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SMOOTH TRANSITION STRUCTURAL VECTOR AUTOREGRESSIONS: APPLICATION TO THE RELATION BETWEEN INFLATION AND OUTPUT GROWTH IN RWANDA

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ABSTRACT

The aim of this paper is to introduce the structural vector with smooth transition and its application to study a relation between inflation and output growth using a five dimensional scheme of Rwandan variables spanning from January, 1981 to June, 2018.

Although VAR has become a standard tool for empirical macroeconomic analysis, it cannot address some of fundamental research questions thus, an extension of the baseline model to a nonlinear framework. The ST-SVAR allowing for heteroskedasticity is more flexible and relatively easy to estimate to the alternative approaches for modeling changes in volatility like GARCH or Markov switching residuals.

The finding shows transition trajectory from downswing to upswing states started from1995 to 2003, consistent with the economic narratives on the Rwandan economy where Rwanda has been experienced rapid and consistent growth after 1994s. The analysis of the impulse response of conventional SVAR model identifies a sunspot shocks while the ST-SVAR model shows a news shocks. Consequently, the empirical finding suggests that the relation between inflation and the output growth seen in a fairly light on ST-SVAR than in a conventional SVAR analysis in the short run.

Keyword: SVAR, Heteroskedasticity, Smooth Transition VAR models.

JEL classification: C32, E52.

1. INTRODUCTION

The relationship between inflation and output growth has long been an unsettled factor of the discussion between policy makers and researchers. The existence and the nature of the relationship between inflation and economic growth have become the subject of an extensive body of theoretical and empirical studies (Temple, 2000).

The basic reduced form linear vector auto regression (VAR) as supported by Sims (1980) has become a standard tool for empirical macroeconomic analysis of interdependence among variables. The standard structural VAR approach derives identifying restrictions for the structural shocks and imposes them on the reduced form of the model. Such restrictions usually come from economic theory related to the variables involved. In their linear form, SVAR models cannot address selected research questions of not study whether the effects of a structural shock depends on when the shock hits the economy, or whether the effects of a shock depend on which

additional shocks hit the economy in the future. For this reason, the literature has developed extensions of the baseline model to a nonlinear framework that allows to model nonlinearities in the data. The features of the data to help with the identification of structural shocks like distributional assumptions (Lanne and Lütkepohl (2010)) as well as hetoroskedasticity (Rigobon (2003), Lanne, Lütkepohl and Maciejowska (2010)) may be valuable for identification purposes.
The application of heteroskedasticity for identification of shocks is attractive approach in different macroeconomic time series and widely discussed in literature by Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), and Stock and Watson (2003) among others. Modeling changes in volatility have been used in this context, Rigobon (2003) and Bacchiocchi and Fanelli (2012) use simply a deterministic shift in the variances while Normandin and Phaneuf (2004) and Bouakez and Normandin (2010) used the changes in volatility by a vector GARCH process and Lanne et al. (2010) propose a Markov switching (MS) mechanism for changes in volatility.

The two last approaches encompass some disadvantage in estimation, since models are more complex and consistent estimation methods are available only for small models with three or four variables and a moderate number of lags and volatility states at best. Whole, assuming an exogenous change in variance as in Rigobon (2003) and others is also not very attractive because, in practice, gradual changes in volatility seem more implausible in many situations.

The intermediate approach considers the SVAR with heteroskedastic residuals modeled by a smooth transition function. A discussion of smooth transition models with heteroskedasticity can be found in Yang (2014). In the smooth transition literature it is more common to model non-linearity in the mean equation (Hubrich and Teräsvirta (2013)). However we use this idea to take into account heterskedasticity present in the data. This setup has a number of advantages compared to other volatility models used in this framework. If the transition function is parameterized parsimoniously, the parameters are relatively easy to estimate. A well developed toolkit for the statistical analysis of smooth transition regression models is available and can potentially be adopted for the purposes of identification of structural shocks.

The purpose of this paper is to introduce the structural vector with smooth transition and its application to study relation between inflation and output growth using a five dimensional scheme of Rwandan variables spanning from January, 1981 to June, 2018.

This paper is structured into five sections after the introduction; section two briefly discusses conventional VAR and SVAR models as well as identification of structural shocks. Section three build the smooth transition SVAR model and explains how it can be used for identification purposes, estimation steps is discussed as well. An application to study relation between inflation and output growth is discussed in section four. The conclusion comes last section.

2.THE BASELINE MODEL

The baseline model is a VAR of order p (VAR(p)) of the form
$y_t = v + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t$ where $y_t = (y_{1t,...,} y_{Kt})'$ is a vector of observable variables, the A_i

are $(K \times K)$ coefficient matrices, v is a $(K \times 1)$ constant term and the u_t are K -dimensional serially uncorrelated reduced form residuals with mean zero and covariance matrix $\sum_u$.

The structural residuals are denoted by ε_t. They have zero mean and are serially uncorrelated. Typically they are also assumed to be instantaneously uncorrelated, that is, $\varepsilon_t \sim (0, \sum_\varepsilon)$ where $\sum_\varepsilon$ is a diagonal matrix. Sometimes it is actually assumed that the variances of the structural shocks are normalized to one so that $\sum_\varepsilon$ is an identity matrix.

The structural residuals are typically obtained from the reduced form residuals, u_t, by a linear transformation,

$u_t = B\varepsilon_t$ or $\varepsilon_t = B^{-1}u_t$

The matrix B contains the instantaneous effects of the structural shocks on the observed variables. Given the relation between the reduced form residuals and the structural residuals, the matrix B has to satisfy $\sum_u = B\sum_\varepsilon B'$. In other words, in principle B can be any matrix satisfying $\sum_u = B\sum_\varepsilon B'$. The relation between the reduced form and structural residuals does not uniquely determine the matrix B and, hence, the structural innovations are not uniquely determined without further assumptions. The conventional approach is to impose further restrictions on B directly to make it unique. These restrictions may be zero restrictions indicating that a certain shock does not have an instantaneous effect on one of the variables or it may be implied by a restriction on the long-run effects of a structural shock or by other kinds of information. The matrix of long-run effects of structural shocks is given by

$\Xi_\infty = (I_K - A_1 - ... - A_p)^{-1} B$.

Assuming that the inverse exists. That condition is satisfied for stable, stationary processes without unit roots. For integrated and cointegrated processes the long-run effects matrix is related to the cointegration structure of the model (Lütkepohl (2005)). For our purposes it is sufficient to know that the matrix of long-run effects can be computed from the reduced form and structural parameters and imposing restrictions on that matrix implies restrictions on B.

Typically the restrictions on B just identify the structural model and, hence, the structural shocks. In other words, there are just enough restrictions for uniqueness of B and no more. If there are two competing sets of just-identifying assumptions or theories implying just-identifying restrictions, they lead to identical reduced forms and cannot be tested against the data. Hence, the conventional setup is often uninformative regarding the validity of specific economic theories. In the next section it is discussed how heteroskedasticity can be used to improve the situation in this case.

3. STRUCTURAL VAR MODEL WITH HETEROSKEDASTIC RESIDUALS

3. 1. Smooth Transition in Variances

Suppose u_t is a heteroskedastic error term with smoothly changing covariances,

$E(u_t u_t^{'}) = \Omega_t = (1 - G(\gamma, c, s_t))\sum_1 + G(\gamma, c, s_t)\sum_2$, where $\sum_1$ and $\sum_2$ are distinct covariance matrices and $G(\gamma, c, s_t)$ is a transition function. It depends on a parameter (vector) γ and c as well as a transition variable s_t. This quantity can be a stochastic variable which determines the transition to another volatility state or it may be a deterministic function of time. This paper uses a logistic transition function proposed by Maddala (1977) with time being the transition variable, i.e., s_t = t so that

$G(\gamma, c, s_t) = (1 + \exp[-\exp(\gamma)(t - c)])^{-1}$ with the term $\exp(\gamma) > 0$ for positive and negative values . Notice that 0 < $G(\gamma, c, s_t)$ < 1. Thus, t is a convex combination of two positive definite matrices and, hence, it is also a positive definite matrix. The transition of the volatility from the covariance matrix $\sum_1$ to $\sum_2$ can be used for identification purposes. There exists a decomposition $\sum_1 = BB^{'}$ and $\sum_2 = B\Lambda B^{'}$ where Λ = diag $(\lambda_1, ..., \lambda_K)$ is a diagonal matrix with positive diagonal elements (Lütkepohl (1996).

3.2 Estimation procedure

A smooth transition structural VAR (ST-SVAR) model can be estimated via maximum likelihood (ML) under the assumption of normality of the residuals. The log-likelihood function for the model is

$\log L = cons - \frac{1}{2}\sum_{t=1}^{T} \log\det(\Omega_t) - \frac{1}{2}\sum_{t=1}^{T} u_t^{'}\Omega_t^{-1}u_t$ where $u_t = y_t - v - A_1 y_{t-1} - ... - A_p y_{t-p}$ and Ω_t is given by the equation.

The model is nonlinear and has many parameters to be estimated. Therefore we use a grid search over γ and c. For a given pair $\{\gamma, c\}$, estimation proceeds in the following two steps.

Step one: For given starting values of the VAR parameters $\{v, A_1, ..., A_p\}$ the structural parameters $\{B, \Lambda\}$ are estimated by maximizing the log likelihood function using nonlinear optimization. This step may be done subject to economic restrictions on the B or Ξ_∞ matrices.

Step two: For the updated structural parameters the VAR part of the model is re estimated. Note that given the transition parameters $\{\gamma, c\}$ and structural parameters $\{B, \Lambda\}$ the model is linear in the VAR part. For that reason the vectorized VAR coefficients $b := vec(v, A_1, ..., A_p)$ can be estimated with a weighted least squares procedure with the weights given by Ω_t^{-1}, that is,

$\hat{b} = [(Z^{'} \otimes I_K)W_T(Z \otimes I_K)]^{-1}(Z^{'} \otimes I_K)W_{Ty}$

Where

$$W_T := \begin{pmatrix} \Omega_1^{-1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Omega_T^{-1} \end{pmatrix}$$

is a $(KT \times KT)$ block-diagonal weighting matrix. Moreover, $(y_1^{'},...,y_T^{'})^{'}$ is a $(KT \times 1)$ data vector, and each row of the $(T \times (1+K_p))$ data matrix Z contains a leading one for the constant as well as lagged observations: $(1, y_{t-1}^{'}, \ldots, y_{t-p}^{'})$

These two steps are iterated until there is no improvement in the log-likelihood value.

As mentioned earlier, a grid search is performed for the parameters of the transition function $\{\gamma, c\}$ and for each pair of values the previously described estimation is carried out. In a first round the grid for c is over a subset of the integers $\{1,...,T\}$ and for γ a grid in steps of 0.1 in the interval $[-3.5, 3.5]$ is used. The range of γ is chosen such that the full range of transition functions from very at to very steep functions is covered. In a final step the grid is refined in the neighbourhood of the values minimizing the likelihood function in the first round grid search. Thereby the ML estimators of all parameters are found. The standard errors are obtained as square roots of the inverted information matrix. The information matrix is estimated using the outer product of the numerical first order derivatives (Hamilton,1994). This procedure is computationally demanding but not infeasible.

In structural VAR analysis impulse responses are usually used for investigating the transmission process of the shocks.

We construct confidence intervals around the impulse responses using a fixed design wild bootstrap procedure. The method preserves the pattern of heteroskedasticity and contemporaneous dependence of the data as noted by Goncalves and Kilian (2004). In the context of structural VAR models identified via heteroskedasticity the method was proposed by Herwartz and Lütkepohl (2011) and used by Lütkepohl and Netsunajev (2014) and Netsunajev (2013) among others.

In that procedure the bootstrap samples are constructed conditionally on the ML estimates as $y_t^* = \hat{v} + \hat{A}_1 y_{t-1} + \hat{A}_p y_{t-p} + u_t^*$ where $u_t^* = \eta_t \hat{u}_t$ and η_t is a Rademacher distributed random variable that assumes values -1 and 1 with probability 0.5.

We bootstrap parameter estimates conditionally on the initially estimated transition parameters $\{\gamma, c\}$ to alleviate the computational burden. Notice that computing the bootstrap impulse responses still requires nonlinear optimization of the log-likelihood and, hence, is computationally demanding. We use the ML estimates as starting values in the bootstrap replications.

4. AN APPLICATION OF ST-SVAR ON INFLATION AND OUTPUT GROWTH IN RWANDA

Ongoing debate have revolved relation between inflation and growth. However, there are mixed findings and the results are fragile with respect to model specifications and information sets.

4.1. Brief literature review

High and volatile inflation interferes with the price signaling mechanism, resulting in confusing information to economic agents on relative prices, which in turn induces distortions in investment decisions and hence impedes efficient allocation of resources (Fischer, 1993; Huybens and Smith, 1998; Khan and Sendhadji,2001).Inflation creates uncertainty in financial markets and increases the risk associated with investment; the financial intermediaries are not eager to provide long term financing for capital formation and tend to maintain liquid portfolios, which translates into reduction of economic activities (Romer 2001). High inflation results also in “shoe leather costs” associated with additional efforts that people make to reduce their holding of cash and “menu costs” arising from the necessity to change prices more often.

The studies that have tested the robustness of the relation between inflation and browth (Levine and Renelt (1992) and Hineline (2007)) have concluded that the inflation–growth nexus is brittle, changing with the model specification employed. Notwithstanding ambiguities concerning the intensity of this relationship, the recent literature is consistent concerning the overall nature of this relationship, i.e., a negative effect of inflation on long-term growth (Fischer, 1993). Nonlinearity tests by Fischer (1993) also suggest that the adverse effect of inflation decreases at excessively high inflation rates.

Based on these findings, Sarel (1996) identifies a specific structural break in this relationship at an 8% inflation rate; below this rate, inflation is innocuous, and above this rate, it is harmful to growth. Khan and Senhadji (2001) find different thresholds for developed and developing countries of 1% and 11% inflation rates, respectively. As stated earlier, most of the previous research on this subject did not properly take into account inflation–growth nonlinearity. Past attempts to take into account these nonlinearities have either exogenously determined the threshold level or used an improper treatment of the endogenous threshold.

4.2 Empirical Analysis

As in Bjornland and Leitemo (2009) a five dimensional VAR with the vector of variables $y_t = (C_t, F_t, M_t, G_{t,} \pi_t)'$ is considered, where

- C_t is growth rate of gross capital formation ,
- F_t is growth rate of foreign direct investment,
- $M_{t,}$ is growth rate of monetary aggregate,
- G_t is growth rate of gross domestic product,
- π_t is inflation rate,

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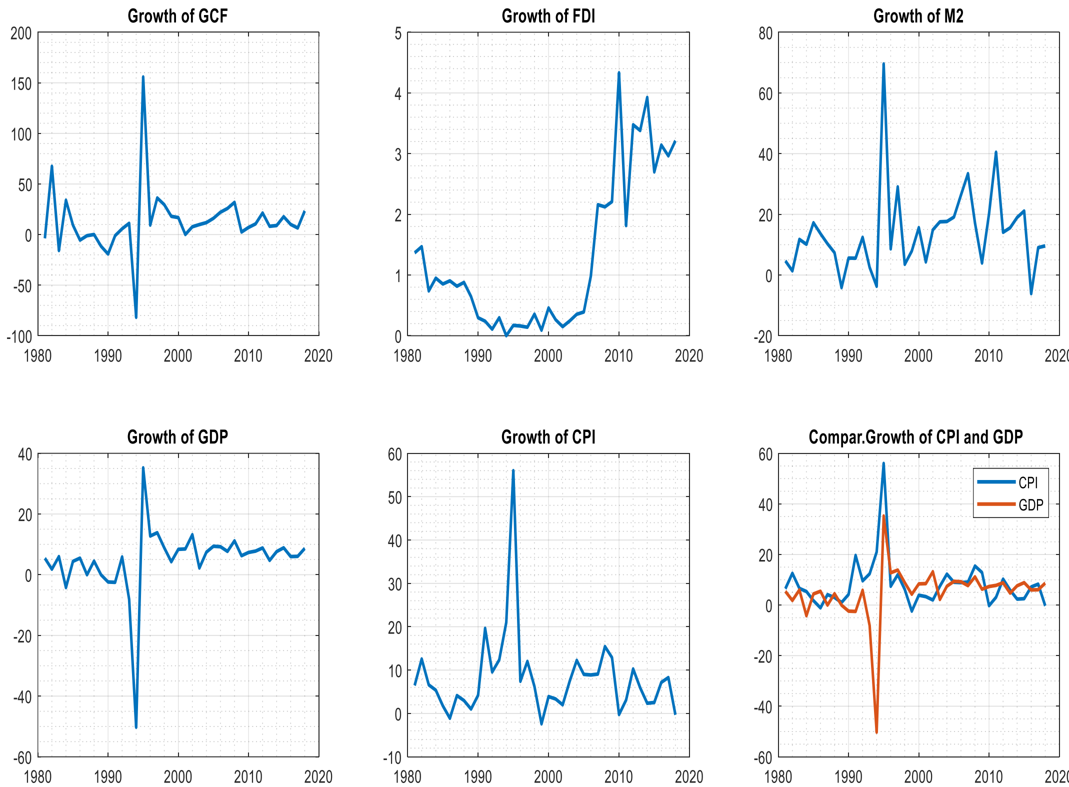
We use transformed monthly data for the period 1981M1 - 2018M6 from World Development Indicator.

4.2.1. Data visualization

Figure1: Data eyeball



Source: Author's computation

In 2018, inflation rate for Rwanda was 1.4 %, though Rwanda inflation rate fluctuated substantially in recent years, it tended to decrease through 1999 - 2018 period ending at 1.4 % in 2018. However, on real GDP growth rate keeps its momentum in recent years through 1999 to 2018 periods ending at 8.6 % in 2018.

It can be observed that from the first to the second inflation ranges, a higher average inflation rate leads to lower economic growth suggesting a negative relationship ; however , the average inflation rates corresponding to the thirds and fifth inflation ranges coexist with impressive average economic growth rates varying between 5.5% and 12%.
These observations provide some pre-evidence that there may be a non-linear relationship

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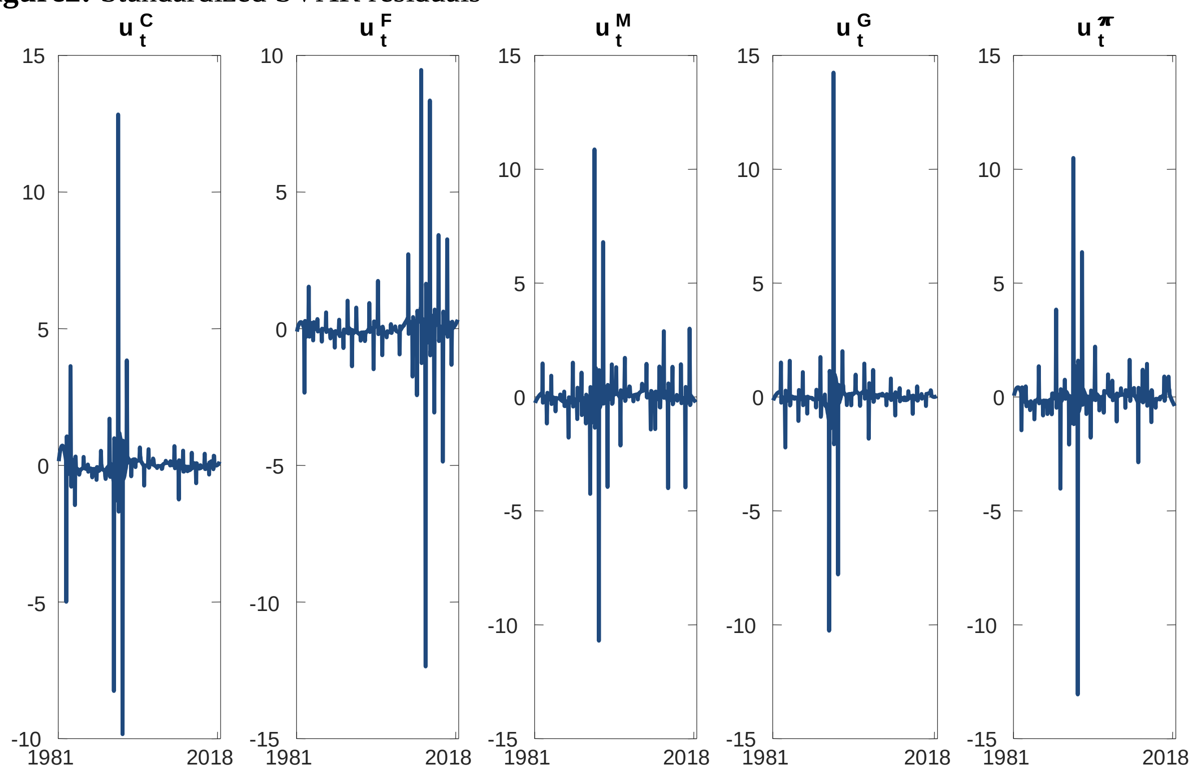
between growth and inflation and raise the question regarding the sign of the relationship between the two variables.

4.2.1. Residual plots of VAR and ST-SVAR

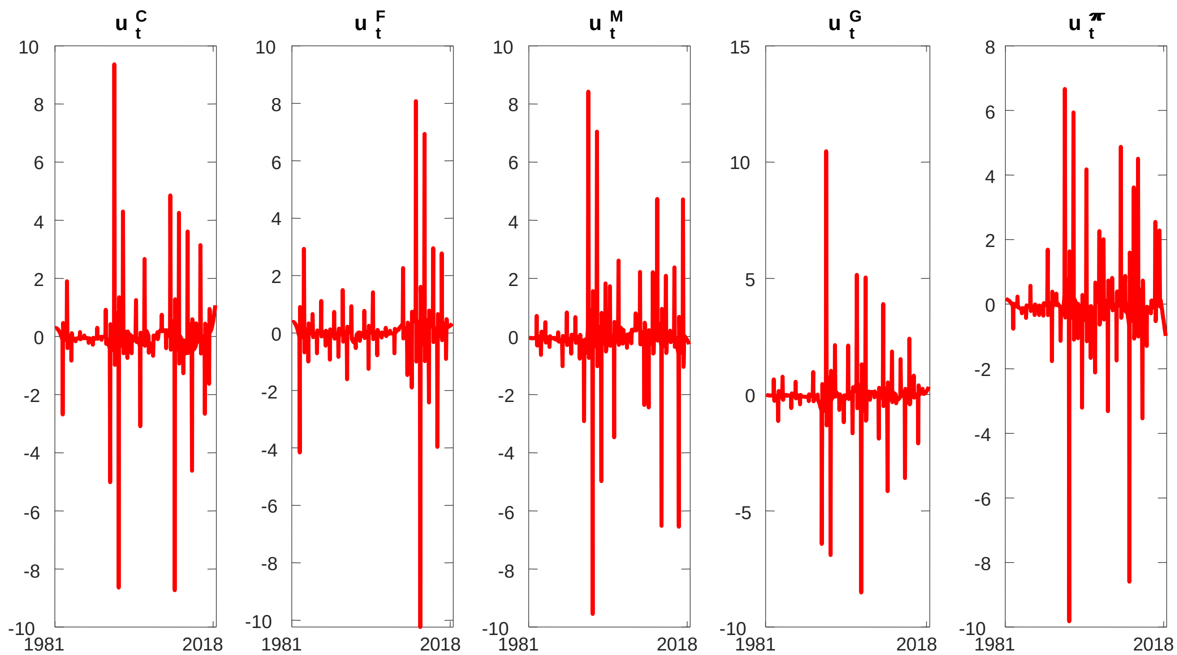
Before turning to formal statistical analysis that will be reported shortly, it is worth pointing out that the change in volatility has to be sufficiently heterogeneous in order to get identification through heteroskedasticity.

Figure2: Standardized SVAR residuals



Source: Author's computation

Figure3: Standardized ST-SVAR residuals



Source: Author's computation

The standardized residuals of the VAR(3) and the ST-VAR (3) models broadly account heteroskedasticity. The residuals are standardized by dividing them by estimated standard deviation and the ST-VAR (3) model are seen to be overall heterogeneous throughout the sample than those of standard VAR(3)model. Thus, the smooth transition model captures the change in the volatility to some extent as confirmed by the statistics in Table 1 ST-SVAR model is clearly better than standard SVAR in residual volatility.

The more generous Akaike Information Criterion (AIC) suggests a VAR(3) for our sample period 1981M1 - 2018M6. Therefore we also use VAR order 3 for the ST-SVAR model. Estimation of the unrestricted ST-SVAR(3) model is done with the relative variances λ_i ordered from smallest to largest. Some statistics for the estimated models without and with smooth transition in variance are presented in Table1 It is obvious that the ST-SVAR model allowing for heteroskedasticity is clearly preferred by AIC and the Schwarz criterion (SC) The transition function of the ST-SVAR(3) model is presented in Figure3. It shows that there is a gradual change in variance from the mid of 1990s to the middle of the 2000s.
This corresponds well to the beginning of the period of Rwanda economic transformation

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Table 1: Comparison of VAR(3) Models

Model	$\log L_T$	**AIC**	**SC**
VAR(3)	-3654.6	7319.2	7339.7
ST-SVAR(3)	-2658.8	5327.6	5348.1

Source: Author's computation

The VAR(3) Models for is considered, of variables $y_t = (C_t, F_t, M_t, G_{t,} \pi_t)'$ is considered,

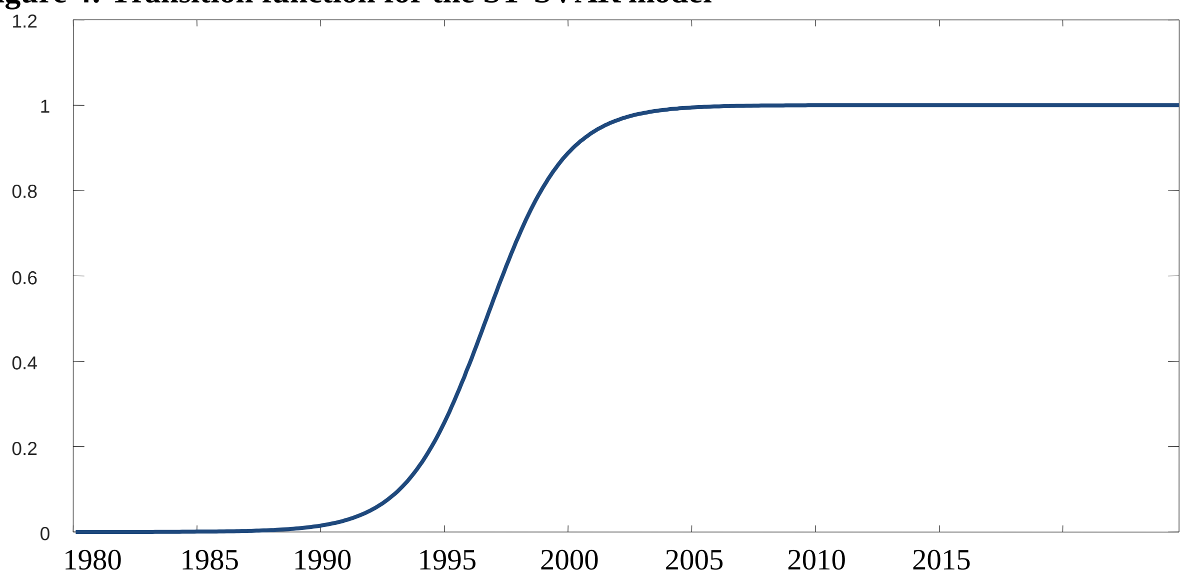
Where:

L_T :likelihood function, $AIC = -2\log L_T + 2 \times$ no of free parameters, $SC = -2\log L_T + \log T \times$ no of free parameters

The "smooth transition" bounded between 0 and 1, correspond quite closely with downswing and upswing respectively, and imply that transitions between the downswing and upswing regimes occur rapidly.

These observations are confirmed by the upper panel of Figure4, which shows how estimated transition functions evolve over time. The lower panel of this figure shows that the transition from 0 to 1 takes a short time. This is consistent with the economic narratives on the Rwandan economy where Rwanda has been experienced rapid significant growth after 1994 up to the present deemed as the one of the African country's economic miracle.

Figure 4: Transition function for the ST-SVAR model



Source: Author's computation

Since we are interested in using changing variances of structural shocks for identification purposes, a central question of interest is whether we have sufficient heterogeneity in the volatility changes to get identification. The estimated λ_i of the ST-SVAR model are shown in Table 2.

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Table 2: Estimates of Relative Variances of ST-SVAR(3) Model

Parameter	Estimate
λ_1	0.0000
λ_2	0.0000
λ_3	0.0000
λ_4	0.0006
λ_5	2.5362

Source: Author's computation

Model for Unrestricted B and Ξ_∞,to test formally if there is sufficient heterogeneity in the variances we use Wald tests. On the one hand, they are attractive in the present context because they are very easy to compute from the estimates of the unrestricted model. On the other hand, they are known to be unreliable for highly nonlinear null hypotheses. For the five-dimensional system 10 pairs of relative variances have to be distinct to get a full set of identified shocks. The corresponding test statistics of the relevant hypotheses are presented in Table 3. For the current model, the null hypotheses of pairwise equality at least one rejected at a 10% significance level for all pairs.

This is no surprise as the estimates in Table 2 show that the estimated λ_4 and λ_5 are not close to each other. Thus, we conclude that we have some statistically identified shocks but perhaps not a fully identified structural model. Not having a full set of identified shocks is not necessarily a problem for our approach because it is enough if there is some extra identifying information that allows us to test conventional identifying restrictions.

Table 3: Tests for Equality of λ_i for Unrestricted ST-SVAR Model

Parameter	Estimate	Std.dev.
$\lambda_1 = \lambda_2$	1.8133	0.1781
$\lambda_1 = \lambda_3$	2.4791	0.1154
$\lambda_1 = \lambda_4$	18.792	0.0000
$\lambda_1 = \lambda_5$	0.0142	0.9050
$\lambda_2 = \lambda_3$	0.0755	0.7835
$\lambda_2 = \lambda_4$	18.329	0.0000
$\lambda_2 = \lambda_5$	0.0142	0.9050
$\lambda_3 = \lambda_4$	18.698	0.0000
$\lambda_3 = \lambda_5$	0.0142	0.9050

$\lambda_4 = \lambda_5$	0.0142	0.9050

Source: Author's computation

We may be able to check a recursively identified model with a triangular B matrix to check whether they are in line with the data. Their restrictions can be visualized in the following way:

$$B = \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix} \text{ and } \Xi_{\infty} = \begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix}$$

where the asterisks indicate unrestricted elements and zeros denote elements restricted to zero. The shocks of particular interest are the shocks ordered fourth and fifth. This identification suggests that the last shock is inflation shock and it has no immediate impact on gross capital formation, foreign direct investment and monetary aggregate as well as no long-run effect on gross domestic product. Given that the first fourth shocks are not of interest for our analysis and should be identified arbitrarily in a conventional SVAR analysis.

It interested to see the impact of the different identifying restrictions on the impulse responses and compare them to impulse responses obtained without imposing the restrictions. Of course, there is one problem with impulse responses computed from our ST-SVAR model identified via heteroskedasticity. The shocks obtained by this kind of identification do not have a natural labelling and may not be interpretable as economic shocks. In Figure 2 the impulse responses are plotted with 68% confidence bands based on 10 bootstrap replications.

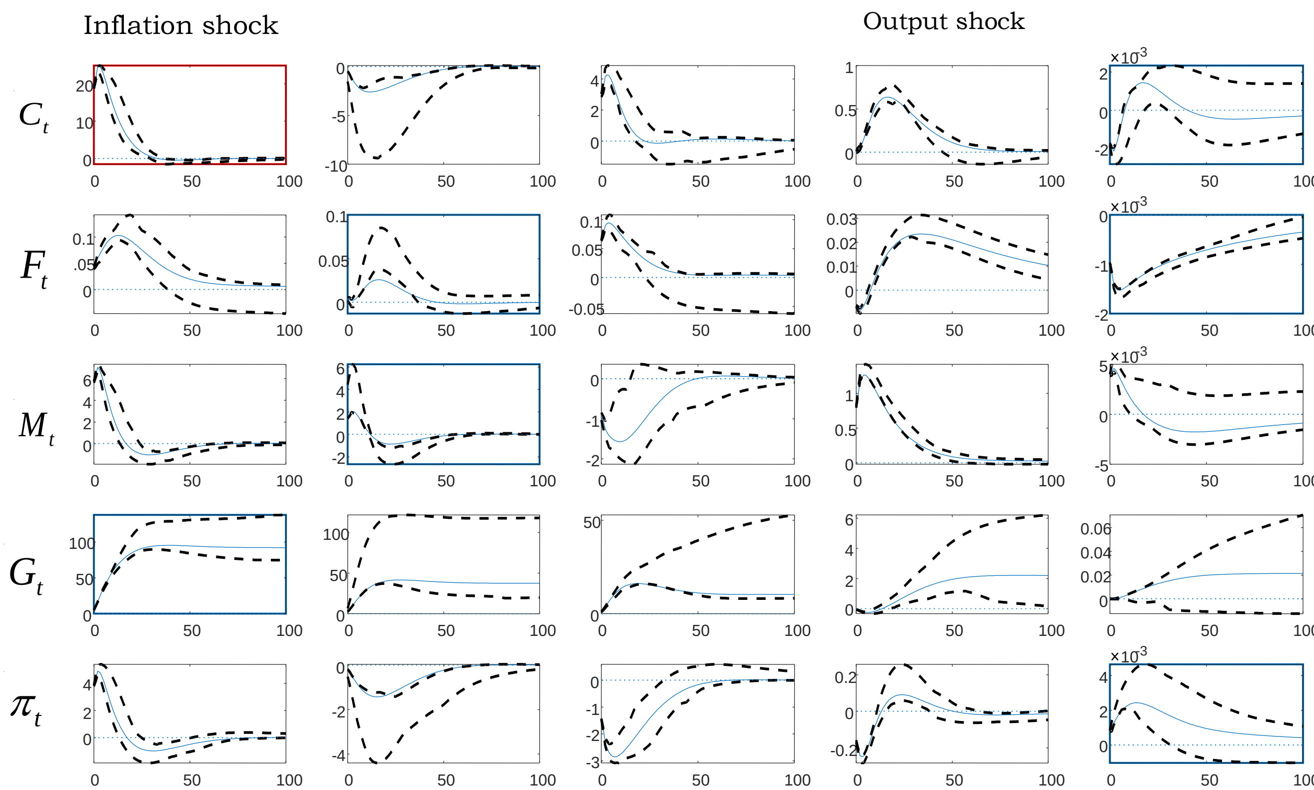
We interested to two shocks that can be interpreted as inflation and output shocks. Clearly, for an inflation shock a minimum characteristic is that the inflation rate moves on impact. There is only one shock where a significant impact effect on the inflation rate is obtained, namely the first one. Likewise, an output shock should affect the output on impact and again there is just one shock where this condition is clearly satisfied, namely the fourth one.

Therefore we label these shocks inflation and output shocks, respectively. In other words, the inflation shock is the one with the smallest relative variance (λ_1) and the output shock is the fourth shock with the second largest relative variance (λ_4). These are also the most plausible inflation and output shocks considering the impulse responses of the variables.

Figure 4: Impulse response functions for ST-SVAR model

Solid line - point estimate of the response, dashed line - 68% confidence bands based on 10 bootstrap replications.
Source: Author's computation

We discuss the interpretation of the shocks and compare them with the conventionally SVAR. The response of the gross capital formation variable C_t to inflation shock is rather standard for



the conventional SVAR models. There is a lagged negative effect reaching its lowest point at around the short period after the shock. On the other hand, ST-SVAR model produces a significantly positive reaction on impact that dies out after several months. Even though the point estimates of the impulse responses are negative after nearly period, the reaction is insignificant at the given confidence level. Looking at the response of foreign direct investment F_t, one can observe a small initial increase for both conventional identification schemes, whereas the initial dynamics is more pronounced in the model identified via heteroskedasticity. The ST-SVAR model reveals a positive reaction of output and impact dies out after several months while SVAR model shows small initial increase, then a negative reaction output and impact rapidly normalized after short period. All the inflation shock identified via heteroskedasticity has some economically intuitive properties as it is broadly similar with standard SVAR model in the long

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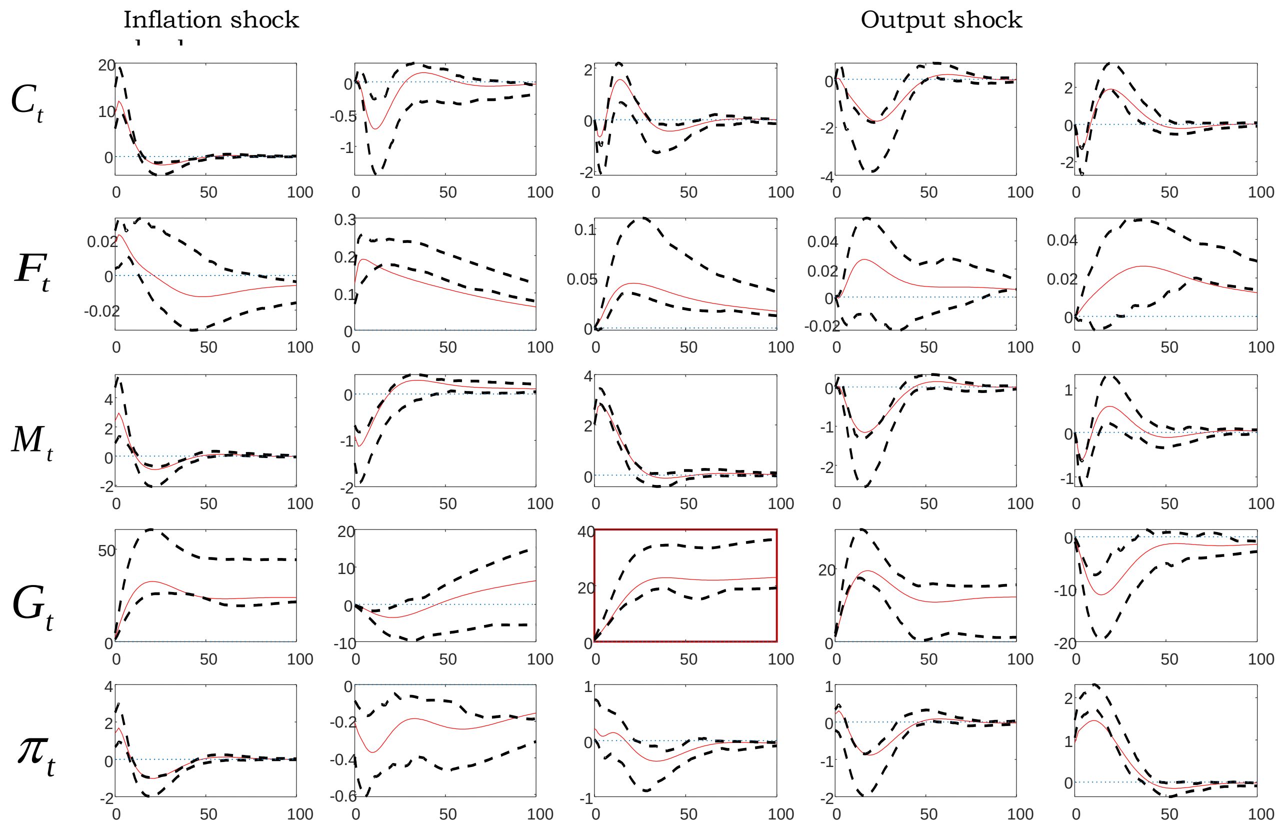
run but more intuitively in the short run.

Figure 4: Impulse response functions for SVAR model



Solid line - point estimate of the response, dashed line - 68% confidence bands based on 10bootstrap replications

Source: Author's computation

These arguments make us think that the economic nature of the conventional SVAR and ST-SVAR output shocks is very different. While conventional SVAR models identify a sunspot shock, the ST-SVAR output shock has a news shocks. This shows the importance of the identifying assumptions and that it makes sense to take into account as much information as possible. In particular, it is worth taking advantage of identifying information in the volatility of the shocks.

5. CONCLUSIONS

This paper apply SVAR model with smooth transition in the variances of the residuals. The model is an alternative to other approaches of modelling changes in variance in VAR models such as Markov switching or multivariate GARCH models.

The ST-SVAR model has the advantage of being reasonably easy to estimate. Moreover, a well developed toolkit for the statistical analysis of smooth transition regression models is available that is adoptable for the ST-SVAR model. We show how the model can be used to identify shocks in SVAR analysis and to test conventional identifying restrictions. Although we use only one transition between downswing and upswing states.

As long as the VAR coefficients are time invariant, impulse response analysis can be performed as discussed in paper. As an application of the ST-SVAR approach we analyze the relation between inflation and the output growth. The estimated model suggests a rather smooth transition from a downswing state to an upswing state at around 1995s.This is consistent with the economic narratives on the Rwandan economy where Rwanda experienced high and consistent growth after 1994s. The economic nature of the conventional SVAR and ST-SVAR shocks is very different. While conventional SVAR models identify a sunspot shock, the ST-SVAR shock has a news shocks. Thus, when identification via heteroskedasticity is used, the relation between inflation and the economic growth is seen in a fairly different light than in a conventional SVAR analysis in the short run.

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