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Abstract

Central banks generally target multiple objectives while having at least the same number of monetary instruments. However, some instruments can be inadvertently collinear, leading to indeterminacy and identification failures. Paradoxically, most empirical studies have shied away from this dependence. In this paper we propose a novel method of identifying simultaneous monetary shocks by introducing a Tobit model within a VAR. An advantage of our method is that it can be easily estimated using only least squares and a maximum likelihood function. Also, the impulse-response analysis can be carried out as in the traditional time-series setting and can be applied in a structural framework. Hence, we model a dual process consisting of a censored foreign exchange intervention policy along with a linear interest rate intervention policy. In simulation exercises we show that our method outperforms a benchmark case of estimating policy functions separately. In fact, as the covariance between shocks increases, so does the performance of our method. In our empirical approach, we estimate the policy covariance for the case of Colombia and Turkey and find significant differences when compared to the benchmark case.

Key Words: Simultaneous policies, Instrumental VAR; Tobit-VAR; Central bank intervention; Monetary trilemma

JEL Classification: C34, E52, E58

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"*Forced to state all of the insights of international macroeconomics while standing on one leg, one could do worse than raise a foot off the ground and say something like: Governments face the policy trilemma –the rest is commentary.*"[1]

1 Introduction

Central bank intervention typically entails a specific number of instruments and *at most* the same number of objectives in order to have an effective monetary policy schedule. In some cases, however, policy instruments are inadvertently collinear, leading to monetary indeterminacy and identification failures. Such is the case of the *monetary trilemma*, which states that a country cannot simultaneously allow for free capital flows while having autonomous monetary policy and a managed exchange rate.[2] Namely, if policymakers are to gain full control of the exchange rate, then they must choose between abandoning monetary policy or enacting capital controls. Ultimately, the pursuit of multiple objectives raises the question of whether central banks sometimes overreach and underdeliver. In some cases, the effects of simultaneous policies can offset each other.

Given that monetary policies are seldom independent, any variation in one instrument most likely alters the probability distribution of others. Paradoxically, most empirical studies have shied away from this dependence, to the point of being almost completely ignored. To the best of our knowledge, only a handful of studies exist that address the issue of having multiple policy instruments.[3] We believe that one of the problems that researchers face is the complexity in which the covariance of policy is estimated, especially when dealing with non-linear functions. As a result, the bulk of the relating literature to date has opted to treat each objective separately, even at the risk of conceding some degree of bias or endogeneity problems, by not controlling for the correlation of other simultaneous monetary shocks. Furthermore, while the existing literature more or less agrees on the effects of interest rate intervention (**IRI**), it has yet to converge on the effects of foreign exchange intervention (**FXI**).[4]

Our main objective is to shed some light on this issue, by clearly detailing a procedure through which policy shocks can be correctly identified. Thus, we believe that our investigation can provide a clear and accessible toolkit for central banks, especially those that carry numerous objectives at

[1]Klein (2013), page 97.

[2]The monetary trilemma goes back to Mundell (1963) and Fleming (1962).

[3]See Bergin and Jorda (2000), Ostry et al. (2012), and Villamizar-Villegas (2015).

[4]Empirical surveys on the effects of foreign exchange intervention include Dornbusch (1980), Meese and Rogoff (1988), Dominguez and Frankel (1993), Edison (1993), Dominguez (2003), Neely (2005), Menkhoff (2010), and Villamizar-Villegas and Perez-Reyna (2017). Alternatively, the literature on the effects of central bank's policy rates is broader and include the works of Christiano et al. (1996), Christiano et al. (1999), and Romer and Romer (2004), among others.

hand. Essentially, we study the effects of simultaneous policies in a unified framework, i.e. when monetary instruments are governed by dependent decision processes. Specifically, we: (i) model the dual strategy of a central bank when it conducts both IRI and FXI, (ii) allow for an auto-regressive process within each policy function, and (iii) model the FXI policy function through a censored Tobit model.

The latter objective is motivated by stylized facts that show numerous purchases of foreign currency but a general absence of sales. For example, Echavarría et al. (2013) argue that "the absence of sales suggests the existence of some external factor or constraint that prevents monetary authorities to symmetrically react to economic conditions." In fact, studies such as Calvo and Reinhart (2002) and Levy-Yeyati and Sturzenegger (2007) have coined this phenomenon as a "*fear of floating*". As such, it is common for studies to assume a Tobit (type-I) model when estimating the FXI policy function.

Also, while asymptotic theory for dynamic Tobit models has been addressed in several works such as de Jong and Herrera (2011) and Hahn and Kuersteiner (2010), few studies have considered the case in which the Tobit model depends on lags of the observable variable (Lee (1999)). We add to this literature by proposing a simpler estimation method. Namely, the novelty of our proposed method is that it introduces a Tobit model within a Vector Autoregression (**VAR**). The advantage of doing so is threefold. First, the model can be easily estimated using only least squares and a maximum likelihood function. Second, the impulse-response analysis can be carried out as in the traditional time-series setting. Third, the model can be easily extended to a structural framework (i.e. SVAR).

To better evaluate the properties of our proposed method, we carry out an extensive simulation study to asses the properties and performance of the estimator and compare it to a benchmark '*naive*' approach, which consists of estimating each equation in the system separately. We thus center our analysis on two scenarios: (i) one in which policies are conditionally independent, and (ii) one in which there is a significant covariance between policies, even when controlling for an informative history. While the former allows for monetary shocks to be computed using separate univariate equations, the latter involves a joint-estimation of policy. Hence, the comparison between these two scenarios reveal some of the perils of estimating separate policy functions when actually faced with a significant level of interdependence.

We next turn to an empirical application of two emerging market economies: the cases of Turkey and Colombia during the period of 1999-2010. These countries are ideally suited to study the effects of various monetary policies, since they are two out of the nearly thirty fully-fledged inflation targeting countries (see Hammond (2012)). Also, both countries have conducted frequent and widespread foreign exchange intervention in order to target exchange rate behavior. Consequently, monetary policy is based on a *two-objective, two-instrument* framework. In addition, the availability of proprietary and high frequency data of both interest rate and foreign exchange intervention, as well as relevant covariates (e.g. internal forecasts) that each central bank used when setting policy decisions, enables us to match the actions of policymakers with their targets, within a clear timing profile.

Our simulation results show that our proposed method for identifying simultaneous monetary shocks outperforms the benchmark case of estimating each policy function separately. This finding is robust across different sample sizes, distributional assumptions and number of exogenous variables. In fact, we find that our method yields a lower bias and root-mean-square-error among estimates even when policy shocks are independent. More importantly, as the covariance between shocks increases (in absolute value), so does the performance of our proposed method.

In our empirical exercises we estimate a small (-0.01) and mild (0.14) policy covariance for the case of Colombia and Turkey, respectively. This covariance carries over to the estimated results and impulse response functions. For example, for the Colombian case we find that the policy rate positively reacts to inflation (as in any version of the Taylor rule) under our proposed method, but not under the $Naive$ approach. For the Turkish economy we find that output growth is only relevant to determine the policy rate but not foreign exchange purchases (the $Naive$ approach suggests that it is significant in determining both policies). Finally, the persistence of monetary shocks are lower (in Turkey) when estimated with our iterative method.

This paper proceeds as follows: In Section 2 we present our method of identifying simultaneous monetary shocks and lay out the procedures to compute the variance of the estimated coefficients, impulse-response functions, and confidence intervals. In Section 3 we conduct simulation exercises and compare the performance of our method with a benchmark '*Naive*' case. In this section we also carry out robustness checks regarding different distributional assumptions, various degrees of covariance, and the inclusion of a different number of exogenous variables. In Section 4 we present the results of our empirical approach. Finally, Section 5 concludes.

2 Methodology

In this section, we extend the current literature by constructing a censored bivariate VAR model, comprised of an observable IRI (r_t) and a latent FXI (Int_t^*). To further clarify, FXI is only observable when a central bank purchases foreign currency, i.e., when the latent variable Int_t^* crosses some positive threshold η, so that $Int_t = \max(\eta, Int_t^*)$.[5]

[5]This cutoff point can be consistently estimated following Carson and Sun (2007).

For simplicity, let $y_t = (Int_t^*, r_t)'$ be the vector of endogenous variables, let z_t be a $m \times 1$ dimensional vector of exogenous variables and define $x_t \equiv (1, y'_{t-1}, ..., y'_{t-p}, z'_t, ..., z'_{t-s+1})'$. The latent bivariate VAR model can be written as

$$y_t = Ax_t + \epsilon_t \qquad \forall t \in [max(p+1, s), T] \tag{1}$$

where $A' \equiv \begin{bmatrix} A'_1 & A'_2 \end{bmatrix}$, A_i is a $1 \times (2 \times p + m \times s + 1)$ vector, ϵ_t is an i.i.d normally distributed error term such that $\epsilon_t \sim N(\mathbf{0}, \Sigma)$ and $\Sigma \equiv \begin{bmatrix} \sigma_{11}^2 & \sigma_{12} \\ \sigma_{21} & \sigma_{22}^2 \end{bmatrix}$ is a positive definite matrix.

For the estimation procedure, note that the bivariate density of the vector y_t can be factored as $f(y_t) = f(Int_t^*|r_t)f(r_t)$, where

$$f(r_t) = \frac{1}{\sigma_{22}}\phi\left(\frac{r_t - A'_2 x_t}{\sigma_{22}}\right) \tag{2}$$

$$f(Int_t^*|r_t) = \frac{1}{\sigma_C}\phi\left(\frac{Int_t^* - m_t}{\sigma_C}\right). \tag{3}$$

In the above expressions, ϕ denotes the standard normal density function, $\sigma_C^2 \equiv \sigma_{11}^2 - \left(\frac{\sigma_{12}}{\sigma_{22}}\right)^2$ and $m_t \equiv A'_1 x_t + \frac{\sigma_{12}}{\sigma_{22}^2}(r_t - A'_2 x_t)$. Hence, the resulting log-likelihood function for the bivariate latent VAR model can be written as

$$l(\theta) = \sum_t \log(f(y_t)) = \sum_t \log(f(r_t)) + \sum_t \log(f(Int_t^*|r_t)) \tag{4}$$

where $\theta \equiv (A'_1, A'_2, \sigma_{11}, \sigma_{12}, \sigma_{22})'$. As suggested by Hamilton (1994), maximizing the expression in (4) with respect to θ yields the same result as maximizing with respect to $\theta_1 = (A'_1, B'_1, b, \sigma_{11}, \sigma_C)'$ as long as the following restrictions: $b = \frac{\sigma_{12}}{\sigma_{22}^2}$ and $B'_1 = A'_1 - \frac{\sigma_{12}}{\sigma_{22}^2}A'_2$ are imposed. The latter maximization is easier to achieve since (A'_1, σ_{11}) only appears in the expression $\sum_t \log(f(r_t))$, while (B'_1, b, σ_C) appears exclusively in $\sum_t \log(f(Int_t^*|r_t))$. Therefore, the maximization of each set of parameters can be done independently using least squares.

In practical applications, the above estimation method would be straightforward if Int_t^* was observable (this is not the case, given that the observed variable Int_t is left-censored at the cutoff η). Nonetheless, the system of equations in (1) can still be estimated by using least squares for the maximization of $\sum_t \log(f(r_t))$, and a Tobit type I model for the maximization of $\sum_t \log(f(Int_t^*|r_t))$.[6] In this case, the lags of the latent variable Int_t^* on the right hand side of (1) have to be replaced by

[6]See Amemiya (1973).

lags of the observable variable Int_t. The latter is clearly a misspecification error, and it is similar to a measurement error problem. Hence, we expect that this leads to inconsistent estimates. This result is confirmed by our simulation exercises in Section 3.

Consequently, in order to correct the bias in the estimated coefficients, we propose a new iterative method which we refer to henceforth as the *Iterative Instrumental Tobit VAR* **(IITV)**. This method seems to correct the asymptotic bias caused by the misspecification error discussed in the paragraph above. The algorithm for the IITV estimation is described in the following six steps:[7]

1. Estimate θ_1 using: least squares in equation 2 and a standard (Type I) Tobit model in equation (3). Replace the lags of the latent variable Int_t^* with lags of the observable variable Int_t. Since the system is exactly identified, then the coefficients $(A_2', \sigma_{12}, \sigma_{22})$ are recovered using the restrictions for (b, B_1', σ_C).

2. Using the least squares residuals of the regression in (2) and $\hat{\Sigma}$, compute the expected value and the variance of the density function $f(\epsilon_{1t}|\hat{\epsilon_{2t}})$ for all t. Notice that this step is simplified since, conditional on ϵ_{2t}, ϵ_{1t} follows a normal distribution with mean $\frac{\sigma_{12}}{\sigma_{22}^2}\epsilon_{1t}$ and variance $\sigma_{11}^2 - \left(\frac{\sigma_{12}}{\sigma_{22}}\right)^2$.

3. Build residuals for $\hat{\epsilon}_1$. That is, if $Int_t > \hat{\eta}$, take $\hat{\epsilon}_{1t} = Int_t - \hat{A}_1' x_t$, else build the expected value of the density function $f(\epsilon_{1t}|\hat{\epsilon_{2t}}, \epsilon_{1t} < (\hat{\eta} - \hat{A}_1' x_t)$ and use that value as an instrument for $\hat{\epsilon}_{1t}$.

4. Once the series for $\hat{\epsilon_1}$ has been obtained, build the instrumental latent variable $Int_t^{**} = \hat{A_1}' x_t + \hat{\epsilon}_{1t}$.

5. Repeat step 1, but now the lags of the latent variable Int_t^* are replaced by the lags of the instrumental latent variable Int_t^{**}. Again, the coefficients $(A_2', \sigma_{12}, \sigma_{22})$ are recovered using the restrictions for (b, B_1', σ_C).

6. Repeat steps 2-5 until the absolute value of the difference between consecutive estimations is less than a predefined tolerance value.

2.1 Variance of IITV coefficients

The simulation exercises in Section 3 suggest that the IITV method of estimation is consistent. And, since it only involves using ordinary least squares and a maximum likelihood estimation, asymptotic normality should follow (formal proofs of IITV's asymptotic properties are subject to an ongoing

[7]See in particular Johnson et al. (1994) for step 2.

investigation). The latter allows us to build the variance of the coefficients in $\hat{\theta}$ using the estimation results for $\hat{\theta}_1$ and the delta method.[8] For that purpose, equations 5-7 are considered:

$$\sigma_{11}^2 = \sigma_C^2 + \left(\frac{\sigma_{12}}{\sigma_{22}}\right)^2 \tag{5}$$

$$\sigma_{12} = b \times \sigma_{22}^2 \tag{6}$$

$$A_1' = B_1' + \frac{\sigma_{12}}{\sigma_{22}^2} A_2'. \tag{7}$$

2.2 Impulse Response Function (IRF) Analysis

For ease in notation, define a $2 \times (2 \times p + m \times s)$ matrix $J_b \equiv (\mathbf{0} : ... : I_2 : \mathbf{0} : ... : \mathbf{0})$ where the sub-index b in J denotes the column where the 2×2 identity matrix (I_2) begins. If we omit the intercept in matrix A, then the model in (1) can be rewritten as:

$$y_t = C_1 y_{t-1} + ... + C_p y_{t-p} + C_{p+1} z_t + C_{p+s} z_{t-s+1} + \epsilon_t, \tag{8}$$

where $C_i = AJ'_{2(i-1)+1}$. Note that the model in (8) is a reduced form VARX(p,(s-1)) and can be represented as a simpler VARX(1,0) using the following notation:

$$Y_t = \mathbf{A} Y_{t-1} + \mathbf{B} z_t + U_t, \tag{9}$$

where the definitions of $Y_t, \mathbf{A}, \mathbf{B},$ and U_t are found in Lütkepohl (2005).[9] From the VARX(1,0) representation, the multiplier matrices M_i (those which reflect the impact of exogenous variables on the whole system) and the impulse response matrices ϕ_i can be computed as follows:

$$M_i = J_1 \mathbf{A}^i \mathbf{B} \tag{10}$$

$$\phi_i = J_1 \mathbf{A}^i J_1' \tag{11}$$

2.3 IRF Confidence Intervals

For the construction of the IRF confidence intervals, we propose using a "pseudo-residual" based bootstrap. Namely, the residuals ϵ_{1t} can be recovered by following steps (2) and (3) of the IITV

[8]Technically, the delta method is asymptotically correct only for the first step of the IITV algorithm. However, we apply it in further iterations of the method, making the underlying assumption that the sampling variability of Int_t^{**} has no effect on the asymptotic validity of the method.

[9]See Lütkepohl (2005), page 403.

estimation procedure. Finally, once the series of $\hat{\epsilon}_1$ has been recovered and using $\hat{\epsilon}_2$, a traditional residual-based bootstrap is implemented. For further details, see Efron and Tibshirani (1994).

3 Simulation Exercises

In this section, we analyze the performance of the *IITV* estimator, and compare results to an approach we call *Naive*. The *Naive* estimation method consists of estimating each equation in the system separately, i.e. it intentionally ignores the covariance between policies. More specifically, it consists of using ordinary least squares and a Type-I Tobit model to estimate the IRI and FXI policy functions, respectively. In addition, in order to better illustrate the benefits of our iterating method, we further present results of the first step of the *IITV* algorithm, for which we refer to as *Step-1*.[10] We thus believe that the comparison between estimates using the $IITV$ and $Naive$ methods will shed light over some of the perils of estimating separate policy reaction functions when faced with a significant level of interdependence.

In the simulation exercises that follow we consider samples of 100, 500, and 1000 observations. For each sample size, we use different levels of covariance between the error terms of the two policy reaction functions ($\sigma_{12} = 0.0, 0.4, 0.8$). Also, 5000 replications are performed for each simulation exercise. Finally, in Appendix A, we present results assuming non-Gaussian distributions of the error term (see equation 1).

The data generating process we consider is a bivariate latent VAR model in which one of the series involved in the analysis (FXI) is censored. In the baseline case, three exogenous regressors are considered, since most papers that estimate policy functions include at least this number of covariates. Namely, variables that are often considered include some measure of exchange rate misalignment, inflation, and output (see Edison (1993) and Sarno and Taylor (2001)).[11] The data generating process is described as:

$$\begin{bmatrix} Int_t^* \\ r_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} Int_{t-1}^* \\ r_{t-1} \end{bmatrix} \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \end{bmatrix} \begin{bmatrix} z_{1t} \\ z_{2t} \\ z_{3t} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{12}$$

In the baseline case, we only include one lag of the dependent variable. We do this following Romer and Romer (2004) who argue (for the US Federal Reserve) that the inclusion of the lagged policy

[10]The *Step-1* estimation is similar to the $Naive$ approach, but instead uses restrictions for (b, B_1', σ_C) to retrieve the coefficients of $(A_2', \sigma_{12}, \sigma_{22})$.

[11]Nonetheless, in Appendix A we present simulation results for cases in which there is only one exogenous variable, and find similar results.

rate captures tendencies toward mean reversion. The specific parameters used in the simulation exercises can be found in Appendix B.

In Tables 1-6, we report results of the simulation exercises that assume multivariate normality of the error term. For all cases, we compute both bias and root-mean-square-error (RMSE) for each of the parameters. Tables 1-3 show results for the regressor coefficients $(\alpha_s, \beta_{s,s}, \gamma_{s,l})$, where $s \in \{1, 2\}$ and $l \in \{1, 2, 3\}$. Tables 4-6 show results for the variance-covariance matrix of the error term.

Table 1 presents the results for the case in which policy shocks are independent ($\sigma_{12} = 0$). We find that the $IITV$ method yields better results in terms of bias and RMSE in most coefficients and across all sample sizes. Additionally, Table 4 shows that the estimated variance-covariance matrix of the error term under the $IITV$ method outperforms that of the $Naive$ approach. For example, both the bias and RMSE of the variances $(\sigma_{11}, \sigma_{22})$ under the $IITV$ method are lower than those of the $Naive$ approach. Note however, that we cannot compare estimates of the covariance between policies since -by construction- the naive approach assumes a zero covariance. Nonetheless, we conclude that even when there is no correlation between policy shocks the $IITV$ method outperforms the naive approach. This follows from the fact that while the conditional error $(\epsilon_{1t} \mid \epsilon_{2t})$ does not provide any additional information, the truncated error $(\epsilon_{1t} \mid \epsilon_{1t} < (\hat{\eta} - A_1' x_t))$ does so.

Tables 2 and 3 show estimates for a policy covariance of 0.4 and 0.8, respectively. These tables suggest that the $IITV$ method improves (reduces bias and RMSE) and greatly outperforms the $Naive$ approach. In fact, even the $Step-1$ estimator outperforms the $Naive$ approach. We note that the main differences are found in the coefficients of the lagged endogenous variables, which are the main driving forces for the impulse-response functions.

Estimation results for the variance-covariance matrix (again for a policy covariance of 0.4 and 0.8) are presented in Tables 5 and 6. The covariance estimates (σ_{12}) are remarkably close to the real values of 0.4 and 0.8, respectively. For example, with a sample size of 500, the estimated covariance under the $IITV$ has a bias of only -0.038 (Table 5) and -0.019 (Table 6). Furthermore, as seen in Table 6 the $Naive$ method behaves poorly when estimating the variance of the error term $(\sigma_{11}, \sigma_{22})$, with a bias of $(0.193, 0.079)$ compared to a bias of $(0.037, 0.015)$ under the $IITV$ method.

In sum, these results highlight the central result of our investigation which is that as the correlation between shocks increases (in absolute value), the $IITV$ increasingly outperforms the $Naive$ approach. It is easy to note that the $IITV$ uses the dependence between policies to improve over the estimates. Formally, consider the conditional distribution of ϵ_1 given ϵ_2, assuming bivariate normality:[12]

$$f(\epsilon_1|\epsilon_2) \sim N\left(\frac{\sigma_{11}}{\sigma_{22}}\rho\epsilon_2, (1-\rho^2)\sigma_{11}^2\right), \tag{13}$$

where ρ is the correlation coefficient between ϵ_1 and ϵ_2. It follows from the above equation that, as the correlation coefficient (ρ) approaches unity, the variance of the conditional distribution goes to zero. This implies that by conditioning the error term of the FXI equation on that of the IRI equation, it provides all the information required to obtain a residual from the censored equation. As such, it becomes clear that the performance of the $IITV$ estimator improves as the correlation between shocks increases.

In Appendix A, we present further simulation exercises. Tables 9-20 show the robustness of the $IITV$ method under the assumption of non-Gaussean errors. Particularly, Tables 9-14 consider multivariate t-distributions with 5 degrees of freedom, while Tables 15-20 consider the same t-distribution with 30 degrees of freedom. Finally, in Tables 21-23, we consider a data generating process with only one exogenous regressor. As shown, results of these exercises are very similar to the main case of Tables 1-6. Hence, the $IITV$ method (and more importantly, its dominance over the *naive* approach) is robust to the different distributional assumptions as well as to the different specifications regarding the number of covariates.

4 Results

In our empirical application we center our analysis on Turkey and Colombia, two emerging market economies that follow an inflation targeting regime. Both countries have also conducted frequent and widespread foreign exchange intervention in order to target exchange rate behavior, so monetary policy is based on a *two-objective, two-instrument* framework. Our results can thus be compared to the findings of the growing empirical literature on these countries.[13]

Our data, of proprietary nature, come directly from both the Central Bank of Turkey and the Central Bank of Colombia. They comprise the timing and amount of both foreign exchange and interest rate intervention. Additionally, we observe the internal forecasts (and *nowcasts*) of variables such as inflation and output that each central bank used when setting their policy decisions. The data cover the period of February 2002 through May 2010 for the Turkish case (9 years), and of February 1999 through February 2010 (11 years) for the Colombian case. Prior to these dates, a more rigid exchange rate regime was implemented in both countries. Also, following 2010, both

[12] See Johnson et al. (1994).

[13] Empirical studies applied to the Turkish case include: Guimaraes and Karacadag (2004), Herrera and Ozbay (2005), Akinci et al. (2006), and Onder and Villamizar-Villegas (2015). Alternatively, studies centered in the Colombian case include: Uribe and Toro (2005), Kamil (2008), Rincón and Toro (2010), and Villamizar-Villegas (2015).

countries adopted additional monetary instruments: a reserve option mechanism and an interest rate corridor in Turkey, and daily foreign exchange interventions in Colombia (see Ordonez-Callamand et al. (2016)).

For the Colombian case, we use purchases of USD conducted in the spot market (22.8 billion), as well as purchases through foreign exchange rate options (3.3 billion). Alternatively, for the Turkish case, we use optional purchases (20.4 billion), which consisted of a discretionary amount of trading that took place during the day of an announced auction.[14] In Appendix C, we provide a detailed description of each variable used for both Turkey and Colombia.

In the exercises that follow we report: (i) Estimation results, (ii) Impulse Response Functions, and (iii) multipliers of the exogenous variables, for both the $IITV$ method and the *naive* approach, as described in Section 3.[15]

4.1 Colombia

Table 7 shows the estimation results for the colombian case. As shown, coefficients for the $IITV$ and $Naive$ methodologies are relatively similar, suggesting that conditional on the information set, the covariance between policies is sufficiently small so as not to generate a large bias among the estimates. This result is consistent with the findings of Villamizar-Villegas (2015), who argues that policies in Colombia are conditionally independent "due to the inclusion of internal forecasts as control variables." Furthermore, our estimation results for the variance-covariance matrix of the error term under the $IITV$ method yield the following:

$$\hat{\Sigma} = \begin{bmatrix} 0.104 & -0.01 \\ -0.01 & 0.068 \end{bmatrix}$$

which confirms the low covariance (σ_{12}) between policy shocks and also reports a small variance of each shock (σ_{11}, σ_{22}). However, a few differences stand out. For instance, the intercept is significant under the $Naive$ approach, but not under the $IITV$ method. More importantly, the policy rate (r_t) positively reacts to inflation (as in any version of the Taylor rule) under the $IITV$ method, but it is not significant under the $Naive$ approach.[16]

[14] We exclude unannounced purchases and sales for the Turkish case, due to the few observations available.

[15] For the *naive* approach, the cross IRFs correspond to the multipliers of the respective lagged policy variable. Also, the following considerations should be taken into account when interpreting the IRFs and multipliers: (i) We use the Choleski decomposition so that FXI is more exogenous than IRI; (ii) the IRF response in horizon $t+0$ can only be interpreted using the estimated multipliers; (iii) the time horizon is measured in meetings of the board of directors as in Romer and Romer (2004); and (iv) in the bootstrapping used in building confidence intervals, we construct the standard deviation using the robust scale estimator S_n, as in Rousseeuw and Croux (1993).

[16] Results also show that inflation is significant in the FXI policy function under the $Naive$ approach, but not under the $IITV$ method. Given that USD purchases were fully sterilized, we believe that they should play little (if

In sum, we find that, under the $IITV$ method, the Central Bank of Colombia intervened in the foreign exchange market by purchasing foreign currency (to depreciate domestic currency) whenever the exchange rate appreciated relative to its forecasted equilibrium value (ERM), and whenever the central bank was a net debtor with respect to the financial system ($NetPos$). These results are similar to those found in Kamil (2008) and Echavarría et al. (2013). Alternatively, the bank conducted contractionary monetary policy whenever inflation and output (IPI) increased.[17]

Figures 1 and 2 depict the IRFs of the FXI and IRI monetary shocks, under the $IITV$ and $Naive$ methods, respectively. Results again are fairly similar, showing a null effect for the cross IRFs. The persistence of each shock, which lasts approximately two periods (recall that periods are measured as the time elapsed between meeting dates of the board of directors) vary slightly across methodologies. Namely, under the $Naive$ approach, the persistence of the FXI (IRI) policy shock is slightly lower (higher) than under the $IITV$ method. We believe however, that the $IITV$ estimates have higher precision (see Section 3), which reflects on the narrower confidence intervals.

Figures 3 and 4 depict the multipliers of the exogenous variables. Results again show narrower bands for the $IITV$ estimates. Also, note that the impact of inflation on the policy rate is significant under the $IITV$, but not under the $Naive$ approach, which is consistent with the results reported in Table 7.

4.2 Turkey

Results for the Turkish case mostly differ in that we find a larger covariance between the policy shocks. In particular, the estimation of the variance-covariance matrix yields:

$$\hat{\Sigma} = \begin{bmatrix} 0.423 & 0.141 \\ 0.141 & 1.063 \end{bmatrix}$$

In fact, Table 8 shows that the lag policy rate ($Lag\ IRI$) is significant (for the IRI policy function) under the $Naive$ approach, but not under the $IITV$ method. Similarly, output growth (IPI) is significant (for the FXI policy function) under the $Naive$ approach, but not under the $IITV$ method. In sum, we find that the Central Bank of Turkey intervened in the foreign exchange market (by purchasing foreign currency) whenever the exchange rate appreciated (ERM). Alternatively, the bank conducted contractionary monetary policy whenever inflation (relative to the yearly

any) part in the decision process to intervene.

[17]This setting, like in Romer and Romer (2004), assumes that unemployment act through output growth, i.e. Okun's law.

target) and output increased. Results that are most similar to ours can be found in Onder and Villamizar-Villegas (2015).

Figures 5 and 6 depict the IRFs of the FXI and IRI monetary shocks under the $IITV$ and $Naive$ methods, respectively. Besides having narrower confidence bands, the $IITV$ method shows a smaller persistence of shocks, especially that of IRI. Finally, Figures 7 and 8 depict the multipliers of the corresponding exogenous variables. Although fairly similar, the impact of: (i) inflation on IRI, (ii) output on FXI, and (iii) output on IRI, turn out larger (and significant over longer periods) with the $Naive$ approach. All multipliers are consistent with the results reported in Table 8.

5 Conclusions

Central bank intervention typically entails a specific number of instruments and *at most* the same number of objectives in order to have an effective monetary policy schedule. In some cases, however, policy instruments are inadvertently collinear, leading to monetary indeterminacy and identification failures. Paradoxically, most empirical studies have shied away from this dependence, to the point of being almost completely ignored.

In this paper we shed some light on this issue, by clearly detailing a procedure through which policy shocks can be correctly identified. The novelty of our proposed method is that it introduces a Tobit model within a VAR. Thus, the model can be easily estimated using only least squares and a maximum likelihood function. Also, the impulse-response analysis can be carried out as in the traditional time-series setting and can be extended to a structural framework.

We carry out an extensive simulation study and find that our method outperforms a benchmark case of estimating policy functions separately. This finding is robust across different sample sizes, distributional assumptions and number of exogenous variables. Our central result is that, as the covariance between shocks increases, so does the performance of our method. In our empirical approach we estimate the policy covariance for the case of Colombia and Turkey. In the Colombian case, we find that the policy rate positively reacts to inflation under our proposed method, but not under the benchmark approach. Alternatively, in the Turkish case we find that output is relevant to determine the policy rate but not to determine foreign exchange purchases. Finally, we find that monetary shocks in Turkey have lower persistence when estimated with our iterative method.

We believe that our investigation can provide a clear and accessible toolkit for central banks, especially those that carry numerous objectives at hand. Studies that can profit most from our investigation are those centered in economies in which policy covariance is high, e.g. where the same monetary committees decide over multiple objectives.

6 References

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FIGURES

Figure 1: IRFs in Colombia using our *IITV* method

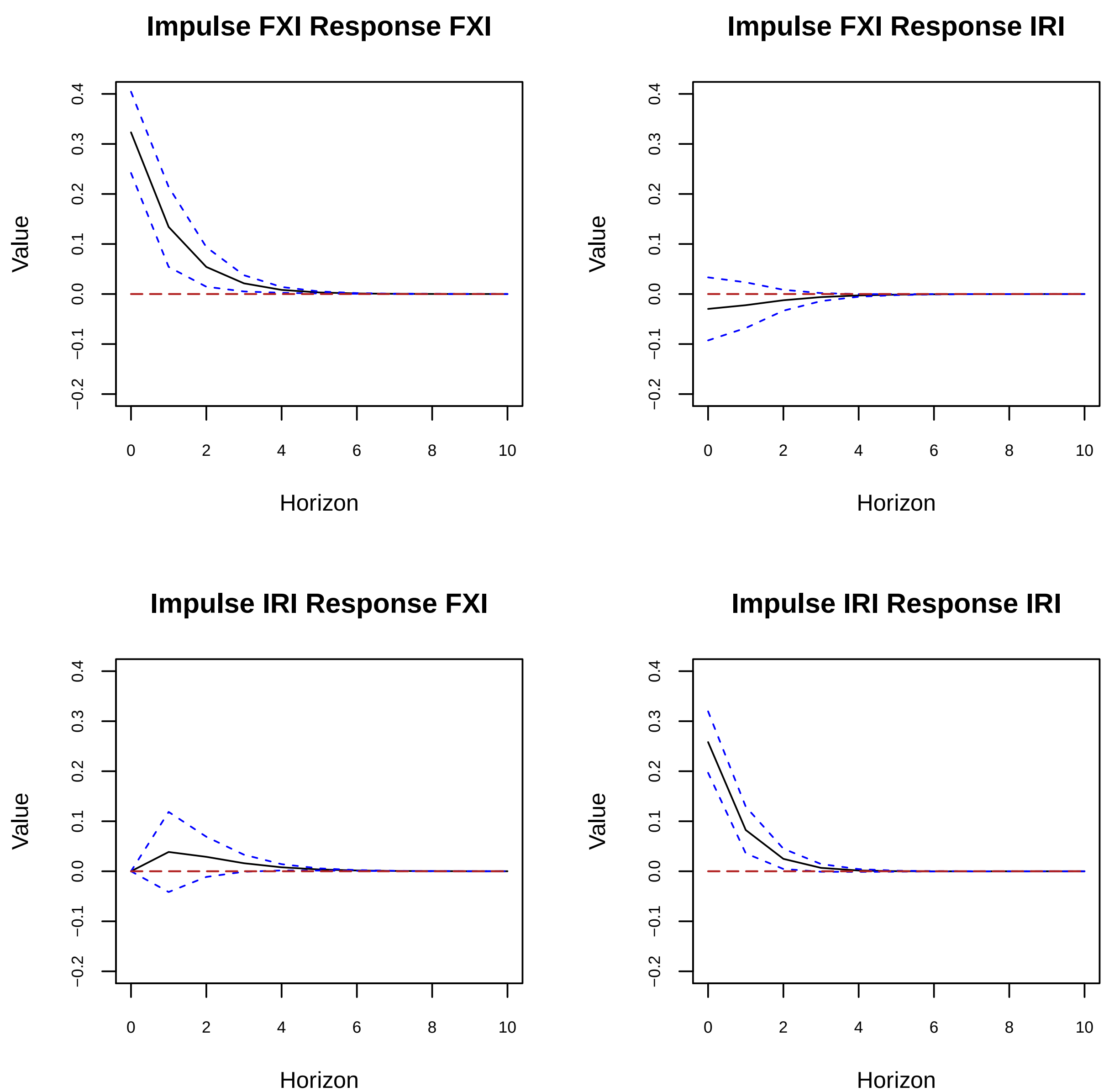


Figure 2: IRFs in Colombia using a *Naive* method

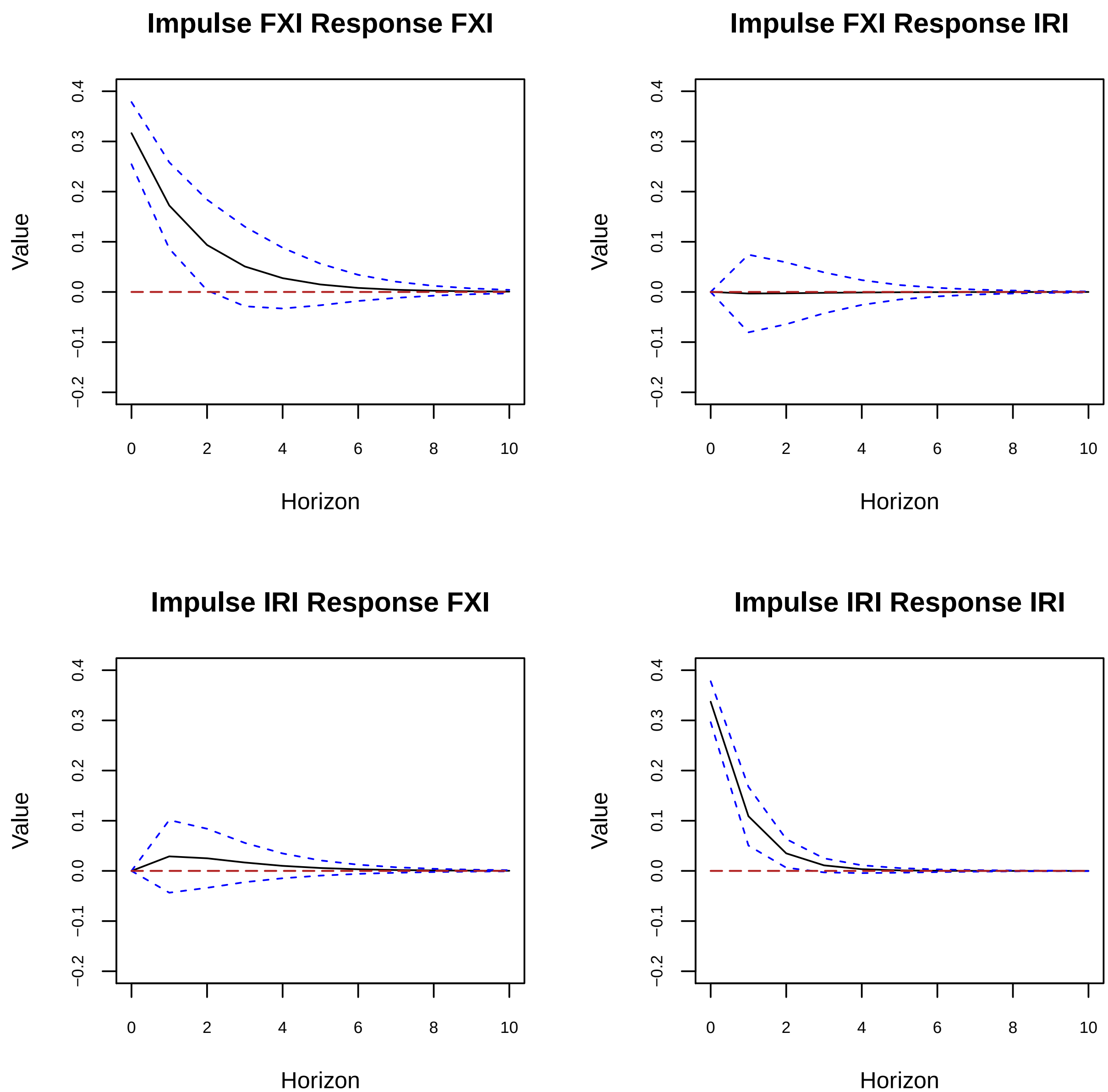


Figure 3: Multipliers in Colombia using our $IITV$ method

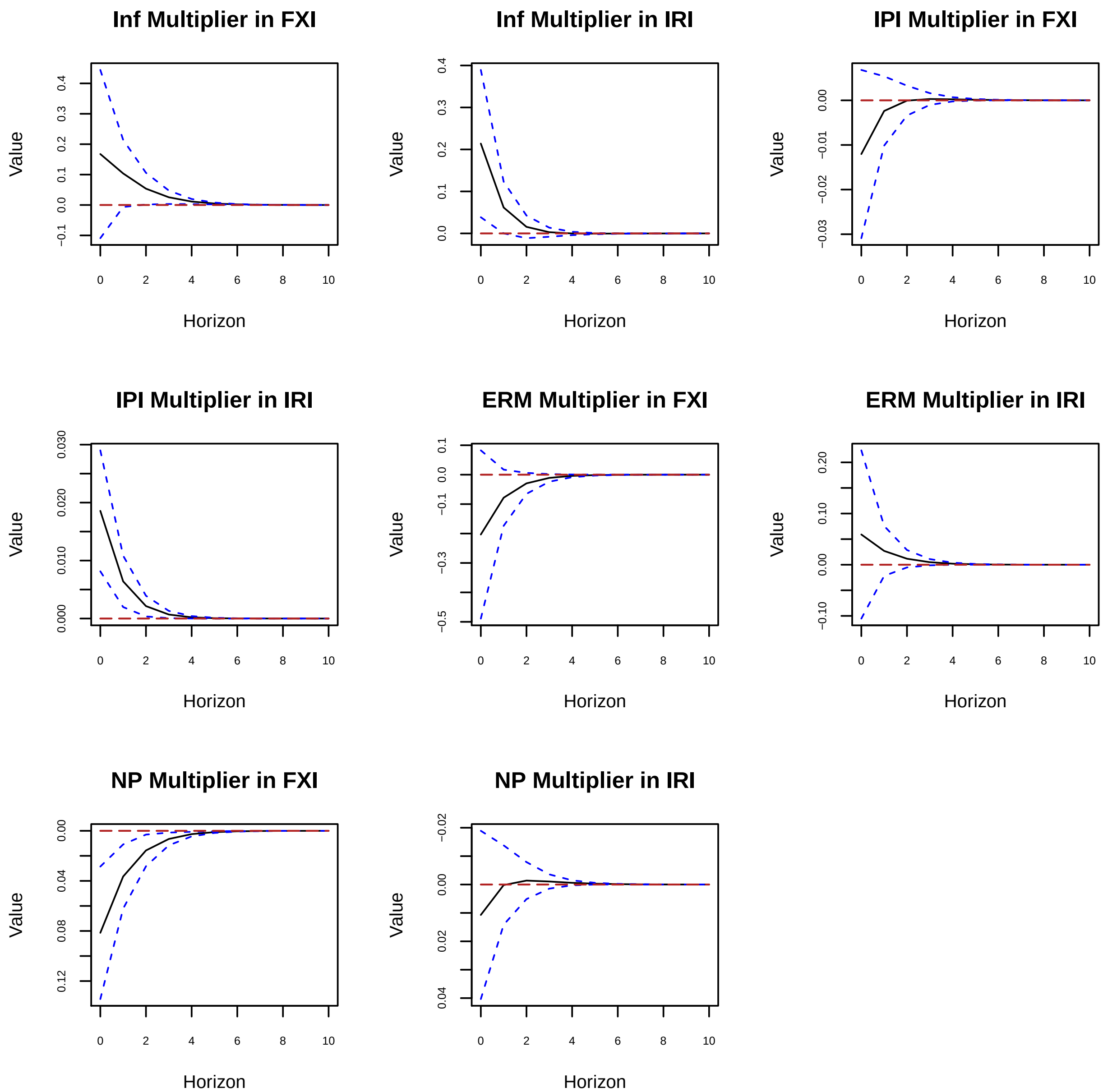


Figure 4: Multipliers in Colombia using a *Naive* method

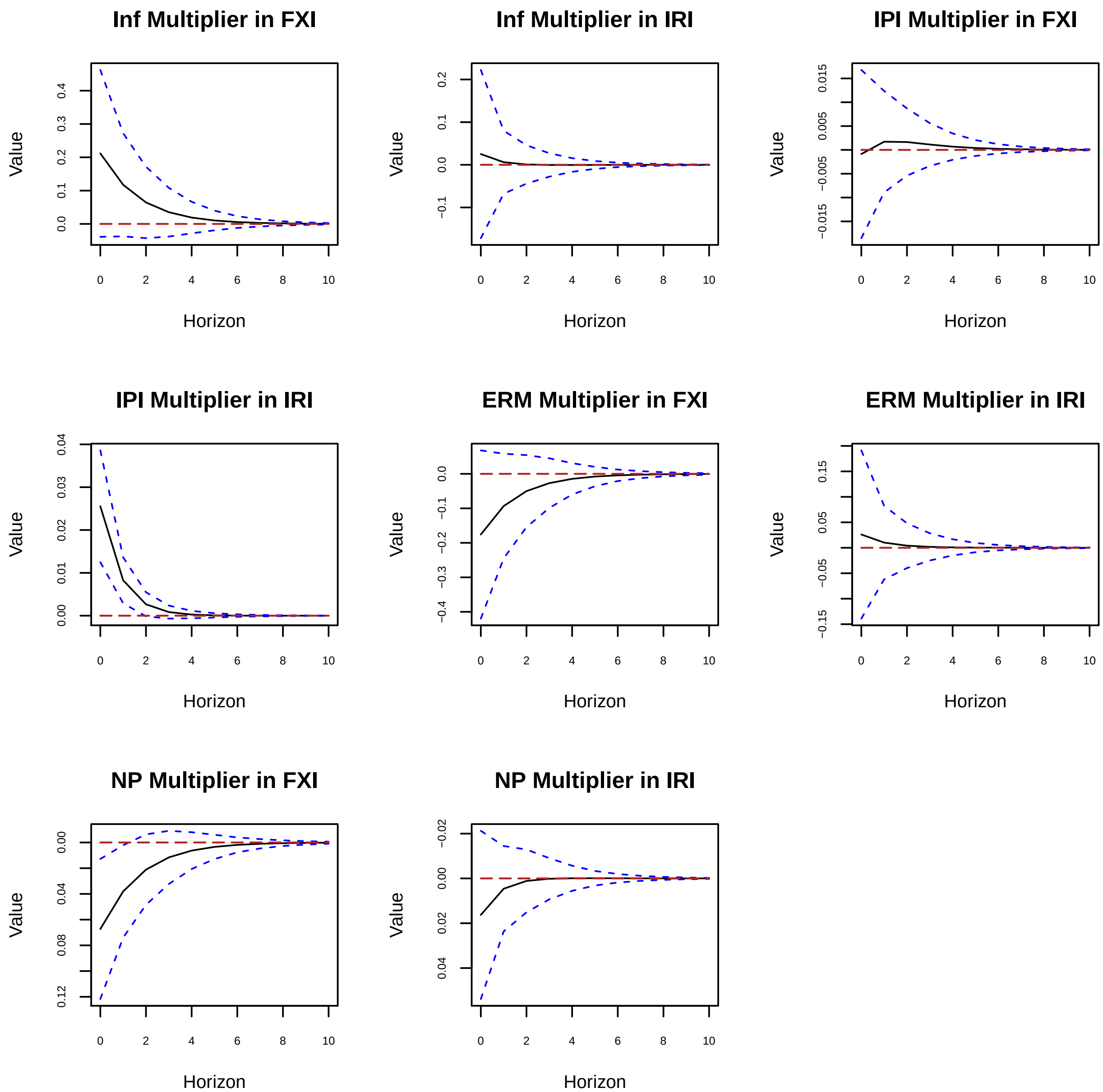


Figure 5: IRFs in Turkey using our $IITV$ method

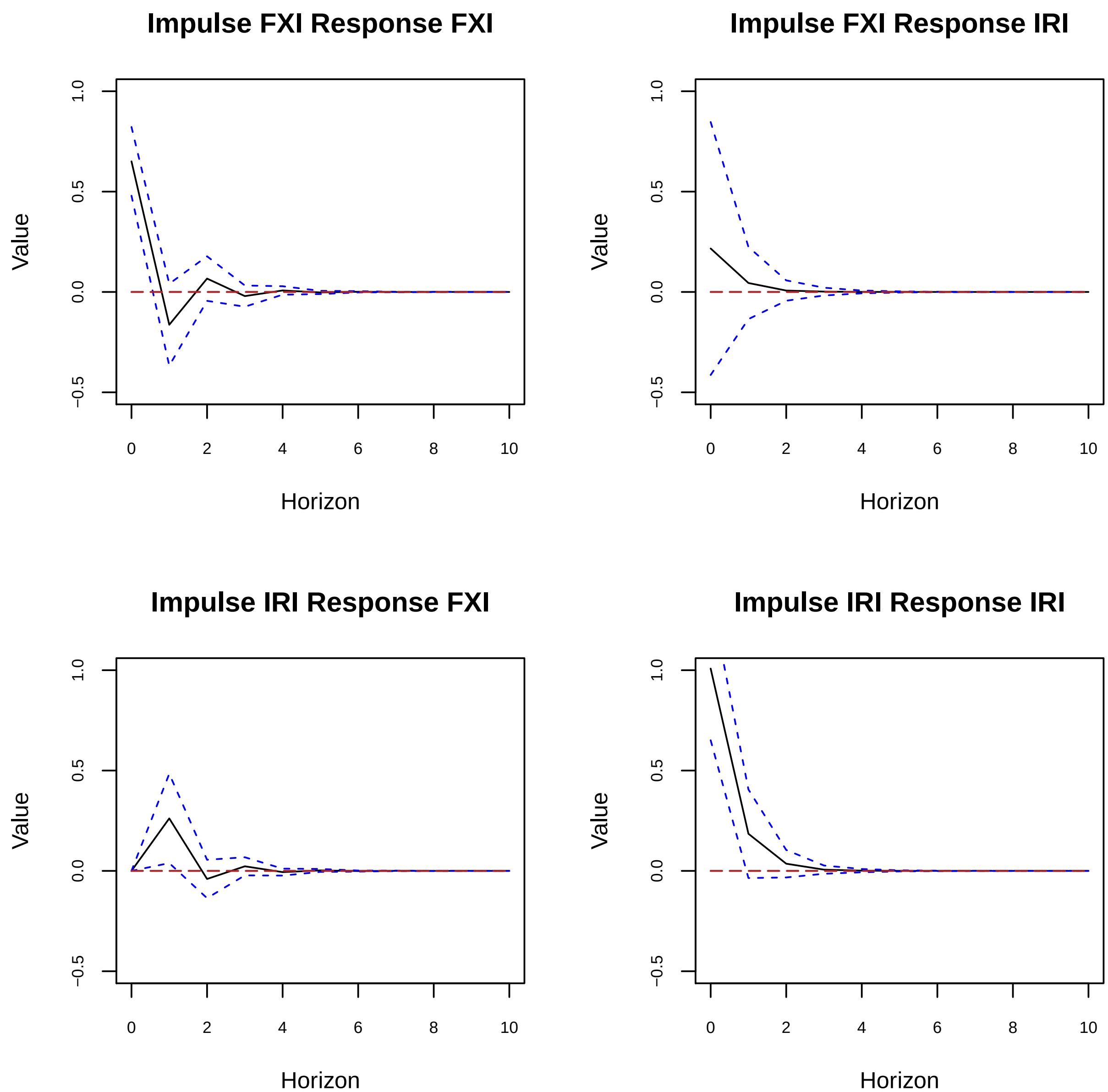


Figure 6: IRFs in Turkey using a *Naive* method

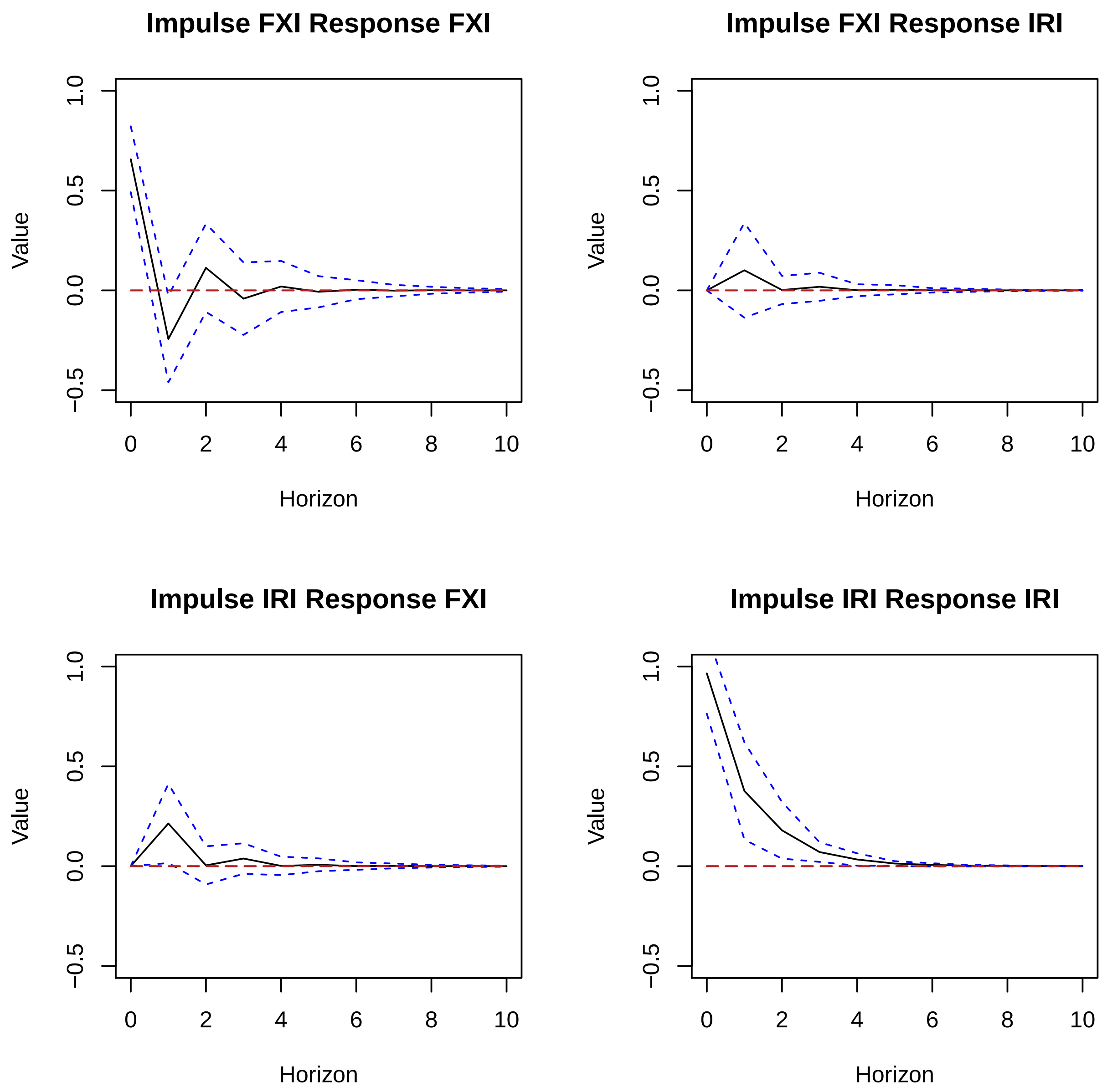


Figure 7: Multipliers in Turkey using our $IITV$ method

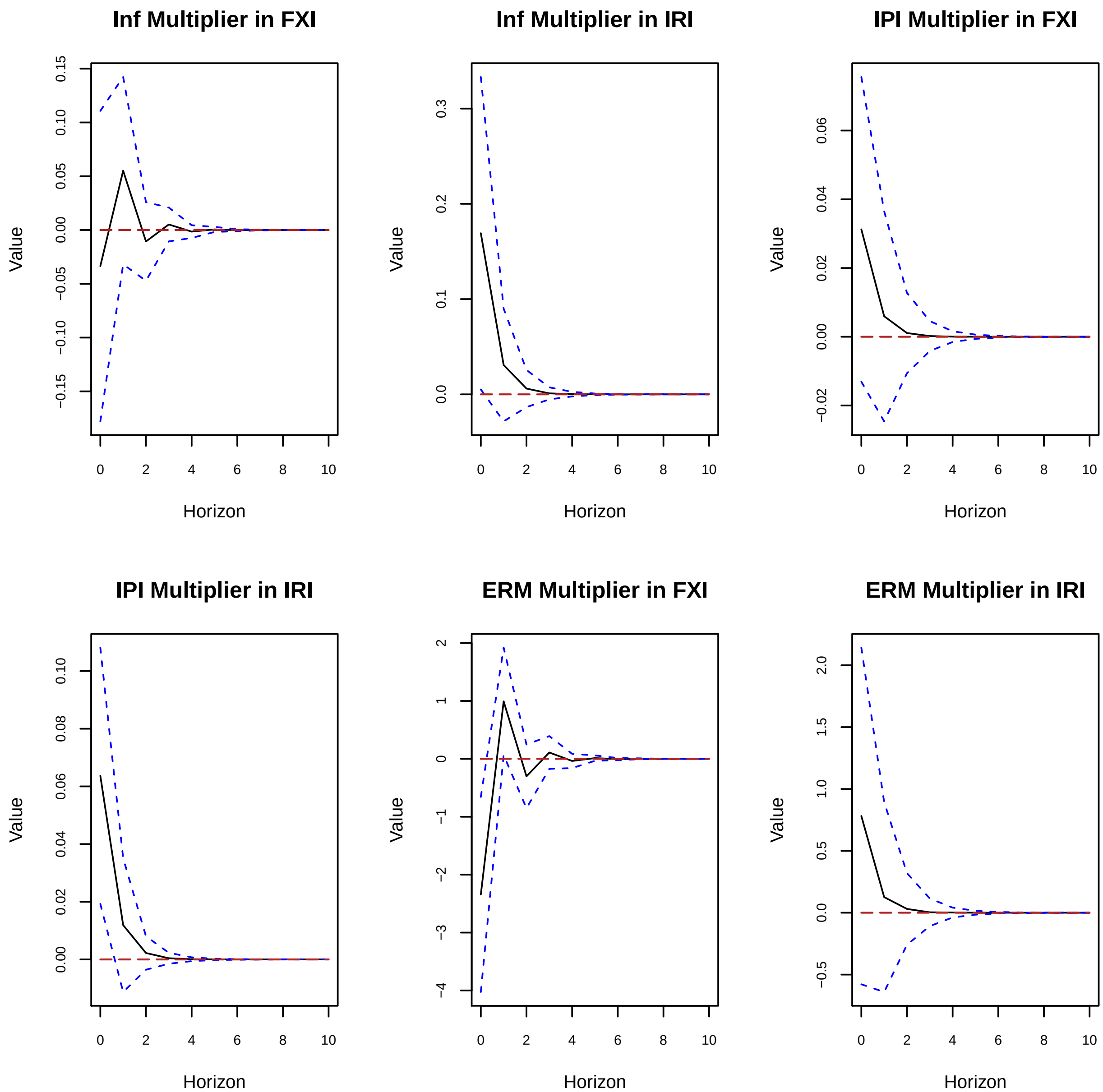
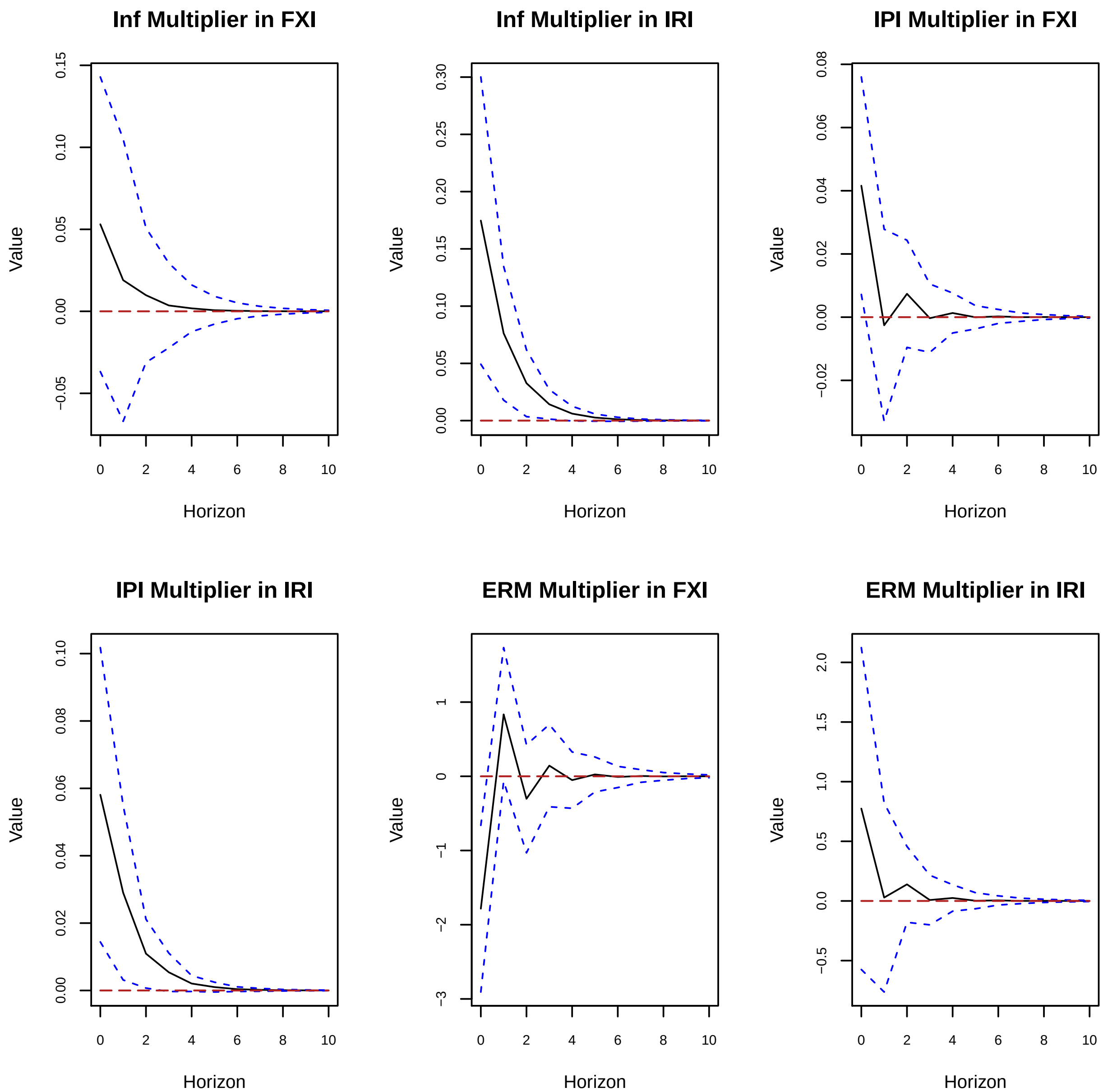


Figure 8: Multipliers in Turkey using a *Naive* method



TABLES

Table 1: Multivariate Normal Errors, 0 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	0.035	0.021	-0.088	-0.021	-0.047	-0.024	0.013	-0.001	0.000	-0.003	-0.011	0.003
	RMSE	0.549	0.186	0.176	0.116	0.158	0.098	0.190	0.082	0.123	0.073	0.128	0.073
Step-1	*Bias*	-0.962	0.552	0.061	-0.066	-0.192	0.097	0.039	-0.022	0.011	-0.005	-0.020	0.019
	RMSE	1.147	0.694	0.228	0.187	0.223	0.110	0.123	0.069	0.116	0.063	0.119	0.064
Naive	*Bias*	-0.954	0.552	0.062	-0.066	-0.187	0.097	0.038	-0.022	0.012	-0.005	-0.019	0.019
	RMSE	1.138	0.694	0.227	0.187	0.217	0.110	0.122	0.069	0.115	0.063	0.118	0.064
T = 500													
IITV	*Bias*	0.029	0.013	-0.025	-0.003	-0.008	0.000	0.000	0.000	0.002	0.000	0.002	0.000
	RMSE	0.097	0.059	0.059	0.041	0.051	0.036	0.043	0.029	0.036	0.023	0.038	0.023
Step-1	*Bias*	-0.936	0.442	0.117	-0.052	-0.171	0.100	0.027	-0.014	0.009	0.001	-0.008	0.007
	RMSE	0.959	0.464	0.146	0.087	0.176	0.103	0.054	0.030	0.042	0.022	0.043	0.023
Naive	*Bias*	-0.932	0.442	0.117	-0.052	-0.168	0.100	0.026	-0.014	0.010	0.001	-0.008	0.007
	RMSE	0.956	0.464	0.146	0.087	0.174	0.103	0.054	0.030	0.042	0.022	0.043	0.023
T = 1000													
IITV	*Bias*	0.033	0.013	-0.020	-0.002	-0.005	0.003	-0.002	0.000	0.001	0.000	0.003	0.000
	RMSE	0.075	0.043	0.042	0.029	0.035	0.025	0.032	0.021	0.025	0.016	0.028	0.017
Step-1	*Bias*	-0.949	0.445	0.112	-0.046	-0.169	0.099	0.022	-0.015	0.001	0.002	0.006	0.004
	RMSE	0.961	0.458	0.128	0.067	0.172	0.101	0.042	0.025	0.029	0.015	0.030	0.017
Naive	*Bias*	-0.945	0.445	0.112	-0.046	-0.167	0.099	0.021	-0.015	0.002	0.002	0.006	0.004
	RMSE	0.957	0.458	0.128	0.067	0.17	0.101	0.041	0.025	0.029	0.015	0.03	0.017

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 2: Multivariate Normal Errors, 0.4 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	0.039	0.022	-0.069	-0.023	-0.032	-0.020	0.007	0.002	0.000	-0.001	-0.011	0.000
	RMSE	0.329	0.182	0.143	0.097	0.124	0.082	0.122	0.083	0.115	0.075	0.124	0.072
Step-1	*Bias*	-1.095	0.677	0.144	-0.124	-0.141	0.078	0.035	-0.018	0.016	-0.004	-0.016	0.017
	RMSE	1.245	0.792	0.249	0.210	0.174	0.093	0.117	0.066	0.114	0.063	0.117	0.062
Naive	*Bias*	-1.117	0.677	0.145	-0.124	-0.151	0.078	0.035	-0.018	0.016	-0.004	-0.018	0.017
	RMSE	1.269	0.792	0.251	0.210	0.184	0.093	0.119	0.066	0.115	0.063	0.119	0.062
T = 500													
IITV	*Bias*	0.029	0.012	-0.024	-0.004	-0.007	0.001	0.000	0.000	0.002	0.000	0.002	-0.001
	RMSE	0.095	0.058	0.051	0.034	0.043	0.030	0.041	0.028	0.035	0.023	0.037	0.023
Step-1	*Bias*	-1.052	0.539	0.190	-0.103	-0.123	0.080	0.023	-0.013	0.013	0.001	-0.008	0.007
	RMSE	1.070	0.557	0.206	0.124	0.130	0.083	0.052	0.029	0.042	0.022	0.043	0.023
Naive	*Bias*	-1.072	0.539	0.194	-0.103	-0.130	0.080	0.023	-0.013	0.012	0.001	-0.009	0.007
	RMSE	1.090	0.557	0.211	0.124	0.137	0.083	0.053	0.029	0.042	0.022	0.043	0.023
T = 1000													
IITV	*Bias*	0.031	0.012	-0.019	-0.002	-0.005	0.003	-0.001	0.000	0.001	0.000	0.002	0.000
	RMSE	0.073	0.042	0.037	0.024	0.030	0.021	0.031	0.021	0.025	0.016	0.027	0.017
Step-1	*Bias*	-1.073	0.544	0.187	-0.097	-0.123	0.079	0.019	-0.014	0.003	0.002	0.008	0.003
	RMSE	1.083	0.554	0.195	0.108	0.126	0.080	0.039	0.024	0.028	0.016	0.030	0.017
Naive	*Bias*	-1.096	0.544	0.192	-0.097	-0.129	0.079	0.020	-0.014	0.002	0.002	0.007	0.003
	RMSE	1.106	0.554	0.2	0.108	0.132	0.08	0.04	0.024	0.029	0.016	0.031	0.017

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 3: Multivariate Normal Errors, 0.8 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	0.012	0.013	-0.050	-0.025	-0.028	-0.021	0.007	0.003	-0.001	-0.001	-0.011	-0.001
	RMSE	0.291	0.171	0.111	0.084	0.106	0.075	0.111	0.084	0.104	0.076	0.114	0.075
Step-1	*Bias*	-1.155	0.786	0.189	-0.175	-0.101	0.062	0.037	-0.016	0.021	-0.005	-0.013	0.017
	RMSE	1.277	0.885	0.267	0.242	0.135	0.078	0.108	0.065	0.107	0.062	0.110	0.062
Naive	*Bias*	-1.218	0.786	0.199	-0.175	-0.124	0.062	0.036	-0.016	0.020	-0.005	-0.017	0.017
	RMSE	1.353	0.885	0.279	0.242	0.161	0.078	0.118	0.065	0.115	0.062	0.119	0.062
T = 500													
IITV	*Bias*	0.017	0.007	-0.016	-0.004	-0.006	-0.001	0.000	0.000	0.001	0.000	0.001	-0.001
	RMSE	0.080	0.054	0.038	0.029	0.034	0.026	0.036	0.028	0.031	0.023	0.033	0.023
Step-1	*Bias*	-1.104	0.612	0.228	-0.143	-0.086	0.063	0.024	-0.011	0.017	0.001	-0.011	0.007
	RMSE	1.118	0.628	0.240	0.158	0.093	0.067	0.049	0.028	0.040	0.021	0.041	0.023
Naive	*Bias*	-1.170	0.612	0.250	-0.143	-0.101	0.063	0.022	-0.011	0.014	0.001	-0.010	0.007
	RMSE	1.186	0.628	0.261	0.158	0.109	0.067	0.052	0.028	0.043	0.021	0.044	0.023
T = 1000													
IITV	*Bias*	0.019	0.007	-0.013	-0.002	-0.004	0.001	-0.001	0.000	0.000	0.000	0.001	0.000
	RMSE	0.059	0.039	0.027	0.020	0.024	0.018	0.028	0.021	0.021	0.016	0.024	0.017
Step-1	*Bias*	-1.119	0.616	0.223	-0.135	-0.088	0.061	0.017	-0.013	0.003	0.002	0.009	0.003
	RMSE	1.126	0.625	0.229	0.143	0.091	0.063	0.037	0.023	0.026	0.015	0.028	0.016
Naive	*Bias*	-1.198	0.616	0.247	-0.135	-0.100	0.061	0.018	-0.013	0.002	0.002	0.007	0.003
	RMSE	1.206	0.625	0.253	0.143	0.105	0.063	0.04	0.023	0.029	0.015	0.031	0.016

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 4: Multivariate normal errors, 0 covariance (Variance-covariance matrix estimation)

		T = 100			T = 500			T = 1000		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	-0.014	-0.054	0.033	0.064	-0.044	0.030	0.069	-0.042	0.028
	RMSE	2.454	0.280	0.169	0.158	0.087	0.071	0.123	0.068	0.055
Step-1	*Bias*	0.036	-0.100	0.068	0.151	-0.098	0.060	0.157	-0.096	0.058
	RMSE	0.335	0.212	0.171	0.214	0.124	0.090	0.191	0.110	0.075
Naive	*Bias*	0.027	-	0.068	0.149	-	0.060	0.155	-	0.058
	RMSE	0.331	-	0.171	0.212	-	0.090	0.189	-	0.075

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 5: Multivariate normal errors, 0.4 covariance (Variance-covariance matrix estimation)

		T = 100			T = 500			T = 1000		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	-0.047	-0.047	0.025	0.060	-0.038	0.027	0.066	-0.037	0.027
	RMSE	0.366	0.215	0.168	0.155	0.086	0.070	0.121	0.066	0.053
Step-1	*Bias*	0.052	-0.114	0.079	0.169	-0.113	0.071	0.176	-0.115	0.069
	RMSE	0.342	0.222	0.179	0.228	0.137	0.098	0.208	0.127	0.084
Naive	*Bias*	0.045	-	0.079	0.174	-	0.071	0.184	-	0.069
	RMSE	0.337	-	0.179	0.233	-	0.098	0.215	-	0.084

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 6: Multivariate normal errors, 0.8 covariance (Variance-covariance matrix estimation)

		T = 100			T = 500			T = 1000		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	-0.009	-0.022	0.012	0.037	-0.019	0.015	0.038	-0.019	0.014
	RMSE	0.360	0.220	0.167	0.132	0.080	0.066	0.095	0.058	0.048
Step-1	*Bias*	0.105	-0.115	0.089	0.186	-0.119	0.079	0.186	-0.125	0.076
	RMSE	0.355	0.233	0.186	0.238	0.146	0.104	0.213	0.138	0.091
Naive	*Bias*	0.062	-	0.089	0.193	-	0.079	0.204	-	0.076
	RMSE	0.338	-	0.186	0.249	-	0.104	0.232	-	0.091

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 7: Estimation results for Colombia

	IIVT				Naive			
	FXI	*S.d*	*IRI Est*	*S.d*	*FXI*	*S.d*	*IRI Est*	*S.d*
Intercept	-0.113	0.089	-0.143***	0.055	-0.210***	0.075	-0.188***	0.059
Lag FXI	0.429***	0.102	-0.040	0.071	0.545***	0.138	-0.010	0.133
Lag IRI	0.149	0.167	0.319***	0.093	0.086	0.119	0.323***	0.081
Inf	0.168	0.140	0.214**	0.095	0.212*	0.111	0.025	0.081
Ipi	-0.012	0.009	0.019***	0.006	-0.001	0.007	0.026***	0.005
ERM	-0.203*	0.113	0.059	0.067	-0.176*	0.094	0.026	0.774
NetPos	0.008***	0.002	0.001	0.002	0.007***	0.002	0.002	0.002
Dum_{2004}	0.354***	0.132	-0.090	0.093	0.333***	0.116	-0.080	0.111
Dum_{2005}	0.532***	0.138	-0.027	0.102	0.520***	0.123	-0.020	0.122
Dum_{2007}	0.284*	0.153	-0.048	0.099	-1.150***	0.105	-0.050	0.120

Authors' calculations. *, **, and *** indicate significance at the 10%, 5 %, and 1% levels, respectively. S.d denotes the standard deviation. *IITV* stands for Instrumental Iterative Tobit VAR. The *Naive* method consists of estimating each equation separately as described in Section 2. Only significant year dummies (Dum_{year}) are reported, and correspond to years with marked exchange rate appreciation.

Table 8: Estimation results for Turkey

	IIVT				Naive			
	FXI	*S.d*	*IRI*	*S.d*	*FXI Est*	*S.d*	*IRI Est*	*S.d*
Intercept	0.448	0.287	-1.075***	0.421	0.148	0.266	-1.238***	0.332
Lag FXI	-0.337**	0.152	0.007	0.217	-0.371**	0.169	0.153	0.239
Lag IRI	0.259**	0.130	0.184	0.174	0.222**	0.104	0.390***	0.134
Inf	-0.034	0.056	0.169**	0.077	0.053	0.048	0.175***	0.060
Ipi	0.031	0.021	0.064**	0.029	0.042**	0.019	0.058***	0.023
ERM	-2.342***	0.767	0.782	0.886	-1.784***	0.653	0.774	0.741
Dum_{2007}	0.825*	0.432	-0.473	0.649	0.825*	0.426	-0.422	0.604
Dum_{2009}	-0.521	0.541	1.449*	0.799	0.015	0.491	1.695***	0.638
Dum_{2010}	1.171**	0.513	-0.249	0.798	1.388***	0.502	0.039	0.728

Authors' calculations. *, **, and *** indicate significance at the 10%, 5 %, and 1% levels, respectively. S.d denotes the standard deviation. *IITV* stands for Instrumental Iterative Tobit VAR. The *Naive* method consists of estimating each equation separately as described in Section 2. Only significant year dummies (Dum_{year}) are reported, and correspond to years with marked exchange rate appreciation.

Appendix A Robustness Checks of the IITV Method

Tables 9-23 present the results of imposing alternative distributional assumptions on the errors of the VAR system. In essence, these exercises help test the sensitivity of our findings to violations of multivariate normality. In brief, the conclusions remain similar: the IITV method performs better in terms of both *RMSE* and *Bias* for all parameters as well as for the variance-covariance matrix. This gain is more evident in the coefficients of the lagged dependent variables.

In addition, it remains true that, as implied by equation 13, the *IITV* method increasingly outperforms the *Naive* estimation when the covariance between the two policy shocks increases. Moreover, even when the errors follow a distribution with heavier tails (e.g. t-distribution with 5 degrees of freedom), there is evidence that the algorithm provided in Section 2 improves over the common practice. Nonetheless, we argue that the inclusion of exogenous variables is crucial for the *IITV* to outperform alternative methods. As such, we conduct further simulations exercises with the inclusion of only one regressor, presented in tables 21-23.[18] We note that the *IITV* method still outperforms the *Naive* method, which again provides evidence of robustness in our results.

Table 9: Multivariate t-distribution with 5 degrees of freedom, 0 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	-0.004	0.001	-0.080	-0.012	-0.043	-0.018	0.017	0.000	-0.003	-0.001	-0.022	0.001
	RMSE	0.376	0.181	0.169	0.110	0.159	0.095	0.128	0.081	0.122	0.071	0.134	0.071
Step-1	*Bias*	-1.050	0.519	0.072	-0.055	-0.197	0.100	0.046	-0.020	0.010	-0.003	-0.032	0.017
	RMSE	1.243	0.653	0.231	0.175	0.231	0.113	0.129	0.068	0.115	0.063	0.131	0.063
Naive	*Bias*	-1.052	0.519	0.075	-0.055	-0.193	0.100	0.046	-0.020	0.011	-0.003	-0.031	0.017
	RMSE	1.248	0.653	0.232	0.175	0.227	0.113	0.129	0.068	0.116	0.063	0.132	0.063
T = 500													
IITV	*Bias*	-0.007	-0.003	-0.024	0.002	-0.009	0.002	0.007	0.001	0.000	0.000	-0.006	0.000
	RMSE	0.107	0.060	0.058	0.041	0.052	0.036	0.046	0.029	0.038	0.023	0.043	0.023
Step-1	*Bias*	-1.009	0.433	0.126	-0.049	-0.175	0.101	0.035	-0.014	0.007	0.001	-0.016	0.007
	RMSE	1.039	0.455	0.154	0.084	0.182	0.104	0.062	0.031	0.043	0.022	0.048	0.023
Naive	*Bias*	-1.009	0.433	0.126	-0.049	-0.173	0.101	0.035	-0.014	0.007	0.001	-0.016	0.007
	RMSE	1.039	0.455	0.155	0.084	0.180	0.104	0.062	0.031	0.043	0.022	0.048	0.023
T = 1000													
IITV	*Bias*	-0.005	-0.003	-0.019	0.002	-0.005	0.004	0.004	0.000	-0.002	0.000	-0.003	0.000
	RMSE	0.075	0.043	0.042	0.029	0.036	0.025	0.034	0.021	0.027	0.016	0.031	0.017
Step-1	*Bias*	-1.033	0.437	0.124	-0.044	-0.172	0.100	0.029	-0.015	-0.002	0.001	0.000	0.003
	RMSE	1.047	0.449	0.139	0.066	0.175	0.101	0.047	0.025	0.030	0.016	0.032	0.017
Naive	*Bias*	-1.031	0.437	0.125	-0.044	-0.169	0.100	0.029	-0.015	-0.002	0.001	0.000	0.003
	RMSE	1.046	0.449	0.14	0.066	0.173	0.101	0.047	0.025	0.03	0.016	0.032	0.017

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

[18] The one regressor is simulated by following an ARMA process with a t-distributed (5 d.f.) error term.

Table 10: Multivariate t-distribution (5 d.f.), 0 covariance (Variance-covariance estimation)

		T = 100			T = 500			T = 1000		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	0.022	-0.045	0.030	0.165	-0.041	0.028	0.173	-0.039	0.031
	RMSE	0.599	0.289	0.308	0.353	0.127	0.124	0.269	0.095	0.096
Step-1	*Bias*	0.111	-0.096	0.063	0.240	-0.093	0.057	0.254	-0.093	0.060
	RMSE	0.601	0.280	0.291	0.390	0.151	0.135	0.327	0.126	0.110
Naive	*Bias*	0.113	-	0.063	0.242	-	0.057	0.254	-	0.060
	RMSE	0.673	-	0.291	0.400	-	0.135	0.335	-	0.110

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 11: Multivariate t-distribution with 5 degrees of freedom, 0.4 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	-0.004	0.002	-0.068	-0.015	-0.034	-0.017	0.017	0.002	-0.001	0.000	-0.022	0.000
	RMSE	0.337	0.171	0.142	0.091	0.128	0.079	0.123	0.081	0.113	0.072	0.128	0.071
Step-1	*Bias*	-1.157	0.644	0.145	-0.113	-0.148	0.082	0.045	-0.018	0.016	-0.004	-0.028	0.017
	RMSE	1.318	0.751	0.250	0.196	0.183	0.096	0.124	0.067	0.114	0.062	0.128	0.062
Naive	*Bias*	-1.194	0.644	0.148	-0.113	-0.160	0.082	0.046	-0.018	0.015	-0.004	-0.030	0.017
	RMSE	1.364	0.751	0.253	0.196	0.196	0.096	0.128	0.067	0.117	0.062	0.132	0.062
T = 500													
IITV	*Bias*	-0.007	-0.002	-0.024	0.001	-0.009	0.002	0.006	0.001	-0.001	0.000	-0.006	0.000
	RMSE	0.104	0.058	0.051	0.035	0.045	0.030	0.045	0.029	0.038	0.023	0.042	0.023
Step-1	*Bias*	-1.118	0.526	0.196	-0.099	-0.130	0.082	0.032	-0.012	0.010	0.001	-0.016	0.007
	RMSE	1.141	0.544	0.213	0.119	0.137	0.085	0.059	0.029	0.043	0.021	0.048	0.023
Naive	*Bias*	-1.147	0.526	0.202	-0.099	-0.138	0.082	0.032	-0.012	0.009	0.001	-0.017	0.007
	RMSE	1.172	0.544	0.219	0.119	0.146	0.085	0.060	0.029	0.044	0.021	0.049	0.023
T = 1000													
IITV	*Bias*	-0.004	-0.002	-0.020	0.002	-0.007	0.003	0.004	0.000	-0.002	0.000	-0.003	0.000
	RMSE	0.074	0.042	0.037	0.025	0.031	0.021	0.033	0.021	0.027	0.016	0.030	0.017
Step-1	*Bias*	-1.142	0.532	0.194	-0.093	-0.127	0.080	0.025	-0.014	-0.001	0.002	0.002	0.003
	RMSE	1.153	0.542	0.202	0.104	0.131	0.081	0.045	0.024	0.030	0.016	0.032	0.016
Naive	*Bias*	-1.172	0.532	0.200	-0.093	-0.134	0.080	0.027	-0.014	-0.002	0.002	0.000	0.003
	RMSE	1.184	0.542	0.208	0.104	0.138	0.081	0.046	0.024	0.03	0.016	0.033	0.016

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 12: Multivariate t-distribution (5 d.f.), 0.4 covariance (Variance-covariance estimation)

		T = 100			T = 500			T = 1000		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	0.027	-0.030	0.028	0.154	-0.025	0.025	0.161	-0.022	0.028
	RMSE	0.578	0.311	0.314	0.336	0.130	0.123	0.255	0.092	0.095
Step-1	*Bias*	0.123	-0.099	0.076	0.249	-0.100	0.067	0.262	-0.100	0.071
	RMSE	0.585	0.298	0.301	0.385	0.159	0.140	0.328	0.133	0.116
Naive	*Bias*	0.137	-	0.076	0.268	-	0.067	0.280	-	0.071
	RMSE	0.721	-	0.301	0.421	-	0.140	0.351	-	0.116

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 13: Multivariate t-distribution with 5 degrees of freedom, 0.8 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	-0.015	0.000	-0.048	-0.019	-0.027	-0.018	0.013	0.003	-0.001	0.000	-0.018	-0.001
	RMSE	0.278	0.158	0.111	0.078	0.103	0.071	0.109	0.082	0.102	0.073	0.113	0.072
Step-1	*Bias*	-1.188	0.743	0.189	-0.161	-0.105	0.066	0.043	-0.016	0.021	-0.005	-0.023	0.017
	RMSE	1.310	0.833	0.265	0.224	0.139	0.081	0.111	0.066	0.106	0.062	0.115	0.062
Naive	*Bias*	-1.299	0.743	0.202	-0.161	-0.134	0.066	0.045	-0.016	0.019	-0.005	-0.031	0.017
	RMSE	1.453	0.833	0.280	0.224	0.172	0.081	0.126	0.066	0.117	0.062	0.131	0.062
T = 500													
IITV	*Bias*	-0.005	-0.002	-0.016	0.000	-0.008	0.000	0.005	0.001	-0.001	0.000	-0.004	0.000
	RMSE	0.087	0.054	0.039	0.029	0.036	0.026	0.038	0.028	0.032	0.023	0.035	0.023
Step-1	*Bias*	-1.141	0.595	0.230	-0.137	-0.092	0.065	0.030	-0.011	0.014	0.001	-0.017	0.007
	RMSE	1.157	0.611	0.241	0.152	0.100	0.068	0.054	0.028	0.041	0.021	0.044	0.023
Naive	*Bias*	-1.246	0.595	0.257	-0.137	-0.110	0.065	0.031	-0.011	0.011	0.001	-0.018	0.007
	RMSE	1.269	0.611	0.269	0.152	0.120	0.068	0.059	0.028	0.044	0.021	0.050	0.023
T = 1000													
IITV	*Bias*	-0.003	-0.002	-0.014	0.001	-0.006	0.002	0.003	0.000	-0.001	0.000	-0.002	0.000
	RMSE	0.063	0.038	0.029	0.021	0.025	0.018	0.028	0.020	0.023	0.016	0.025	0.017
Step-1	*Bias*	-1.161	0.601	0.226	-0.130	-0.091	0.063	0.023	-0.013	-0.001	0.002	0.004	0.003
	RMSE	1.168	0.609	0.232	0.138	0.095	0.065	0.040	0.023	0.027	0.015	0.028	0.016
Naive	*Bias*	-1.276	0.601	0.255	-0.130	-0.107	0.063	0.026	-0.013	-0.002	0.002	0.000	0.003
	RMSE	1.287	0.609	0.26	0.138	0.112	0.065	0.046	0.023	0.03	0.015	0.032	0.016

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 14: Multivariate t-distribution (5 d.f.), 0.8 covariance (Variance-covariance estimation)

		T = 100			**T = 500**			**T = 1000**		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	0.038	-0.005	0.014	0.094	-0.003	0.011	0.100	0.001	0.016
	RMSE	0.507	0.341	0.324	0.249	0.136	0.121	0.187	0.097	0.091
Step-1	*Bias*	0.141	-0.097	0.086	0.233	-0.103	0.073	0.241	-0.103	0.078
	RMSE	0.522	0.323	0.312	0.335	0.169	0.144	0.293	0.140	0.122
Naive	*Bias*	0.160	-	0.086	0.290	-	0.073	0.302	-	0.078
	RMSE	0.750	-	0.312	0.438	-	0.144	0.367	-	0.122

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 15: Multivariate t-distribution with 30 degrees of freedom, 0 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	0.040	0.017	-0.083	-0.017	-0.043	-0.020	0.011	-0.001	0.003	-0.002	-0.013	0.002
	RMSE	0.339	0.178	0.173	0.109	0.154	0.094	0.127	0.080	0.115	0.072	0.127	0.072
Step-1	*Bias*	-0.979	0.543	0.066	-0.063	-0.193	0.097	0.039	-0.021	0.012	-0.004	-0.021	0.018
	RMSE	1.164	0.680	0.231	0.182	0.224	0.110	0.124	0.067	0.114	0.062	0.120	0.063
Naive	*Bias*	-0.974	0.543	0.068	-0.063	-0.188	0.097	0.039	-0.021	0.012	-0.004	-0.020	0.018
	RMSE	1.157	0.680	0.230	0.182	0.219	0.110	0.123	0.067	0.113	0.062	0.120	0.063
T = 500													
IITV	*Bias*	0.028	0.011	-0.025	-0.003	-0.008	0.002	0.000	0.001	0.001	0.000	0.002	0.000
	RMSE	0.098	0.059	0.060	0.041	0.051	0.035	0.043	0.029	0.036	0.023	0.039	0.023
Step-1	*Bias*	-0.944	0.444	0.119	-0.053	-0.171	0.101	0.027	-0.014	0.008	0.001	-0.008	0.007
	RMSE	0.968	0.467	0.148	0.088	0.177	0.104	0.055	0.031	0.042	0.022	0.043	0.023
Naive	*Bias*	-0.940	0.444	0.119	-0.053	-0.168	0.101	0.026	-0.014	0.008	0.001	-0.007	0.007
	RMSE	0.965	0.467	0.148	0.088	0.174	0.104	0.055	0.031	0.042	0.022	0.043	0.023
T = 1000													
IITV	*Bias*	0.030	0.011	-0.020	-0.001	-0.005	0.003	-0.002	0.000	0.001	0.000	0.003	0.000
	RMSE	0.074	0.042	0.042	0.028	0.035	0.024	0.031	0.021	0.026	0.016	0.029	0.017
Step-1	*Bias*	-0.956	0.446	0.114	-0.047	-0.169	0.099	0.022	-0.015	0.001	0.001	0.007	0.003
	RMSE	0.968	0.457	0.128	0.066	0.172	0.101	0.041	0.025	0.029	0.015	0.031	0.016
Naive	*Bias*	-0.952	0.446	0.114	-0.047	-0.167	0.099	0.021	-0.015	0.001	0.001	0.007	0.003
	RMSE	0.964	0.457	0.129	0.066	0.17	0.101	0.041	0.025	0.029	0.015	0.031	0.016

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 16: Multivariate t-distribution (30 d.f.), 0 covariance (Variance-covariance estimation)

		T = 100			T = 500			T = 1000		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	-0.047	-0.048	0.029	0.069	-0.043	0.031	0.078	-0.042	0.029
	RMSE	0.368	0.216	0.178	0.164	0.090	0.075	0.132	0.070	0.057
Step-1	*Bias*	0.038	-0.097	0.063	0.156	-0.097	0.061	0.167	-0.096	0.058
	RMSE	0.343	0.215	0.176	0.221	0.125	0.093	0.201	0.112	0.077
Naive	*Bias*	0.030	-	0.063	0.154	-	0.061	0.164	-	0.058
	RMSE	0.339	-	0.176	0.219	-	0.093	0.199	-	0.077

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names ($\sigma_{11}, \sigma_{12}, \sigma_{22}$) are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 17: Multivariate t-distribution with 30 degrees of freedom, 0.4 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	0.034	0.018	-0.069	-0.020	-0.035	-0.019	0.009	0.001	0.002	-0.001	-0.011	0.001
	RMSE	0.322	0.175	0.144	0.093	0.129	0.080	0.121	0.082	0.113	0.073	0.124	0.074
Step-1	*Bias*	-1.100	0.674	0.143	-0.124	-0.142	0.078	0.037	-0.019	0.017	-0.005	-0.017	0.018
	RMSE	1.251	0.784	0.250	0.207	0.176	0.092	0.119	0.066	0.113	0.062	0.118	0.062
Naive	*Bias*	-1.123	0.674	0.144	-0.124	-0.154	0.078	0.038	-0.019	0.016	-0.005	-0.019	0.018
	RMSE	1.275	0.784	0.252	0.207	0.187	0.092	0.121	0.066	0.114	0.062	0.119	0.062
T = 500													
IITV	*Bias*	0.027	0.011	-0.024	-0.003	-0.007	0.002	0.000	0.001	0.000	0.000	0.002	0.000
	RMSE	0.095	0.058	0.051	0.035	0.043	0.030	0.042	0.029	0.036	0.023	0.038	0.023
Step-1	*Bias*	-1.059	0.541	0.191	-0.104	-0.124	0.081	0.023	-0.012	0.011	0.001	-0.008	0.007
	RMSE	1.078	0.559	0.208	0.124	0.131	0.084	0.053	0.029	0.042	0.021	0.043	0.023
Naive	*Bias*	-1.080	0.541	0.196	-0.104	-0.131	0.081	0.024	-0.012	0.010	0.001	-0.008	0.007
	RMSE	1.099	0.559	0.213	0.124	0.138	0.084	0.054	0.029	0.042	0.021	0.043	0.023
T = 1000													
IITV	*Bias*	0.030	0.011	-0.020	-0.001	-0.006	0.003	-0.002	0.000	0.001	0.000	0.003	0.000
	RMSE	0.073	0.042	0.037	0.024	0.030	0.021	0.031	0.021	0.025	0.016	0.028	0.017
Step-1	*Bias*	-1.075	0.544	0.187	-0.097	-0.123	0.079	0.018	-0.014	0.002	0.001	0.009	0.003
	RMSE	1.084	0.553	0.195	0.107	0.127	0.080	0.039	0.024	0.028	0.015	0.031	0.016
Naive	*Bias*	-1.098	0.544	0.191	-0.097	-0.130	0.079	0.019	-0.014	0.002	0.001	0.008	0.003
	RMSE	1.107	0.553	0.2	0.107	0.133	0.08	0.04	0.024	0.029	0.015	0.032	0.016

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 18: Multivariate t-distribution (30 d.f.), 0.4 covariance (Variance-covariance estimation)

		T = 100			**T = 500**			**T = 1000**		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	-0.036	-0.037	0.026	0.064	-0.038	0.029	0.072	-0.036	0.027
	RMSE	0.369	0.219	0.178	0.161	0.088	0.074	0.127	0.068	0.056
Step-1	*Bias*	0.059	-0.106	0.076	0.173	-0.113	0.071	0.182	-0.113	0.069
	RMSE	0.350	0.222	0.184	0.234	0.139	0.101	0.214	0.128	0.085
Naive	*Bias*	0.053	-	0.076	0.179	-	0.071	0.190	-	0.069
	RMSE	0.345	-	0.184	0.240	-	0.101	0.222	-	0.085

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 19: Multivariate t-distribution with 30 degrees of freedom, 0.8 Covariance Simulation

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}
T = 100													
IITV	*Bias*	0.002	0.008	-0.049	-0.022	-0.032	-0.022	0.009	0.003	0.000	0.000	-0.011	-0.001
	RMSE	0.290	0.164	0.112	0.081	0.107	0.074	0.114	0.085	0.103	0.076	0.113	0.075
Step-1	*Bias*	-1.164	0.773	0.190	-0.172	-0.103	0.062	0.039	-0.017	0.021	-0.006	-0.015	0.018
	RMSE	1.284	0.869	0.268	0.238	0.136	0.077	0.110	0.066	0.108	0.062	0.111	0.062
Naive	*Bias*	-1.235	0.773	0.199	-0.172	-0.128	0.062	0.038	-0.017	0.019	-0.006	-0.020	0.018
	RMSE	1.367	0.869	0.280	0.238	0.165	0.077	0.121	0.066	0.115	0.062	0.119	0.062
T = 500													
IITV	*Bias*	0.015	0.006	-0.015	-0.003	-0.006	0.000	0.001	0.001	0.000	0.000	0.001	0.000
	RMSE	0.080	0.054	0.039	0.029	0.035	0.026	0.037	0.028	0.031	0.023	0.033	0.023
Step-1	*Bias*	-1.112	0.612	0.230	-0.143	-0.087	0.064	0.024	-0.011	0.014	0.001	-0.011	0.008
	RMSE	1.127	0.628	0.242	0.158	0.094	0.067	0.049	0.029	0.040	0.021	0.041	0.023
Naive	*Bias*	-1.181	0.612	0.252	-0.143	-0.102	0.064	0.022	-0.011	0.012	0.001	-0.010	0.008
	RMSE	1.197	0.628	0.263	0.158	0.110	0.067	0.052	0.029	0.043	0.021	0.044	0.023
T = 1000													
IITV	*Bias*	0.017	0.006	-0.012	-0.001	-0.004	0.001	-0.001	0.000	0.000	0.000	0.002	0.000
	RMSE	0.059	0.038	0.028	0.020	0.024	0.018	0.027	0.020	0.022	0.016	0.024	0.017
Step-1	*Bias*	-1.124	0.615	0.224	-0.135	-0.088	0.061	0.017	-0.013	0.002	0.002	0.009	0.003
	RMSE	1.131	0.624	0.230	0.142	0.091	0.063	0.036	0.023	0.026	0.015	0.029	0.016
Naive	*Bias*	-1.204	0.615	0.248	-0.135	-0.101	0.061	0.018	-0.013	0.002	0.002	0.008	0.003
	RMSE	1.212	0.624	0.253	0.142	0.105	0.063	0.039	0.023	0.029	0.015	0.032	0.016

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 20: Multivariate t-distribution (30 d.f.), 0.8 covariance (Variance-covariance estimation)

		T = 100			**T = 500**			**T = 1000**		
		σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}	σ_{11}	σ_{12}	σ_{22}
IITV	*Bias*	0.004	-0.015	0.013	0.040	-0.018	0.015	0.042	-0.018	0.014
	RMSE	0.377	0.231	0.177	0.136	0.084	0.070	0.102	0.061	0.050
Step-1	*Bias*	0.113	-0.109	0.086	0.190	-0.118	0.078	0.192	-0.122	0.076
	RMSE	0.368	0.237	0.191	0.242	0.147	0.107	0.220	0.138	0.092
Naive	*Bias*	0.075	-	0.086	0.200	-	0.078	0.212	-	0.076
	RMSE	0.354	-	0.191	0.257	-	0.107	0.242	-	0.092

Authors' calculations. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ are defined in Section 2. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 21: Multivariate Normal Errors with One Exogenous Regressor

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	σ_{11}	σ_{12}	σ_{22}
Cov = 0												
IITV	*Bias*	0.036	0.015	-0.030	-0.006	-0.003	-0.002	-0.003	0.000	0.049	-0.037	0.024
	RMSE	0.086	0.057	0.061	0.047	0.051	0.039	0.044	0.029	0.159	0.076	0.069
Step-1	*Bias*	-0.885	0.456	0.295	-0.162	-0.060	0.032	0.028	-0.020	0.071	-0.062	0.038
	RMSE	0.900	0.478	0.310	0.187	0.082	0.049	0.055	0.034	0.168	0.091	0.075
Naive	*Bias*	-0.881	0.456	0.293	-0.162	-0.059	0.032	0.028	-0.020	0.069	-	0.038
	RMSE	0.897	0.478	0.309	0.187	0.081	0.049	0.054	0.034	0.167	-	0.075
Cov = 0.4												
IITV	*Bias*	0.035	0.014	-0.030	-0.007	-0.006	-0.001	-0.002	0.001	0.044	-0.037	0.022
	RMSE	0.085	0.056	0.058	0.044	0.049	0.038	0.043	0.030	0.157	0.080	0.068
Step-1	*Bias*	-0.901	0.484	0.316	-0.186	0.002	-0.005	0.030	-0.022	0.070	-0.073	0.038
	RMSE	0.915	0.506	0.330	0.210	0.055	0.038	0.055	0.035	0.167	0.101	0.075
Naive	*Bias*	-0.931	0.484	0.330	-0.186	0.002	-0.005	0.032	-0.022	0.078	-	0.038
	RMSE	0.944	0.506	0.343	0.210	0.055	0.038	0.057	0.035	0.173	-	0.075
Cov = 0.8												
IITV	*Bias*	0.022	0.010	-0.021	-0.007	-0.005	-0.001	-0.001	0.001	0.028	-0.022	0.012
	RMSE	0.074	0.053	0.054	0.044	0.052	0.043	0.040	0.030	0.139	0.083	0.065
Step-1	*Bias*	-0.805	0.447	0.254	-0.162	0.074	-0.050	0.038	-0.027	0.062	-0.073	0.034
	RMSE	0.820	0.471	0.273	0.192	0.091	0.064	0.056	0.039	0.154	0.108	0.073
Naive	*Bias*	-0.879	0.447	0.289	-0.162	0.083	-0.050	0.045	-0.027	0.078	-	0.034
	RMSE	0.895	0.471	0.307	0.192	0.101	0.064	0.065	0.039	0.172	-	0.073

Authors' calculations. Sample size=500. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 22: Multivariate t-distribution (5 d.f.) with One Exogenous Regressor

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	σ_{11}	σ_{12}	σ_{22}
Cov = 0												
IITV	*Bias*	-0.046	-0.019	-0.023	0.008	-0.007	0.000	0.018	0.001	0.242	-0.036	0.022
	RMSE	0.103	0.059	0.057	0.045	0.055	0.040	0.052	0.029	0.432	0.113	0.122
Step-1	*Bias*	-1.001	0.407	0.304	-0.138	-0.072	0.035	0.054	-0.021	0.251	-0.061	0.035
	RMSE	1.020	0.427	0.318	0.165	0.095	0.051	0.076	0.035	0.431	0.122	0.126
Naive	*Bias*	-1.002	0.407	0.303	-0.138	-0.072	0.035	0.054	-0.021	0.255	-	0.035
	RMSE	1.021	0.427	0.317	0.165	0.094	0.051	0.077	0.035	0.444	-	0.126
Cov = 0.4												
IITV	*Bias*	-0.045	-0.018	-0.025	0.006	-0.012	0.000	0.018	0.001	0.229	-0.011	0.019
	RMSE	0.099	0.056	0.055	0.043	0.054	0.038	0.052	0.029	0.410	0.121	0.121
Step-1	*Bias*	-1.004	0.431	0.321	-0.160	-0.015	-0.001	0.056	-0.023	0.240	-0.051	0.035
	RMSE	1.020	0.450	0.333	0.185	0.060	0.038	0.077	0.036	0.408	0.126	0.125
Naive	*Bias*	-1.051	0.431	0.339	-0.160	-0.016	-0.001	0.060	-0.023	0.273	-	0.035
	RMSE	1.069	0.450	0.351	0.185	0.063	0.038	0.081	0.036	0.459	-	0.125
Cov = 0.8												
IITV	*Bias*	-0.031	-0.013	-0.020	0.003	-0.012	0.000	0.013	0.001	0.154	0.019	0.009
	RMSE	0.084	0.052	0.053	0.043	0.055	0.043	0.045	0.030	0.304	0.142	0.120
Step-1	*Bias*	-0.848	0.395	0.246	-0.137	0.050	-0.044	0.056	-0.028	0.178	-0.035	0.030
	RMSE	0.864	0.418	0.265	0.168	0.075	0.061	0.072	0.039	0.312	0.139	0.124
Naive	*Bias*	-1.016	0.395	0.305	-0.137	0.059	-0.044	0.074	-0.028	0.288	-	0.030
	RMSE	1.035	0.418	0.322	0.168	0.087	0.061	0.092	0.039	0.470	-	0.124

Authors' calculations. Sample size=500. *Bias* denotes the bias of the estimator, built as $\hat{\beta} - \beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Table 23: Multivariate t-distribution (30 d.f.) with One Exogenous Regressor

		α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	σ_{11}	σ_{12}	σ_{22}
Cov = 0												
IITV	*Bias*	0.027	0.009	-0.029	-0.004	-0.004	0.000	-0.001	0.000	0.071	-0.036	0.026
	RMSE	0.082	0.055	0.061	0.046	0.052	0.038	0.043	0.029	0.172	0.078	0.073
Step-1	*Bias*	-0.901	0.449	0.297	-0.159	-0.062	0.033	0.030	-0.021	0.093	-0.061	0.039
	RMSE	0.916	0.472	0.312	0.185	0.084	0.049	0.055	0.035	0.184	0.092	0.079
Naive	*Bias*	-0.897	0.449	0.295	-0.159	-0.061	0.033	0.029	-0.021	0.091	-	0.039
	RMSE	0.912	0.472	0.311	0.185	0.083	0.049	0.055	0.035	0.183	-	0.079
Cov = 0.4												
IITV	*Bias*	0.026	0.009	-0.029	-0.005	-0.007	0.000	-0.001	0.000	0.066	-0.033	0.023
	RMSE	0.080	0.054	0.058	0.044	0.050	0.037	0.043	0.029	0.170	0.081	0.072
Step-1	*Bias*	-0.916	0.478	0.318	-0.183	0.000	-0.003	0.032	-0.023	0.092	-0.069	0.039
	RMSE	0.930	0.500	0.332	0.208	0.055	0.037	0.056	0.036	0.184	0.100	0.079
Naive	*Bias*	-0.948	0.478	0.333	-0.183	0.000	-0.003	0.035	-0.023	0.103	-	0.039
	RMSE	0.961	0.500	0.346	0.208	0.056	0.037	0.058	0.036	0.192	-	0.079
Cov = 0.8												
IITV	*Bias*	0.016	0.006	-0.021	-0.005	-0.007	0.000	0.000	0.000	0.044	-0.015	0.013
	RMSE	0.072	0.052	0.053	0.044	0.053	0.043	0.039	0.030	0.147	0.084	0.069
Step-1	*Bias*	-0.811	0.441	0.253	-0.160	0.071	-0.048	0.039	-0.028	0.079	-0.066	0.034
	RMSE	0.827	0.466	0.273	0.190	0.089	0.063	0.057	0.039	0.166	0.106	0.077
Naive	*Bias*	-0.896	0.441	0.292	-0.160	0.081	-0.048	0.047	-0.028	0.104	-	0.034
	RMSE	0.912	0.466	0.310	0.190	0.100	0.063	0.066	0.039	0.192	-	0.077

Authors' calculations. Sample size=500. *Bias* denotes the bias of the estimator, built as $\hat{\beta}-\beta$. *RMSE* denotes the root-mean-square error. Parameter names as in equation 12. *IITV* stands for Instrumental Iterative Tobit VAR; *Step-1* and *Naive* methods as defined in Section 2.

Appendix B Parameters Used in Simulation Exercises

The parameters used in the simulation exercises of Section 3 are reported in the following table:

Table 24: Specific Parameters Used in Simulation Exercises

α_1	α_2	β_{11}	β_{12}	β_{21}	β_{22}	γ_{11}	γ_{12}	γ_{13}	γ_{21}	γ_{22}	γ_{23}	σ_{11}	σ_{22}
0.10	0.10	0.50	-0.10	-0.20	0.50	0.30	-0.21	-0.35	-0.10	0.20	0.34	1	1

The β_{ij} coefficients were chosen so as to guarantee stability in the system of equations (VAR).

Recall that the error terms are drawn from multivariate normal distributions (Section 3) and t-distributions (Appendix A). Also, the covariance ($\sigma_{12} = \sigma_{21}$) varies between 0.0, 0.4 and 0.8 across the different simulation exercises.

Appendix C Description of the variables used in the estimation

Below we describe the data used in our empirical analysis. Note that, as in Romer and Romer (2004), the frequencies of all variables were consolidated according to the meeting dates of the board of directors of both the Central Bank of Turkey and the Central Bank of Colombia. Namely, we computed the mean of each variable for periods between meetings (this is the case for all variables, except FXI, for which we summed over all purchases). We find this consolidation useful, given that our aim is to model policy decisions undertaken by monetary authorities. Hence, the meeting days dictate when these decisions are undertaken.

Colombia:

Outcome variables in y_t:

- Δr_t: Changes in the policy rate of the Central Bank of Colombia. It corresponds to the minimum overnight lending interest rate, measured in percentage changes. (IRI)
- Int: Foreign Exchange Intervention conducted by either of the following mechanisms: purchases of foreign currency in the spot market, or purchases of foreign exchange rate options for reserves accumulation. Measured in USD billions. (FXI)

Exogenous variables in z_t:

- Inf: Yearly inflation growth. Measured in percentage.
- Ipi: Industrial Production Index growth. Measured in log-differences.
- ERM: Exchange Rate Misalignment. Dummy variable switched on whenever the exchange rate is greater than the average of seven in-house models of the Central Bank of Colombia.
- $NetPos$: Total Net credit/debit Position with respect to the financial system. Measured in USD millions x 100.
- Dum_i: Yearly dummies.

Turkey:

Outcome variables in y_t:

- Δr_t: The policy rate corresponded to the central bank's overnight borrowing rate between February 20, 2002 and May 16, 2008 (due to the abundant liquidity in the market); to the overnight lending rate between May 17, 2008 and May 20, 2010 (due to the liquidity shortage); and to the one-week repo lending rate after May 21, 2010. Measured in percentage changes.
- Int: During auctions of announced purchases and sales, the Central Bank of Turkey optionally exceeded the predetermined amount of FX purchases. Measured in USD millions.

Exogenous variables in z_t:

- Inf: Inflation minus yearly target. Measured in percentage.
- Ipi: Industrial output growth. Measured in log-differences.
- ERM: Daily (1 business day) exchange rate returns.
- Dum_i: Yearly dummies.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