Unemployment and Welfare Participation in a Structural VAR: Rethinking the 1990s in the United States

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ABSTRACT *A report by the Council of Economic Advisers (1997) is the first of a group of studies, known as caseload studies, analyzing the relationship between the U.S. unemployment rate and the welfare participation rate, with special regard to the 1990s. We examine this relationship in a structural VAR model over the period of 1960-2000 and find that the unemployment rate does not help to predict the welfare participation rate while the converse is more likely to hold. These results are robust to State and year heterogeneity over a period of unprecedented positive correlation between unemployment and welfare participation, i.e. 1990-1998. Further, we find that a shock to the welfare participation rate has a contemporaneous impact on the unemployment rate while the converse is less likely to hold. The main conclusion is that several caseload studies may be based on the wrong assumption that the unemployment rate is an exogenous explanatory variable of the welfare participation rate.*

KEY WORDS: Welfare, Unemployment, VAR.
JEL CODE: J2, I3.

1. Introduction

During the 1990s, the United States deeply reformed their most important welfare program, the Aid to Families with Dependent Children (AFDC). The reforms started in 1992-1993 (at State level) through the so-called federal waivers and culminated in August 1996 (at federal level) with the approval of the Personal Responsibility and Work Opportunity Reconciliation Act, which replaced the AFDC by the Temporary Assistance to Needy Families (TANF).

The reforms implied a deep restriction in conditions of permanence on welfare assistance for thousands of single mothers and their children. The share of population on welfare rolls, the welfare participation rate, rapidly felt from 1994 to 2002 (last observation available) and few would have probably questioned the reforms to be the main explanation of this fall, in absence of an unprecedented positive association between the welfare participation rate and the U.S. unemployment rate over the last decade (see Figure 1). Indeed, this association led many researchers to inspect for the relative contribution of unemployment and policy changes behind the movement of the welfare caseload.

Figure 1 here

An initial attempt of studying determinants of welfare caseload dynamics is made by the Council of Economic Advisers (1997, hereinafter CEA) whose technical report is the first

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of a group of studies known as caseload studies[1]. These studies are based on State-level administrative data and conclude that the unemployment rate level is the major determinant of the welfare caseload level while social policy plays a less important role. A different approach is taken by Robert Moffitt (1999) who uses individual-level data to estimate an empirical model *a la* CEA (1997), studies determinants of welfare use (a binary dummy variable), and reports findings that are consistent with those of the CEA (1997). Moffitt's paper, however, has a special relevance in a group of studies looking at the transition from welfare assistance to labor market for thousands of single mothers, i.e. the so-called welfare-to-work studies. A related field of research includes the so-called leavers' studies, which are based on interviews to former welfare recipients about their living conditions after welfare exit.

Caseload studies are generally based on a regression model where the welfare participation rate is partly explained by the unemployment rate, using ordinary least squares. Although the welfare-to-work studies do not explicitly regress the unemployment rate on the welfare participation rate, as they use individual-level data and focus on hours of work and earnings, the existence of these studies makes interesting the exercise of inspecting whether the unemployment rate is partly explained by the welfare participation rate, using State-level data. However existing literature does not deal with this issue[2].

All in all, based on the current 'state of the art', what do we know about the relationship between the welfare participation rate and the unemployment rate? We know that the unemployment rate is an exogenous explanatory variable of the welfare participation rate, while the converse is doubtful[3]. Our paper suggests a different answer to the above question: we will argue that the unemployment rate is not an exogenous explanatory variable of the welfare participation rate and the converse is more likely to hold. The aim of our paper is not to build up a new empirical model to explain U.S. unemployment or AFDC-TANF participation. This is the reason why we will not consider other variables than the unemployment rate and the welfare participation rate. We will mainly focus on the relationship between these two variables, because - we will show - this is enough to question the validity of several caseload studies.

The reminder of the paper is as follows. Section 2 inspects for reciprocal causality between unemployment and welfare participation and estimates a bivariate structural VAR, using annual time series data over the period of 1960-2000. Section 3 inspects for robustness of empirical results in Section 2, by controlling for year and State heterogeneity over the period of highest positive correlation than ever between the two main variables of our study, i.e. 1990-1998. Section 4 compares our evidence with caseload studies and concludes the article.

2. Time Series VAR: 1960-2000

The first part of the empirical analysis in this paper is based on annual data for the period of 1960-2000 (Figure 1). Data prior to 1960 are not used as the AFDC program was still Aid to Dependent Children and assisted a very small number of adults. Data after 2000 are compared with model forecasts. As ERS and KPSS tests in Table 1 suggest, both the welfare participation rate (B) and the unemployment rate (U) can be treated as stationary series. Hence, non-transformed data are used in our empirical model.

Table 1 here

Our model allows for existence of two-side causality since U and B are modeled as dynamic functions of each other, constant intercepts C and structural shocks Z, i.e.:

$$(1) \qquad U_t = C_U + \sum_{i=1}^{p} \phi_i U_{t-i} + \sum_{i=0}^{p} \delta_i B_{t-i} + Z_{Ut}$$

$$(2) \qquad B_t = C_B + \sum_{i=1}^{p} \eta_i B_{t-i} + \sum_{i=0}^{p} \theta_i U_{t-i} + Z_{Bt}.$$

The reduced-form model is the following:

$$(3) \qquad y_t = A_0^{-1} c + \sum_{i=1}^{p} A_0^{-1} A_i y_{t-i} + A_0^{-1} z_t$$

where $y_t = \begin{bmatrix} U_t \\ B_t \end{bmatrix}$, $c = \begin{bmatrix} C_U \\ C_B \end{bmatrix}$, $z_t = \begin{bmatrix} Z_{Ut} \\ Z_{Bt} \end{bmatrix}$, $A_0 = \begin{bmatrix} 1 & -\delta_0 \\ -\theta_0 & 1 \end{bmatrix}$ and A_i is a 2×2 matrix for i = 1,…, p.

To simplify notation, model (3) can be re-written in the following form:

$$(4) \qquad y_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i y_{t-i} + v_t$$

where $v_t = \begin{bmatrix} V_{Ut} \\ V_{Bt} \end{bmatrix}$, $E(v_t v_t') = A_0^{-1} E(z_t z_t')(A_0^{-1})'$ and $E(z_t z_t')$ is a diagonal matrix.

Structural decomposition is based on a Sims-Bernanke procedure as described by Enders (1995, pp. 324-327). Identification is Cholesky-type with the welfare participation rate ordered last. Therefore, we assume that a shock to the welfare participation rate does not have an immediate effect on the unemployment rate while the converse holds. We make this assumption in order to have the highest probability of getting results that are consistent with caseload studies, which only stress the influence of unemployment on welfare participation (Bell, 2001). However, although the shape of the impulse-response functions does not radically change, a better option would be to order the unemployment rate last, as a generalized approach (Pesaran and Shin, 1998) shows that a shock to the welfare participation rate has a contemporaneous impact on the unemployment rate while the converse is less likely to hold (see Figure 2).

Figure 2 here

The order of the VAR is chosen through the maximum likelihood ratio test and the null hypothesis of $\Phi_2 = 0$ is rejected[4]. Then, equation (4) with order p = 2 is named Model 1 and estimated by ordinary least squares (OLS). Results are presented in columns (a)-(b) of Table 2, fitted and forecasted series are plotted in Figure 1, Granger-causality tests are reported in Table 3, Cholesky IRFs are plotted in Figure 3. Following Christiano *et al.* (1996), we use the VAR approach to derive stylized facts and get the following two facts:

Table 2 here
Table 3 here

Figure 3 here

1. The unemployment rate (U) does not Granger-cause the welfare participation rate (B). It is doubtful whether a shock reducing (increasing) U predicts a reduction (increase) in B. The accumulated response of B to U converges to a neighborhood of zero.
2. The welfare participation rate does Granger-cause the unemployment rate (at 10% level). A shock reducing (increasing) B predicts a reduction (increase) in U. The accumulated response of U to a negative (positive) shock to B converges to a negative (positive) number.

The above implies - among other things - that the unemployment rate significantly responds to a permanent negative shock to the national welfare participation rate, like a restrictive federal welfare reform, while the converse is less likely to hold.

3. Panel VAR: 1990-1998

In this Section we analyze whether results of Model 1 are robust to State and year heterogeneity over the period of 1990-1998, which is a period of special interest since, as emphasized by the CEA (1999), unemployment and welfare participation show the highest positive correlation than ever (0.78), almost double than in the 1970s (0.41), much bigger than in the 1980s (0.23), much bigger than in the whole period from 1970 to 1998 (0.28). To perform our inspection, it is useful writing Model 1 in the following reduced-form:

$$(5) \qquad U_t = C_U + \phi_1 U_{t-1} + \phi_2 U_{t-2} + \delta_1 B_{t-1} + \delta_2 B_{t-2} + V_{Ut}$$

$$(6) \qquad B_t = C_B + \eta_1 B_{t-1} + \eta_2 B_{t-2} + \theta_1 U_{t-1} + \theta_2 U_{t-2} + V_{Bt}$$

Therefore, the next step is to carry on estimating a Panel-VAR model with the following reduced-form (Arellano, 2003, p. 117):

$$(7) \qquad U_{st} = u_s + u_t + \phi_1 U_{st-1} + \phi_2 U_{st-2} + \delta_1 B_{st-1} + \delta_2 B_{st-2} + V_{Ust}$$

$$(8) \qquad B_{st} = b_s + b_t + \eta_1 B_{st-1} + \eta_2 B_{st-2} + \theta_1 U_{st-1} + \theta_2 U_{st-2} + V_{Bst}$$

where u_s and b_s contain State specific effects, while u_t and b_t contain annual effects. Equations (7)-(8) are named Model 2 and estimated by the generalized method of moments (GMM), using CEA (1999) data.

Before presenting estimation results, we inspect data persistence and, following Blundell and Bond (2000), estimate several AR(1) processes for each series[5] using the ordinary least squares (OLS), the fixed-effects estimator (FE) as well as the generalized method of moments (GMM). The latter method uses as instruments all available lags of unemployment and welfare participation up to t–2. Particularly, Table 4 shows that two-step difference-GMM (say GMM2 DIFF[6]) performs poorly with the welfare participation rate, due to weak instruments. Indeed, the estimated autoregressive coefficient is lower than the one calculated by the FE estimator, which is based downward in presence of State effects. However, two-step system-GMM (say GMM2 SYS[7]) does not work better, due to second order auto-correlated residuals[8]. Indeed, the estimated coefficient is higher than the one calculated by the OLS estimator, which is based upward in presence of State effects. This suggests to choose the appropriate GMM estimator by using the Hansen difference test, which - in turn - suggests to estimate Model 2 by GMM2 SYS.

Table 4 here

Estimation results for Model 2 are presented in Tables 2-3. We begin using as instruments all available lags of unemployment and welfare participation up to t–2. A non-singular instrument matrix is obtained by 'collapsing' the number of instruments[9] (Roodman, 2004a; 2004b). Nevertheless our procedure fails for equation (8) since residuals are found to be second order auto-correlated. However, this problem disappears when using as instruments all lags up to t–3 (Blundell and Bond, 2000, p. 332).

Although not reported, OLS estimates of equation (8) - which are consistent in absence of State heterogeneity - are not closed to GMM2 SYS estimates, suggesting presence of State specific effects. The latter is less likely to hold for equation (7), whose reported estimates are closed to those obtained by OLS[10]. Finally, year dummies are jointly significant in both equation (7) and (8).

All in all, results of Model 2 support those of Model 1 and both question the validity of any single-equation model finding that U is the most important explanatory variable of B, including the standard empirical model of the caseload studies. This conclusion is supported by three additional arguments. First, a change in the unemployment rate level may not imply a change in the labor demand for poor single-mothers, which is more likely to affect welfare participation from a theoretical point of view. Second, the latest data show that the rise in the unemployment rate since its 2000 minimum has not implied a rise in the welfare participation rate[11]. Third, a reconstruction of the legislative history of the U.S. welfare system may help to better understand the key-role of policy in driving welfare caseloads with special regard to the analogy between the positive impact of President Johnson's 'war on poverty' and the negative impact of TANF implementation (see Andini, 2004).

Regarding our second empirical result, that the share of population of welfare rolls (weakly) helps to predict the unemployment rate level, it is consistent with several old and new theoretical arguments and calls for the insertion of the welfare participation rate, as additional explanatory variable, in single-equation regression models for the unemployment level in the United States, specially when exploring the experience of the last decade. We do not discuss our second result in the light of previous research on U.S. unemployment as we mainly focus on its implications for caseload studies. Next Section is devoted to compare our evidence with previous research on AFDC-TANF recipients.

4. Discussion

It is uneasy to make a direct comparison between our study and caseload studies as the objective of the analysis is different. Caseload studies have explored movements in welfare caseloads, while we have studied the causality-link between unemployment and welfare participation. As consequence of a different research objective, adopted empirical techniques are different and there is not *a priori* reason to maintain that a bivariate structural VAR is better or worse than a single-equation regression model. In addition, there is an issue of different data-sets: caseload studies have analyzed annual State-level data from 1976/1977 to 1996/1998 or monthly State-level data for 1986:10-1996:9, while we have (first) analyzed annual time-series data for the period of 1960-2000 and (then) annual State-level data for the period of 1990-1998.

All in all, our exercise is somehow preliminary to the standard regression analysis of caseload studies and concludes that caseload studies may be based on the wrong assumption that the unemployment rate is an exogenous explanatory variable of the welfare participation rate. First, we question the unemployment rate to be an explanatory variable as we find that, allowing for possibility of reciprocal causality to take place, the unemployment rate does not help to predict the welfare participation rate while the converse is more likely to hold. Second, we question the unemployment rate to be exogenous to the welfare participation rate as we find that a shock to the welfare participation rate has a contemporaneous impact on the welfare participation rate while the converse is less likely to hold[12].

The only caseload study comparable to our paper is due to Rebecca Blank (1997), who performs the OLS estimation of a bivariate VAR model with unemployment rate and (logarithm of) AFDC caseloads, uses monthly State-level data between 1976:1 and 1996:12, and controls for State effects by means of 51 dummy variables. Blank finds that unemployment and caseloads Granger-cause each other, but unemployment seems to be a more robust predictor of caseloads than the converse is. She appeals to the latter result in order to justify the OLS estimation of a standard single-equation regression where welfare participation is partly explained by unemployment and uses annual data, without worrying about a possible problem of endogeneity. However, this problem is likely to exist since the finding that AFDC caseloads Granger-cause the unemployment rate[13], when using monthly data, implies that welfare participation is likely to have a contemporaneous impact on unemployment, when using annual data. In addition, even though Blank's results should worry authors using monthly data (Ziliak *et al.* 1997; 2000) about a possible problem of endogeneity between caseloads and unemployment, they only worry about a possible problem of endogeneity between caseloads and welfare reforms, concluding for the latter not being a real problem[14].

Regarding the result that the unemployment rate Granger-causes AFDC caseloads, Blank (1997) reports that a one point increase in the unemployment rate may increase, after 18 months, the Basic caseloads by 3.5% and the Unemployed-Parent caseloads by 20% (she does not provide confidence intervals for impulse-responses). Therefore the effect of unemployment of welfare participation is likely to mainly depend on Unemployed-Parent caseloads[15], that only represent a very small share of total caseloads, with an average of 8% over the period of 1962-1996, falling to 3% if only adults are considered. Moreover, we believe that our Granger-causality results are more reliable than those provided by Blank since we use the latest techniques for dynamic panel data models with fixed effects, control for year effects, focus on a period of unprecedented correlation.

To conclude, our paper may open two new research lines. On the one hand, we may be interested in finding a new State-level economic indicator, more likely to capture the effect of the business cycle on welfare participation decisions of poor single mothers and exogenous to these decisions. On the other hand, we may be interested in revising previous caseload studies and re-estimating their single-equation models (with the unemployment rate as explanatory variable) by means of instrumental-variable techniques, in order to avoid the risk of inconsistent OLS estimates.

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Notes

[1] The most important caseload studies are due to CEA (1997; 1999), Blank (1997; 2001), and Ziliak *et al.* (1997; 2000).
[2] The only exception is due to Blank (1997) and will be discussed in Section 4.
[3] Standard caseload studies, from CEA (1997) onwards, assume that the all regressors - including the unemployment rate - are exogenous, meaning that each right-hand-side variable is not contemporaneously affected by the left-hand-side variable, the welfare participation rate. Under this assumption, implicit when estimating single-equation models by means of ordinary least squares, caseload studies find a significant impact of unemployment on welfare participation. The converse impact is discussed by Blank (1997, pp. 11-14) and found less significant.
[4] Akaike and Schwarz criteria confirm the result of the maximum likelihood ratio test.
[5] That is, we assume $\phi_2 = \delta_1 = \delta_2 = 0$ in equation (7) and $\eta_2 = \theta_1 = \theta_2 = 0$ in equation (8). Year dummies are found jointly significant in both equations.
[6] See Arellano and Bond (1991).
[7] See Blundell and Bond (1998).
[8] This problem cannot be solved by reducing the number of instruments.
[9] If the instrument matrix is singular, two-step estimates may be no longer more efficient than one-step. It is worth stressing that all the results in this article are not sensitive to use of 'collapsed' instruments.
[10] See also the AR(1) estimates for the unemployment rate in Table 4.
[11] This will be clearer as soon as the 2003 observation on the welfare participation rate will be available.
[12] As we use annual data, caseload studies using monthly data may be not affected by our critique.
[13] Blank uses a 24-months lag length, which is consistent with our 2-years lag length, and argues in favor of causal economic factors behind the statistical result that caseloads help to predict unemployment.
[14] 'A key issue for model specification is the potential endogeneity of the welfare waivers. States with high AFDC caseloads may be more likely to request federal welfare waivers, resulting in an identification problem, since the direction of causality might go in both directions. [...] Fortunately, we believe that endogeneity is not a problem in our model. Even if rising caseloads are the impetus for waivers requests, a lag may occur before such requests are made. Therefore, waivers requests are not likely to be correlated with contemporaneous caseloads.' (Ziliak *et al.*, 1997, pp. 12-13)
[15] Instead, according to Blank, the effect of welfare participation on unemployment is mainly due to Basic caseloads.

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Table 1

Unit Root and Stationarity Tests

	ERS	KPSS
Null hypothesis	Unit root	Stationarity
Test statistic for U	–2.42	0.19
Test statistic for B	–1.84	0.33
Critical value at 1%	–2.62	0.73
Critical value at 5%	–1.94	0.46
Critical value at 10%	–1.61	0.34

Notes
Sample period of 1960-2000.
ERS = Elliot, Rothenberg and Stock (1996).
KPSS = Kwiatkowski, Phillips, Schmidt and Shin (1992).
ERS tests assume intercept and one lagged difference.
KPSS tests assume intercept only.

Table 2

VAR Estimates

	Model 1		Model 2	
	1960-2000 OLS		1990-1998 GMM2 SYS	
Column index	(a)	(b)	(c)	(d)
Dependent variable	U	B	U	B
Instruments option	No	No	t–2	t–3
State and year effects	No	No	Yes	Yes
Intercept	0.84	0.34 **	No	No
B(–1)	0.47	1.71 *	0.32 **	1.75 *
B(–2)	–0.16	–0.77 *	–0.25	–0.82 **
U(–1)	0.94 *	0.05	0.64 *	–0.21
U(–2)	–0.30 ***	–0.06 ***	0.08	0.23 ***

Notes
All columns:
Significant at 1% level *. Significant at 5% level **. Significant at 10% level ***.
Columns (a)-(b):
Autocorrelogram analysis shows that residuals are not auto-correlated. White's test does not reject to null of homoschedasticity in residuals. Jerque-Bera test rejects the null of normality for residuals of column (a). Multicollinearity might affect B's estimates in column (a) due to high linear correlation (r = 0.95; p-value = 0.00). If either B(–1) or B(–2) is removed from the regression model, the estimated effect of B on U is significant at 5% and approximately equal to the sum of B's coefficients in column (a), and residual test outcomes are the same as for column (a).
Columns (c)-(d):
Windmeijer (2000) corrected standard errors are computed.

Selected p-values	(c)	(d)
Hansen test of over identifying restrictions	0.43	0.50
Arellano-Bond test for AR(1) in first differences	0.00	0.03
Arellano-Bond test for AR(2) in first differences	0.86	0.11
Hansen difference test with respect to GMM2 DIFF	0.42	1.00

Table 3

Granger Causality Tests

	Model 1 1960-2000		Model 2 1990-1998	
Null hypothesis	F-stat.	P-value	F-stat	P-value
U does not Granger cause B	1.63	0.20	2.16	0.12
B does not Granger cause U	2.59	0.08	2.59	0.08

Table 4

AR(1) Estimates

	FE	OLS	GMM2 DIFF	GMM2 SYS
Unemployment rate	0.50	0.89	0.84	0.80
Welfare participation rate	0.85	1.00	0.63	1.15

Notes

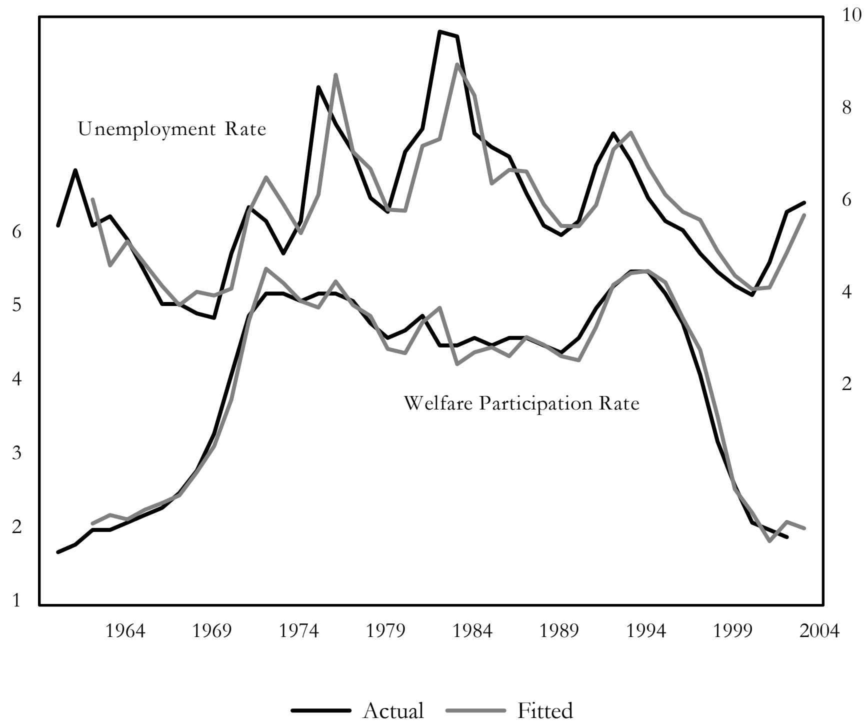
Sample period is of 1990-1998. Year effects are included in all models. OLS does not include State effects. All reported coefficients are significant at 1% level. GMM estimation uses Windmeijer (2000) corrected standard errors.

Unemployment rate p-values	GMM2 DIFF	GMM2 SYS
Hansen test of over identifying restrictions	0.07	0.15
Arellano-Bond test for AR(1) in first differences	0.00	0.00
Arellano-Bond test for AR(2) in first differences	0.53	0.52

Welfare participation rate p-values	GMM2 DIFF	GMM2 SYS
Hansen test of over identifying restrictions	0.24	0.28
Arellano-Bond test for AR(1) in first differences	0.32	0.04
Arellano-Bond test for AR(2) in first differences	0.13	0.01

Figure 1

Unemployment Rate and Welfare Participation Rate



<u>Notes</u>
Fitted values are based on Model 1. Values from 2001 to 2003 are forecasted. The 2003 actual observation for the welfare participation rate will be not available till to the 2005 issue of *Indicators of Welfare Dependence*.

Source: US Department of Health and Human Services <http://www.acf.hhs.gov/news/stats/6097rf.htm>; <http://www.hhs.gov/hsp/indicators04>; US Bureau of Labor Statistics <http://www.bls.gov/cps/cpsaat1.pdf>.

Figure 2

Generalized Impulse-Response Functions

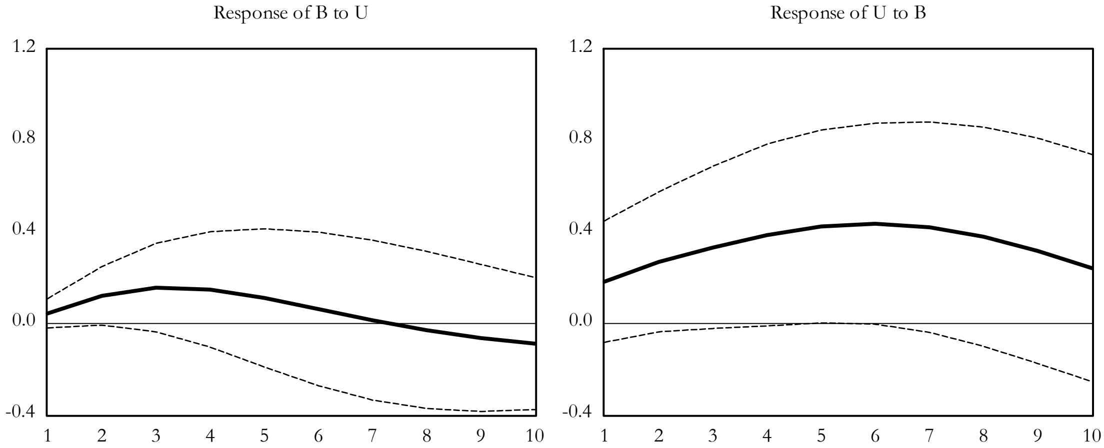


Figure 3

Cholesky Impulse-Response Functions