is mostly seldom; when measuring the impact of financial shocks during the global financial crisis (Sugihara (2010) and Chudik and Fratzscher (2010)) and even more during the European sovereign debt crisis. That is why our sample covers the global financial crisis as well as the European sovereign debt crisis. The financial shocks in the literature are appreciated with liquidity and risk aversion shocks (Chudik and Fratzscher, 2010). Liquidity shock is measured with U.S. TED spread, whereas risk aversion is measured with U.S. VIX index. De Haan and Van den End (2011) study the funding liquidity shocks and Baumeister, Durinck and Peersman (2008) measure liquidity shocks with monetary aggregate. We follow Chudik and Fratzscher (2010) as we are interested in financial shocks. They evaluate the role of tightening in liquidity conditions and the role of collapse in risk appetite in the transmission of the GFC. They apply G-VAR model with a large dataset of 26 economies (both advanced and emerging countries). They find different transmission processes among economies. While advanced countries seem to be more affected by the liquidity shocks, the emerging countries were impacted by a decline in risk appetite. Baumeister, Durinck and Peersman (2008) investigate the dynamic effects of excess liquidity shocks on economic activity, assets prices and inflation over time. Using TVP-VAR for the Euro area countries between 1971 and 2005, they show that the impact varies considerably over time depending on the source of increased liquidity and of the underlying state of the economy. Finally, De Haan and Van den End (2011) with a panel VAR model, show that, in response to a negative funding liquidity shock, bank would first reduce lending, second they would hoard liquidity in the form of liquid bonds and central bank reserves and third they would conduct firesale of securities.

Different VAR models have been developed to study financial shocks. The simplest is the basic form of the VAR model (Morales and Andreosso-O'Callaghan (2009)). They investigate market interdependences and volatility transmission effects from emerging Asia with more mature economies. They use Asian daily stock market indices with multivariate VAR-EGARCH, and find that there is contagion effect and interdependences. Moreover, Global VAR models are considered when studying a large dataset of countries as in Chudik and Fratzscher (2010). Baumeister et al. (2008) who investigate the impact of liquidity shocks on a set of variables in the Euro area use the TVP VAR to capture time variation in the underlying state of the economy. This is the specification that we use as Nakajima (2011), Sugihara (2010), Mumtaz and Sunder-Plassmann (2010), Darvas (2009), Clark and Terry (2009) and Clark and Davig (2008). Finally, Helbling et al. (2010) study the linkages between credit markets and global business cycles fluctuations. Using VAR and FAVAR for the G7 countries, they focus on credit, policy, productivity and demand shock. They show that the U.S. credit market shock have significant impact on the evolution of global growth during the global financial crisis. Bagliano and Morana (2010) look for the impact of macroeconomic shocks. They use FAVAR of Stock and Watson (2005) and find that the U.S. financial shocks have spilled over to foreign countries through U.S. house and stock price channel dynamics and liquidity creation. They find that the trade channel is the key transmission of the real shock.

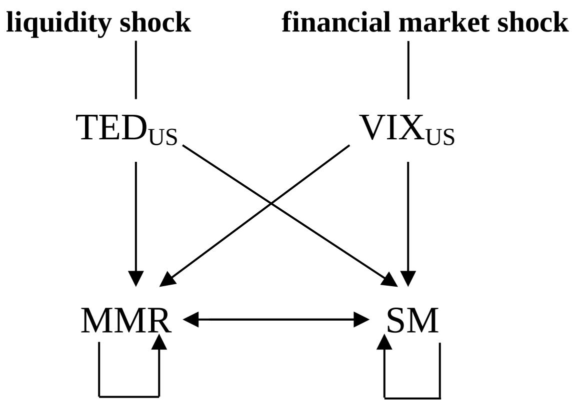
In the literature, two types of TVP -VAR models are considered: the constant volatility type (the volatility of the structural shock is constant over time) and the stochastic volatility type (where the volatility varies over time). Cogley and Sargent (2005) estimate time-varying parameters vector autoregressive model with constant volatility. The constant volatility assumption is strong and could neglect possible heteroscedasticity of shocks and any non-linearities in the relation among variables of the model. As a consequence, they allow for time-varying variance, although the simultaneous relations among the variables (covariance) are still modeled as time invariant. Primiceri (2005) stresses the importance of allowing for time variation in the variance covariance matrix of innovations and estimates the TVP-VAR model with stochastic volatility. Sugihara (2010) apply this model to examine global contagion effects on financial markets during the global financial crisis of 2008-2009. Sugihara (2010) assesses the interdependencies among equity markets of Japan, Europe and U.S. He studies if the financial shocks from U.S. lead to contagion or spillover to the rest of the countries. However, he only focuses on stock market indices. Using the TVP–VAR model from Cogley and Sargent (2005), he shows that the volatility shows reciprocal dependency among the three markets after Lehman Brothers failure (henceforth, LBB). As for the risk premium contagion, the interdependencies became stronger after LBB particularly from Europe to U.S.

To summarize, we adopt a financial market perspective with TVP-VAR model (Nakajima, 2011) as we look at the impact of liquidity and risk aversion shocks on a set of countries. Besides, weekly data as Chudik and Fratzscher (2010) presents the advantages of more accurate measures of liquidity and risk aversion shocks. Our goal is to analyze the crisis dynamics and its drivers during BNP, LBB and GDC events.

3. Data and settings

Our analysis of global financial crisis transmission is restricted to the G7 countries (Germany, Canada, U.S., United Kingdom, France, Italy, and Japan). These countries comprised half of the global nominal gross domestic product (GDP)[7]. We collect our financial variables from Datastream.

For stock markets, we use *MSCI* (Morgan Stanley Corporate Index) in local currency for each country. We prefer local currency indices in order to avoid changes in the comovements across equity markets resulting from changes in exchange rates consistent with Chudik and Fratzscher (2010). For money market rates, we collect national *3 month money market rates (MMR)*. For European countries, we have Euribor, for Canada, we collect Canada Treasury bill auction, for United Kingdom, we have UK interbank 3 month middle-rate, and for Japan 3 month interbank offered rate. As Chudik and Fratzscher (2011), we use local currency returns in order to be consistent with the measurement of the money market rates, as well as to avoid changes in the comovement across equity markets resulting from change in exchange rate comovements. We use the *VIX* index for S&P 500 as a proxy for financial market risk and *TED* spread as a proxy for liquidity shock. TED spread is defined as the difference between U.S. 3 month money market rates and U.S. Treasury. We summarize our questions by the following schema:



Schema 1: questions

NB: → *means what is the shock and on which market.*

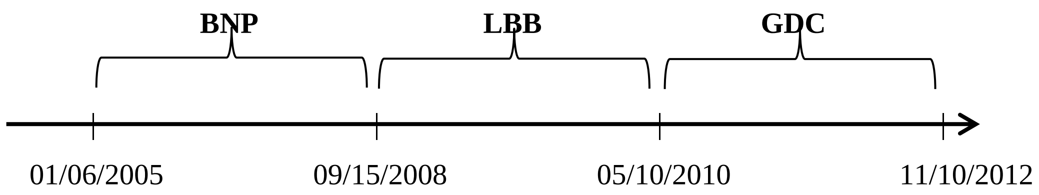
Firstly, we look at the impact of liquidity shocks from U.S. (TEDus) on money markets and stock markets. Secondly, we measure the impact of risk shocks from U.S. (VIXus) on monetary markets and stock markets. Thirdly, we analyze the impact of stock market (SMindividuals) on monetary markets and stock markets. Fourthly, we focus on the impact of money market (MMRindividuals) on monetary

[7] Gross Domestic Product, measured in current prices, from 2007 to 2012 extracted from the World Economic Outlook database from the International Monetary Fund (IMF) website.

markets and stock markets. Especially, the shock to liquidity is measured with a higher TED interpreted as higher pressure on the market to obtain liquidity. This shock should lead money market to rise and stock market to decline. On the other hand, the shock to risk aversion is assessed with a higher VIX. The money market and the stock market should decline then. Liquidity risk is defined as the potential losses with respect to a reference mark-to-mark value, due to the action of trading. Market risk (or risk aversion) is the uncertainty of the profit and loss at a given horizon in the future.

A TVP-VAR model is estimated with weekly data for each of the G7 countries from January 6th, 2005 until November 10th 2012. This timeframe allow us to cover the global financial crisis as well as the European sovereign debt crisis. Besides, this timeframe include several periods which differ in terms of market conditions, therefore it is likely that properties of the data changed in time and amplitude of shocks as well. Indeed, we identify three periods during the crises matching with three major shocks during the crises. 1/BNP Paribas announcement of cash withdrawals from fund managed on August 9th, 2007, 2/Lehman Brothers bankruptcy announcement of Chapter 11 bankruptcy on September 15th 2008 and 3/European union and International Monetary Fund announcement of providing financial help to Greece on May 9th, 2010 as the issue was no longer the solvency of banks, but the solvency of governments. It is important to notice that there is no consensus about the timeline of the crises; however, we select our two first events according to previous works such as Sugihara (2010) and Salloy (2012). These three shocks allow us to consider three key stages during the crisis (Figure 1). A pre-crisis period, running from January 2004 until third quarter of 2008 with Lehman Brothers bankruptcy called BNP Paribas event (BNP). Then from Lehman bankruptcy until second quarter of 2010 with the triggering of the Euro crisis called the Lehman Brothers bankruptcy (LBB). And thirdly, from the second quarter of 2010 to end 2012 defined as the Greek debt crisis (GDC).

Figure 1: Three stages during the crisis



Weekly data has the advantage of better capturing the transmission of shocks in financial markets than lower frequency data (Chudik and Fratzscher, 2011). Besides, using higher than weekly frequency data will complicated our analysis because of the non-overlapping trading times across countries. Finally, we consider a number of lag factors equal to two, which are determined by highest marginal likelihood. On top of that, we assure the stationnarity of our data with unit root test. As our data are not stationary in levels, we transform them. We finally work with first difference logarithm for the stock markets indices and the U.S. VIX index. And first difference for data of money market rates and U.S. ted spread[8]. Finally table 2 presents some descriptive statistics for the different data series for the whole sample and each time period. All series of the whole sample, except TED and VIX are skewed to the left which means that there were relatively more declines than increases (on the other hand, these relatively few increases had a relatively higher magnitude). Besides, all series are leptokurtic, which is very common to financial time series. Several properties of subsamples are the following. First, we observe that during BNP event, all the variables have a positive mean, except the Italian equity market. On the contrary, during LB event, all the variables have a negative mean or very close to zero. Second, the highest maximum and minimum values are also reached during LB period and the standard deviations of the variables are higher during LB event.

A four variables TVP-VAR model is estimated for weekly data from the period January 6th, 2005 until November 10th 2012. One set of variables is examined (t,s,m,v). The number of VAR lags[9] is 2. For parsimony, we assume that Σb is diagonal. For the i-th diagonals of the covariance matrices following priors are assumed:

$$(\Sigma_\beta)_i^{-2} \sim gamma(40, 2.02),$$
$$(\Sigma_a)_i^{-2} \sim gamma(40, 2.02),$$
$$(\Sigma_h)_i^{-2} \sim gamma(40, 2.02)$$

Flat priors are set for the initial state of the time-varying parameters $\mu_{\beta 0} = \mu_{a0} = \mu_{h0} = 0$, and $\Sigma_{\beta 0 =}\Sigma_{\beta 0 =}\Sigma_{\beta 0 =}10 * I$. Figures 1 in the Appendix show the sample autocorrelation functions, the sample paths and the posterior densities for the selected parameters of the TVP-VAR model. We draw 30,000 samples after discarding the initial 15,000 samples. Moreover, Figure 1 in the appendix report the estimation results for selected parameters of the TVP-VAR model for the variable set (*t,m,s,v*). Panel 1.A shows the sample autocorrelations functions for the selected parameters of the TVP-VAR model for the variable set (t,m,s,v) of U.S. Panel 1.B show their sample paths, i.e. the time behavior of equation coefficients. And Panel 1.C. draws the posterior densities. The sample autocorrelations functions drop stably indicating that the sampling method produces sample with low autocorrelation, and the sample paths look stable with the estimated coefficients varying in time which justified using TVP-VAR. These results indicate that the MCM algorithm produces posterior draws efficiently and very good estimations as in Nakajima (2011). The results are similar for the other countries of the sample[10].

Table 2: Descriptive statistics on the whole period and subsample periods.
Source: Datastream and author's calculations.

[8] Not presented here, but available upon request.
[9] The selection criterion is based on the highest marginal likelihood estimated for different lags lengths.
[10] Figures for other countries are not presented here for a constraint of space, but are available upon request.

Whole sample		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
MMR_CAN	first diff.	-0,36	0,02	27,18	-75,04	8,23	-4,03	35,76
MMR_EUR	first diff.	-0,48	0,10	21,10	-34,70	5,77	-2,04	12,88
MMR_JP	first diff.	0,06	0,00	37,31	-37,46	2,92	-0,33	134,57
MMR_UK	first diff.	-1,05	0,00	40,00	-135,00	10,37	-6,45	77,12
MMR_US	first diff.	-0,55	0,00	270,00	-125,00	18,17	6,38	129,90
SM_CAN	log and first diff.	0,03	0,18	5,94	-8,61	1,21	-1,30	12,41
SM_FR	log and first diff.	-0,01	0,11	4,39	-6,03	1,26	-0,63	5,42
SM_GER	log and first diff.	0,03	0,16	4,55	-6,45	1,29	-0,70	6,23
SM_IT	log and first diff.	-0,07	0,07	4,65	-6,62	1,43	-0,66	6,02
SM_JP	log and first diff.	-0,04	0,08	4,03	-7,66	1,29	-0,81	6,60
SM_UK	log and first diff.	0,02	0,11	3,74	-5,21	1,11	-0,89	6,54
SM_US	log and first diff.	0,02	0,13	7,25	-8,81	1,22	-1,53	17,83
TED_US	first diff.	-0,05	0,00	405,00	-177,00	26,10	7,99	150,74
VIX_US	log and first diff.	0,01	-0,36	25,01	-18,83	5,41	0,57	5,47

BNP period		Mean	Median	Maximum	Minimum	Std, Dev,	Skewness	Kurtosis
MMR_CAN	first diff.	0,25	0,02	27,18	-50,64	7,77	-1,98	23,62
MMR_EUR	first diff.	1,44	1,30	17,70	-15,80	3,99	-0,19	9,72
MMR_JP	first diff.	0,39	0,00	10,70	-2,10	1,19	4,49	34,64
MMR_UK	first diff.	0,45	0,00	22,50	-45,00	7,17	-1,58	14,17
MMR_US	first diff.	0,16	1,00	18,00	-66,00	9,34	-3,87	23,36
SM_CAN	log and first diff.	0,08	0,25	2,16	-3,12	0,90	-0,81	4,01
SM_FR	log and first diff.	0,03	0,12	2,10	-3,10	0,86	-0,90	4,66
SM_GER	log and first diff.	0,06	0,19	1,85	-3,32	0,88	-0,96	4,79
SM_IT	log and first diff.	-0,03	0,11	2,01	-2,56	0,83	-0,65	3,92
SM_JP	log and first diff.	0,02	0,13	2,60	-3,30	1,09	-0,39	3,28
SM_UK	log and first diff.	0,02	0,15	2,35	-2,89	0,79	-0,82	5,17
SM_US	log and first diff.	0,01	0,06	1,59	-2,74	0,72	-0,83	4,53
TED_US	first diff.	0,41	0,00	96,00	-58,00	15,09	1,28	13,41
VIX_US	log and first diff.	0,13	-0,32	19,15	-13,45	4,69	0,48	4,58

LB period		Mean	Median	Maximum	Minimum	Std, Dev,	Skewness	Kurtosis
MMR_CAN	first diff.	-3,17	0,00	3,05	-75,04	12,54	-4,13	19,74
MMR_EUR	first diff.	-4,95	-1,40	21,10	-34,70	8,99	-1,18	5,56
MMR_JP	first diff.	-0,51	-0,23	5,46	-14,92	2,05	-4,44	32,47
MMR_UK	first diff.	-5,78	-1,00	40,00	-135,00	18,74	-4,34	29,36
MMR_US	first diff.	-2,80	0,00	270,00	-125,00	36,95	3,95	37,27
SM_CAN	log and first diff.	-0,06	0,08	5,94	-8,61	2,00	-1,09	7,35
SM_FR	log and first diff.	-0,06	0,00	3,75	-6,03	1,68	-0,74	4,05
SM_GER	log and first diff.	-0,07	-0,03	3,94	-6,45	1,80	-0,73	4,43
SM_IT	log and first diff.	-0,13	0,14	4,59	-6,62	1,98	-0,82	4,27
SM_JP	log and first diff.	-0,12	-0,02	4,03	-7,66	1,78	-0,80	5,84
SM_UK	log and first diff.	0,00	-0,05	3,74	-5,21	1,68	-0,85	4,30
SM_US	log and first diff.	-0,04	0,15	7,25	-8,81	2,07	-1,23	9,67
TED_US	first diff.	-1,03	0,00	405,00	-177,00	52,19	4,76	45,47
VIX_US	log and first diff.	0,16	-0,72	25,01	-16,80	5,88	1,13	6,49

GDC period		Mean	Median	Maximum	Minimum	Std, Dev,	Skewness	Kurtosis
MMR_CAN	first diff.	0,57	0,03	25,33	-1,18	3,69	6,33	41,57
MMR_EUR	first diff.	-0,34	-0,30	7,70	-14,40	3,03	-1,03	7,00
MMR_JP	first diff.	-0,06	0,00	37,31	-37,46	4,61	-0,01	66,28
MMR_UK	first diff.	-0,11	0,00	20,00	-25,00	3,44	-1,53	30,86
MMR_US	first diff.	-0,06	0,00	11,00	-9,00	2,13	0,41	9,58
SM_CAN	log and first diff.	-0,01	0,07	2,40	-3,19	0,92	-0,40	3,70
SM_FR	log and first diff.	-0,04	0,05	4,39	-4,83	1,43	-0,16	4,25
SM_GER	log and first diff.	0,02	0,08	4,55	-5,02	1,40	-0,18	4,97
SM_IT	log and first diff.	-0,12	-0,14	4,65	-5,85	1,66	-0,13	4,08
SM_JP	log and first diff.	-0,10	-0,10	2,33	-5,88	1,19	-0,87	6,08
SM_UK	log and first diff.	0,01	0,09	2,97	-3,68	1,05	-0,44	4,65
SM_US	log and first diff.	0,04	0,21	2,99	-3,53	1,06	-0,74	4,46
TED_US	first diff.	-0,02	0,00	10,00	-10,00	2,89	0,12	4,89
VIX_US	log and first diff.	-0,06	-0,35	25,01	-18,83	6,43	0,64	5,49

4. Methodology of time varying VAR with stochastic volatility

Higher integration between financial markets could have modified the process of transmission of shocks between countries. While studying the international propagation of shocks, it is important to capture the possible changes in the underlying structure of the economies, such as the different impact of negative and positive shocks, the time variation in the size of the shocks, the different transmission mechanisms, the amplitude of shocks and their duration. As the way economies experience shocks changed with the new financial derivative products, with gradual changes, this characteristic of smooth transition is relevant. Indeed, financial shocks during the global financial crisis and the European sovereign debt crisis are assessed with the time-varying parameters vector autoregressive (TVP-VAR) model with stochastic volatility. The TVP-VAR model allows the autoregressive coefficients and the covariance matrix to change over the time. Especially, the effects and the contributions of liquidity and risk aversion shocks may have changed over time. The time-varying parameters capture possible non linearities or time variation in the underlying structure of the economy, whereas the stochastic volatility allow for heteroskedasticity of the shocks. This section develops the TVP-VAR model.

4.1 Model

The analysis of impulse responses reveals information about the transmission of shocks from U.S. to other countries. The measure of the impact of liquidity and risk shocks on stock and monetary markets is conducted with the analysis of impulse responses drawn from VAR model. First, as we are studying the interaction between multivariate time series, we use VAR model. The basic framework for TVP-VAR is defined as:

$$Ay_t = F_1 y_{t-1} + \ldots + F_s y_{t-s} + u_t \qquad t = s+1, \ldots, n, \quad (1)$$

where y_t is the $k \times 1$ vector of observed variables (k is the number of endogenous variables, here equals four, containing stock market indices, volatility index, money market rates and TED spread), while $A, F_1, \ldots, F_s$ are $k \times k$ matrices of coefficients. The disturbance u_t is a $k \times 1$ structural shock, assuming that $u_t \sim \mathrm{N}(0, \Sigma\Sigma)$, where:

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix} \quad (2)$$

$\sum$ is the diagonal variance covariance matrix of the disturbance u_t. This matrix is supposed to be constant. This model is a basic homoscedastic vector autoregression.

We assume that A is a lower-triangular matrix that models the contemporaneous interactions among the endogenous variables. This specifies the simultaneous relation of structural shocks by recursive identification.

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix} \quad (3)$$

We rewrite the equation (1), as reduced form VAR model:

$$y_t = B_1 y_{t-1} + ... + B_s y_{t-s} + A^{-1} \sum \varepsilon_t, \quad (4)$$

$$\varepsilon_t \sim N(0, I_k),$$

where $B_i = A^{-1} F_i$, for $i = 1,..., s.$ and I_k the information matrix (the matrix containing the data).

Defining $X_t = I_k \otimes (y'_{t-1},..., y'_{t-s}),$ where the symbol $\otimes$ signifies the Kronecker product, the model can be written as:

$$y_t = X_t \beta + A^{-1} \Sigma \varepsilon_t. \quad (5)$$

Where β stacks the elements of the rows of B and A is a time invariant matrix.

However, as we want to capture possible changes in the underlying structure of the economy, such as changes in the size of shocks, in the propagation mechanism and in the duration, we extend the basic VAR framework to a time-varying parameters VAR model (TVP-VAR) by allowing the parameters from equation (5) to vary over time[11] such as Cogley and Sargent (2001).

$$y_t = X_t \beta_t + A_t^{-1} \Sigma \varepsilon_t \qquad t = s+1,..., n, \quad (6)$$

The limitation of Cogley and Sargent (2001) model is the homoscedastic volatility assumption. This could neglect possible hetereosckedasticity of shocks and any non linearities in the relations among the variables of the model. On top of that, empirical literature review on the impact of financial shocks has proven that relaxing the hypothesis of residuals homoscedasticicty can improve the model as volatility of financial time series' tend to cluster. As a consequence, we use the TVP -VAR model with stochastic volatility in the spirit of Cogley and Sargent (2002, 2005), Primiceri (2005) and Benati and Mumtaz (2007) specified by:

$$y_t = X_t \beta_t + A_t^{-1} \Sigma_t \varepsilon_t \qquad t = s+1,..., n, \quad (7)$$

[11] Note that we could also model changes in the transmission mechanism by splitting the model and estimate the model into subsamples. However, there is no consensus about major official timeline about crisis. Moreover, as suggested by Koop et al. (2009), the economy is changing gradually, as opposed to sudden abrupt changes.

where y_t is an (4 x 1) vector of observed endogenous variables *(TED,VIX,SM,MMR)*, the β_t (coefficients), and the A_t (parameters) and Σ_t (the stochastic volatility) are all time varying. There are several ways to model the process for the vector of time-varying parameters.

$$At = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1,t} & \cdots & a_{k,k-1,t} & 1 \end{pmatrix} (8) \text{ and } \sum t = \begin{pmatrix} h_{1,t} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & h_{k,t} \end{pmatrix} (9)$$

We follow Primiceri (2005) to model the process of these parameters, assuming they all follow a random walk process. By checking permanent changes, this assumption decreases the number of parameters to estimate.

Let us note that $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, ..., a_{k,k-1},)'$ is a stacked vector of the lower triangular elements in A_t from (8) and $h_t = (h_{1t}, ..., h_{kt})'$ the diagonal elements of ∑t from (9) with $h_{jt} = \log \sigma_{jt}{}^2$, with for $j = 1,...,k,\ t = s+1,...,n.$

The dynamics of the model's time varying parameters model as drift less random walks is specified as follows:

$$\beta_{t+1} = \beta_t + u_{\beta t},$$

$$a_{t+1} = a_t + u_{at},$$

$$h_{t+1} = h_t + u_{ht},$$

Where:

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N \left(0, \begin{pmatrix} \mathrm{I} & \mathrm{O} & \mathrm{O} & \mathrm{O} \\ \mathrm{O} & \Sigma_\beta & O & \mathrm{O} \\ \mathrm{O} & O & \Sigma_a & \mathrm{O} \\ \mathrm{O} & \mathrm{O} & O & \Sigma_h \end{pmatrix} \right),$$

where $\beta_{s+1} \sim N(\mu_{\beta 0}, \Sigma_{\beta 0}),\ a_{s+1} \sim N\ (\mu_{\alpha 0}, \Sigma_{\alpha 0})$ and $h_{s+1} \sim N\ (\mu_{h0}, \Sigma_{h0})$.

The variance and covariance structure for the innovations of the time-varying parameters are governed by the parameters $\sum_\beta, \sum_a,$ and $\sum_h$ which are assumed to be diagonal matrices. The error terms of the three transitions equations are independent of each other and of the innovations of the observation equation.

We discuss five issues related to the TVP-VAR methodology we use: the type of TVP-VAR, the lag length, the shock identification, the impulse response analysis and the initial conditions. First, we assume that our parameters follow a random walk process as Primiceri (2005). This assumption helps in keeping the parsimony (which decreases the number of parameters to estimate), as the TVP-VAR model has already a high number of parameters to estimate. On top of that, the random walk specification is a flexible model which can capture various time paths of the parameters resulting from changes in the economy. Generally empirical literature with TVP-VAR methodology relies on this assumption for the innovations of parameters. Second, the selection of the number of lags in the TVP-VAR is a key issue. Indeed, larger lags assume the estimation of a larger number of parameters. We determine the number of lags by the highest marginal likelihood ratio (MLR). Third, we use recursive identification scheme for the estimation algorithm with the assumption of a lower triangular matrix At because of simplicity[12]. Fourth, as we are using TVP-VAR model, impulse responses are drawn for each observation of the sample. We use the parameter set of time t to calculate the impulse response function for t, t+1, t+2. Fifth, we develop initial conditions. Following our assumption of time varying parameters, we cannot use their means as initial conditions. As a consequence, we estimate a fixe parameter VAR equation by equation, with ordinary least squares (OLS) for the first observations and use these estimates for initial conditions for the TVP and their covariance matrix. Besides, as the TVP-VAR model is estimated under Bayesian framework, selection of the appropriate priors is important as parameters being time-variant may cause an over-identification problem. To resolve, this problem, Primiceri (2005) argues the advantages of tight prior for the covariance matrix of the disturbance in the random walk process. A tighter prior is comparatively required for time-varying coefficient $\left(\beta = \left(\beta_{s+1,\ldots,}\beta_n\right)\right)$ than the simultaneous relations $\left(a = \left(a_{s+1,\ldots,}a_n\right)\right)$ and the volatility $\left(h = \left(h_{s+1,\ldots,}h_n\right)\right)$ of structural shock for the variance of disturbance in their time varying framework as done by the related literature. To insure the robustness of the empirical result in regards to prior tightness, a prior sensitivity analysis is required.

4.2 Estimation methodology

Bayesian approach is used to evaluate the posterior distributions of the parameters of interest under a certain prior probability distribution. We use Markov Chain Monte Carlo (MCMC) for a precise and efficient estimation of the TVP-VAR method. MCMC, as a smoothing method deliver smoothed estimates of the parameters based on the entire available set of data[13]. In addition, using

[12] (see Nakajima, 2011)

[13] See Primiceri (2005) who argue the suitability of smoothed estimates, as opposed to filtered ones. He point out that smooth estimates are more efficient than filtered ones when the goal is to investigate the true evolution of the unobservable states over time. Filtered estimates would appear inappropriate because they would exhibit moving variation in time invariant models.

Bayesian inference, we have to choose carefully the priors. As suggested by Pimiceri (2005), we select a tight prior for the covariance matrix of the disturbance in the random walk process to avoid the implausible behaviors of the time-varying parameters. We estimate then a time invariant VAR on the training sample (small subsample of the dataset) to choose the key priors. The priors are calibrated on the point estimates of a constant-coefficient VAR (p) estimated over the training sample.

The mean and the variance of the time-varying parameters β are chosen to be the ordinary least squares (OLS) point estimates and four times its variance from time invariant VAR on the training sample:

$$\beta_0 \sim N(\beta_{OLS,} 4 * var(\beta_{OLS,})) \quad (11)$$

The mean and the variance of the coefficients of the contemporaneous interrelations A are chosen in the same way:

$$A_0 \sim N(A_{OLS,} 4 * var(A_{OLS,})) \quad (12)$$

For the coefficients of the stochastic volatility h_0 , the mean of the prior distribution is assumed to be the logarithm of the OLS estimate of the standard errors from the same time invariant VAR and the variance-covariance matrix is set as the identity matrix:

$$h \sim N(h_{OLS,} I_n) \quad (13)$$

Last, with regard to the hyperparameters, we make the following assumptions:

$$\sum\beta \sim IW\left(k_Q^2 * \tau * var\beta_{OLS}, \tau\right)$$
$$\sum h \sim IW\left(k_W^2 * (1 + \dim(W)) * I_n, (1 + \dim(W))\right)$$
$$s_1 \sim IW(k_S^2 * 1 + \dim(S_1)) * varA_{1,OLS}, (1 + \dim(S_1)))$$
$$s_2 \sim IW(k_S^3 * 1 + \dim(S_2)) * varA_{2,OLS}, (1 + \dim(S_2)))$$

Where τ is the size of the training sample, S_1 and S_2 denote two blocks $\sum a$ while $A_{1,OLS}$ and $A_{2,OLS}$ stand for the two corresponding blocks of A_{OLS}. We set by one plus the dimension of each matrix the degrees of freedom of scale matrices for the inverse-Whishart prior distribution of the hyperparameters so as to allow the prior to be proper. As indicated by Cogley and Sargent (2001), the scale matrices are chosen to be constant fraction of the variances of the corresponding OLS estimates on the training sample multiplied by the number of degrees of freedom.
See Appendix 2 for the simulation method by the Gibbs sampler.

5. Results

We present the main estimation results from our TVP-VAR model.

Figure 2 in the appendix represents the data in first differences for MMR and TED and in logarithm and first differences for SM and VIX and their time-varying standard deviations (posterior volatility) for U.S[14]. These plots depict dynamics of posterior draws on each date. TED spread and VIX are the same for all countries since we are interested in liquidity and risk shocks arising from the U.S. On the contrary, money market and stock market are different by countries.

All U.S. variables in Panel 2.A are jumping up in the last quarter of 2008, around Lehman Brothers bankruptcy. Moreover, we observe a jump during August 2007 for TED spread and VIX, which correspond to BNP event. On top of that, another jump is observed in May 2010 with the GDC event. Besides, individual stock market and VIX are erratic.

In panel 2.B., we observe that standard deviation generally increases in time of crisis, around Lehman Brothers bankruptcy, which is an expected result. Besides, the time-varying variance justifies inclusion of the stochastic volatility in our model, instead of constant volatility. Indeed, stochastic volatility of TED, money market, VIX and stock market exhibits a spike around Lehman Brothers bankruptcy and show a general downward trend before and after. Especially, it remains particularly low and stable outside the event. Stochastic volatility of the volatility index show sharper movement than for other variables. It is relatively low until mid-2006 with a first little peak, and then it declines until mid-2006 with a second little peak with BNP announcement. A third peak is reach with Lehman Brothers bankruptcy announcement in September 2008. It declines then until its highest peak with the Greek debt crisis in May 2010. After that it reduces and reaches other high points in 2011 before declining in 2012. To sum up, the stock market adjusts more quickly than the money market to a shock.

Besides, we look at the time-varying simultaneous relations $\tilde{a}_{it}$ for the variables (t,m,s,v); which measure the size of simultaneous responses of other variables to one unit of the structural shock based on recursive identification scheme. Figure 3 presents the simultaneous responses for the U.S[15]. The simultaneous relation of TED shock on money market (t => m) is always positive and highly positive at early 2008 with a peak of 0.8 until end of 2010. On the contrary, the simultaneous relation of stock market to volatility (s => v) is always negative and significant. Besides, the relation between TED and stock market (t => s) varies over time where remaining positive for some period, it turned

[14] Figures for other countries are not presented here for a constraint of space, but are available upon request.
[15] Figures for other countries are not presented here for a constraint of space, but are available upon request.

negative though insignificant over the whole period. The same conclusion is found for other simultaneous relations, such as money market impact on stock market, money market impact on VIX and TED impact on VIX. For Canada, Japan, U.K., Germany, France and Italy, most of the simultaneous relations are insignificant except for the risk aversion shock on stock market (v => s) which is significantly negative.

The impulse responses are a basic tool to see the dynamics captured by the estimated VAR system. For the TVP-VAR model, the impulse responses at computed at all points in time using the estimated time-varying parameters. On the one hand, figures 4 in the appendix show the time-varying impulse responses of TVP-VAR for the set of variables (t, m, s, v) for U.S. in a time-series manner by showing the size of the impulse response with BNP freezing (BNP), Lehman Brothers bankruptcy (LBB) and Greek debt crisis (GDC). As a consequence, a three dimensional plot are drawn for the time-varying impulse responses. On the other hand, time-varying impulse responses are drawn in a time-series manner by showing the size of the impulse responses of TVP-VAR for the set of variables (t, m, s, v) for U.S. for 4 weeks, 8 weeks and 12 weeks horizons over time.

Figure 4 show the impulse responses of a set of variables (t, m, s, v) due to a shock for 3 particular points in time (BNP on August 2007, LBB on September 2008 and GDC on May 2010). From Figure 4.A., liquidity shock will not impact money markets (t => m) the same manner during BNP, LBB or GDC event; whatever the country. For instance money market will not be impacted by liquidity shock during BNP announcement on August 9th, 2007 but after a week, they will react positively for one week, however two weeks later they will be negatively impacted. On the contrary, money market will be positively impacted during LBB and the effect will last two weeks. We observe that any shocks given to any variables move to zero in the end, interpreted as convergence. In other words, the elasticity of stock markets to liquidity shocks has decreased with time. While money markets in the U.S. were less sensitive to liquidity shocks during BNP event, than Canada, or the European countries, they were clearly more impacted by LBB event. The effect of liquidity shocks on stock markets is high with GDC. When given a shocks on error terms of TED, we observe that BNP shocks have a positive impact on ted (t => t), however after 5 weeks the effect goes down to zero.

From Figure 4.B., we see a strong increase in the sensitivity of stock markets to VIX shocks during the crisis with a peak with Lehman Brothers' bankruptcy. With considering 8 or 12 weeks horizons, there is almost not impact. A risk shocks had a negative impact on stock markets, whatever the event considered, expect for U.S. which are negatively impacted two weeks after the event. Stock markets are more impacted with GDC event than with BNP or LBB events. While the effect of liquidity shocks on stock market is fast, its effect on money markets appear two weeks after the shocks. This is interpreted as the quick reaction of stock markets to a liquidity shocks. Money markets take more time to adjust.

From Figure 4.C., the comovoments of foreign stock markets with the U.S. stock market have not changed during the three events. This implies that while the elasticity of stock markets with a risk shocks had increased during some event, equity market comovements have not changed significantly as this increased sensitivity has been as strong in the U.S. itself as in the rest of the world. On the contrary, the effect of U.S. stock market shock has different impact on money markets. Monetary markets are more sensitive to the shock during BNP and LB event and less with the GDC. We observe that, first money markets reacted positively to the shock and after one or two weeks, they become negatively impacted.

From Figure 4.D, the comovements of foreign money markets with the U.S. money markets have a little bit changed during the three event, but more than the comovements of foreign stock markets with U.S. stock markets. Only, U.S., Germany and U.K. had impact with a delay of one or two weeks in time. The impact of a U.S. money market shocks on U.S. stock markets is almost zero during BNP and LBB events, which is not the case during the GDC. For Canada and Japan stock markets, the impact of U.S. money market shock is strong during the three events: BNP, LBB and GDC.

We give our attention to the liquidity shock. During BNP event, the liquidity shock has a more important impact on money markets than on stock markets. Stock markets do not react highly to liquidity shock; this is true for all countries, except the U.S., for which the monetary market is not sensitive to liquidity shock. For all countries, stock markets are less sensitive than money markets to a liquidity shocks during BNP event (the size of the impact is not high). During LBB event, stock markets do not seem to react to liquidity shock, except for the U.S. stock market. The U.S. monetary market is very sensitive to liquidity shocks during LBB, which was not the case during BNP event. Monetary markets react to liquidity shock during LBB. First, they react immediate positive and after two weeks, the effect becomes negative, whereas for the U.S. monetary market the impact is immediate strongly negative. During the GDC, the Japanese monetary market has been strongly reacted to the U.S. liquidity shock. Other monetary markets countries are less sensitive to liquidity shock. All stock markets are very sensitive to liquidity shock during the GDC, whereas they were less during BNP or LBB event. Monetary markets adjust more to liquidity shock during BNP and LBB event than stock markets. There is a change in the dynamic transmission of the liquidity shock between the crises. First, liquidity shocks were transmitted through monetary markets during BNP and LBB, whereas during the GDC it is through the stock markets in a very fast and strong reaction for all countries. To conclude, during BNP and LBB, it was clearly first a liquidity crisis on monetary markets with a freezing liquidity, and during the GDC, investors are clearly first worried on the stock markets.

We focus now on the risk aversion shock. Generally, during BNP event, the risk aversion shock has an impact on monetary market, that is first highly positive and negative two weeks later. For stock markets, the reaction is different. They do not react positively to a risk aversion shock. They all react negatively and highly during BNP event, even though the effect is less strong for the U.S. compared to other countries. During LB, U.S. stock market are more sensitive than during BNP. In conclusion, stock markets react more to risk aversion shock during LBB than BNP event. During the GDC, the impact of risk aversion shock on monetary shock is very low, whereas stock markets have been impacted. The risk aversion shock is transmitted through the stock markets than monetary markets, which were not the case for the liquidity shock. Moreover, the monetary markets take more time to adjust to liquidity shocks than stock markets to a risk aversion shocks. In addition, risk-averse investors require higher expected return if the asset's market-liquidity risk is greater. The higher the liquidity risk, the higher the expected return on the asset or the lower is its price.

We analyze results on the effect stock market shock. Generally, stock markets react immediate and very highly to a shock coming from the U.S. on their market. During BNP, the monetary market will react first positively to a stock market shocks, and then adjust negatively whatever the period considered. This is explained because the monetary markets reflect a "flight to quality" market for investors when stock markets are hit by a shock. Prices and expected returns of assets are affected by the market liquidity. Theory and empirical literature suggests that investors require higher return on assets with lower market liquidity to compensate for the higher cost of trading these assets. The higher its market liquidity, the higher its price and the lower is its expected return.

We develop results on the impact of monetary shock. Monetary markets adjust immediate and strongly to a shock on the U.S. monetary market. During BNP, monetary shocks have a negative impact on stock market, even though for the U.S. the impact is low. In general, during BNP event, U.S. stock and monetary markets do not seem to react to shocks. The impact is higher during LBB and GDC.

From figure 5, all the impulse responses vary significantly over time. From a global view, impulse responses functions seem more volatile while considering short term horizon (such as 4 weeks) than longer horizon terms (8 or 12 weeks). Figure 5 show the impulse responses of a set of variables (t, m, s, v) due to a shocks for three horizon time periods[16]. For U.S., in 2005, when giving a shocks on ted (liquidity shocks) and looking on the impact on money market (t => m), we see that for the different horizon in time (4, 8 or 12 weeks), money market would go down, however a liquidity shocks in 2007 will have a positive impact on money market when considering a 4 weeks period ahead but no impact when considering 8 or 12 weeks impact. A shock on ted will make stock market (t => s) rises in early 2005, but at the beginning of 2006 stock market would go down. Moreover, the impact

[16] Presented here only for U.S but available upon request for other countries.

of liquidity shocks on stock market (t => s) is almost zero when considering 8 and 12 periods ahead. However, stock market will be negatively affected from end of 2008 with 4 weeks period ahead. For Canada, Japan and U.K., (t => m) shock has a negative impact since 2009, whereas for Germany and France the negative impact starts at the end of 2010. With consideration of the impact of liquidity shocks on stock markets, while U.K. and France alternate positive and negative impact after 2010, they reach the highest negative value at the end 2011 with -0.2. On the contrary, Canada is positively impacted early 2010, but negatively in 2012. Japan and Italy are negatively impacted in 2010. A risk shock in early 2005 would affect negatively other markets (v => t, v => m, v =>s). However a risk shocks in 2007 would affect them positively for 4 weeks period ahead. Then the impulse responses of ted, money market and stock markets decline rapidly and even reach negative values in 2009. After that, money markets are no more impacted and ted and stock markets are positively impacted until 2012 with negative impact.

In conclusion, different behaviors of each time periods are observed for the impact of liquidity shock and risk shock. A liquidity shock will not impact in the same way stock markets during different events; interpreted as a change in the transmission of the crisis. Investors will not react to similar news during different event date; such as LBB or GDC. To sum up, the impact of liquidity shocks or risk shocks are changing over time, interpreting as a changing nature of channels of contagion. Our results draw two main results. Firstly, we analyze the impact of liquidity shock (t) on other markets. Overall, the elasticity of stock market to liquidity shocks has decreased during the global financial crisis. With 8 and 12 weeks horizons, the impulse responses were closed to zero. Money markets seem to be highly responsive to shocks, especially to a negative U.S. money market shock and a negative stock market shock at the beginning of the considered period. Even, with consideration of short term window horizon, money markets seem to react highly. Moreover, the highest reaction of a liquidity shock on ted is for BNP freezing and Lehman Brothers' bankruptcy. However, the effects of the shocks tend to disappear with time. Secondly, we turn our attention on the impact of risk shocks on other markets. Stock markets react more to risk aversion shock during LBB than BNP event. The risk aversion shock is transmitted through the stock markets than monetary markets, which were not the case for the liquidity shock. Moreover, we see that money markets take more time to adjust than stock markets.

Conclusion

The financial crisis of 2007-2010 had huge impact worldwide, severely affecting financial markets as well as finally economic activity. In this paper, we are interested in the factors of contagion through which the crisis has spread in the G7 countries. More precisely, we give our attention on two types of shocks: a tightening in liquidity conditions and a severe repricing of risk and flight of investors into safe asset classes. Our empirical work is based on TVP-VAR analysis. Moreover, we identify three shocks which require a particular attention: BNP freeze three investment funds in August 2007, Lehman Brothers' bankruptcy on September 2008 and the Greek debt crisis on May 2010. We show that channels of transmission of contagion have changed. Investors' behavior to same news will depend of the period of announcement and of the horizon of time considered. In conclusion, the impact of liquidity shocks or risk shocks are changing over time, there is a changing nature of channels of contagion.

Our results show that: firstly, both types of shocks have played an important role in the transmission of the crisis to other markets (Chudik and Fratzscher, 2011) even if there are changing in the transmission of shocks over time (Eickmeier et al., 2010). Secondly, the amplitude if the channels of transmission of financial contagion changed during these two crisis even if the effects of shocks tends to disappear with time. And thirdly, the magnitude of the impact of the crisis was different across countries. However, the factors of contagion of financial crisis are more complex than assumed in this paper, as they can be the consequence of the crisis. The liquidity conditions could be downgraded because of the severe recession, which could in turn worsen the liquidity conditions as induced with a vicious circle.

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Appendix:

Table 1: Literature review on studies on the impact of macroeconomic and financial shocks using different types of VAR techniques. *Source: authors*.

Authors	Problem	Types of shocks	Period	Countries	Variables	Methodology	Results
Nakajima (2011)	Explore the time-varying nature of the dynamic relationships between macroeconomic variables.	Macroeconomic shocks	1977-2007 (quaterly)	Japan	Inflation rate/output/medium-term interest rates/short-term interest rates	TVP -VAR	Anlaysis of two sets of variables : 1/ output, inflation and short-term interest rates and 2/ output, inflation and long-term interest rates.
Kazi, Wagan and Akbar (2011)	Transmission of U.S. monetary policy shocks on OECD countries.	Monetary shock - effective fed fund rates shocks (contractionary monetary policy)	1981 - 2010 (quaterly)	14 major OECD countries	Financial variables/variables related to real economy/aggregate price variables/trade variables/exchange rates	FAVAR (Bernanke et al., 2005) and TVP-FAVAR (Koop and Korobilis, 2010)	Negative U.S. monetary policy shocks could have a positive or a negative impact on GDP growth depending on the countries. The transmission to GDP growth has increased in OECD countries since the early 1980s. Asset prices, interest rates and trade channel seem to play major role in propagation of monetary policy shocks.
Mumtaz and Sunder-Plassmann (2011)	Investigate dynamics in the real exchange rate for UK, EURO and Canada.	Monetary policy shock (leads to a real exchange rate shock)	1957 - 2009 (quaterly)	U.S., UK, EURO AREA and CA	Real exchange rate/output (GDP) and inflation (consumer prices)	TVP-VAR (Cogley and Sargent, 2005)	Real exchange rate dynamics have changed over time. Closer association between the real exchange rate and fundamentals in more recent period.
Darvas (2009)	Transmission of monetary policy in three new member states of the EU.	Monetary shock	1993 - 2008 (quaterly)	3 central EU countries (Czech, Hungary and Poland)	Output, prices, interest rates, real exchange rate (4 endogeneous standard variables for monetary transmission VAR)	TVP-VAR (Cogley and Sargent, 2005)	The monetary transmission changed in the three countries.
Sugihara (2010)	Evaluate interdependencies of equity markets in Japan, Europe and U.S. (the country which originates shocks and the direction of contagion).	Financial shocks (contagion or spillover)	July 2003 - October 2009	3 regions (JP, EU, U.S.)	Stock price indices	TVP-VAR (Cogley and Sargent, 2005) => constant volatility type and stochastic volatility type	The volatility shows reciprocal dependency among the three markets after Lehman Brothers failure. As for the risk premium contagion, the interdependencies became stronger after Lehman shock particularly from Europe to U.S.

Authors	Problem	Types of shocks	Period	Countries	Variables	Methodology	Results
Galesi and Sgherri (2009)	Transmission of financial shocks accross borders.	Financial shocks in U.S. (slowdown in equity prices)	June 1999 - April 2008 (monthly)	27 countries (U.S., advanced EUROPE advanced, emerging EUROPE)	Real interbank rate/rate of growth of real equity prices/of real credit to corporations/of real GDP/real interest rates	GVAR (Pesaran, Schuermann and Weiner, 2004)	Asset prices are the main channel of contagion in the short run. In the long run, cost and quantity of credit matter.
Eickmeir, Lemke and Marcellino (2011)	Temporal evolution in the dynamic transmission of US financial shocks to major advanced countries.	financial shocks (Financial Conditions Index, FCI) USA	1971 - 2009 (quaterly)	G7 + 2 countries (U.S., CA, UK, JP, DE, FR, IT, SP, AU)	Real activity variables/prices/trade/ monetary and financial variables	TVP-FAVAR (Eickmeier, Lemke and Marcellino, 2009)	Positive U.S. financial shocks have a positive impact on the 9 countries (and vice versa for negative shocks). Improvements in U.S. FCI are positively transmitted through trade and financial markets.
Chudik and Fratzscher (2011)	Evaluate the role of tightenning in liquidity conditions and the role of collapse in risk appettite in the transmission of the GFC.	Liquidity shocks/risk shocks.	January 2005 - July 2009 (weekly)	26 economies (advanced and emerging)	3 month rates/ MSCI country indices/ VIX of S&P 500/ TED spread	G-VAR model	Diversity of the transmission process. Liquidity shock seem to have affected advanced economies contray to decline in risk appetite which had an impact on emerging markets.
De Haan and Van den End (2011)	Evaluate banks'response to funding liquidity shocks.	Funding liquidity shock	January 2004 - April 2010 (monthly)	17 banks (Netherlands)	Balance sheet banks data	p - VAR (panel)	Banks response to a negative funding liquidity shocks in a number of ways. First, they reduce lending (wholesale lending). Second, they hoard liquidity in the form of liquid bonds and central bank reserves. Third, they conduct firesale of securities (equity).
Baumeister, Durinck and Peersman (2008)	Investigate how the dynamics effects of excess liquidity shocks on economic activity, asset prices and inflation vary over time.	Liquidity shocks	1971 - 2005 (quaterly)	Euro Area	Economic activity/asset prices/inflation/M1/M3/credit	TVP - VAR	The impact varies considerably over time depending on the source of increased liquidity (M1, M3 - M1 or credit) and the underlying state of the economy.

Authors	Problem	Types of shocks	Period	Countries	Variables	Methodology	Results
Morales and Andreosso-O'Callaghan (2009)	Investigate market interdependances and volatility transmission effects from some Asian emerging and more mature economies.	Financial shocks (pure contagion)	2003 - 2009 (daily)	Asia and U.S.	Stock market indices	Multivariate VAR - EGARCH	Contagion effects. Interdependance effects. Volatility spillover.
Clark and Terry (2009)	Estimate the passthrough energy price inflation to core inflation.	Oil price shocks and monetary policy response	1965 - 2008 (quaterly)	U.S., UK, EURO AREA and CA	Core inflation, energy inflation, economic activity, effective fed fund rates	TVP - VAR (Cogley and Sargent, 2005)	A reduction in the passthrough of energy price inflation to core inflation in the U.S. since 1975. Monetary policy has been less responsive to energy price inflation since 1975.
Clark and Davig (2008)	Assess the link between inflation and survey measure of long and short-term expectations.	Inflation shock	1982 - 2008 (quaterly)	U.S.	Long-term expectations, short-term expectations and core inflation	TVP - VAR (Cogley and Sargent, 2005)	A relative stable relationship between inflation and survey measures of inflation. Measures of volatility of expectations and core inflation have declined susbtantially throughout the period.
Helbling, Huidrom, Kose and Otrok (2010)	Linkages between credit markets and global business cycles fluctuations.	Macroeconomic shocks - credit/policy/productivity and demand shocks in U.S.	1988 - 2009 (quaterly)	G7 countries	Credit growth/credit spread/GDP growth/labor productivity growth /inflation/interest rates spread	VAR and FAVAR	U.S. credit market shocks have a significant impact on the evolution of global growth during the global financial crisis (2007 - 2009).
Bagliano and Morana (2010)	Assessing the mechanists of the crisis, the domestic propagation in the US and its spillover outside USA.	Macroeconomic shocks - financial/demand/economic policy shocks	1980 -2009 (quaterly)	50 countries (advanced economies, advanced emerging, secondary emerging)	real activity variables/ prices/trade (macroeconomic variables)/financial variables/liquidity variables/exchange rates	FVAR (Stock and Watson, 2005)	A boom-bust credit cycle during the GFC. Asset prices channel concerning the real effect of the crisis within the US. Effectiveness of the expansionnary fiscal/monetary policy mix. Concerning the spillover to the world economy, the financial shocks has spilled over to foreign countries through USA housing and stock price dynamics and liquidity creation. The trade channel is the key tranmission of the real shock.

Appendix 2: Markov Chain Monte Carlo methodology

We estimate our TVP-VAR model with Markov Chain Monte Carlo (MCMC) methodology in the context of Bayesian inference to assess the joint posterior distribution of parameters under a certain prior probability density that is set in advance.

The prior density is denoted $\pi(\omega)$ for a vector of unknown parameters ω. The prior density reflects a set of beliefs that the researcher has about ω before seeing the data. The likelihood function for $y = y_1, \dots, y_n$ which reflects some probabilities of the data is given by $f(y\backslash\omega)$. The objective is to draw the coefficients from the posterior distribution denoted by $\pi(\theta\backslash y)$ obtained by the Bayes' theorem.

$$\pi(\theta\backslash y) = \frac{f(y\backslash\theta)\pi(\theta)}{\int f(y\backslash\theta)\pi(\theta)d(\theta)}$$

Prior information concerning θ is usually updated by observing the data y, not the case of the marginal distribution $\int f(y\backslash\theta)\pi(\theta)d(\theta)$ due to tractable issue. Among the different methods to sample from the posterior distribution, the MCMC is very used, specifically the Gibbs sampler.

Let's consider $y = (y_t)_{t=1}^{n}$ and $\omega = \left(\Sigma_\beta, \Sigma_a, \Sigma_h\right)$. The prior probability density of ω is given by $\pi(\omega)$ and the posterior distribution. As the posterior distribution is unknown, that is not the case of the conditional posteriors, so we can draw from the following MCMC algorithm.

(1) Initialize β, a, h and ω.
(2) Sample $\beta | a, h, \Sigma_\beta, y$.
(3) Sample $\Sigma_\beta | \beta$.
(4) Sample $a | \beta, h, \Sigma_a, y$.
(5) Sample $\Sigma_a | a$.
(6) Sample $h | \beta, a, \Sigma_h, y$.
(7) Sample $\Sigma_h | h$.
(8) Go to (2).

After a large number of iterations, the draws obtained are draws from the joint posterior. The impulse responses are computed from the draws obtained. Posteriors of each block of the GIBSS sampler are conditional on the observed data y and on the rest of the parameters drawn at previous steps.

The details of the procedure are enumerated as follows.

Sample β

To Sample β from the conditional posterior distribution, the state space model with respect to βt (the state variable), is expressed as:

$$y_t = X_t \beta_t + A_t^{-1} \Sigma_t \varepsilon_t, \quad t = s+1,\ldots,n, (14)$$

$$\beta_{t+1} = \beta_t + u_{\beta t}, \ t = s,\ldots,n-1,$$

where $\beta_s = \mu_{\beta 0}$, and $\mu_{\beta s} \sim N\ (0, \Sigma_{\beta 0})$. To reduce sample autocorrelation for β we run simulation smoother (introduced by de Jong and Shephard (1995) and Durbin and Koopman (2002))[17], with the correspondence of the variables to equations (14) as follows:

$$X_t \beta \ = 0_k, \qquad Z_t = X_t, \quad G_t = (A_t^{-1} \Sigma_t, O_{k\beta}),$$

$$T_t = I_{k\beta}, \qquad H_t = (O_k, \Sigma_\beta^{1/2}), \quad H_0 = (O_k, \Sigma_{\beta 0}^{1/2}),$$

where k_β is the number of rows of β_t.

Sample a

To sample a from the conditional posterior distribution, the state space model with respect to a_t is a key element in the application of simulation smoother. Particularly,

$$\hat{y}_t = \hat{X}_t a_t + \Sigma_t \varepsilon_t, \quad t = s+1,\ldots,n,$$

$$a_{t+1} = a_t + u_{at}, \quad t = s,\ldots,n-1,$$

where $a_s = \mu_{\alpha 0}, \mu_{\alpha s} \sim N\ (\mu_{h0}, \Sigma_{h0}),\ \hat{y}_t = y_t - X_t \beta_t,$ and

$$\hat{X}_t = \begin{pmatrix} 0 & \cdots & & & & & & 0 \\ -\hat{y}_{1t} & 0 & 0 & \cdots & & & & \vdots \\ 0 & -\hat{y}_{1t} & -\hat{y}_{2t} & 0 & \cdots & & & \\ 0 & 0 & 0 & -\hat{y}_{1t} & \cdots & & & \\ \vdots & & & & \ddots & 0 & \cdots & 0 \\ 0 & \cdots & & & 0 & -\hat{y}_{1t} & \cdots & -\hat{y}_{k-1,t} \end{pmatrix}$$

[17] For detailed description of the algorithm of the simulation smoother, see Nakajima (2011).

for $t = s+1,...,n.$ We run the simulation smoother to sample a with the correspondence of the variables:

$$X_t\beta = 0_k, \qquad Z_t = \hat{X}_t, \qquad G_t = (\Sigma_t, O_{ka}),$$

$$T_t = I_{ka}, \; H_t = (O_k, \Sigma_a^{1/2}), \qquad H_0 = (O_k, \Sigma_{a0}^{1/2}),$$

where k_a is the number of rows of a_t .

Sample h

To sample stochastic volatility h we make inference for $\{h_{jt}\}_{t=s+1}^{n}$ separately for j $(=1,...,k),$

as we assume that Σ_h and Σ_{h0} are diagonal matrices. Let y_{it}^* represents the i-th element of $A_t\hat{y}_t$. This can be written as:

$$y_{it}^* = exp(h_{it}/\,2)\,\varepsilon_{it} \qquad t = s+1,...,n,$$

$$h_{i,t+1} = h_{it} + \eta_{it}, \; t = s,...,n-1,$$

$$\begin{pmatrix}\varepsilon_{it}\\ \eta_{it}\end{pmatrix} \sim N\left(0, \begin{pmatrix}1 & 0\\ 0 & \upsilon_i^2\end{pmatrix}\right),$$

when $\eta_{\mathrm{is}} \sim N\ (0, \upsilon_{\mathrm{i}_0}^2),$ and υ_{i}^2 and $\upsilon_{\mathrm{i}_0}^2$ are the i-th diagonal elements of Σ_h and Σ_{h0}, respectively, and η_{it} is the i-th element of u_{ht}. We sample $((h_{i,s+1},..., h_{in})$ using multi-move sampler following Shephard and Pitt (1997) and Watanabe and Omori (2004).[18]

Sample ω

We **s**ample Σ_β from its conditional posterior distribution in the same way as in Nakajima (2011), to sample Σ in the TVP regression model, also sampling of the diagonal elements of Σ_a and Σ_h is carried out in the same way as to sample σ_n in TVP regression model.

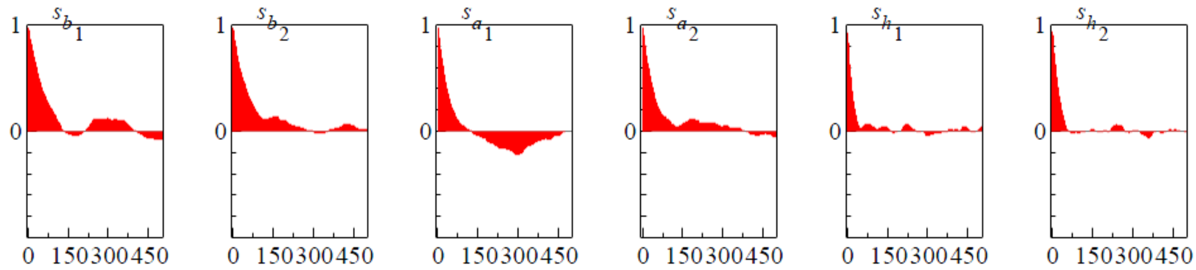
[18] For detailed description of the algorithm see Nakajima (2011).

Appendix 3: Results

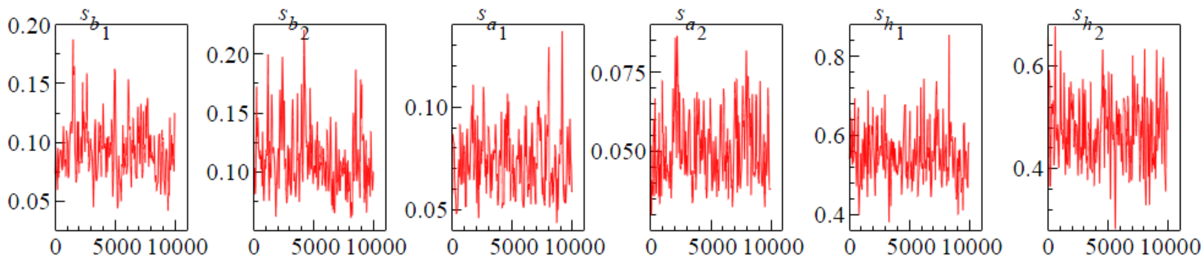
Figure 1: Estimation results of selected parameters in the TVP-VAR model variable set of (t, m, s, v) for U.S.

Note: the estimates are multiplied by 100.

1.A Sample autocorrelations functions



1.B. Sample paths



1.C Posterior densities

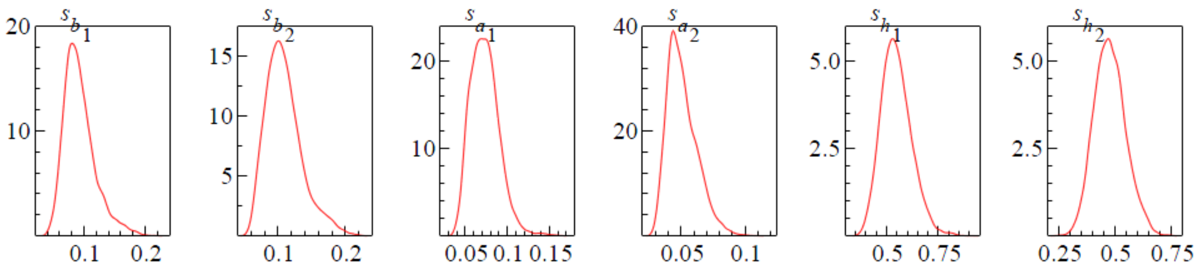
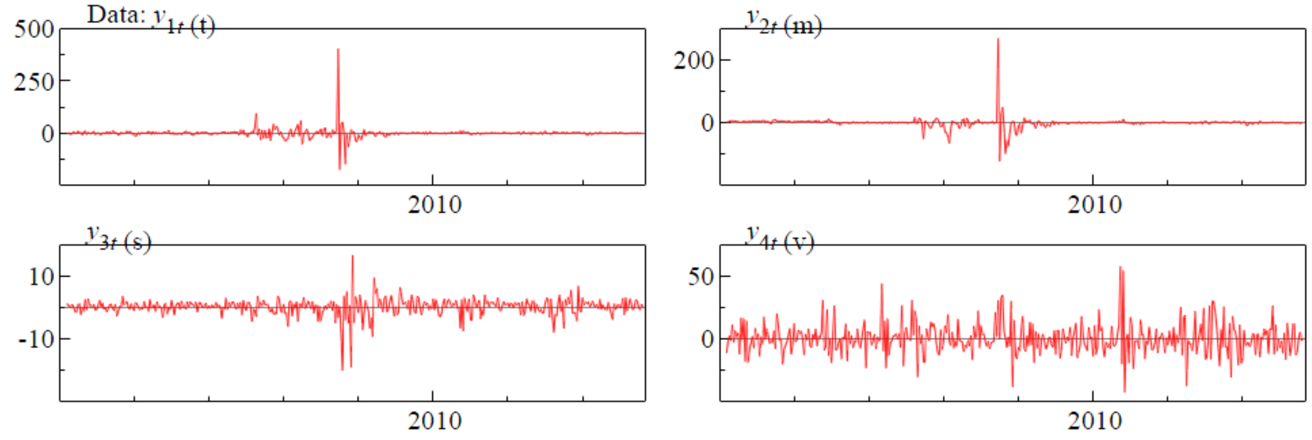


Figure 2 : Figures of the data and standard deviation for our set of variables for U.S.

One set of variables is examined : (*t*, *m*, *s*, *v*), where *t* is the U.S. TED spread, *m* is the 3 month money market rate, *s* is the stock market index and *v* is the U.S volatility index.

2.A Figure for the set of variables (t,m,s,v) of the U.S.



2.B Figure of the posterior standard deviation for the set of variables (t,m,s,v) of U.S

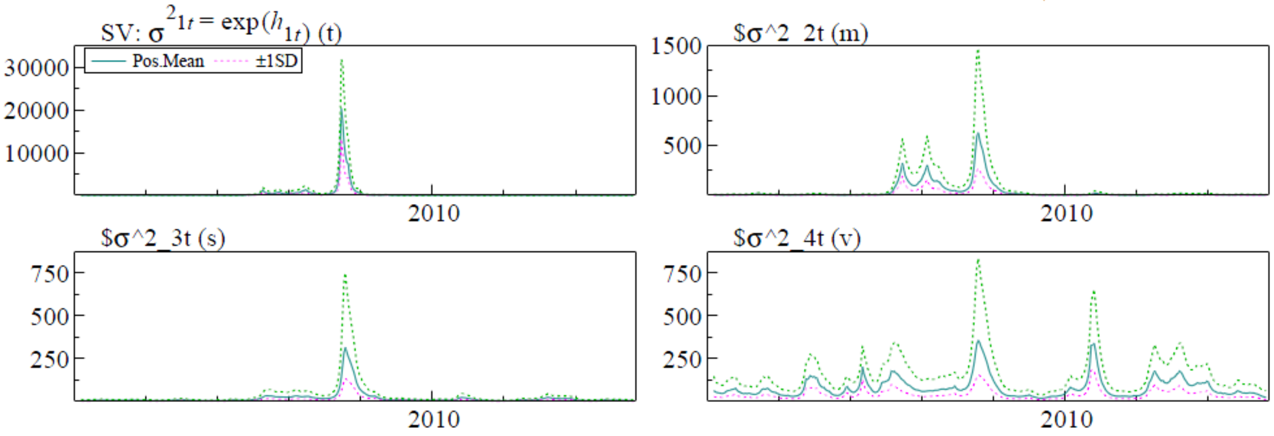


Figure 3: **Simultaneous Relation $\tilde{a}_{it}$, for the variable Set of *(t, m, s, v)* for U.S.**

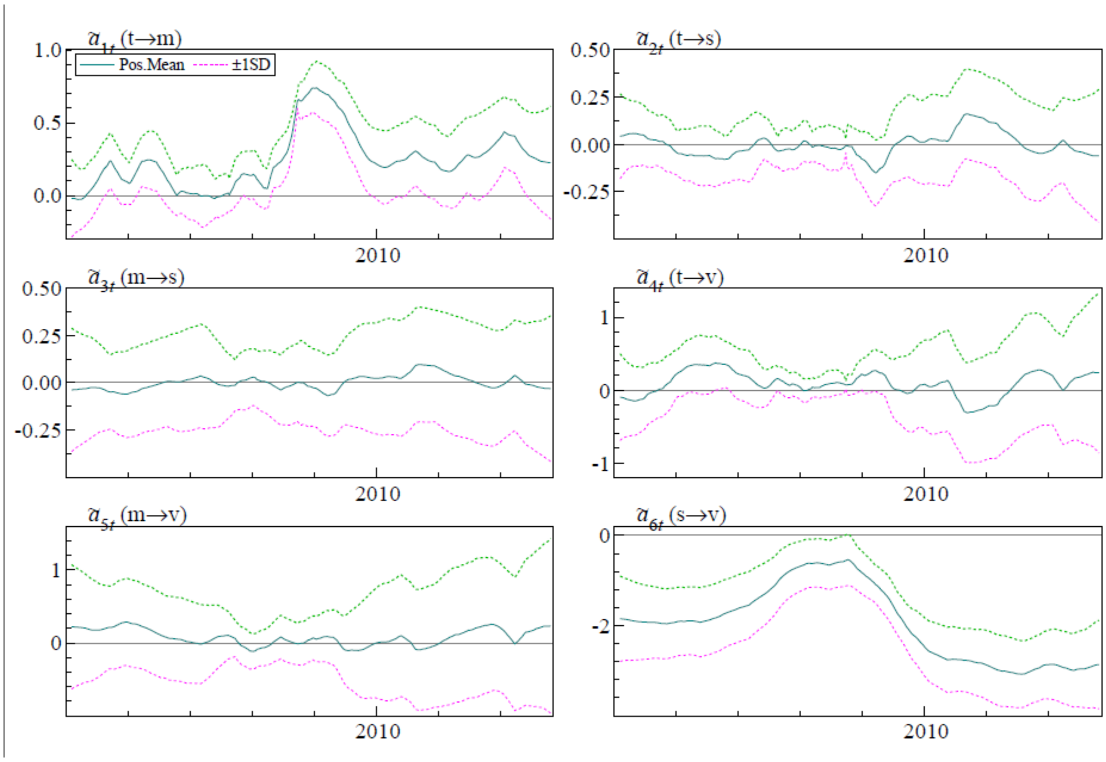


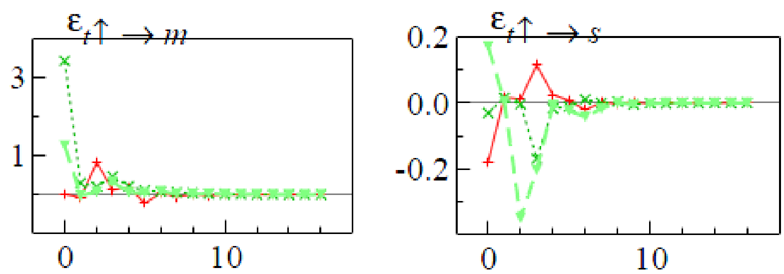
Figure 4: Impulse responses of TVP-VAR for the domestic set of variables (t,m,s,v) with 3 shocks in time : BNP, LBB and GDC.

First, we analyze the effect of liquidity shocks (Figure 4.A.) on money markets and stock markets. Second, we look at the impact of risk shock (Figure 4.B.) on money markets and stock markets. Third, we focus on the effect of U.S. stock market shock (Figure 4.C.) on money markets and stock markets. And fourth, the impact of U.S. money market shock (Figure 4.D.) on money markets and stock markets. For each shock, we have the impulse response by country and market. In the horizontal axis, we have the weeks (from 0 to 13) and in the vertical axis, the measure of the impact.

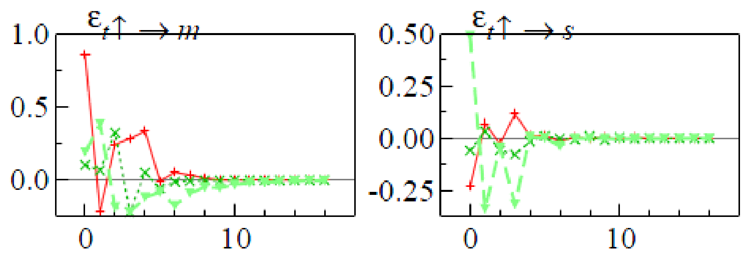
Note: the red lines show impact during BNP event. The dotted green lines with cross show the impact during LBB event. The dotted green lines with triangle show the impact during GDC event.

4.A. Impulse response function of a shock to U.S. TED spread (liquidity shock), impact on money markets (m) and stock markets (s).

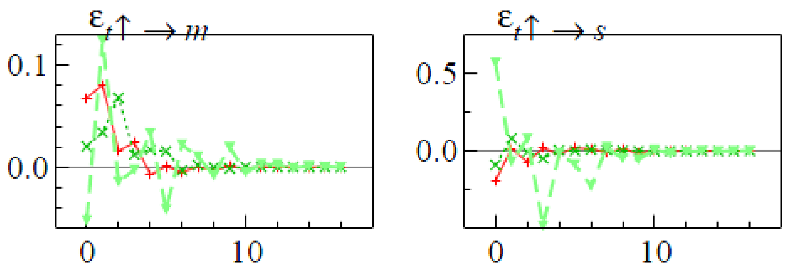
U.S.



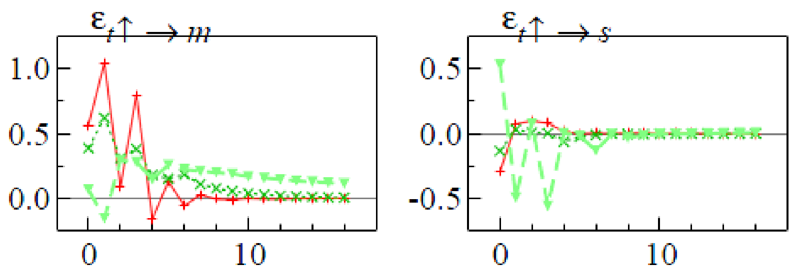
Canada



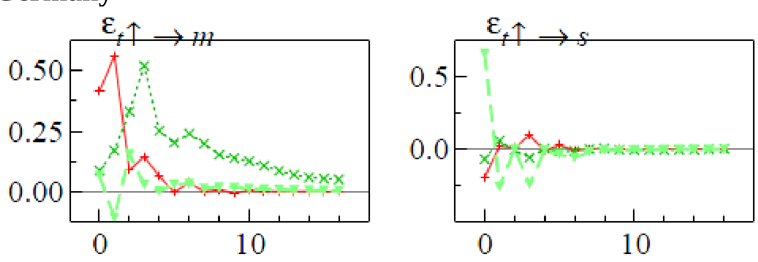
Japan



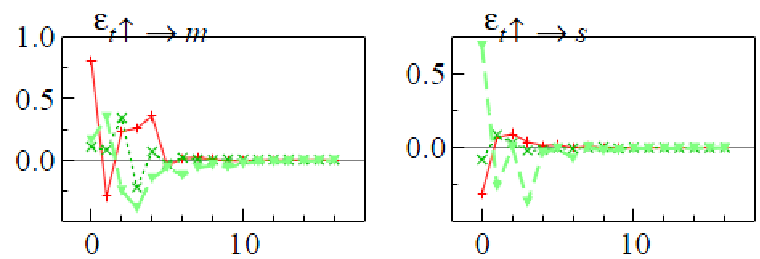
U.K.



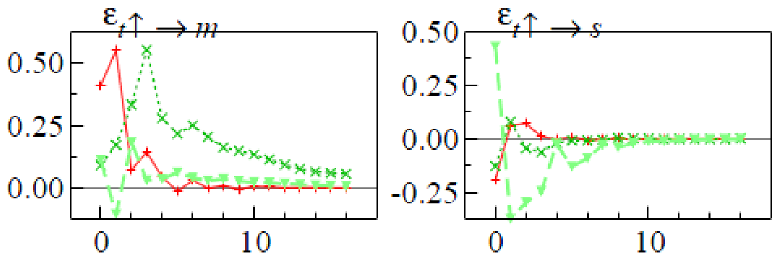
Germany



France

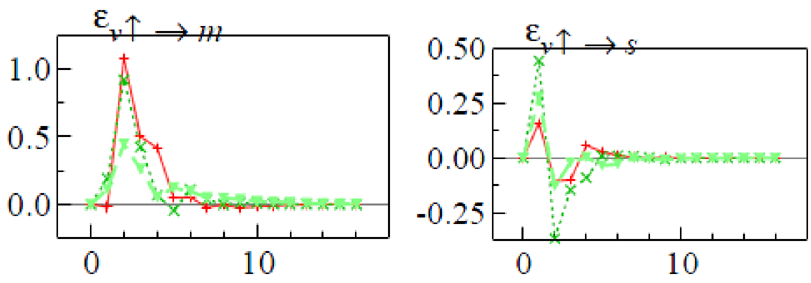


Italy

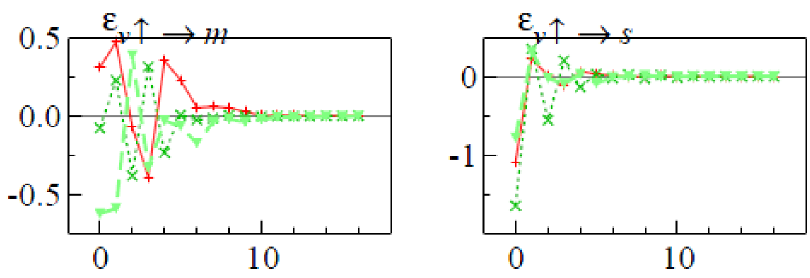


4.B. Impulse response function of a shock to VIX (risk shock), impact on money markets (m) and stock markets (s).

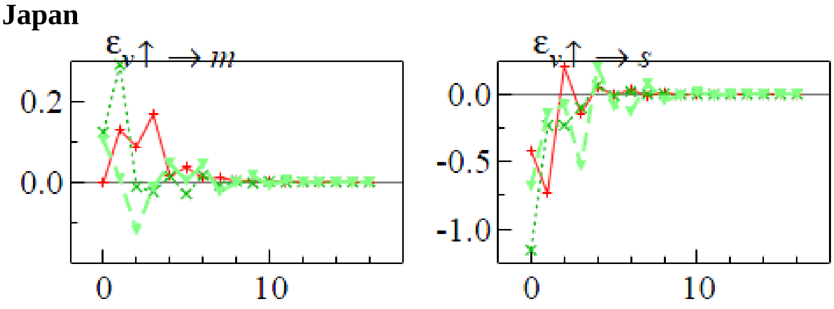
U.S.



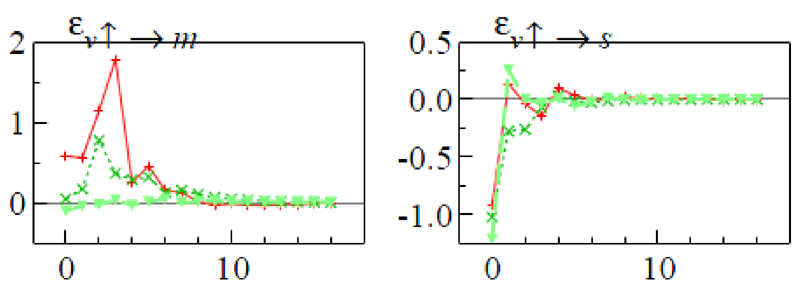
Canada



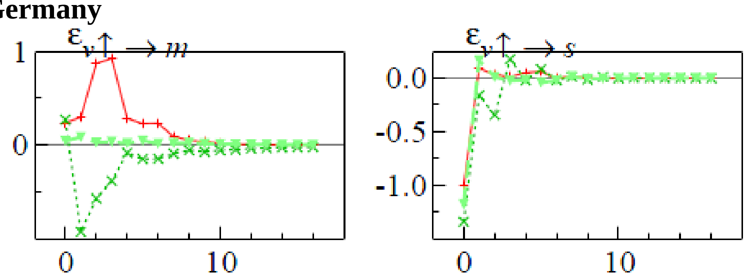
Japan



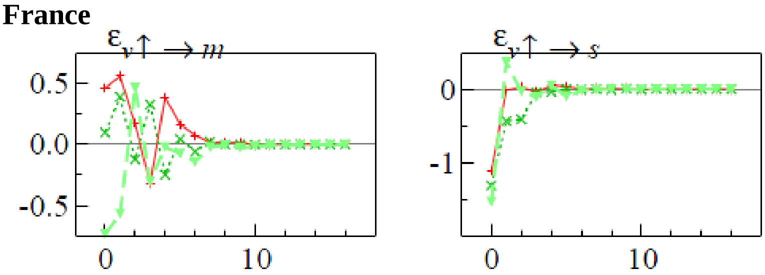
U.K.



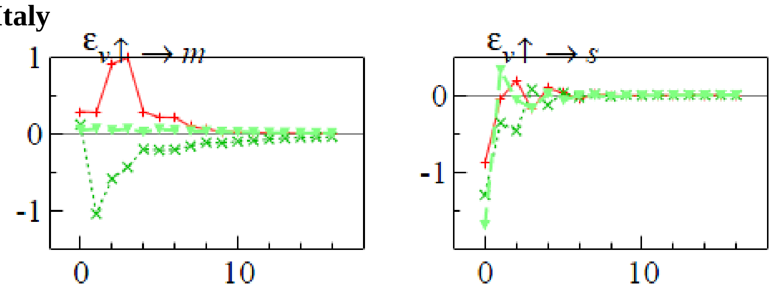
Germany



France

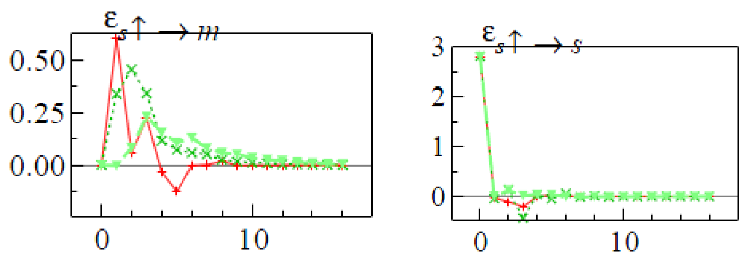


Italy

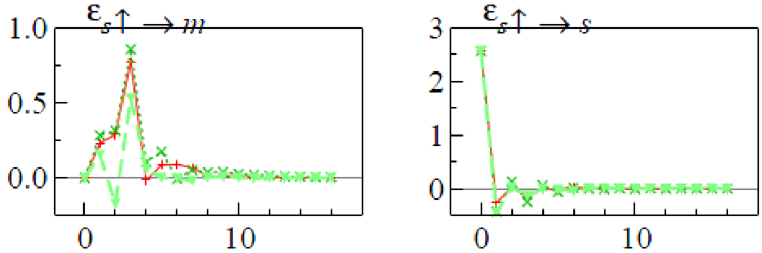


4. C. Impulse response function of a U.S. stock market shock, impact on money markets (m) and stock markets (s).

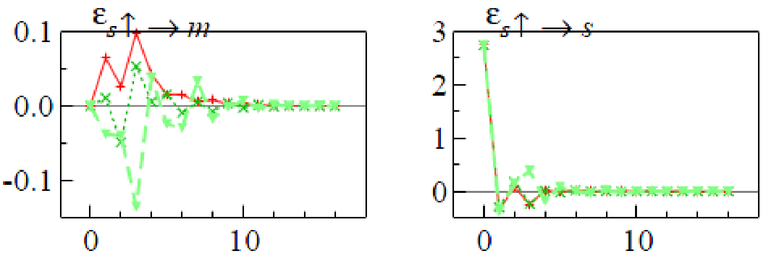
U.S.



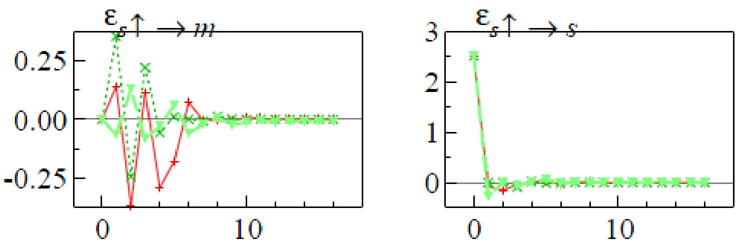
Canada



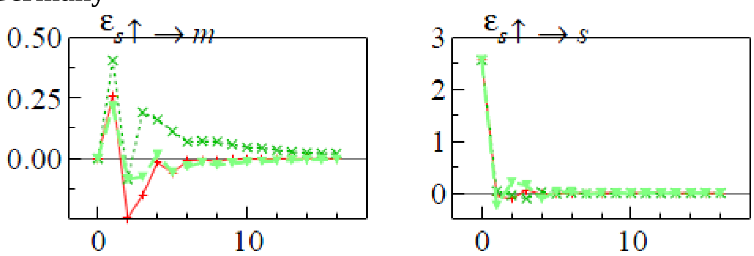
Japan



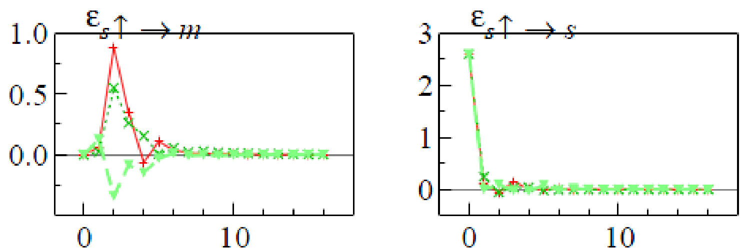
U.K.



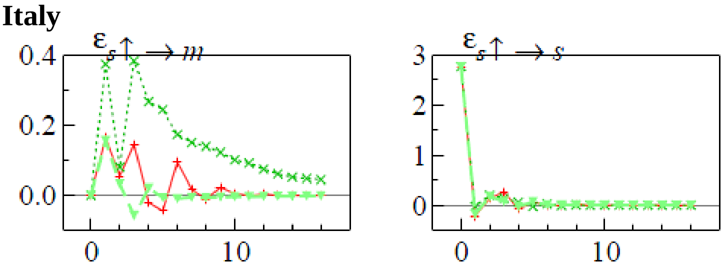
Germany



France

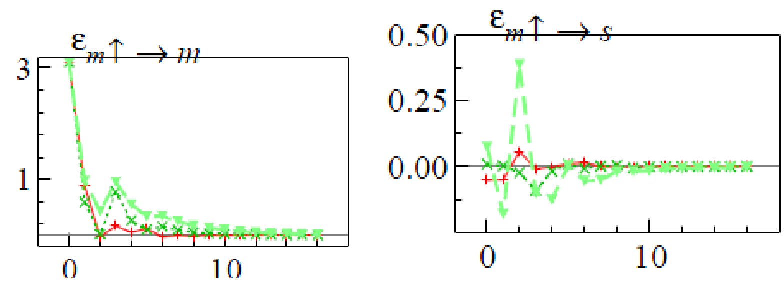


Italy

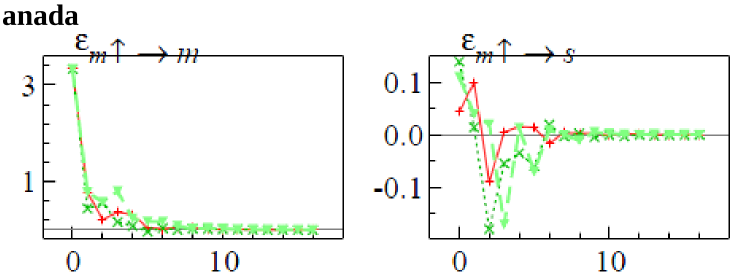


4.D. Impulse response function of a U.S. money market shock, impact on money markets (m) and stock markets (s).

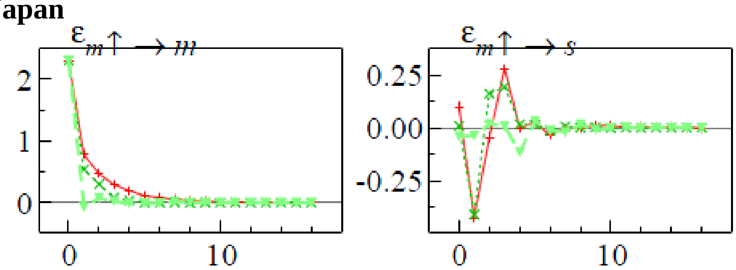
U.S.



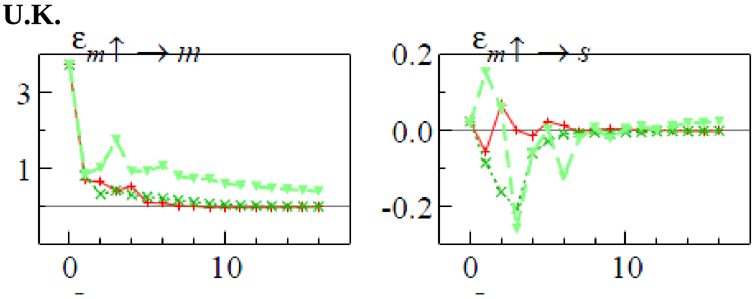
Canada



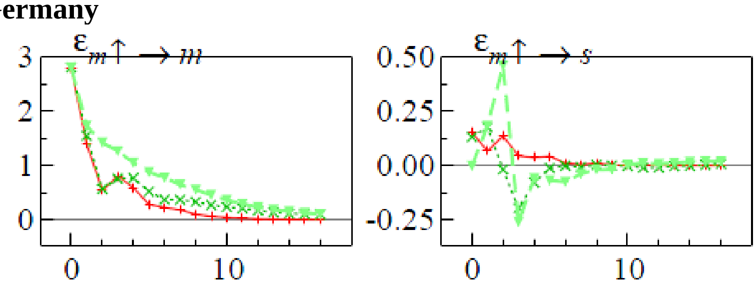
Japan



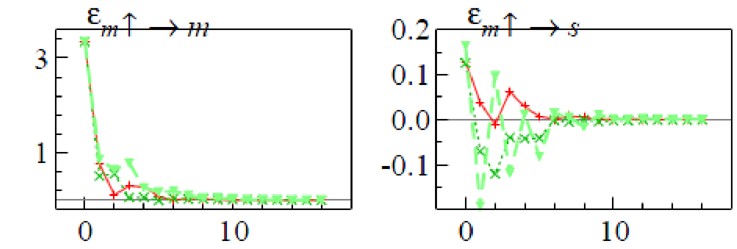
U.K.



Germany



France



Italy

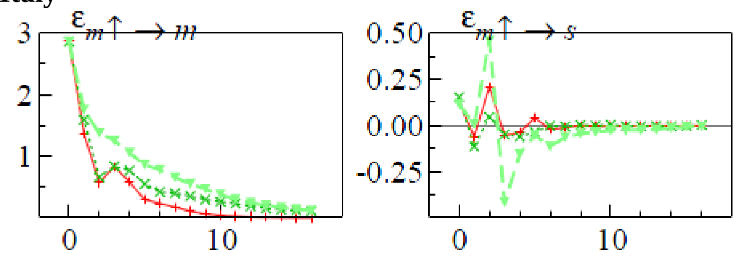
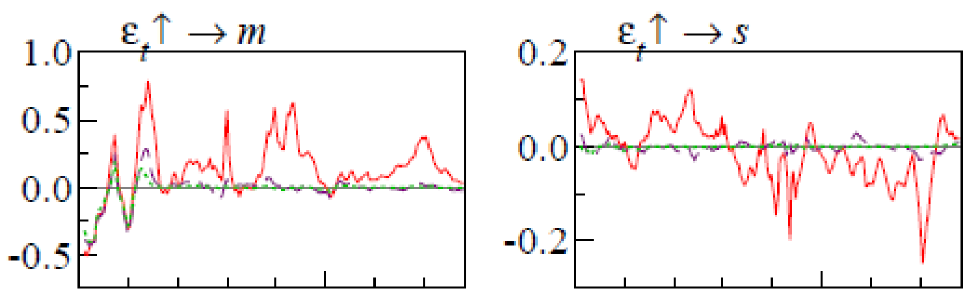


Figure 5: Impulse responses of TVP-VAR for the domestic set of variables (t,m,s,v) for U.S. with 4 weeks, 8 weeks and 12 weeks impact.

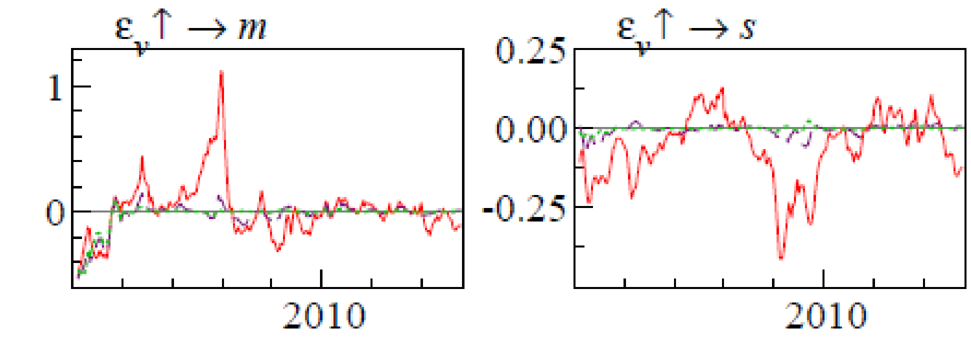
In the horizontal axis, we have the time (from 2005 to 2012). For U.S. in graph 5.A, we represent the impulse responses of a set of variables (t, m, s, v) to a shocks on the error terms of ted (epsilon t), namely a liquidity shock. In graph 5.B, we show the impulse responses of a set of variables (t, m, s, v) to a shock on the error terms of vix (epsilon v), namely a risk shock. In graph 5.C, we draw the impulse responses of a set of variables (t, m, s, v) to a shock on the error terms of money market of stock market index (epsilon s). In graph 5.D, we show the impulse responses of a set of variables (t, m, s, v) to a shock on the error terms of money market of stock market index (epsilon s).

Note: the red lines show impact during for 4 period-ahead. The purple lines show the impact for 8 period-ahead. The dotted green lines with cross show the impact for 12 period-ahead.

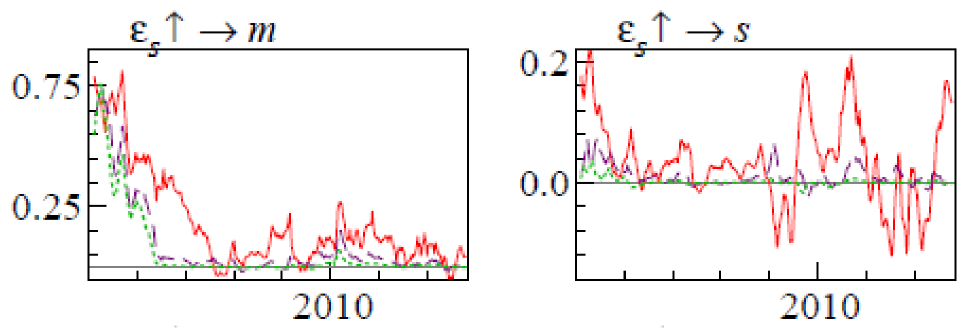
5.A. Impulse response function of a shock to U.S. TED spread (liquidity shock), impact on money markets (m) and stock markets (s).



5.B. Impulse response function of a shock to VIX (risk shock), impact on money markets (m) and stock markets (s).



5. C. Impulse response function of a U.S. stock market shock, impact on money markets (m) and stock markets (s).



5.D. Impulse response function of a U.S. money market shock, impact on money markets (m) and stock markets (s).