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Economic policy uncertainty: Consequences for the labor market dynamics

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"Alle 3 donne della mia vita
e al mio babbo
Grazie per avermi so(u)pportato"

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Introduction

> *"There's pretty strong evidence that the rise in uncertainty is a significant factor holding back the pace of recovery now. [...] research shows that heightened uncertainty slows economic growth, raises unemployment, and reduces inflationary pressures. [...] There's no question that slow growth, high unemployment, and significant uncertainty are challenges for monetary policy."*

John Williams, President and Chief Executive Officer of the Federal Reserve Bank of San Francisco, FRBSF Economic Letter, January 21, 2013.

The literature on the macroeconomic effects of uncertainty shocks has developed quite fastly in the last few years. This is mainly due to the recent contribution by Bloom (2009), which builds on a previous model by Bernanke (1983) to show that entrepreneurs facing an uncertain economic environment assign a higher value to the option of implementing "wait-and-see" strategies which lead to a pause in investments. As a consequence, economic activities go bust in the short run, which consequences involving prices and monetary policy setting.

Bloom (2009) established that volatility shocks are strongly correlated with other measures of uncertainty, like the cross-sectional spread of firm- and industry-level earnings and productivity growth. Moreover, he noticed that the uncertainty is also a ubiquitous concern of policymakers, as the opening statement of this thesis also confirms.

After Bloom's article, there has been a number of contributions in this literature. Fernandez-Villaverde et al. (2011) set up a theoretical model to investigate whether all the increased uncertainty about mix and timing of fiscal austerity has had a detrimental impact on current business conditions through its effect on expectations and behavior of households and firms. They find that the fiscal volatility shocks reduce economics activity: aggregate output, consumption and investment; the increase in fiscal policy uncertainty of two standard deviation has an effect similar to 25-basis-point innovation in federal funds rate and finally that heightened fiscal policy uncertainty is "stagflationary": it creates inflation while output falls.

Recent empirical VAR-based investigations confirm that shocks to uncertainty are an important driver behind macroeconomic fluctuations (Bloom (2009), Baker, Bloom and Davis (2013), Leduc and Liu (2013), Mumtaz and Theodoridis (2012)). Typically, uncertainty matters in a context in which risk matters. In particular, some recent research has pointed out the time-dependence of risk aversion and discount factors and risk aversion tends to be high during phases of stress like recessions. In particular, Leduc and Liu (2013) show that, in an economy featuring real matching frictions in the labor market and using a dynamic stochastic general equilibrium model, uncertainty shocks act as "demand" shocks, in that they increase unemployment and decrease inflation. This is so because positive uncertainty shocks negatively affect potential output and this occurs because firms pause hiring new workers when uncertainty hits the economy due to lower expected value of a filled vacancy. As a consequence, firms post a lower number of vacancies, so inducing a drop in the job finding rate and an increase in unemployment rate.

Mumtaz and Theodoridis (2012) propose a model in which nominal frictions affecting wage and price re-setting induce a reaction to uncertainty shocks similar to the one that occurs when supply shocks hit the economy. This is due to the fact that risk-averse workers ask for a wage-premium to ensure themselves against the scenario which may be seen them called to work extra-hours at a predetermined wage (due to wage stickiness). In reaction to workers' request of a higher wage, firms increase their prices to lower the burden of real wages on their marginal costs. As a result, uncertainty shocks act as inflationary, supply shocks in their model.

Baker, Bloom and Davis (2013) investigate the role of economic policy uncertainty shocks. They create a new economic policy uncertainty index based on a variety of components (news, forecasters' disagreement), and employ it in a VAR context to investigate the effects of exogenous variations of uncertainty on the U.S. macroeconomic environment. They find that an increse in uncertainty comparable to the one recorded in the U.S. after the acceleration of the financial crises may have been an important driver of the economic downturns observed in 2009 and 2010.

This thesis aims at contributing to this literature by asking the following question: Does economic policy uncertainty influence the labor market dynamics in the United States? To tackle this question, we use actual U.S. data from the first quarter of 1985 to the third quarter of 2010 and estimate a VAR including labor market's variables (the unemployment rate, the job creation's rate, the job destruction's rate, the job finding rate), the policy uncertainty index à la Baker et al (2013), the Federal Funds rate, the inflation rate, the output gap and the VIX index related to the U.S. economy. After estimating our VAR, we make extensive use of the impulse response and variance decomposition analyses to pin down the role played by economic policy uncertainty shocks in affecting the U.S. labor market dynamics.

Our results point to a clear impact on exogenous increases in the economic policy uncertainty indicator on unemployment and other-labor market related variables. This is true even when controlling for alternative, broader volatility indicators like the VIX, measures of the business cycle like real GDP, and indicators of monetary policy stance like the nominal interest rate and inflation. Differently, we find the reaction of inflation to be quantitatively mild and, above all, statistically insignificant for most of the horizons following our simulated uncertainty shock. Our results corroborate those proposed by Leduc and Liu (2013) on the relevance of uncertainty shock as far as the real side of the economy is concerned. Differently, we find mild evidence at best on such shocks as being behind inflation dynamics in the United States. Therefore, we cast some doubts on the robustness of Leduc and Liu's results as far as the uncertainty-inflation relationship is concerned.

This thesis is structured as follows. In the first section, we introduce the VAR theory and how to use it and all the functions useful for the analysis (the impulse response function, the causality test, etc). In the second section, we explain the theoretical model à la Leduc and Liu (2013) to have a theoretical benchmark to interpret the impulse response functions of interest. The third section proposes our VAR analysis based on the U.S. data from the first quarter of 1985 to the third quarter in 2010. First of all, we present and describe all the variables that we use in the models and we analyse two different models, one with the VIX index, which is a key measure of market expectations of near-term volatility conveyed by S&P 500 stock index option prices, and the other without it. In practice we try to study, using the VIX index, if the stock market influences the economic policy uncertainty and if there are possible new relationships between the labor market variables and the economic policy uncertainty shocks. Since we identify some clear outliers during the 2008-2009 financial crisis, we move to an analysis focusing on pre-crisis data. Then, we introduce in our investigation the policy uncertainty index à la Baker, Bloom, and Davis (2013) and check if there are some differences respect to the other previous models in terms of impulse response function and variance decomposition. In the last section, we conclude our thesis and in the appendix we explain some important economic events related to our analysis, some mathematical proofs and some FEVD tables.

Chapter 2

VAR and SVAR Models

In this chapter we introduce the stationary finite order vector autoregressive (VAR) model, it is one of the most successful, flexible and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. As Sims (1980) used, the VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for the forecasting and structural analysis.

In addition to data description and forecasting, the VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumption about the causal structure of data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with impulse response function and forecast error variance decomposition.

The model of interest is assumed to be known, but this assumption is not true in the real life, and it helps us to see the problems related to VAR models without contamination by estimation and specification issues. In the following section, we describe the principal properties and the important functions of a VAR model.

2.1 Basic Assumptions and Properties of VAR Model

2.1.1 Stable VAR Model

We start our analysis from the VAR(p) model (Vector Autoregressive model of order p)

$$y_t = \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \quad t = 0, \pm 1, \pm 2, \ldots \tag{2.1}$$

where $y_t = (y_{1t}, \dots, y_{Kt})'$ is a $(K \times 1)$ random vector, the A_i are fixed $(K \times K)$ coefficient matrices, $\nu = (\nu_1, \dots, \nu_K)'$ is a fixed $(K \times 1)$ vector of intercept terms allowing for the possibility of a nonzero mean $E(y_t)$. Than the $u_t = (u_{1t}, \dots, u_{Kt})'$ is a $(K \times 1)$ vector, called *white noise or innovation process*, such that $E(u_t) = 0$ and

$$E(u_t u_s) = \begin{cases} \Sigma_u, & \text{if } t = s \\ 0, & \text{if } t \neq s \end{cases}$$

where the Σ_u is assumed to be nonsingular (invertible)

To understand the general VAR model of order p described by (2.1), we consider the VAR(1) model:

$$y_t = \nu + A_1 y_{t-1} + u_t. \tag{2.3}$$

If this generation mechanism starts at some time $t = 1$, we have:

$$\begin{aligned} y_1 &= \nu + A_1 y_0 + u_1 \\ y_2 &= \nu + A_1 y_1 + u_2 = \nu + A_1(\nu + A_1 y_0 + u_1) + u_2 \\ &= (I_K + A_1)\nu + A_1^2 y_0 + A_1 u_1 + u_2 \\ &\vdots \\ y_t &= (I_K + A_1 + \dots + A_1^{t-1})\nu + A_1^t y_0 + \sum_{i=0}^{t-1} A_1^i u_{t-i} \\ &\vdots \end{aligned} \tag{2.4}$$

The vectors $y_1, \dots, y_t$ are uniquely determined by $y_0, u_1, \dots, u_t$ and also the joint distribution of $y_1, \dots, y_t$ is determined by the joint distribution of $y_0, u_1, \dots, u_t$. We consider the VAR(1) process and using the (2.4) we have

$$\begin{aligned} y_t &= \nu + A_1 y_{t-1} + u_t \\ &= (I_K + A_1 + \dots + A_1^j)\nu + A_1^{j+1} y_{t-j-1} + \sum_{i=0}^{j} A_1^i u_{t-i}. \end{aligned}$$

If all eigenvalues of A_1 have modulus less than 1, the sequence $A_1^i, i = 0, 1, \dots$ is absolutely summable [1] and we have also that

$$(I_K + A_1 + \dots + A_1^j)\nu \xrightarrow[j\to\infty]{} (I_K - A_1)^{-1}\nu.$$

[1] A sequence of $(K \times K)$ matrices $\{A_i = (a_{mn,i})\}, i = 0, \pm 1, \pm 2, \dots$ is **absolutely summable** if each sequence $\{a_{mn,i}\}, m, n = 1, \dots, K; i = 0, \pm 1, \pm 2$ is absolutely summable. $\{A_i\}$ is absolutely summable if the sequence $\{||A_i||\}$ is summable, where

$$||A_i|| = \left(\sum_m \sum_n a_{mn,i}^2 \right)^{1/2}$$

exists and it is finite

Furthermore, A_1^{j+1} converges to zero rapidly as $j \to \infty$ and so we ignore the term $A_1^{j+1} y_{t-j-1}$ in the limit. Also if all eigenvalues of A_1 have modulus less than 1, then y_t is the well-defined stochastic process:

$$y_t = \mu + \sum_{i=0}^{\infty} A_1^i u_{t-i}, \quad t = 0, \pm 1, \pm 2, \dots$$

where $\mu := (I_K - A_1)^{-1} \nu$. The distribution and the joint distributions of the y_t's are uniquely determined by the distributions of the u_t process. We calculate the first and the second moment:

$$\mathrm{E}[y_t] = \mu \quad \forall t$$

$$\Gamma_y(h) := \mathrm{E}[(y_t - \mu)(y_t - \mu)'] = \sum_{i=0}^{\infty} A_1^{h+i} \Sigma_u A_1^{i'}.$$

Definition 1. We call a VAR(1) process **stable** if all eigenvalues of A_1 have modulus less than 1 and it is equivalent to:

$$\det(I_K - A_1 z) \neq 0 \quad \text{for} |z| \leq 1. \tag{2.5}$$

We extend this discussion to a VAR(p) process, in fact a VAR(p) corresponds to a Kp-dimensional VAR(1):

$$Y_t = \nu + \mathbf{A} Y_{t-1} + U_t \tag{2.6}$$

where: $Y_t := \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix} \qquad \nu := \begin{bmatrix} \nu \\ 0 \\ \vdots \\ 0 \end{bmatrix}$

$$\mathbf{A} := \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_K & 0 & \cdots & 0 & 0 \\ 0 & I_K & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_K & 0 \end{bmatrix} \qquad U_t := \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

where Y_t, ν and U_t are $(Kp \times 1)$ vectors and the matrix $\mathbf{A}$ is $(Kp \times Kp)$.

Definition 2. The VAR(p) process is **stable** if

$$\det(I_{Kp} - \mathbf{A} z) \neq 0 \quad \text{for} |z| \leq 1 \iff \det(I_K - A_1 z - \dots - A_p z^p) \neq 0 \quad \text{for} |z| \leq 1.$$

A stochastic process is **stationary** if its first and second moments do not change with time t. So a stochastic process y_t is stationary if

$$E(y_t) = \mu \quad \text{for all } t \tag{2.7}$$

$$E[(y_t - \mu)(y_{t-h} - \mu)'] = \Gamma_y(h) = \Gamma_y(-h)' \quad \text{for all t and } h = 0, 1, 2, \dots \tag{2.8}$$

From (2.7) all the y_t have the same finite mean vector μ and from (2.8) the autocovariances of the process do not depend on t but only on h that is the lag period.

Proposition 1. *If a VAR process is stable, then it is stationary.*

2.1.2 The Moving Average Representation of a VAR Process

The VAR(p) process Y_t have also an other representation under the stability assumption:

$$Y_t = \mu + \sum_{i=0}^{\infty} \mathbf{A}^i U_{t-i} \tag{2.9}$$

and this form is called the *Moving Average* (MA) representation, where Y_t is expressed in terms of past and present errors or innovation vectors U_t and the mean term μ. This representation of y_t can be found by using the matrix $(K \times Kp)$, $J := [I_K : 0 : \cdots : 0]$:

$$y_t = JY_t = J\mu + \sum_{i=0}^{\infty} J\mathbf{A}^i J' JU_{t-i} = \mu + \sum_{i=0}^{\infty} \phi_i u_{t-i} \tag{2.10}$$

where $\mu := J\mu$, $\phi_i := J\mathbf{A}^i J'$, $u_t = JU_t$ and the $\mathbf{A}^i$ and ϕ_i are absolutely summable. We can also calculate the mean and the autocovariances

$$\begin{aligned} E(y_t) &= \mu \\ \Gamma_y(h) &= E[(y_t - \mu)(y_{t-h} - \mu)'] \\ &= E\Big[\Big(\sum_{i=0}^{h-1} \phi_i u_{t-i} + \sum_{i=0}^{\infty} \phi_{h+i} u_{t-h-i}\Big)\Big(\sum_{i=0}^{\infty} \phi_i u_{t-h-i}\Big)'\Big] \\ &= \sum_{i=0}^{\infty} \phi_{h+i} \Sigma_u \phi_i'. \end{aligned} \tag{2.11}$$

2.1.3 Forecasting and Interval Forecasts

In this section we discuss predictors based on a VAR process, we want to know the future values of variables $y_1, \ldots, y_K$.

Forecasting

First we define an information set, called Ω_t, containing the available informations in period t and may contain also the past and the present variables of the system under consideration: $\Omega_t = \{y_s | s \leq t\}$, where $y_s = (y_{1s}, \ldots, y_{Ks})'$. The period t, where the prediction is made, is called the *forecast origin*, the number of periods into the future is the *forecast horizon* and the predictor h periods ahead is called the *h-step predictor*.

Suppose $y_t = (y_{1t}, \dots, y_{Kt})$ is a K-dimensional stable VAR(p) process, then the minimum mean squared errors (MSE) predictor for forecast horizon h at forecast origin t is the conditional expected value:

$$E_t(y_{t+h}) := E(y_{t+h}|\Omega_t) = E(y_{t+h}|\{y_s|s \leq t\}). \tag{2.12}$$

This predictor minimizes the MSE of each component of y_t, if $\bar{y_t}(h)$ is h-step predictor at origin t,

$$\begin{aligned} &MSE[\bar{y_t}(h)] = E[(y_{t+h} - \bar{y_t}(h))(y_{t+h} - \bar{y_t}(h))'] \\ &\geq MSE[E_t(y_{t+h})] = E[(y_{t+h} - E_t(y_{t+h}))(y_{t+h} - E_t(y_{t+h}))']. \end{aligned} \tag{2.13}$$

The optimality of the conditional expectation can be seen by noting that:

$$MSE[\bar{y_t}(h)] = MSE[E_t(y_{t+h})] + E\{[E_t(y_{t+h}) - \bar{y_t}(h)][E_t(y_{t+h}) - \bar{y_t}(h)]'\}$$

where the second element of the right-hand side is null, so we have that:

$$E_t(y_{t+h}) = \nu + A_1 E_t(y_{t+h-1}) + \cdots A_p E(y_{t+h-p}) \tag{2.14}$$

is the optimal h-step predictor of a VAR(p) process such that $E_t(u_{t+h}) = 0$ for $h > 0$.

Interval Forecasts

We have to make an assumption about the distributions of the y_t or the u_t. We have to consider that $y_t, y_{t+1}, \dots, y_{t+h}$ have a multivariate normal distribution for any t and h and also that u_t are multivariate normal, $u_t \sim \mathcal{N}(0, \Sigma_u)$ and u_t and u_s are independent for $s \neq t$. Under these assumptions, the forecast errors are also normally distributed as linear transformations of normal vector.

$$y_{t+h}(h) - y_t(h) \sim \mathcal{N}(0, \Sigma_y(h)) \Rightarrow \frac{y_{k,t+h} - y_{k,t}(h)}{\sigma_k(h)} \sim \mathcal{N}(0, 1) \tag{2.15}$$

where $y_{k,t}(h)$ is the k-th component of $y_t(h)$ and $\sigma_k(h)$ is the square root of the k-th diagonal element of $\Sigma_y(h)$. Let's $z_{(\alpha)}$ the upper $\alpha 100$ percentage point of the normal distribution, we get:

$$1 - \alpha = Pr\left\{-z_{(\alpha/2)} \leq \frac{y_{k,t+h} - y_{k,t}(h)}{\sigma_k(h)} \leq z_{(\alpha/2)}\right\}$$

and the $(1-\alpha)100\%$ interval forecast, h periods ahead, for the k-th component of y_t is

$$y_{k,t}(h) \pm z_{(\alpha)/2}\sigma_k(h).$$

2.2 Structural Analysis

We use the VAR models to analyze the relationships between variables of interest and we start our analysis from the two different definitions of causality, Granger and instantaneous.

2.2.1 Granger-Causality, Instantaneous Causality

Granger-Causality

The concept of causality (Granger 1969) is that a cause can not come after the effect. Suppose that Ω_t is the information set containing all the relevant information in the universe and including period t. Let $z_t(h|\Omega_t)$ be the optimal (minimum MSE) h-step predictor of the process z_t at origin t based on the information in Ω_t. The corresponding forecast MSE will be denoted by $\Sigma_z(h|\Omega_t)$. The process x_t is said to *cause* z_t *in Granger's sense* if

$$\Sigma_z(h|\Omega_t) < \Sigma_z(h|\Omega_t \setminus \{x_s|s \leq t\}) \quad \text{for at least one } h = 1, 2, \dots \tag{2.16}$$

where the $\Omega_t \setminus \{x_s|s \leq t\}$ is the set containing all the relevant information in the universe except for the information in the past and present of the x_t process. If x_t causes z_t and vice versa, the process $(z_t', x_t')'$ is called *feedback system*.

If we have a VAR process y_t, written in the canonical MA representation:

$$y_t = \mu + \sum_{i=0}^{\infty} \phi_i u_{t-i} = \mu + \phi(L)u_t, \quad \phi_0 = I_K \tag{2.17}$$

where u_t is a white noise process with nonsingular covariance matrix Σ_u. We write the VAR process as

$$y_t = \begin{bmatrix} z_t \\ x_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}. \tag{2.18}$$

Proposition 2. *Let y_t be a VAR process as in 2.18, then z_t is not Granger-caused by x_t if and only if $\phi_{12} = 0$.*

Corollary 1. *If we take a stationary and stable VAR(p) process:*

$$y_t = \begin{bmatrix} z_t \\ x_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} A_{11,1} & A_{12,1} \\ A_{21,1} & A_{22,1} \end{bmatrix} \begin{bmatrix} z_{t-1} \\ x_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} A_{11,p} & A_{12,p} \\ A_{21,p} & A_{22,p} \end{bmatrix} \begin{bmatrix} z_{t-p} \\ x_{t-p} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$$

we have that z_t is not Granger-caused by x_t if and only if $A_{12,i} = 0$ for $i = 1, \dots, p$.

Instantaneous Causality

There is also another kind of causality, called *instantaneous causality* between z_t and x_t if

$$\Sigma_z(1|\Omega_t \cup \{x_{t+1}\}) \neq \Sigma_z(1|\Omega_t).$$

In period t, adding x_{t+1} to the information set Ω_t helps to improve the forecast of z_{t+1} and also if there is the instantaneous causality between z_t and x_t, then there is also instantaneous causality between x_t and z_t. If we take the nonsingular innovation covariance matrix

$$\Sigma_u = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$$

where $\Sigma_u = PP'$ and P is a lower triangular nonsingular matrix with positive diagonal elements. We can write our VAR model:

$$y_t = \mu + \sum_{i=0}^{\infty} \phi_i P P^{-1} u_{t-i} = \mu + \sum_{i=0}^{\infty} \Theta_i w_{t-i} \tag{2.19}$$

where $\Theta_i := \phi_i P$ and $w_t := P^{-1} u_t$ is white noise with covariance matrix: $\Sigma_w = P^{-1} \Sigma_u (P^{-1})' = I_K$ and the w_t have uncorrelated components and they are called *orthogonal* residuals or innovations.

Proposition 3. *Using the Σ_u matrix, there is no instantaneous causality between z_t and x_t if and only if*

$$\Sigma_{12} = E(u_{1t} u'_{2t}) = 0. \tag{2.20}$$

2.2.2 Impulse Response Function

We have seen that the Granger-causality may not tell us all the things about the interactions between two or more variables. In this case it's better knowing the response of one variable to an impulse in another variable in a system, and it's important because we can see the effect of an exogenous shock or innovation in one of the variables on all the other variables. We will study the causality by finding the effect of an exogenous shock or innovation in one of the variables on the others.

Using the Granger-causality, we have that an innovation in variable k has no effect on the other variables if the former variable does not Granger-cause the set of remaining variables, and using the mathematical functions, we have:

$$\phi_{jk,i} = 0 \quad \text{for i} = 1, 2, \ldots \iff \phi_{jk,i} = 0 \quad \text{for i } = 1, \ldots, p(K-1)$$

and we know that y_t is a K-dimensional stable VAR(p) process and $j \neq k$. The meaning is that if the first $pK - p$ responses of variable j to an impulse in variable k are zero, all the following responses must also be zero.

We use the MA coefficient matrices for searching the impulse and accumulate responses. In fact the $\Psi_n := \sum_{i=0}^{n} \Phi_i$ contains the accumulated responses over n periods to a unit shock in the k-th variable of the system, and this quantities are called *interim multipliers*. The total accumulated effects for all future periods are obtained by summing the MA coefficient matrices. $\Psi_\infty := \sum_{i=0}^{\infty} \Phi_i$ is called the matrix of *long-run effects* or *total multipliers* and it is obtained by:

$$\Psi_\infty = \Phi(1) = (I_K - A_1 - \cdots - A_p)^{-1}.$$

We have shocks that occur in more variables and the correlation of the error terms may indicate that a shock in one variables is likely to be accompanied by a shock in another variable. If the correlation is null, then we have an orthogonal response impulse function. Also we use the MA representation:

$$y_t = \sum_{i=0}^{\infty} \Theta_i w_{t-i} \tag{2.21}$$

where the components of $w_t = (w_{1t}, \ldots, w_{Kt})'$ are uncorrelated and have unit variance, $\Sigma_w = I_K$ and (2.21) is obtained by decomposing [2] $\Sigma_u = PP'$, where P is a lower triangular matrix and $\Theta_i = \Phi_i P$ and $w_t = P^{-1} u_t$ and this says that a change in one component of w_t has no effect on the other components because the components are orthogonal (uncorrelated). The elements of the Θ_i are interpreted as responses of the system to such innovations and the jk-th element of Θ_i is assumed to represent the effect on variable j of a unit innovation in the k-th variable that has occurred i periods ago.

If we want to verify that there is no response at all of one variable to an impulse in one of the other variables, we must use the matrix Θ_i and its elements $\theta_{jk,i}$. In fact, if y_t is a K-dimensional stable VAR(p) process for $j \neq k$:

$$\theta_{jk,i} = 0 \quad \text{for i} = 0, 1, 2, \ldots \iff \theta_{jk,i} = 0 \quad \text{for i} = 0, 1, \ldots, p(K-1).$$

There is a problem related to the ordering of the variables, because we can not determined it. The ordering has to be such that the first variable is the only one with a potential immediate impact on all other variables. The second variable may have an immediate impact on the last $K-2$ components of y_t but not on y_{1t} and so on.

2.2.3 Forecast Error Variance Decomposition

The *forecast error variance decomposition* (FEVD) answers the following question: what portion of the variance of the forecast error in predicting $y_{i,t+h}$ is due to the structural shock w_i?

We take the MA representation of a VAR process with orthogonal white noise innovations:

$$y_t = \mu + \sum_{i=0}^{\infty} \Theta_i w_{t-i} \tag{2.22}$$

with $\Sigma_w = I_K$, the error of the optimal h-step forecast is:

$$y_{t+h} - y_t(h) = \sum_{i=0}^{h-1} \Phi_i u_{t+h-i} = \sum_{i=0}^{h-1} \Theta_i w_{t+h-i}.$$

[2]The **Choleski Decomposition** says that if A is a positive definite $(m \times m)$ matrix, then there exists a lower (upper) triangular matrix P with positive main diagonal such that:

$$P^{-1} A P'^{-1} = I_m \quad \text{or} \quad A = PP'.$$

Let's $\theta_{mn,i}$ the mn-th element of Θ_i, the h-step forecast error of the j-th component of y_t is:

$$y_{j,t+h} - y_{j,t}(h) = \sum_{k=1}^{K}(\theta_{jk,0}w_{k,t+h} + \cdots + \theta_{jk,h-1}w_{k,t+1}).$$

Then we have that $w_{k,t}$'s are uncorrelated and have unit variances, the MSE of $y_{j,t}(h)$ is:

$$MSE(y_{j,t}(h)) = \sum_{k=1}^{K}(\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2)$$

and the contribution of innovations in variable k to the forecast error variance of variable j

$$\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2 = \sum_{i=0}^{h-1}(e_j'\Theta_i e_k)^2.$$

Using all these equations, we have the proportion of the $h-$step forecast error variance of variable j:

$$w_{jk,h} = \sum_{i=0}^{h-1}(e_j'\Theta_i e_k)^2/MSE[y_{j,t}(h)]. \tag{2.23}$$

2.3 Estimation of a VAR model

In this section we assume that our VAR(p) process is stationary and stable:

$$y_t = \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \tag{2.24}$$

and we assume that all the coefficients $\nu, A_1, \ldots, A_p, \Sigma_u$ are unknown and we use this time series data to estimate the coefficients.

2.3.1 Multivariate Least Square Estimation

We analyze the multivariate least squares (LS) estimation, we consider our VAR(p) model and we define:

$$\begin{aligned}
Y &:= (y_1, \ldots, y_T) && (K \times T)\\
B &:= (\nu, A_1, \ldots, A_p) && (K \times (Kp+1))\\
Z_t &:= (1, y_t, \ldots, y_{t-p+1})' && ((Kp+1) \times 1)\\
Z &:= (Z_0, \ldots, Z_{T-1}) && ((Kp+1) \times T)\\
U &:= (u_1, \ldots, u_T) && (K \times T)\\
y &:= \mathrm{vec}(Y) && (KT \times 1)\\
\beta &:= \mathrm{vec}(B) && ((K^2p + K) \times 1)\\
b &:= \mathrm{vec}(B') && ((K^2p + K) \times 1)\\
u &:= \mathrm{vec}(U) && (KT \times 1)
\end{aligned}$$

where $\text{vec}(A) = \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix}$ trasforms an $(m \times n)$ matrix A into an $(mn \times 1)$ vector by stacking the columns. We have the VAR(p) model for $t = 1, \dots, T$ in the compactly formula[3]:

$$Y = BZ + U \quad \text{or} \quad \text{vec}(Y) = (Z' \otimes I_K)\text{vec}(B) + \text{vec}(U) \tag{2.25}$$

or $y = (Z' \otimes I_K)\beta + u$. Remind that $\Sigma_u = I_T \otimes \Sigma_u$, we can obtain the multivariate LS estimation (or also the generalized least squares (GLS) estimation) of β by minimize the following function of β:

$$\begin{aligned} S(\beta) &= u'(I_T \otimes \Sigma_u)^{-1}u = [y - (Z' \otimes I_K)\beta]'(I_T \otimes \Sigma_u^{-1})[y - (Z' \otimes I_K)\beta] \\ &= y'(I_T \otimes \Sigma_u^{-1})y + \beta'(ZZ' \otimes \Sigma_u^{-1})\beta - 2\beta'(Z \otimes \Sigma_u^{-1})y. \end{aligned} \tag{2.26}$$

Then using the first order condition, deriving the function $S(\beta)$ respect to β and equating it at zero we have:

$$\hat{\beta} = ((ZZ')^{-1} \otimes \Sigma_u)(Z \otimes \Sigma_u^{-1})y = ((ZZ')^{-1}Z \otimes I_K)y. \tag{2.27}$$

The LS estimator is the same that we can obtain by the OLS regression and we can also write this estimator in a different form:

$$\text{vec}(\hat{B}) = ((ZZ')^{-1}Z \otimes I_K)\text{vec}(Y) = \text{vec}(YZ'(ZZ')^{-1}) \iff \hat{B} = YZ'(ZZ')^{-1}.$$

We consider the LS estimator and we define: $\Gamma := \text{plim}ZZ'/T$, so we have the following:

Proposition 4. *Let y_t be a stable, K-dimensional VAR(p) process with standard white noise residuals, $\hat{B} = YZ'(ZZ')^{-1}$ is the LS estimator of the VAR coefficient B and plim$\hat{B} = B$:*

$$\sqrt{T}(\hat{\beta} - \beta) = \sqrt{T}vec(\hat{B} - B) \xrightarrow{d} \mathcal{N}(0, \Gamma^{-1} \otimes \Sigma_u). \tag{2.28}$$

2.3.2 Testing for Causality

If we want to test the Granger-causality, we need to test zero constraints for the coefficients:

$$H_0 : C\beta = c \quad \text{against} \quad H_1 : C\beta \neq c$$

[3]Let $A = (a_{ij})$ and $B = (b_{ij})$ be $(m \times n)$ and $(p \times q)$, the $(mp \times nq)$ matrix

$$A \otimes B := \begin{bmatrix} a_{11}B & \dots & a_{1n}B \\ \vdots & & \vdots \\ a_{m1}B & \dots & a_{mn}B \end{bmatrix}$$

is the Kronecker product or direct product.

where C is an $(N \times (K^2 p + K))$ matrix of rank N and c is an $(N \times 1)$ vector. Using the estimator for Σ_u and Γ we find the following statistic:

$$\lambda_W = (C\hat{\beta} - c)' \left[C((ZZ')^{-1} \otimes \hat{\Sigma}_u)C' \right]^{-1} (C\hat{\beta} - c) \xrightarrow{d} \chi^2(N).$$

Otherwise if we want to testing the instantaneous causality, we need to test zero restrictions for the $\sigma = \text{vech}(\Sigma_u)$: [4]

$$H_0 : C\sigma = 0 \quad \text{against} \quad H_1 : C\sigma \neq 0.$$

We have the following statistic:

$$\lambda_W = T\tilde{\sigma}'C'[2CD_K^+(\tilde{\Sigma}_u \otimes \tilde{\Sigma}_u)D_K'^+ C']^{-1} C\tilde{\sigma} \xrightarrow{d} \chi^2(N)$$

where $\tilde{\Sigma}_u$ is a plausible estimator and is asymptotically equivalent to $\hat{\Sigma}_u$.Then D_K^+ is the Moore-Penrose[5] (generalized) inverse of the duplication matrix D_K and C is an $(N \times K(K+1)/2)$ matrix of rank N.

If we use the Choleski decomposition of Σ_u and the lower triangular matrix P, we note that instantaneous noncausality implies zero elements of Σ_u and so also of P and we have the following hypothesis:

$$H_0 : C\text{vech}(P) = 0$$

and the statistics:

$$\lambda_W = T\text{vech}(\tilde{P})'C'[C\hat{\bar{H}}\hat{\Sigma}_{\tilde{\sigma}}\hat{\bar{H}}'C']^{-1} C\text{vech}(\tilde{P}) \xrightarrow{d} \chi^2(N)$$

where $\bar{H} = [L_K(I_{K^2} + K_{KK})(P \otimes I_K)L_K']^{-1}$, then K_{mn} is the commutation matrix defined such that $\text{vec}(G) = K_{mn}\text{vec}(G')$ for any matrix G and L_K is the elimination matrix defined such that $\text{vech}(F) = L_K\text{vec}(F)$ for any matrix F and finally the $\tilde{P}$ and $\tilde{\sigma}$ are derived from the asymptotic distribution.

2.4 Criteria for VAR order selection

We use different criteria for choosing the VAR order selection: FPE,AIC, HQ and SC.

i) The Akaike's Final Prediction Error criterion, called FPE, was designed as an estimator of the prediction error and it is strongly biased in the finite sample case, i.e, in the case that the number of given data is not large compared to the maximum candidate order. The criterion is:

$$\begin{aligned} \text{FPE}(m) &= \det \left[\frac{T + Km + 1}{T} \frac{T}{T - Km - 1} \tilde{\Sigma}_u(m) \right] \\ &= \left[\frac{T + Km + 1}{T - Km - 1} \right]^K \det \tilde{\Sigma}_u(m). \end{aligned}$$

[4] The vech operator takes only the elements below and on the main diagonal of a square matrix. If A is an $(m \times m)$ matrix, $\text{vech}(A)$ is an $m(m+1)/2$ vector.

[5] A matrix B is called *Moore-Penrose (generalized) inverse* of A if its satisfies the following four conditions: $ABA = A$; $BAB = B$; $(AB)' = AB$; $(BA)' = BA$ and we denote it by A^+.

The VAR order estimate is obtained as that value for which the two forces are balanced optimally.

ii) The Akaike's Information Criterion, called AIC, is based on the minimization of the forecast MSE, it is an objective measure of model suitability which balances model fit and model complexity. For a VAR(m) process the criterion is:

$$\begin{aligned}\mathrm{AIC}(m) &= \ln|\tilde{\Sigma}_u(m)| + \frac{2}{T}(\text{number of freely estimated parameters})\\ &= \ln|\tilde{\Sigma}_u(m)| + \frac{2mK^2}{T}.\end{aligned}$$

iii) The Hannan-Quinn Criterion, called HQ, is a consistent criterion and can be applied to regression model and for the VAR(m) process the criterion is:

$$\begin{aligned}\mathrm{HQ}(m) &= \ln|\tilde{\Sigma}_u(m)| + \frac{2\ln\ln T}{T}(\#\text{ freely estimated parameters})\\ &= \ln|\tilde{\Sigma}_u(m)| + \frac{\ln T}{T}mK^2.\end{aligned}$$

iv) The Bayesian Information Criteria or Schwarz Criteria, called SC or BIC, is a consistent criterion and it focuses on the Bayesian arguments and for the VAR(m) process the criterion is:

$$\begin{aligned}\mathrm{SC}(m) &= \ln|\tilde{\Sigma}_u(m)| + \frac{\ln T}{T}(\#\text{ freely estimated parameters})\\ &= \ln|\tilde{\Sigma}_u(m)| + \frac{\ln T}{T}mK^2.\end{aligned}$$

In the last three different criteria we choose the order estimated $\hat{p}$ so that it minimizes the value of the criteria. In the last two criteria we also substitute the non negative function of the AIC criterion with the logarithm.

Proposition 5. *Let $y_{T_M+1}, \dots, y_o, y_1, \dots, y_T$ be any K-dimensional multiple time series and suppose that VAR(m) models, $m = 0, 1, \dots, M$ are fitted to $y_1, \dots, y_T$. Then we have the following results:*

$$\begin{aligned}\hat{p}(SC) &\leq \hat{p}(AIC) \quad \textit{if } T \geq 8\\ \hat{p}(SC) &\leq \hat{p}(HQ) \quad \textit{for all } T\\ \hat{p}(HQ) &\leq \hat{p}(AIC) \quad \textit{if } T \geq 16.\end{aligned}$$

2.5 Structural Vector Autoregressions

We define our K-dimensional stationary, stable VAR(p):

$$y_t = A_1 y_{t-1} + \cdots + A_p t - p + u_t$$

where y_t is a $(K \times 1)$ vector of observable time series variables, A_j is a $(K \times K)$ matrices and u_t is a K-dimensional white noise, with $u_t \sim (0, \Sigma_u)$. In this section we analyze the Structural Vector Autoregression, called SVAR and the restrictions that we do to identify the relevant innovations and impulse responses.

The SVAR models are usually used to study the average response of the model variables to a given one-time structural shock, they allow the construction of forecast error variance decompositions that quantify the average contribution of a given structural shock to the variability of the data.

The SVAR models use nonsample information in specifying unique innovations and unique impulse responses, we introduce three different SVAR models: the A-Model, the B-Model and the AB-Model.

2.5.1 The A-Model

If we want to find a model with instantaneously uncorrelated residuals, we have to model the instantaneous relations between the observable variables directly. We consider a structural form model:

$$Ay_t = A_1^* y_{t-1} + \cdots + A_p^* y_{t-p} + \varepsilon_t \tag{2.29}$$

where $A_j^* := \mathbf{A}A_j$ $(j = 1, \ldots, p)$ and $\varepsilon_t := \mathbf{A}u_t \sim (0, \Sigma_\varepsilon = \mathbf{A}\Sigma_u\mathbf{A}')$ The restrictions have to be such that the system of equations has an unique solution:

$$\mathbf{A}^{-1}\Sigma_\varepsilon\mathbf{A}'^{-1} = \Sigma_u \quad \text{and} \quad C_{\mathbf{A}}\text{vec}(\mathbf{A}) = c_{\mathbf{A}} \tag{2.30}$$

where $C_{\mathbf{A}}\text{vec}(\mathbf{A}) = c_{\mathbf{A}}$ are the arbitrary restrictions on $\mathbf{A}$ and $C_{\mathbf{A}}$ is a $\frac{1}{2}K(K+1) \times K^2)$ selection matrix and $c_{\mathbf{A}}$ is a suitable $\frac{1}{2}K(K+1) \times 1)$ fixed vector.

Proposition 6 (*Identification of the* $\mathbf{A}$*-Model*)**.**
Let Σ_ε be a $(K \times K)$ positive diagonal matrix and let $\mathbf{A}$ be a $(K \times K)$ nonsingular matrix. Then for a given symmetric, positive definite $(K \times K)$ matrix Σ_u, an $(N \times K^2)$ matrix $C_{\mathbf{A}}$ and a fixed $(N \times 1)$ vector $c_{\mathbf{A}}$, the system of equations in (2.30) has a locally unique solution for $\mathbf{A}$ and the diagonal elements of Σ_ε if and only if

$$rk \begin{bmatrix} -2D_K^+(\Sigma_u \otimes \mathbf{A}^{-1}) & D_K^+(\mathbf{A}^{-1} \otimes \mathbf{A}^{-1})D_K \\ C_{\mathbf{A}} & 0 \\ 0 & C_\sigma \end{bmatrix} = K^2 + \frac{1}{2}K(K+1)$$

where the D_K is the duplication matrix and C_σ is a selection matrix which selects the elements of vech(Σ_ε) below the main diagonal.

2.5.2 The B-Model

If we want to identify the structural innovations ϵ_t directly from the forecast errors or reduced form residuals u_t, we have to think of the forecast errors as linear functions of the structural innovations. We have the following relations:

$u_t = \mathbf{B}\varepsilon_t$ and $\Sigma_u = \mathbf{B}\Sigma_\varepsilon\mathbf{B}'$ and we assume that $\varepsilon_t \sim (0, I_K)$. We have the following restrictions:

$$\Sigma_u = \mathbf{B}\mathbf{B}' \quad \text{and} \quad C_\mathbf{B}\text{vec}(\mathbf{B}) = 0 \tag{2.31}$$

where $C_\mathbf{B}$ is an $(N \times K^2)$ selection matrix.

Proposition 7 (*Local Identification of the* **B**-*Model*).
Let $\mathbf{B}$ *be a nonsingular* $(K \times K)$ *matrix. Then for a given symmetric, positive definite* $(K \times K)$ *matrix* Σ_u *and an* $(N \times K^2)$ *matrix* $C_\mathbf{B}$*, the system in (2.31) has a locally unique sollution if and only if:*

$$rk \begin{bmatrix} 2D_K^+(\mathbf{B} \times I_k) \\ C_\mathbf{B} \end{bmatrix} = K^2.$$

2.5.3 The AB-Model

We consider both types of restrictions of the two previously models and we have a **AB**-Model: $\mathbf{A}u_t = \mathbf{B}\varepsilon_t$ and $\varepsilon_t \sim (0, I_K)$. In this case a simultaneous equations system is formulated for the errors of the reduced form model rather than the observable variables directly. We write the following two restrictions for our model:

$$\Sigma_u = \mathbf{A}^{-1}\mathbf{B}\mathbf{B}'\mathbf{A}'^{-1}; \quad C_\mathbf{A}\text{vec}(\mathbf{A}) = c_\mathbf{A} \quad \text{and} \quad C_\mathbf{B}\text{vec}(\mathbf{B}) = c_\mathbf{B}. \tag{2.32}$$

Proposition 8 (*Local Identification of the* **AB**-*Model*).
Let $\mathbf{A}$ *and* $\mathbf{B}$ *be nonsingular* $(K \times K)$ *matrices. Then, for a given symmetric, positive definite* $(K \times K)$ *matrix* Σ_u*, the system of equations in (2.32) has a locally unique solution if and only if*

$$rk \begin{bmatrix} -2D_K^+(\Sigma_u \otimes \mathbf{A}^{-1}) & 2D_K^+(\mathbf{A}^{-1}\mathbf{B} \otimes \mathbf{A}^{-1}) \\ C_\mathbf{A} & 0 \\ 0 & C_\mathbf{B} \end{bmatrix} = 2K^2.$$

2.5.4 Estimation of Structural Parameters

We used a **AB**-model and the **A**$-$ and **B**$-$models are special cases of the **AB**$-$model. We want to estimate the following SVAR model:

$$\mathbf{A}y_t = \mathbf{A}AY_{t-1} + \mathbf{B}\varepsilon_t \tag{2.33}$$

where the $Y'_{t-1} := [y'_{t-1}, \ldots, y'_{t-p}]$, $A := [A_1, \ldots, A_p]$ and ε_t is assumed to be white noise with covariance matrix I_K, $\varepsilon_t \sim \mathcal{N}(0, I_K)$. The reduced form residuals corresponding to (2.33) have the form $u_t = \mathbf{A}^{-1}\mathbf{B}\varepsilon_t$ and we have that $a_t \sim \mathcal{N}(0, \Sigma = \mathbf{A}^{-1}\mathbf{B}\mathbf{B}'(\mathbf{A}^{-1})')$.

We have that the log-likelihood function for a sample $y_1, \ldots, y_T$ is seen to be:

$$\begin{aligned}\ln l(A, \mathbf{A}, \mathbf{B}) =& -\frac{KT}{2}\ln 2\pi - \frac{T}{2}\ln|\mathbf{A}^{-1}\mathbf{B}\mathbf{B}'\mathbf{A}'^{-1}| \\ &- \frac{1}{2}\mathrm{tr}\{(Y - AX)'[\mathbf{A}^{-1}\mathbf{B}\mathbf{B}'\mathbf{A}'^{-1}]^{-1}(Y - AX)\} \\ =&\text{constant} + \frac{T}{2}\ln|\mathbf{A}|^2 - \frac{T}{2}\ln|\mathbf{B}|^2 \\ &- \frac{1}{2}\mathrm{tr}\{\mathbf{A}'\mathbf{B}'^{-1}\mathbf{B}^{-1}\mathbf{A}(Y - AX)(Y - AX)'\}\end{aligned}$$

where $Y := [y_1, \ldots, y_T]$, $X := [Y_0, \ldots, Y_{T-1}]$ and we have the following two rules: $|\mathbf{A}^{-1}\mathbf{B}\mathbf{B}'(\mathbf{A}^{-1})'| = |\mathbf{A}^{-1}|^2|\mathbf{B}|^2 = |\mathbf{A}|^{-2}|\mathbf{B}^2|$ and $\mathrm{tr}(VW) = \mathrm{tr}(WV)$

We maximize the log-likelihood function with respect to A and we obtain:

$$\hat{A} = YX'(XX')^{-1}. \tag{2.34}$$

If only just-identifying restrictions are imposed on the structural parameters, we have for the ML estimator of Σ_u,

$$\tilde{\Sigma}_u = T^{-1}(Y - \hat{A}X)(Y - \hat{A}X)' = \tilde{\mathbf{A}}^{-1}\tilde{\mathbf{B}}\tilde{\mathbf{B}}'\tilde{\mathbf{A}}'^{-1}.$$

Otherwise if over-identifying restrictions have been imposed on $\mathbf{A}$ and/or $\mathbf{B}$, the corresponding estimator for

$$\tilde{\Sigma}_u^r := \tilde{\mathbf{A}}^{-1}\tilde{\mathbf{B}}\tilde{\mathbf{B}}'\tilde{\mathbf{A}}'^{-1}$$

will differ from $\tilde{\Sigma}_u$.

We see that both the impulse response function and the forecast error variance decomposition are based on the structural innovations and we have that the impulse response coefficients are obtained from the matrices:

$$\Theta_j = \Phi_j\mathbf{A}^{-1}\mathbf{B} \quad j = 0, 1, 2, \ldots.$$

Chapter 3

The Theoretical Model

In this chapter we introduce a theoretical model for the analysis of our problem, this model is related to the unemployment and the job finding and the policy uncertainty. Our VAR analysis is justified by a recent work by Leduc and Liu (2012)[18], who work out a structural DSGE model with labor market and nominal frictions to investigate the effects of uncertainty shocks on labor market dynamics.

To study the macroeconomic effects of uncertainty we introduce a stylized Dynamic Stochastic General Equilibrium (DSGE) model with labor market search frictions. DSGE model starts specifying a number of economic agents (like households, firms, governments) and embodying them with behavioral assumptions, like the maximization of an objective function (utility).

First the economists assume sources of shocks to model (shocks to productivity, to preferences, to taxes, to monetary policy, etc), after that they study how agents make their decisions over time as a response to these shocks. Finally they focus on investigation of aggregate outcomes, the called general equilibrium, which are situation where the agents in the model follow a concrete behavioral assumption (maximization or minimization) and where the decisions of the agents are consistent with each other (the number of units of goods sold must be equal to the number of units of goods bought).

The economy is populated by a continuum of infinitely lived and identical households, where an household is a continuum of workers members and owns a continuum of firms, each of which uses one worker to produce an intermediate good.

In the economy at time t a fraction of the workers is unemployed and is searching for jobs, while the firms post vacancies at a fixed cost. We try to match these two components and the number of successful matches are the matching technology that transforms searching workers and vacancies into an employment relation.

The real wages are Nash bargaining between searching workers and hiring firms, the households consume differential retail goods and the retailers are in a perfectly competitive market and they set a price for each products. The monetary policy is described by the *Taylor rule*, under which nominal interest rate responds to deviations of inflation from a target and of output from its potential.

Definition 3. The **Taylor Rules** are monetary policy rules that prescribe how a central bank should adjust its interest rate policy instrument in a systematic way in response to developments in inflation and macroeconomic activity. In formula the Taylor Rules are:

$$i - i^* = \theta_\pi(\pi - \pi^*) + \theta_y(y - y^*) \tag{3.1}$$

where i is the short-term nominal interest rate, i^* is the target of interest rate, π and π^* are the rate of inflation and the inflation target, y is the real output and θ_π and θ_y are the response parameters. The (3.1) can be rewritten as follows:

$$i = (1 - \theta_i)(r^* + \pi^*) + \theta_i i_{-1} + \theta_\pi(\pi - \pi^*) + \theta_y(y - y^*) + \theta_{\Delta y}(\Delta y - \Delta y^*)$$

where the inertial behavior in setting interest rates is $\theta_i > 0$ and we have that the policy response to level of output gap $(y - y^*)$ and to difference between output growth and its potential $(\Delta y - \Delta y^*)$ and the r^* is the natural interest rate in equilibrium.

If there is a positive shock to inflation, then the Federal Reserve (FED) would raise the nominal interest rate more than point-for-point, increasing the real interest rate. The FED raises the nominal interest rate of inflation if inflation rises above its target and/or if output is above potential output. We can write the monetary policy rule:

$$r_t^* = \pi_t + \delta(\pi_t - \pi^*) + w\hat{y}_t + R^*$$

where the r_t^* is the short-term nominal interest rate target, called Federal funds rate; the π^* is about 2%, the $\hat{y}_t$ is the deviation of output from its long-run trend, called output gap. The R^* is the equilibrium level of interest rate (real) and it is about 2%.

3.1 The Model

The Households

The households consume and invest a quantity of retail goods and the utility function of the households is:

$$\mathrm{E}\left[\sum_{t=0}^{\infty} \beta^t A_t(\ln C_t - \chi N_t)\right] \tag{3.2}$$

where $\beta \in (0, 1)$ is a parameter and is the subjective discount factor; A_t is the intertemporal preference shock; C_t is the consumption. χ is a parameter, the disutility from working and N_t is the fraction of household members who are employed.

The growth rate of the intertemporal preference shocks is γ_{at} and it is the ratio between A_t and A_{t-1}. This growth rate follows the stochastic process[1]

$$\ln \gamma_{at} = \rho_a \ln \gamma_{a,t-1} + \sigma_{at}\varepsilon_{at}$$

where $\rho_a \in (-1, 1)$ is the persistence of preference shock, ε_{at} is a normal independent identified distribution and σ_{at} denotes the time-varying standard deviation of innovation to preference shock and it is called preference uncertainty shock, which follows the stationary process:

$$\ln \sigma_{at} = (1 - \rho_{\sigma_a}) \ln \sigma_a + \rho_{\sigma_a} \ln \sigma_{a,t-1} + \sigma_{\sigma_a}\varepsilon_{\sigma_a,t}$$

where $\rho_{\sigma_a} \in (-1, 1)$ measures the persistence of preference uncertainty; $\varepsilon_{\sigma_a,t}$ is the innovation to preference uncertainty shock and it is distributed as a normal process; σ_{σ_a} is the constant standard deviation of the innovation.

The households maximize the utility function (3.2) subject to a budget constraint, holds for all t:

$$C_t + \frac{B_t}{P_t R_t} = \frac{B_{t-1}}{P_t} + (1 - \tau_t)[w_t N_t + \phi(1 - N_t)] + d_t - T_t \qquad (3.3)$$

where P_t is the price level; B_t denotes the household's holdings of nominal risk-free bond; R_t denotes the nominal interest rate; w_t denotes the real wage rate; ϕ denotes the unemployment benefit; d_t denotes the profit income from household's ownership of intermediate goods producers and of retailers and T_t is the lump-sum taxes.

We assume that τ_t is the labour income tax rate and it follows the stochastic process:

$$\ln \tau_t = (1 - \rho_\tau) \ln \tau + \rho_\tau \ln \tau_{t-1} + \sigma_{\tau t}\varepsilon_{\tau t}$$

where $\rho_\tau \in (-1, 1)$ is the persistence of tax shock; $\varepsilon_{\tau t}$ is an independent and identically distributed (i.i.d.) normal process and $\sigma_{\tau t}$ is the time-varying standard deviation of innovation to tax shocks and it is called the tax uncertainty shock. The $\sigma_{\tau t}$ follows the stationary process:

$$\ln \sigma_{\tau t} = (1 - \rho_{\sigma_\tau}) \ln \sigma_\tau + \rho_{\sigma_\tau} \ln \sigma_{\tau,t-1} + \sigma_{\sigma_\tau}\varepsilon_{\sigma_\tau,t}$$

where $\rho_{\sigma_\tau} \in (-1, 1)$ measures the persistence of tax uncertainty, $\varepsilon_{\sigma_\tau,t}$ is the innovation to the tax uncertainty shock and is a standard normal process and σ_{σ_τ} is the (constant) standard deviation of the innovation.

The optimal bond-holding decisions result in the intertemporal Euler equation:

$$1 = E_t \beta \gamma_{a,t+1} \frac{\Lambda_{t+1}}{\Lambda_t} \frac{R_t}{\pi_{t+1}}$$

where Λ_t denotes the marginal utility of consumption and $\pi_t = \frac{P_t}{P_{t-1}}$ is the inflation rate.

[1] A *stochastic process* is a family of random variables $\{x_t : t \in T\}$ defined on a probability space $\{\Omega, \mathcal{F}, P\}$, where T is a set of time point.

The aggregation sector

The final consumption good, which is a basket of differentiated retail goods, is written as:

$$Y_t = \left\{ \int_0^1 Y_t(j)^{\frac{\eta-1}{\eta}} \right\}^{\frac{\eta}{\eta-1}}$$

where $Y_t(j)$ is a type j retail good for $j \in [0,1]$ and $\eta > 1$ denotes the elasticity of substitution between differentiated products. We have the following problem:

$$\min \int_0^1 P_t(i)Y_t(i)di \quad \text{s.t} \quad 1 = Y_t$$

where $P_t(j)$ is the price of retail good of type j and the demand for a type j retail good is inversely related to the relative price:

$$Y_t^d(j) = \left(\frac{P_t(j)}{P_t} \right)^{-\eta} Y_t.$$

The price index P_t is related to the individual prices $P_t(j)$ through the following relation:

$$P_t = \left(\int_0^1 P_t(j)^{\frac{1}{1-\eta}} \right)^{1-\eta}.$$

The retail goods producers

We take a continuum of retail goods producer that produce a differentiated product using a homogenous intermediate good as input. The production function of retail good of type $j \in [0,1]$ is given by:

$$Y_t(j) = X_t(j)$$

where $X_t(j)$ is the input of intermediate goods used by retailer j and $Y_t(j)$ is the output. The retail goods producers are price takers in the input market and monopolistic competitors in the product markets, where they set prices for their products. We assume that the price adjustment costs are in units of aggregate output and are subject to a quadratic cost

$$\frac{\Omega_p}{2} \left(\frac{P_t(j)}{\pi P_{t-1}(j)} - 1 \right)^2 Y_t$$

where the parameter $\Omega_p \geq 0$ measures the cost of price adjustments and π denotes the steady-state inflation rate.

A retail firm that produces good j solves the following profit-maximizing problem

$$\max_{P_t(j)} \mathrm{E}_t \sum_{i=0}^{\infty} \frac{\beta^i \Lambda_{t+i}}{\Lambda_t} \left[\left(\frac{P_{t+i}(j)}{P_{t+i}} - q_{t+i} \right) Y_{t+i}^d(j) - \frac{\Omega_p}{2} \left(\frac{P_{t+i}(j)}{\pi P_{t+i-1}(j)} - 1 \right)^2 Y_{t+i} \right]$$

where q_{t+i} denotes the relative price of intermediate goods in period $t+i$. In a symmetric equilibrium with $P_t(j) = P_t$ for all j we have

$$q_t = \frac{\eta - 1}{\eta} + \frac{\Omega_p}{\eta}\left[\frac{\pi_t}{\pi}\left(\frac{\pi_t}{\pi} - 1\right) - \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\frac{Y_{t+1}}{Y_t}\frac{\pi_{t+1}}{\pi}\left(\frac{\pi_{t+1}}{\pi} - 1\right)\right].$$

If $\Omega_p = 0$ (i.e. there is no price adjustment costs) the optimal pricing rule implies that real marginal cost q_t is the inverse of the steady state markup $(q_t = (\eta - 1)/\eta)$.

The labor market

We assume that at the beginning of our analysis in period t there are u_t unemployed workers searching for jobs and there are v_t vacancies posted by firms. The matching variable is described using a Cobb-Douglas function[2]

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}$$

where m_t is the number of successful matches and the parameter $\alpha \in (0, 1)$ denotes the elasticity of job matches with respect to the number of searching workers and μ scales the matching efficiency.

We define two different rates related to the matching theory:

i) The **job filling rate** is the probability that an open vacancy is matched with a searching workers, $q_t^v = m_t/v_t$.

ii) The **job finding rate** is the probability that an unemployed and searching worker is matched with an open vacancy, $q_t^u = m_t/u_t$.

In period t there are N_{t-1} workers, a fraction ρ of these workers lose their jobs and we have that $(1-\rho)N_{t-1}$ is the number of workers who survive the job separation. At time t m_t matches are formed and we can assume that new hires start working in the period they are hired, so we have that aggregate unemployment in period t evolves according to

$$N_t = (1-\rho)N_{t-1} + m_t.$$

The number of unemployed workers searching for jobs in period t is

$$u_t = 1 - (1-\rho)N_{t-1}.$$

We assume full participation, i.e. at all times all individuals are either employed or willing to work and we have that the unemployment rate is:

$$U_t = u_t - m_t = 1 - N_t$$

and means the fraction of the population who are left without a job after hiring takes place in period t.

[2] The Cobb-Douglas function has the following form $F(K, AL) = BK^{\alpha}(AL)^{1-\alpha}$ where the parameters $\alpha \in (0, 1)$ and B is assumed positive, the K,AL are variables that in the growth theory describe the capital and the effective labor force.

The firms (intermediate goods producers)

We know that a firm can produce a good only if a match with a worker is formed. The production function for a firm with one worker is

$$x_t = Z_t$$

where x_t is the output and Z_t is an aggregate technology shock, which follows the stochastic process

$$\ln Z_t = (1-\rho_z)\ln Z + \rho_z \ln Z_{t-1} + \sigma_{zt}\varepsilon_{zt}.$$

The $\rho_z \in (-1,1)$ measures the persistence of the technology shock. The term ε_{zt} is an i.i.d innovation to the technology shock and is a standard normal process. The term σ_{zt} is a time-varying standard deviation of the innovation, denotes the technology uncertainty shock and it follows the stationary stochastic process

$$\ln \sigma_{zt} = (1-\rho_{\sigma_z})\ln \sigma_z + \rho_{\sigma_z}\ln \sigma_{z,t-1} + \sigma_{\sigma_z}\varepsilon_{\sigma_z,t}.$$

The parameter $\rho_{\sigma_z} \in (-1,1)$ measures the persistence of the technology uncertainty, the $\varepsilon_{\sigma_z,t}$ is the innovation to the technology uncertainty and is a standard normal process and the parameter $\sigma_{\sigma_z} > 0$ is the standard deviation of the innovation.

If a match is formed, the firms obtain a flow profit in the current period after paying the worker. In the $t+1$ period, if the match survives (with probability $1-\rho$), the firm continues, otherwise (with probability ρ) the firm posts a new job vacancy at a fixed cost κ with the value V_{t+1}. The value of a firm with a match is therefore given by the Bellman equation

$$J_t^F = q_t Z_t - w_t + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\rho)J_{t+1}^F + \rho V_{t+1}\right]. \tag{3.4}$$

Each new vacancy posted in period t costs κ units of final goods, the vacancy can be filled with probability q_t^v and the firms obtain the value of the match. Otherwise the vacancy remains unfilled and the firms go into the next period with the value V_{t+1}, so we have that the value of an open vacancy is:

$$V_t = -\kappa + q_t^v J_t^F + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-q_t^v)V_{t+1}.$$

Free entry implies that $V_t = V_{t+1} = 0$ and

$$\kappa = q_t^v J_t^F. \tag{3.5}$$

If we put the equation (3.5) in the equation (3.4) we obtain:

$$\frac{\kappa}{q_t^v} = q_t Z_t - w_t + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\rho)\frac{\kappa}{q_{t+1}^v}. \tag{3.6}$$

Workers' value function

If a worker is employed, he obtains an after-tax wage income and suffers a utility cost for working in period t. In the next period, the match is dissolved with probability ρ and the separated worker can find a new match with probability q^u_{t+1}. Otherwise the worker does not find a new job in $t+1$ period with probability $\rho(1-q^u_{t+1})$ and so he enters in the unemployment pool. The (marginal) value of an employed worker satisfies the Bellman equation:

$$J^W_t = (1-\tau_t)w_t - \frac{\chi}{\Lambda_t} + \mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\left\{[1-\rho(1-q^u_{t+1})]J^W_{t+1} + \rho(1-q^u_{t+1})J^U_{t+1}\right\} \quad (3.7)$$

where J^U_t is the value of an unemployed household member. If a worker is currently unemployed, then he obtains an after-tax unemployment benefit and can find a new job in period $t+1$ with probability q^u_{t+1}. Otherwise he remains unemployed. The value of an unemployed worker thus satisfies the Bellman equation is

$$J^U_t = \phi(1-\tau_t) + \mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[q^u_{t+1}J^W_{t+1} + (1-q^u_{t+1})J^U_{t+1}\right]. \quad (3.8)$$

The Nash bargaining wage

The firms and the workers bargain over wages and we have the following Nash bargaining problem:

$$\max_{w_t} \quad (J^W_t - J^U_t)^b (J^F_t)^{1-b}$$

where $b \in (0,1)$ is the bargaining weight for workers. We can define the total surplus as $S_t = J^F_t + J^W_t - J^U_t$ and the bargaining solution is given using the first order condition and the total surplus equation:

$$J^F_t = (1-b)S_t \quad J^W_t - J^U_t = bS_t. \quad (3.9)$$

Then from equations (3.7) and (3.8) we have that the total surplus is a function of the total surplus at time $t+1$

$$bS_t = (1-\tau_t)(w^N_t - \phi) - \frac{\chi}{\Lambda_t} + \mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\rho)(1-q^u_{t+1})bS_{t+1}\right]. \quad (3.10)$$

Using the equations (3.5),(3.9) and (3.10) we have the Nash bargaining wage[3]:

$$w^N_t[1-\tau_t(1-b)] = (1-b)\left[\frac{\chi}{\Lambda_t} + \phi(1-\tau_t)\right] + b\left[q_t Z_t + \beta(1-\rho)\mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\frac{\kappa v_{t+1}}{u_{t+1}}\right].$$

The Nash bargaining wage is a weighted average of the worker's reservation value and the firm's productive value of a job match adjusted for labor income taxes borne by the worker. By forming a match, the worker incurs a utility cost of working and foregoes the after-tax unemployment benefit; the firm receives the marginal product from labor in the current period and saves the vacancy cost from the next period.

[3]See the Appendix B for the complete proof.

Government policy

The government finances exogenous spending G_t and unemployment benefit payments ϕ through labor income taxes and lump-sum taxes. We assume that:

i) the government balances the budget in each period so that

$$G_t + \phi(1 - N_t) = T_t + \tau_t[w_t N_t + \phi(1 - N_t)]$$

ii) the ration of government spending to output $g_t = G_t/Y_t$ follows the stationary stochastic process:

$$\ln g_t = (1 - \rho_g)\ln g + \rho_g \ln g_{t-1} + \sigma_g \varepsilon_{gt}$$

where $\rho_g \in (-1, 1)$ is the persistence parameter, the innovation ε_{gt} is an i.i.d standard normal process, and σ_g is the time-varying standard deviation of the innovation and it is an uncertainty shock to government spending.

The government spending uncertainty shock follows the stationary stochastic process

$$\ln \sigma_{gt} = (1 - \rho_{\sigma_g})\ln \sigma_g + \rho_{\sigma_g} \ln \sigma_{g,t-1} + \sigma_{\sigma_g}\varepsilon_{\sigma_g,t}$$

where the parameter $\rho_{\sigma_g} \in (-1, 1)$ is the persistence of uncertainty shock to government spending, the term $\varepsilon_{\sigma_g,t}$ denotes the innovation to the uncertainty shock and is a standard normal process and the parameter $\sigma_{\sigma_g} > 0$ is the standard deviation of the innovation.

The government conducts a monetary policy by following the Taylor Rule

$$R_t = r\pi^* \left(\frac{\pi_t}{\pi^*}\right)^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_y}$$

where the parameters ϕ_π and ϕ_y determine respectively the aggressiveness of monetary policy against deviations of inflation from the target π^* and the extent to which monetary policy accommodates output fluctuations. The parameter r is the steady-state real interest rate and is equal R/π.

Search equilibrium

In a search equilibrium, the markets for bonds, capital, final consumption goods, and intermediate goods all clear.

Since the aggregate supply of the nominal bond is zero, the bond market-clearing condition implies that

$$B_t = 0.$$

The goods market clearing condition, that is $Y = C^d + I^d + G$ where Y is the current production function, the C^d is the current demand for consumption; I^d is the demand for investment and G is government spending, implies:

$$C_t + \kappa v_t + \frac{\Omega_p}{2}\left(\frac{\pi_t}{\pi} - 1\right)^2 Y_t + G_t = Y_t.$$

where Y_t is the aggregate output of final goods.

The intermediate goods market clearing implies that:

$$Y_t = Z_t N_t.$$

Chapter 4

Data Analysis

In this chapter we examine the theoretical model using actual data and we analyze the US quarterly data from the first quarter in 1985 to the third quarter in 2010. The data are: VIX Index, Economic Policy Uncertainty Index (created by Baker, Bloom and Davis), unemployment rate, quarterly inflation rate, job creation rate, job destruction rate, job-finding rate, Federal Funds rate and CBO's output gap.

In the first part of this chapter we make a description of all these data. Then we create two different models and we estimate using a VAR model and we search the possible relationships between the policy uncertainty shock and the data related to the labor market (unemployment rate, job creation rate, job destruction rate and job-finding rate) and to the inflation.

In the second part we delete the data related to the 2008 financial crisis and search for possible differences between the two models. Finally we introduce a new variable, the new economic policy uncertainty index, created in 2013 and we focus on possible differences.

4.1 Data Description

VIX Index

The **VIX index** is the CBOE[1] volatility index, which shows the market's expectation of 30-day volatility. The VIX is based on the $S\&P$ 500 Index (SPX)[2], the core index for US equities, and estimates expected volatility by averaging the weighted prices of SPX puts and calls over a wide range of strike prices.

VIX is a volatility index comprised of options rather than stocks, with the price of each option reflecting the market's expectation of future volatility. The

[1] Chicago Board Options Exchange is the world's largest options exchange and it focuses on options contracts for individual equities, indexes and interest rates.

[2] The Standard & Poor's 500 Index (S&P 500) is a stock market index based on market capitalizations of 500 leading companies publicly traded in the U.S. stock market.

generalized formula for VIX index calculation is:

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \tag{4.1}$$

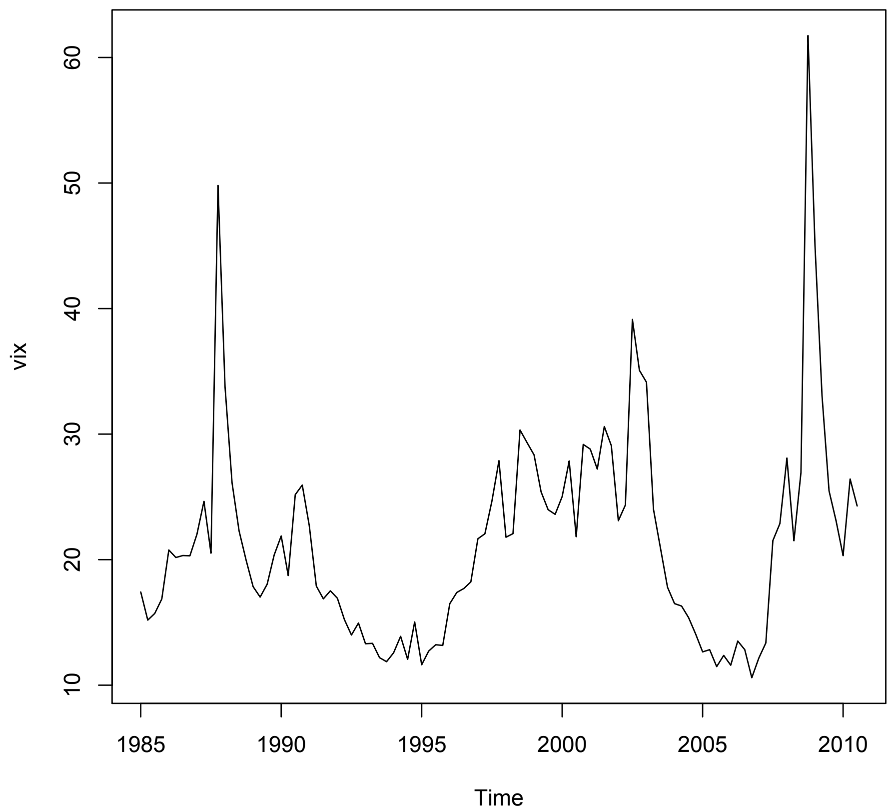

Figure 4.1: **VIX Index (1985:01-2010:03)**

where σ is VIX/100 and VIX $= \sigma \times 100$; T is the time to expiration; F is the Forward index level[3] derived from the index option prices; K_0 is the first strike below the forward index level; K_i is the strike price of the i-th out-of-the-money option (if $K_i > K_0$ it's a call, otherwise it's a put, if $K_i = K_0$ it's both a put and a call); R is the risk-free interest rate to expiration and $Q(K_i)$ represents

[3]To determine it, the CBOE chooses a pair of put and call options with prices that are closest to each other.

the average of the call and put option prices at strikes. Since $K_0 \leq F$, the average at K_0 implies that CBOE uses one unit of the in-the-money call at K_0. The last term in the equation (4.1) represents the adjustment needed to convert this in-the-money call into an out-of-the-money put using put-call parity.

ΔK_i is the interval between strike prices, it's the difference between the strike on either side of K_i: $\Delta K_i = (K_{i+1} - K_{i-1})/2$.

From the Figure 4.1, we see that there are some spikes in the 1987:04 and 1988:01 (Black Monday and stock market crash[4].), also in the period between 2002 and 2004. In the period around 2008:04 and 2009:01, we have the biggest and strong increase and peak due to the financial crisis. Otherwise there are decreases in the period between 1992-1995 and 2005-2006 (where we have also the minimum in 2006) and in the mid of 2007. So an increase in the VIX index is related to the economic recession.

Economic Policy Uncertainty Index

Baker, Bloom and Davis [2] construct the **economic policy uncertainty index** using three types of underlying components. The first component quantifies the newspaper coverage of policy-related economic uncertainty, the second one uses the number of federal tax code provisions set to expire in future years and the third one utilizes disagreement among economic forecasters as a proxy of uncertainty.

a) *News coverage* is an index of search results from 10 U.S. newspapers: *USA Today*, the *Miami Herald*, the *Chicago Tribune*, the *Washington Post*, the *Los Angeles Times*, the *Boston Globe*, the *San Francisco Chronicle*, the *Dallas Morning News*, the *New York Times* and the *Wall Street Journal*.

Baker, Bloom and Davis make month-by-month searches of each paper, starting in January 1985, for terms related to economic and policy uncertainty. They search in particular for articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'policy', 'tax', 'spending', 'regulation', 'federal reserve', 'budget', or 'deficit'. Then they count the number of articles that satisfy our search criteria each month, which create our monthly series.

They normalize the raw counts by the number of news articles in the same newspapers that contain the term 'today', and then calculate a backwards-looking 36-month moving average to smooth this series at a monthly level. For each newspaper they divide the policy-related uncertainty counts by the smoothed value of 'today' series and they sum each paper's series and normalize them to an average value of 100 from 1985 to 2010.

b) The *tax code expiration* is based on reports by the CBO[5] that makes lists of temporary federal tax code provisions. The temporary tax code provisions

[4] See in Appendix A.1

[5] The CBO is the Congressional Budget Office, it produces independent analyses of budgetary and economic issues to support the Congressional budget process.

lead to outlooks for federal spending and borrowing and to discrepancies between the tax revenues projections of the CBO and OMB[6]. The CBO uses 'current law' as a baseline taking into account all scheduled tax expirations, while the OMB uses 'current policy' as a baseline under its assessment of which temporary provisions are likely to be extended.

The CBO reports describe the tax code provisions and identifies the scheduled expiration month and then they weight these data in January of each year multiplying expirations by $0.5^{((T+1)/12)}$ for T equal to the number of months in the future when the tax code provision expires. Then they sum the discounted number of tax code expirations to have an index value for each January.

c) The *economic forecaster disagreement* is based on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. This survey is also called the Anxious Index, is a highly report on the prospects for the economy of the United States. This index often goes up just before the recessions began and is a quarterly one, each quarter every forecaster receives a form in which to fill out values corresponding to previsions for variables in each of the next five quarters. They use it for three of the forecast variables, the consumer price index (CPI)[7], purchase of goods and services by state and local governments, and purchase of goods and services by the federal government. They look at the quarterly previsions for the next year and they choose it because they are directly influenced by monetary policy and fiscal policy actions.

To build the dispersion component, they take the interquartile range of each set of inflation rate forecasts in each quarter, then they use the raw interquartile range. For both federal and state/local government purchases, we divide the interquartile range of four-quarter-ahead forecasts by the median four-quarter-ahead forecast and multiply that quantity by a 5-year backward-looking moving average for the ratio of nominal purchases to nominal GDP. They sum the two weighted values to build up the single federal/state/local index and they look at the interquartile range scaled by the ratio of governments purchases to the economy.

To build up our index they normalize each component by its own standard deviation and then they compute an average value of the components, using weights of 1/2 on news-index and 1/6 on each of the other three measures (tax expirations index, the CPI forecast disagreement measure, and the federal/state/local purchases disagreement measure).

The policy uncertainty index can be calculated using other two weighting methodologies. First, they equally weight the news-based measure, the combi-

[6]The OMB is the Office of Management and Budget and it assists the U.S. President to prepare the budget.

[7]The CPI is a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer good and services. It can be used as a measure of inflation and is viewed as an indicator of the effectiveness of government economic policy. It's computed by the Bureau of Labor Statistics.

nation of the forecast disagreement measures, and the tax expiration measure. Second, they perform a principle component analysis on four previously series to obtain weights for each components and the weights are: 0.35 on news-based index. 0.37 on tax expirations index, 0.24 on the CPI forecast disagreement measure, and 0.04 on our federal expenditure disagreement measure.

From the figure 4.2 we find spikes related to Lehman Brother's bankruptcy and TARP[8] and banking crisis and Obama election in 2008-2009. We can see also a spike at the end of 2001, due to the 9/11, and a spike in the 2003, due to the Second Gulf War. In the plot we can also see a spike at the beginning of 1987 (the Black Monday) and in 1990 (the First Gulf War).

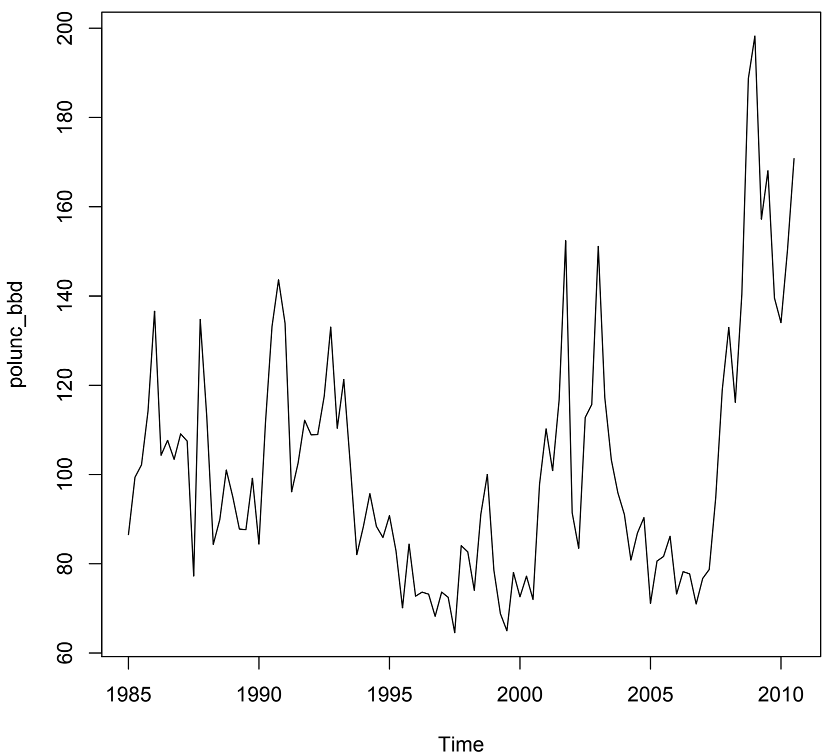

Figure 4.2: **Policy-Related Economic Uncertainty Index (1985:01-2010:03)**

[8]The Troubled Asset Relief Program(TARP) is created to implement programs to stabilize the financial system during the financial crisis of 2008.

Unemployment Rate

The **unemployment rate** is calculated by the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor and it's the percent of the labor force that is unemployed. Persons are classified as unemployed if they do not have a job, have actively looked for a work in the prior 4 weeks, and are currently available for work.

Actively looking for a work may consist of: having a job interview, sending out resumes or filling out applications, placing or answering advertisements, etc. The research is based on questions related to work and searching jobs and it is based on the civilian noninstitutional population 16 years old and over.

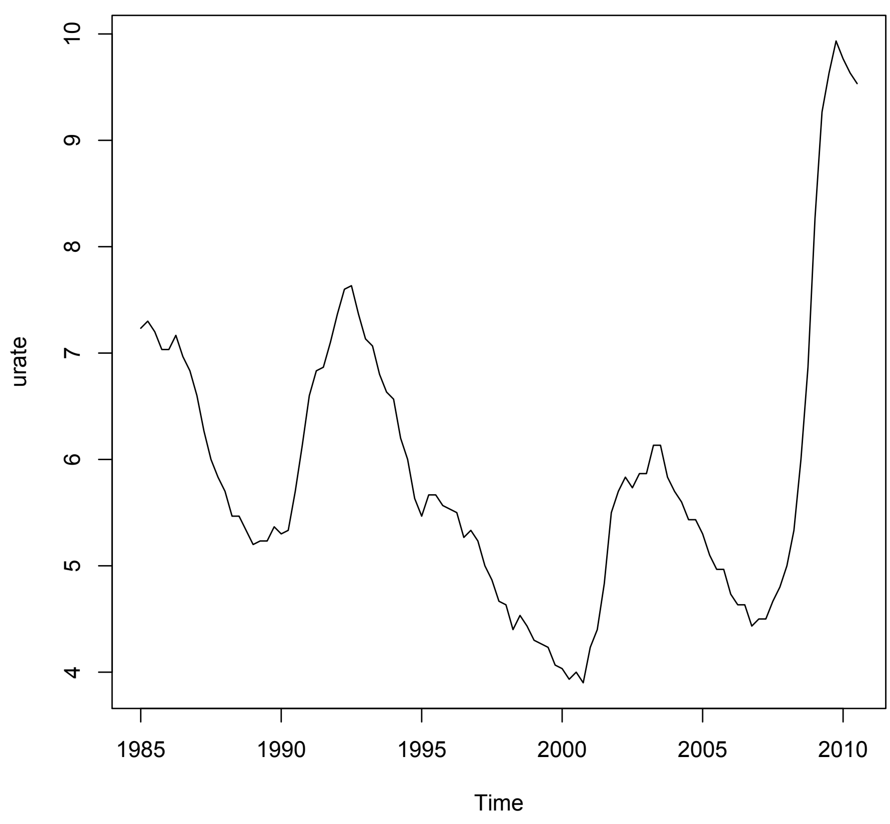

Figure 4.3: **Unemployment Rate (1985:01-2010:03)**

From the figure 4.3 we can see that we have high spikes from 2009 till our days, the unemployment rate grows up till 9.7% and this increase is due to the subprime mortgage crisis[9] (Lehman Brother crisis).

There are also some spikes from the end of 1991 to the beginning of 1993, because the 1990s began with a recession caused by several contractionary shocks to aggregate demand: tight monetary policy, the savings-and-loan crisis, and a fall in consumer confidence coinciding with the Gulf War. The unemployment rate decreased during the long expansion of the 1990s due to the increase in technological progress.

Otherwise the unemployment rate decreases in 1999 and 2000, when it was only 3.9%, but then it increases again. By the end of recession in 2001, the unemployment rate continue to increase, specially one year and a half after the official end of recession (in 2003). This was called the jobless recovery, because many firms and consumers had turned skeptical of the New Economy and despite the good news on productivity they did not want to make the same mistake as in the 1990s. So in 2002-2003 there was a period in which high productivity growth led to an increase rather than a decrease in unemployment.

Quarterly Inflation Rate

We analyze the annualized quarterly inflation rate calculated using the GDP deflator. The inflation rate is the rate at which the general level of prices for goods and services is rising and purchasing power is falling.

The GDP Deflator is a measure of the prices of all the goods and services produced in the domestic economy and it's also called the implicit price deflator for GDP. This deflator takes the value of output produced in a given year and compares the value of that output using that year's prices to the value of that output using some base year's prices. The GDP deflator in year t is defined P_t:

$$P_t = \frac{\text{Nominal GDP}_t}{\text{Real GDP}_t}$$

and is an index number, its level is chosen arbitrarily and has no economic interpretation. The nominal GDP is the value of goods and services measured at current prices, otherwise the real GDP is the same value but measures using a constant set of prices. Its rate of change $(P_t - P_{t-1})/P_{t-1}$ gives the rate at which the general level of prices increases over time, the rate of inflation.

The GDP deflator and the CPI have three differences. The first difference is that the GDP deflator measures the price of all goods and services produced, whereas the CPI measures the price of only the goods and services bought by consumers. The second difference is that the GDP deflator includes only those goods produced domestically and the imported goods are not part of the GDP. The third difference is related to the weights of prices in the economy. The CPI assigns fixed weights to the different goods, whereas the GDP deflator assigns changing weights. So the CPI is computed using a fixed basket of goods, whereas the GDP deflator allows the basket of goods to change over time as the composition of GDP changes.

[9] See in the Appendix A.3.

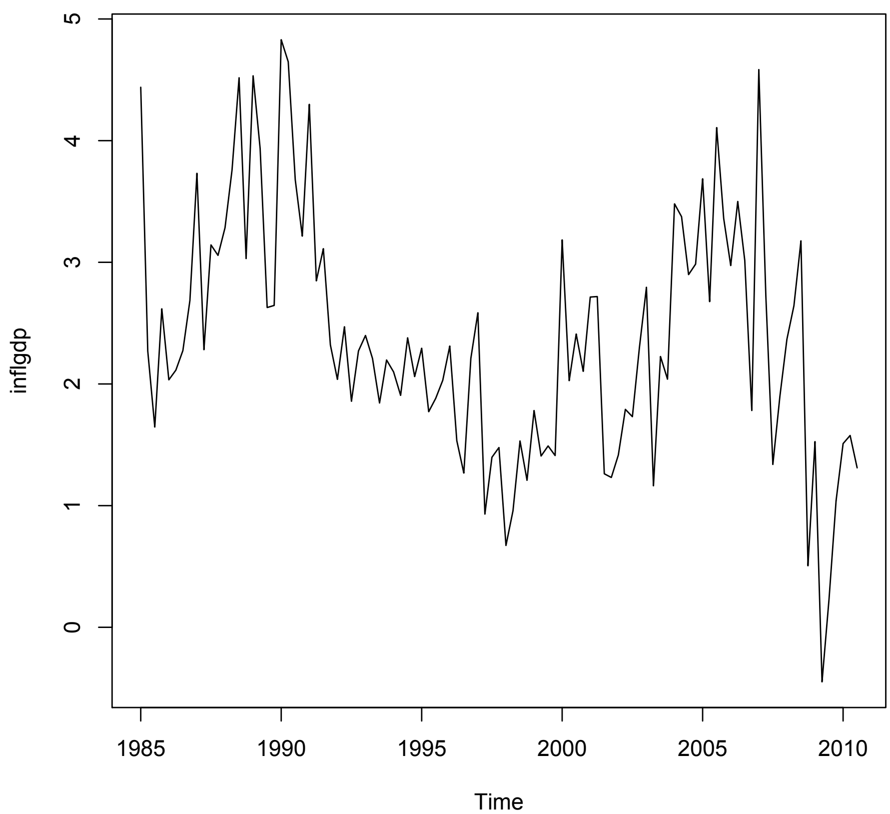

Figure 4.4: **Inflation Rate (1985:01-2010:03)**

In the figure 4.4 there are some interesting decreasing spikes around the 2009, due to Fed actions (interest rate were cut to virtually zero and Fed massively expanded its balanced sheet by purchasing Treasury Bonds and Mortgage Backed securities) and also between the 1997 and 1998. Otherwise there are some spikes at the beginning of the plot in 1989-1990 (due to Black Monday) and also after some period of stationarity (in the last quarter of 2005 and in the beginning of 2007).

Figure 4.5: **Job Creation Rate (1985:01-2010:03)**

Job Creation Rate

The **job creation rate** is a rate related to the creation of new jobs. We can write the rate of job creation from $t-1$ to t:

$$JC_t = \sum_e \left(\frac{Z_{et}}{Z_t}\right) |\max\{0, g_{et}\}| = \sum_e |\max\{0, \text{EMP}_{et} - \text{EMP}_{e,t-1}\}|/Z_t \quad (4.2)$$

where $Z_t = \sum Z_{et}$, $Z_{et} = 0.5(\text{EMP}_{et} - \text{EMP}_{e,t-1})$ is a measure of employer size and EMP denotes the number of employees and $g_{et} = (\text{EMP}_{et} - \text{EMP}_{e,t-1})/Z_{et}$ is the growth rate from $t-1$ to t at employer e.

From the figure 4.5 we see that there are important spikes at the beginning of the plot, specially from the 1986 to 1989. Then there is a decrease till the begin of 1992, but there is also an increase with a spike in 2000. After that big spike, there is no more spikes and our function is decreasing till our days. This decrease is due to the economic crisis and the Lehman Brother's crisis that do not create new jobs.

Job Destruction Rate

The **job destruction rate** is a rate related to the job "destruction". We can write the rate of job destruction from $t-1$ to t:

$$JD_t = \sum_e \left(\frac{Z_{et}}{Z_t}\right) |\min\{0, g_{et}\}| = \sum_e |\min\{0, \mathrm{EMP}_{et} - \mathrm{EMP}_{e,t-1}\}|/Z_t. \quad (4.3)$$

Equation (4.3) says that job destruction from $t-1$ to t is the sum of all employment reductions at shrinking units and it's expressed as a rate by dividing through by total employment.

We see that the job destruction rate is a decreasing function, we have the maximum at the beginning in the 1985 and then we have a minimum in the first quarter of the 2007 and after this decrease we have an increase with a spike at the end of 2008 and begin of 2009, but then there is only a continuously decrease till our days.

Job-finding Rate

The **job-finding rate** is defined as the ratio of the flow from another activity into employment to the number of people seeking jobs and also is the fraction of unemployed workers who find new jobs in a given period.

We have f_m the job-finding rate that potentially varies across the length of the unemployment period, m. The number of persons unemployed for m months is U_m that satisfies the differential equation:

$$\dot{U}_m = -f_m U_m$$

such that

$$U_m = e^{-\int_0^m f_s ds} U_0$$

where U_0 is the constant number of workers that flows into unemployment. The total number of unemployed persons in the economy is $U = \int_0^\infty U_m dm$ and the fraction of the workers that find a job is:

$$f = \frac{1}{U} \int_0^\infty f_m U_m dm = \frac{U_0}{U}$$

which is the average job-finding rate across unemployed workers.

In our case (see figure 4.7) there are spikes in the first two quarter of 1989 but then there is a decrease till 1992 and then we have an increase till the maximum of our rate in 2000-2001. After this increase it starts a continuously decrease till our days (the minimum is in the begin of 2010).

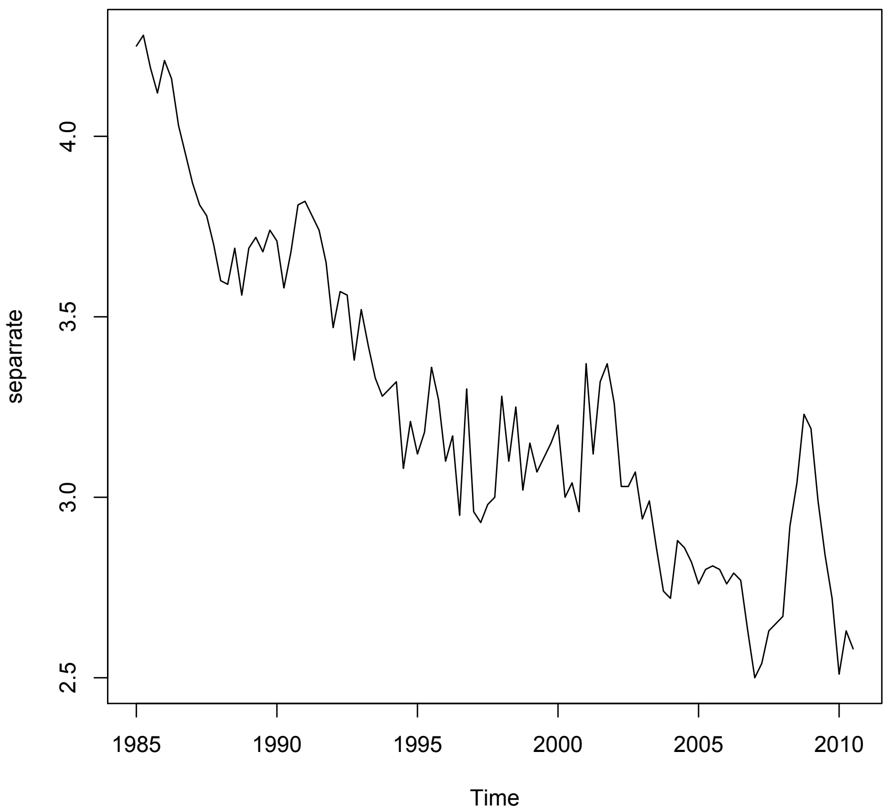

Figure 4.6: **Job Destruction Rate (1985:01- 2010:03)**

Federal Funds Rate

The **Federal Funds Rate** is the interest rate on overnight loans between banks. The Federal Funds Rate is the interest rate at which a depository institution lends immediately available funds (balances at the Federal Reserve) to another depository institution overnight.

When the Federal Open Market Committee (FOMC)[10] wishes to reduce the interest rates, they will increase the supply of money by buying government securities. When additional supply is added, the interest rate (cost of money)

[10]The FOMC set the target federal funds rate and is composed of the board of governors, which has seven members, and five reserve bank presidents. The FOMC decide whether increase or decrease the money supply, which the FED does by buying and selling government securities.

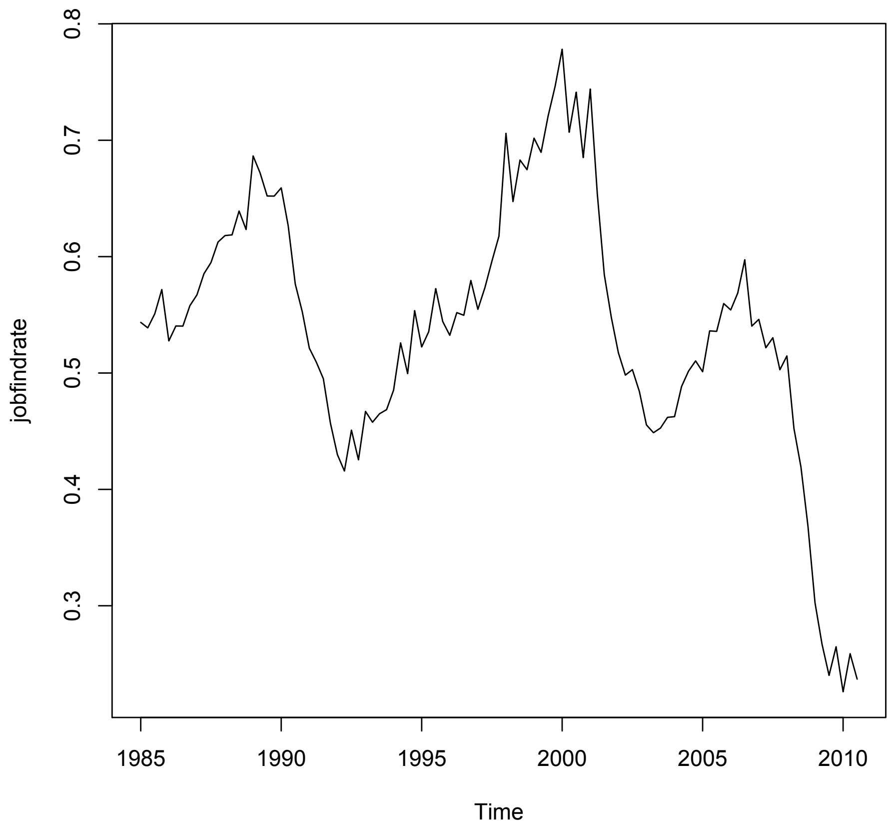

Figure 4.7: **Job-Finding Rate (1985:01-2010:03)**

falls, otherwise when the Committee wishes to increase the Fed Funds Rate, they will instruct the Desk Manager to sell government securities and then the cost of money will rise again.

We see from the figure 4.8 that the Federal Funds Rate is a decreasing function with some important spikes. The most important spike is between the end of 1988 and the end of 1989 due to confusion about FED response to the stock market fall. Then there are other important spikes around the 2000 (important US recession) and in 2006-2007, but after that spikes we can see that there are only substantial decreases and in the last years the Fed Funds Rate is only 0.12%, it is smaller than the 1990s FFR, around 9%.

The sharp decline in the federal funds rate in the early 1990s, from close 10% in 1989 to around 3% in 1992, was not enough to avoid recession, it reduces its

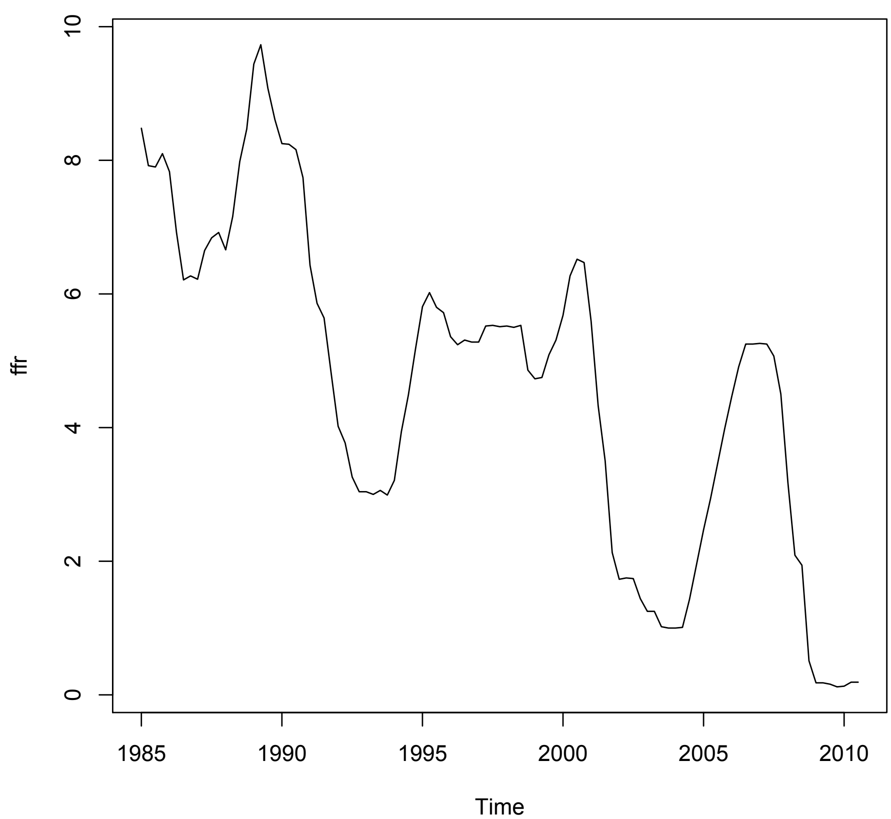

Figure 4.8: **Federal Funds Rate (1985:01-2010:03)**

depth and its length. In 2001 again, the Fed aggressively cut the federal funds rate from 7% down to 2% at end of the year. Again, these cuts were not enough to avoid recession, they clearly limited its depth and its length and also in 2009-2010 they cut from 5% down to 0.1% but the recession is still present.

CBO's Output Gap

The **CBO's output gap** is the gap between actual GDP and potential GDP and we use it to estimate the future course of inflation. The potential GDP is computed from the real gross domestic product, which comprises the output of five sectors: nonfarm business (GDP_{nfb}), government (GDP_{govt}), farm (GDP_{farm}), households and nonprofit institutions (GDP_{hhnp}), and residential

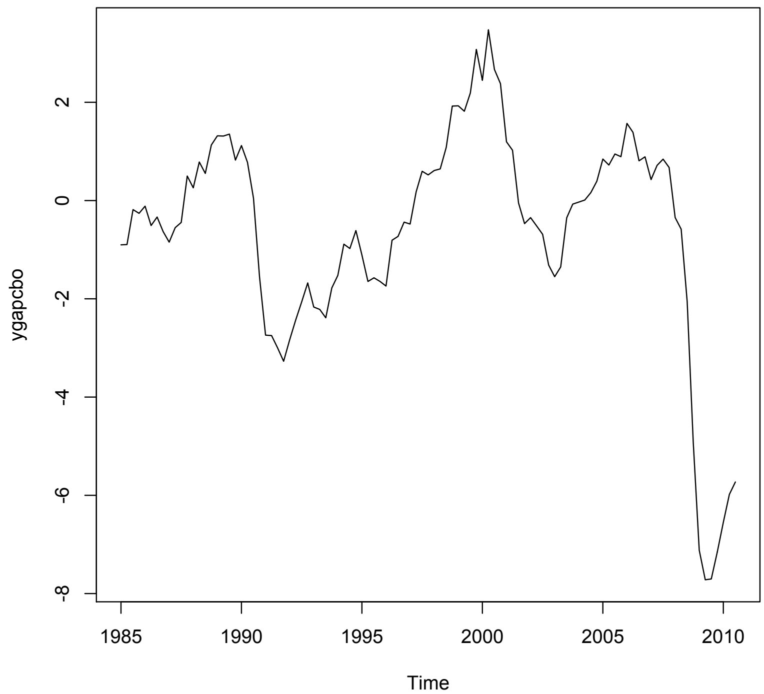

Figure 4.9: **CBO's Output Gap (1985:01-2010:03)**

housing ($\mathrm{GDP}_{\mathrm{housing}}$):

$$\mathrm{GDP} = \mathrm{GDP}_{\mathrm{nfb}} + \mathrm{GDP}_{\mathrm{govt}} + \mathrm{GDP}_{\mathrm{farm}} + \mathrm{GDP}_{\mathrm{hhnp}} + \mathrm{GDP}_{\mathrm{housing}}$$

where GDP is the gross domestic product.

In the figure 4.9 we see a small spike in the 1989, but also in the 2006. There is a big spike in the 1999-2000, reflecting the fact that the period was one of high optimism on the part of both firms and consumers. For firms, the New Economy appeared to promise high profits and thus to justify the high rates of investment, for the consumers the rise of the stock market justified high rates of consumption.

We see that in 2001 there is a decrease in the output gap, a short recession[11], because, feeling that economy was slowing down, the Fed aggressively decreased interest rates to stimulate demand. This was, however, not enough to avoid a small recession, but it would have surely been deeper and longer in the absence of the decrease in interest rate. This short recession followed a record-long US

[11]See the Appendix A.2.

expansion.

Otherwise the CBO's output gap decreases after the spikes and there is a collapse around the 2006, when the gap starts to decrease significantly till our days (the minimum (-7.7)) and it's related to the Great Recession.

4.2 Model without VIX index (1985:01-2010:03)

We estimate our model and we search the possible relationships between the policy uncertainty shocks, the labor market's variables and the inflation rate. We define the model without the VIX Index.

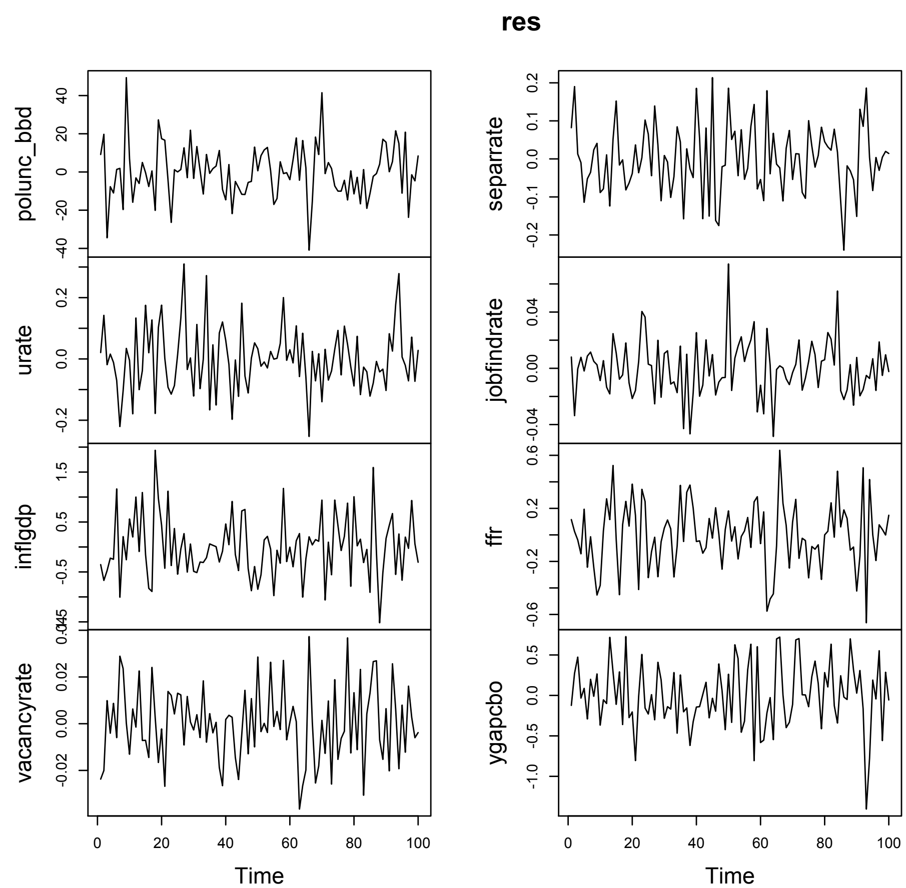

Figure 4.10: Residuals of the model without VIX index (1985:01-2010:03)

Our model is composed by a constant, a trend and then a vector of variables (data): POLUNCBBD is the policy uncertainty index, URATE is the unemployment rate, INFLGDP is the quarterly inflation rate, VACANCYRATE is the job creation rate, SEPARRATE is the job destruction rate, JOBFINDRATE is the finding rate, FFR is the federal fund rate and YGAPCBO is the CBO's output gap.

In this section we use the Vector Autoregressive (VAR) model and some of its function (the impulse response function and the forecast error variance decomposition) to understand and to discover the possible relationships between the policy uncertainty shocks and the labor market's variables.

VAR Analysis

Using the Akaike's Information Criterion we have a VAR(3) model and we estimate all the variables related to a VAR(3) model with constant and trend. After the VAR estimation, we see the residuals and their progresses and there are some positive and negative peaks in all the series and all the residuals have an oscillatory and stationary movement. Also we see that there are some problems due to last quarters of our data, specially during the financial crisis in 2008 and in the following section we study our results without the financial crisis' data.

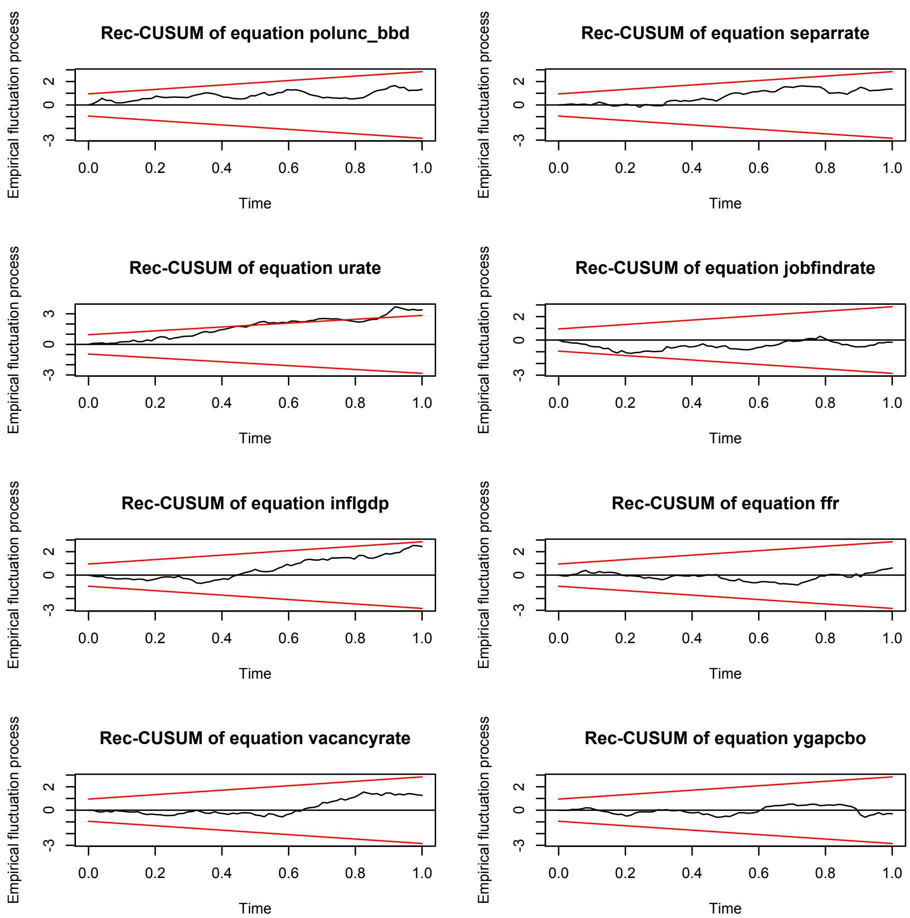

Figure 4.11: Rec-CUSUM stationary process

We analyze if in our model there are some important and structural changes and we use the Rec-CUSUM stationary function[12] for all the series.

From the figure 4.11 we see that we have some structural changes in the unemployment rate and also in the inflation rate, but if we do also the Recursive CUSUM test we see that:

```
> sctest(reccusum$stability$urate)

Recursive CUSUM test

data:  reccusum$stability$urate
S = 1.3021, p-value = 0.002142
```

and we reject the null hypothesis and we have structural changes in the unemployment rate. Analyzing the graphic 4.11, there are structural changes around the 1995-1996 and also in 2007-2008.

In fact in 1995-1996 there was the US federal government shutdown, conflicts between democratic president Clinton and the Congress over finding the medicare, education, environment and public health in the 1996 federal budget. In the 2007-2008 U.S. were affected by the subprime mortgage crisis, called "Great Recession".

Otherwise if we take the inflation rate test, we have:

```
> sctest(reccusum$stability$inflgdp)

Recursive CUSUM test

data:  reccusum$stability$inflgdp
S = 0.8593, p-value = 0.09391
```

and if we take the confidence level α by default 0.05, we accept the null hypothesis and we have no structural changes in the inflation rate that means that the inflation rate is stationary, otherwise if we take the confidence level equal to 0.1, we should refuse the null hypothesis and we have structural changes.

[12] The Rec-CUSUM processes contain cumulative sums of recursive standardized residuals.

Impulse Response Analysis

We know that if a variable k does not Granger-cause the set of remaining variables, then there is no effect between the former variable and all the other ones. In our case we have that all the variables cause the other so we proceed to the impulse response analysis.

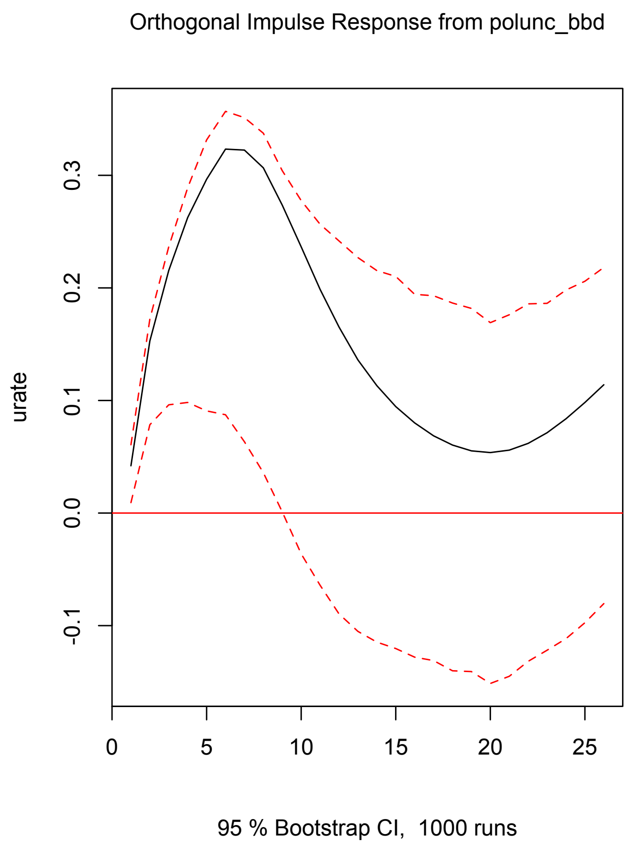

Figure 4.12: IRF of unemployment rate to policy uncertainty shocks (1985:01-2010:03)

First of all we start our analysis from the response of *unemployment* to an impulse in policy uncertainty index and we have from the figure (4.12) that a shock in economic policy leads to a strong increase in unemployment in the first 7 quarters. About 8 quarters after the shock there is a constant and persistent decrease in unemployment rate and after that it becomes constant. We can notice that a shock in economic policy leads always to a positive response in unemployment rate. So the policy uncertainty influences positively the unemployment rate.

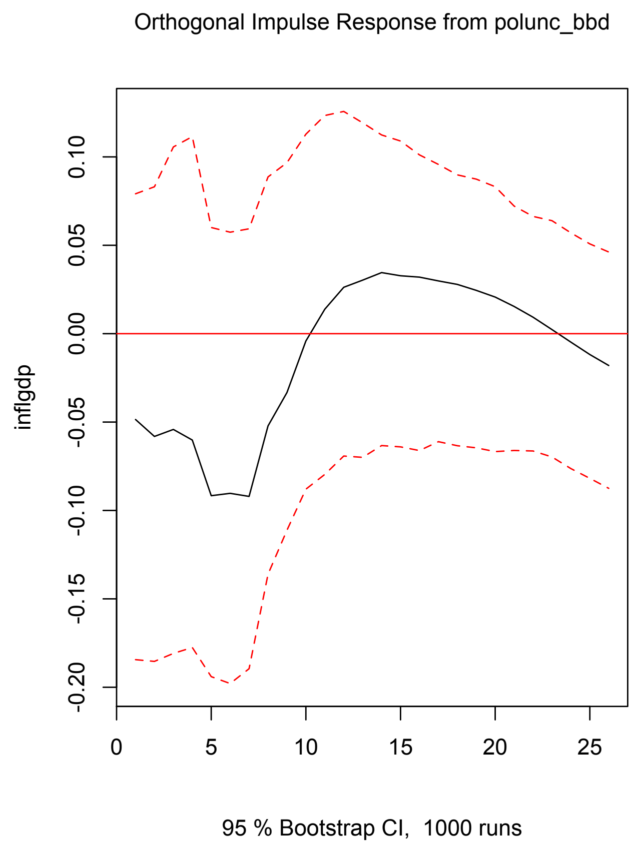

Figure 4.13: IRF of inflation rate to policy uncertainty shocks (1985:01-2010:03)

If we see (figure 4.13) the response of *inflation* to an impulse in policy uncertainty index, we have that a shock in economic policy leads to a negative and decreasing effect in inflation rate in the first 5/6 quarters. After 8 quarters we have an increasing and positive effect in inflation (for a small period) and then we have only a decrease effect in inflation. So we have that a shock in economic policy influences negatively the inflation rate and just for a small period this influence is positively, but the inflation rate is not influenced by the policy uncertainty shocks.

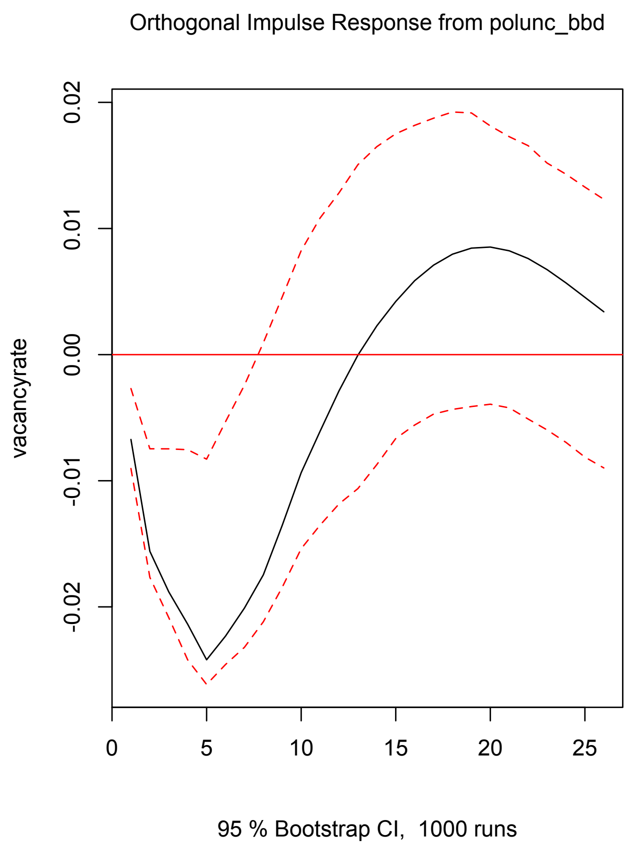

Figure 4.14: IRF of job creation's rate to policy uncertainty shocks (1985:01-2010:03)

Now we focus (figure 4.14) on the response of *job creation rate* to an impulse in policy uncertainty index and the shock in economic policy leads to a strong decrease in the job creation rate in the first 5 quarters (we can see a negative peak around 5 quarters after the shock). After that decreasing function, we have an increase in the job creation rate that leads to positive values. So we have that a shock in economic policy influences strongly and negatively the job creation rate in the first period.

If we analyze (figure 4.15) the response of *job destruction rate* to an impulse in economic policy, we have that a shock in economic policy leads to a positive increase in job destruction rate in the first 5 quarters (reaches a peak about 2 quarter after the shock). After 6 quarters there is a significant decrease that leads to a negative shock around 8 quarter. A shock leads to positive effects in job destruction rate in the first period.

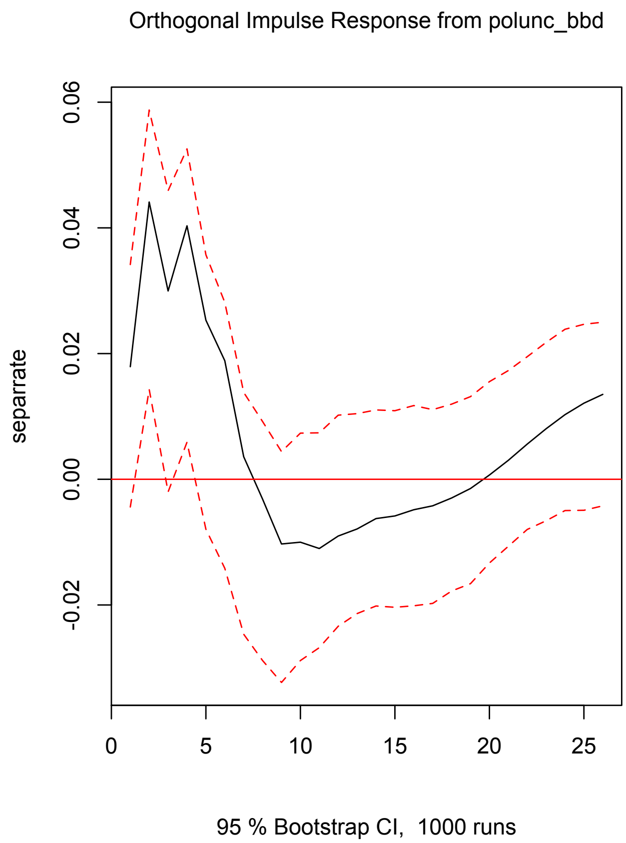

Figure 4.15: IRF of job destruction's rate to policy uncertainty shocks (1985:01-2010:03)

We can also analyze (figure 4.16) the response of *job finding rate* to an impulse in economic policy and a shock in economic policy leads to a decrease in job finding rate in the first 7 quarters. So we have that a shock in policy uncertainty influences negatively the job finding rate during all the period.

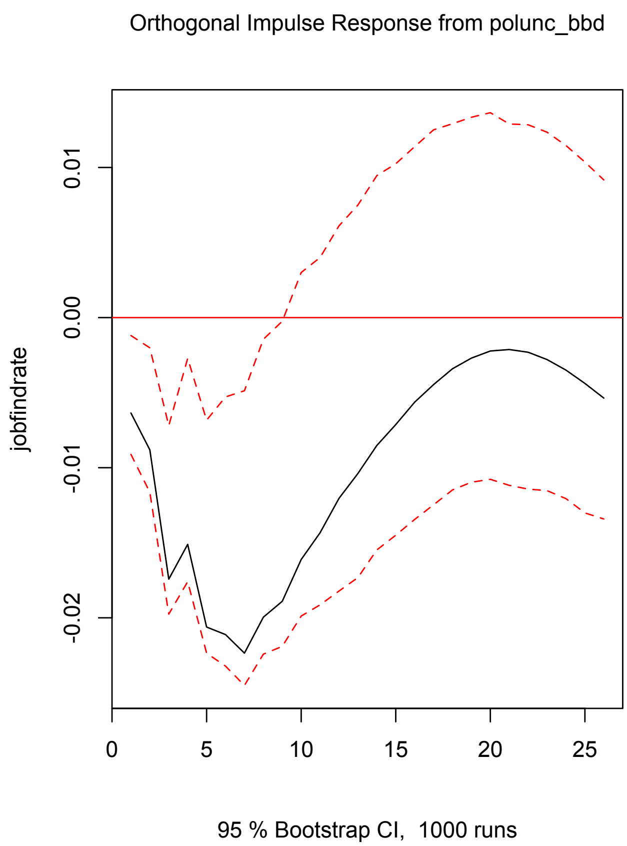

Figure 4.16: IRF of job finding rate to policy uncertainty shocks (1985:01-2010:03)

Forecast Error Variance Decomposition

We focus on the Forecast error variance decomposition (FEVD), which is based upon the orthogonalized impulse response coefficient matrices and allow us to analyze the contribution of variable j to the $h-$step forecast error variance of variable k. From Table 4.1 as years go by the economic policy uncertainty is influenced more by the unemployment, the inflation and the job finding rate

Table 4.1: FEVD of policy uncertainty index

	polunc	urate	inflgdp	vacancyr	separ	jobfind	ffr	ygap
2yrs ahead	73%	7%	3%	2%	2%	9%	2%	1%
4yrs ahead	58%	12%	10%	5%	2%	9%	2%	1%
10yrs ahead	37%	14%	16%	5%	2%	23%	1%	1%

shocks and less by its own shocks. From Table 4.2 the influence of economic

Table 4.2: FEVD of unemployment rate

	polunc	urate	inflgdp	vacancyr	separ	jobfind	ffr	ygap
2yrs ahead	50%	21%	3%	3%	2%	15%		6%
4yrs ahead	37%	20%	23%	3%	1%	11%	2%	3%
10yrs ahead	26%	18%	22%	5%	2%	23%	1%	2%

policy uncertainty shocks on the unemployment rate falls as years go by, otherwise the unemployment rate is influenced by the job finding and the inflation rate shocks. From Table 4.3 the inflation rate is always influenced by own shocks

Table 4.3: FEVD of inflation rate

	polunc	urate	inflgdp	vacancyr	separ	jobfind	ffr	ygap
2yrs ahead	4%	3%	66%	2%	3%	6%	1%	14%
4yrs ahead	3%	3%	62%	2%	4%	6%	2%	16%
10yrs ahead	5%	4%	60%	2%	4%	7%	2%	15%

and by the output gap shocks. From Table 4.4 the influence of economic policy uncertainty shocks and own shocks on the job creation's rate fall as years go by, otherwise the job creation's rate is influenced more by the inflation rate shocks.

From Table 4.5 the job destruction rate is influenced more by the inflation rate and job finding rate shocks and less by the economic policy uncertainty and own shocks.

From Table 4.6 the influence of economic policy uncertainty shocks fall as years go by and on the other hand the inflation rate and the unemployment rate shocks increase as years go by. From the last tables we have that the economic policy uncertainty shocks and the own shocks fall and in both cases we have that the influence of inflation rate and unemployment rate shocks increase as years go by.

We conclude that in a model without VIX index, the policy uncertainty shocks influence all the variables except the inflation rate, but this influence falls down as years go by and on the other hand the influence of the inflation rate increases.

Table 4.4: FEVD of job creation's rate

	polunc	urate	inflgdp	vacancyr	jobfind	ffr	ygap
2yrs ahead	47%	7%	14%	24%	3%	1%	3%
4yrs ahead	29%	6%	35%	15%	7%	2%	3%
10yrs ahead	25%	6%	36%	13%	9%	4%	6%

Table 4.5: FEVD of job destruction's rate

	polunc	urate	inflgdp	vacancyr	separ	jobfind	ffr	ygap
2yrs ahead	21%	16%	3%	3%	37%	7%	2%	12%
4yrs ahead	19%	15%	5%	9%	30%	7%	3%	10%
10yrs ahead	19%	14%	12%	7%	21%	16%	3%	8%

Table 4.6: FEVD of job finding rate

	polunc	urate	inflgdp	vacancyr	separ	jobfind	ffr	ygap
2yrs ahead	43%	6%	9%	8%	3%	27%		3%
4yrs ahead	29%	10%	36%	5%	1%	13%	2%	2%
10yrs ahead	24%	13%	31%	7%	3%	19%	2%	2%

Table 4.7: FEVD of federal fund rate

	polunc	urate	inflgdp	vacancyr	separ	jobfind	ffr	ygap
2yrs ahead	45%	2%	10%	16%	4%	7%	15%	
4yrs ahead	37%	10%	19%	12%	3%	5%	12%	2%
10yrs ahead	34%	8%	21%	13%	2%	7%	11%	2%

Table 4.8: FEVD of output gap

	polunc	urate	inflgdp	vacancyr	separ	jobfind	ffr	ygap
2yrs ahead	40%	9%	4%	4%		17%		24%
4yrs ahead	30%	11%	24%	4%		12%	2%	15%
10yrs ahead	24%	14%	24%	5%	2%	20%	1%	8%

4.3 Model with VIX index (1985:01 - 2010:03)

What happens if we add the VIX index? In this section we explore the effects of the VIX's introduction on our model.

VAR Analysis

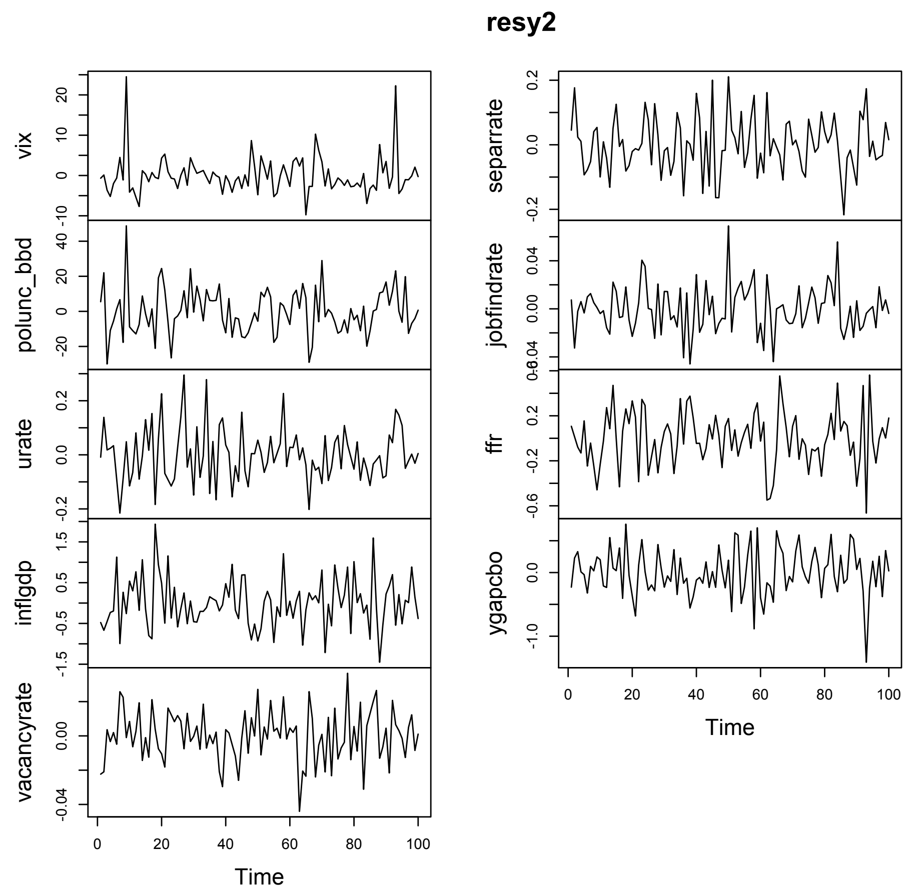

Figure 4.17: Residuals of the model with VIX index

We estimate the model using the VAR function and using the Akaike's information criterion (AIC) we have a VAR(3) model and we are interested in the estimation using a trend and a constant. As in the previous model we see (figure 4.17) that the residuals have the same trend and the same problem due to the 2007-2008 crisis period.

We keep attention on the presence or absence of structural changes in our model using the Rec-CUSUM stationary function.

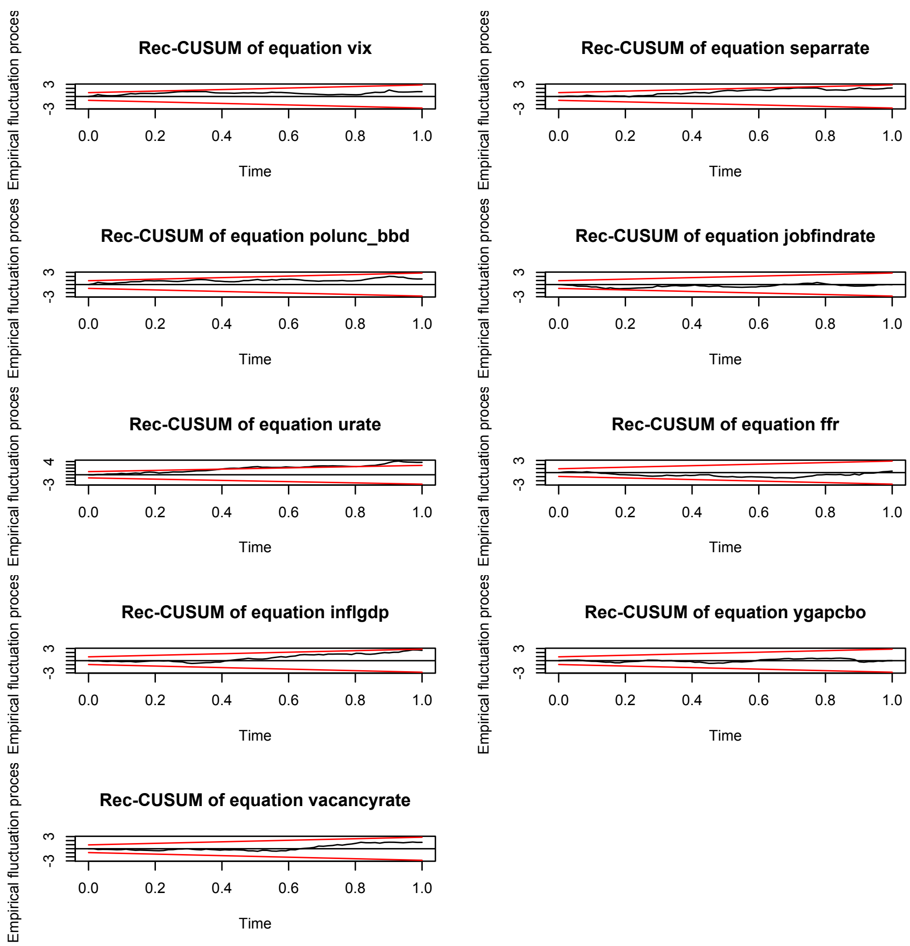

Figure 4.18: Rec-CUSUM stationary process

From the figure 4.18 we have possible structural changes in the unemployment rate, in the job destruction rate and in the inflation rate. Using the Recursive CUSUM test for the unemployment rate we have:

```
>  sctest(reccusumy2$stability$urate)

Recursive CUSUM test

data:  recura2
S = 1.4516, p-value = 0.0004182
```

and we reject the null hypothesis of absence of structural changes, so in our model we have structural changes in the unemployment rate. If we look at the job destruction rate we have:

```
>  sctest(reccusumy2$stability$separrate)

Recursive CUSUM test

data:  recsep2
S = 0.865, p-value = 0.09035
```

and if we take the confidence level α by default 0.05, we accept the null hypothesis and there are no structural changes in the job destruction rate. Otherwise if we decide to take the confidence level 0.1, we reject the null hypothesis and we have structural changes in the job destruction rate.

We can make the same analysis for the inflation rate, in fact we have that:

```
> sctest(reccusumy2$stability$inflgdp)

Recursive CUSUM test

data:  reccusumy2$stability$inflgdp
S = 0.902, p-value = 0.06982
```

and so there are some structural changes in the inflation rate only if we take a small confidence level α.

Impulse Response analysis

We study the impulse response function of a variable k to an impulse in policy uncertainty shocks.

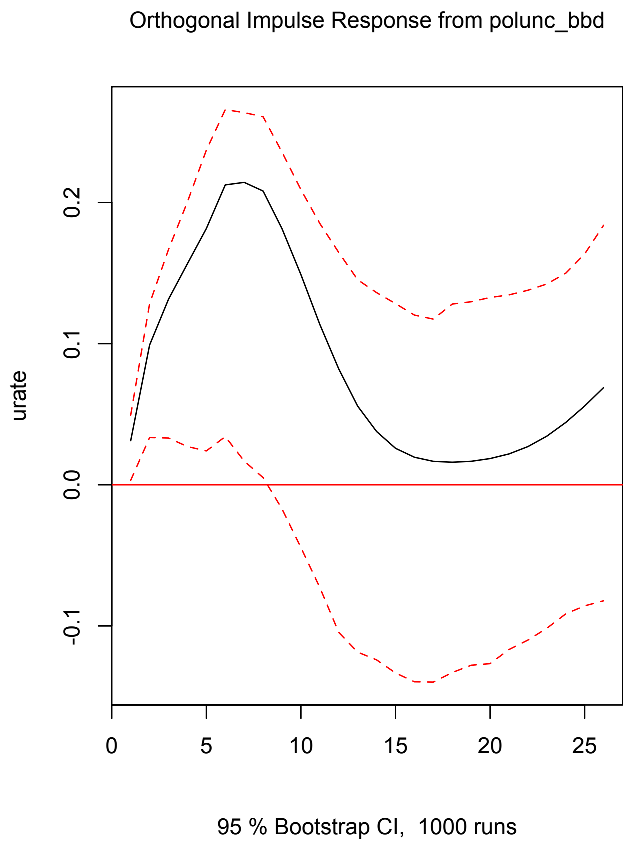

Figure 4.19: IRF of unemployment rate to policy uncertainty shocks (1985:01-2010:03)

We start our analysis from the response of unemployment rate to a policy uncertainty shocks and we have from the figure 4.19 that a shock in policy uncertainty leads to a strong increase in the first seven quarters (with a peak in 7 quarter). About 8 quarters after the shock there is a persistent decrease in the unemployment rate and we see that a shock in policy uncertainty leads always to a positive response in unemployment rate. Comparing the figure 4.12 and 4.19 there are not significant differences if we introduce or not the VIX index.

Is the inflation rate influenced by a shock in policy uncertainty? From the figure 4.20 a shock in policy uncertainty leads to a negative and decreasing effect in the inflation rate in the first six quarters and after the first period we have that the shock in policy uncertainty does not appear to drive changes in inflation rate. So we have that a shock in policy uncertainty influences negatively the inflation rate in the first period and after a certain period the inflation has no more changes.

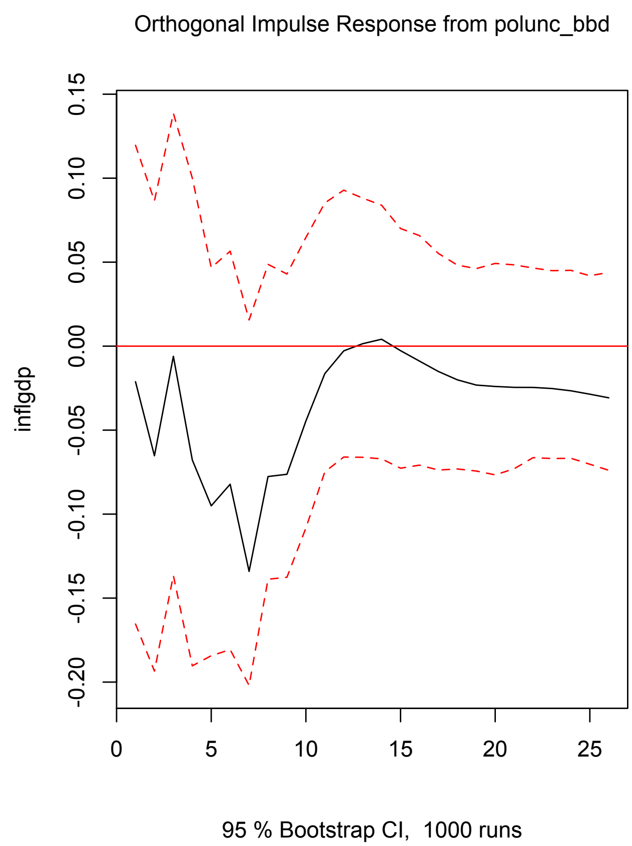

Figure 4.20: IRF of inflation rate to policy uncertainty shocks (1985:01-2010:03)

Now we focus on the labor market's variables and on their relationship with the policy uncertainty shocks. First of all, we focus on the response of the job creation rate to an impulse in policy uncertainty shocks.

From figure 4.21 we have that this shock leads to a strong decrease in the job creation rate in the first 5 quarters and after this shock of policy uncertainty we have a constant and persistent increase in the job creation rate that leads to positive values. So we have that a shock in policy uncertainty influences negatively the job creation rate and comparing figure 4.14 and 4.21 we have no changes.

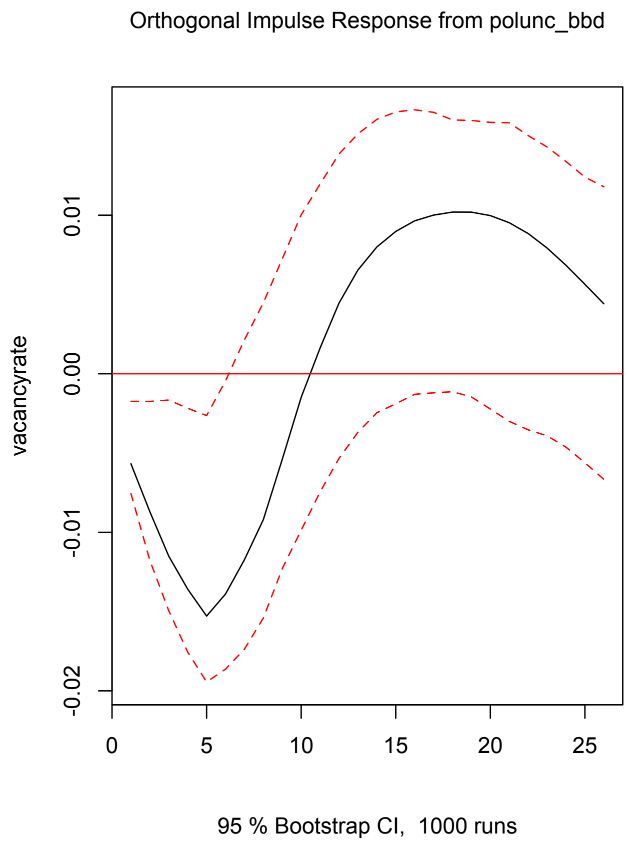

Figure 4.21: IRF of job creation rate to policy uncertainty shocks (1985:01-2010:03)

We continue our analysis with the impulse response of job destruction rate to our policy uncertainty shocks. From figure 4.22, we have that a shock in policy uncertainty leads to an increase in the first 4 quarters in the job destruction rate (with an important peak after 2 quarters) and after which we have a decreasing and negative function in the following 11 quarters. At the end we have that the policy uncertainty shocks become again positive and these shocks do not appear to drive changes in job destruction rate. So we have that a shock in policy uncertainty influences positively the job destruction rate.

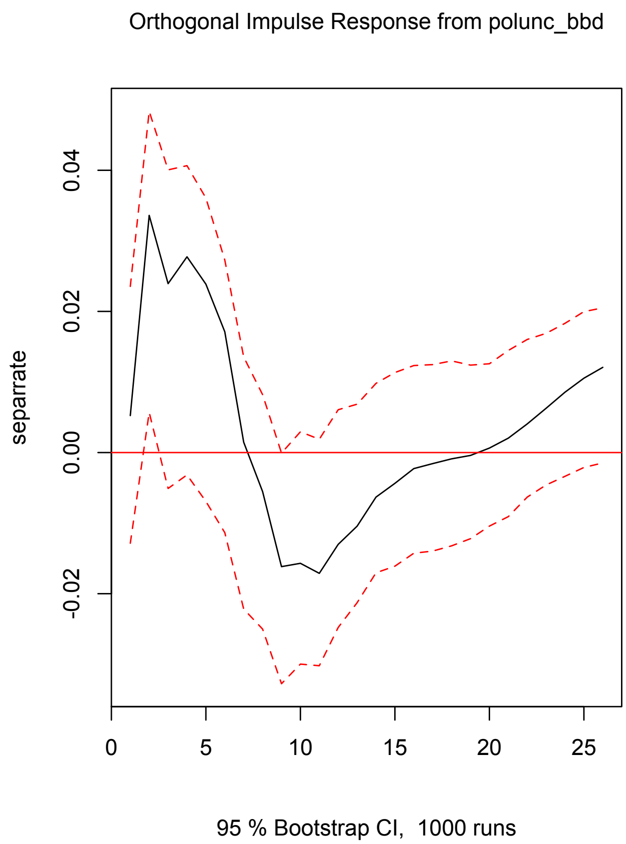

Figure 4.22: IRF of job destruction rate to policy uncertainty shocks (1985:01-2010:03)

In the last figure (4.23) we have that the response of job finding rate to an impulse in policy uncertainty shocks. A shock in policy uncertainty leads to a negative decrease in the job finding rate in the first 7 quarters. After 8 quarters there is a negative increase that does not influence so much the job finding rate and so we have that a shock in policy uncertainty influences negatively the job destruction rate.

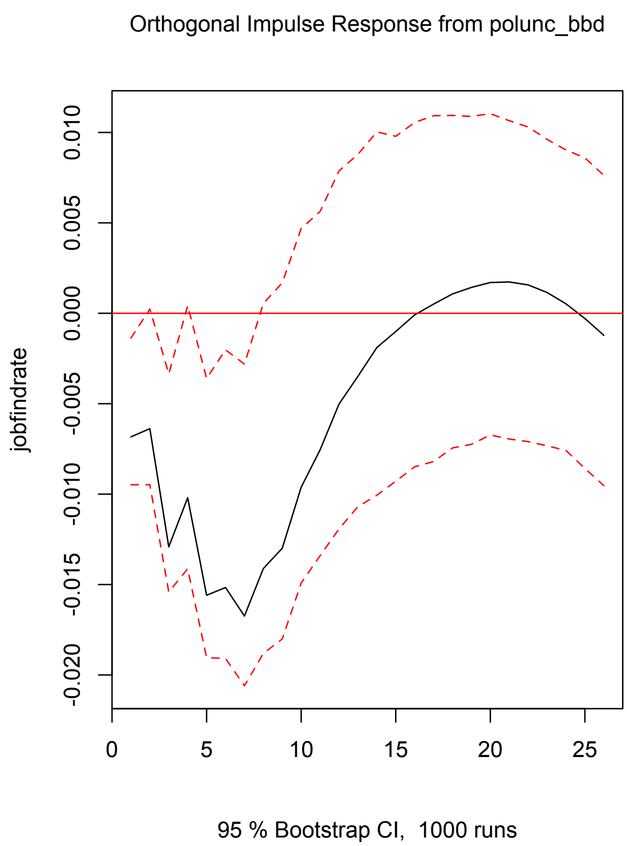

Figure 4.23: IRF of job finding rate to policy uncertainty shocks (1985:01-2010:03)

Forecast Error Variance Decomposition Analysis

We have some changes in the forecast variance decomposition analysis when we add the VIX index. From Table 4.10 the economic policy uncertainty is influenced more by the inflation, job finding rate shocks as years go by and

Table 4.9: FEVD of VIX index

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	76%	2%	2%	4%		5%	7%	3%	
4yrs ahead	69%	2%	2%	6%	3%	4%	7%	3%	2%
10yrs ahead	49%	6%	5%	15%	3%	3%	12%	3%	3%

less by its own shocks and by VIX shocks The same situation happens if we

Table 4.10: FEVD of policy uncertainty

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	42%	29%	5%	5%	3%	2%	9%	2%	1%
4yrs ahead	35%	23%	8%	13%	6%	1%	10%	3%	1%
10yrs ahead	21%	18%	10%	19%	5%	1%	22%	2%	1%

look the Table 4.11, in fact the influence of economic policy uncertainty and VIX shocks on the unemployment rate falls as years go by, when the inflation and job finding rate shocks increase. As in the model without VIX index, the

Table 4.11: FEVD of unemployment rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	32%	21%	19%	5%	4%		12%		5%
4yrs ahead	22%	14%	16%	28%	4%		9%	2%	3%
10yrs ahead	14%	12%	14%	28%	4%	2%	22%	1%	2%

inflation rate follows the same properties and it is influenced only by own shocks.

If we look at the labor market variables (from Table 4.13 to Table 4.15), we have that as years go by these variables are influenced more by own shocks and inflation rate shocks and on the other hand less by the economic policy shocks and VIX shocks. From Table 4.16 the influence of inflation rate shocks on the federal funds rate increases as years go by, and on the other hand we have that the influence of economic policy uncertainty, VIX, job destruction's rate and own shocks falls. The last Table 4.17 tells us that the output gap is influenced more by inflation and job finding rate shocks as years go by and less by the VIX, economic policy uncertainty and own shocks.

So the introduction of the VIX index leads some changes in the forecast error variance decomposition, because the policy uncertainty shock loses importances and the VIX index influences the variables.

In the next section we focus on the data analysis without the financial crisis' data and we study the differences, if exist, between the two previous models and the following two.

Table 4.12: FEVD of inflation rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	5%	5%	3%	64%	2%	3%	4%	1%	13%
4yrs ahead	5%	5%	3%	58%	2%	4%	4%	3%	15%
10yrs ahead	5%	2%	4%	57%	2%	4%	5%	3%	14%

Table 4.13: FEVD of job creation's rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	25%	19%	5%	17%	26%		3%	3%	2%
4yrs ahead	15%	13%	4%	40%	16%		5%	5%	3%
10yrs ahead	12%	13%	5%	40%	12%		5%	5%	6%

Table 4.14: FEVD of job destruction's rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	12%	13%	15%	2%	3%	35%	6%	2%	11%
4yrs ahead	10%	14%	14%	6%	8%	29%	6%	4%	9%
10yrs ahead	10%	14%	13%	13%	7%	20%	11%	4%	8%

Table 4.15: FEVD of job finding rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	21%	24%	5%	10%	10%	3%	23%		3%
4yrs ahead	14%	14%	7%	41%	5%	2%	12%	3%	1%
10yrs ahead	11%	11%	8%	38%	6%	2%	18%	3%	3%

Table 4.16: FEVD of federal fund rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	31%	17%	1%	9%	19%	2%	6%	14%	
4yrs ahead	25%	13%	6%	22%	13%	2%	4%	14%	1%
10yrs ahead	21%	14%	6%	24%	13%	2%	4%	12%	3%

Table 4.17: FEVD of output gap

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	27%	20%	8%	5%	4%		13%	2%	20%
4yrs ahead	19%	13%	9%	28%	4%		10%	4%	13%
10yrs ahead	13%	12%	11%	29%	4%	1%	20%	2%	7%

4.4 Model without VIX index (1985:01-2008:02)

What happens before the financial crisis in the 2008? In this section we decide to analyse the situation till the second quarter of 2008. For doing that we delete the data related to the crisis' year from the second quarter of 2008 to the third quarter of 2010 and we would like to know if there are some differences respect to the previous analysis.

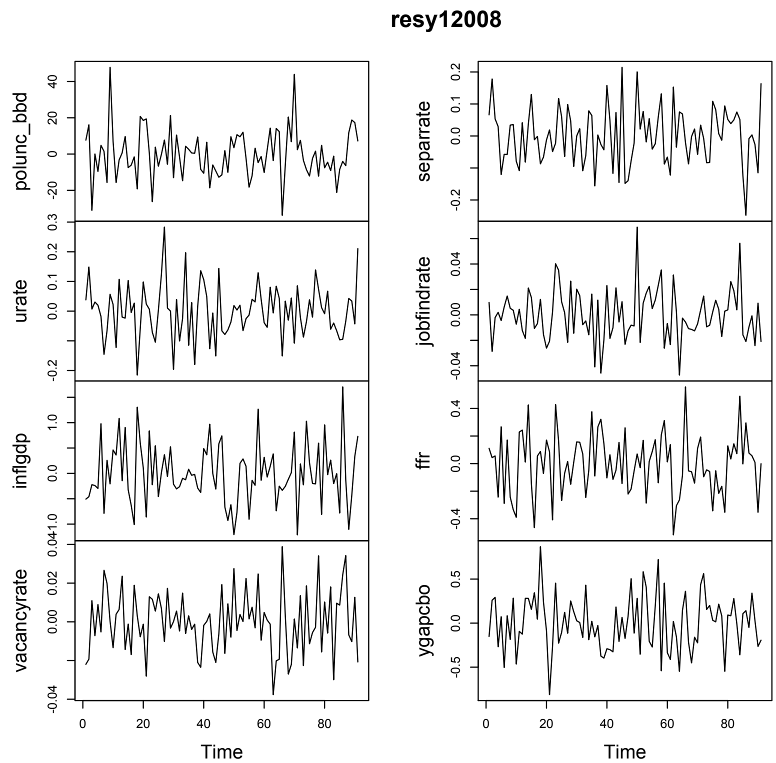

Figure 4.24: Residuals of the model without VIX index (1985:01-2008:02)

VAR Analysis

We estimate using the AIC criterion and we have as before a VAR(3) with a constant and trend. We start our analysis from the residuals of our model and from the figure 4.24 we have a loss of the peaks at the end of all the series specially in the output gap series.

We study if there are some structural changes and we use the same function as before and from figure 4.25 we have the possibility of structural changes in the unemployment rate.

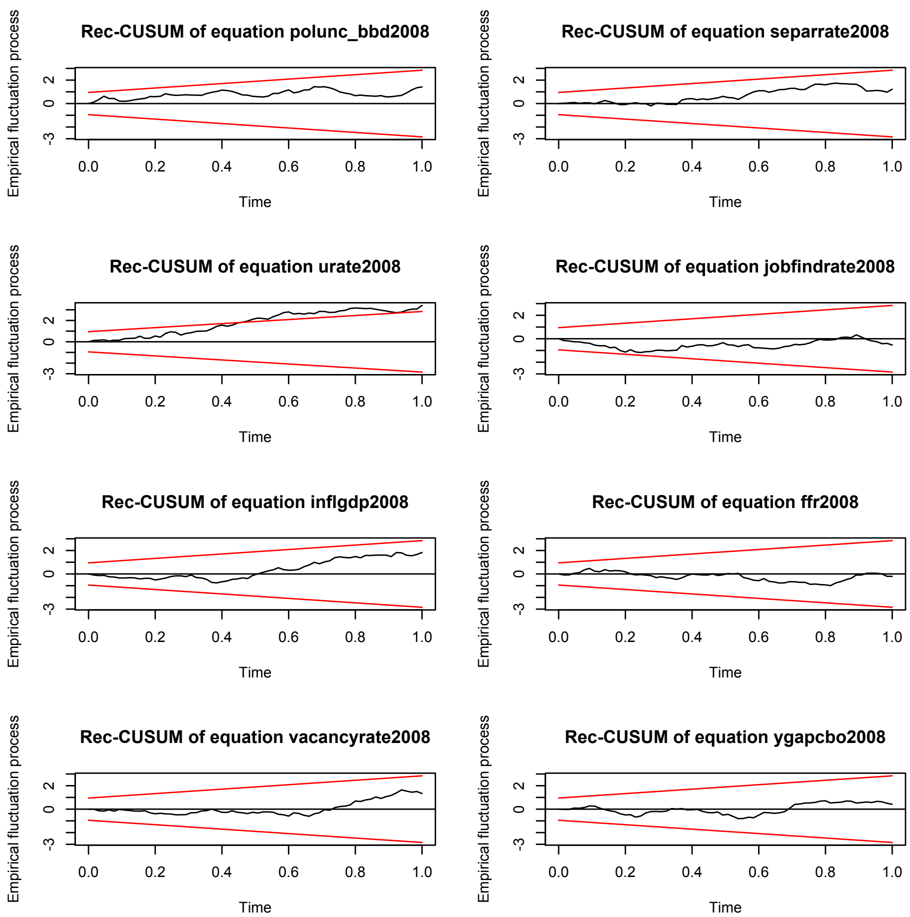

Figure 4.25: Rec-CUSUM stationary process (1985:01-2008:02)

In fact we make the recursive-CUSUM test and we see:

```
>  sctest(recy12008$stability$urate)

Recursive CUSUM test

data:  recy12008$stability$urate
S = 1.274, p-value = 0.002856
```

and we reject the null hypothesis and so there are some structural changes in the unemployment rate like in the general model and we have the same peak around 1995/1996. Otherwise the situation is completely different in the other variables, because we accept always the null hypothesis and we have no structural changes, specially for the inflation rate:

```
> sctest(recy12008$stability$inflgdp)

Recursive CUSUM test

data:  recy12008$stability$inflgdp
S = 0.6418, p-value = 0.3379
```

Impulse Response Analysis

If we cut the financial crisis's data, what happens to the impulse response function of a labor market's variable subject to a policy uncertainty shock? We start our analysis from the unemployment rate.

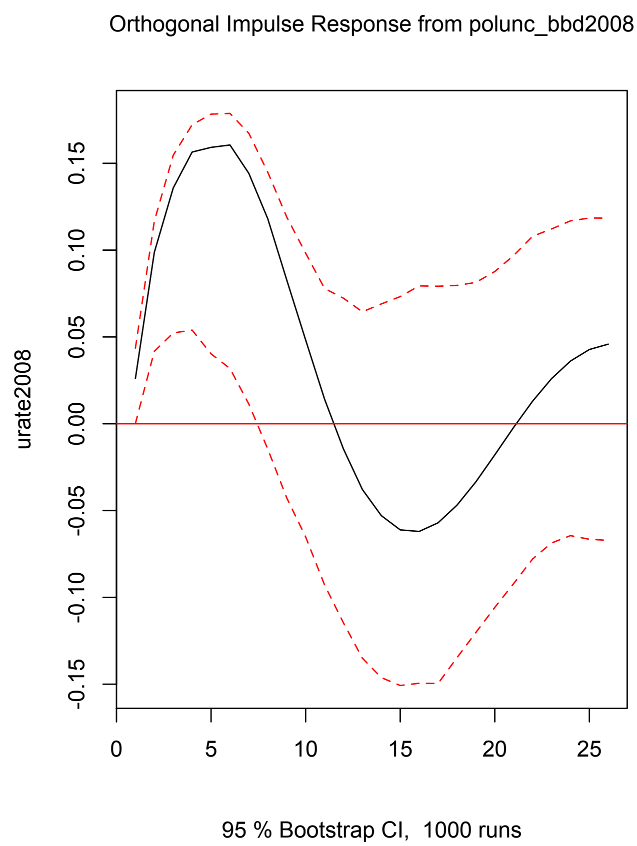

Figure 4.26: IRF of unemployment rate to policy uncertainty shocks to 2008:02

From Figure 4.26, we see that a shock in policy uncertainty leads to the same increase as in the previous case, we have only a variation, because the decreasing function becomes also negative. The cut of the financial crisis' data does not change the impulse response analysis and the policy uncertainty shock influences positively the unemployment rate.

We focus on the inflation rate and on the relationships between the policy uncertainty shocks and the inflation rate.

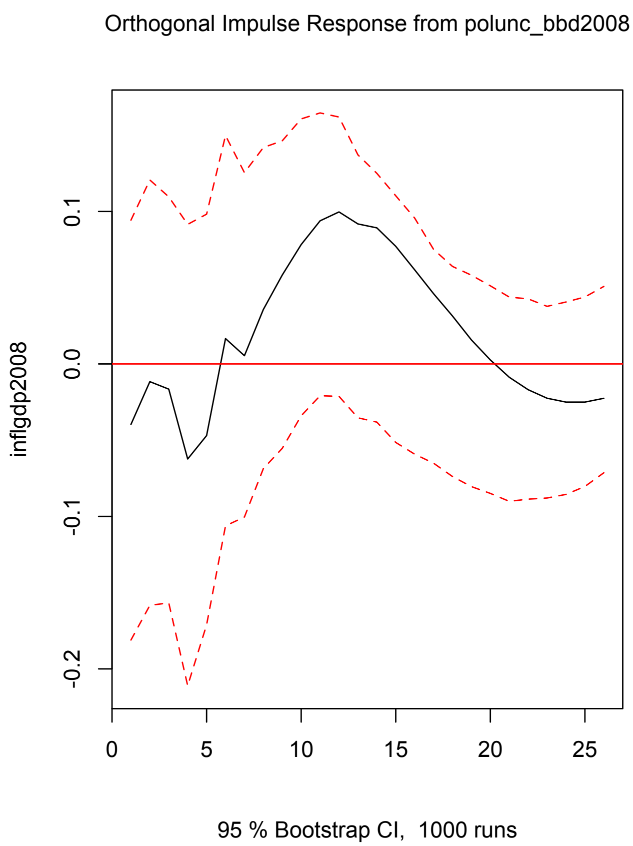

Figure 4.27: IRF of inflation rate to policy uncertainty shocks to 2008:02

From figure 4.27 we see that there are no reactions of the inflation rate to a policy uncertainty shock.

Now we focus on the labor market's variable: the job creation rate, the job destruction rate and the job finding rate.

From figure 4.28, a shock in policy uncertainty leads to a decrease in the job creation rate in the first period and the shocks in policy uncertainty have negative effects on the job creation rate as in the general model.

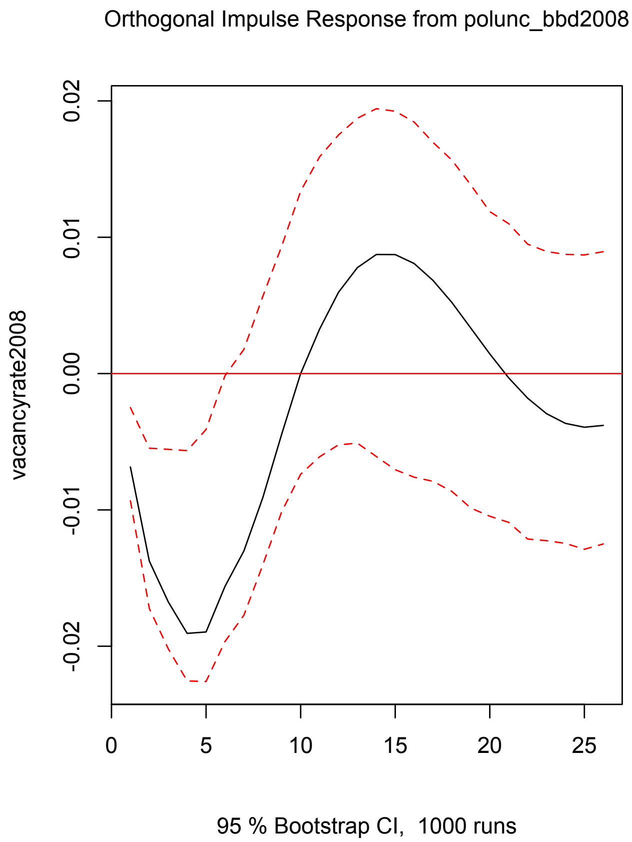

Figure 4.28: IRF of job creation rate to policy uncertainty shocks to 2008:02

In the following figure 4.29 we have that a shock in policy uncertainty leads to a strong increase in the job destruction rate in the first period and the job destruction rate is influenced positively and strongly by a shock in policy uncertainty shock.

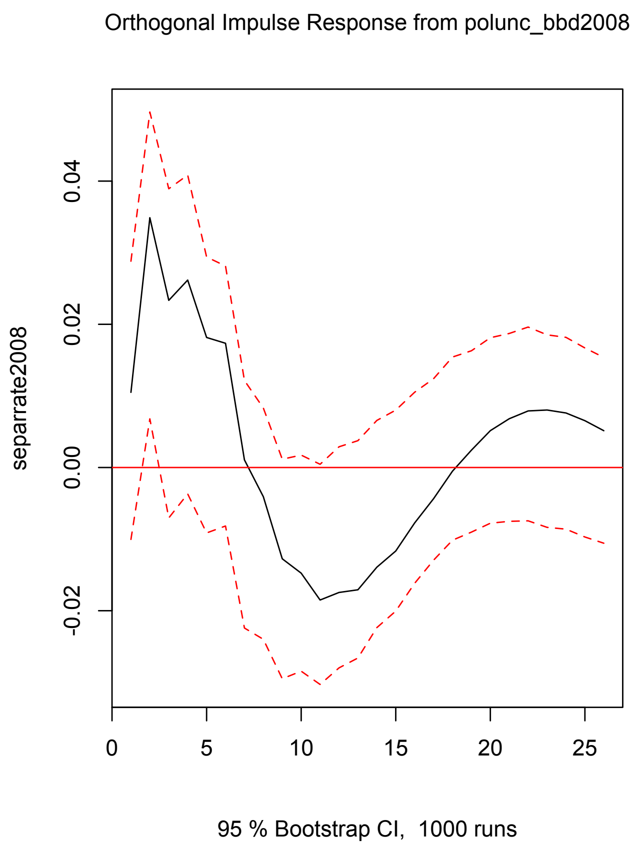

Figure 4.29: IRF of job destruction rate to policy uncertainty shocks to 2008:02

Finally in the job finding rate (figure 4.30), there is a decrease in the job finding rate due to a policy uncertainty shock and this shock has negative effects on the opportunity of finding a new job.

If we continue our analysis[13], we have that there are some differences between the forecast error variance decomposition in general and restricted model. The unemployment rate is influenced more by the output gap and the federal funds rate shocks than the general model as years go by and less by the job finding rate and unemployment shocks.

From Table C.4 and Table C.6 the output gap shocks influence more the job creation's rate and the job finding rate than the general model.

From Table C.8 the output gap is influenced more by the own, the federal funds rate and job creation's rate shocks as years go by and less by the

[13]See the tables in Appendix C.1.

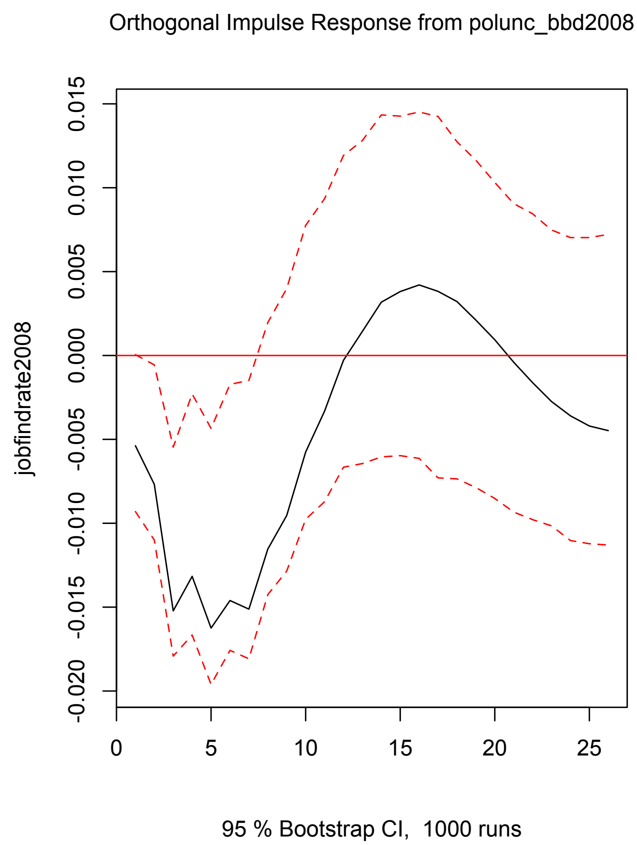

Figure 4.30: IRF of job finding rate to policy uncertainty shocks to 2008:02

unemployment rate and the job finding rate shocks.

4.5 Model with VIX index (1985:01- 2008:02)

In this section we continue the latter analysis introducing the VIX index. So we have delete the data related to the financial crisis and we search if there are some relations between the policy shocks and the unemployment rate and if these relationships are more (respectively less) important than in the general model.

VAR Analysis

From the figure 4.31, as in the previous model the residuals improve, because we lose the negative peaks, specially in the output gap variable.

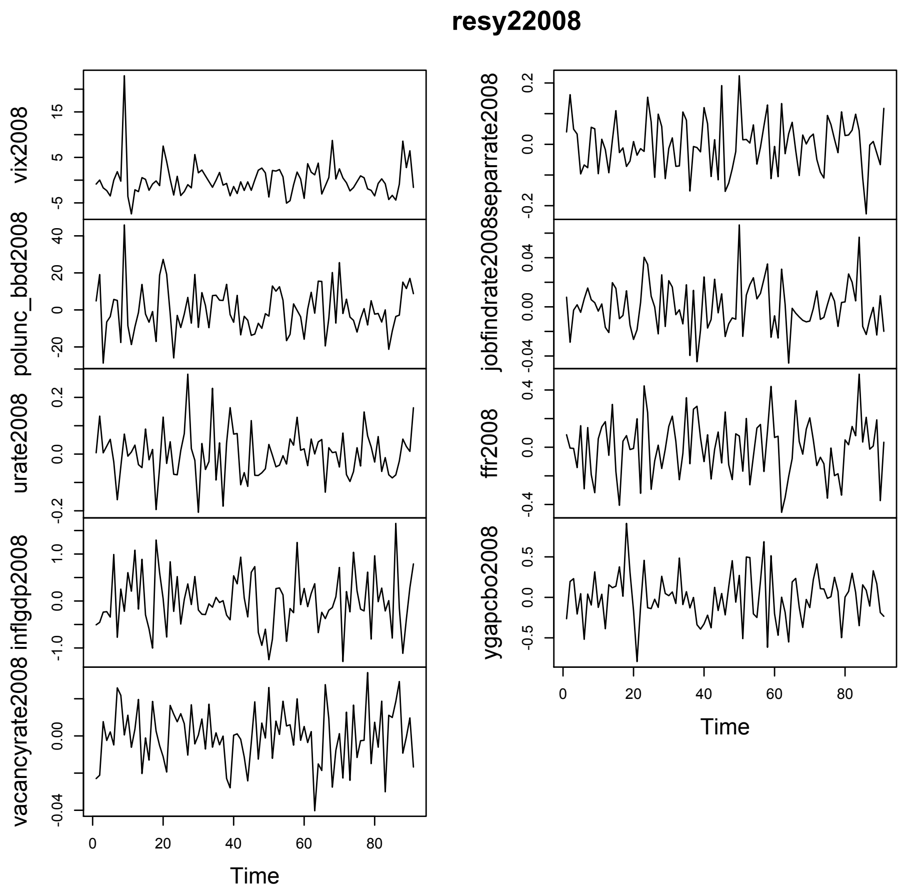

Figure 4.31: Residuals of the model with VIX index (1985:01 - 2008:02)

We have estimated as always the model using the same criterium and we have a VAR(3) model with trend and constant. Comparing this model with the general one, there are some important structural changes specially in the unemployment rate, in the job destruction one and in the VIX index (Figure 4.32), but not in the inflation rate.

If we do the the Recursive CUSUM test for these three variables, we can see:

```
>  sctest(recy22008$stability$urate)
```

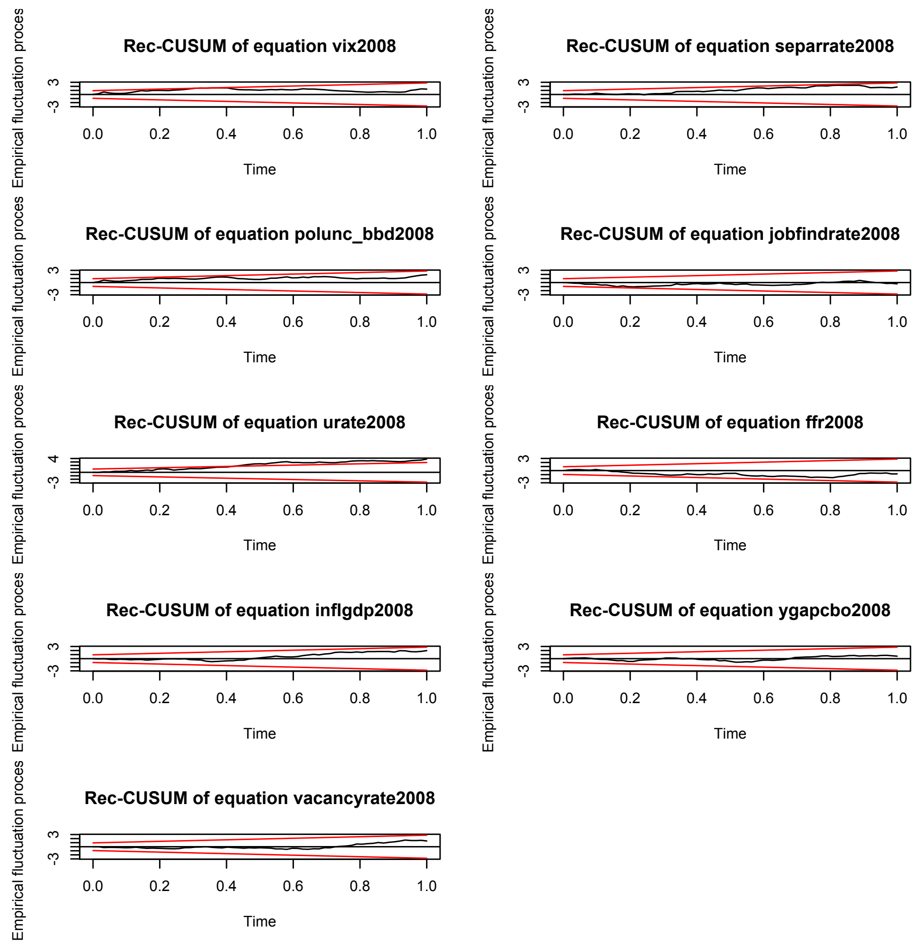

Figure 4.32: Rec-CUSUM stationary process with VIX(1985:01- 2008:02)

```
Recursive CUSUM test

data:  recy22008$stability$urate
S = 1.4238, p-value = 0.0005747
```

and we refuse the null hypothesis and so there are some structural changes in the unemployment rate. If we construct the same test for the VIX index and the job destruction rate:

```
>  sctest(recy22008$stability$vix)

Recursive CUSUM test

data:  recy22008$stability$vix
```

```
S = 0.9745, p-value = 0.04088

>  sctest(recy22008$stability$separrate)

Recursive CUSUM test

data:  recy22008$stability$separrate
S = 0.8599, p-value = 0.09354
```

So we have structural changes in the VIX index and also in the job destruction rate, but only if we choose a confidence level $\alpha = 0.1$, otherwise we accept the null hypothesis.

If we look at the inflation rate in this model and in the relative figure, there are no structural changes:

```
> sctest(recy22008$stability$inflgdp)

Recursive CUSUM test

data:  recy22008$stability$inflgdp
S = 0.6933, p-value = 0.2583
```

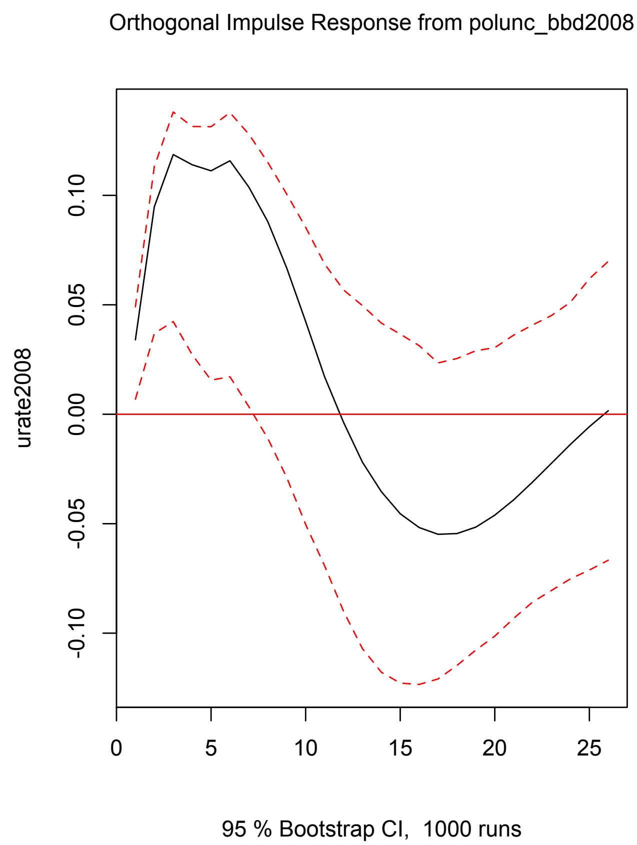

Figure 4.33: IRF of unemployment rate to policy uncertainty shocks to 2008

Impulse Response Analysis

What about the relations between the policy uncertainty shocks and the labor market's variables (unemployment rate, job destruction rate,...)? Do we see some important changes? In this section we focus on possible effects of the policy uncertainty shocks in the period before the current financial crisis.

We start our analysis from the possible relations between the policy uncertainty shocks and the unemployment rate. From figure 4.33, there are positive effects of policy uncertainty shocks on the unemployment rate in the first period as in the general model and then negative effects for a short period. Finally the policy uncertainty shocks in both the models have the same effects on the unemployment rate.

From Figure 4.34 we have that the shock to policy uncertainty does not

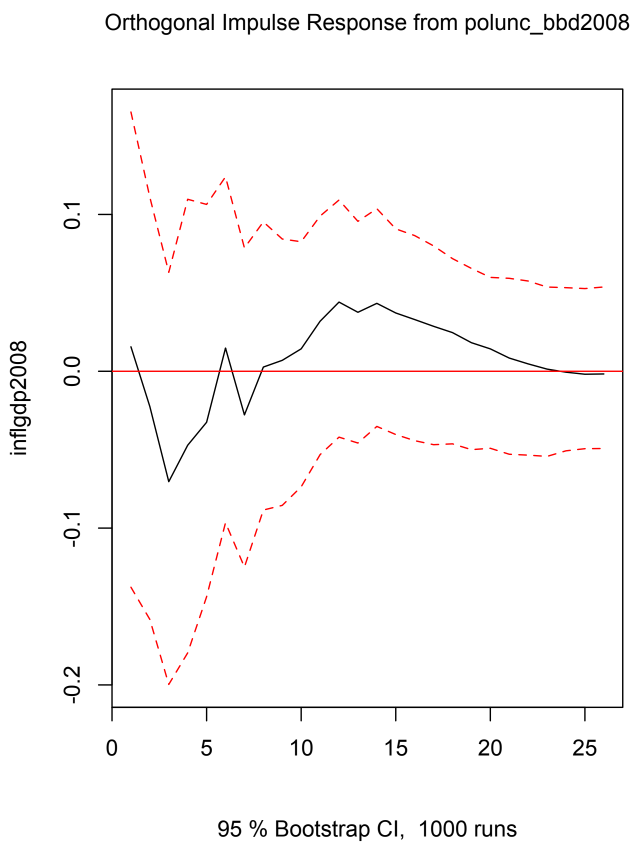

Figure 4.34: IRF of inflation rate to policy uncertainty shocks to 2008

appear to drive changes in inflation rate as in the model without VIX and without financial crisis' data. In the job creation, job destruction and job finding rate the differences between the "restricted" and general models are indifferent in the impulse response analysis function.

In the forecast error variance deviation[14] there are some differences in the unemployment rate, in the labor market variables and in the output gap. In fact the unemployment rate is influenced more by the federal funds rate and output gap shocks and less by own shocks and job finding rate shocks as years go by.

From Table C.13 to Table C.15 the labor market's variables are influenced more by the output gap and federal funds rate shocks, on the other hand they

[14]See the tables in Appendix C.2.

are influenced less by the job finding rate shocks and VIX shocks.

From Table C.17 we have that the output gap is influenced more by the own, the federal funds rate and the job creation's rate shocks than in the general model and less by the unemployment rate and job finding rate shocks as years go by.

In the next section we continue our analysis using a new policy uncertainty index and we look if there are some differences between the old and the new index.

4.6 New Policy Uncertainty Index

In 2013 Baker, Bloom and Davis [3] revised the economic policy uncertainty index and in this section we see the possible differences between the original and the new index and if these differences influence the impulse response analysis and the possible relationship between shocks and labor market's variables.

This index has three component as the old one. The first component quantifies newspaper coverage of policy-related economic uncertainty, the second one reflects the number and size of federal tax code provisions set to expire in future years and the last component uses disagreement among economic forecasters about policy variables as a proxy for uncertainty.

News coverage about policy-related economic uncertainty

This component is an index related to search results from 10 large US newspapers as in the previous index. They perform month-by-month searches of each paper, starting in January 1985, for terms related to economic and policy uncertainty. They search for articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'congress'. 'deficit', 'federal reserve', 'legislation', 'regulation' or 'white house'.

To create the index, they normalize the raw counts of EPU[15]- related articles by the total number of monthly news articles in the same newspapers. Then they normalize each newspaper index to have a standard-deviation of 1 over 1985-2009 and add up the indices for all 10 papers. They rescale the overall series so it averages to an average values of 100 from 1985-2009.

Tax Code Expiration Data

The Tax Code Expiration Data base on data from the CBO: lists of temporary federal tax code provisions set to expire in future years. Temporary tax measures are a source of uncertainty for both businesses and households because Congress often decides to extend them at the last minute, undermining stability of and certainty about the tax code.

[15]Economic Policy Uncertainty Index

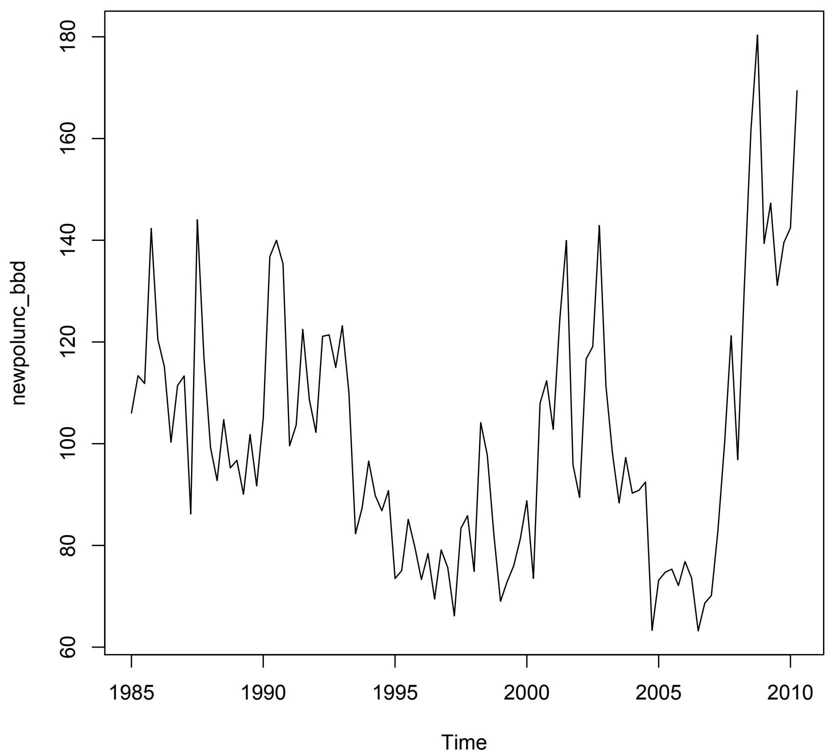

Figure 4.35: **New Policy-Related Economic Uncertainty Index (1985:01-2010:03)**

Two examples are related to Bush-era and Obama-era. The first one involves the Bush-era income tax cuts originally set to expire at the end of 2010, Democrats and Republicans keep opposing positions about whether reverse these tax cuts and for which taxpayers. Instead of solving the uncertainty in advance, Congress waited until December 2010 before acting.

The second example is related to Fiscal Cliff crisis in December 2012. There was a discussion between Democrats and Republicans on the increase in the payroll tax and at the end an agreement was reached: an increase in the payroll tax by two percentage points to 6.2% for income up to $113,700 and a reversal of the Bush tax cuts for individuals making more than $400,000 and couples making over $450,000, and also an increase in the tax on investment income from 15% to 23.8% for filers in the top income bracket and a 3.8% surtax on investment income for individuals earning more than $200,000 and couples making more than $250,000.

The CBO reports contain data on scheduled expirations of federal tax code provisions in the contemporaneous calendar year and each of the following 10 years. They apply a simple weighting to the data in January of each year, they sum the total amount of the expiring tax provisions for each year in a 10-year horizon (using the absolute value of dollars, as some expiring provisions are taxes and some are tax cuts). Then they discount these future expirations by 50% per year, and sum the discounted number of dollar-weighted tax code expirations to obtain an index values for each January. They use a high discount rate because many expiring tax code provisions are regularly renewed, and are unlikely to be a major source of uncertainty until the expiration date looms near.

Economic Forecaster Disagreement

The last component of the index draws on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF). This quarterly survey covers a wide range of macroeconomic variables. Each quarter, every forecaster receives a form in which to fill out values corresponding to forecasts for a variety of variables in each of the next five quarters.

They use the individual-level data for three of the forecast variables, the consumer price index (CPI), purchase of goods and services by state and local governments, and purchase of goods and services by the federal government. For each series, they forecast quarterly for one year in the future and they choose these variables because they are directly influenced by monetary policy and fiscal policy decisions.

They deal the dispersion in the forecasts of these variables as proxies for uncertainty about future monetary policy and about government purchases of goods and services at the federal, state, and local level. For inflation, they look at the individual forecasts for the quarterly inflation rates four quarters in the future, and to construct the dispersion component, they take the interquartile range.

For both federal and state and local government purchases, they divide the interquartile range of four-quarter-ahead forecasts by the median four-quarter-ahead forecast and multiply that quantity by a 5-year backward-looking moving average for the ratio of nominal purchases, either federal or state/local, to nominal GDP. We keep the values of the forecasters disagreement measures constant within each calendar quarter. At the end, they sum the two indices, weighted by their nominal sizes, to construct a single federal/state/local index.

Construction of Economic Policy Uncertainty Index

To construct the overall index of policy-related economy uncertainty, they normalize each component by its own standard deviation prior to January 2012, then compute the average value of the components, using weights of 1/2 on broad news-based policy uncertainty index and 1/6 on each of other three measures (the tax expirations index, the CPI forecast disagreement measure, and the federal/state/local purchases disagreement measure). They set the pre-1991 tax expiration index equals to its 1991 value and at the end they normalize overall index to have a value of 100 from 1985 to 2009.

From figure 4.35 the new policy uncertainty index has no differences with respect to the old policy uncertainty index.

VAR Analysis

Using the new policy uncertainty variable, we have the same results as before, in fact we have some structural changes in the unemployment rate:

```
>  sctest(n1reccusum1$stability$urate)

Recursive CUSUM test

data:  n1reccusum1$stability$urate
S = 1.3074, p-value = 0.002028
```

But we have no more structural changes in the inflation rate, but only in the job finding rate, if we use the right confidence level $\alpha = 0.1$:

```
>  sctest(n1reccusum1$stability$jobfindrate)

Recursive CUSUM test

data:  n1reccusum1$stability$jobfindrate
S = 0.8701, p-value = 0.08727
```

Also using the impulse response function we have no more changes between the old and the new policy uncertainty index.

What happens if we add the VIX index? Are there any change in our analysis? If we look at the residuals, there are no changes, but doing the recursive CUSUM test, we have some differences. In fact we have the structural changes in the job destruction rate and in the unemployment rate but no more in the inflation rate:

```
> sctest(n1reccusum2$stability$inflgdp)

Recursive CUSUM test

data:  n1reccusum2$stability$inflgdp
S = 0.6241, p-value = 0.3687
```

Studying the impulse response function and the forecast error variance decomposition, we have no differences in the relationships between the policy uncertainty shocks and the labor market's variables.

In conclusion the new policy uncertainty index is not different from the old one, except from some theoretical aspects. In the last part of the paper, we draw the conclusions from all these different models that we have analyzed.

Chapter 5

Conclusions

Uncertainty has become the subject of hot debates and the focus on a variety of articles from the recession of 2007-2009. The thesis seeks to investigate the importance of a particular type of uncertainty, namely, economic policy uncertainty. It does so by employing an indicator of economic policy uncertainty for the U.S. economy recently developed by Baker, Bloom, and Davis (2013). We exploit exogenous variations of such indicator, identified in the context of a VAR approach, to isolate the role played by such type of uncertainty as for the dynamics of the U.S. labor market. We find such shocks to be quite relevant for understanding the dynamics of unemployment and a number of other labor market-related indicators in the United States in the post-WWII period.

The recent contribution of Bloom (2009) has revamped the interest in uncertainty shocks. If firms has no-convex adjustment costs, these uncertainty shocks will generate powerful real-option effects, pausing the build up of investments and the hiring process by entrepreneurs. Recessions might very well be caused by exogenous variations in uncertainty – indeed, some recent macroeconomic investigations have found a high, negative correlation between uncertainty and the business cycle in the U.S. and other industrialized countries (Bloom, 2009; Leduc and Liu, 2013; Baker, Bloom, and Davis, 2013). Castelnuovo et al. (2013) find evidence in favor of non-linear reactions of unemployment to uncertainty shocks. In particular, they find that such shocks are more powerful during recession than expansions. However, Castelnuovo el al. (2013) miss to investigate a number of obvious dimensions of the labor market, including job destruction, job creation, and vacancies. Leduc and Liu (2013) show that uncertainty shocks act as demand shocks if standard real business cycle (RBC) models are augmented with search and matching frictions in the labor market and nominal rigidities in the good market. Mumtaz and Theodoridis (2012) demonstrate that such shocks have a supply flavor in presence of nominal price and wage stickiness. Our empirical investigation shows that the economic policy uncertainty influences the labor market's variables in different ways. In fact, in both models (with or without the VIX index), the policy uncertainty influences positively the unemployment rate and the job destruction's rate. If the economic policy is uncertain, there is less opportunity to find a job due to recessions and to difficult political situations (instability) and also the firms have less opportunity to invest and to create new jobs. Therefore the unemployment rate and the job destruction's rate increase. Otherwise the policy uncertainty influences negatively the variables related to the job's creation (the job creation's rate and the job finding rate). Therefore, economic policy uncertainty hikes, firms pause their hirings, rendering more difficult to workers to find a job for the workers and also the firms have difficulties to create jobs, because the economic policy-induced uncertainty increases the value of the "wait-and-see" option.

Our results are robust to a variety of robustness checks. In particular, economic policy uncertainty shocks turn out to be important even in VARs embedding a more general measure of stock-market related volatility (uncertainty) known as VIX (Volatility IndeX). Moreover, our results are robust to dropping financial crisis' data. Actually, the analysis conducted with Great Moderation data only leads us to a statistical improvement as for our model, with residuals which turn out to be well-behaved. As said, however, our impulse responses predict a reaction of unemployment, job creation, job finding, and job destruction in line with what suggested by theoretical models. Finally, our results remain unaffected when we consider a different, more recent version of the economic policy uncertainty index by Baker, Bloom, and Davis (2013).

Our analysis suggests that economic policy uncertainty may trigger important reactions in the U.S. labor market dynamics. Therefore, it supports the call by Nick Bloom (2009) for timely and clearly communicated policies. Policies decisions taken timely, even if suboptimal (because hastily determined), may be preferable to hard-thought policies taken with substantial delay and/or unconvincingly communicated to the public. The trade-off between policy correctness and decisiveness is likely to be one of the most exciting ones to investigate in the future. Future analysis should also be concerned with other realities, e.g., European countries. Baker, Bloom, and Davis (2013) have already developed an economic policy uncertainty index for the major European countries. It will be interesting to see what empirical analysis conditional on such version of index will tell as for the power of uncertainty shocks hitting Europe.

Appendix A

Economic Events

Here we present a few events which have boosted the economic policy uncertainty in the U.S.

A.1 The 1987 Stock Market Crash and the Black Monday

On October 1987 the stock market crashed with the S&P 500 stock market index falling about 20 percent. On Black Monday it happens that many specialists did not open for trading during the first hour and so the values of stock market indicies did not decline so much. Otherwise the future market opened on time with heavy selling. So with stale quotes in the cash market and declining prices in the futures market, a gap was created between the value of stock indexes in the cash market and in the futures market. When stock finally opened, prices gapped down and the index arbitragers discovered they had sold stocks considerably below what they had been expecting and tried to cover themselves by buying in the futures market. The S&P 500 index declined between 18 and 23 percent on the day.

The 1987 stock market crash was a shock to the stability of the financial system because market functioning was significantly impaired. The Federal Reserve responses to the stock market crash illustrates three varieties of tools that can be used when responding to a crisis. The first one include the high-profile public actions taken to support market sentiment, the second one were those that boosted the liquidity of the financial system (use of open market operations and lowering of federal funds rate to support the liquidity of the banking system). At the end, the Federal Reserve encouraged various market participants, in particular banks lending to brokers and dealers, to work cooperatively and flexibly with their costumers.

A.2 Recession of 2001

In 2001, the US economy experienced a pronounced slowdown in economic activity. The unemployment rate rose and the aggregate demand falls. Three notable shocks explain this event.

The first was a decline in the stock market. during the 1990s, the stock market experienced a boom of historic proportions, as investor became optimistic about the prospects of the new information technology. The fall in the market reduced household wealth and thus consumer spending and the declining perceptions of the profitability of the new technologies led to a fall in investment spending.

The second shock was the terrorist attack on New York City and Washington D.C., on September 11, 2001. In the week after the attacks, the stock market fell another 12 percent, which at time was the biggest weekly loss since the Great Depression of the 1930s. Moreover the attacks increased uncertainty about was the future would hold. Uncertainty can reduce spending because households and firms postpone some of their plans until the uncertainty is resolved.

The third shock was a series of accounting scandals at some of the nation's most prominent corporations, including Enron and WorldCom. The result of these scandals was the bankruptcy of some companies that had fraudulently represented themselves as more profitable than they truly were. These events further depressed stock prices and discouraged business investment.

Fiscal and monetary policymakers responded quickly to these events. Congress passed a major tax cut in 2001, including an immediate tax rebate, and a second major tax cut in 2003. One goal of these tax cuts was to stimulate consumer spending and Congress increased government spending by appropriating funds to assist the New York's recovery and to bail out the ailing airline industry.

At the same time the Federal Reserve pursued expansionary monetary policy and the money growth accelerated and interest rate fell.

Expansionary monetary and fiscal policy had the intended effects. Economic growth picked up in the second half of 2003 and was strong throughout 2004. The unemployment rate was back down and it stayed at or below that level for the next several years and begin rising again in 2008, when the economy experienced another recession.

A.3 The Financial Crisis and Economic Downturn of 2008 and 2009

In 2008 the US economy experienced a financial crisis, but this crisis starts a few years earlier with a substantial boom in the housing market. The boom was fueled by low interest rates, which helped the economy recover, but by making it less expensive to get a mortgage and but a home.

Developments in the mortgage market made it easier for subprime borrowers-those borrowers with higher risk of default based on their income and credit history- to get mortgages to buy homes. One of these developments was securitization, the process by which a financial institution makes loans and then bundles them together into a variety of "mortgage-backed securities". These one are then sold to banks or insurance companies.

The high price of housing proved unsustainable and from 2006 to 2008 housing prices fell about 20 percent. Moreover, the price of housing in 2008 was merely a return to the level that had prevailed in 2004, but, in this case, the price decline led to a series of problematic repercussions.

The first of these repercussions was a substantial rise in mortgage defaults and home foreclosures. Many homeowners were underwater, they owned more on their mortgages than their homes were worth and so they stopped paying their loans. The banks started to taking the houses and selling them off searching to recoup money.

A second repercussion was large losses at the various financial institutions that owned mortgage-backed securities. By borrowing large sums to buy high-risk mortgages, these companies had bet that housing prices would keep rising, but when this bet turned bad, they found themselves in bankruptcy.

A third repercussion was a substantial rise in stock market volatility. Many companies rely on the financial system to get resources they need for business expansion or to help them manage their short-term cash flows. This third repercussion implies the forth one: a decline in consumer confidence

The Fed cut its target for the federal funds rate and Congress sell money to use to rescue the financial system and were used for equity injections into banks. So the US government became a part owner of these banks and the goal of the rescue was to stem the financial crisis on Wall Street and prevent it from causing depression.

Appendix B

Mathematical Results

In this section we proof the Nash bargaining wage:

$$w_t^N[1-\tau_t(1-b)] = (1-b)\left[\frac{\chi}{\Lambda_t} + \phi(1-\tau_t)\right] + b\left[q_t Z_t + \beta(1-\rho)\mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\frac{\kappa v_{t+1}}{u_{t+1}}\right]. \tag{B.1}$$

We need the following equations from the theoretical model:

$$\kappa = q_t^v J_t^F \tag{B.2}$$

$$J_t^F = (1-b)S_t, \quad J_t^W - J_t^U = bS_t \tag{B.3}$$

$$bS_t = (1-\tau_t)(w_t^N - \phi) - \frac{\chi}{\Lambda_t} + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\rho)(1-q_{t+1}^u)bS_{t+1}\right]. \tag{B.4}$$

We know from (B.2) that:

$$\frac{\kappa}{q_t^v} = q_t Z_t - w_t^N + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\rho)\frac{\kappa}{q_{t+1}^v} = (1-b)S_t$$

and we solve it for S_t:

$$S_t = \frac{1}{1-b}\left[q_t Z_t - w_t^N + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\rho)\frac{\kappa}{q_{t+1}^v}\right]. \tag{B.5}$$

We put (B.5) inside (B.4) and we have:

$$\frac{b}{1-b}\left[q_t Z_t - w_t^N + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\rho)\frac{\kappa}{q_{t+1}^v}\right] =$$
$$(1-\tau_t)(w_t^N - \phi) - \frac{\chi}{\Lambda_t} + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\rho)(1-q_{t+1}^u)bS_{t+1}\right].$$

Multiplying both the part by $(1-b)$, we have:

$$-bw_t^N - (1-b)(w_t^N - w_t^N\tau_t) + \phi(1-b)(1-\tau_t) = -(1-b)\frac{\chi}{\Lambda_t} - bq_t Z_t$$
$$-b\mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\rho)\frac{\kappa}{q_{t+1}^v} + (1-b)\mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\rho)(1-q_{t+1}^u)bS_{t+1}\right].$$

Solving it and deleting some values, we have as follows:

$$w_t^N[1-\tau_t(1-b)] = (1-b)\left[\phi(1-\tau_t+\frac{\chi}{\Lambda_t})\right] + bq_tZ_t +$$
$$+ b\mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\rho)\frac{\kappa}{q_{t+1}^v} - (1-b)\mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\rho)(1-q_{t+1}^u)bS_{t+1}\right].$$

Now we solve the expected value using some properties of the expected value and (B.2) and (B.3)

$$b\mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\rho)\frac{\kappa}{q_{t+1}^v} - b\mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\rho)(1-q_{t+1}^u)(1-b)S_{t+1}\right] =$$
$$= b\beta(1-\rho)\mathrm{E}_t\frac{\Lambda_{t-1}}{\Lambda_t}\left[\frac{\kappa}{q_{t+1}^v} - \frac{\kappa(1-q_{t+1}^u}{q_{t+1}^v}\right].$$

We solve the expression in the brackets as follows:

$$\frac{\kappa-\kappa-\kappa q_{t+1}^u}{q_{t+1}^v} = \frac{\kappa q_{t+1}^u}{q_{t+1}^v} = \frac{\kappa v_{t+1}}{u_{t+1}}$$

using the fact that

$$u_{t+1} = \frac{m_{t+1}}{q_{t+1}^u} \quad v_{t+1} = \frac{m_{t+1}}{q_{t+1}^v}.$$

If we use all the expressions below, we have the (B.1).

Appendix C

FEVD Tables

C.1 Model without VIX index (1987:01 - 2008:02)

In this section we explain the tables related to the Forecast Error Variance Decomposition in the model without VIX and from the first quarter of 1985 to the second quarter of 2008:

Table C.1: FEVD of policy uncertainty

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	80%	5%	3%	4%		4%	1%	1%
4yrs ahead	71%	5%	7%	4%	1%	3%	2%	5%
10yrs ahead	65%	6%	8%	4%	1%	3%	5%	7%

Table C.2: FEVD of unemployment rate

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	48%	19%	6%	14%		6%	4%	2%
4yrs ahead	25%	10%	30%	7%		3%	5%	18%
10yrs ahead	18%	9%	27%	5%	2%	2%	12%	22%

Table C.3: FEVD of inflation rate

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	1%	3%	67%	2%	2%	2%	6%	16%
4yrs ahead	6%	6%	58%	2%	3%	2%	8%	15%
10yrs ahead	6%	7%	56%	3%	3%	2%	8%	15%

Table C.4: FEVD of job creation's rate

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	39%	1%	13%	37%		3%	3%	5%
4yrs ahead	21%	5%	23%	17%	1%	4%	4%	23%
10yrs ahead	15%	5%	26%	12%	2%	5%	11%	24%

Table C.5: FEVD of job destruction's rate

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	15%	25%	3%	4%	39%	3%		10%
4yrs ahead	18%	21%	4%	7%	32%	4%	2%	11%
10yrs ahead	16%	18%	10%	6%	26%	3%	5%	14%

Table C.6: FEVD of job finding rate

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	37%	4%	9%	15%	6%	20%	3%	5%
4yrs ahead	20%	3%	34%	9%	3%	10%	4%	17%
10yrs ahead	15%	4%	30%	7%	4%	7%	10%	22%

Table C.7: FEVD of federal fund rate

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	56%	11%	5%	10%			15%	3%
4yrs ahead	44%	10%	11%	7%		2%	17%	7%
10yrs ahead	33%	10%	16%	5%	1%	2%	19%	14%

Table C.8: FEVD of output gap

	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	21%		7%	22%	3%	8%	7%	31%
4yrs ahead	13%	3%	26%	13%	2%	5%	7%	31%
10yrs ahead	11%	4%	25%	10%	3%	4%	12%	30%

C.2 Model with VIX index (1987:01 - 2008:02)

In this section we explain the tables related to the Forecast Error Variance Decomposition in the model with VIX and from the first quarter of 1985 to the second quarter of 2008:

Table C.9: FEVD of VIX index

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	70%	3%	1%	13%		4%	2%		4%
4yrs ahead	61%	3%	1%	17%	4%	3%	2%		6%
10yrs ahead	48%	4%	2%	21%	4%	4%	2%	3%	11%

Table C.10: FEVD of policy uncertainty

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	45%	32%	5%	2%	6%	2%	6%	2%	1%
4yrs ahead	40%	29%	5%	5%	6%	2%	5%	3%	5%
10yrs ahead	34%	25%	6%	8%	6%	2%	5%	5%	8%

Table C.11: FEVD of unemployment rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	19%	29%	17%	6%	16%		6%	4%	3%
4yrs ahead	10%	15%	11%	30%	9%		3%	5%	16%
10yrs ahead	8%	11%	9%	28%	7%	2%	2%	12%	20%

Table C.12: FEVD of inflation rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	1%	1%	4%	67%	3%	2%	2%	3%	5%
4yrs ahead	5%	1%	5%	59%	2%	3%	2%	5%	21%
10yrs ahead	5%	2%	6%	56%	3%	3%	3%	11%	22%

Table C.13: FEVD of job creation's rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	20%	18%	1%	11%	39%		2%	3%	5%
4yrs ahead	10%	12%	7%	23%	19%	1%	2%	5%	21%
10yrs ahead	8%	9%	6%	27%	12%	2%	3%	11%	22%

Table C.14: FEVD of job destruction's rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	7%	12%	20%	4%	4%	40%	2%	2%	10%
4yrs ahead	8%	14%	17%	4%	6%	35%	2%	4%	10%
10yrs ahead	7%	12%	15%	12%	6%	27%	3%	6%	13%

Table C.15: FEVD of job finding rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	16%	24%	3%	8%	15%	6%	19%	3%	6%
4yrs ahead	8%	13%	3%	33%	9%	3%	10%	3%	16%
10yrs ahead	7%	9%	4%	30%	7%	4%	6%	10%	20%

Table C.16: FEVD of federal fund rate

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	39%	16%	11%	6%	9%			13%	5%
4yrs ahead	30%	13%	11%	11%	9%			14%	8%
10yrs ahead	21%	11%	11%	17%	6%	1%	1%	16%	15%

Table C.17: FEVD of output gap

	VIX	polunc	urate	infl	vacanr	separ	jobfind	ffr	ygap
2yrs ahead	12%	15%		6%	19%	2%	6%	8%	30%
4yrs ahead	7%	9%	4%	26%	20%	2%	3%	6%	29%
10yrs ahead	7%	7%	4%	26%	9%	2%	3%	11%	28%

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