

A. More on the Theoretical Framework

OPTIMAL MONETARY POLICY. Assume that the aggregate economy is best approximated by a standard New Keynesian model under the rational expectations hypothesis., i.e.,

$$x_t = E_t x_{t+1} - \sigma^{-1} (i_t - E_t \pi_{t+1}) + g_t \quad (\text{A.1})$$

$$\pi_t = \beta E_t \pi_{t+1} + \lambda x_t + e_t. \quad (\text{A.2})$$

In this model, i_t denotes the nominal interest rate controlled by the central bank. β and σ are structural parameters, λ is a composite term comprising several structural parameters. g_t denotes an exogenous demand disturbance and e_t denotes an exogenous supply disturbance. We assume $g_t \sim \text{iid}(0, \sigma_g^2)$, $e_t \sim \text{iid}(0, \sigma_e^2)$ and $\sigma_{eg} = 0$.¹

Consider optimal monetary policy under discretion (as elaborated in [Clarida et al., 1999](#)). The central bank minimizes (1) subject to (A.2) in each period. The first-order necessary condition is $\pi_t = -(\omega_x/\lambda)x_t$ and one can show that, under this policy, the model implies an inflation output variability tradeoff as first developed in [Taylor \(1979\)](#). In particular, solving the model for given parameters implies a minimum state variable solution $\pi_t = a_\pi e_t$ and $x_t = a_x e_t$, where $a_\pi \equiv \omega_x/(\omega_x + \lambda^2)$ and $a_x \equiv -\lambda/(\omega_x + \lambda^2)$. This implies the long-run relationships in unconditional variances (2) and (3).

¹In the theoretical literature e_t is usually denoted a cost-push shock. Notice that allowing for autocorrelation in the exogenous shocks would not alter any conclusion.

TAYLOR (1993) RULE. It is easy to verify that the model (A.1), (A.2) and (4) has the solution $\pi_t = b_{\pi,e}e_t + b_{\pi,g}g_t$ and $x_t = b_{x,e}e_t + b_{x,g}g_t$, where $b_{\pi,e} \equiv (1 + \sigma^{-1}\phi_\pi\lambda)^{-1}$, $b_{\pi,g} \equiv (1 + \sigma^{-1}\phi_\pi\lambda)^{-1}\lambda$, $b_{x,e} \equiv -\sigma^{-1}\phi_\pi/(1 + \sigma^{-1}\phi_\pi\lambda)$ and $b_{x,g} \equiv (1 + \sigma^{-1}\phi_\pi\lambda)^{-1}$. This solution implies the long-run relationships in unconditional variances given by (5) and (6).

INPUT-ORIENTED TTF. Next we show that the input-oriented TTF provides us with a functional form that captures the basic characteristics of an inflation output variability tradeoff. Formally, one assumes that the relationship between the supply and demand shock (as the $M = 2$ outputs, y) and the variances of inflation and output gap (as the $K = 2$ inputs, z) can be described by $Af(y, z) = 1$, where we have M outputs y and K inputs z . Moreover, A captures factors that affect the TTF neutrally. We will be more specific about the assumptions further below. Next, we assume a *translog* functional form, i.e.,

$$\begin{aligned} \ln(f(y, z)) &= \sum_m \alpha_m \ln(y_m) + \frac{1}{2} \sum_m \sum_n \alpha_{m,n} \ln(y_m) \times \ln(y_n) \\ &+ \sum_k \beta_k \ln(z_k) + \frac{1}{2} \sum_k \sum_l \beta_{k,l} \ln(z_k) \times \ln(z_l) \\ &+ \sum_m \sum_k \gamma_{m,k} \ln(y_m) \times \ln(z_k), \end{aligned} \tag{A.3}$$

where the following symmetry is imposed: $\beta_{k,l} = \beta_{l,k}$ and $\gamma_{m,n} = \gamma_{n,m}$. Equation (A.3) requires $M + K + 2$ additional identification, or, normalization restrictions. As discussed in [Kumbhakar \(2012\)](#), it is possible to impose the restrictions such that a single equation framework emerges that allows for simultaneous estimation of more than one endogenous input (e.g., input-oriented) or output (e.g., output-oriented).

Since, in the case of the inflation output variability tradeoff, we have simultaneous endogeneity of σ_π^2 and σ_x^2 , while σ_e^2 and σ_g^2 are exogenous, we can consider the former two variances as inputs, while the latter two variances are the outputs. Therefore, we adopt a

normalization with respect to an input. This gives rise to an input-oriented TTF. Following [Kumbhakar \(2012\)](#), we rewrite (A.3) as

$$\begin{aligned}\ln(f(y, z)) &= \sum_m \alpha_m \ln(y_m) + \frac{1}{2} \sum_m \sum_n \alpha_{m,n} \ln(y_m) \times \ln(y_n) \\ &+ \sum_k \beta_k \ln(z_k/z_1) + \frac{1}{2} \sum_k \sum_l \beta_{k,l} \ln(z_k/z_1) \times \ln(z_l/z_1) \\ &+ \sum_m \sum_k \gamma_{m,k} \ln(y_m) \times \ln(z_k/z_1) + \Upsilon,\end{aligned}$$

where each input k has to be combined with the remaining inputs l as described in this equation. Υ is a composite term that follows from writing the second and third line in expression (A.3) in ratios (see, e.g., [Kumbhakar, 2012](#), for the details).

Next we impose the normalization restrictions, $\sum_k \beta_k = 1$, $\sum_l \beta_{k,l} = 0 \forall k$, and, $\sum_k \gamma_{m,k} = 0 \forall m$.² As a consequence, the composite term Υ is eliminated and we obtain the input-oriented TTF that we use as our empirical specification

$$\begin{aligned}-\ln(z_1) &= \alpha_0 + \sum_m \alpha_m \ln(y_m) + \frac{1}{2} \sum_m \sum_n \alpha_{m,n} \ln(y_m) \times \ln(y_n) \\ &+ \sum_{k=2} \beta_k \ln(z_k/z_1) + \frac{1}{2} \sum_{k=2} \sum_{l=2} \beta_{k,l} \ln(z_k/z_1) \times \ln(z_l/z_1) \\ &+ \sum_m \sum_k \gamma_{m,k} \ln(y_m) \times \ln(z_k/z_1) + v,\end{aligned}$$

where $\ln(A) = \alpha_0 + v$. In this case we normalize our function on z_1 . We would get exactly the same econometric results by normalizing the function on z_k . In the particular case of the inflation output variability tradeoff, we have $y_1 = \sigma_e^2$, $y_2 = \sigma_g^2$, $z_1 = \sigma_x^2$ and $z_2 = \sigma_\pi^2$.

²The normalization restrictions imply homogeneity, symmetry and monotonicity properties of the TTF.

B. Estimation of Structural Shocks

In order to derive our structural shocks we consider a vector autoregression with exogenous variables (VARX), whose reduced form of order p can be represented by

$$\mathcal{Y}_t = \sum_{i=1}^p A_i \mathcal{Y}_{t-i} + C \mathcal{X}_t + u_t, \quad (\text{B.1})$$

where \mathcal{Y}_t is a 3×1 vector of endogenous variables including a measure of the output gap, inflation (as difference from target) and nominal interest rate. We consider all countries with the exception of USA as open economies (for a more detailed discussion of this choice see [Favero and Giavazzi, 2008](#)). Therefore, the models for the other countries in the sample include \mathcal{X}_t , which is a 3×1 vector of exogenous variables including US output gap, inflation (as difference from target) and a nominal interest rate, aimed at capturing the world macroeconomic stance. $u_t \sim N(0, \Sigma_{u,t})$ is a vector of reduced-form disturbances with $E[u_t] = 0$ and $E[u_t u_t'] = \Sigma_{u,t}$. u_t is independently but not identically distributed across time. $\Sigma_{u,t}$ is time-varying, rendering volatility stochastic and introducing heteroskedasticity. We model stochastic volatility as in [Cogley and Sargent \(2005\)](#). It is assumed that $\Sigma_{u,t}$ can be decomposed as

$$\Sigma_{u,t} = F \Lambda_t F',$$

where F is a lower triangular matrix with ones on the main diagonal. Λ_t is a time-varying diagonal matrix equal to $(\bar{s}_1 \exp(\lambda_{1,t}), \bar{s}_2 \exp(\lambda_{2,t}), \dots, \bar{s}_n \exp(\lambda_{n,t}))$, where n is the number of endogenous variables. $\bar{s}_1, \bar{s}_2, \dots, \bar{s}_n$ are known scaling terms and $\lambda_{1,t}, \lambda_{2,t}, \dots, \lambda_{n,t}$ are dynamic processes generating the heteroskedasticity that are characterized by the autoregressive

process

$$\lambda_{i,t} = \gamma\lambda_{i,t-1} + \nu_{i,t} \quad \nu_{i,t} \sim N(0, \phi_i).$$

The parameters to be estimated are: the parameters of the reduced form VAR, the elements of the F matrix, the dynamic coefficients $\lambda_{i,t}$ and the heteroskedasticity parameters ϕ_i . With regard to the priors, for A_i , C and covariance matrix Ω_0 we adopt classical Minnesota priors. Considering the inverse of F , that is, F^{-1} we adopt a multinormal diffuse prior with mean f_{i0}^{-1} (which is set as a vector of zeros) and covariance diagonal matrix Υ_{i0} with large diagonal entries. The prior for $\pi(\lambda_i | \phi_i)$ are not simple to formulate since each term $\lambda_{i,t}$ depends on its previous value. The solution to this problem is given by separating $\pi(\lambda_i | \phi_i)$ into T different priors, with prior in each period t conditional on period $t - 1$. To obtain the conditional posterior for ϕ_i , the previous prior will be combined with a joint prior for $\lambda_{i,1}, \dots, \lambda_{i,T}$, since the joint formulation is faster for ϕ_i . We make 5000 draws of which the first 1000 are discarded as burn in draws.

The identification structural shocks requires to impose restrictions. Our preferred choice in this paper are sign restrictions. Uhlig (2005) and others, show how to obtain identification of the above VAR (B.1) by imposing sign restrictions on a (sub)set of the variables responses to shocks as discussed in the main text. An advantage of this procedure is that only a minimum amount of economically meaningful sign restrictions are required in order to identify the structural shocks.

In case of a single shock, Uhlig (2005) shows that any impulse vector a can be recovered if there is an n -dimensional vector q of unit length such that $a = \tilde{A}q$, where \tilde{A} is the Cholesky factor of $\Sigma_{u,t}$. More precisely, starting with estimation of the above reduced form model, identification of a single shock by sign restrictions can be obtained as follows:

1. derive the impulse-responses for the n variables corresponding to a given impulse

- vector a_j up to period f on which sign restrictions are intended to be imposed;
2. draw an n -dimensional q vector of independent $N(0, 1)$ and divide it by its norm, obtaining a candidate draw q from which an impulse vector $a_j = Aq$ can be derived for then calculating the corresponding impulse responses;
 3. if the resulting impulse responses meet the sign restrictions imposed accept the draw, otherwise discard it;
 4. repeat 2 and 3 until a desired number of accepted draws is obtained.

For robustness purposes we also consider zero short run restrictions via Cholesky decomposition of Σ . Exact identification requires that $(n^2 - n)/2$ restrictions must be placed between the regression residuals and structural innovations. Given that the Cholesky decomposition is triangular, it forces exactly $(n^2 - n)/2$ elements of the matrix of contemporaneous relationships to be zero. The resulting recursive structure impose a causal ordering on the variables in the VAR: shocks to one equation contemporaneously affect variables below that equation but only affect variables above that equation with a lag. With this interpretation in mind, the causal ordering one chooses reflects his beliefs about the relationships among variables in the VAR.

C. Details on the Interpretation of Coefficient Estimates

$\hat{\beta}_2$: Ignore all other terms in (9) except for the one involving $\hat{\beta}_2$, thus

$$\begin{aligned}
 -\ln(\sigma_{x,i,t}^2) &= \hat{\beta}_2 \ln(\sigma_{\pi,i,t}^2 / \sigma_{x,i,t}^2) = \hat{\beta}_2 [\ln(\sigma_{\pi,i,t}^2) - \ln(\sigma_{x,i,t}^2)] \\
 \Leftrightarrow \ln(\sigma_{x,i,t}^2) &= [\hat{\beta}_2 / (-1 + \hat{\beta}_2)] \ln(\sigma_{\pi,i,t}^2),
 \end{aligned}$$

where $\hat{\beta}_2 \in [0, 1)$ implies that $[\hat{\beta}_2 / (-1 + \hat{\beta}_2)] < 0$, i.e., a higher inflation variability implies a lower output variability. An estimate of $\hat{\beta}_2 \in [0, 1)$ significantly different from zero already implies a non-linear inflation output variability tradeoff. The equation is linear in the

natural logarithms of variances. However, if we apply $\exp(\cdot)$ on both sides, one can see that the relationship between the variances in inflation and output is non-linear and convex as suggested by economic theory.

$\hat{\alpha}_e$: Ignore all other terms in (9) apart from the ones involving $\hat{\alpha}_e$ and $\hat{\beta}_2$, thus

$$\begin{aligned} -\ln(\sigma_{x,i,t}^2) &= \hat{\alpha}_e \ln(\sigma_{e,i,t}^2) + \hat{\beta}_2 \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2) \\ \Leftrightarrow \ln(\sigma_{x,i,t}^2) &= [\hat{\alpha}_e/(-1 + \hat{\beta}_2)] \ln(\sigma_{e,i,t}^2) + [\hat{\beta}_2/(-1 + \hat{\beta}_2)] \ln(\sigma_{\pi,i,t}^2) \\ \Leftrightarrow \ln(\sigma_{\pi,i,t}^2) &= -[\hat{\alpha}_e/\hat{\beta}_2] \ln(\sigma_{e,i,t}^2) + [(-1 + \hat{\beta}_2)/\hat{\beta}_2] \ln(\sigma_{x,i,t}^2) \end{aligned}$$

and, as $\hat{\alpha}_e < 0$ and $\hat{\beta}_2 \in [0, 1)$, it follows that $[\hat{\alpha}_e/(-1 + \hat{\beta}_2)], -[\hat{\alpha}_e/\hat{\beta}_2] > 0$. We conclude from the equations above that the relationship between the variance of the supply shock and the variances of the output gap and inflation is positive, which is consistent with the economic theory discussed above. The same arguments and conclusions apply to $\hat{\alpha}_g < 0$.

$\hat{\beta}_E$: Similar arguments as above, yield

$$\begin{aligned} \ln(\sigma_{x,i,t}^2) &= [\hat{\alpha}_e/(-1 + \hat{\beta}_2)] \ln(\sigma_{e,i,t}^2) + [\hat{\alpha}_g/(-1 + \hat{\beta}_2)] \ln(\sigma_{g,i,t}^2) \\ &\quad + [\hat{\beta}_2/(-1 + \hat{\beta}_2)] \ln(\sigma_{\pi,i,t}^2) + [\hat{\beta}_E/(-1 + \hat{\beta}_2)] \mathcal{E}_{i,t} \\ \ln(\sigma_{\pi,i,t}^2) &= -[\hat{\alpha}_e/\hat{\beta}_2] \ln(\sigma_{e,i,t}^2) - [\hat{\alpha}_g/\hat{\beta}_2] \ln(\sigma_{g,i,t}^2) + [(-1 + \hat{\beta}_2)/\hat{\beta}_2] \ln(\sigma_{x,i,t}^2) - [\hat{\beta}_E/\hat{\beta}_2] \mathcal{E}_{i,t}, \end{aligned}$$

and, as $\hat{\beta}_E < 0$ and $\hat{\beta}_2 \in [0, 1)$, it follows that $[\hat{\beta}_E/(-1 + \hat{\beta}_2)], -[\hat{\beta}_E/\hat{\beta}_2] > 0$. Therefore, a significant coefficient estimate $\hat{\beta}_E < 0$ is interpreted as a deterioration of the tradeoff.

D. Further Robustness

Herein we present further robustness checks:

1. *Alternative shadow rate.* The literature has proposed several measures of the shadow rate with different characteristics. However, there is no consensus yet on how to compute the shadow rate. Therefore we assess robustness of our results by computing the structural shocks with the shadow rate provided by [Krippner \(2013, 2015\)](#). Tables [8](#) and [9](#) show that these results are fully in line with our main findings.
2. *Considering financial instability.* Financial instability has played an important role during the considered sample period, especially in the recent past. Therefore we carried out a robustness exercise, where we augmented our baseline VAR for the computation of the structural shocks with [Ahir et al.'s \(2023\)](#) financial stress index based on text analysis. Their index covers almost our entire sample but ends already in 2018Q4. The latter implies that period 10 includes 11 observations from 2016Q2 to 2018Q4 instead of 15 observations. Tables [10](#) and [11](#) show that our results are robust to including a financial stress index in the computation of structural shocks.

Table 8: Estimated parameters for all countries, core and periphery for DiD model.^a Observations are based on the [Hamilton \(2018\)](#) filter. Shocks are identified with sign restrictions. [Wu and Xia \(2016\)](#) shadow rate replaced by [Krippner \(2013, 2015\)](#) shadow rate.

Variables	Coefficient	Estimates ^b					
		(9)			(11)		
		All	Core	Periphery	All	Core	Periphery
$\mathcal{E}_{i,t}$	$\beta_{\mathcal{E}}$	-0.672** (0.254)	-0.633** (0.295)	-0.729** (0.327)			
\mathcal{E}_{i,T_0}	$\beta_{\mathcal{E},0}$				-0.602* (0.289)	-0.685** (0.326)	-0.437 (0.391)
\mathcal{E}_{i,T_0+1}	$\beta_{\mathcal{E},1}$				-0.446 (0.375)	-0.709 (0.491)	-0.111 (0.365)
\mathcal{E}_{i,T_0+2}	$\beta_{\mathcal{E},2}$				-0.823* (0.405)	-0.741 (0.449)	-0.908 (0.529)
\mathcal{E}_{i,T_0+3}	$\beta_{\mathcal{E},3}$				-1.157*** (0.345)	-1.089*** (0.373)	-1.216*** (0.400)
\mathcal{E}_{i,T_0+4}	$\beta_{\mathcal{E},4}$				-0.672* (0.337)	-0.261 (0.387)	-1.476*** (0.255)
\mathcal{E}_{i,T_0+5}	$\beta_{\mathcal{E},5}$				-0.274 (0.278)	-0.322 (0.212)	-0.338 (0.633)
$\ln(\sigma_{e,i,t}^2)$	α_e	-0.452*** (0.084)	-0.453*** (0.083)		-0.475*** (0.086)		-0.443*** (0.089)
$\ln(\sigma_{g,i,t}^2)$	α_g	-0.178 (0.107)	-0.183 (0.114)		-0.147 (0.107)		-0.172 (0.112)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{g,i,t}^2)$	α_{eg}	0.201 (0.156)	0.198 (0.158)		0.189 (0.153)		0.100 (0.162)
$\ln(\sigma_{e,i,t}^2)^2$	α_{ee}	-0.301** (0.109)	-0.300** (0.110)		-0.259* (0.125)		-0.274** (0.125)
$\ln(\sigma_{g,i,t}^2)^2$	α_{gg}	-0.166 (0.113)	-0.168 (0.114)		-0.148 (0.125)		-0.097 (0.135)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	β_2	0.541*** (0.026)	0.540*** (0.026)		0.565*** (0.033)		0.531*** (0.037)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)^2$	$\beta_{2,1}$	-0.036 (0.022)	-0.035 (0.024)		-0.022 (0.020)		0.012 (0.028)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,e}$	0.030 (0.045)	0.028 (0.044)		0.022 (0.047)		-0.004 (0.045)
$\ln(\sigma_{g,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,g}$	-0.144** (0.062)	-0.142** (0.064)		-0.142** (0.063)		-0.098 (0.067)
Country fixed effect		yes	yes		yes		yes
Time fixed effect		yes	yes		yes		yes
N		20	20		20		20
Number of observations		200	200		200		200
R^2		0.845	0.845		0.851		0.863
Specification tests ^c :							
Ramsey (1969) Reset		0.188	0.171		0.243		0.252
$\beta_{\mathcal{E},-3} = \beta_{\mathcal{E},-2} = \beta_{\mathcal{E},-1} = 0$					0.748		0.562
$\beta_{\mathcal{E},0} = \beta_{\mathcal{E},1} = \dots = \beta_{\mathcal{E},5} = 0$					0.005		0.000

^a The dependent variable is the variance of the output gap, i.e., $-\ln(\sigma_{x,i,t}^2)$.

^b ***p<0.01; **p<0.05; *p<0.10; Standard errors are in parentheses (cluster-robust standard errors, robust to serial correlation and heteroskedasticity).

^c p-values are reported for all tests.

Table 9: Estimated parameters for all countries, core and periphery for LDV model.^a Observations are based on the [Hamilton \(2018\)](#) filter. Shocks are identified with sign restrictions. [Wu and Xia \(2016\)](#) shadow rate replaced by [Krippner \(2013, 2015\)](#) shadow rate.

Variables	Coefficient	Estimates ^b					
		(12)			(13)		
		All	Core	Periphery	All	Core	Periphery
$\mathcal{E}_{i,t}$	$\beta_{\mathcal{E}}$	-0.614*** (0.198)	-0.383** (0.169)	-0.853*** (0.232)			
\mathcal{E}_{i,T_0}	$\beta_{\mathcal{E},0}$				-0.698** (0.328)	-0.616* (0.296)	-0.611 (0.377)
\mathcal{E}_{i,T_0+1}	$\beta_{\mathcal{E},1}$				-0.457 (0.315)	-0.546* (0.285)	-0.234 (0.413)
\mathcal{E}_{i,T_0+2}	$\beta_{\mathcal{E},2}$				-0.531* (0.290)	-0.211 (0.282)	-0.843** (0.328)
\mathcal{E}_{i,T_0+3}	$\beta_{\mathcal{E},3}$				-1.041*** (0.293)	-0.810** (0.335)	-1.270*** (0.280)
\mathcal{E}_{i,T_0+4}	$\beta_{\mathcal{E},4}$				-0.741** (0.305)	-0.179 (0.277)	-1.865*** (0.217)
\mathcal{E}_{i,T_0+5}	$\beta_{\mathcal{E},5}$				-0.146 (0.346)	-0.174 (0.293)	-0.349 (0.541)
$\ln(\sigma_{e,i,t}^2)$	α_e	-0.409*** (0.075)	-0.427*** (0.081)		-0.420*** (0.085)		-0.377*** (0.086)
$\ln(\sigma_{g,i,t}^2)$	α_g	-0.487*** (0.151)	-0.471*** (0.146)		-0.480** (0.176)		-0.495*** (0.155)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{g,i,t}^2)$	α_{eg}	0.155 (0.246)	0.149 (0.245)		0.205 (0.216)		0.098 (0.208)
$\ln(\sigma_{e,i,t}^2)^2$	α_{ee}	-0.235* (0.129)	-0.236 (0.138)		-0.201 (0.145)		-0.222 (0.159)
$\ln(\sigma_{g,i,t}^2)^2$	α_{gg}	-0.289*** (0.099)	-0.320*** (0.091)		-0.305** (0.113)		-0.271** (0.110)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	β_2	0.599*** (0.044)	0.588*** (0.048)		0.633*** (0.048)		0.578*** (0.054)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)^2$	$\beta_{2,1}$	0.002 (0.033)	-0.005 (0.032)		0.026 (0.035)		0.073 (0.044)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,e}$	0.054 (0.041)	0.049 (0.041)		0.052 (0.045)		0.007 (0.032)
$\ln(\sigma_{g,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,g}$	-0.059 (0.068)	-0.058 (0.069)		-0.046 (0.070)		0.028 (0.064)
Country fixed effect		no	no		no		no
Time fixed effect		yes	yes		yes		yes
N		20	20		20		20
Number of observations		120	120		120		120
R^2		0.881	0.886		0.889		0.913
Specification tests ^c :							
Ramsey (1969) Reset		0.123	0.062		0.242		0.269
$\beta_{\mathcal{E},-3} = \beta_{\mathcal{E},-2} = \beta_{\mathcal{E},-1} = 0$							
$\beta_{\mathcal{E},0} = \beta_{\mathcal{E},1} = \dots = \beta_{\mathcal{E},5} = 0$							

^a The dependent variable is the variance of the output gap, i.e., $-\ln(\sigma_{x,i,t}^2)$.

^b ***p<0.01; **p<0.05; *p<0.10; Standard errors are in parentheses (cluster-robust standard errors, robust to serial correlation and heteroskedasticity).

^c p-values are reported for all tests.

Table 10: Estimated parameters for all countries, core and periphery for DiD model.^a Observations are based on the [Hamilton \(2018\)](#) filter. Shocks are identified with sign restrictions. The VAR is augmented with [Ahir et al.'s \(2023\)](#) financial stress index.

Variables	Coefficient	Estimates ^b					
		(9)			(11)		
		All	Core	Periphery	All	Core	Periphery
$\mathcal{E}_{i,t}$	$\beta_{\mathcal{E}}$	-0.503** (0.238)	-0.423 (0.284)	-0.614* (0.303)			
\mathcal{E}_{i,T_0}	$\beta_{\mathcal{E},0}$				-0.502* (0.281)	-0.549 (0.326)	-0.358 (0.355)
\mathcal{E}_{i,T_0+1}	$\beta_{\mathcal{E},1}$				-0.350 (0.307)	-0.553 (0.418)	-0.078 (0.319)
\mathcal{E}_{i,T_0+2}	$\beta_{\mathcal{E},2}$				-0.592 (0.348)	-0.466 (0.358)	-0.763 (0.466)
\mathcal{E}_{i,T_0+3}	$\beta_{\mathcal{E},3}$				-0.971*** (0.323)	-0.890** (0.329)	-1.048** (0.414)
\mathcal{E}_{i,T_0+4}	$\beta_{\mathcal{E},4}$				-0.588 (0.374)	-0.113 (0.383)	-1.449*** (0.308)
\mathcal{E}_{i,T_0+5}	$\beta_{\mathcal{E},5}$				0.017 (0.327)	-0.026 (0.394)	-0.071 (0.563)
$\ln(\sigma_{e,i,t}^2)$	α_e	-0.405*** (0.072)	-0.406*** (0.071)		-0.427*** (0.081)		-0.407*** (0.089)
$\ln(\sigma_{g,i,t}^2)$	α_g	-0.299** (0.112)	-0.310** (0.114)		-0.275** (0.115)		-0.279** (0.111)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{g,i,t}^2)$	α_{eg}	0.195* (0.108)	0.192* (0.110)		0.185 (0.107)		0.144 (0.113)
$\ln(\sigma_{e,i,t}^2)^2$	α_{ee}	-0.364*** (0.104)	-0.361*** (0.109)		-0.325*** (0.097)		-0.356*** (0.110)
$\ln(\sigma_{g,i,t}^2)^2$	α_{gg}	-0.090 (0.084)	-0.093 (0.083)		-0.086 (0.098)		-0.041 (0.090)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	β_2	0.580*** (0.033)	0.576*** (0.034)		0.593*** (0.039)		0.559*** (0.041)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)^2$	$\beta_{2,1}$	-0.008 (0.030)	-0.007 (0.028)		-0.004 (0.024)		0.030 (0.026)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,e}$	0.039 (0.046)	0.036 (0.046)		0.029 (0.044)		0.002 (0.044)
$\ln(\sigma_{g,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,g}$	-0.064 (0.061)	-0.063 (0.059)		-0.070 (0.058)		-0.031 (0.046)
Country fixed effect		yes	yes		yes		yes
Time fixed effect		yes	yes		yes		yes
N		20	20		20		20
Number of observations		200	200		200		200
R^2		0.861	0.861		0.868		0.880
Specification tests ^c :							
Ramsey (1969) Reset		0.055	0.043		0.071		0.236
$\beta_{\mathcal{E},-3} = \beta_{\mathcal{E},-2} = \beta_{\mathcal{E},-1} = 0$					0.769		0.151
$\beta_{\mathcal{E},0} = \beta_{\mathcal{E},1} = \dots = \beta_{\mathcal{E},5} = 0$					0.011		0.004

^a The dependent variable is the variance of the output gap, i.e., $-\ln(\sigma_{x,i,t}^2)$.

^b ***p<0.01; **p<0.05; *p<0.10; Standard errors are in parentheses (cluster-robust standard errors, robust to serial correlation and heteroskedasticity).

^c p-values are reported for all tests.

Table 11: Estimated parameters for all countries, core and periphery for LDV model.^a Observations are based on the [Hamilton \(2018\)](#) filter. Shocks are identified with sign restrictions. The VAR is augmented with [Ahir et al.'s \(2023\)](#) financial stress index.

Variables	Coefficient	Estimates ^b					
		(12)			(13)		
		All	Core	Periphery	All	Core	Periphery
$\mathcal{E}_{i,t}$	$\beta_{\mathcal{E}}$	-0.533** (0.196)	-0.366** (0.173)	-0.727** (0.261)			
\mathcal{E}_{i,T_0}	$\beta_{\mathcal{E},0}$				-0.703** (0.307)	-0.658** (0.280)	-0.582 (0.353)
\mathcal{E}_{i,T_0+1}	$\beta_{\mathcal{E},1}$				-0.443 (0.316)	-0.515 (0.308)	-0.230 (0.413)
\mathcal{E}_{i,T_0+2}	$\beta_{\mathcal{E},2}$				-0.335 (0.285)	-0.110 (0.339)	-0.694** (0.325)
\mathcal{E}_{i,T_0+3}	$\beta_{\mathcal{E},3}$				-0.865** (0.319)	-0.749* (0.375)	-1.003*** (0.350)
\mathcal{E}_{i,T_0+4}	$\beta_{\mathcal{E},4}$				-0.750** (0.307)	-0.224 (0.301)	-1.732*** (0.178)
\mathcal{E}_{i,T_0+5}	$\beta_{\mathcal{E},5}$				-0.053 (0.304)	-0.137 (0.293)	-0.182 (0.528)
$\ln(\sigma_{e,i,t}^2)$	α_e	-0.393*** (0.101)	-0.397*** (0.098)		-0.391*** (0.099)		-0.372*** (0.099)
$\ln(\sigma_{g,i,t}^2)$	α_g	-0.523*** (0.135)	-0.503*** (0.136)		-0.565*** (0.167)		-0.492** (0.177)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{g,i,t}^2)$	α_{eg}	0.450*** (0.150)	0.470*** (0.158)		0.489*** (0.159)		0.499** (0.186)
$\ln(\sigma_{e,i,t}^2)^2$	α_{ee}	-0.402*** (0.125)	-0.397*** (0.124)		-0.354*** (0.121)		-0.421** (0.154)
$\ln(\sigma_{g,i,t}^2)^2$	α_{gg}	-0.332*** (0.103)	-0.376*** (0.109)		-0.382*** (0.127)		-0.351** (0.131)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	β_2	0.623*** (0.050)	0.609*** (0.050)		0.626*** (0.053)		0.578*** (0.049)
$\ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)^2$	$\beta_{2,1}$	0.036 (0.023)	0.029 (0.023)		0.042** (0.018)		0.075*** (0.021)
$\ln(\sigma_{e,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,e}$	0.105*** (0.035)	0.110*** (0.036)		0.099** (0.037)		0.078* (0.043)
$\ln(\sigma_{g,i,t}^2) \times \ln(\sigma_{\pi,i,t}^2/\sigma_{x,i,t}^2)$	$\gamma_{2,g}$	-0.075 (0.076)	-0.096 (0.076)		-0.088 (0.075)		-0.056 (0.072)
Country fixed effect		no	no		no		no
Time fixed effect		yes	yes		yes		yes
N		20	20		20		20
Number of observations		120	120		120		120
R^2		0.898	0.900		0.906		0.924
Specification tests ^c :							
Ramsey (1969) Reset		0.430	0.305		0.162		0.302
$\beta_{\mathcal{E},-3} = \beta_{\mathcal{E},-2} = \beta_{\mathcal{E},-1} = 0$							
$\beta_{\mathcal{E},0} = \beta_{\mathcal{E},1} = \dots = \beta_{\mathcal{E},5} = 0$							

^a The dependent variable is the variance of the output gap, i.e., $-\ln(\sigma_{x,i,t}^2)$.

^b ***p<0.01; **p<0.05; *p<0.10; Standard errors are in parentheses (cluster-robust standard errors, robust to serial correlation and heteroskedasticity).

^c p-values are reported for all tests.