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RESEARCH ARTICLE

State Dependence of Fiscal Multipliers in Chile - An Independent Component Approach to Identification*

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Abstract

In studying the economic cycle dependency of fiscal multipliers in Chile, we implement an independent component analysis for structural shock identification within a non-linear vector autoregressive setting with generalized impulse response functions. Thereby we relax more restrictive assumptions adopted in previous studies, namely the a-priori assumption of a recursive model structure and the use of linear impulse response functions. As a result, we cannot fully confirm core insights from more restrictive structural models: we find no significant differences in neither government spending nor government revenues multipliers when comparing different states of the economy. Moreover, our estimates imply that fiscal multipliers in Chile do not differ significantly from zero.

Keywords: Threshold vector autoregressions, generalized impulse response, independent components, fiscal multiplier
JEL codes: C32, G15.

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1. Introduction

Fiscal policy in general has received significant attention since the Great Recession, as governments have widely implemented fiscal policy packages to fight the economic slump. Whether fiscal multipliers vary with business cycles is a question that has become particularly relevant to economists and policy makers since then, and this relevance will most likely remain, as governments struggle to reactivate economies and get through the current global economic conditions.

The so-called Fiscal Multiplier (FM) quantifies the effect that a shock in a fiscal policy instrument exerts on some economic outcome of interest, typically the gross domestic product. More precisely, Spilimbergo et al. (2009) define FMs as "the ratio of change in output to an exogenous change in a fiscal instrument with respect to their respective baselines". FMs have been subject of a long history of theoretical debates among economists, where Keynesians propose fiscal policies as suitable instruments for stabilizing economic cycles, while Monetarists discard them to have any permanent effects on output (Mustea, 2015; Perotti, 2007; Woodford, 2011). The possible channels and mechanisms through which fiscal policies may transmit and affect other economic outcomes are manifold (Perotti, 2007; Hall, 2009; Woodford, 2011; Michaillat, 2014; Gechert, 2017), and may vary among economies or over time (Barrell et al., 2012, 2009). Unsurprisingly, estimates of FMs vary greatly across studies (Banerjee and Zampolli (2019); Hall (2009); Gechert and Rannenberg (2018), see also the review provided in Section 2 of this work).

For the case of Chile, a single study addressing directly the cycle dependence of FMs has been put forth by Allegret and Lemus (2019), who find significant differences for the FM of government spending during recessions and expansions, with the estimated FM being larger during periods of economic downturn. A couple of studies examining FMs for Chile by means of a comparable methodology can be found. Differing mainly in the used data and the consideration of linear models that do not distinguish between different economic cycles, Cerda et al. (2005) conclude an overall null effect of fiscal policies in the long term, while Fornero et al. (2019) find small but significant positive multipliers for government consumption.

As it has become a regular practice in the empirical literature, Allegret and Lemus (2019) adopted a threshold vector autoregressive model (TVAR) to capture the nonlinearities emanating from the economic cycles. Their identification strategy consists of assuming a recursive model structure (i.e. a lower triangular covariance decomposition) based on assumptions of Blanchard and Perotti (2002), to finally estimate the FMs by means of linear impulse response functions (IRFs). By implication, the authors assume that the state of the business cycle remains unaffected in the aftermath of the presumed fiscal shocks. Recently, it has been found for the U.S. that the outcome of this widespread empirical approach is not necessarily robust after lifting the lower triangular recursion and using impulse responses that account for the intrinsic nonlinearity of TVARs (Laumer and Philipps, 2020).

As an alternative to assuming a lower triangular structural pattern in an ad-hoc manner, more agnostic identification schemes have been proposed recently (Matteson and Tsay, 2017; Moneta et al., 2012) based on the uniqueness of independent components exhibiting non-Gaussian marginal distributions (for applications of this data-based approach to identification in structural VARs (SVARs) see, e.g., Gouriéroux et al., 2017; Herwartz, 2018; Moneta and Pallante, 2020; Guerini et al., 2020). Moreover, to quantify the FMs of interest the restrictions implied by linear IRFs can be relaxed by means of so-called generalized impulse response functions (GIRFs) introduced by Koop et al. (1996). As a particular merit, GIRFs can conceptually adapt to state dependencies as formalized in a TVAR framework. In this work, we investigate if the main findings of Allegret and Lemus (2019) for the Chilean economy remain robust after relaxing both the ad-hoc assumption of a recursive structural model and the use of linear IRFs in the context of the benchmark TVAR. In doing so we i) provide further insights into the FMs of a developing economy and updated estimates thereof, ii) introduce data-based identification by means of independent component analysis (ICA) into a TVAR setting, and (iii) trace the effects of independent component shocks within a framework of GIRFs which naturally adapt to regime dependence and, hence, to the intrinsic non-linearity of TVARs.

Conditioning on slightly different data, we can largely replicate core findings of Allegret and Lemus (2019). Specifically, using a recursive structural model and common linear IRFs yields evidence for sizeable and significant FMs which are stronger if triggered by expansionary spending shocks during periods of low economic growth in comparison with periods of higher growth rates. In addition, contractionary revenue shocks do not appear to have significant effects in neither situation. These core findings remain robust when adopting flexible nonlinear GIRFs in place of linear IRFs. When relaxing the assumption of a recursive model structure in the framework of a more agnostic ICA-based identification, however, core insights from the restrictive benchmark approach lack robustness. Aligning with similar results of Caggiano et al. (2015); Ramey and Zubairy (2018); Laumer and Philipps (2020), we find no significant differences in neither government spending nor government revenue multipliers when comparing economic states of relatively lower and higher growth rates. Moreover, estimates using the agnostic approach show in general no significant FMs. In this respect, results from a recursive model structure align with findings of Allegret and Lemus (2019) and Fornero et al. (2019), while ICA identification yields results similar to findings of Cerda et al. (2005) for Chile and Holland et al. (2020) for Brazil as another Latin American economy.

Our findings suggest that results from previous studies could reflect the ad-hoc imposition of a hierarchical model structure (i.e. of a Cholesky factorization of the reduced form covariance). Such an imposition restricts the model to accommodate the interaction between the variables in rigid manner. Relaxing these rigidities by adopting a more agnostic identification scheme that builds upon the uniqueness of independent non-Gaussian shocks results in finding no significantly different FMs for periods of (relatively) high versus low economic growth.

The remainder of this paper is structured as follows. Section 2 resumes the empirical FM literature. Section 3 provides a detailed description of our empirical approach, the model, the identification strategy and the data. Section 4 discusses our estimation results. Section 5 concludes. In addition, some methodological details are described in Appendix A. Variable definitions and data sources are provided in Appendix B. Some intermediate estimation results can be found in Appendix C (marginal effects, model eigenvalues, normality tests and covariance matrix estimates).

2. Fiscal Multiplier literature

2.1. General overview and main findings

The FM refers to the ratio of change in GDP to the change in the fiscal policy instrument that causes it. As an example, a government spending multiplier of 0.2 implies that a one billion US Dollar expansion of fiscal spending will rise GDP by 200 million US Dollar. On the one hand FMs allow for a classification with regard to the considered time span i.e., impact or cumulative FMs with the latter referring typically to horizons between two or three years. On the other hand, one might categorize FMs according to the nature of the shocks, i.e., spending vs. revenue shocks. Dynamic stochastic general equilibrium (DSGE) and VAR models have been traditionally used for FM estimation (Ramey, 2016; Woodford, 2011; Mustea, 2015). The literature following the family of VAR models mostly builds upon the work of Blanchard and Perotti (2002). We next provide a brief chronological summary of the most relevant empirical literature, starting from works using linear VAR models in the early 2000's to results of more recent nonlinear modelling frameworks[1].

Based on linear VARs, early FM studies find, in general, different effects for spending and revenue shocks. Taking some studies that use US data as an example, Blanchard and Perotti (2002) derive from quarterly data for the period 1947 to 1997 that spending FMs are higher at impact (about 0.8) than revenue multipliers (about 0.7), while the relation reverses after one year (0.5 for spending and 0.7 for revenue multipliers). Perotti (2005) analyses annual data from 1960 to 2001 and finds spending multipliers above unity after one year (1.4) reaching to 2.2 in a three years period, while tax multipliers evolve from 1.2 at the end of the first year to 0.2 by the third. Using quarterly data for the period 1955 to 2000 and identification by means of sign restrictions, Mountford and Uhlig (2009) detect spending multipliers going from 0.65 at quarter one to a negative value of -0.74 after two years, and revenue multipliers rising from 0.28 at the first quarter to 2.05 after eight quarters. Tenhofen and Wolff (2007) condition their analysis on quarterly data from 1947 to 2006 in an expectation extended VAR and find negative spending multipliers. Afonso and Sousa (2012) employ a Bayesian SVAR approach using quarterly data from 1971 to 2007 and find small positive effects of spending and revenue shocks on GDP. In parallel, DSGE-based studies from this period find in general spending multipliers to be larger than revenue multipliers, although the magnitudes of the estimations vary largely from estimated FMs close to zero to above one (see, for example, An and Schorfheide, 2007; Barrell et al., 2009, 2012).

The rise of consolidation fiscal policies after the government deficits led by the Great Recession, gave a strong impulse to an already growing FM literature, leading upfront the discussion whether FMs may be dependent on the economic state (Gechert and Rannenberg, 2018; Woodford, 2011; Mustea, 2015; Ramey, 2016). Gechert and Rannenberg (2018) performed a meta-analysis using FM estimations from 98 studies published from 1992 to 2013 that allow for regime differentiation and employ single equation models. They conclude government expenditure multipliers to be larger during downturns, and tax multipliers to have no significant difference across business cycle regimes and to be overall smaller than expenditure multipliers. Representing DSGE-based modeling approaches, Barrell et al. (2009) and Barrell et al. (2012), also find spending multipliers to be larger during recessions.

The relation between FMs and the economic cycles became particularly relevant after the work of Auerbach and Gorodnichenko (2012). Using a smooth transition regime-switching SVAR model and quarterly US data for the period 1947 to 2008, these authors hint at the role of the (endogenous) economic cycle and "find large differences in the size of spending multipliers in recessions and expansions with fiscal policy being considerably more effective in recessions than in expansions". Inquiring these results further, a sizeable TVAR FM literature emerged (e.g., Batini et al., 2012; Baum and Koester, 2011; Baum et al., 2012; Afonso et al., 2018; Farrazzy et al., 2015; Allegret and Lemus, 2019; Holland et al., 2020). Although having somewhat mixed and inconclusive results overall, findings in this literature confirm main insights of Auerbach and Gorodnichenko (2012) and show generally larger spending multipliers during recessions than during expansions, and overall smaller revenue multipliers. For the case of the US, Baum et al. (2012) analyze quarterly data from 1965 to 2011 and find spending multipliers of 1.3 and revenue multipliers of -0.1 for expansions, while in recessions spending FMs are of about 1.8 and revenue FMs are of about 0.1 after one year. Batini et al. (2012) use quarterly data for the period 1975 to 2010, and find spending FMs of 0.33 and revenue FMs of 0.15 in expansions after one year,

[1] The vast quantity of studies available render a complete review beyond the scope of this paper. As the estimation methodologies evolve throughout our exposition, we will cite some remarkable examples illustrating the main results and the follow up discussion, along with some results from the DSGE-based literature.

while in downturns spending and revenue FMs are about 2.18 and 0.16, respectively. With a focus on transition economies, Mirdala and Kameník (2017) run TVAR models with quarterly data for the Czech Republic, the Slovak Republic and Hungary and the period 1995 to 2015. Employing GIRFs they find larger spending multipliers during recessions in the Czech Republic and Hungary, while opposite results obtain for the case of the Slovak Republic. Çebi and Özdemir (2016) run a TVAR model for Turkey with quarterly data covering the period from 1995 to 2015. Using a Cholesky decomposition as identification strategy and linear IRFs, they find that the effectiveness of fiscal policy is larger in times of low growth compared with times of relatively high growth.

For the purpose of identification, most of the quoted studies follow arguments of Blanchard and Perotti (2002), and rely on a lower triangular Cholesky decomposition with government spending ordered first in the vector of variables. The work of Laumer and Philipps (2020) is a noteworthy exception in this regard, since these authors complement the lower triangular recursion with a sign restriction approach as advocated by Mountford and Uhlig (2009). Another crucial aspect concerns the impulse/response functions used in the computation of the FMs. A good part of these studies, including the influential work of Auerbach and Gorodnichenko (2012), uses linear IRFs for each state of the economy, assuming implicitly that the imposed fiscal stimulus will not provoke a state change (e.g., a switch from a low growth regime to a high growth regime or vice versa). To solve this issue, some studies employ GIRFs as suggested by Koop et al. (1996) (e.g., Batini et al., 2012; Baum et al., 2012; Farrazzy et al., 2015; Laumer and Philipps, 2020).

Although the vast majority of studies trying to distinguish FMs between recessions and expansions focus mainly on developed economies, there is some recent work investigating cases of developing economies. Zhang et al. (2018) estimate a TVAR model for China with quarterly data from 1992 to 2014. Using GIRFs to determine FMs from recursive model structures as well as by means of sign restrictions, they find that China's FM tends to be procyclical with larger multipliers characterizing expansion periods. López-Vera et al. (2018) estimate a smooth transition TVAR with recursive structure and standard IRFs for Colombia with quarterly data from 1995 to 2015 and find that expenditure and revenue multipliers are larger during periods featuring negative output gaps. Holland et al. (2020) use quarterly data from 1997 to 2018 to estimate FMs for Brazil by means of a TVAR model as well as other estimation approaches. The TVAR estimations using recursive structural models and regular IRFs hint at larger multipliers for the expansion regime. However, these authors conclude that, overall, fiscal policy hardly exhibits any effect on output in Brazil.

2.2. Fiscal Multipliers in Chile

Turning to the specific case of FMs in Chile, earlier work has mostly dealt with linear SVARs. Cerda et al. (2005) find small negative spending and tax multipliers, and conclude that, overall, fiscal policy does not affect output. Restrepo and Rincón (2006) find a long-run spending multiplier in excess of unity, while a rise in taxes exerts a small negative effect on output. Suggesting the effectiveness of fiscal policies, Céspedes et al. (2011) use a DSGE model to estimate impact spending multipliers of 0.7 and a cumulative multiplier of 2.8 after two years. Fornero et al. (2019) find spending multipliers of 0.2 on impact and 0.6 in the long term. The only work so far for Chile that distinguishes between economic states is Allegret and Lemus (2019). Imposing recursive model structures within their TVAR model and using linear IRFs, these authors find a positive spending multiplier for recessions (0.35 on impact and 1.23 after 10 quarters, both significant), and a negative one for expansions (0.22 on impact and -0.56 after 10 quarters, both significant). Corresponding results for tax policies amount to small positive revenue multipliers for recessions (insignificant on impact and 0.2 significant after 10 quarters) and to insignificantly small multipliers for expansion regimes.

3. Methodology

Our empirical analysis starts with a replication of the study of Allegret and Lemus (2019). From this exercise we expect largely similar results as provided in the benchmark study, since our data are similar to those of Allegret and Lemus (2019) but not exactly the same[2]. Accordingly, we estimate a structural TVAR model, identify the structural shocks by means of lower triangular covariance decompositions to obtain linear IRFs and, finally, determine the model implied FMs. In a similar fashion as Laumer and Philipps (2020), we continue the analysis by relaxing some restrictive assumptions of the benchmark approach one-by-one. In a first step, we allow for eventual state changes to occur in response to a shock of interest and employ non-linear GIRFs instead of linear IRFs. Secondly, we relax the assumption of a recursive structural pattern (i.e. the lower triangular covariance decomposition), and opt for an agnostic identification method based on ICA. We next provide a more detailed description of the model, the identification strategy, the GIRFs, the determination of FMs and the model specification.

3.1. The structural TVAR model

TVARs have become a popular approach to capture non-linearities in economic time-series data (see, e.g., Hubrich and Teräsvirta (2013), for a review of threshold models). Yet, applications of these models comprise a wide range of fields, e.g., monetary policy analysis (Allen and Robinson, 2015; Tena and Tremayne, 2009; Calza and Sousa, 2006; Schmidt, 2020), financial market models (Balke, 2000), real exchange-rate and price differential models (Lo and Zivot, 2001). TVARs have been generally promoted for modeling and analyzing business cycles fluctuations (Koop et al., 1996; Galvão, 2003; Grynkiv and Stentoft, 2018), and they are particularly popular in the FM literature, where a growing body of work emerged after the Great Recession (e.g., Batini et al., 2012; Baum and Koester, 2011; Baum et al., 2012; Mirdala and Kameník, 2017; Allegret and Lemus, 2019).

TVARs are piecewise linear models which chain the dynamics of a set of variables over two or more distinct states or regimes, defined by an observed (endogenous or exogenous) transition variable joint with threshold values (Hansen, 1996, 1997; Tsay, 1998; Galvão, 2003). In a structural form and with given presample values, a K-dimensional TVAR process z_t reads as

$$z_t = c^{(s)} + \sum_{p=1}^{p} A_p^{(s)} z_{t-p} + B^{(s)} \varepsilon_t, t = 1, 2, ..., T \tag{1}$$

where $c^{(s)}$ is a deterministic (intercept) term and P is the (common) lag order. The index s, $s = 1, \ldots, S$, in (1) indicates that the model is state-specific. By assumption, the orthogonalized structural shocks in ε_t are serially uncorrelated, have mean zero and - without loss of generality - unit variances, i.e.

[2] We follow closely the data construction procedure of Allegret and Lemus (2019). However, as we did not have access to the full original data set used by these authors, some slight differences are to be expected, for instance, due to updates of data-sources. Moreover, we have used the X13-ARIMA seasonal adjustment method instead of the X11 employed by Allegret and Lemus (2019), and added two more years of observations to the data.

$Cov[\varepsilon_t] = I_K$, where I_K is the K-dimensional identity matrix. Reduced form residuals $u_t^{(s)} = B^{(s)}\varepsilon_t$ are of mean zero and subject to contemporaneous correlation according to state-specific positive definite covariance matrices $Cov[u_t^{(s)}] = \sum^{(s)}$. Let γ_{t-d} be the transition variable and γ_{t-d} its value at time $t-d$, where d is a fixed positive integer value. The state s at time t is determined as

$$s_t(\gamma_{t-d}) = \begin{cases} 1 & \text{if } \gamma_{t-d} \leq m_1; \\ 2 & \text{if } m_1 < \gamma_{t-d} \leq m_2; \\ & \vdots \\ S-1 & \text{if } m_{S-2} < \gamma_{t-d} \leq m_{S-1}; \\ S & \text{if } m_{S-1} < \gamma_{t-d}, \end{cases} \tag{2}$$

where $m_j, j = 1, \ldots, S-1$, are fixed threshold values, and the delay d denotes the number of time periods it takes for the model to change from one regime to another once a threshold is crossed. With known values for P, S, d and $m_j, j = 1.2, .., S-1$, the model in (1) can be estimated by OLS by subdividing the sample according to the distinct regimes. Tsay (1998) suggests a methodology for joint estimation of the delay d, the thresholds mj's and the state specific parameters $c^{(s)}$, $A_p^{(s)}$, $p = 1, \ldots, P$ and $\sum^{(s)}$. [3] As an alternative, however, the delay d - as well as the transition variable γ_t and the number of regimes S - are often selected a-priory, due to the large number of parameters subject to estimation (see, e.g, Baum and Koester, 2011; Batini et al., 2012; Baum et al., 2012).

3.2. Shock identification strategy

Similar to the case of standard SVARs (Sims, 1980), the structural shocks ε_t are unidentified in TVAR models, i.e. hidden within the set of infinitely many possible decompositions of the reduced form covariance matrices $\sum^{(s)}$. Retrieving the structural shocks has generally relied on theoretical assumptions, and the search for some sort of contemporaneous or long–run structural relations (see, e.g., Mustea, 2015; Laumer and Philipps, 2020, for examples in the FM literature). As mentioned above, in the FM literature authors have generally followed structural approaches based on the work of Blanchard and Perotti (2002). Their main identifying assumption is that a government cannot react and adapt its expenditures to changes in output within one quarter (the usual data frequency). This implies imposing a structural zero effect of shocks to output on government spending. Although Blanchard and Perotti (2002) go further by imposing some non-zero restrictions to the covariance matrix using elasticity values from several sources, most studies following Blanchard and Perotti (2002) employ a lower triangular Cholesky decomposition, with the variable ordering being government consumption, output, government revenues (and eventually further variables). This approach was also adopted by Allegret and Lemus (2019).

Drawing upon Allegret and Lemus (2019), we start our empirical exercise assuming a lower triangular covariance factor, and then relax this restrictive assumption in favor of a more agnostic and data-driven structural model. As an alternative identification scheme, we adopt ICA-based identification as described in Matteson and Tsay (2017). Similar shock identification strategies have been recently implemented in SVARs (e.g., Gouriéroux et al., 2017; Herwartz, 2018; Moneta and Pallante, 2020; Guerini et al., 2020). In comparison with the standard lower triangular recursion, ICA has the advantage to be

[3] The joint estimation procedure relies on model selection, by trying all possible threshold values present in the data - provided a sufficiently large fraction of the available sample is left in each regime for estimation - and a finite set of possible values for d. The values for d and $m_j, j = 1, \ldots, S-1$, that minimize a likelihood-based selection criterion - usually AIC - are kept. With given common lag order P the selection can also be made by selecting the model that obtains the minimum sum of squared residuals (Tsay, 1998; Lo and Zivot, 2001).

completely agnostic with regard to possible parameter restrictions, and relies only on data characteristics. In particular, it has been shown that the ICA approach results in a unique structural parameter matrix if the underlying structural shocks are independent (not just orthogonal) and at most one of these shocks exhibits a marginal Gaussian distribution (Comon, 1994). [4] Let U_s represent the matrix of all reduced form residuals consistent with regime s in the data, so that

$$U_s = B^{(s)} E_s' \tag{3}$$

where E_s is a matrix containing K columns of structural shocks for regime s, and $B^{(s)}$ is the nonsingular $K \times K$ dimensional mixing matrix. Under mutual independence of the columns of E_s and allowing for at most one series of shocks exhibiting a Gaussian distribution, Matteson and Tsay (2017) suggest to minimize the joint distance covariance between the columns of E_s to find $B^{(s)}$.[5] Matteson and Tsay (2017) also show that the suggested procedure is consistent, and argue that it works well in simulations and real data examples.

3.3. Generalized impulse response functions

Although the TVAR model described in (1) is linear within a regime, the overall model specification is non-linear. Accordingly, the typical IRFs derived from VAR models might suffer from misspecification. As an alternative to linear IRFs, GIRFs as suggested by Koop et al. (1996) can be straightforwardly constructed to cope with the intrinsic non-linearity. Let Ω_{t-1} summarize the state of the dynamic system in time $t-1$. Conditional on Ω_{t-1}, a GIRF at forecast horizon h obtains as the difference between two expectations, i.e.

$$GIRF_t(h, \delta_t, \Omega_{t-1}) = E(z_{t+h}|\delta_t, \nu_{t+h}, \Omega_{t-1}) - E(z_{t+h}|\nu_{t+h}, \Omega_{t-1}) \tag{4}$$

In (4), $E(z_{t+h}|\delta_t, \nu_{t+h}, \Omega_{t-1})$ signifies the expectation of z_{t+h} conditional on the information set Ω_{t-1} (which includes information about the initial state s) and the presumption that an exogenous shock δ_t hits the system in time t. The shock vector δ_t will have magnitude δ_t in a particular position of interest and zero otherwise, and occurs in addition to the system's 'natural noise' $\nu_{t+h} = (\varepsilon_t, \varepsilon_{t+1}, ..., \varepsilon_{t+h})$, whose elements exhibit the unconditional distribution of the TVAR innovations. For tracing out the effects of the shock δ_t, $E(z_{t+h}|\nu_{t+h}, \Omega_{t-1})$ is the corresponding expectation derived under the assumption that the system is not hit by an exogenous shock, or, put differently, that the system is affected just by the disturbances in ν_{t+h}. To obtain unconditional GIRFs, the moment evaluation in (4) is repeated for each history Ω_{t-1} and averaged subsequently conditional on the initial regime s. GIRFs for each regime s obtain as

$$GIRF^{(s)}(h, \delta_t) = \frac{1}{|S|} \sum_{t \in S} GIRF_t(h, \delta_t, \Omega_{t-1})$$

[4]The independence assumption goes beyond the standard orthogonality condition for the structural shocks. Although this might seem restrictive, the objective of IRFs and GIRFs is to study the effects of shocks that occur in isolation or independently of each other. In addition, the requirement of non Gaussianity is a data characteristic that can be subjected to testing.

[5]The distance covariance is a measure of dependence between two (groups of) random vectors. Its population counterpart is the distance between the joint characteristic function of these random variables and the product of the marginal characteristic functions (Székely et al., 2007; Székely and Rizzo, 2009). The detection of $B^{(s)}$ requires the solution of a non-linear optimization problem. For computation purposes we use the R package steadyICA of Risk and Matteson (2015)

where $GIRF_t$ is defined in (4) and $|S|$ is the number of histories starting in state s.

Apparently, the main difference between GIRFs and IRFs is that the latter are conditional on setting all disturbances in ν_{t+h} - the disturbances other than the exogenous shock - to values of zero, while GIRFs are unconditional in this sense. GIRFs allow the expectations in the right side of (4) to vary across regimes independently at any time point if the considered dynamic profiles invoke some threshold crossing in the TVAR system. To implement this perspective, the estimation of GIRFs builds upon replications of bootstrap samples $\tilde{\nu}_{t+h} = (\tilde{\varepsilon}_t, \tilde{\varepsilon}_{t+1}, ..., \tilde{\varepsilon}_{t+h})$, where vectors $\tilde{\varepsilon}_i$, $t \leq i \leq t+h$ are drawn with replacement from $\{\hat{\varepsilon}_t\}_{t=1}^T$. For a detailed description of the algorithm used for the computation of the GIRFs we refer the reader to Appendix A. It is noteworthy that the random variables in $\tilde{\nu}_{t+h}$ are drawn from orthogonalized estimates of residuals $\{\hat{\varepsilon}_t\}_{t=1}^T$. Hence, the adopted identification strategy is a key determinant of this process outcome, samples $\{\hat{\varepsilon}_t\}_{t=1}^T$ differ when using either an a-priori suggestion of a lower triangular recursion or of independent components.

3.4. The Fiscal Multiplier

Two measures of FMs can be found in the literature, the impact multiplier, which is determined at the time when the shock hits the system, and the cumulative multiplier, which adds longer term effects up to a given horizon. Let y_t denote output, g_t government spending and τ_t government revenues in per capita terms. FMs for both government spending (SM) and government revenues (RM) up to horizon H can be derived, respectively, as

$$SM(H) \approx \frac{\sum_{h=0}^{H} dlog(y_{t+h})}{\sum_{h=0}^{H} dlog(g_{t+h})} * \frac{\bar{y}}{\bar{g}} \; and \; RM(H) \approx \frac{\sum_{h=0}^{H} dlog(y_{t+h})}{\sum_{h=0}^{H} dlog(\tau_{t+h})} * \frac{\bar{y}}{\bar{\tau}} \tag{5}$$

where $dlog(y_{t+h})$, $dlog(g_{t+h})$ and $dlog(\tau_{t+h})$ comes from the IRFs and GIRFs estimates using a shock to expenditures and revenues to determine SM(H) and RM(H), respectively. Moreover, $\bar{y}$, $\bar{g}$ and $\bar{\tau}$ typically refer to sample means of per capita output, per capita government spending and per capita government revenues, respectively (Céspedes et al., 2011; Allegret and Lemus, 2019). [6] Impact multipliers obtain from setting the horizon $H = 0$ in (5), while choices of $H = 4, 8, 10$ are typical for the determination of cumulative multipliers.

3.5. The empirical model and the data

Following Allegret and Lemus (2019), we run two TVAR specifications. The first setup (model 1) is based on the Blanchard and Perotti (2002) model. Due to its parsimony this specification has been widely employed as benchmark for fiscal multiplier TVAR models (see, for example, Batini et al., 2012; Baum et al., 2012; Holland et al., 2020; Soederhuizen et al., 2019; Allegret and Lemus, 2019; Mirdala and Kameník, 2017; Çebi and Özdemir, 2016). In model 1, the vector of endogenous variables contains the stationary quarter-on-quarter growth rates of real government expenditures (i.e. first differences of quarterly aggregates in natural logarithm), $(z_{1t} = \triangle\, log(g_t))$, real output $(z_{2t} = \triangle\, log(y_t))$ and real net taxes $(z_{3t} = \triangle\, log(\tau_t))$in per capita terms. For the second specification (model 2) real

[6] Although the possible bias for including ratios of sample means of trending variables in the computation of FMs has been pointed out in the literature (Owyang et al., 2013; Ramey, 2016), it remains the standard way to approximate FMs from IRFs/GIRFs of variables in logarithms.

interest rates in differences are added to the system ($z_{4t} = \triangle\ r_t$). As in Allegret and Lemus (2019), the vectors of endogenous variables for models 1 and 2 are $z_t = (\triangle\ log(g_t), \triangle\ log(y_t), \triangle\ log(\tau_t))$ and $z_t = (\triangle\ log(g_t), \triangle\ log(y_t), \triangle\ log(\tau_t), \triangle\ r_t))$, respectively.

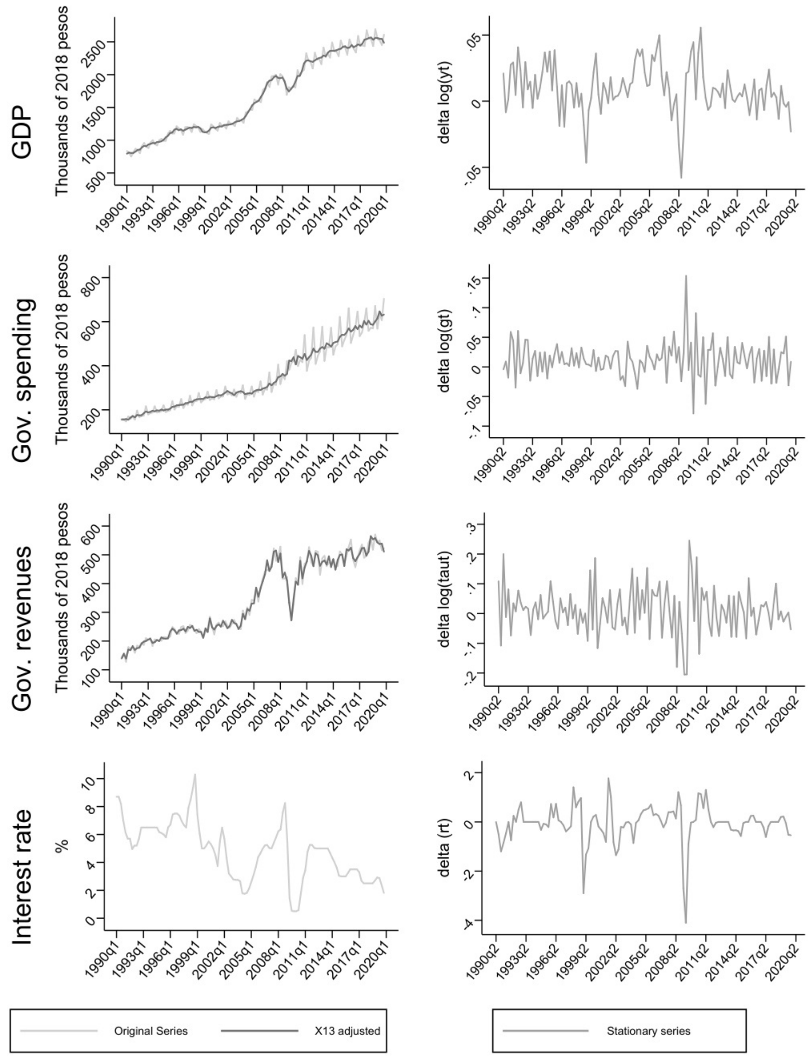

Figure 1: *Plots for the time series variables. Left hand side column: Original series; right: Series in (log) differences as used in the TVAR model.*

Regarding the selection of variables and the employed model specification two remarks are worth making: First, as the relative price of inter-temporal consumption, variations in the interest rate have a direct effect on private consumption decisions. Moreover, interest rate changes reflect the interaction between fiscal and monetary policies, and play an important role for the effects of fiscal policies on output (Spilimbergo et al. (2009); Batini et al. (2012); Fornero et al. (2019), and others). Monetary policies adjusting to government expansions should imply changes in the real interest rate that crowd out private consumption and attenuate the effect of the fiscal stimulation, while sticky interest rates would lead to multipliers closer to unity. Multipliers in excess of unity could be achieved in the case of a reaction of the interest rate that pushes consumption in the same direction of a fiscal stimulus (Woodford, 2011). Second, despite its widespread use for analysing fiscal policies in small open economies (SOEs) (see, for example, Restrepo and Rincón, 2006; Allegret and Lemus, 2019; Holland et al., 2020), the

Table 1: *Descriptive statistics of the variables and unit root tests*

					ADF		Phillips-Perron	
		variable	mean	variance	statistic	$p-val$	statistic	$p-val$
Levels	GDP*	$\log(y_t)$	7.349	0.136	-1.880	0.342	-1.509	0.529
	Gov. Spending*	$\log(g_t)$	5.764	0.173	-0.490	0.894	-0.405	0.909
	Gov. Revenues*	$\log(\tau_t)$	5.779	0.158	-1.837	0.362	-1.816	0.373
	Interest Rate	r_t	4.781	4.136	-2.255	0.187	-2.742	0.067
Differences	GDP**	$\triangle\log(y_t)$	0.959	3.358	-6.611	0.000	-6.714	0.000
	Gov. Spending**	$\triangle\log(g_t)$	1.169	8.963	-15.592	0.000	-16.494	0.000
	Gov. Revenues**	$\triangle\log(\tau_t)$	1.091	62.413	-14.500	0.000	-14.669	0.000
	Interest Rate	Δr_t	-0.058	0.565	-6.573	0.000	-6.344	0.000

Source: Own preparation.

[*] Original y_t, g_t and τ_t series in thousands of pesos of 2018, dispayresults are for the log transformed data.
[**] Multiplied by 100.
Critical values for both unit root tests, Augmented Dickey-Fuller (ADF) and Phillips-Perron, are -3.504, -2.889 and -2.579 at the 1%, 5% and 10% significance level, respectively

considered model appears more suited for analysing closed economies. Unlike some authors who opt for modeling SOEs by including related control variables, as, for instance, terms of trade data or measures of openness (see, for example, Sanches and Galindo, 2013; López-Vera et al., 2018), we follow closely the benchmark study of Allegret and Lemus (2019) for two reasons. On the one hand, a main objective of our study is to compare results obtained from distinct identification methods. On the other hand, as the number of parameters to be estimated is an important concern in a TVAR setting with short to medium time series dimension, we opt for a more parsimonious lower-dimensional model specification.

We use quarterly data for the Chilean economy, covering the period from 1990:q1 to 2019:q4. [7] Data sources and definitions for the variables under scrutiny are provided in Appendix B. Table 1 displays some descriptive statistics and unit root diagnostics for the variables employed. Both unit root tests performed, Augmented Dickey-Fuller (ADF) and Phillips-Perron, obtain a rejection of the null hypothesis of a unit root for all variables in differences. Plots of the series used in the main model can be found in Figure 1 for visual inspection.

The considered TVARs build upon two regimes $s = 1, 2$, depending on the per capita GDP growth (the transition variable γ_t) being below or above some threshold value m, which we estimate jointly with the dynamic model parameters and the intercept terms. Following the reference study of Allegret and Lemus (2019), the delay parameter is not subject to estimation and set to $d = 1$. We indicate a period following a growth rate below the threshold value with $s = 1$ (i.e. a low-growth regime). In analogy, $s = 2$ indicates an expansionary or high-growth state, where the growth rate has been above the threshold value in the previous period. Also following the benchmark study, we estimate fiscal multipliers for government spending and revenues assuming positive shocks of size one standard deviation. Hence our spending multiplier refers to expansionary policies (i.e. a one standard deviation increase in government spending), while the revenue multiplier refers to contractionary policies (i.e. a one standard deviation increase in tax revenues). Formally, the shock vectors used in our GIRF computations have the form $\delta_t^{SM} = (1, 0, 0)$, $\delta_t^{RM} = (0, 0, 1)$ for model 1 and $\delta_t^{SM} = (1, 0, 0, 0)$, $\delta_t^{RM} = (0, 0, 1, 0)$ for model 2.

For inferential purposes we employ a so-called recursive design wild bootstrap as suggested by Gonçalves and Kilian (2004). Bootstrap replications of the data read as

[7] We left out the COVID pandemic as the expansionary fiscal policy in Chile during this period was largely driven by vaccine purchases and direct transfers to population, which might imply an overly specific policy response in the context of a more general fiscal policy analysis. Our main results remain robust to using the sample period 1990:Q1 to 2017:Q4, as in Allegret and Lemus (2019)

$$z_t^* = \hat{c}^{(s)} + \sum_{p=1}^{p} \hat{A}_p^{(s)} z_{t-p}^* + u_t^* \,, t = 1, 2, ..., T \quad (6)$$

where $\hat{A}_p^{(s)}$, $p = 1, .., P$, and $\hat{c}^{(s)}$, $s = 1, 2$, are estimated TVAR parameters. The bootstrap reduced form residuals are $u_t^* = \omega_t \hat{u}_t^{(s)}$, where the scalar ω_t is drawn independently of the data and exhibits a Rademacher distribution (i.e., $p(\omega_t = 1) = p(\omega_t = -1) = 0.5$). In (7) the process is conditional on the threshold value estimated by means of the original data, which is used to define the regime s at each period t depending on z_{t-1}^*. After generation of the bootstrap data they are subjected to the same estimation steps as the original data.

4. Results

4.1. TVAR estimation

As it is common in the literature (see, for example, Farrazzy et al., 2015; Baum and Koester, 2011), lag order selection is based on pooled samples, i.e. on a standard linear VAR, and the obtained lag order is subsequently imposed on the TVAR specification. For both specifications, model 1 and model 2, the Hannan-Quinn and Schwartz criterion obtain their minimum when choosing P=1. [8]

Following the procedure suggested by Tsay (1998) obtains threshold values of 0.018 (i.e., a 1.8% growth rate) for model 1 and of 0.017 (1.7% growth rate) for model 2, which slightly exceed their counterparts in the benchmark study of Allegret and Lemus (2019) (i.e., 1.1% for model 1 and 1.0% for model 2).[9] Accordingly, the low and high-growth regime cover 85 (72.03%) and 33 (27.97%) observations, respectively, in the case of model 1. For model 2 we have that 82 (69.49%) and 36 (30.51%) observations are attributed to the low and high-growth regime, respectively. Similar to findings of Farrazzy et al. (2015) for the USA, the Chilean economy spend most of its time in a tight economic regime. Parameter estimates for both models, as well as the estimated reduced form covariance matrices and other intermediate estimation results can be found in Appendix C.

4.2. Recursive model structures

In their panels A Figure 2 and Figure 3 show cumulative fiscal multipliers for models 1 and 2, respectively, that are obtained from linear IRFs and a recursive model structure as suggested in Allegret and Lemus (2019). Similar to benchmark results of Allegret and Lemus (2019), we find significant spending multipliers for the low-growth regime that exceed unity, and insignificantly negative average spending multipliers for the high-growth regime. In the literature, average revenue multipliers are often found smaller than spending multipliers for shocks of a given size. We confirm this result for model 1. With a lack of significance, however, the average revenue multiplier changes from being positive in model 1 to negative in model 2. The differences of multiplier estimates between regimes are also indicated in the Figures. As it turns out, the replication of the benchmark model reveals significant state dependence of multipliers at all horizons for model 1. In the case of model 2, the difference between state specific cumulative multipliers become insignificant after two quarters.

[8] We consider Akaike (AIC), Schwartz (BIC) and Hannan-Quinn (HQC) information criteria. As it turns out, a lag order of P = 1 minimizes two out of the three criteria. Moreover, opting for a more restrictive model order better aligns with the postulate of model parsimony in the present non-linear model context.

[9] All main results documented in this work are robust to using the threshold values of Allegret and Lemus (2019).

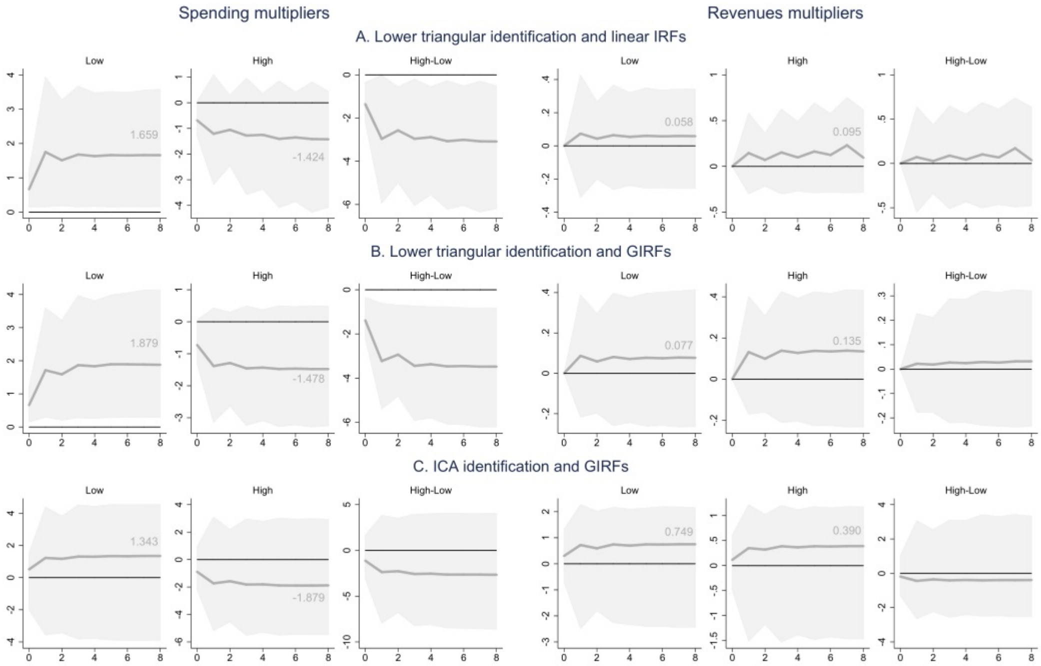

Figure 2: *Cumulative FMs for Model 1*[10]

As in Laumer and Philipps (2020), we next relax the linearity assumption that is typical for conventional IRFs, and discuss FMs as implied by GIRFs that take account of potential regime changes in the aftermath of the shocks under scrutiny. Cumulative multipliers obtained from GIRFs are shown in the panels B of Figure 2 (model 1) and Figure 3 (model 2). Generally, results from using IRFs remain robust when using GIRFs to quantify FMs. A slight increase of average spending multipliers can be observed for both regimes in model 1. Conditional on model 2, the GIRF implied spending multipliers exceed the IRF results for the low growth regime, while they get closer to zero in periods of higher growth. The significant difference between spending multipliers assigned to distinct regimes observed in model 2 is persistent and holds at all considered horizons. Overall, revenue multipliers still accord in general with the literature in being smaller than spending multipliers. Moreover, revenue multiplier estimates lack significance at conventional levels. Confirming results for linear IRFs, average revenue multipliers change from being negative in model 1 to positive in model 2. Somewhat differing from results for linear IRFs, however, GIRF implied revenue multipliers are of a similar pattern for both regimes and stay below unity.

4.3. Identification by means of independent components

We next relax the lower triangular identification assumption by using the more agnostic ICA approach. Results for identification by means of ICA are shown in panels C of Figure 2 (model 1) and Figure 3 (model 2). Dramatic changes can be seen, particularly for the spending multipliers that are implied by both models. Conditional on low-growth regimes, the 10% significance now vanishes for the revenue multipliers. Conditional on model 2, the average spending multiplier during recessions falls below unity. Moreover, the response differences across regimes lack significance throughout in both models.

Table 7 shows independence diagnostics for orthogonalized residuals of models 1 and 2. The population counterpart of the documented distance covariances is zero, if and only if the random variables

[10] X axis in quarters. 90% bootstrap confident area. Numerical results are for horizon quarter 8.
[11] For notes see Figure 2.

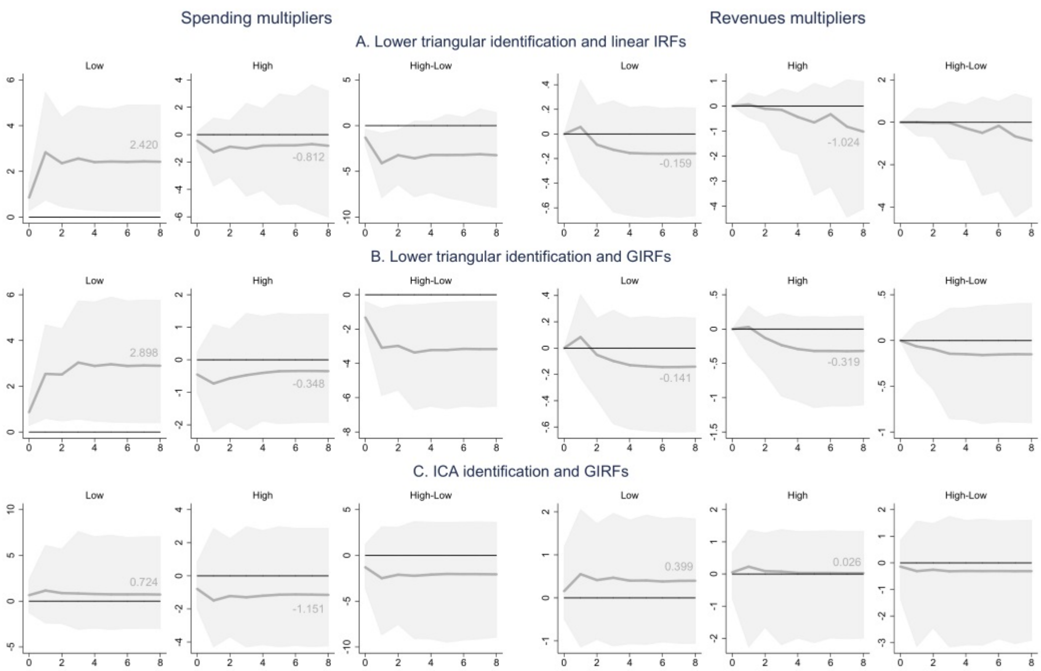

Figure 3: *Cumulative FMs for Model 2*[11]

Table 2: *Multivariate distance covariance statistics (multiplied by 100) and percentage of rejected tests for the null hypothesis of independent shocks.*

		Model 1				Model 2			
ID-Scheme	Regime	Q5	Mean	Q95	H_0	Q5	Mean	Q95	H_0
Cholesky	Low	-0.37	2.21	5.23	46.40%	0.71	4.82	9.46	78.60%
	High	-5.15	0.66	6.75	11.20%	-6.48	0.1	7.34	13.40%
ICA	Low	-1.97	-0.3	1.73	3.20%	-2.54	-0.25	2.92	6.00%
	High	-8.16	-3.38	1.71	0.20%	-10.24	-5.21	0.52	0.20%

Q5, Q95 and 'mean' refer, respectively, to the 5th and 95th quantile and the empirical average of distance covariance statistics from 500 wild-bootstrap replications. H_0 indicates in percentages the frequency of rejections of the null hypothesis of independence with 10% significance out of 500 wild bootstrap replications.

subjected to testing are independent (Székely and Rizzo, 2009). As a first tool for independence diagnosis, we consider orthogonalized residuals as dependent, if the 5% and 95% quantiles of bootstrap distance covariance statistics do not cover a value of zero. With this criterion we find that subjecting model 2 to a recursive structure results in dependent structural shocks for the low growth regime. Moreover, conditional on the recursive model, the null hypothesis of having independent orthogonalized residuals is rejected with considerably larger frequencies throughout. Hence, unlike the shocks implied by the more agnostic identification scheme, shocks retrieved from a recursive model structure lack independence. While being orthogonal, these shocks can hardly be considered as fully exogenous, i.e. in a higher order sense they are subject to joint determination.

Table 3 shows the estimated Cholesky factors and B matrices for models 1 and 2. For the three baseline variables g, y and τ , the lower triangular sign pattern of the Cholesky matrices also holds for the ICA-identified structural parameter matrix, although all estimates loose significance. An increase in government spending contemporaneously raises the GDP in a low growth regime, although not in the high growth regime. GDP shocks seem to have a positive effect on government revenues and

Table 3: *Estimated structural parameters (i.e. covariance factors, multiplied by 100) for models 1 and 2*

			Model 1			Model 2			
Matrix	Regime	Equation	g	y	τ	g	y	τ	r
Cholesky	Low	$\triangle\log(g_t)$	2.636*	0.000	0.000	2.538*	0.000	0.000	0.000
		$\triangle\log(y_t)$	0.375*	1.575*	0.000	0.457*	1.548*	0.000	0.000
		$\triangle\log(\tau_t)$	-1.889	1.765*	5.554*	-1.923*	1.753*	5.529*	0.000
		$\triangle r_t$				-13.600	-14.236	10.421	53.442*
	High	$\triangle\log(g_t)$	2.726*	0.000	0.000	2.818*	0.000	0.000	0.000
		$\triangle\log(y_t)$	-0.403	1.559*	0.000	-0.267	1.436*	0.000	0.000
		$\triangle\log(\tau_t)$	-1.086	0.963	7.241*	-1.130	0.283	7.152*	0.000
		$\triangle r_t$				-2.834	-0.151	26.312*	52.355*
ICA	Low	$\triangle\log(g_t)$	2.335*	0.090	0.138	1.809*	0.072	0.309	-0.737
		$\triangle\log(y_t)$	0.183	1.394*	0.293	0.208	1.324*	0.244	-0.437
		$\triangle\log(\tau_t)$	-2.230	0.788	4.827*	-1.515	0.983	4.784*	1.000
		$\triangle r_t$				3.589	-3.669	2.195	51.641*
	High	$\triangle\log(g_t)$	2.424*	0.140	-0.391	2.422*	0.323	-0.110	-0.114
		$\triangle\log(y_t)$	-0.407	1.420*	0.165	-0.357	1.237*	0.039	0.016
		$\triangle\log(\tau_t)$	-0.076	0.127	6.779*	-0.417	-0.214	5.663*	1.895
		$\triangle r_t$				1.353	-1.579	9.184	51.121*

* 0 not included in the Q5 - Q95 bootstrap quantiles interval. For more detailed information on bootstrap quantiles see Table 6 (model 1) and Table 7 (model 2) in Appendix C.

a negligible one on government spending, which is largely in line with the assumption of Blanchard and Perotti (2002), that output lacks a contemporaneous effect on government spending. When using ICA identification for both models, an increase in taxes invokes a contemporaneous yet insignificant increase in output for both regimes, an increase in spending for the low-growth regime and a decrease in spending for the high growth regime. When inspecting the covariance matrices identified by means of a Cholesky decomposition for model 2, we observe a contemporaneous negative reaction of the interest rate to spending and a positive reaction to revenue shocks (this last one significant during high-growth regimes). By implication, these estimates signify a crowding out effect of government expansions on private consumption. As another feature of the ICA-identified matrix for model 2, we observe a positive average response of interest rates to government spending shocks, clouding the previous hints of crowded out consumption for spending shocks. Also, the positive contemporaneous increase of interest rates following revenue shocks during high-growth regimes found when imposing a lower triangular structure loses its significance when using ICA identification.

5. Conclusion

We study the dependence of fiscal multipliers in Chile on the economic cycle. For this purpose we relax some restrictive assumptions that have been made in a previous benchmark study of Allegret and Lemus (2019). In particular, we employ flexible generalized impulse responses (GIRFs) instead of stylized linear impulse response functions, and opt for a data-based identification of the structural parameter matrix instead of using an ad-hoc lower triangular recursion. Specifically, the identification scheme exploits the uniqueness of linear combinations of non-Gaussian independent components (Comon, 1994). Thereby, this study is first in deriving non-Gaussian independent components within the non-linear setting of threshold VAR models.

In spite of slight differences with regard to the definition of variables our baseline results obtained from a most restrictive framework (i.e., linear IRFs and a recursive structural model) are in line with earlier findings of Allegret and Lemus (2019). Government spending multipliers are significantly state dependent on impact, above unity and significant conditional on the low growth regime and (insignificantly) negative for high growth regimes. The revenue multipliers appear to be overall smaller than the spending multipliers and lack significance.

With the imposition of less restrictive assumptions, i.e. identification by means of an agnostic data-based structural model, and the use of GIRFs that account for non-linear threshold dynamics our empirical FM results change in two important respects. First, we find no significant differences in neither spending nor revenue FMs. These results are in contrast to some earlier literature, but align with recent findings of Caggiano et al. (2015); Ramey and Zubairy (2018) and Laumer and Philipps (2020). Second, our estimates show in general no significant evidence for non-zero FMs. In this respect, results from the lower triangular identification scheme are supportive for findings of Allegret and Lemus (2019) and Fornero et al. (2019). (2019), while an agnostic identification scheme yields results that align with findings of Cerda et al. (2005) for Chile or Holland et al. (2020) for Brazil as another Latin American economy. Our findings suggest that results from previous studies could reflect the ad-hoc imposition of a hierarchical model structure (i.e. of a Cholesky factorization of the reduced form covariance). Relaxing these rigidities by adopting a more agnostic identification scheme that builds upon the uniqueness of independent non-Gaussian shocks results in finding no significantly different FMs for periods of (relatively) high versus low economic growth.

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Appendix A. GIRF computation

Let $\hat{B}^{(s)}$ be the decomposition matrix of the estimated covariance matrix $\hat{\Sigma}^{(s)}$for regime s (for instance, a lower triangular Cholesky factor or other matrix that fulfils $\hat{B}^{(s)} \times (\hat{B}^{(s)})' = \hat{\Sigma}^{(s)}$). A along the lines of Koop et al. (1996) GIRFs up to an horizon h obtain from the following algorithm:

1. From the estimation of the TVAR model in (1) and (2), get the orthogonal residuals

$$\hat{\varepsilon_t} = (\hat{B}^{(s)})^{-1}\hat{u_t}^{(s)}, t = 1, 2, \ldots, T$$

2. Sample randomly h+1 error vectors $\hat{\varepsilon_t}$ from step 1, to get a series of random errors

$$\hat{\nu} = (\tilde{\varepsilon_0}, \tilde{\varepsilon_1}, \ldots, \tilde{\varepsilon_h})$$

.

3. Let $z_1, \ldots, z_T$ be the full sample of data. For a given history $\Omega_{t-1} = z_{t-P}, \ldots, z_{t-1}$, where P is the model lag order and $t \in \{P+1, \ldots, T\}$, expectations in equation (4) can be estimated by

$$E(z_{t+h} \mid \delta_t, \hat{\nu_{t+h}}, \Omega_{t-1}) = \hat{c}^{(s)} + \sum_{p=1}^{P} \hat{A_p}^{(s)} z_{t-p} + \hat{B}^{(s)}(\tilde{\varepsilon_0} + \delta_t) \tag{7}$$

and

$$E(z_{t+h} \mid \hat{\nu_{t+h}}, \omega_{t-1}) = \hat{c}^{(s)} + \sum_{p=1}^{P} \hat{A}_p^{(s)} z_{t-p} + \hat{B}^{(s)}\tilde{\varepsilon_0} \tag{8}$$

where $\hat{c}^{(s)}, \hat{A}_1^{(s)}, \ldots, \hat{A}_P^{(s)}$are the estimated model parameters and δ_t is the shock vector with magnitude δ in the k-th position and zero otherwise[12]. Notice that the initial regime s is defined this way by Ω_{t-1}.

4. From there, obtain estimations for $E(z_{t+h} \mid \delta_t, \nu_{t+h}, \Omega_{t-1})$ and $E(z_{t+h} \mid \nu_{t+h}, \Omega_{t-1})$ recursively using the remaining error vectors from $\hat{\nu}$, allowing the process at times, t+1,...,h to change the regime if a threshold is crossed.

5. Repeat Steps 3 and 4 for all histories Ω_{t-1} present in the data and take the means for each initial regime s.

6. Repeat Steps 2 to 5 a number of times and take the means for the GIRFs.

[12]Other ways of implementing the shock can be found in the literature. For example, Batini et al. (2012) replaces the k-th element of the unconditional disturbance vector by δ or Galvão (2003) suggests to just use δ_t instead of the unconditional disturbance vector. In this regard, we follow the procedure described in Laumer and Philipps (2020)

Appendix B. Data description

As pointed out in the main text, the original data used in the analysis comprises four series spanning from 1990:Q1 to 2019:Q4, corresponding to the three variables used in Blanchard and Perotti (2002)(GDP, government spending and government revenues) plus the interest rate used in a second model as in Allegret and Lemus (2019). GDP at current prices in pesos from year 1996 onward, comes from the Central Bank of Chile database (accessed June 24, 2021); the data was extended to year 1990 by means of year-to-year quarterly GDP growth rates coming from estimates in Correa et al. (2002). Government spending and revenues data come from the DIPRES (Budget Department of the Treasury Ministry) web site, and has been compiled from the Quarterly Operations Reports using government budget information (DIPRES, 1990 to 2019). Following Allegret and Lemus (2019) government taxes has been defined as current income minus transfers, and government expenditures as current expenditures plus capital expenditures. Each of these variables, valued in current Chilean pesos from source, were deflated by the consumer price index (base year 2018) and expressed in per capita terms. The consumer price index with base year 2018 comes from the OECD database (accessed June 24, 2021). Population to year 2019 has been drawn from the World Bank online dataset, annual values were repeatedly applied to each quarter of a specific year. Real per capita GDP, per capita government spending and per capita government revenues have been seasonally adjusted using X13-ARIMA with standard settings. The monetary policy interest rate from year 1995 and onward comes from the Central Bank of Chile public database, the series was extended to year 1990 using reference rates available at https://si3.bcentral.cl/estadisticas/Principal1/Excel/EMF/TASAS/excel.html (accessed June 25, 2021).

Appendix C. Intermediate results

Estimated parameters for models 1 and 2 TVARs can be found in Table 4. The moduli of maximum eigenvalues of the characteristic polynomials of the estimates VARs are well inside the unit circle ($\simeq 0.43$ and $\simeq 0.72$ conditional on the low- and high-growth regime, respectively, for both models). Normality tests for the estimated error terms can be found in Table 5. Finally, estimated covariance matrix decompositions using both, lower triangular and ICA identification strategies are available in tables 6 and 7 for models 1 and 2, respectively.

Table 4: *Estimated parameters for the TVAR models 1 and 2*

		Model 1			Model 2			
	Parameter	$\triangle$ log(g_t)	$\triangle$ log(y_t)	$\triangle$ log(τ_t)	$\triangle$ log(g_t)	$\triangle$ log(y_t)	$\triangle$ log(τ_t)	$\triangle$ τ_t.
Low-growth regime	L.$\triangle$ log(g_t)	-0.355(0.00)	0.032(0.65)	0.162(0.57)	-0.355(0.00)	0.064(0.39)	0.203(0.50)	0.568(0.84)
	L.$\triangle$ log(y_t)	-0.501(0.03)	0.285(0.05)	1.537(0.01)	-0.327(0.17)	0.231(0.12)	1.263(0.04)	10.92(0.06)
	L.$\triangle$ log(τ_t)	-0.001(0.99)	0.013(0.65)	-0.395(0.00)	0.015(0.74)	0.019(0.51)	-0.378(0.00)	1.259(0.25)
	L.$\triangle$ τ_t	0.018(0.00)	0.004(0.05)	0.002(0.78)	0.007(0.17)	-0.006(0.05)	-0.018(0.15)	0.473(0.00)
	Const.				0.018(0.00)	0.004(0.04)	0.002(0.80)	-0.139(0.07)
High-growth regime	L.$\triangle$ log(g_t)	-0.410(0.01)	0.028(0.74)	-0.912(0.03)	-0.408(0.01)	0.006(0.94)	-0.870(0.03)	-8.239(0.01)
	L.$\triangle$ log(y_t)	-0.069(0.90)	0.327(0.34)	2.169(0.18)	0.333(0.55)	0.623(0.04)	2.032(0.18)	4.046(0.75)
	L.$\triangle$ log(τ_t)	-0.101(0.06)	0.020(0.52)	-0.363(0.02)	-0.119(0.04)	0.039(0.20)	-0.326(0.04)	0.499(0.69)
	L.$\triangle$ τ_t	0.020(0.31)	0.010(0.37)	-0.021(0.70)	00000(0.99)	-0.007(0.04)	-0.008(0.61)	0.429(0.00)
	Const.				0.005(0.79)	-0.002(0.85)	-0.017(0.73)	0.123(0.77)

p-values in parentheses.

Table 6: *Structural parameter estimates (multiplied by 100). Model 1*

ID Scheme	Regime	Q5	Mean	Q95	Q5	Mean	Q95	Q5	Mean	Q95
Cholesky	Low	2.06	2.64	3.29	0.00	0.00	0.00	0.00	0.00	0.00
		0.08	0.38	0.70	1.33	1.58	1.80	0.00	0.00	0.00
		-3.47	-1.89	-0.28	0.60	1.77	2.96	4.88	5.55	6.22
	High	2.18	2.73	3.28	0.00	0.00	0.00	0.00	0.00	0.00
		-0.79	-0.40	0.03	1.30	1.56	1.79	0.00	0.00	0.00
		-3.85	-1.09	1.72	-1.52	0.96	3.54	5.37	7.24	8.92
ICA	Low	1.31	2.34	3.10	-1.12	0.09	1.06	-2.23	0.14	1.17
		-0.58	0.18	0.77	0.74	1.39	1.79	-0.61	0.29	1.22
		-4.85	-2.23	2.76	-2.88	0.79	3.90	3.69	4.83	5.96
	High	1.61	2.42	3.07	-1.08	0.14	1.01	-1.97	-0.39	1.11
		-1.07	-0.41	0.41	1.06	1.42	1.73	-0.57	0.17	0.88
		-4.77	-0.08	4.38	-3.69	0.13	3.65	4.84	6.78	8.65

Q5 and Q95 refers respectively to the 5th and 95th quantiles from the 500 wild-bootstrap iterations.
For further notes see Table 3 in the main text.

Table 5: *Normality tests for the estimated reduced form residuals*

		Model 1				Model 2			
		Mardia Skewness	Mardia Kurtosis	Henze-Zirkler	Doornik-Hansen	Mardia Skewness	Mardia Kurtosis	Henze-Zirkler	Doornik-Hansen
Low growth	Statistic	2.935	21.491	0.832	23.732	10.027	43.469	1.403	51.378
	p-value	0.000	0.000	0.376	0.001	0.000	0.000	0.000	0.000
High growth	Statistic	1.324	14.484	0.749	8.166	3.978	25.445	0.877	16.173
	p-value	0.599	0.787	0.359	0.226	0.143	0.531	0.206	0.040
Pooled VAR	Statistic	1.740	21.838	0.953	29.567	5.478	40.834	1.732	70.493
	p-value	0.000	0.000	0.156	0.000	0.000	0.000	0.000	0.000

Table 7: *Structural parameter estimates (multiplied by 100). Model 2*

ID	Regime	Q5	Mean	Q95	Q5	Mean	Q95	Q5	Mean	Q95	Q5	Mean	Q95
Cholesky	Low	1.97	2.54	3.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		0.12	0.46	0.79	1.32	1.55	1.78	0.00	0.00	0.00	0.00	0.00	0.00
		-3.57	-1.92	-0.18	0.58	1.75	3.03	4.85	5.53	6.26	0.00	0.00	0.00
		-39.62	-13.60	11.62	-26.62	-14.24	-1.72	-0.92	10.42	20.08	39.94	53.44	69.79
	High	2.24	2.82	3.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		-0.63	-0.27	0.12	1.18	1.44	1.67	0.00	0.00	0.00	0.00	0.00	0.00
		-3.93	-1.13	1.55	-2.08	0.28	2.58	5.36	7.15	8.86	0.00	0.00	0.00
		-21.86	-2.83	16.50	-18.81	-0.15	16.77	6.91	26.31	47.64	36.03	52.36	68.09
ICA	Low	0.99	1.81	2.56	-0.85	0.07	0.92	-0.64	0.31	1.14	-2.92	-0.74	1.10
		-0.41	0.21	0.77	0.74	1.32	1.71	-0.39	0.24	1.17	-1.15	-0.44	0.17
		-4.02	-1.52	1.56	-2.26	0.98	3.98	3.35	4.78	5.97	-1.80	1.00	4.45
		-45.60	3.59	39.81	-32.82	-3.67	16.84	-11.24	2.20	15.05	37.56	51.64	67.21
	High	1.57	2.42	3.07	-0.91	0.32	1.38	-1.61	-0.11	1.35	-1.44	-0.11	1.03
		-0.94	-0.36	0.38	0.82	1.24	1.55	-0.69	0.04	0.76	-0.57	0.02	0.71
		-4.46	-0.42	3.34	-3.64	-0.21	3.23	2.78	5.66	7.88	-2.38	1.90	6.93
		-31.84	1.35	32.64	-25.24	-1.58	22.74	-27.14	9.18	44.16	33.50	51.12	68.18

Q5 and Q95 refers respectively to the 5th and 95th quantiles from the 500 wild-bootstrap iterations.
For further notes see Table 3 in the main text.