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LABOR MARKET AND FINANCIAL SHOCKS:
A TIME VARYING ANALYSIS

by Francesco Corsello* and Valerio Nispi Landi*

Abstract

Motivated by the events of the Great Recession, we estimate a time-varying structural VAR model to analyze the effects of a financial shock on the labor market, focusing on the US. Our results indicate that a tightening of financial conditions is highly detrimental to the labor market. Moreover, we show that financial shocks have affected the unemployment rate asymmetrically in the last three decades, an implication that a standard VAR cannot capture: while negative financial shocks have been responsible for increases in unemployment, our model does not find significant contributions of financial shocks during periods of expansion. The source of this asymmetry is the time-varying standard deviation of the identified shock, which is higher in times of financial distress; on the other hand, we find the transmission mechanism is almost constant over time.

JEL Classification: C32, E24, E44.
Keywords: VAR, labor market conditions, financial markets.

Contents

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1 Introduction[1]

The Great Recession has been particularly detrimental for the US labor market, in terms of both magnitude and persistence of the effects (Figure 1). The unemployment rate reached a peak of about 10% at the end of 2009 and it fully recovered only in 2016; this employment collapse was mainly driven by an impressive layoffs growth in the private sector; in addition, hours worked per employee have heavily fallen down throughout the crisis and in 2017 they are still not back to their pre-crisis level. Labor force participation was also strongly affected and has accelerated the downward trend started in the early 2000s. Finally, not surprisingly, the vacancy rate experienced a significant drop.

Given that the last recession was generated by a large turmoil in the financial sector (Figure 2), studying the linkages between financial and labor markets seems crucial to gain a better comprehension of business cycle fluctuations. Moreover, the last crisis has fostered a large debate about effectiveness of macroprudential policies aiming to maintain financial stability and to dampen financial shock impact: therefore, analyzing the effects of a financial tightening on the real economy, and especially on the labor market, can provide some useful guidance to policy makers.

In the empirical economic literature there are several works analyzing the macroeconomic effects of a financial shock, defined as a tightening of financial conditions (Gilchrist et al., 2009, and Gilchrist and Zakrajšek, 2012 are eminent examples). These works typically use a VAR model with constant standard deviations (CVAR henceforth) to identify the impact of a financial shock, using sign or short-run restrictions. However, the assumption of constant shock's standard deviation seems quite restrictive when the object of interest is a financial shock: financial time series are typically asymmetric and exhibit changes in volatility over time.[2] Figure 3 shows the time series of the Chicago Fed National Financial Condition Index (NFCI henceforth) and the Gilchrist and Zakrajsek Spread (GZ, from now on). These indicators measure the tightness of financial conditions in the US, with higher values denoting periods of tighter conditions: both measures feature small fluctuations on average (associated with periods of financial calm) and few big and volatile peaks (associated with periods of financial distress); a VAR with stochastic volatility is able to distinguish between periods of high and low volatility: as a result the estimated

[1]We are especially grateful to our supervisor Massimiliano Marcellino for his guidance. We also thank Martin Eichenbaum, Nicola Gennaioli, Francesco释Paternò, Giorgio Primiceri, Marco Taboga, Antonella Trigari and Francesco Zanetti for very useful suggestions. All remaining errors are ours. The views expressed in this paper are our own and do not necessarily reflect those of the Bank of Italy.

[2]See Kim et al. (1998) for an overview of stochastic volatility models.

standard deviation of financial shocks is likely to be high in periods of financial turbulence, as the data seem to suggest. Furthermore, the bias resulting from a CVAR estimation is magnified if the sample period includes the recent financial crisis: the estimated impact of a shock in a CVAR tries to summarize the effects of such a shock over time. Given that the Great Recession faced a huge drop in the real activity due to massive distress in financial markets, a CVAR may overestimate the effect of a financial innovation across the sample. In Section 4 we argue that this overestimation is particularly strong for the unemployment rate.

Nevertheless, time-varying volatility may not be enough to correctly capture the effect of a financial shock. Indeed, not only the size of a financial shock can be time-varying, but also its transmission mechanism. As shown, for instance, by Gaiotti (2013), Hubrich and Tetlow (2015) and Prieto et al. (2016), a change in financial conditions has a higher impact on the real economy during periods of financial distress: this can be explained theoretically by the presence of financial constraints that can be binding during recessions, as pointed out by Mendoza (2010), Bianchi (2011) and Guerrieri and Iacoviello (2017). Moreover, several recent papers show that labor market time series feature a significant degree of skewness.[3] Accordingly, as highlighted by Ng and Wright (2013), it is now accepted that parameter instability and stochastic volatility are crucial features that must be considered in a macroeconometric framework.

Motivated by all these considerations, we assess the interactions between labor market and financial shocks in a time-varying framework. In particular, the following research questions are tackled: i) What is the effect of a financial tightening on the labor market? ii) How relevant are financial shocks in explaining historical labor market fluctuations? iii) Is the response of labor market time-varying? iv) Is the size of financial shocks changing over time? And v) what are the main transmission mechanisms and how are they captured by VAR models?

The empirical macroeconomics literature focusing on the time-varying effects of financial shocks in the labor market is quite scant and this is particularly surprising, given what happened during the Great Recession. Therefore, following the work of Primiceri (2005), we estimate a time-varying VAR with stochastic volatility (TV-VAR-SV henceforth), over the sample period 1973-2016. We include in the model eight US quarterly time series: five labor-market variables (unemployment rate, participation rate, hours worked per employee, nominal wage and vacancy rate), two macroeconomic variables (inflation

[3]See, for instance, McKay and Reis (2008), Ferraro (2017) and Pizzinelli and Zanetti (2017).

rate and real GDP) and the National Financial Condition Index (the NFCI henceforth). The NFCI series and its three components (risk, credit and leverage) are published by the Federal Reserve of Chicago at weekly frequency. This index is a dynamic factor built from a balanced panel of 100 mixed-frequency indicators of financial activity. The financial shock that we aim to identify is a tightening of financial conditions, modeled as an unanticipated exogenous increase in the NFCI: as such, this is a credit supply shock, deeply analyzed by theoretical studies.[4] The shock is identified through a short-run restriction: the labor market and the macroeconomy cannot simultaneously react to innovations in the NFCI, a standard assumption in the structural VAR literature. This restriction is even more reasonable in our framework, since the labor market is by its own nature sluggish to respond to economic shocks.

Our contribution to the literature is threefold. First we show that a tightening of financial conditions depresses the labor market and the GDP while the effect on inflation is positive and borderline significant.[5] Second, we find that financial shocks have hit the unemployment rate asymmetrically over the last three decades: while negative financial shocks have been responsible for the high unemployment rates in the early 1980s and during the Great Recession, our model does not find relevant contribution of financial shocks throughout expansion periods. We show that a CVAR is not able to capture this asymmetry. Third, we observe strong evidence of time variation in the financial shock volatility, with peaks during economic downturns, consistently with the works of Justiniano and Primiceri (2008), Stock and Watson (2012) and Prieto et al. (2016): accordingly, we find larger negative than positive shocks. Since the systematic transmission mechanism does not display time variation, we can conclude that the asymmetric response of the unemployment rate is entirely due to financial shock's drifting volatility.

The remainder of the paper is organized as follows: in Section 2 we provide a brief review of theoretical and empirical literatures on the transmission of financial shocks to real activity; Section 3 presents the time series used in the analysis; Section 4 introduces the estimation methodology; Section 5 describes the results; in Section 6 some robustness checks are reported; Section 7 concludes.

[4]See, for instance, the DSGE model by Jermann and Quadrini (2012).

[5]Notice that the DSGE literature is not unanimous about the effects of financial shocks on the inflation rate.

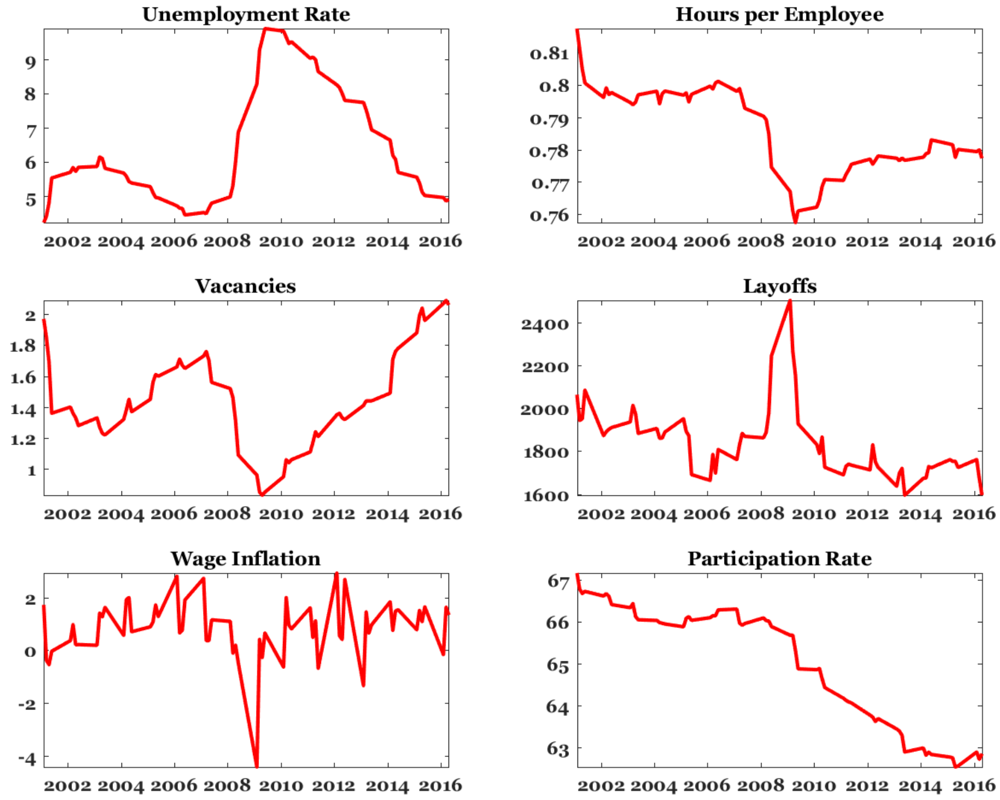

Figure 1: US labor market during the Great Recession. Unemployment rate, participation rate and wage inflation are expressed in percentage points. Hours per employee is the ratio between hours in nonfarm business sector (an index with base year 2010), and the number of employees in that sector. Layoffs in nonfarm business sector are expressed in thousands of workers. Vacancies are measured by the Help-Wanted Index developed by Barnichon (2010). All these variables but the vacancy index come from the BLS database.

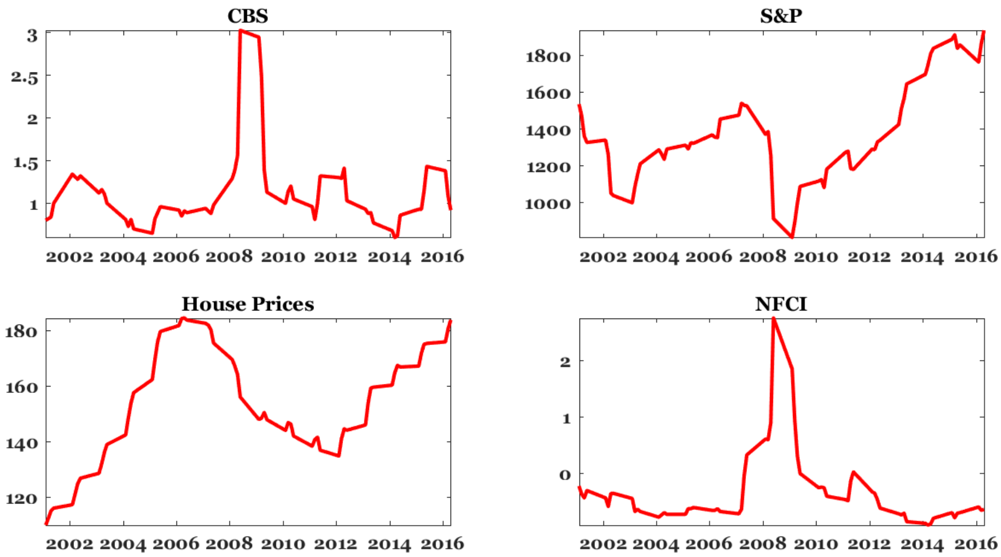

Figure 2: US financial markets during the Great Recession. CBS is the Moody's BAA-AAA corporate bond spread expressed in percentage points. S&P is the Standard & Poor stock market index. House prices are measured by the Standard & Poor's Case–Shiller Home Price Index (base year 2000). NFCI is the National Financial Condition Index developed by the Chicago Fed. Source: St. Louis Fed.

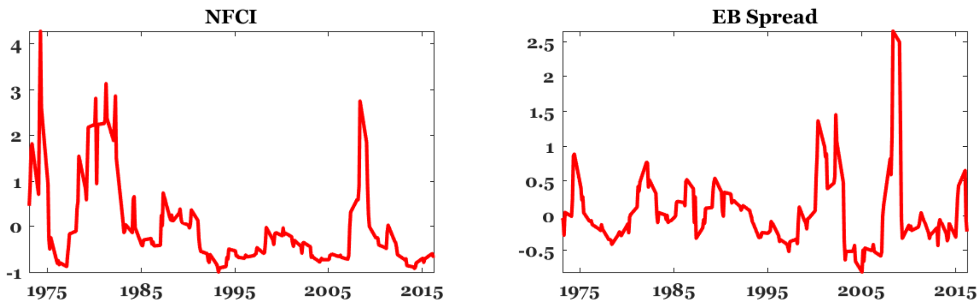

Figure 3: EBP spread is the excess bond premium component of the GZ spread built by Gilchrist and Zakrajšek (2012).

2 Related Literature

2.1 Theoretical Literature

The macroeconomic theoretical literature has deeply analyzed the transmission mechanism linking real activity with the financial sector. The seminal paper by Bernanke and

Gertler (1989), Bernanke and Gertler (1995) and Kiyotaki and Moore (1997) introduce the concept of financial accelerator, whereby financial frictions amplify the response of the real economy to economic shocks. These studies formed the basis for business cycle models that incorporate the financial accelerator mechanism in a general equilibrium framework.[6] In particular, Jermann and Quadrini (2012) develop a model in which the financial sector is not only a source of amplification but also a driver of business cycle fluctuations, as witnessed by the Great Recession. In this model, a tightening of financial conditions reduces firms' borrowing ability and forces them to cut hours of work and production. Also in Gertler and Karadi (2011), the main driver of fluctuations originates in the financial sector: a deterioration in the quality of financial assets reduces the net worth of banks. In turn, banks raise the lending cost to remain profitable and avoid deposit withdrawals. The shock that we aim to identify in our model resembles those in Jermann and Quadrini (2012) and Gertler and Karadi (2011): it is a credit supply shock that makes it harder for firms to borrow funds; using the NFCI goes precisely in this direction, given that this indicator captures the tightness of financial conditions.

A recent strand of the macro-financial literature has departed from the assumption - made for computational reasons - that financial constraints are always binding: scholars have been starting to set up models characterized by occasionally binding collateral constraints, in order to study the (potentially) non-linear effects of economic shocks.[7] During recessions, such constraints bind and firms deleverage; on the other hand, in expansions, a loosening of financial conditions does not have a direct impact on collateral constraints, which continue to be slack.

Our time-varying model points out that the early 1980s and the Great Recession were two periods characterized by negative and highly volatile financial shocks. Some recent papers argue that the time-varying volatility of economic shocks is *per se* a source of macroeconomic fluctuations. In a DSGE framework, Christiano et al. (2014) show that risk shocks, i.e. shocks to the idiosyncratic uncertainty in the return of firms' projects, are an important driver of the business cycle: in this model, higher risk increases the probability of firms' default, accordingly banks raise loan rate and this depresses aggregate demand, triggering the financial accelerator. In a model for an emerging economy, Fernández-Villaverde et al. (2011) analyze the effects of an increase in the interest rate's volatility, which emerging countries take as given: a higher volatility triggers a recession,

[6] See also Bernanke et al. (1999) and Christiano et al. (2003).

[7] For example, occasionally binding collateral constraints characterize the model of Mendoza (2010) and Guerrieri and Iacoviello (2017).

since households cut external debt which becomes more riskier and, as a consequence, reduce consumption. In an estimated DSGE model for the US, Justiniano and Primiceri (2008) argue that the Great Moderation was mainly the result of a reduced volatility in the investment-specific shock, i.e. an exogenous change in the technology transforming investment in capital goods: this is interpreted by the authors as a reduced volatility in financial factors.

A common denominator of these papers is the abstraction from unemployment issues: the labor input is modeled as an intensive margin and so there is no room for unemployment. The Great Recession has provided motivation to fill this gap: frictional financial markets have been introduced in models featuring equilibrium unemployment à la Mortensen and Pissarides (1994): one contribution of our work is to qualitatively capture the dynamics highlighted in these models. A not comprehensive list includes Christiano et al. (2011), Petrosky-Nadeau and Wasmer (2013), Petrosky-Nadeau (2013), Iliopulos et al. (2014) and Zanetti (2017). In these works, financial and labor-matching frictions coexist: in particular, firms need external funding to finance the cost of posting vacancies and attracting unemployed workers. During crises, firms have limited access to external credit and thus reduce the number of posted vacancies, so that financial frictions magnify the role played by search and matching frictions in creating unemployment. Notably, Petrosky-Nadeau (2013) examines the impact of a credit shock on the labor market. In this model, a worsening of financial conditions induces firms to reduce the number of vacancies: the probability to find a job for an unemployed falls and the unemployment rate rises; as a consequence, labor market tightness (defined as the vacancy-unemployment ratio) collapses, making easier for firms to fill a vacancy. The obvious by-product of such a negative shock is a drop of aggregate production. On the other hand, Monacelli et al. (2011) propose a different mechanism. The authors argue that external debt allows firms to get a better position when bargaining wage with workers. In such a case, a negative financial shock forces firms to reduce borrowing and places them in a less favorable bargaining position with workers: as a result, firms will create less jobs.

2.2 Empirical Literature

There is a growing empirical literature analyzing the effects of financial shocks. One seminal paper of this literature is Gilchrist and Zakrajšek (2012): they construct the GZ credit spread index, an indicator with a significant predictive power for economic activity. The GZ spread is decomposed in two components: the expected default and the excess bond premium (EBP); the latter is used as financial variable in a macroeconomic VAR: an innovation in the excess bond premium leads to economically and statistically significant declines in the real activity. Fornari and Stracca (2012) estimate a panel VAR for a large set of advanced economies, in order to evaluate the effects of a credit supply shock, identified with sign restrictions. Their findings show that financial shocks exert a relevant influence on the real economy, both in terms of shock's size and variance explained. These results are confirmed by Caldara et al. (2016): they distinguish between financial and uncertainty shocks, finding that the former ones significantly affect economic conditions and are an important source of business cycle fluctuations; moreover, they amplify the negative effects of adverse uncertainty shocks. One of our goals is contributing to this literature, by augmenting the set of endogenous variables typically included in VAR with some labor-market variables.

The previous works all consider linear frameworks, in which estimated parameters are constant over time. Our work goes one step ahead by allowing time variation in parameters and shock standard deviations. Indeed, some papers point out that including time variation in a financial shock analysis yields some important insights. In particular, many studies find that standard deviation of financial shocks is changing over time and it is relatively higher in periods of financial distress. Using Italian firm-level, Gaiotti (2013) shows that quantitative credit constraints have a larger effect during economic slack. Hubrich and Tetlow (2015) estimate a Markow Switching VAR model, finding that output reacts differently to financial shocks in periods of financial distress; moreover, they also find that shock variances were relatively high during the Great Recession and the dot-com bubble. Prieto et al. (2016) estimate a time-varying VAR for the US economy with three financial market variables (house prices, stock prices and credit spread). They find that during financial crisis, contribution of financial shocks in explaining fluctuations in GDP more than doubles, and this is mainly explained by a higher shock volatility. Alessandri and Mumtaz (2017) argue that a threshold VAR which includes financial indicators outperforms a linear VAR in predicting the probability distribution of US industrial production. Silvestrini and Zaghini (2015) study the linkages between financial shocks and the macroeconomy in a time-varying framework. They estimate a time-varying VAR with euro-area variables, finding evidence of time variation in the transmission mechanism of a shock to the Composite Indicator of Systemic Stress, identified with short-run restrictions: notably, this financial shock has a more significant adverse impact during financial crises. In a reduced-form model, Alessandri et al. (2017) find that changes in the EBP have stronger predictive power for crisis than for expansions.

3 Data

The estimation is performed over the sample period 1973Q1-2016Q3, using eight US time series; the observations going from 1973Q1 to 1980Q4 are used as training sample to calibrate prior distributions. The sample starting point is dictated by availability of the NFCI.

In order to capture financial shocks' effects both on the extensive and intensive margin, the vector of endogenous variables comprises the unemployment rate, the log-first difference of the participation rate (defined as labor force over working age population) and the log-first difference of hours of work per capita in the non-farm business sector; in addition, we include the log-first difference of nominal wage, the vacancy index constructed by Barnichon (2010), GDP deflator and real GDP. Our financial measure is the NFCI.[8]

It deserves to spend some words about the NFCI, given the crucial role played in our analysis. The NFCI, published at weekly frequency by the Federal Reserve Bank of Chicago, is a weighted average of a set of financial indicators: the weight of each indicator is estimated by means of the principal component technique. The index captures measures of risk, liquidity and leverage. The risk component summarizes the premium yielded by risky assets and their volatility; the liquidity component provides an index of willingness to borrow and lend at prevailing prices; the leverage component assesses the economy-wide level of financial debt relative to equity. The index and its components are rescaled to have a zero mean and a unitary standard deviation; positive (negative) values denote financial conditions that are tighter (looser) than average. The main advantage of this indicator comes from an overall description of US financial conditions: this is particularly important due to the strong interconnectivity of US financial markets, in which shocks tend to have an impact on aggregate financial conditions rather than on one specific segment.[9]

In Figure 4 we plot the seven non-financial series we use in estimation, excluding training sample observations. The unemployment rate is above 5% in several periods of our sample:[10] it is particularly high during the 1980s and throughout the Great Recession.

[8] We are not the first ones to use the NFCI in a structural VAR: Fink and Schüler (2015) identify a financial shock as an innovation in the NFCI; Metiu et al. (2015) include the NFCI in a VAR in order to capture the transmission mechanism of a financial shock defined as an innovation to EBP.

[9] See Brave and Butters (2011) and Brave and Butters (2012) for more details.

[10] According to FED estimates, the long-run normal rate of unemployment ranges from 4.5 to 5.0 percent.

During the recent financial crisis we also observe unusual negative values for price and wage inflation along with a large drop in hours of work, vacancies and GDP. Figure 5 plots the NFCI and its subcomponents. The index displays positive values at the beginning of the sample (in correspondence with the less-developed-countries debt crisis occurred in the early 1980s), and in the late 1980s, in addition to the big spike in 2009; the years between the 1990's and the boom preceding the Great Recession were characterized by relatively looser financial conditions. The three NFCI components exhibit similar patterns: interestingly, the leverage component is much more volatile, while the credit index is more persistent.

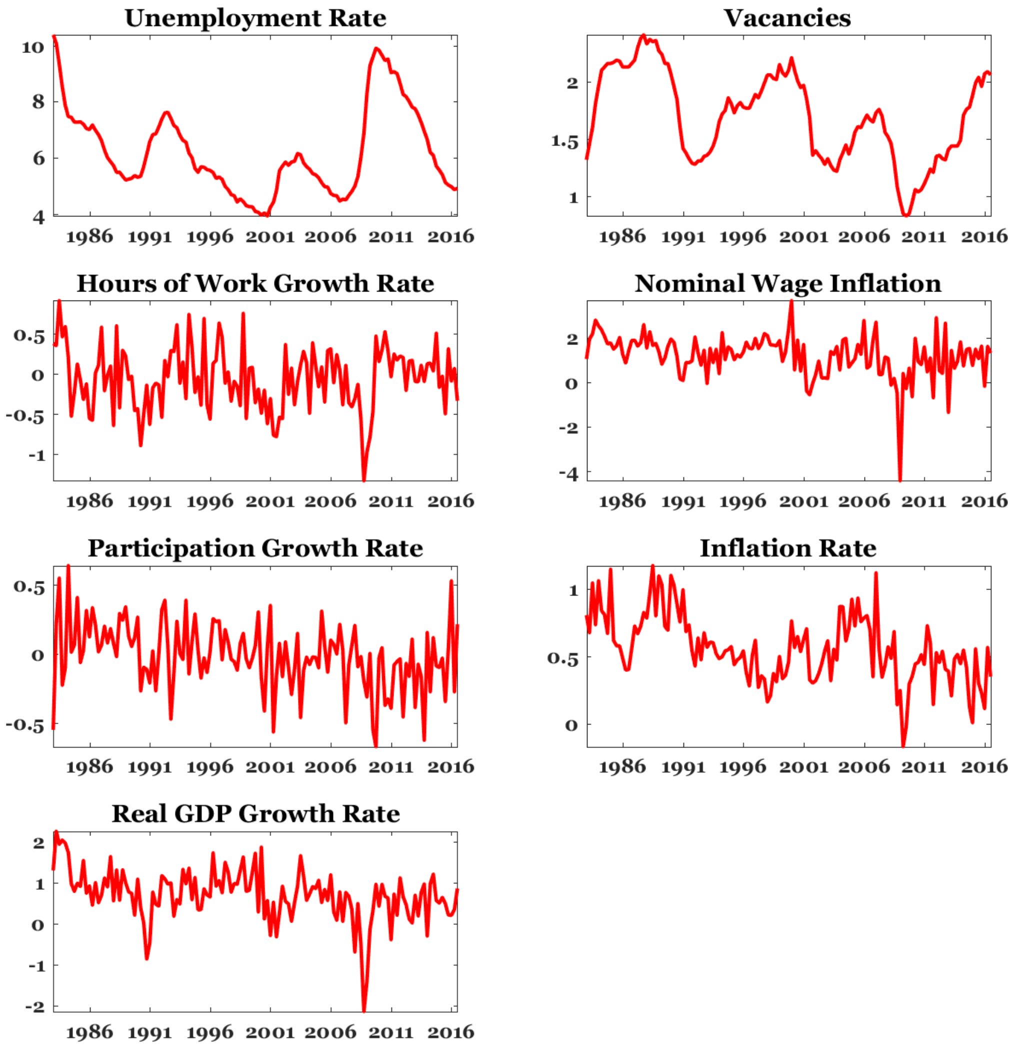

Figure 4: Labor and macroeconomic variables. Variables are expressed in percentage points except vacancies.

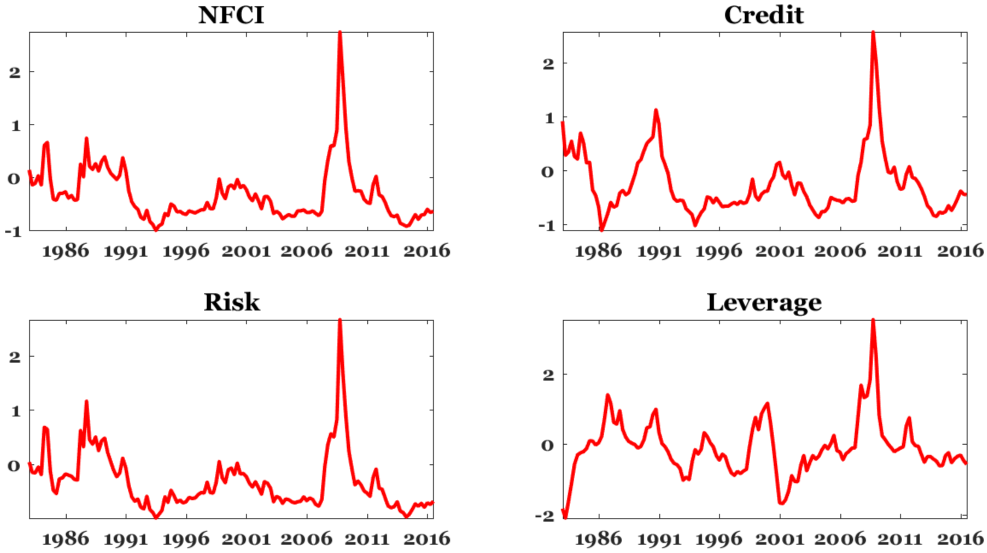

Figure 5: NFCI and its subcomponents.

4 Econometric Methodology

4.1 TV-VAR-SV and rank reduction

The n variables of interest are modeled through a time-varying coefficient VAR with stochastic volatility, whose reduced form follows the seminal work of Primiceri (2005):

$$\underbrace{y_t}_{n\times 1} = c_t + \sum_{\ell=1}^{p} \underbrace{B_{\ell,t}}_{n\times n} y_{t-\ell} + u_t, \qquad u_t \overset{i}{\sim} \mathcal{N}\left(\mathbf{0},\ \underbrace{\Omega_t}_{n\times n} \right).$$

Following the literature, for estimation purposes the model is transformed as:

$$y_t = X_t'\beta_t + A_t^{-1}\Sigma_t\varepsilon_t, \qquad \varepsilon_t \overset{iid}{\sim} \mathcal{N}\left(\mathbf{0},\ I_n \right),$$

$$\underbrace{X_t'}_{n\times k} \equiv I_n \otimes \begin{bmatrix} 1 & y_{t-1}' & y_{t-2}' & \dots & y_{t-p}' \end{bmatrix}$$

where the time-varying coefficients are stacked in a set of k-dimensional[11] vectors $(\beta_t)_{t=1}^{T}$ and the $n \times n$ reduced form covariances $(\Omega_t)_{t=1}^{T}$ face a triangular reduction, producing the

[11] $k = n\,(np + 1)$.

lower triangular matrices $(A_t)_{t=1}^T$ and diagonal matrices $(\Sigma_t)_{t=1}^T$:

$$\underbrace{\beta_t}_{k\times 1} \equiv vec\left(\begin{bmatrix} c_t & B_{1,t} & \dots & B_{p,t}\end{bmatrix}'\right)$$

$$\Omega_t = A_t^{-1}\Sigma_t\Sigma_t\left(A_t^{-1}\right)'.$$

Each group of time-varying elements follows a multivariate random walk with Gaussian innovations, whose covariances are parametrized by matrices $\{Q_\alpha, Q_\beta, Q_\sigma\}$. Indeed, defining the r-dimensional vectors[12] $(\alpha_t)_{t=1}^T$ and the n-dimensional vectors $(\sigma_t)_{t=1}^T$ as the sets of vectors containing, respectively, the off-diagonal elements in $(A_t)_{t=1}^T$ and the diagonal elements in $(\Sigma_t)_{t=1}^T$, we can write the assumed law of motions:

$$\begin{aligned} \beta_t &= \beta_{t-1} + \nu_{\beta,t}, & \nu_{\beta,t} &\overset{iid}{\sim} \mathcal{N}(\,\mathbf{0},\ Q_\beta\,) \\ \alpha_t &= \alpha_{t-1} + \nu_{\alpha,t}, & \nu_{\alpha,t} &\overset{iid}{\sim} \mathcal{N}(\,\mathbf{0},\ Q_\alpha\,) \\ \log\sigma_t &= \log\sigma_{t-1} + \nu_{\sigma,t}, & \nu_{\sigma,t} &\overset{iid}{\sim} \mathcal{N}(\,\mathbf{0},\ Q_\sigma\,)\,. \end{aligned}$$

As stressed in Primiceri (2005), the random walk assumption is not harmful for estimation purposes, especially since the process is operating for a finite number of periods. Moreover, the random walk specification is parsimonious and does not restrict much the elements' dynamics.

However, a rank reduction strategy proposed by de Wind and Gambetti (2014, WG henceforth) is implemented for the time-varying coefficients. The reason is twofold: first, the rank reduction methodology makes possible to reduce the computational burden of non-small TV-VAR-SV models (say, for larger models than the small one estimated in Primiceri, 2005); second, in line with the findings of Cogley and Sargent (2005) and WG, these models typically do not show large time variation of VAR coefficients when estimated with macro-financial variables. Therefore, a smaller number of components are able to capture coefficients time variation, especially considering that the number of VAR coefficients increases very fast with the number of variables and lags, and there is no reason to conceive such a large number of economic forces able to alter the transmission mechanism at every period.

In particular, Q_β is assumed to be a reduced-rank matrix with rank $q_\beta < k$ and it is

[12] $r = n\,(n-1)\,/2$.

eigendecomposed in the following way:

$$Q_\beta = \underbrace{\Lambda_\beta}_{k\times q_\beta} \Lambda'_\beta = \underbrace{V_\beta}_{k\times q_\beta} \underbrace{D_\beta}_{q_\beta\times q_\beta} V'_\beta, \qquad \Lambda_\beta \equiv V_\beta D_\beta^{1/2}$$

where D_β is a diagonal matrix containing the non-zero eigenvalues of Q_β and V_β is the matrix where the associated eigenvectors are stacked in columns. Following the procedure of WG, the time-varying coefficient law of motion can be transformed (projecting onto the column space of Λ_β) in order to reduce the number of time-varying components to q_β. WG highlight that this assumption is reasonable with macroeconomic variables, especially when k gets large; in these circumstances the time variation can be spanned using a smaller space without significant changes in the inference. To sum up, the time-varying coefficients are eventually linear combinations of time-varying components with the following associated laws of motion and time-invariant residual:[13]

$$\underbrace{\beta_t}_{k\times 1} = \Lambda_\beta \widetilde{\beta}_t + M_\beta \beta_0, \qquad \underbrace{\widetilde{\beta}_t}_{q_\beta\times 1} = \widetilde{\beta}_{t-1} + \widetilde{\nu}_{\beta,t}, \qquad \underbrace{\widetilde{\nu}_{\beta,t}}_{q_\beta\times 1} \overset{iid}{\sim} \mathcal{N}\left(\mathbf{0},\ I_{q_\beta}\right).$$

Inference on the covariance matrices of states' innovations and on the unobservable states (time-varying coefficients, off-diagonal elements and stochastic volatilities) is produced by means of a Gibbs Sampler that draws from conditional posteriors. The Gibbs Sampler steps are listed below.

Gibbs Sampler Steps[14]

1. Initialize the Gibbs Sampler at some $(\beta_t^0,\ \alpha_t^0,\ \sigma_t^0)_{t=0}^T,\ Q_\beta^0, Q_\alpha^0, Q_\sigma^0$, set $i = 1$.
2. Draw a history of time-varying coefficients $(\beta_t^i)_{t=1}^T$:
    (a) Draw a history of time-varying components $\left(\widetilde{\beta}_t^i\right)_{t=1}^T$;
    (b) Draw a vector of time invariant component $M_\beta \beta_0$ of $(\beta_t^i)_{t=1}^T$.
3. Draw a reduced-rank covariance matrix Q_β^i.
4. Draw a history of off-diagonal elements $(\alpha_t^i)_{t=1}^T$.

[13]The time invariant residual is obtained through the matrix $M_\beta \equiv I_m - \Lambda_\beta \left(\Lambda'_\beta \Lambda_\beta\right)^{-1} \Lambda'_\beta$. As shown in Corsello (2018), the residual only depends on the initial condition β_0.

[14]See Corsello (2018) for analytical details on each step.

5. Draw a full rank covariance matrix Q_α^i.

6. Draw a history of volatilities $(\sigma_t^i)_{t=1}^T$.

7. Draw a full-rank covariance matrix Q_σ^i, set $i = i + 1$ and restart at [2].

Draws from the posterior of unobservable states are obtained by means of the Carter and Kohn (1994) algorithm. Draws from the Singular Inverse Wishart are implemented differently from what proposed by WG, following the approach of Corsello (2018). The stochastic volatilities draws are implemented as in Primiceri (2005), but respecting the correct order described in Del Negro and Primiceri (2015). The $\log \chi_1^2$ distribution is approximated using the mixture of normal components proposed by Omori et al. (2007), which improves upon the previous standard set by Kim et al. (1998).

The prior distribution is set following Primiceri (2005) for $\{Q_\alpha, Q_\sigma\}$ and for the initial conditions α_0 and σ_0, while WG is used as benchmark for calibrating the prior distributions of Q_β and β_0. In particular, the training sample used to calibrate prior distributions runs from 1973Q1 to 1980Q4. Dealing with quarterly data, we set $p = 2$ lags (as in Primiceri, 2005), so having a total of $k = 78$ coefficients in the VAR. The reduced rank of the time-varying coefficients is chosen to be $q_\beta = 40$, which constitutes a good compromise between dimensionality and span time variation.[15]

4.2 Identification Strategy

Our identification scheme relies on a short-run restriction: we assume that both the labor market (unemployment, vacancies, participation, hours and wage) and the macroeconomy (GDP and inflation) do not contemporaneously respond to innovations in the NFCI equation. Accordingly, we order NFCI last in the endogenous vector and impose a Cholesky structure to the matrix of contemporaneous relations.

This identification strategy is quite standard in the economic literature dealing with structural shocks identification. Christiano et al. (1999) and Bernanke et al. (2005) are pioneering examples for the identification of monetary shocks using a Cholesky approach. Gilchrist and Zakrajšek (2012), Hubrich and Tetlow (2015), Prieto et al. (2016) and Silvestrini and Zaghini (2015) use short-run restrictions to identify a financial shock.

[15]Increasing the rank does not produce any variation on time-varying coefficient inference, showing that the chosen dimension is sufficient to span the measured time-varying coefficient variations over time.

The rationale behind this assumption is that the private sector typically tends to react with a delay to economic shocks, due to real and nominal rigidities, such as, price and wage adjustment costs or habits persistence in consumption. Clearly, we are well aware that this identification strategy entails some limitations and may lead to biased estimates if these restrictions are too strong or if we are omitting some relevant variables in the endogenous vector of observables. Nevertheless, we think that this approach is a good mix between simplicity and plausibility, also considering that our focus is on labor market, which is sluggish by its own nature. In addition, in Section 6 we estimate the model using monthly data, making the short-run assumption more realistic, although still not completely clean, and we show that results are barely affected.

5 Results

5.1 Impulse responses and stochastic volatilities

Following Lopez-Salido and Nelson (2010) and Prieto et al. (2016), we group quarterly observations available in the sample into financial crisis and non-financial crisis periods. In particular, we consider five periods of US financial distress: the Less-Developed-Countries Debt Crisis (1982-1984), the stock market crash of 1987, the Savings and Loan Crisis (1988-1991), the stock market crash of 2001 and the Global Financial Crisis (2008-2009). For these financially distressed periods (and for the non-crisis observations), we compute the averaged response of each variable to a standardized impulse (unitary increase) to the NFCI.[16] Standardization across periods allows to isolate the transmission mechanism from changes in shock volatilities.

All figures report the 16th and 84th percentiles as bounds for the credible region. We do not detect noticeable time variation in the transmission mechanism, between crisis and non-crisis period, since the response to a standardized impulse is almost constant over time. We find that a one-unit increase in the NFCI significantly increases the unemployment rate by about 0.8% within 10 quarters and depresses hours of work per employee (figure 6). Unemployed workers get discouraged and some of them exit the labor force, given the negative and persistent response of the participation rate. Moreover, wage inflation response shows a significant reduction by about 0.4% at the peak, because of lower labor demand, captured by a significant drop in the vacancy rate. The simultaneous

[16] Remind that NFCI is constructed to have zero mean and unitary standard deviation.

reduction in employment and vacancy results in a fall in labor market tightness:[17] according to search and matching models, when labor market is less tight, the job finding rate decreases, while the vacancy filling rate rises. The labor market slack drives a reduction in GDP (by more than 1% in levels at the peak). Interestingly, price inflation is slightly positive and borderline significant: this result is consistent with the VAR estimates by Abbate et al. (2016), who, however, use a different identification strategy.[18]

As shown in Figure 7, we find evidence of time-varying volatility of the identified financial shock. In particular, the estimated standard deviation is very high in the beginning of the sample (in correspondence to the Less-Developed-Countries Debt Crisis) and during the Global Financial Crisis. On the other hand, consistently with a large strand of the literature, during the Great Moderation the identified financial shock displays a relatively small standard deviation. In particular, Justiniano and Primiceri (2008) report that the key factor to understand the Great Moderation is the reduction in volatility of the investment shock, defined as innovation to the technology that transforms investments in capital goods. They mention that this innovation may be tied with the cost of external financing for firms, which has shown an important reduction in those years, due to massive financial liberalization.

To better assess the role of drifting volatilities, Figure 8 reports the non-standardized responses to a one-standard-deviation impulse. Time variation is driven by the stochastic volatility that determines the size of the impulse.

As stated previously, there is a growing theoretical literature analyzing the linkages between financial frictions and the labor market. Some of these works focus on the effects of a financial shock on labor market variables: our estimated impulse responses are consistent with these models, at least qualitatively. For instance, in Monacelli et al. (2011) a negative credit shock (by one standard deviation) decreases the employment rate by about

[17] Labor market tightness is defined as the vacancy/unemployed ratio. The numerator decreases after the shock; the denominator is affected by two countervailing forces: unemployment rate goes up but labor participation is lower. However, given that the reduction in the participation rate is small in magnitude, we conclude that labor market is less tight following a financial shock.

[18] Theoretical models are not unanimous on the effects of a financial tightening on inflation; on the one hand, tighter financial conditions reduce households' expenditure via negative wealth effects, generating a reduction in aggregate demand and so a lower price level (this is the mechanism at work in Gertler and Karadi (2011)); on the other hand, if firms borrow in order to buy intermediate inputs, an increasing risk-premium boosts the marginal cost of firms, which respond by raising the price of their products (as in Atta-Mensah and Dib (2008)). On top of that, Gilchrist et al. (2016) build a model in which firms increase prices when an adverse shock weakens their balance sheets, in order to maintain profitability; this paper provides also empirical evidence showing that, during the Great Recession, firms with a limited internal liquidity decided to raise their prices.

0.35% of the steady state value (which is close to one) at the response peak: this value is close to our median estimate for the crisis periods; GDP and wage responses are close to our median values as well. In Petrosky-Nadeau (2013) a two standard deviations negative credit shock raises the unemployment rate by 2% points at the peak, a value higher than our median estimates during crisis periods; however, both shape and persistence of the reaction are very similar.

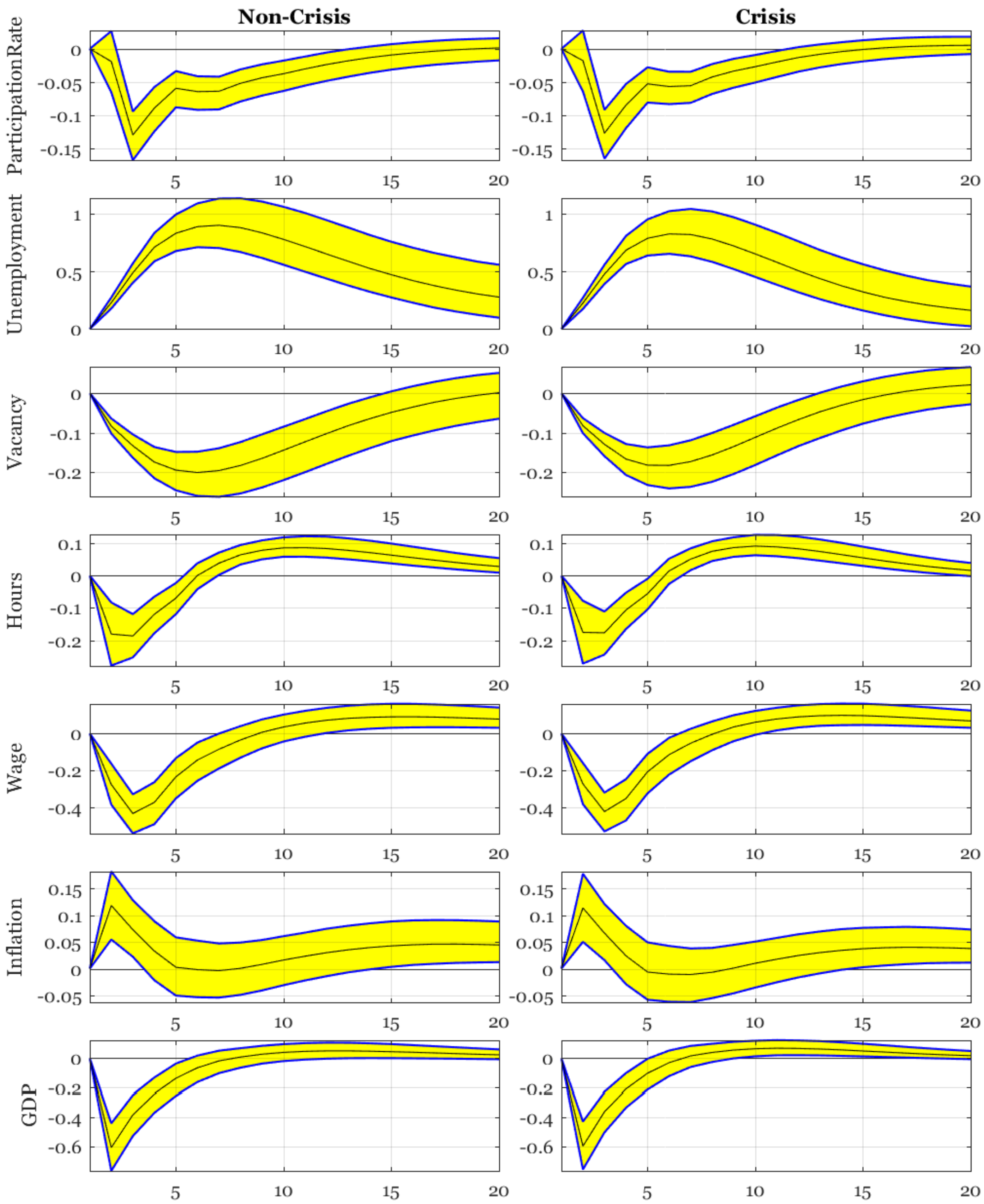

Figure 6: Time-varying impulse response functions to a standardized shock NFCI shock.

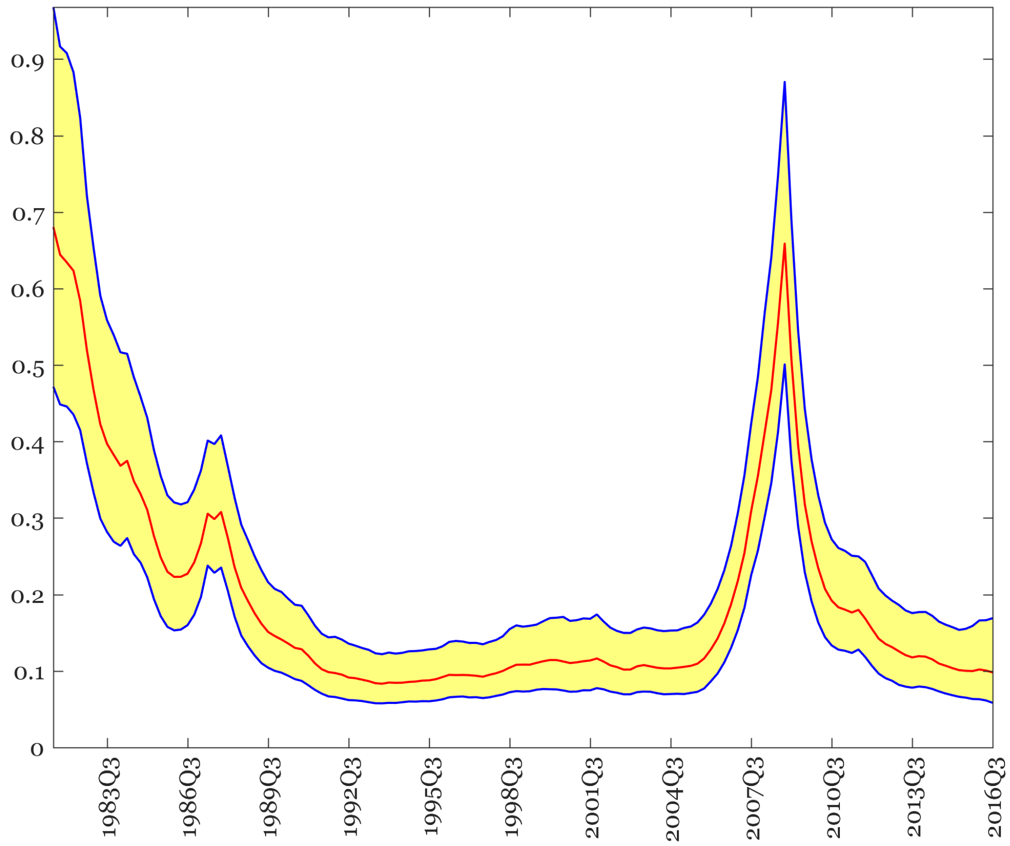

Figure 7: Stochastic volatility of the identified shock.

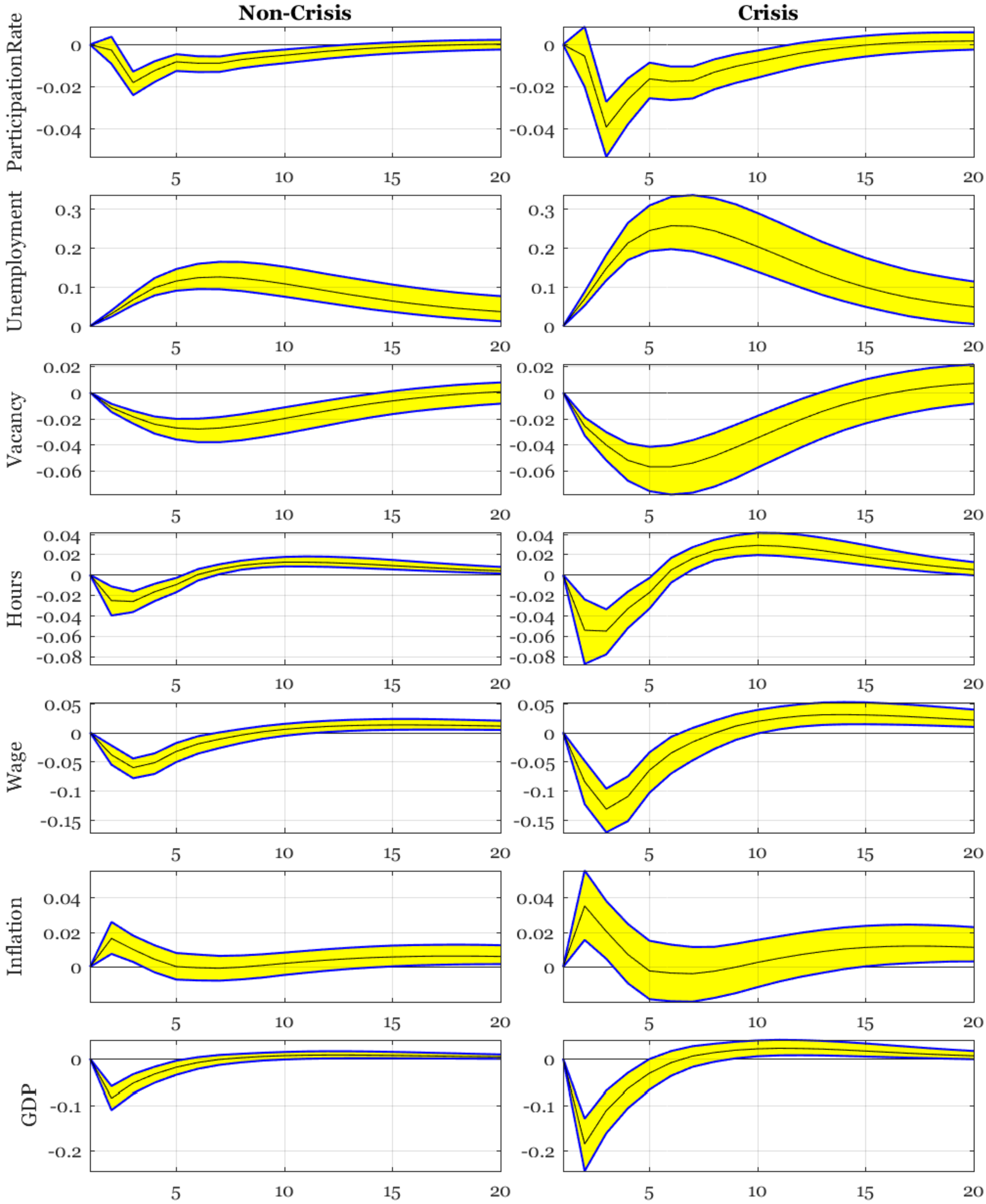

Figure 8: Time-varying impulse response functions to a (non-standardized shock) NFCI shock
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5.2 Historical Decomposition: comparing CVAR and TV-VAR-SV

Having observed significant time variation in the identified financial shock volatility, where larger levels of volatility tend to be associated with financial distress periods, we perform a historical decomposition analysis for the variables of interest.

A CVAR assumes constant volatility of the identified shock. When estimated using financial crisis observations, i.e. when large economic reactions follow financial distress, a CVAR framework may overstate the role of financial shocks in explaining unemployment over the sample. The TV-VAR-SV, instead, is able to discriminate between periods of large and small volatility, complying with the asymmetry of observed financial shocks: large and negative or small and positive.

If we estimate a CVAR using the entire sample (Figure 10), we find that the financial shock's role in explaining unemployment rate fluctuations is roughly as important as for other non-identified shocks. This finding is consistent with Caldara et al. (2016) that use a CVAR to estimate the effects of financial and uncertainty shocks on macroeconomic variables.[19] However, when the CVAR estimation sample ends in 2007Q4 (Figure 9), the picture changes: the financial shock contribution is much smaller across the entire sample period. In these experiments we observe that Great Recession observations are driving the importance of financial shocks across the sample.

Figure 11 displays the historical decomposition of unemployment in a TV-VAR-SV framework. The financial shock hits the unemployment rate asymmetrically: contributions are large and negative in periods of severe financial distress like the Great Recession and the 1982-1984 crisis, while there is almost no positive contributions in the 1990s and early 2000s. This result is in contrast with the previous CVAR analysis and provides solid ground for more general time-varying models when performing structural analysis. This asymmetric behavior is explained by the time-varying volatility of the financial shock, which is estimated to be higher in period of financial distress: indeed, we find that negative shocks tend to be larger and less frequent than positive shocks.

Also for the vacancy rate, negative financial shocks are the main responsible for the fall in 1982-1984 crisis and during the Great Recession, while positive financial shocks cause only mild response in other periods (figure 12). This difference between the CVAR and

[19] See figure B-1 in the working paper version of Caldara et al. (2016).

TV-VAR historical decomposition is less evident for hours and GDP, as shown in the Appendix. Hours of work enter the VAR in (log) first differences: while the level of hours worked per employee is not fully back to the pre-crisis level, the growth rate turned to be positive in 2009 (most recent observations are above the pre-crisis mean).

Accordingly, our identified financial shock was less severe on hours worked in terms of persistence: it is the prolonged negative effect on the unemployment rate that generates this sizable differences between the CVAR and TV-VAR historical decomposition. The same reasoning holds for real GDP, that, like hours worked, enters our model in (log) first differences.

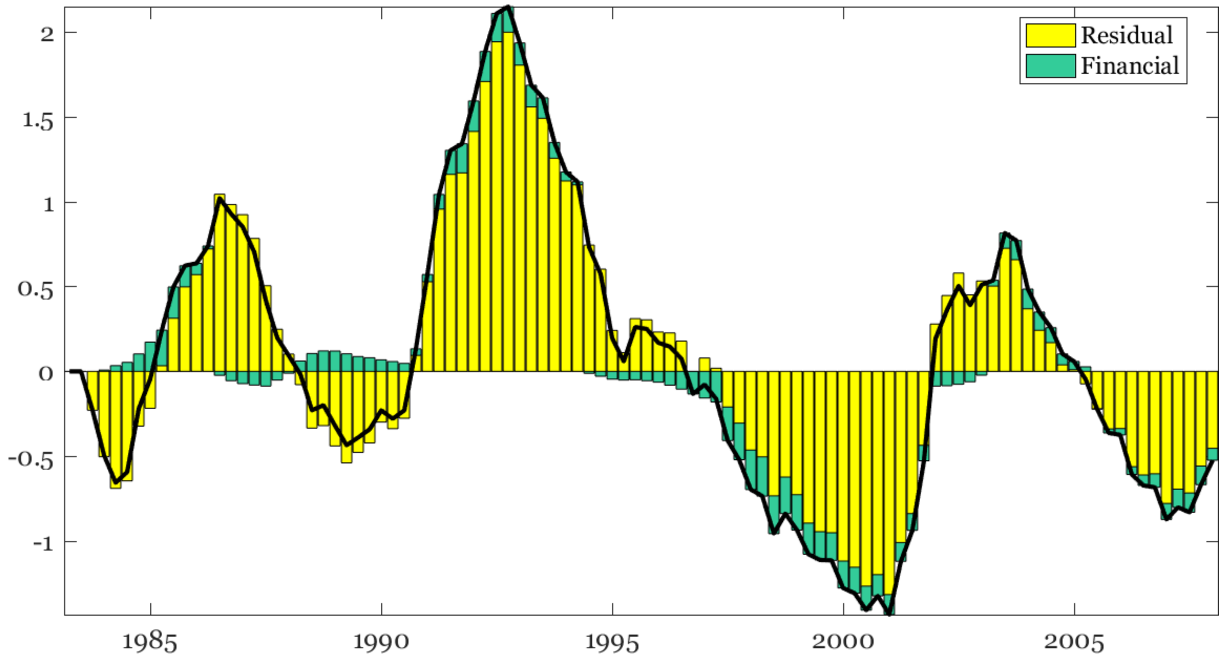

Figure 9: CVAR historical decomposition of unemployment, sample 1983Q1-2007Q4.

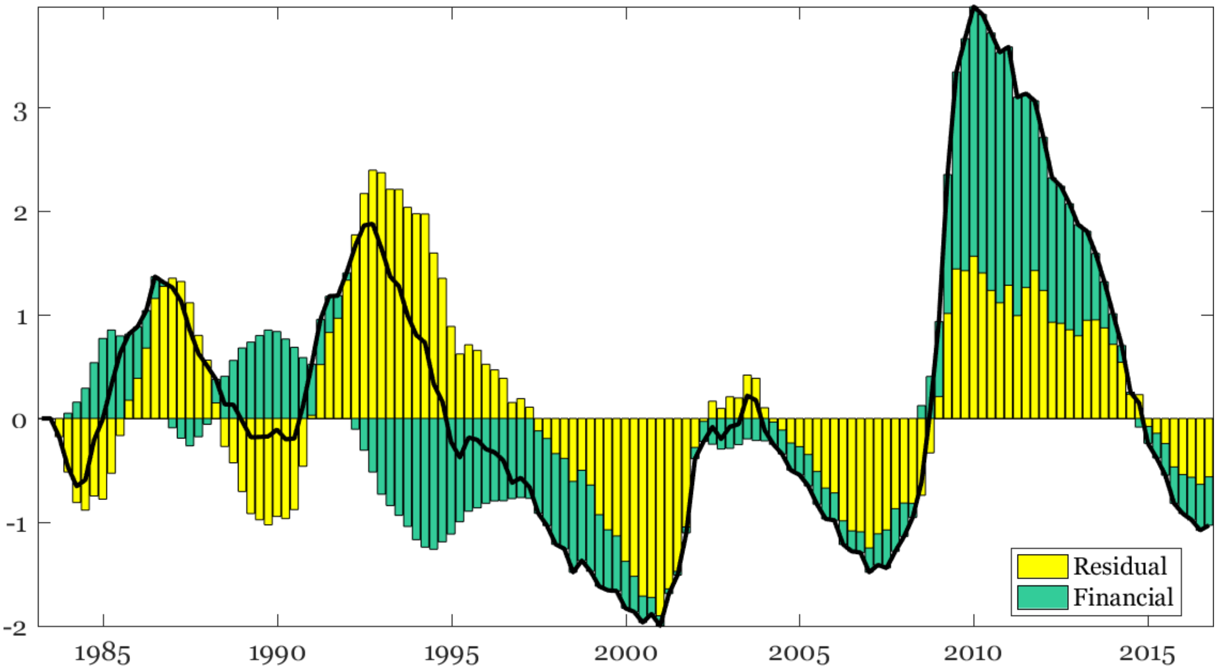

Figure 10: CVAR historical decomposition of unemployment, sample 1983Q1-2016Q3.

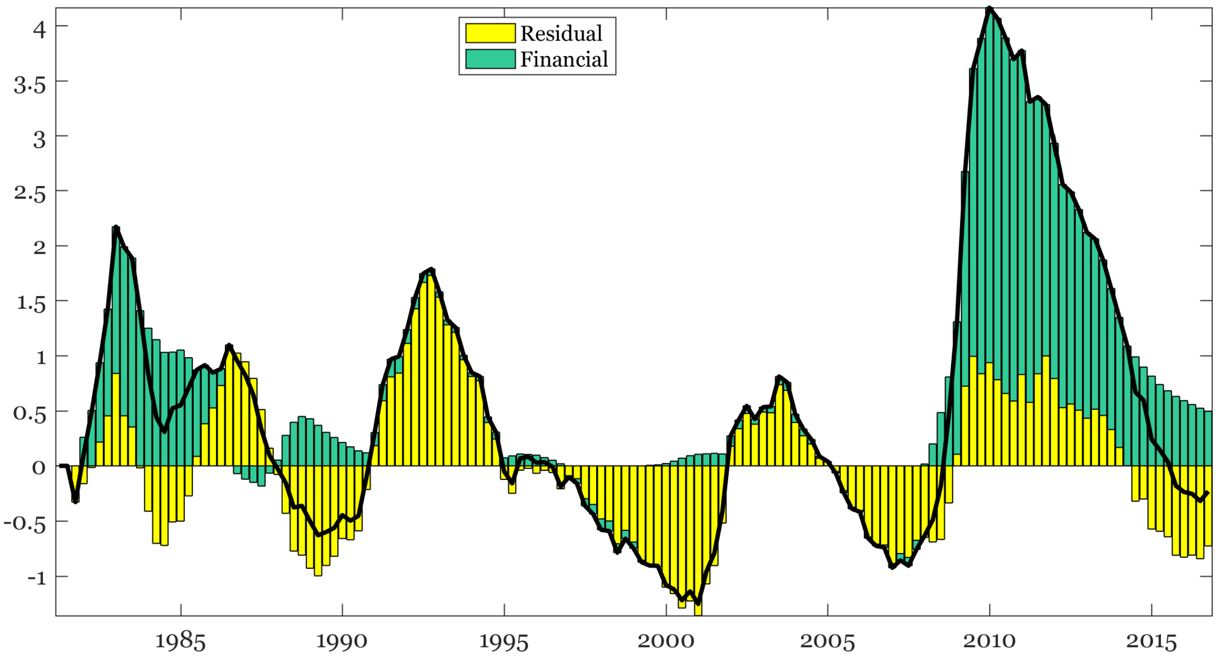

Figure 11: Historical decomposition of unemployment (TV-VAR-SV).

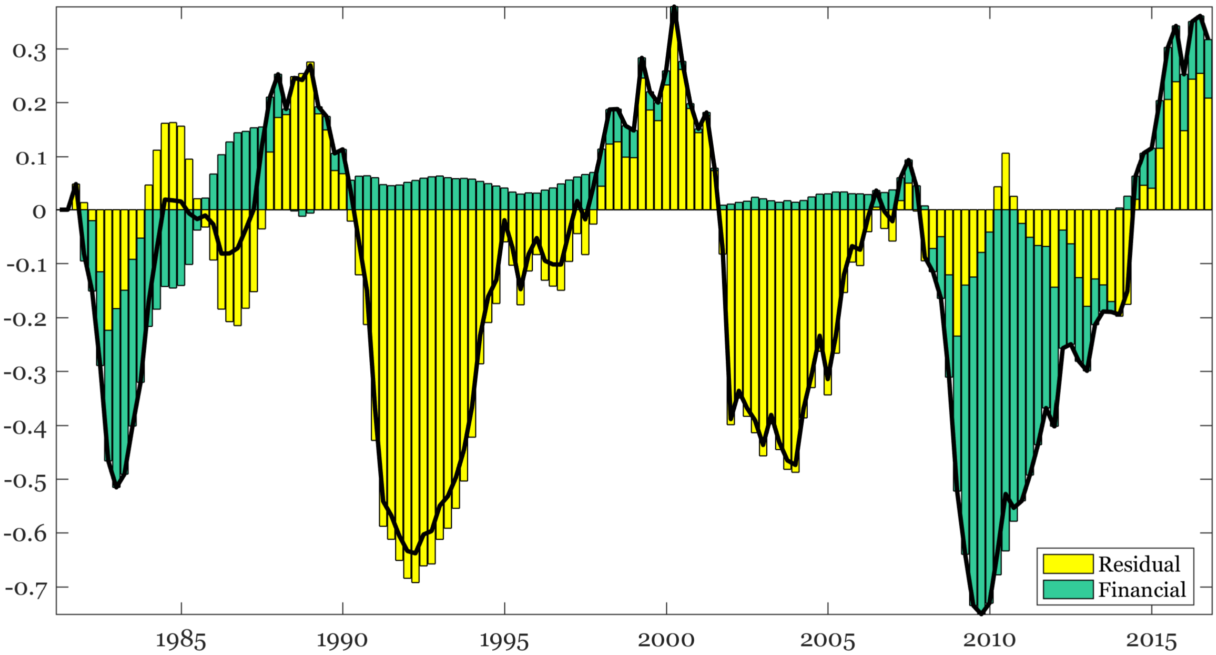

Figure 12: Historical decomposition of vacancies (TV-VAR-SV).

6 Robustness

In this section we perform three experiments to challenge the robustness of our results. First, we repeat the analysis using the credit spread index built by Gilchrist and Zakrajšek (2012). Second, we estimate the model by using monthly data. Third, we estimate the model excluding the Great Recession from the estimation sample. Most of the resulting figures for these robustness exercises are left in the Appendix.[20]

6.1 Excess Bond Premium

Gilchrist and Zakrajšek (2012) decompose their credit spread index in two components: the first one captures movements in expected defaults, the second one represents the excess bond premium (EBP, henceforth) which measures cyclical changes in the relationship between default risk and credit spreads. In this subsection we verify the robustness of our results by using EBP as financial variable, as in the VAR analysis of Gilchrist and Zakrajšek (2012); since the correlation between EBP and NFCI is not so high (0.40),

[20] Additional figures are available upon request.

this represents a good test bench for our findings.[21] According to the CVAR historical decomposition, the 1990s were a period of positive financial shocks contribution. On the other hand, using a time-varying model, this positive contribution almost disappears, as in our benchmark specification.

Financial shock standard deviation is very low and pretty constant until the late 1990s, when it starts to increase, reaching a peak during the Great Recession (figure 15). Impulse responses seem constant over time, when the impulse is standardized (figure 16). Signs and sizes of responses are in line with the benchmark specification, except for the inflation response, which is negative but not statistically different from zero. Given that stochastic volatility is relatively high mainly in 2001 and during the Great Recession, only during these crises impulse responses functions are time varying, after a non-standardized financial shock. Figures 17 and 18 show the impulse response function of unemployment and vacancy in each crisis period.

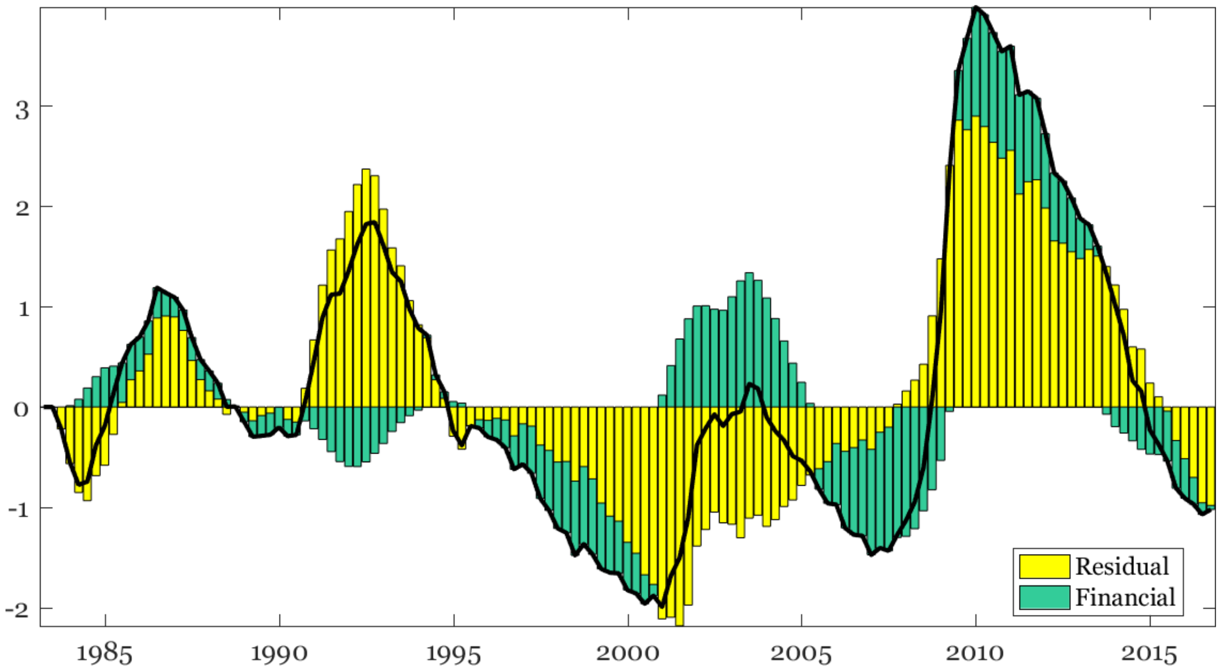

Figure 13: Historical decomposition of unemployment (EBP specification, CVAR).

[21]An empirical analysis in a time-varying framework using EBP has been conducted by Abbate and Marcellino (2016), who, however, do not consider the labor market.

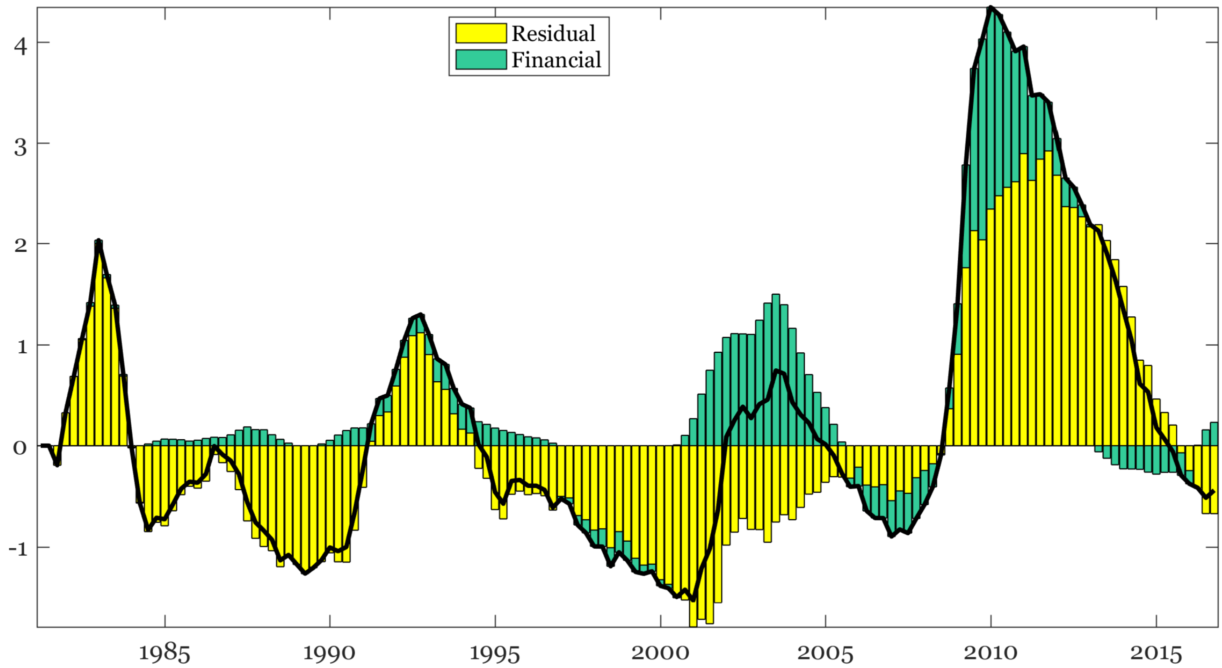

Figure 14: Historical decomposition of unemployment (EBP specification, TV-SV-VAR).

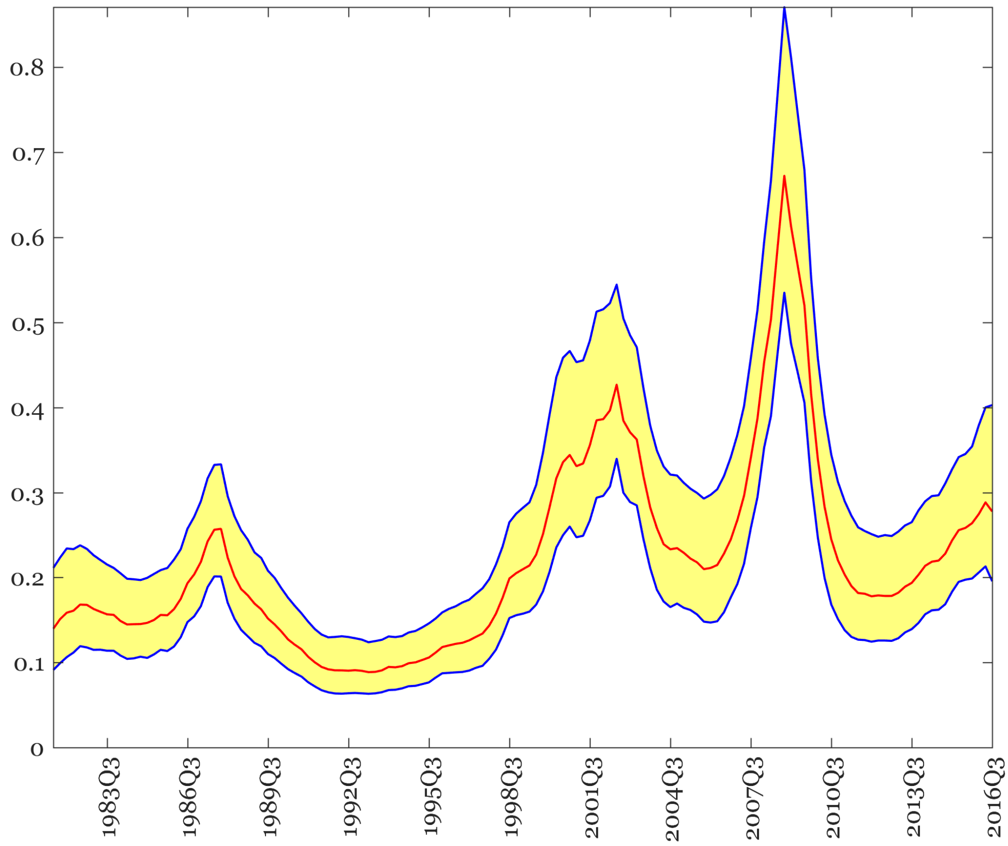

Figure 15: Stochastic volatility of the identified financial shock (EBP specification).

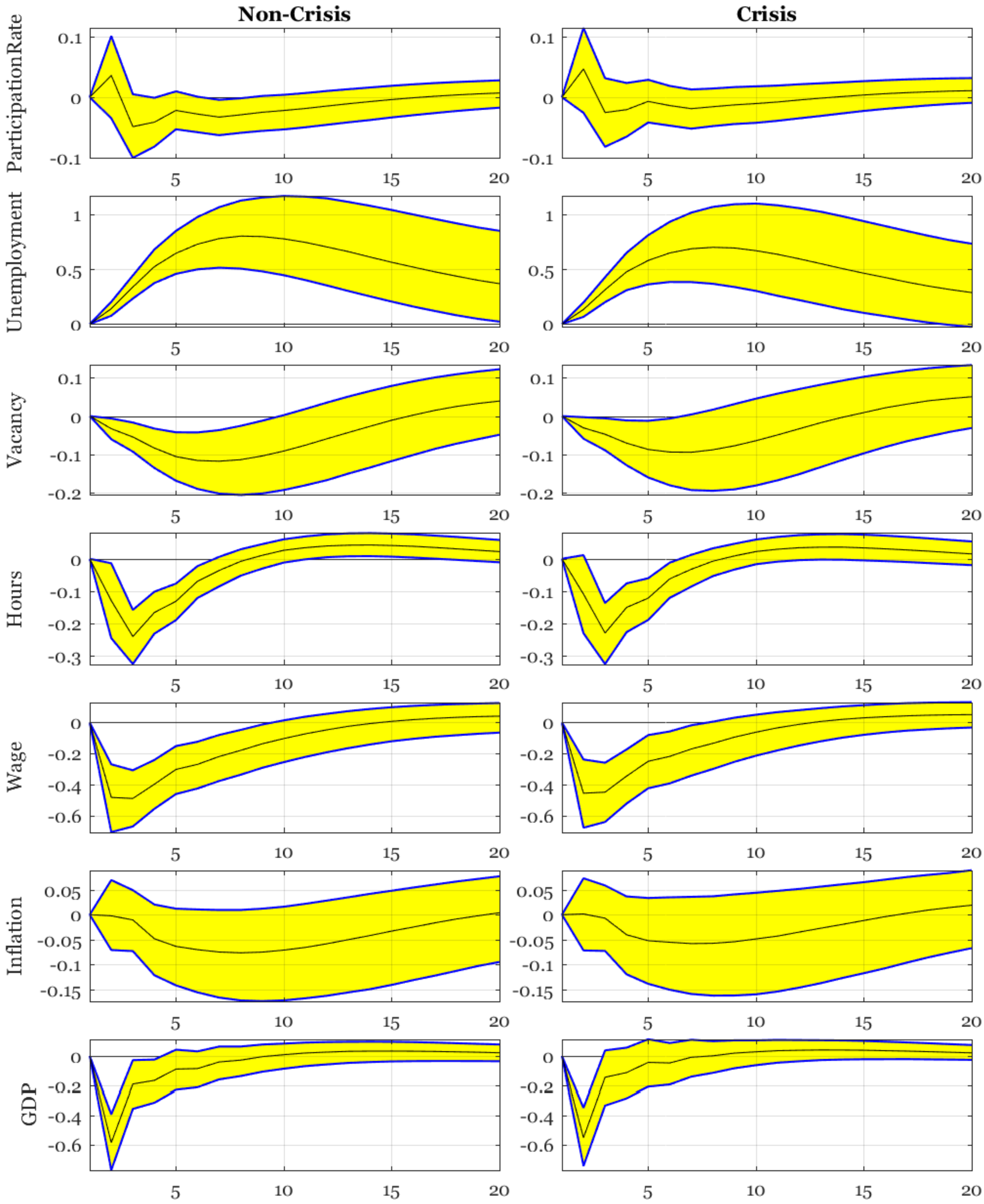

Figure 16: Time-varying impulse response functions to an EBP standardized shock.

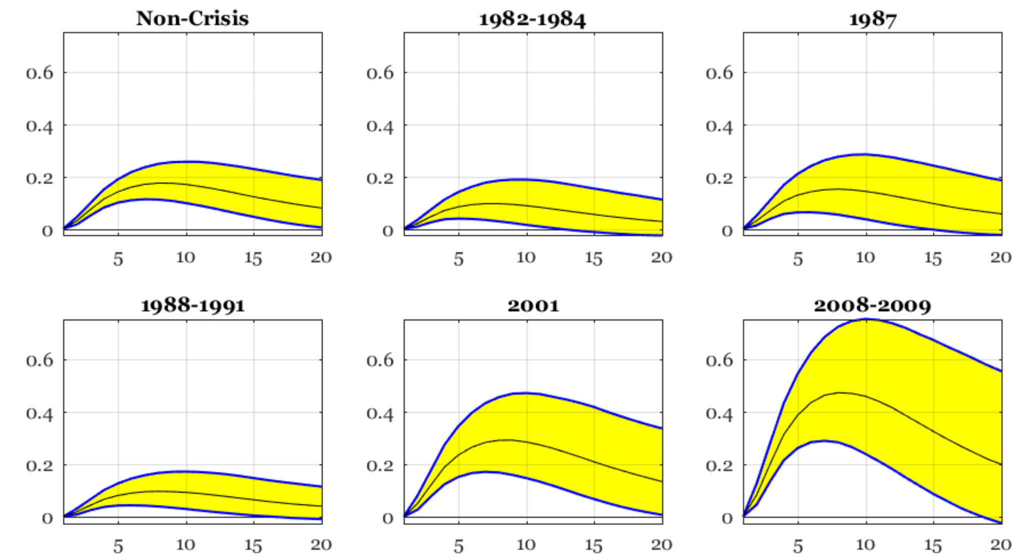

Figure 17: Time-varying impulse response function of unemployment to an EBP non-standardized shock.

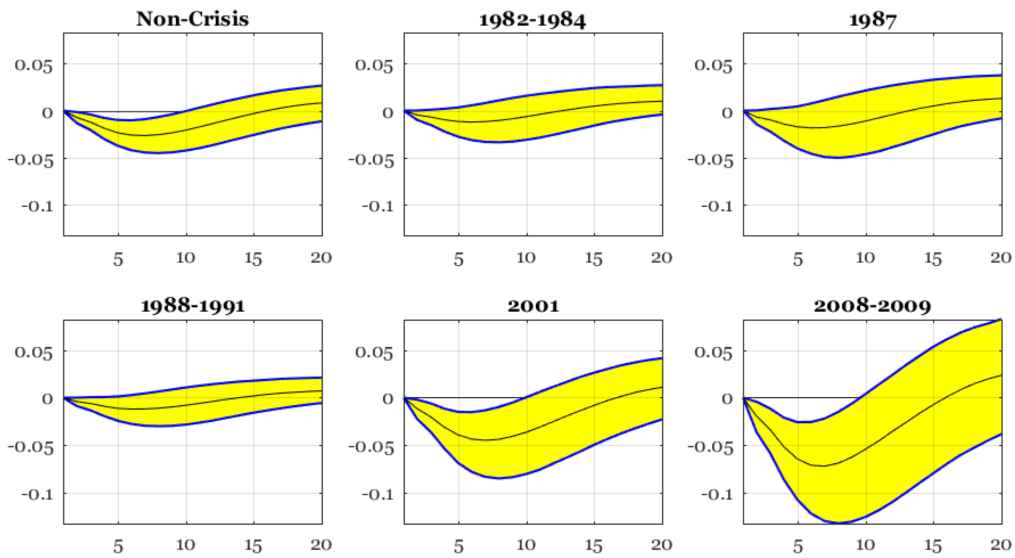

Figure 18: Time-varying impulse response function of vacancy to an EBP non-standardized shock.

6.2 Fixed VAR Coefficients and Monthly Data

Our identification strategy is based on a short-run restriction: variables cannot contemporaneously react to an innovation in NFCI equation residuals. This assumption may seem questionable, if applied to quarterly data. In order to address this issue, we estimate the model using monthly data, keeping fixed the VAR coefficients, thus allowing time variation only in shocks' standard deviations. Indeed, when the model is estimated at monthly frequency, the number of coefficients to estimate gets huge. This is because, when the frequency switches from quarterly to monthly, the number of observations is multiplied by three, causing an increase in the number of lags p, as well as an increase of periods in which $k = n\,(np+1)$ coefficients have to be estimated. However, since the benchmark specification does not find much time variation in VAR coefficients, a CVAR with stochastic volatility seems a good compromise.

The Gibbs Sampler to estimate a CVAR with stochastic volatility is a modification of the counterpart for the TV-VAR-SV described above, in which the coefficients' draw step is simply a Bayesian regression with informative prior, obtained by stacking the model in the following form:

$$\underbrace{Y}_{nT\times 1} = \underbrace{X}_{nT\times k} \cdot \beta + U, \qquad U \sim \mathcal{MN}\left(\mathbf{0},\ \underbrace{V_u}_{n\times n}\right)$$

where V_u is conditional on the history of stochastic volatilities drawn in the previous step. Prior information is incorporated in the posterior as suggested by Gelman et al. (2013).

Some of the series used in the baseline specification are not available at monthly frequency. The new series that we use are the following:

- Average hours of production and nonsupervisory employees in the private sector.
- Average hourly earnings of production and nonsupervisory employees in the private sector.
- The consumption price index.
- The industrial production.

The unemployment rate, the participation rate and the NFCI are available at monthly frequency, while the vacancy index is not and it is dropped from the estimation sample. All the transformations are the same of the baseline specification, except for hours worked that now are not divided for number of employees, being an average measure.

Results from this new specification do not change the picture: positive financial shocks have a mild impact on unemployment fluctuations (figure 20) and this result cannot be captured by a VAR with constant shocks' variance (figure 19). The estimated stochastic volatility has a pattern similar to the correspondent graph of the quarterly baseline specification (figure 21). The impulse response functions of unemployment, hours, GDP and inflation do not qualitatively differ from the baseline specification (figure 22). Now nominal wage inflation grows on impact; nevertheless, given the inflation response, real wage decreases and this is consistent with a fall in labor demand by firms.

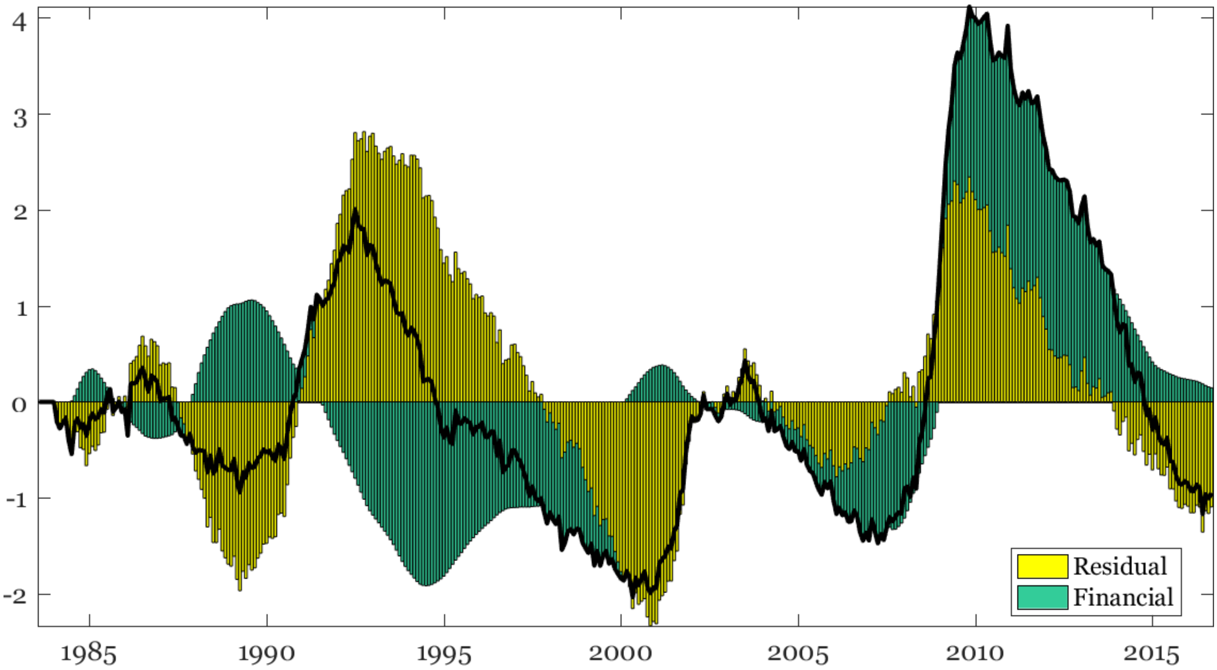

Figure 19: Historical decomposition of unemployment (CVAR, monthly specification).

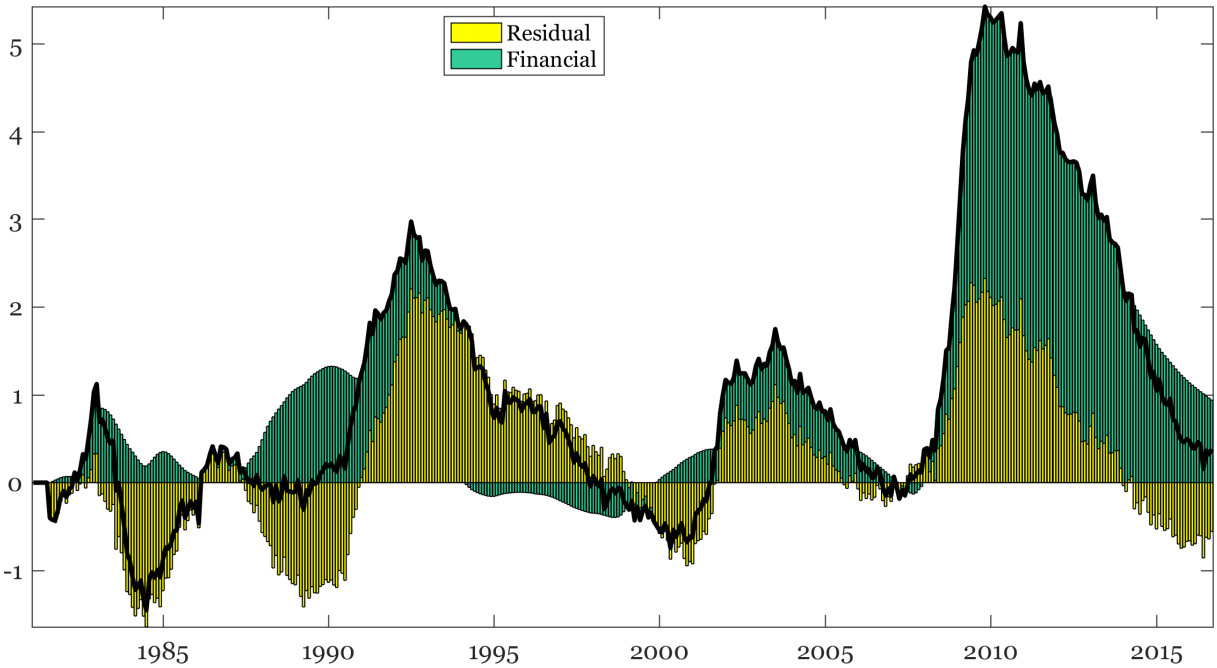

Figure 20: Unemployment historical decomposition (CVAR-SV, monthly specification).

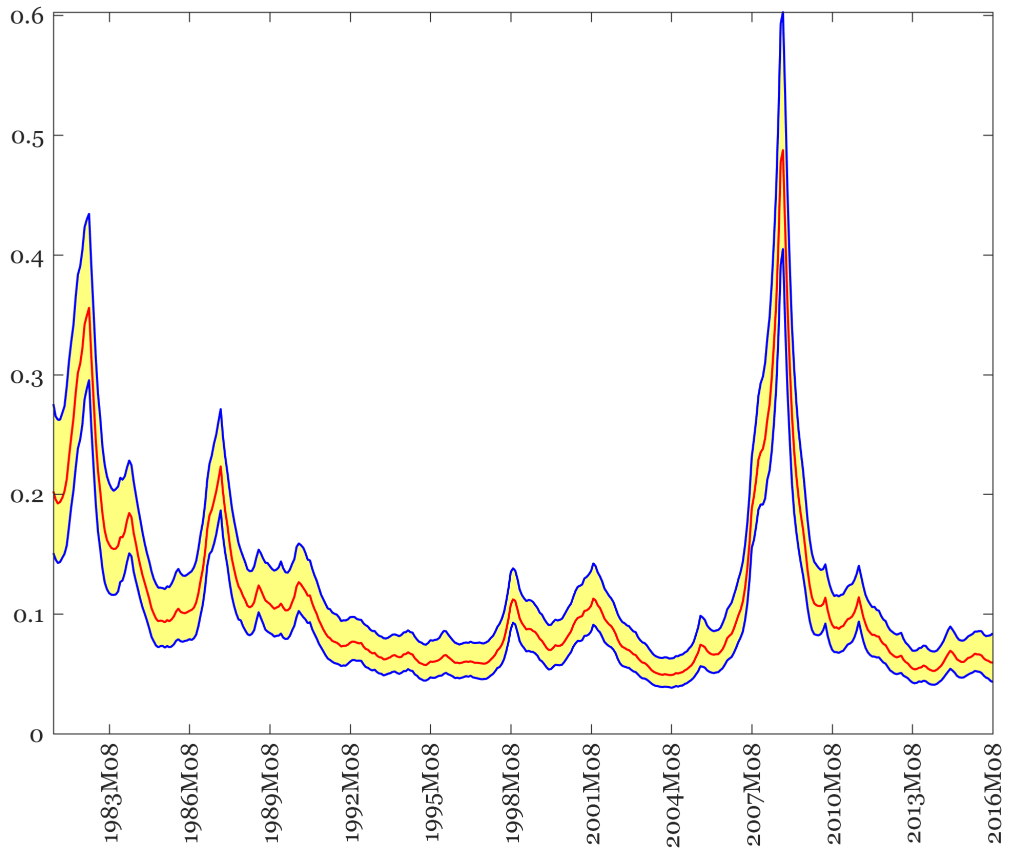

Figure 21: Stochastic volatility of the identified shock (monthly specification).

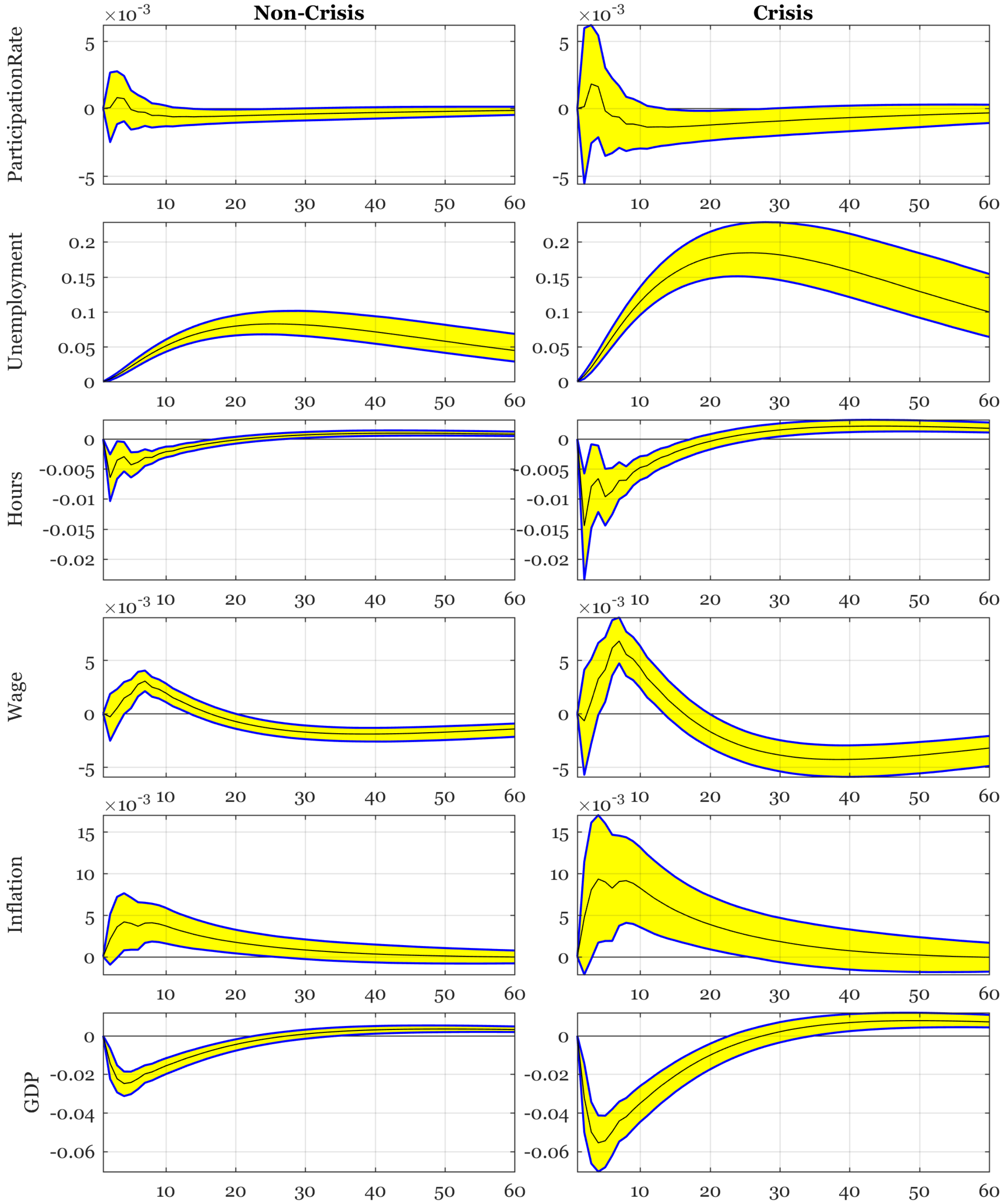

Figure 22: Impulse response functions (non-standardized, monthly specification).

6.3 Excluding the Great Recession

In order to assess how much the Great Recession is driving our results, we re-estimate the model by ending the estimation sample in 2007Q4. The historical decomposition of unemployment and the plot of stochastic volatility (figures 23 and 24) resemble their full-sample counterparts. Therefore, the only period in which financial shocks contribute to explain unemployment fluctuations was the 1980s. Moreover, the financial shock's volatility, after the initial peak, has maintained low until the end of the (truncated) sample. Impulse response functions are quantitatively and qualitatively similar to the full-sample counterparts (figure 25). Thus, our results do not seem affected by the Great Recession period.

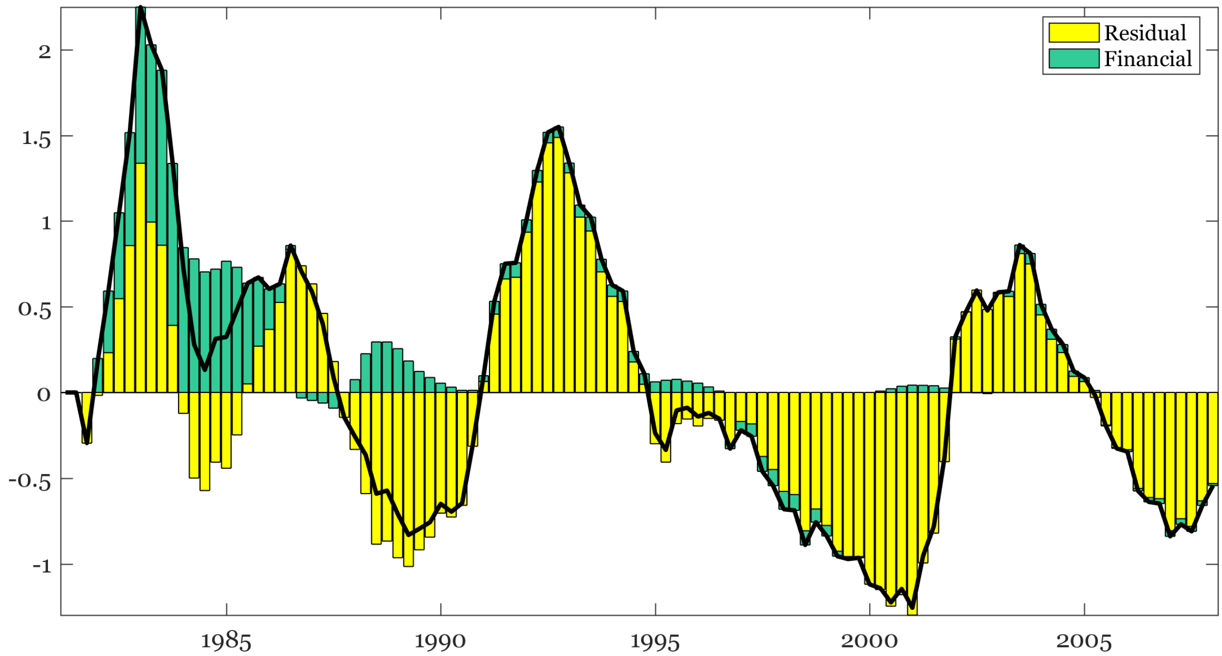

Figure 23: Unemployment historical decomposition (TV-VAR-SV, no Great Recession).

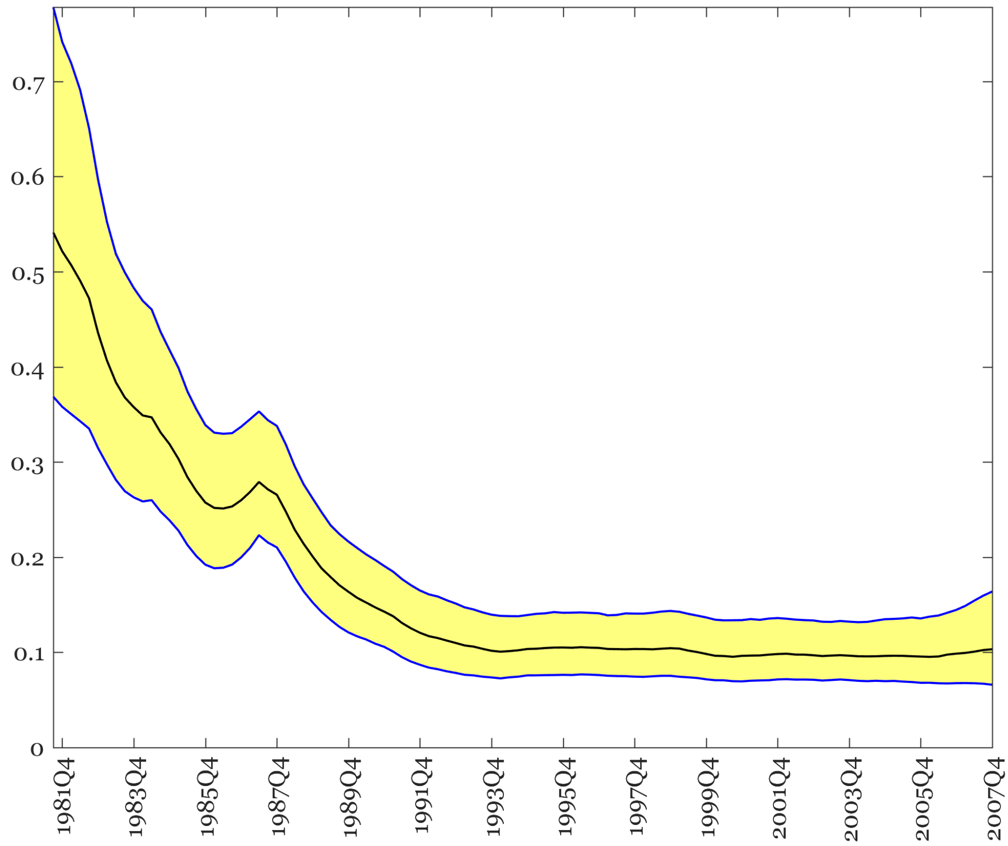

Figure 24: Stochastic volatility of the identified shock (no Great Recession).

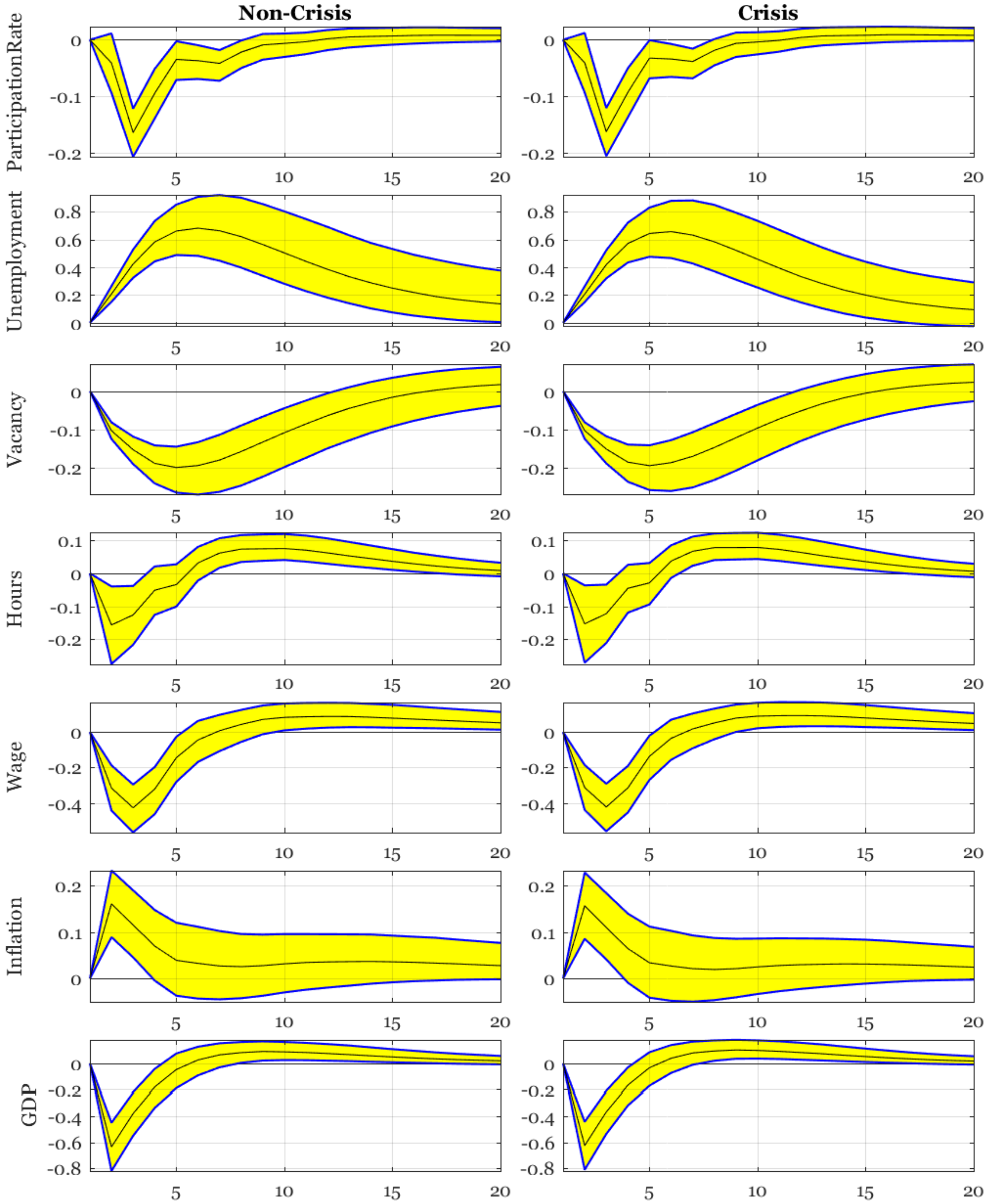

Figure 25: Impulse response functions (standardized, no Great Recession).

7 Conclusions

In this paper we estimate a TV-VAR-SV in order to detect the effects of financial shocks on labor market variables, using the NFCI as financial indicator.

Differently from a CVAR framework, all the elements of a TV-VAR-SV are potentially time-varying: our findings report a relevant degree of time variation in the estimated financial shock's standard deviation, which is high in correspondence of periods of financial distress and low during the Great Moderation. However, our model does not find significant time variation in the transmission mechanism, since the estimated autoregressive coefficients are highly stable over time.

We show that positive financial shocks have been almost irrelevant in explaining unemployment fluctuations in the last three decades, while negative shocks have given a remarkable contribution. This result relies on the changing size of financial shocks, which is high during periods of financial turbulence, such as the Great Recession. This feature cannot be captured by a CVAR, which indeed finds both positive and negative contributions of financial shocks on the unemployment rate, in our estimation horizon.

In addition, we show that estimated response signs to an adverse financial impulse, identified with a short-run restriction, are reasonable and in line with the theoretical literature. A financial tightening generates a crisis in the labor market: firms reduce unemployment and per-capita hours worked to face the reduction in borrowing ability; they post less vacancies, so that resulting lower labor demand produces a fall in nominal wages; some unemployed workers get discouraged and the labor participation rate decreases; the response of real GDP is negative as well, due to a drop in labor input and a smaller demand of households, who become poorer. The response of inflation is positive but only borderline significant, reflecting both supply and demand effects at work.

From a policy perspective, our findings point out that macroprudential measures limiting the probability of a financial crisis may yield significant benefits to the economic activity via the labor market channel. Nonetheless, our model can not say anything about the effectiveness of these policies in reducing the standard deviation of financial shocks: thus, including a macroprudential indicator in macro-financial VARs with stochastic volatility seems an additional promising avenue to extend this line of research.

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A Appendix

A.1 Baseline Specification: Additional Figures

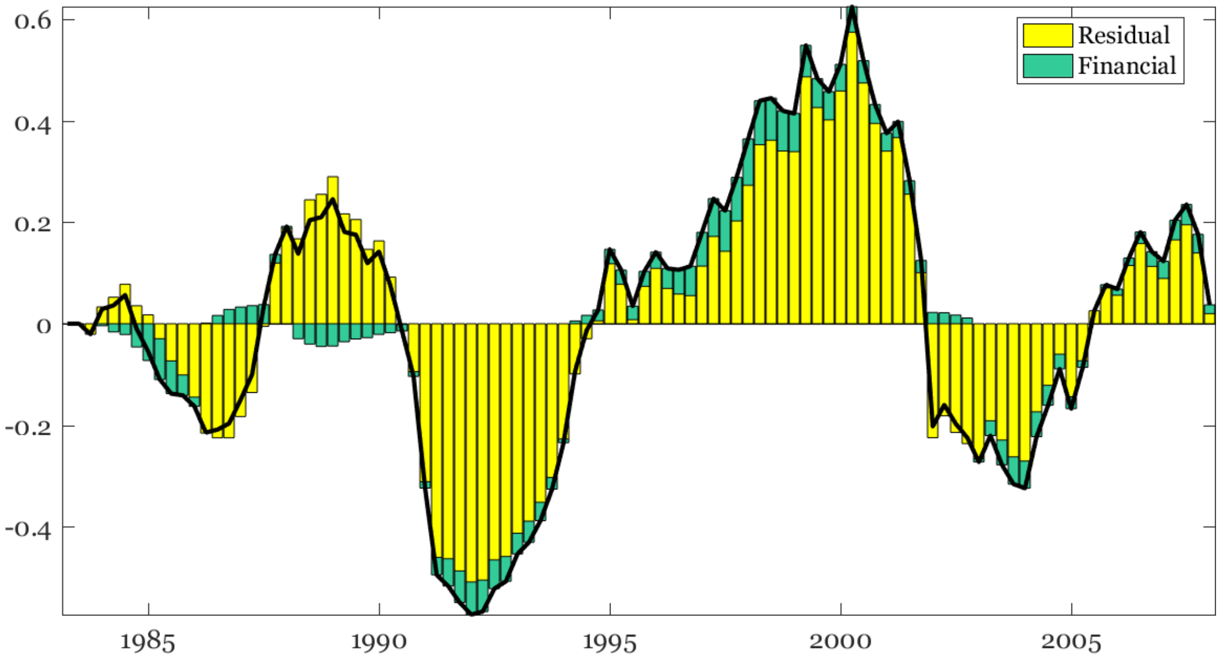

Figure A.1: CVAR historical decomposition of vacancy rate, sample 1983Q1-2007Q4.

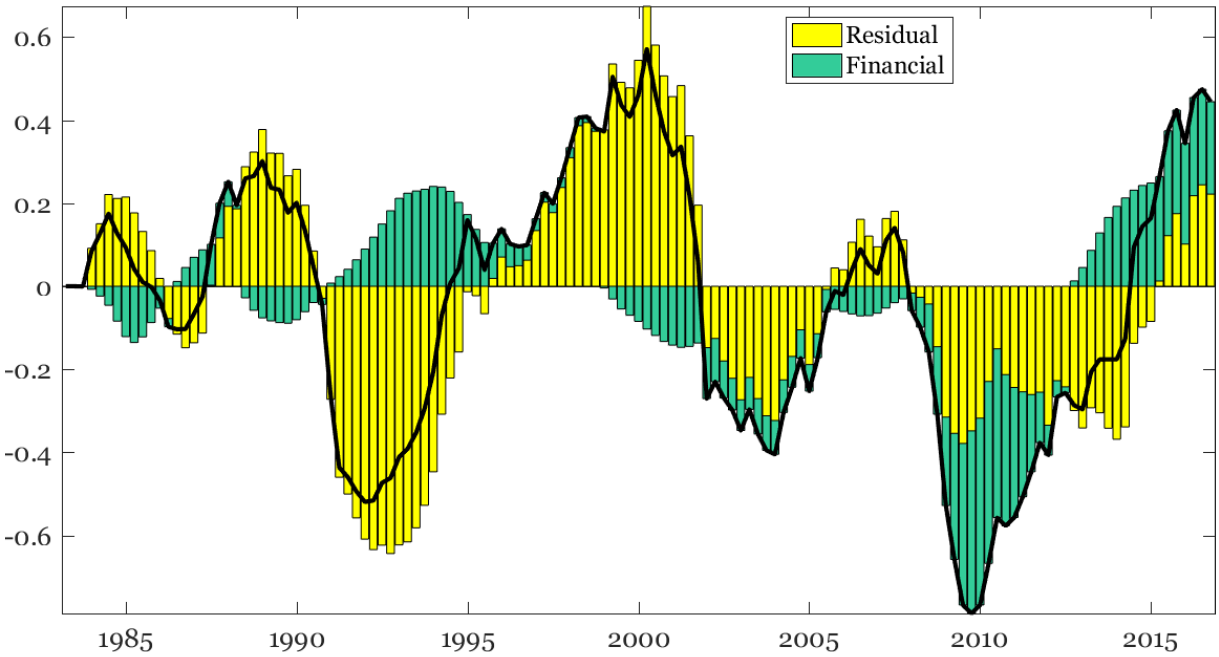

Figure A.2: CVAR historical decomposition of vacancy rate, sample 1983Q1-2016Q3.

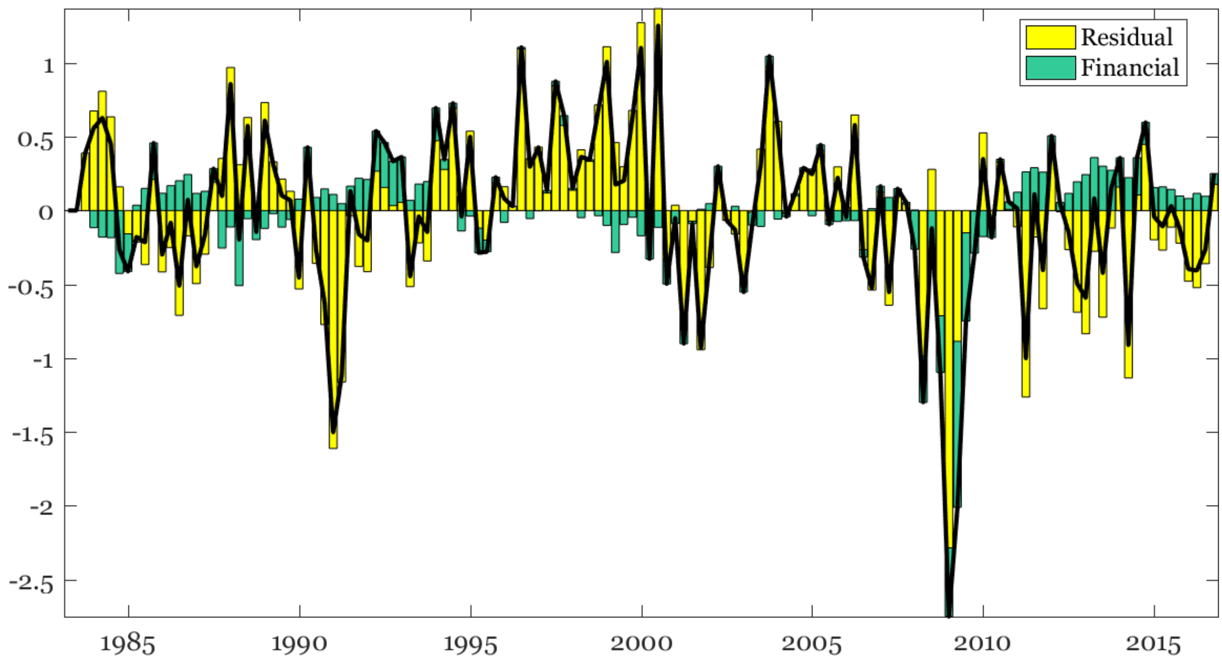

Figure A.3: Historical Decomposition of GDP (CVAR).

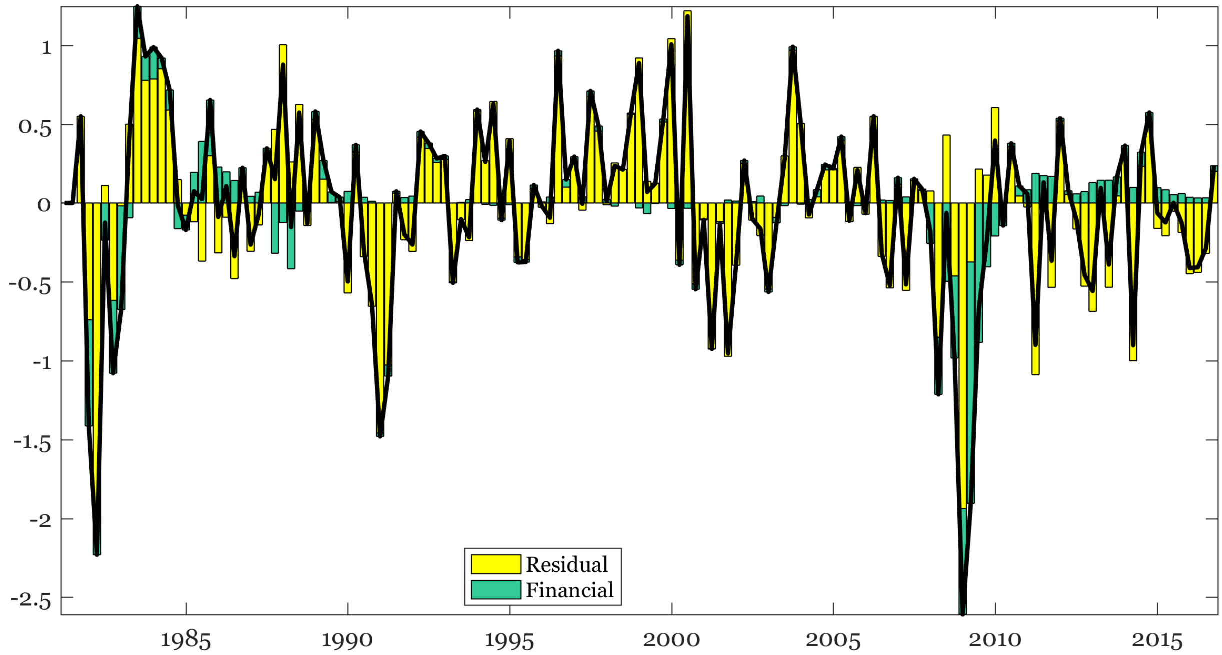

Figure A.4: Historical Decomposition of GDP (TV-VAR-SV).

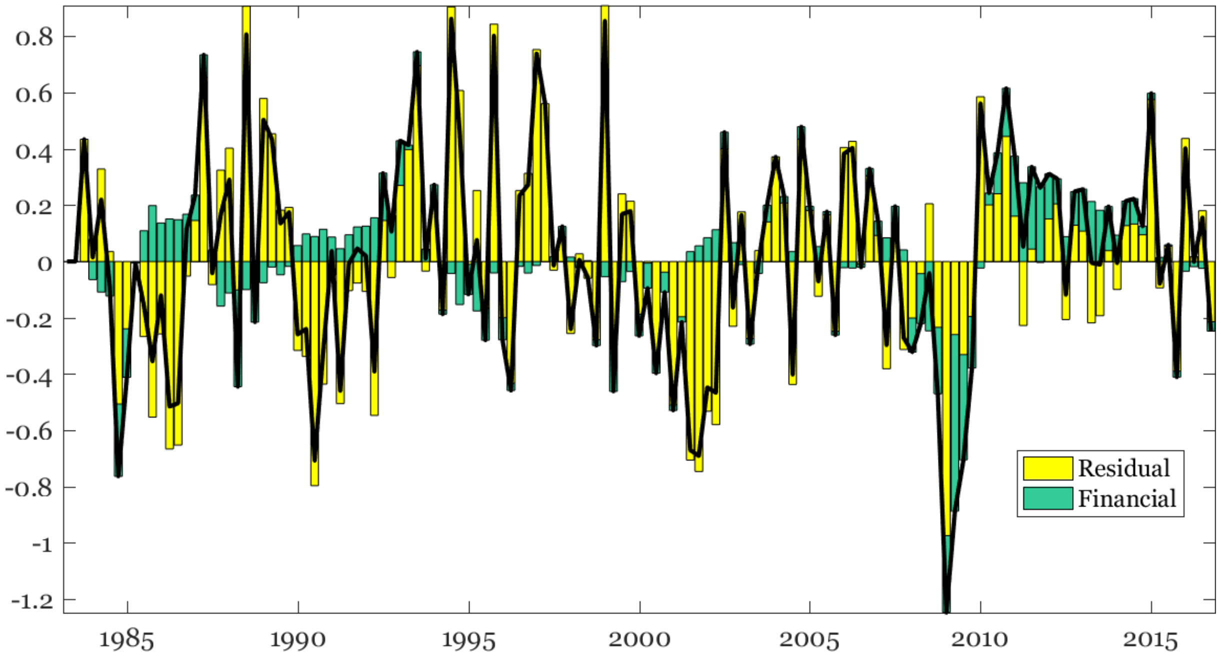

Figure A.5: Historical Decomposition of hours (CVAR).

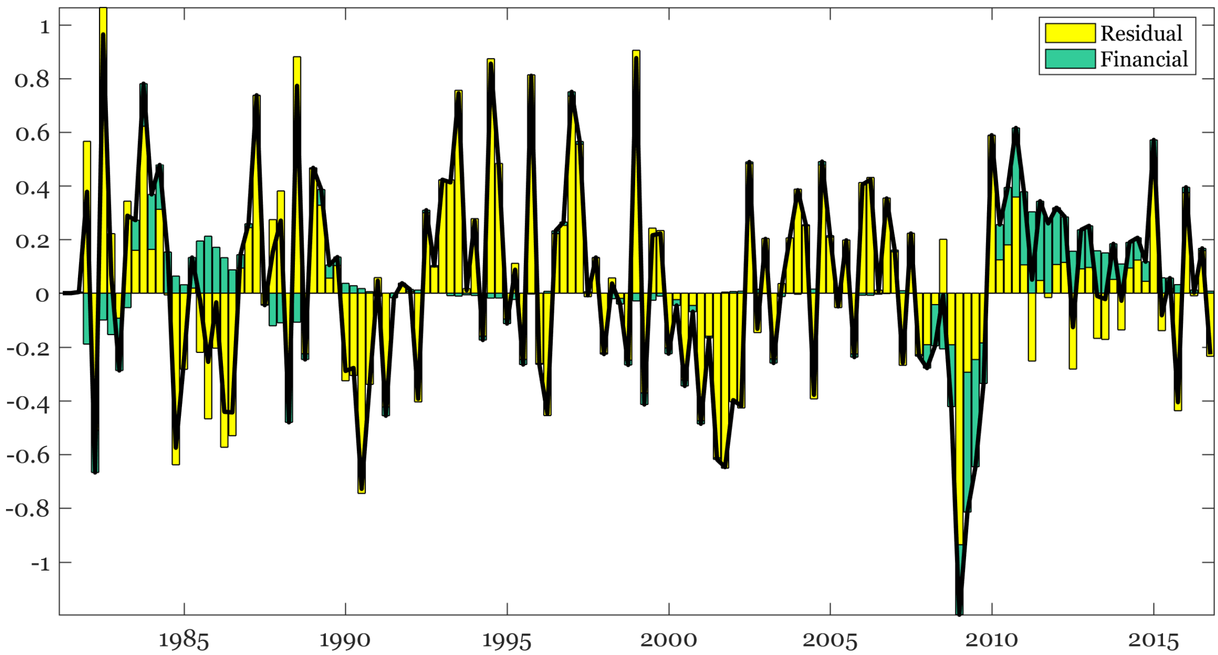

Figure A.6: Historical Decomposition of hours (TV-VAR-SV).

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