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Fiscal multipliers in a small open economy: the case of Austria*

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Abstract

We estimate fiscal multipliers for Austria in a framework of model uncertainty emanating from the choice of a particular econometric model. We present a comprehensive framework which allows to assess the effects of different multiplier definitions and choices related to the data, the model employed, and further technical choices associated with the specification of the model exert on fiscal multiplier estimates. The mean present-value government spending multiplier over all models entertained, based on over one thousand estimates, is 0.94. Estimates of the peak spending multiplier tend to be larger than present-value spending multipliers, with a mean value of 1.08. The value of the mean present-value tax multiplier is -0.76 and the mean peak tax multiplier is -0.58 for all specifications used.

Keywords: Fiscal multiplier, structural VAR, predictive ability, small open economy, Austria

JEL codes: E62, C32

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1 Introduction

The interest in assessing the macroeconomic effects of fiscal policy in industrialized countries has gained renewed momentum since the Great Recession. Given the limited scope of action of monetary policy in the context of very low nominal interest rates, fiscal policy re-emerged as a policy of choice and a large literature has concentrated on investigating how fiscal policy affects macroeconomic variables and GDP in particular.[1] A convenient way to communicate the effects of fiscal stimulus on the economy is the fiscal multiplier, measured as the dollar reaction of GDP as a result of a one dollar fiscal stimulus. Fiscal multipliers are easily comparable across countries and over time, and the precision of their estimation contributes significantly to the quality of GDP growth predictions (Blanchard and Leigh, 2013). The estimates of fiscal multipliers are infamously heterogeneous both across countries and methods used for their calculation, and may be very sensitive to arguably minor specification choices, as recently shown in Čapek and Crespo Cuaresma (2020).

There is little evidence on the size of fiscal multipliers for developed European small open economies.[2] Ravn and Spange (2012) enhance the Blanchard-Perotti methodology based on structural vector autoregression (SVAR) models to estimate spending multipliers for Denmark and obtain a point estimate of approximately 0.6 after four quarters. Jemec et al. (2011) investigate Slovenian fiscal policy employing a standard SVAR approach and estimate an impact spending multiplier of 1.5, which diminishes in subsequent periods. Unfortunately, not all studies investigating the effects of fiscal stimuli report the results in the form of multipliers (e.g. Afonso and Sousa, 2011, for Portugal or Benetrix and Lane, 2009, for Ireland). In addition to estimates for single countries, evidence from panel studies also exists. Ilzetzki et al. (2013) report that the subgroups of countries corresponding to high income, open, low-debt and fixed exchange rate countries have average spending multipliers of 0.4, 0, 0.2, and 0.6, respectively. The empirical evidence can be supplemented making use of the work by Barrell et al. (2012), where a model-based consumption multiplier of 0.5 is reported for Austria. Breuss et al. (2009) provides an overview of fiscal multipliers derived by Austrian forecasting institutions from large-scale macroeconometric models (within the tradition of the *Cowles commission approach*). Spending multipliers over the first year after the fiscal shock are typically below unity, first year wage and income tax multipliers are below 0.5. Recent papers by Koch et al. (2019) and Schuster (2019) complement the existing results by simulating fiscal multipliers for Austria using calibrated New-Keynesian general equilibrium models and derive multipliers of comparable magnitudes. However, to our knowledge, a pure empirical assessment of fiscal multipliers specifically for Austria, as a stereotypical small open economy within the group of industrialized countries, does not exist. In this contribution, we provide for the first time a rigorous analysis of fiscal multiplier estimates in a small open economy (Austria) incorporating the uncertainty related to specification choice in several dimensions including that related to the particular variables included in the model, shock identification strategies, data preparation or the analytical structure of the model. Given the importance of economic openness to determine the size of the fiscal multiplier, such an exercise allows the results to be interpreted in the framework of theoretical models of fiscal policy effects in small open economy settings. Theoretical results of this literature predict lower domestic effects of fiscal policy through the leaking of fiscal shocks to imported goods, combined with a higher sensitivity to international economic policy spillovers (see Karras, 2014, for example).

The main bulk of the existing literature on the macroeconomic effects of fiscal interventions can be categorized as either model-based or empirical. Model-based approaches typically employ calibrated DSGE models to study the effects of fiscal stimuli in an internally-consistent theoretical framework. Kilponen et al. (2015), for instance, compare such estimates of fiscal multipliers across models and countries in

[1] See e.g. Hebous (2011) or Ramey (2011a) for earlier surveys on the issue, or Ramey (2019) for a recent contribution.

[2] See the extensive summary of existing multiplier estimates in Mineshima et al. (2014) or the data used for the broad meta-analysis in Gechert (2015).

Europe, while Barrell et al. (2012) focus on model-based fiscal multipliers in the context of fiscal consolidation. The advantage of the model-based approach lies in the ability to analyse counterfactual scenarios by simulating the dynamics of the model variables under different conditions. On the other hand, empirical approaches, mostly based on SVAR models, tend to be more data-driven and typically impose less stringent restrictions on the structure of the economic model. The availability of long time series for some countries allow for the use of modern identification methods such as the narrative approach (Ramey, 2011b) to extract exogenous fiscal shocks or the assessment of different regimes (Auerbach and Gorodnichenko, 2012) where fiscal multipliers may differ. In cases where such long time series are not available, countries are often pooled and the empirical analysis is conducted on a panel setting (Beetsma and Giuliodori, 2011; Ilzetzki et al., 2013), or fiscal multipliers for single economies with shorter time series are studied using SVAR models inspired by the seminal contribution by Blanchard and Perotti (2002).[3]

The estimates of fiscal multipliers tend to differ, sometimes strongly, from study to study (see the evidence presented in the meta-analysis provided by Gechert, 2015). These differences can be attributed to various identification strategies (Caldara and Kamps, 2017) as well as to other technical choices made in the analysis (Čapek and Crespo Cuaresma, 2020). Given the additional dimension of uncertainty on fiscal multiplier estimates implied by the particular methodological choices, even within the class of SVAR models, the approach of this study is to present a consistent framework which encompasses a wide range of reasonable settings and choices which are routinely used in the empirical literature on fiscal multipliers. The framework delivers over one thousand multiplier estimates, each for a particular model specification. We exploit the differences in out-of-sample predictive power of the models entertained for GDP in order to gain insights into the size of fiscal multipliers in Austria. Our analysis expands the methodological setting put forward in Čapek and Crespo Cuaresma (2020) in several respects. First of all, by concentrating on a single economy, we gain comparability in the multiplier estimates, which correspond to the responses to fiscal impulses within the same institutional and historical setting. Furthermore, we expand the set of econometric specifications and modelling choices in Čapek and Crespo Cuaresma (2020) by including new models based on factor-augmented VAR structures and using out-of-sample predictive ability as a model selection tool. The focus on a single small open economy allows us to link the results in a more direct manner to the methodological framework provided by economic theory, in particular when interpreting the results of the analysis, and allows for the assessment of additional sources of model uncertainty as compared to Čapek and Crespo Cuaresma (2020). This is the case, for example, for the composition of government spending and tax aggregates, or for the calculation of the values of tax and spending elasticities required for several identification techniques. In our analysis, we also contribute to the literature by identifying structural fiscal shocks in models where subcomponents of spending and tax revenues are used, making use of elasticities of disaggregated components of the fiscal variables to output and the price level obtained using the fiscal forecasting model by the Austrian Fiscal Advisory Council (2014).

Our results expose the uncertainty and heterogeneity that is inherent to empirical estimates of fiscal multipliers. In addition to entertaining different SVAR specifications based on Blanchard and Perotti (2002) and Perotti (2004), we also estimate fiscal multipliers from structural Factor Augmented VAR (FAVAR) models. These specifications provide a more adequate framework to account for fiscal foresight and omitted variable biases (Fragetta and Gasteiger, 2014). Furthermore, we also exploit the existing data on government spending and tax composition in Austria in order to obtain additional multiplier estimates. We compare the results for the two most widely used formulations in the literature – the present-value multiplier and the peak multiplier and deliver the first set of credible multiplier estimates for a representative European small open economy after accounting for model uncertainty.

[3]See e.g. Ramey (2016) for a review of the methods used for the identification of exogenous fiscal shocks.

The mean spending multiplier for Austria is estimated at 0.94 for the present-value multiplier and 1.08 for the peak multiplier. The present-value tax multiplier is -0.76 and its peak counterpart is -0.58. Comparing the multipliers to the existing literature, our estimates suggest a stronger reaction of GDP after the increase of government spending as compared to the results for relevant subgroups of countries reported in Ilzetzki et al. (2013). Our estimate of present-value multiplier specification is comparable to that of Denmark (see Ravn and Spange, 2012). As in the case of the study on the Slovenian economy, our results also suggest that peak spending multipliers tend to be higher than their present-value counterparts (see Jemec et al., 2011). The multiplier estimates obtained using the subset of models with relatively superior predictive ability for GDP tend to be smaller in case of present value spending multiplier. Our results also indicate that the models based on subcomponents of government spending and taxes that deliver the best predictive ability for GDP dynamics tend to include compensation of employees, intermediate consumption, gross capital formation, and transfers in kind as part of government expenditures and taxes on production, imports, income, and wealth, and household social contributions. On average, SVAR models of small dimension and using the Cholesky decomposition as an identification device tend to result in relatively lower spending multipliers. On the other hand, using more variables for estimation and employing identification schemes that follow the Blanchard-Perotti or sign restriction approach deliver results with relatively higher values of spending multipliers. For tax multipliers, Blanchard-Perotti identification delivers a lower magnitude of estimates as compared to other specifications. We also find evidence corroborating a conclusion in Ramey (2019) that the specific definition of the multiplier used may lead to significantly different estimates.

The paper is organized as follows. Section 2 briefly presents the methodological setting used to estimate fiscal multipliers, based on SVAR and structural FAVAR models. Section 3 describes the different specification designs assessed for the estimation of fiscal multipliers in Austria. Section 4 presents the results of the analysis in detail and section 5 concludes.

2 Estimating Fiscal Multipliers: SVAR and structural FAVAR models

We can nest the set of models used to estimate fiscal multipliers in the stacked form of a dynamic factor model, following Stock and Watson (2016). A set of q dynamic factors are stacked to yield r static factors in the vector F_t and, abstracting from further deterministic terms (all our models contain a linear time trend), a FAVAR structure is be given by

$$\begin{pmatrix} \underset{n\times 1}{Y_t} \\ \\ \underset{m\times 1}{X_t} \end{pmatrix} = \begin{pmatrix} \underset{n\times n}{\mathbf{I}} & \underset{n\times r}{\mathbf{0}} \\ \\ \underset{m\times n}{\mathbf{\Lambda}^Y} & \underset{m\times r}{\mathbf{\Lambda}^F} \end{pmatrix} \begin{pmatrix} \underset{n\times 1}{\tilde{F}_t} \\ \\ \underset{r\times 1}{F_t} \end{pmatrix} + \begin{pmatrix} \underset{n\times 1}{\mathbf{0}} \\ \\ \underset{m\times 1}{e_t} \end{pmatrix} \tag{1}$$

$$\underset{(n+r)\times(n+r)}{\mathbf{\Phi}(L)} \begin{pmatrix} \underset{n\times 1}{\tilde{F}_t} \\ \\ \underset{r\times 1}{F_t} \end{pmatrix} = \begin{pmatrix} \underset{(n+q)\times(n+q)}{\mathbf{I}} \\ \\ \underset{(r-q)\times(n+q)}{\mathbf{0}} \end{pmatrix} \underset{(n+q)\times 1}{\eta_t} \tag{2}$$

$$\underset{(n+q)\times(n+q)}{\mathbf{A}} \underset{(n+q)\times 1}{\eta_t} = \underset{(n+q)\times(n+q)}{\mathbf{B}} \underset{(n+q)\times 1}{\varepsilon_t} \tag{3}$$

where equation (1) is the measurement equation, equation (2) is the transition equation, and equation (3) is the identification equation, while the (matrix) lag polynomial $\mathbf{\Phi}(L)$ is given by $\mathbf{\Phi}(L) = \mathbf{I} - \mathbf{\Phi}_1 L -$

$\cdots - \mathbf{\Phi}_p L^p$ for matrices $\mathbf{\Phi}_l$, $l = 1, \ldots, p$. The variables in Y_t (output, fiscal variables and other covariates) are assumed to be measured without error by the observed factors $\tilde{F}_t$. X_t contains m observed time series (not contained in Y_t) summarizing information about other macroeconomic and financial phenomena, as well as variables related to labour markets, production and sectoral developments. Variables in X_t are assumed to depend on observed factors $\tilde{F}_t$, unobserved factors F_t and an idiosyncratic component e_t, with matrix $\mathbf{\Lambda}^F$ comprising the corresponding factor loadings. Equation (3) specifies the relationship between reduced-form (η_t) and structural shocks (ε_t). If the number of unobserved factors r is set to zero, the model collapses to a standard SVAR model which can be utilized to implement the methods in Blanchard and Perotti (2002) or Perotti (2004) for structural shock identification. The unobserved factors of the model (F_t) are estimated as principal components and the identification of the model is reached once matrices $\mathbf{A}$ and $\mathbf{B}$ are chosen (see Stock and Watson, 2016).

Various identification methods can be used to retrieve the structural shocks in ε_t. The method pioneered by Blanchard and Perotti (2002) relies on exact restrictions imposed on the error terms of a VAR model which includes GDP, government expenditure and taxes through an identification scheme based on lags in the implementation of fiscal policy. More modern methods (Rubio-Ramírez et al., 2010) use sign restrictions that constrain the direction of the response of variables to particular shocks. Once the structural shocks have been identified, government spending and tax multipliers can be computed. In line with recent literature (e.g. Caggiano et al., 2015; Gechert and Rannenberg, 2014; Ilzetzki et al., 2013; Mountford and Uhlig, 2009), we report present-value (or discounted cumulative) multipliers at lag T,

$$\text{present-value spending multiplier} = \frac{\sum_{t=0}^{T}(1+i)^{-t} y_t}{\sum_{t=0}^{T}(1+i)^{-t} g_t} \frac{1}{g/y}, \tag{4}$$

where y_t is the response of output at time t (in logs), g_t denotes the response of government expenditures at time t (in logs) and g/y is the average share of government expenditures in GDP over the sample. The multiplier is discounted with the interest rate i, which is set to four percent *per annum*.[4] In the context of data at quarterly frequency, we report discounted cumulative multipliers for $T = 4$. The tax multiplier is calculated analogously, after substituting government expenditures in equation (4) with taxes.

If we concentrate on the non-cumulative reaction of GDP, such effects can be summarized using the so-called peak multipliers (see e.g. Blanchard and Perotti, 2002; Caggiano et al., 2015; Fragetta and Gasteiger, 2014; Ramey, 2011b),

$$\text{peak spending multiplier} = \frac{\max_{t=0,\ldots,H}\{y_t\}}{\max_{t=0,\ldots,H}\{g_t\}} \frac{1}{g/y}. \tag{5}$$

In order to account for the business cycle nature of the multipliers (and the known unreliability of results for longer horizons in these specifications), we restrict the horizon to a maximum of two years and set $H = 8$.

3 Model Specifications and Data

Specification choices

As reported in Čapek and Crespo Cuaresma (2020), in the context of estimating multipliers using SVAR specifications, seemingly harmless modelling choices may have a significant effect on the size and precision of fiscal multiplier estimates. In addition to the structural shock identification strategy, these modelling choices include the definition of spending and taxes, the national accounts system employed, the

[4]The discounting does not tend to play a major role for moderate interest rates, while it becomes more important in environments of high interest rates, such as emerging economies. The selection of a four percent interest rate corresponds to a commonly used discount factor of 0.99 per period.

use of particular interest rates or inflation measures in the model, or whether data are smoothed prior to estimation. Using a sample of European countries, Čapek and Crespo Cuaresma (2020) show that the cumulative effects of such apparently innocuous methodological choices can lead to large changes in the estimates of spending and tax multipliers. We explicitly integrate such uncertainty into our estimates for Austria, entertaining the large number of models which can be obtained by combining such possible methodological choices.

Table 1: Modelling choices for the estimation of fiscal multipliers

Dimension	**Variants considered**
Government data composition	Seven variants, see Table 2; ESA2010 codes and time series in the Appendix A
Deflating index	GDP deflator and HICP (not lagged and lagged by 4 quarters)
Model	VAR and FAVAR models with 3–5 vars. (factors ordered first or last)
Identification strategy	Cholesky ordering (only for spending multipliers), Blanchard-Perotti, sign restrictions
Number of factors	1–2 (FAVARs only)
Lags	1–4 lags

Table 1 lists all the methodological choices considered to construct models aimed at estimating fiscal multipliers for Austria. The set of possible variants is obtained by combining choices relating to (i) the data employed, (ii) the model used, and (iii) the particular specification within the model class. As for the data choices, these mainly concern the composition of government spending and revenues, but can also differ in the choice of the price index used to deflate nominal variables (CPI versus GDP deflator). Since a large part of government spending in Austria is linked to the lagged CPI (e.g. pension payments), we additionally consider lagged CPI (four-quarters lag) as a deflator in our analysis. The basic modelling choices in terms of specification structure are related to (a) the use of a simple VAR model versus employing a specification that incorporates unobserved factors, i.e., a FAVAR model, (b) the selection of variables in the (FA)VAR model, and (c) the choice of the identification strategy. Given a model specification, the technical choice relates to the number of lags in the (FA)VAR equation. For each model specification, we bootstrap 4000 multipliers and use the median as our point estimate.[5] The main analysis includes 1175 different specifications that can be obtained by combining all sensible choices, each yielding a (peak and present-value) spending median multiplier. For the estimation of tax multipliers, Cholesky identification is discarded, since it always results in zero impact multiplier, and thus 587 different specifications are used in the analysis.

Table 2 presents the different compositions of government spending and revenues used to obtain fiscal multipliers. Each choice consists of a specific composition of the government spending and government taxes aggregate. The *Baseline* setting ("Core/Tax Tiny") employs a simple composition which contains just three components of spending (compensation of employees, intermediate consumption and gross capital formation) and two components of revenues (taxes on production, imports, income and wealth).[6] The following two combinations adjust the baseline setting by including also social contributions and subsidies as part of the fiscal aggregate (as in Crespo Cuaresma et al., 2011, for instance). To reflect the

[5] In sign restriction identification schemes, the 4000 solutions are the actual draws. Other identification approaches rely on bootstrapping to compute the 4000 draws. The bootstrap employed builds on resampling raw residuals (with replacement) and subsequent refitting of the model. Portmanteau tests for residual autocorrelation suggest that around two thirds of the estimated models do not exhibit significant residual autocorrelation at any sensible lag.

[6] See Appendix A for the ESA2010 codes corresponding to each component.

Table 2: Government spending and revenues composition

Tag	Gov't spending composition	Gov't revenues composition
core/tax tiny (*Baseline*)	Compensation of employees, intermediate consumption, and gross capital formation	Taxes on production, imports, income, and wealth
core/tax small net soc.t.		*Baseline* adjusted for actual social contributions
core/net tax small		*Baseline* adjusted for social contributions and subsidies
corefix+soc.t.kind/tax mid	*Baseline* (gross fixed capital) + transfers in kind	*Baseline* + household social contributions
corefix+soc.t.kind/net tax mid		*Baseline* + household social contributions adjusted for subsidies
corefix+soc.t.kind/net tax large		*Baseline* + household social contributions adjusted for subsidies and transfers
core/net tax all	*Baseline* + acquisitions of assets	*Baseline* + household social contributions adjusted for subsidies and transfers (incl. capital transfers)

Note: We use seven sets of compositions of government spending and revenues. Starting from ”core/tax tiny”, which is the *Baseline* composition (shaded in grey), the other composition sets add extra spending and/or revenue items. These are ordered from narrower to broader sets, comprising different spending and/or revenue items. The corresponding tag is constructed with abbreviations of spending composition separated from abbreviations of revenue composition using a slash ”/” . The term ”core” refers to the *Baseline* spending composition, ”corefix” highlights the use of fixed capital formation. The abbreviations for taxes range from ”tiny”, with only several items, to ”all”, with a broad selection of revenue items. For specific ESA codes for each composition set, see Appendix A.

particularities of the Austrian economy, we also use other composition choices reflecting the importance of transfers in kind, household social contributions, subsidies, and transfers for the country. Deviating from the existing literature, so as to cover the specific case of Austria, we introduce three new data compositions, whose tag starts with ”corefix” in Table 2. The inclusion of social transfers in kind in this government spending aggregate accounts for the fact that social transfers in kind amount to more than 8% of overall government spending in the country. Due to their use to finance large parts of the healthcare and social protection system, changes in the provision of social transfers in kind create important economic spillovers (for example by substituting private expenditure for old-age and long-term care) that should be considered in the analysis. The particular revenue compositions used reflect the importance of household social contributions, subsidies and transfers for overall disposable household income in Austria. Following Muir and Weber (2013), we also entertain models based on government spending aggregates that contain acquisitions of assets and a battery of adjustments regarding social contributions, subsidies, and transfers (including capital transfers).

The Cholesky identification strategy identifies a fiscal shock using a particular ordering based on the contemporaneous responses across shocks. The first and most exogenous variable is assumed to be government spending, followed by GDP, inflation (in VAR models with four and five variables), taxes, and the interest rate (in VAR models with five variables only). Since GDP is ordered before taxes, the impact tax multiplier is zero by construction, so we use the identification strategy based on the Cholesky decomposition exclusively for spending multipliers. The Blanchard-Perotti identification scheme follows Blanchard and Perotti (2002) for VAR models with three variables and Perotti (2004) for specifications with more variables. The output and price elasticities required to carry out the identification procedure

Table 3: Output and price elasticities of spending and tax composition

	Output elasticity	**Price elasticity**
Spending compositions		
core	0	-0.542
corefix+soc.t.kind	0	-0.542
Revenue compositions		
tax tiny	0.832	-0.005
tax small net soc.t.	2.375	1.923
net tax small	2.725	2.355
tax mid	0.721	0.064
net tax mid	1.579	1.127
net tax large	1.750	1.344
net tax all	2.205	1.856

Note: Elasticities are calculated using the fiscal forecasting model by Austrian Fiscal Advisory Council (2014). Compositions in Table 2. For detailed ESA codes for each composition, see Appendix A.

in Blanchard and Perotti (2002) are computed for every net tax and spending composition specification using the fiscal forecasting model of the Austrian Fiscal Advisory Council (see Table 3). The model partitions government revenue and expenditure into around 120 budget items that are corrected for structural breaks and then projected individually (see Austrian Fiscal Advisory Council, 2014). We shock the model in the year 2019 using a 1 % increase in real GDP to obtain estimates of output elasticities and a 1% increase in the price level for price elasticities. The real GDP shock is decomposed into its subcomponents (tax bases) so as to represent an average historical shock in the country. The reaction of the individual budget items is then aggregated to the corresponding compositions (see Table 2 and Appendix A) using the average weights of these items during the period 2000–2019. As a last step, for the case of the output elasticity, we deflate the nominal budget reactions using the rise in inflation induced by the GDP shock. For the price elasticity estimates, we substract one (the size of the original shock) to the percentage reaction in the price level.

Our implementation of sign restrictions identifies three shocks: the business cycle shock is identified by requiring the impulse responses of output and taxes to be positive for at least the four quarters following the shock. The tax shock is identified by a positive response of taxes for at least the four quarters following the shock (and the shock is required not to meet the identifying restrictions for the business cycle shock). For the identification of a government spending shock, the responses of government spending need to be positive for at least the four quarters following the shock (and the shock is required not to meet the identifying restrictions for the business cycle shock).

The identification strategies mentioned above are unable to explicitly address the issue of fiscal foresight. If a fiscal policy change is known before its (official) implementation and economic agents react accordingly, the reaction in the real economy may be apparent earlier. This timing mismatch is known as fiscal foresight and essentially amounts to a limited information problem (Fragetta and Gasteiger, 2014). Forni and Gambetti (2014) suggest to remedy the problem by extending the VAR model with principal components (as estimates of unobservable factors), which are calculated from a broad range of additional time series containing relevant information. We add one or two principal components to the VAR specification with three variables, making the model a proper FAVAR specification. We estimate the principal components with the aid of 26 additional time series that relate to macroeconomic dynamics, financial markets, and the labour market.[7]

Additionally, we add dummy variables to the baseline specification so as to reflect the impact and consequences of the Great Recession on the economic variables used in the models. We add a dummy taking value one for the period 2008Q4–2009Q2 and a step dummy starting from 2009Q1 until the end of the sample.[8]

Data

The main source of data is Eurostat, while some financial variables used for the estimation of the unobserved factors are sourced from the European Central Bank. We use time series of the corresponding disaggregated components of government spending and tax revenues to construct the various fiscal variables required to estimate our models (see Appendix). For extended versions of the VAR model with four and five variables, we also use inflation and the interest rate. The data cover the period span from the first quarter of 2001 to the fourth quarter of 2018, yielding 72 quarterly observations. If available, seasonally adjusted variables are employed. If seasonally adjusted data are unavailable, we use the X-13 toolbox to remove seasonal patters from those variables that contain a seasonal component.[9] All the time series for spending and tax categories, as well as GDP, are obtained from the source in nominal terms and subsequently deflated using the corresponding deflator (see Table 1).[10] The corresponding fiscal variables and GDP enter the (FA)VAR models in logs, while inflation and the interest rate are added to the VAR without further transformation (i.e., in percentage points). The methodological framework employed for the identification of fiscal shocks, which corresponds to the standard specifications used in the modern literature on fiscal multipliers, implies that the variables in the VAR model are assumed to be stationary or trend-stationary (i.e., stationary around deterministic linear trend). All time series used to estimate the factors are transformed to reach stationarity prior to obtaining estimates of the factors.[11]

4 Fiscal Multipliers in Austria: The Role of Forecasting Performance and Specification Choices

The estimated fiscal multipliers for Austria are summarized in Table 4. We make use of out-of-sample predictive accuracy as a validation device of the models used in our exercise. We utilize the last four observations of our GDP series as an out-of-sample period and compute the mean absolute error (MAE) of one-step-ahead GDP predictions for all specifications used to obtain multiplier estimates, after estimating the models using a sample that excludes the out-of-sample observations. The results of this forecasting exercise allow us to refine the inference on Austrian expenditure and tax multipliers by concentrating on the estimates corresponding to the set of models with best predictive ability.

The mean present-value spending multiplier over all models is 0.94 and reduces to 0.87 if we focus on the group of best models according to predictive ability (specifications corresponding to the 40% best models in terms of MAE). Generally, peak spending multipliers are larger than present-value spending

[7] See the Appendix A for the list of the time series used to estimate the factors.

[8] See the Appendix for the results without crisis dummies and with different dummification strategies for the Great Recession period.

[9] We employ the X-13 Toolbox for Seasonal Filtering by Yvan Lengwiler in *Matlab File Exchange*. The default setting lets TRAMO select additive or multiplicative filtering and then decomposes the series into a trend, cycle and seasonal component using X-11, with additive outliers allowed, as well as trading day dummies.

[10] Revenue categories are not available in real terms. In order to investigate the effects of deflating with different price indices while keeping consistency, we choose to source all time series in nominal terms and deflate them with the same deflator.

[11] See the Appendix A for the transformations carried out in each of the time series used to estimate the factors.

Table 4: Fiscal multiplier estimates

Multiplier type	min	16-th p.	mean	median	84-th. p	max
Spending multiplier (present value)	-1.81	0.63	0.94	0.99	1.22	2.43
— best 40%	-1.38	0.52	0.87	0.89	1.21	2.15
Tax multiplier (present value)	-2.30	-1.28	-0.76	-0.82	-0.23	1.92
— best 40%	-2.30	-1.23	-0.76	-0.84	-0.24	1.11
Spending multiplier (peak)	0.25	0.87	1.08	1.06	1.30	2.22
— best 40%	0.25	0.83	1.07	1.03	1.34	1.99
Tax multiplier (peak)	-2.17	-0.90	-0.58	-0.58	-0.19	-0.02
— best 40%	-2.17	-0.90	-0.59	-0.57	-0.22	-0.05

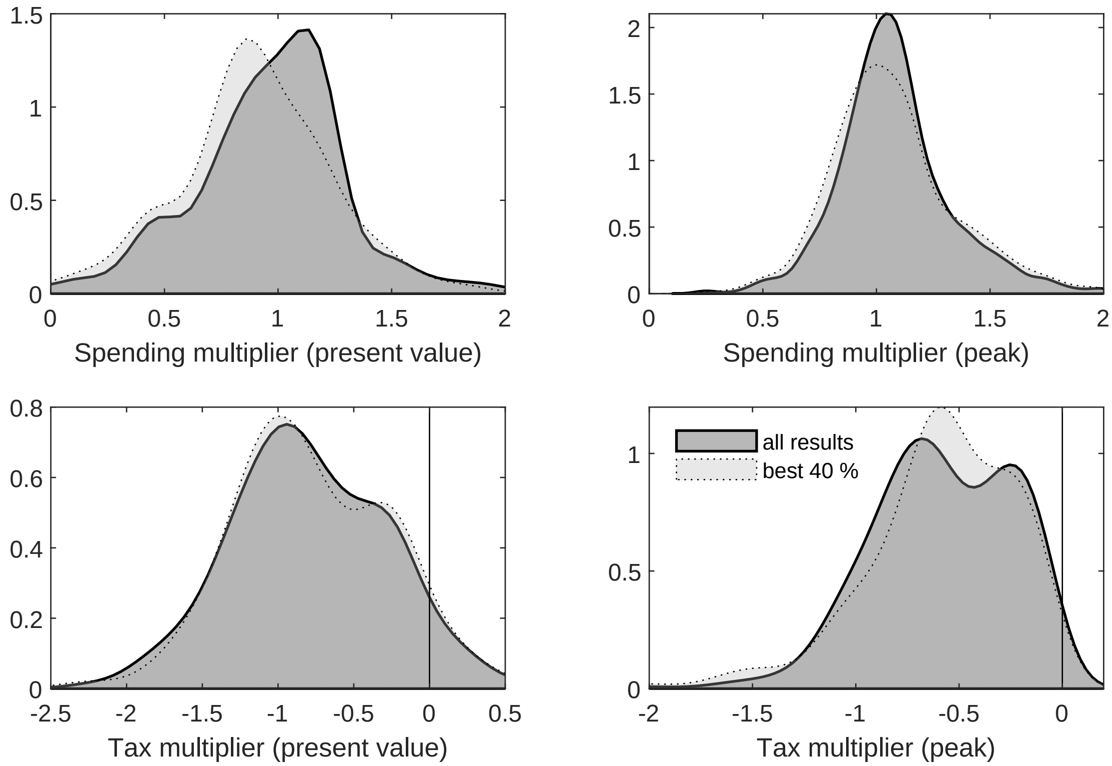
Note: Descriptive statistics of the full set of results based on 1175 spending and 587 tax median multipliers estimates. The group based on the 40% best-forecasting models consists of 465 spending and 236 tax multipliers. See Figure 1 for kernel densities.

multipliers. The mean peak spending multiplier is 1.08 over all models and 1.07 in the group of models with best predictive power. As for the tax multipliers, the value of present-value tax multiplier is -0.76 across all models and also concentrating on the models with particularly good forecasting ability. The mean peak tax multiplier is -0.58 for the whole set of specifications entertained and -0.59 once we concentrate on the models with best forecasting performance. Our findings support the hypothesis that spending multipliers are larger (in absolute value) than tax multipliers. The smoothed densities of the estimated multipliers are presented in Figure 1 for the full sample of fiscal multiplier estimates, as well as for the top 40% models in terms of out-of-sample predictive ability.

With the exception of present-value spending multiplier, comparing the means of the multiplier distributions across all models and focusing on the models with best predictive ability delivers very similar results. However, within certain types of specifications, sizeable differences can be found when zooming into the group of models which have a higher predictive power. The most pronounced differences between variants of the same type of specification are depicted in Figure 2, which shows the empirical densities of present value spending multiplier for the full sample and for subsets based on predictive ability (best 20%, 40%, 60%, and 80% models), split in four panels depending on the number of lags of the (FA)VAR. The (FA)VAR models with one or two lags tend to higher values of the spending multiplier. The first two panels of Figure 2 demonstrate that the modes of the distributions are almost 1.2. In contrast, models with three or four lags results in a distribution of spending multipliers with a mode around 1. However, concentrating on the best specifications according to predictive ability, the distribution of multipliers in the models with one or two lags is concentrated around significantly lower values. The mode of the distribution for models with one lag (first panel) is around 0.9, whereas the mode of the distribution for models with two lags is below 0.8. These findings suggest that although some specifications tend to deliver values of spending multipliers larger than 1, many of these disappear once we focus on models which predict well. The patterns observed in first two panels of Figure 2 help explain the differences between distributions in the first panel of Figure 1.

Table 5 summarizes the share of models with best forecasting performance in the full set of specifications by variable definition. The data composition which tends to improve forecasting performance for GDP data is the composition tagged ”corefix+soc.t.kind/tax mid”, which covers 16.8% of the models in the top 40% specifications by predictive ability. Adjusting the revenue part of this composition by subsidies, social benefits other than social transfers in kind, and other current transfers, is the composition (tagged ”corefix+soc.t.kind/net tax large”) that leads to the relatively worst predictive ability, covering only 9.7% of the models among the top 40%. However, as the results for the last composition in the table (”core/net tax all”) show, broader compositions do not necessarily lead to worse predictive ability.

Figure 1: Fiscal multiplier estimates: kernel densities



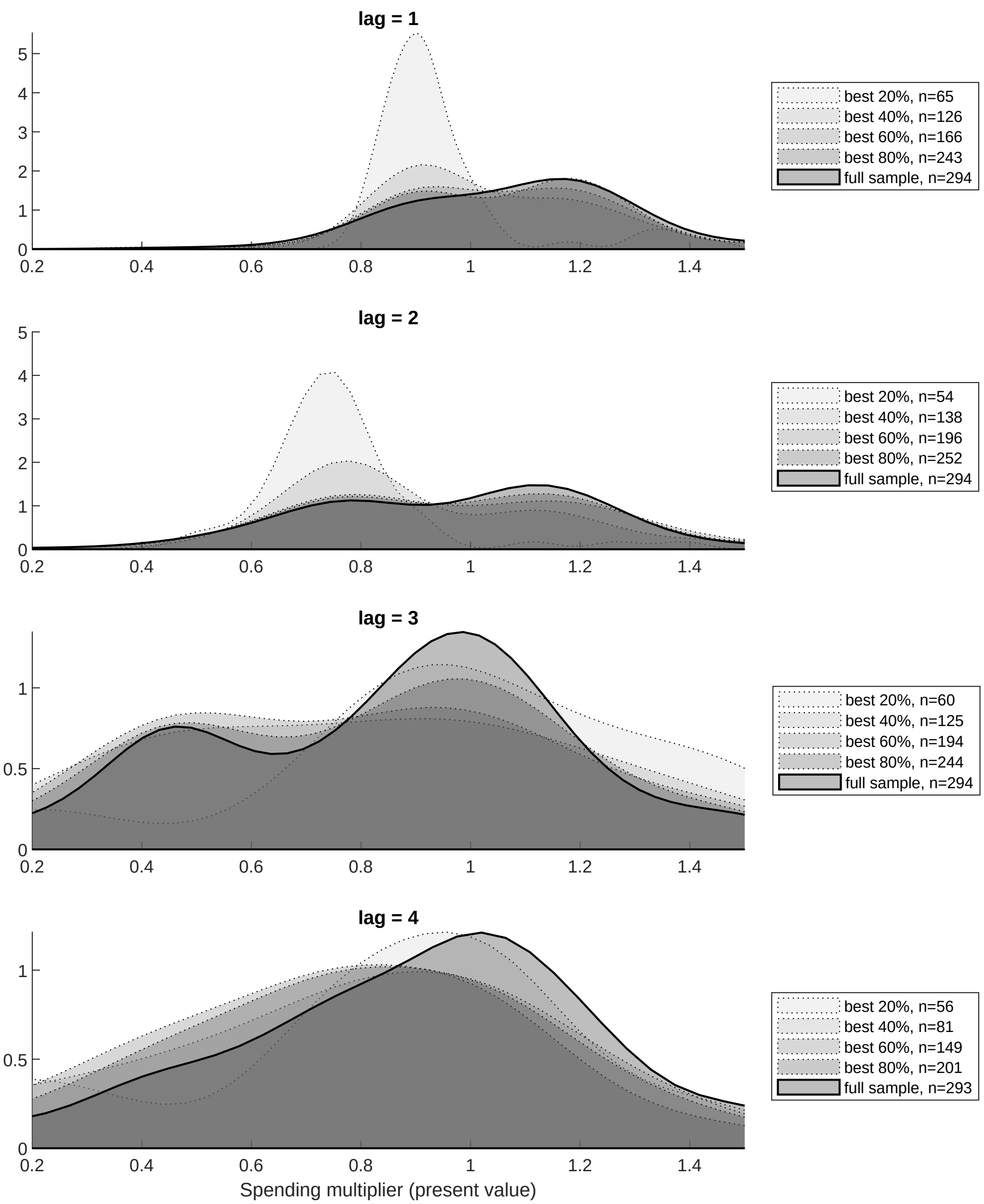
Note: The dark density corresponds to the full set of results, the light density refers to the top 40% best models in terms of predictive ability. See also notes to Table 4.

Data compositions which lead to models featuring particularly good predictive ability are the *Baseline* (”core/tax tiny”), the “corefix+soc.t.kind/tax mid”, and the “core/tax small net soc.t.” variants (see Table 2 for a description of data composition and the Appendix A for ESA codes).

Figure 3 shows multiplier estimates across different sets of government spending and revenue compositions. While most of the empirical densities for spending multipliers are relatively similar, tax multipliers seem to be more sensitive to varying composition of government spending and taxes. For the case of the spending multiplier (see top panels of Figure 3), models using the composition that includes acquisition of assets (“core/net tax all”, inspired by Muir and Weber, 2013) lead to a distribution of multiplier estimates that has a similar mean as that of other data composition choices, but is more spread around the mode. This indicates that adding acquisition of assets as part of spending composition leads to a less precise point estimate of the spending multiplier across models.

Our results further highlight that for tax multipliers, the choice of a particular group of fiscal variables in the model may have a larger effect on multiplier estimates than in the case of spending multipliers. The empirical distributions of some multiplier estimates tend to be rather flat for certain cases, while a composition set including capital transfers “core/net tax all”, delivers more precise peak tax multiplier estimates (albeit relatively low in magnitude). The lower magnitude of tax multiplier is also due to a potentially misleading identification of exogenous shocks, especially for a revenue variable (net taxes) that

Figure 2: Spending multiplier densities based on forecasting performance, split over lags of the (FA)VAR



Note: Kernel densities estimated on subsets of multipliers according to the number of lags in the (FA)VAR equation. The darkest density corresponds to the full set of results, the lighter ones correspond to subsets of models by predictive ability (best 20%, best 40%, best 60%, and best 80%).

Table 5: Data composition and forecasting performance

	Count		Percentage	
	total	**best 40%**	**total**	**best 40%**
core/tax tiny	168	77	14.3	16.6
core/tax small net soc.t.	168	76	14.3	16.3
core/net tax small	168	57	14.3	12.3
corefix+soc.t.kind/tax mid	168	78	14.3	16.8
corefix+soc.t.kind/net tax mid	168	62	14.3	13.2
corefix+soc.t.kind/net tax large	168	45	14.3	9.7
core/net tax all	167	70	14.2	15.1
total	1175	465	100%	100%

Note: **Count** contains numbers of existing specifications across different spending/tax compositions. **Percentage/best 40%** illustrates the relative representation of various spending/tax composition sets among the best 40% specifications. For a graphical representation of all results based on selected compositions, see Figure 3.

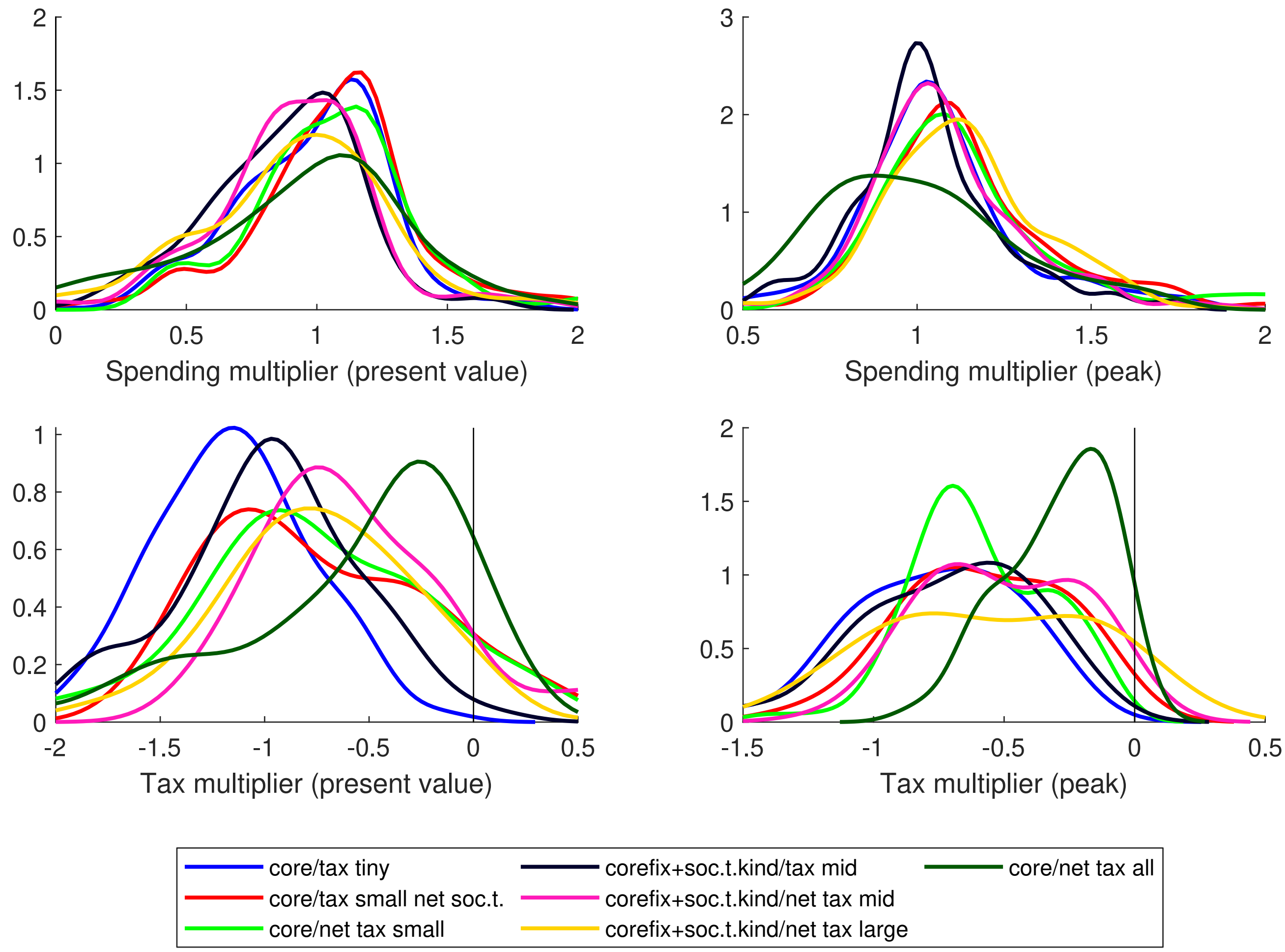
includes capital transfers. In recent years, virtually all of the variation in capital transfers in Austria has been due to sizable banking support programs, which arguably had only mild effects on GDP. This leads to more precise but lower magnitudes of (net) tax multipliers once capital transfers are included, however providing little information on how more common types of taxes affect output. While the “core/net tax all” composition delivers the lowest average magnitude of the estimate of the present value tax multiplier, the Baseline composition “core/tax tiny” delivers the highest one. More inclusive specifications (”tax small net soc.t.” and ”net tax small”) tend to deliver estimates closer to zero, which are estimated with less precision.

Turning to the effects of using different econometric specifications, identification strategies, and number of variables (see Figure 4), on average, models with three variables and a shock identification design based on the Cholesky decomposition tend to result in lower spending multiplier estimates compared to models which employ more variables and different identification schemes. Whereas VAR models with 3 variables or models estimated with Cholesky ordering lead to present value median spending multipliers centered around 0.8, following more modern approaches yield spending multiplier estimates with a median above unity. However, sign restriction and Blanchard-Perotti identification strategies tend to have higher variance around the mean and deliver therefore less precise estimates. For tax multipliers, which do not include estimates based on Cholesky identification, the patterns indicate that those based on the Blanchard-Perotti identification scheme tend to be smaller in magnitude. In the case of present value tax multipliers, the estimates calculated using Blanchard-Perotti identification are less precise and have a higher frequency of outlying values.

5 Conclusions

This paper estimates fiscal multipliers for Austria, a stereotypical advanced small open economy, with a focus on the dimension of model uncertainty that emanates from the choice of a particular econometric model to obtain point estimates of the reaction of GDP to shocks in fiscal variables. We present a comprehensive framework which allows to assess the effects of different multiplier definitions and choices related to the data, the model employed, and further technical choices associated with the specification of the model exert on fiscal multiplier estimates.

Figure 3: Multiplier densities and data composition, based on all results

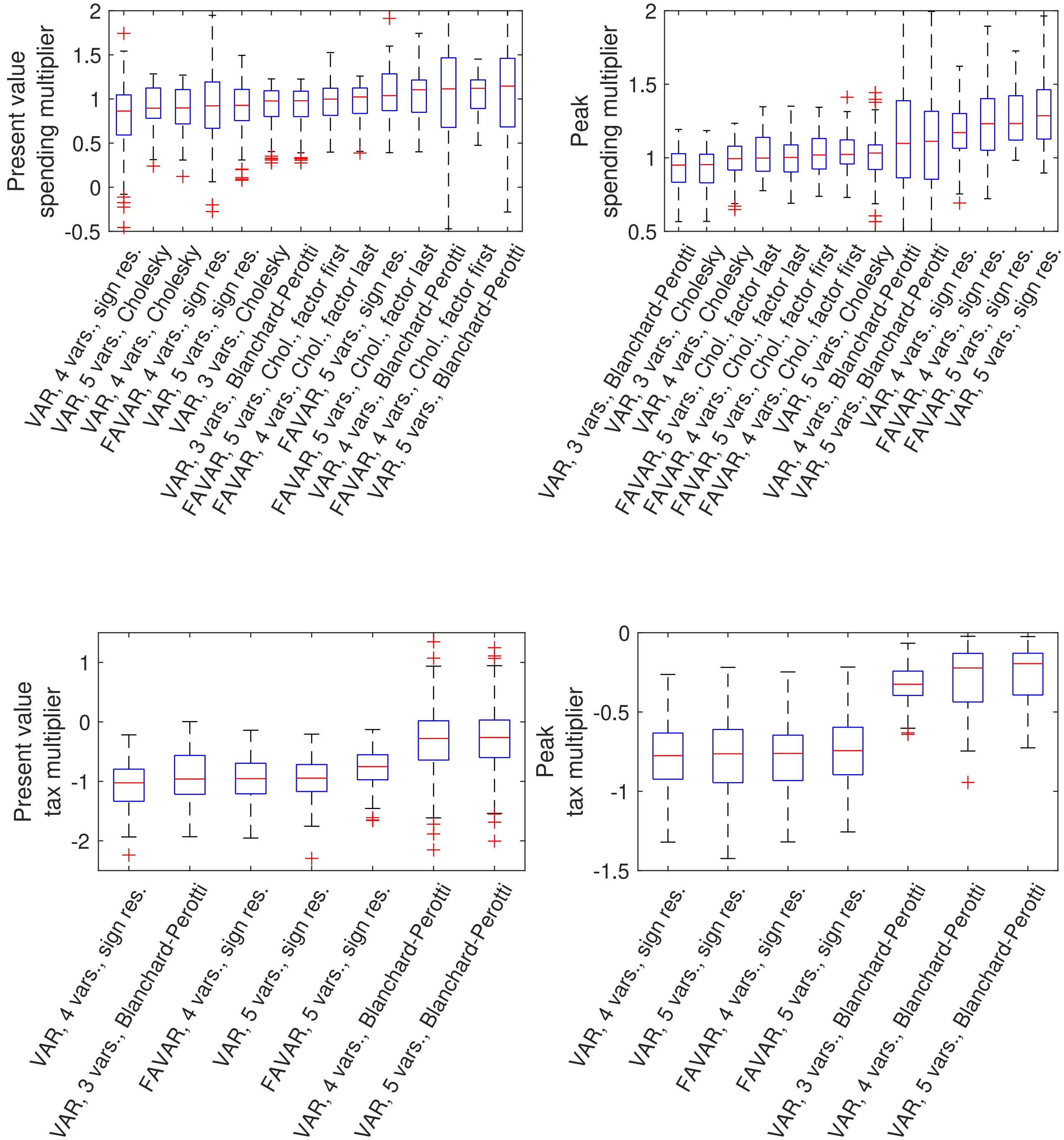


Note: For details on data compositions, see Table 2.

The mean present-value spending multiplier over all models entertained is 0.94 and reduces to 0.87 once we focus on the best models according to out-of-sample predictive ability. Generally, estimates of the peak spending multiplier for Austria tend to be larger than present-value spending multipliers. The mean peak spending multiplier is 1.08 and 1.07 if calculated on the basis of the group of models with best predictive performance. As for the tax multipliers, the mean of the present-value tax multiplier is -0.76, with no effect of selecting models with best predictive ability. The mean peak tax multiplier is -0.58 for all specifications used and -0.59 once we concentrate on the models with the best forecast performance.

Splitting our results based on the number of lags in the (FA)VAR model, our findings suggest that even though some specifications tend to lead to values of spending multiplier larger than unity, many of these are discarded once we focus on models which predict well. Comparable results are found when we focus on forecasting performance and split models over different compositional definitions of government expenditures and taxes. The particular composition that delivers the highest percentage of models that predict well uses compensation of employees, intermediate consumption, gross capital formation, and transfers in kind as part of government expenditures and taxes on production, imports, income, and wealth, and household social contributions.

Figure 4: Fiscal multipliers by model and identification strategy types



Note: Boxplots are sorted by the median multiplier, the central (red) mark of the boxplot. The bottom and top edges of the box indicate the 25th and 75th percentiles.

On average, multipliers obtained from models that require few variables and use Cholesky identification for the structural shocks tend to result in lower estimates of the spending multiplier. On the other hand, using more variables for estimation and employing identification schemes that follow the Blanchard-Perotti approach or sign restrictions deliver higher estimates of spending multipliers. For tax multipliers, Blanchard-Perotti identification delivers estimates of lower magnitude as compared to other specifications.

In line with conclusions in Ramey (2019), we find that the specific method used to obtain multipliers can make a big difference in terms of inference. Given the scarce evidence on multipliers in developed small open economies, the results we present for Austria have a value of their own for policymakers and fiscal authorities.

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