

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 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. The mean present-value government spending multiplier over all models entertained, based on around 3000 estimates, is 0.68. Estimates of the peak spending multiplier for Austria tend to be larger than present-value spending multipliers, with a mean value of 0.85. The magnitude of the present-value tax multiplier is relatively high, with an average value across specifications of -1.12 and the mean peak tax multiplier is -0.54 for all specifications used. In absolute value, multiplier estimates tend to be larger if they are estimated using the subset of models with the best out-of-sample predictive ability.

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 the GDP as a result of a one dollar fiscal stimulus. Fiscal multipliers are easily comparable across time and countries and the precision of their estimation contributes significantly to the quality of GDP growth predictions (Blanchard and Leigh, 2013). In addition, 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 Capek and Crespo Cuaresma (2018).

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 SVAR methodology to estimate spending multiplier 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). Apart from articles publishing results for single countries, there is also evidence from panel studies. 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 Koch and Reiter (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 does not exist at the moment.

Based on the broad methodological choice, the main bulk of the existing literature on the 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 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 structural vector-autoregressive (SVAR) models tend to be more data-driven and typically impose less stringent restrictions on the economic model. The availability of long time series, which can be obtained for the US, for instance, allow for the use of modern identification methods such as the so-called 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, coun-

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

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

tries are often pooled and the empirical analysis is conducted on a panel setting (Beetsma and Giuiliodori, 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-analyses provided by Gechert, 2015; Capek and Crespo Cuaresma, 2018). These differences can be attributed to various identification strategies (Caldara and Kamps, 2017) as well as to other technical choices made in the analysis (Capek and Crespo Cuaresma, 2018). 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 made in the analysis. The framework delivers thousands of multiplier estimates, each for a particular model specification. When it comes to using these multiplier estimates for policy, not all specifications are equally interesting for the researcher, so we exploit the 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 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.

The mean spending multiplier for Austria is estimated at 0.68 for the present-value multiplier and 0.85 for the peak multiplier. The present-value tax multiplier is -1.12 and its peak counterpart is -0.54. 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 larger in magnitude. 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, and gross capital formation as part of government expenditures and taxes on production, imports, income, and wealth. On average, SVAR models of a smaller dimension and using the Cholesky decomposition as an identification device tends 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. Similar patterns hold for peak tax multipliers, although the differences are smaller. These observations are in line with general results from Capek and Crespo Cuaresma (2018) based on a much larger number of specifications for all European countries. We also find evidence corroborating a conclusion in Ramey (2019) that the specific definition of the multiplier used may lead to significantly different estimates. After carrying out several sensitivity checks, we find that peak multipliers for Austria tend to appear more stable than their present-value counterparts.

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

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, the structural FAVAR can be written as

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

$$\begin{pmatrix} \tilde{F}_t \\ F_t \end{pmatrix}_{\substack{n \times 1 \\ r \times 1}} = \begin{pmatrix} \mathbf{I} \\ \mathbf{0} \end{pmatrix}_{\substack{(n+q) \times (n+q) \\ (r-q) \times (n+q)}} \eta_t_{(n+q) \times 1} \quad (2)$$

$$\begin{pmatrix} \mathbf{A} \\ \mathbf{B} \end{pmatrix}_{\substack{(n+q) \times (n+q) \\ (n+q) \times (n+q)}} \eta_t_{(n+q) \times 1} = \begin{pmatrix} \mathbf{B} \\ \mathbf{A} \end{pmatrix}_{\substack{(n+q) \times (n+q) \\ (n+q) \times (n+q)}} \varepsilon_t_{(n+q) \times 1} \quad (3)$$

where equation (1) is the measurement equation, (2) is the transition equation, and (3) is the identification equation, while the (matrix) lag polynomial $\Phi(L)$ is given by $\Phi(L) = \mathbf{I} - \Phi_1 L - \dots - \Phi_p L^p$ for matrices Φ_l , $l = 1, \dots, p$. 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) that relate to other macroeconomic and financial covariates, 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 \(2004\)](#). The unobserved factors F_t of the model 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 a recursive 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 :

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

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 (4) with taxes.

The approach that concentrates on the non-discounted reaction of GDP draws also attention in the literature and 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](#)):

$$\text{peak spending multiplier} = \frac{\max_{t=0,\dots,H} \{y_t\}}{\max_{t=0,\dots,H} \{g_t\}} \frac{1}{g/y}, \quad (5)$$

In order to respect 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 by setting $H = 8$.

3 Model Specifications and Data

Specification choices

As reported in [Capek and Crespo Cuaresma \(2018\)](#), in the context of estimating multipliers using SVAR specifications many seemingly harmless modelling choices 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 use of particular interest rates or inflation measures in the model, or whether data are smoothed prior to estimation. On the sample of European countries, the cumulative effects of such arguably innocuous methodological choices can lead to large changes in the spending multipliers. We explicitly integrate such uncertainty into our estimated 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	9 variants; see Table 2, ESA2010 codes and time series in the Appendix
Deflating index	GDP deflator and HICP (not lagged and lagged by 4q)
Model	VAR and FAVAR models with 3–5 vars. (factors incl./excl., ordered first or last)
Identification strategy	Cholesky ordering, Blanchard-Perotti, sign restrictions
Number of factors	1–2 (FAVARs only)
Deterministics and lags	Constant or linear trend, 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 details related to the specification of the model. As

⁴The discounting does not play major role in case of moderate interest rates, while it becomes more important in changing the results in emerging economies with high interest rate. The selection of a four percent interest rate corresponds to a commonly used discount factor of 0.99 per period.

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). The modelling choices refer to the use of a simple VAR model or including unobserved factors, which makes the model a FAVAR model, the selection of number of variables in the (FA)VAR model, and the choice of the identification strategy. The technical choices relate to the number of deterministic terms in the (FA)VAR equation and the number of lags. For each model specification, we bootstrap 4000 multipliers and use the median as our point estimate.⁵ The main analysis includes 2987 different specifications that can be obtained by combining the choices at hand, each yielding a (peak and present-value) spending and a tax median multiplier.

Table 2: Government spending and revenues composition

Tag	Gov't spending composition	Gov't revenues composition
core/tax tiny		Taxes on production, imports, income, and wealth
core/tax small net soc.t.	Compensation of employees, intermediate consumption, and gross capital formation	Baseline adjusted for actual social contributions
core/net tax small		Baseline adjusted for social contributions and subsidies
core+m.soc.t./net tax small	Baseline + social benefits	
corefix+soc.t.kind/tax mid		Baseline + household social contributions
corefix+soc.t.kind/net tax mid	Baseline (gross fixed capital) + transfers in kind	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)
top down spend./top down rev.	Total expenditures - subsidies and various transfers	Total revenues - subsidies, transfers, and various transfers

Note: For specific ESA codes, see the Appendix.

Table 2 presents the compositions of government spending and revenues employed to obtain fiscal multipliers. Each choice consists of specific composition of the government spending and government taxes aggregate. The *baseline* setting (“Core/Tax Tiny”) starts from very 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 three combinations adjust the baseline setting by including also social contributions, benefits, and subsidies as part of the fiscal aggregate (as in Crespo Cuaresma et al., 2011, , for instance). Other compositional choices include transfers in kind, household social contributions, subsidies, and transfers, reflecting the fiscal policy sensitivity of these categories. Fiscal policy changes can address and influence these categories in manifold ways. Following Muir and Weber (2013), we also entertain models based on government spending aggregates that contain acquisitions of assets and a bat-

⁵In sign restriction identification schemes, the 4000 solutions are the actual draws. Other identification approaches rely on bootstrapping to compute the 4000 draws.

⁶See the Appendix for the ESA2010 codes corresponding to the different components.

tery of adjustments regarding social contributions, subsidies, and transfers (including capital transfers). These spending and tax aggregate compositions follow a bottom-up approach and are created by adding together the particular parts of spending and revenues that are relevant for the estimation of the fiscal shock. The last compositional choice considered (“Top Down Spend./Top Down Rev.”) takes a top-down approach by starting from the full aggregates of total spending and total revenues and subtracting the parts that are not relevant for the estimation of the fiscal shock.

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 4 and 5 variables), taxes, and the interest rate (in VAR models with 5 variables only). The “Blanchard-Perotti” identification scheme follows [Blanchard and Perotti \(2002\)](#) for VAR models with 3 variables and [Perotti \(2004\)](#) for specifications with more variables. The specific elasticities are calculated following [Burriel et al. \(2010\)](#), with the use of data in [Mourre et al. \(2014\)](#) and [Price et al. \(2014\)](#). The output and price elasticities of government revenue are taken to be 1.66 and 0.78, respectively. The price elasticity of spending is assumed to be -0.5 (in line with the literature, e.g. [Crespo Cuaresma et al., 2011](#)). 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).

To address fiscal foresight (or the limited information problem) as discussed in [Fragetta and Gasteiger \(2014\)](#), we follow the procedure of [Forni and Gambetti \(2014\)](#) and add one or two unobserved factors to the VAR specification with three variables, making the model a FAVAR. For the estimation of the FAVAR model, we estimate the factors with the aid of 26 additional time series that relate to macroeconomic dynamics, financial markets and the labour market.⁷

Data

The main source of data is Eurostat, while some financial data used for the estimation of the unobserved factors are sourced from the European Central Bank. We use 30 disaggregated time series to construct the various government spending and revenue aggregates required to estimate our models. For extended versions of VAR model with four and five variables, we also use inflation and the interest rate. The data cover the period spanned from the first quarter of 2001 to the fourth quarter of 2018, yielding 72 quarterly observations. If available, seasonally adjusted variables are employed. When seasonally adjusted data are unavailable, we use the X11 seasonal adjustment method to remove seasonal patterns from those datasets that contained seasonality. 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). All time series used to estimate the factors were transformed to reach stationarity beforehand.⁸

⁷See Table A.1 in the Appendix for the list of the time series used to estimate the factors.

⁸See the Table A.1 in the Appendix for the transformations carried out in each of the time series.

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

We make use of out-of-sample predictive accuracy as a validation device of the models used in our exercise. We use 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. 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 estimated fiscal multipliers for Austria are summarized in Table 3. The mean present-value spending multiplier over all models is 0.68 and increases to 0.79 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 multipliers. The mean peak spending multiplier is 0.85 and reaches 0.90 in the group of models with best predictive power. As for the tax multipliers, the magnitude of present-value tax multiplier is quite high in absolute value at -1.12 and gets even larger when concentrating on the models with particularly good forecasting ability. The mean peak tax multiplier is -0.54 for the whole set of specifications entertained and -0.68 once we concentrate on the models with best forecasting performance. The smoothed densities of the estimated multipliers are presented in Figure ?? for the full sample of fiscal multiplier estimates, as well as for the top 40% models in terms of out-of-sample predictive ability.

Table 3: Fiscal multiplier estimates

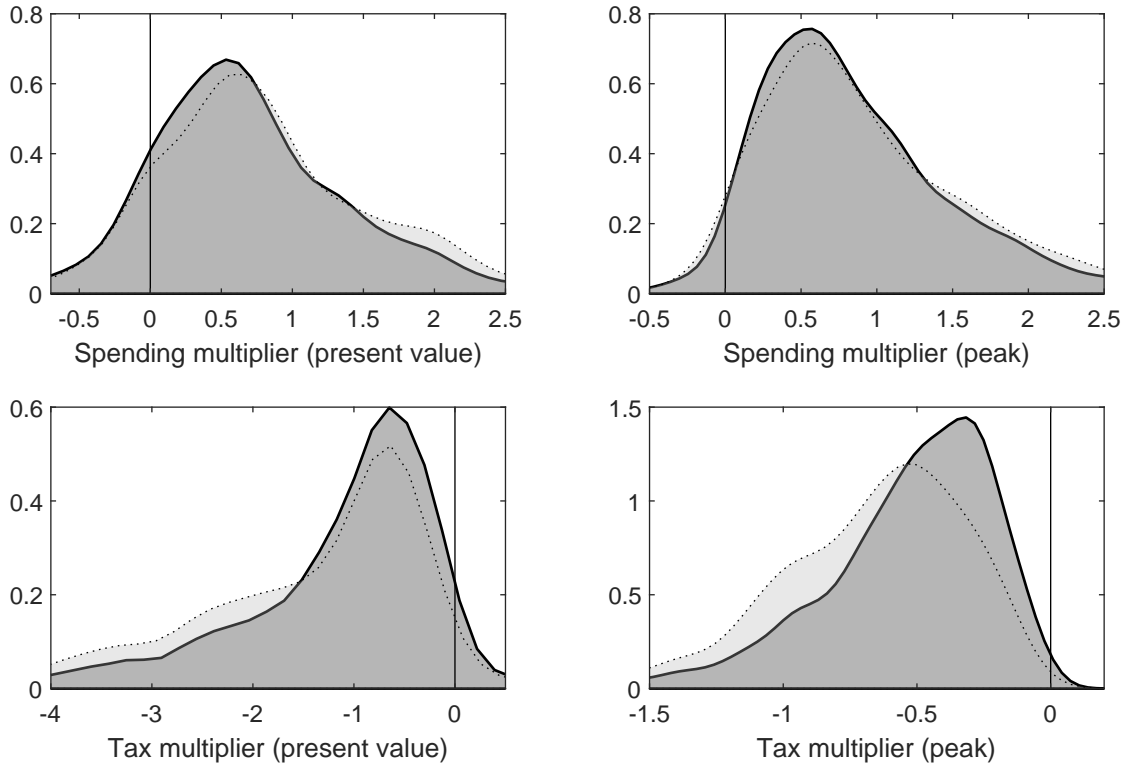
Multiplier type	min	16-th p.	mean	median	84-th. p	max
Spending multiplier (present value)	-4.52	0.05	0.68	0.60	1.39	3.39
— best 40%	-4.52	0.07	0.79	0.69	1.60	3.39
Tax multiplier (present value)	-9.20	-2.15	-1.12	-0.85	-0.28	7.03
— best 40%	-9.20	-2.67	-1.41	-1.06	-0.42	7.03
Spending multiplier (peak)	-1.58	0.27	0.85	0.72	1.47	3.49
— best 40%	-0.74	0.27	0.90	0.77	1.59	3.49
Tax multiplier (peak)	-2.76	-0.85	-0.54	-0.47	-0.24	0.08
— best 40%	-2.76	-1.02	-0.68	-0.61	-0.32	0.08

Note: The descriptive statistics of the full set of results are based on 2987 median multipliers estimates, whereas the group based on the 40% best-forecasting models consists of 1196 multipliers.

Note: Each panel displays kernel densities calculated on subsets of multipliers according to the used deflating index in the (FA)VAR equation. The darkest density corresponds to the full set of results, the light density refers to the top 40% best models in terms of predictive ability.

Across all specifications, focusing on the models with best predictive ability leads to larger multiplier estimates in absolute value. However, within certain types of specifications, sizeable differences can be found when zooming into the group of models with best predictive ability. The most pronounced differences between variants of the same type of specification are depicted in Figure 2, which shows the empirical densities of peak tax multiplier for the full sample and for subsets based on predictive ability (best 20%, 40%, 60%, 80% models), split in three panels depending on the particular deflator used for nominal variables. The first panel shows that within the group of models using the GDP deflator to transform nominal variables into their real counterparts, models with relatively good forecast performance tend to deliver larger tax multipliers, with the mode of the distribution moving from approximately -0.4

Figure 1: Fiscal multiplier estimates: kernel densities



to -0.9. A similar tendency is observed for models using HICP as a deflator, albeit in a less pronounced manner than for the GDP deflator.

For the cumulative spending multiplier, the effects of abstracting away from evaluating models with relatively poor forecasting performance are different in specifications when we use only a constant as a deterministic term in the (FA)VAR equation to specifications in which we also add a time trend, presented in Figure 3. Cutting away 80 percent of worst forecast-performing models leaves 417 (out of 1496) models in case that the time trend is present, but only 182 (out of 1491) models which feature only a constant. In models with only a constant, focusing on the best predictive models shifts the whole distribution towards higher value of the spending multiplier (the mode of the distribution increases from approximately 0.6 to 0.9). For models with constant and trend, the picture is different: The distribution becomes flatter once we focus on multipliers calculated for well-performing models, but the mode remains basically unchanged.

Table 4 summarizes the share of models with best forecasting performance in the full set of specifications by variable definition. The data composition best linked to forecasting performance is the *Baseline* composition, which represents 17% of the models in the top 40% specifications by predictive ability. On the other side of the spectrum is the data composition corresponding to “core/tax small net soc.t.” with a representation of 8.2% in the group of best forecasting models. Since these two settings are quite similar, we can identify the role played by particular components in terms of being responsible for the difference in predictive ability. The government spending is the same in both settings, but on the revenue side, the

use of the “core/tax small net soc.t.” composition, which adjusts the taxes for actual social contributions, leads to a decline in forecasting ability. In case the researcher is interested in fiscal multipliers based on data compositions in models featuring good predictive ability, the Baseline, the “corefix+soc.t.kind/tax mid”, and the “top down spend./top down rev.” variants appear particularly promising (see Table 2 for a description of data composition and the Appendix for ESA codes).

Table 4: Data composition and forecasting performance

	Count		Percentage	
	total	best 40%	total	best 40%
core/tax tiny	327	204	10.9	17.1
core/tax small net soc.t.	330	98	11.0	8.2
core/net tax small	324	100	10.8	8.4
core+m.soc.t./net tax small	336	110	11.2	9.2
corefix+soc.t.kind/tax mid	335	171	11.2	14.3
corefix+soc.t.kind/net tax mid	335	131	11.2	11.0
corefix+soc.t.kind/net tax large	333	94	11.1	7.9
core/net tax all	336	120	11.2	10.0
top down spend./top down rev.	331	168	11.1	14.0

This section reports results for the types of specifications listed in Table 1 that were not addressed by the previous section.

Figure 4 shows the heterogeneity of multiplier estimates across variable definitions. While most of the empirical densities obtained are relatively similar, three variable composition choices differ markedly from the others. In the case of the spending multiplier (see top panels of Figure 4), the “core+m.soc.t./net tax small” composition (inspired by [Crespo Cuaresma et al., 2011](#)) has a similar mode as the remaining data compositions, but a distribution with more mass around the mode, which indicates that adding monetary social transfers as part of spending composition leads to a higher precision of spending multiplier point estimates across models. The sensitivity of spending multiplier estimates to the inclusion of monetary social transfers is a nice example to underline the importance of variable definitions/data composition. In the case of Austria, changes of monetary social transfers (more than 20% of total expenditure) mainly account for changes of pension payments. Despite the fact that pension payments are legally linked to the lagged national price index, VAR models tend to interpret many of the changes in monetary social transfers as exogenous impulses, which is potentially narrowing the distribution of estimates. The second data composition worth discussing is “top down spend./top down rev.” since it tends to shift the distribution of multiplier estimates towards zero. The reason can again be found in the employed data composition of the spending variable. Models that consider such a broad definition of spending tend to result in lower multiplier estimates, since almost all changes in spending are interpreted as exogenous impulses. Besides the ignored endogenous reaction of monetary social transfers already discussed, changes of interest payments (which are part of government spending in this broad variable definition) should also not be treated as exogenous fiscal policy impulses, as governments have only limited power to influence interest payments in the short run. The ignored endogenous reaction of certain spending categories substantially changes multiplier estimates, as indicated by 4. Our results further highlight that for tax multipliers the choice of a particular group of fiscal variables may change estimates even more significantly than in the case of spending multipliers. The empirical distributions of multiplier estimates tends to be rather flat for certain cases, while other variable choices, like e.g. “core/net tax all” (inspired by [Muir and Weber,](#)

2013), featuring rather rich structure of adjustments of government revenues, deliver more precise (albeit relatively low) tax multiplier estimates. The latter is again due to misleading identification of exogenous shocks which is especially the case for a revenue variable (net taxes) that includes capital transfers. In recent years virtually all of the variation in capital transfers in Austria was due to sizable banking support programs, which arguably had only mild effects on GDP. This leads to more precise but lower estimates of (net) tax multipliers once capital transfers are included, however providing little information on how common taxes affect output.

Turning to the effects of using different econometric specifications, identification strategies, and number of variables (see Figure 5), on average, models with three variables and a shock identification design based on the Cholesky decomposition tend to result in lower spending multiplier point 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 median spending multipliers around 0.5, following more modern approaches can yield spending multiplier estimates with a median above unity. Similar patterns hold for peak tax multipliers, but the differences are smaller: models with fewer time series used for model estimation and following Cholesky identification scheme tend to result in a median peak tax multiplier around -0.5, whereas the approach delivering the highest median magnitude (VAR model with 5 variables estimated with sign restrictions) reaches -0.7. As is evident in Figure 4, present-value tax multiplier estimates present a much larger spread than their counterparts based on peak responses.

Varying the output elasticity of taxes used to calibrate the identification schemes based on the Blanchard-Perotti method has negligible effect on spending multipliers, but a notable effect on tax multipliers, especially when calculated as present-value tax multiplier. The effect is larger in VAR models with 3 variables than in VARs with 4 or 5 variables, increasing the output elasticity of taxes from its baseline setting of 1.66 to 2 reduces the present-value tax multiplier by 0.3 in VARs with 3 variables and by 0.1 in VARs with 4 and 5 variables. Varying the price elasticity of taxes, which is only present in VAR models with 4 and 5 variables, causes changes in the estimates in both spending and tax multipliers. Doubling the price elasticity of taxes from the baseline value of 0.78 to 1.5 increases (both the present-value and peak) spending multiplier by approximately 0.3. The effect of the same change on tax multiplier is very different if we focus on present-value or peak tax multiplier. In case of present-value tax multiplier, the change in the price elasticity pushes the multiplier towards unity, whereas the peak multiplier is largely unaffected.⁹

Subsample stability in the estimation of multipliers was assessed by means of discarding one (first or last) observation at a time and re-estimating the multipliers. We thus investigate the possible effects of influential observations at the beginning or the end of the sample on the multiplier estimates. The main result of the analysis is that peak multipliers are much more stable than present-value multipliers. Peak tax multipliers are stable in all checks, but the present-value tax multiplier is sensitive to discarding some initial observations (while leaving the last observations unchanged). Discarding the observations corresponding to 2002 and 2003 from the sample lowers the magnitude of the mean multiplier from -1.12 to -0.97 when 2002 is omitted and further to -0.75 if we eliminate the observations corresponding to 2003. As for the spending multipliers, both types display some variability when changing the estimation sample. Present-value spending multiplier estimates get considerably lower once the first quarter of 2018 is considered in the recursive analysis (we observe a drop in mean present value spending multiplier from 0.96 to 0.64). Peak spending multipliers are subject to similar drop in the same time frame (from 1.02 to 0.85), but the values of the peak multiplier are generally higher than their present-value multiplier counterparts. The peak spending multiplier is rather robust to discarding observations from the beginning of the time frame, whereas the present-value multiplier drops once years 2002 and 2003 are removed

⁹See the Appendix for more detailed results on these robustness checks.

from the sample (from 0.60 to 0.48 to 0.44). Detailed results on the subsample stability exercise can be found in the Appendix.

5 Conclusions

This paper estimates fiscal multipliers for Austria 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.

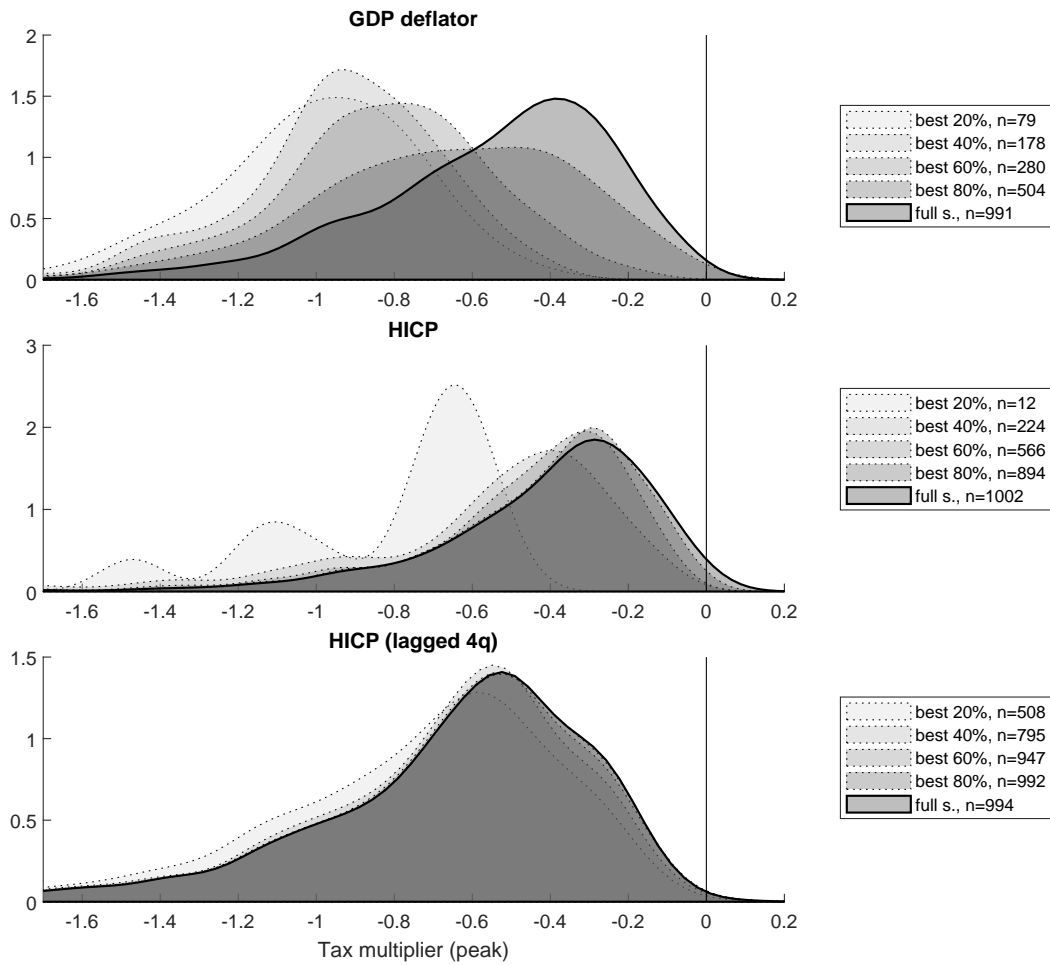
The mean present-value spending multiplier over all models entertained is 0.68, which increases to 0.79 once we focus on the best models according to out-of-sample predictive ability. Generally, estimates of the peak spending multiplier for Austria tend to be larger than present-value spending multipliers. The mean peak spending multiplier is 0.85 and reaches 0.90 if calculated on the basis of the group of models with best predictive performance. As for the tax multipliers, the magnitude of the present-value tax multiplier is relatively high, with an average value across specifications of -1.12 and gets even larger in absolute value when concentrating on the best models in terms of predictive ability. The mean peak tax multiplier is -0.54 for all specifications used and -0.68 once we concentrate on the models with the best forecast performance.

For some multiplier definitions and modelling choices, major differences in estimates are found if we focus on the set of models with best predictive ability. Our results indicate that if the GDP deflator is used to deflate nominal variables, concentrating on best performing models leads to a larger peak tax multiplier in absolute value (the mode of the distribution shifts from approximately -0.4 to -0.9). 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, and gross capital formation as part of government expenditures and taxes on production, imports, income, and wealth.

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 results with rather higher estimates of spending multipliers. Similar patterns hold for peak tax multipliers, but the differences are smaller.

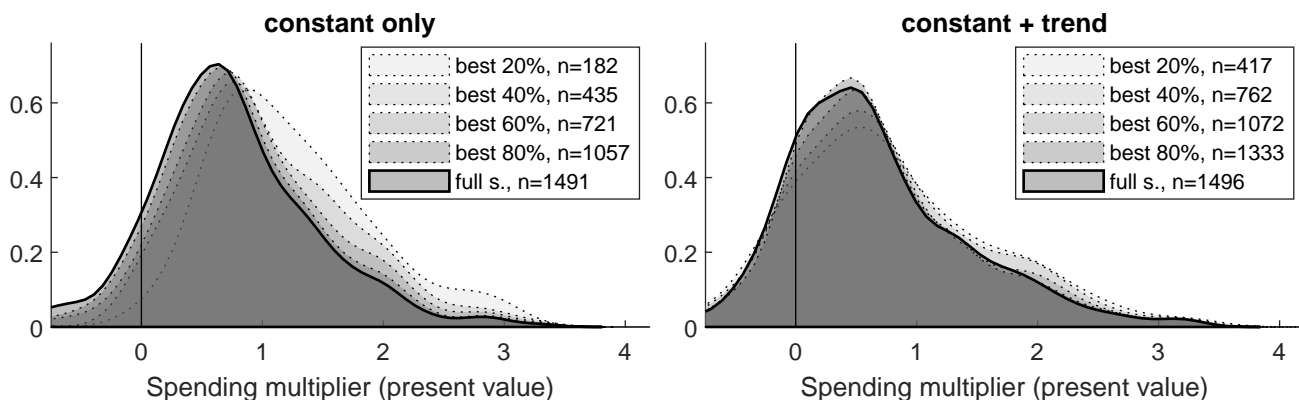
Our analysis provides evidence that in a framework of model uncertainty in terms of the specification used to calculation of fiscal multipliers, concentrating on the subgroup of models that present good forecasting ability can deliver different results than assessing the full set of potential specifications. In line with conclusions in [Ramey \(2019\)](#), we find that the specific way 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.

Figure 2: Tax multiplier densities based on forecasting performance, split over used deflating index



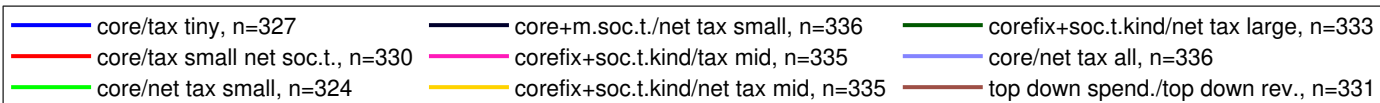
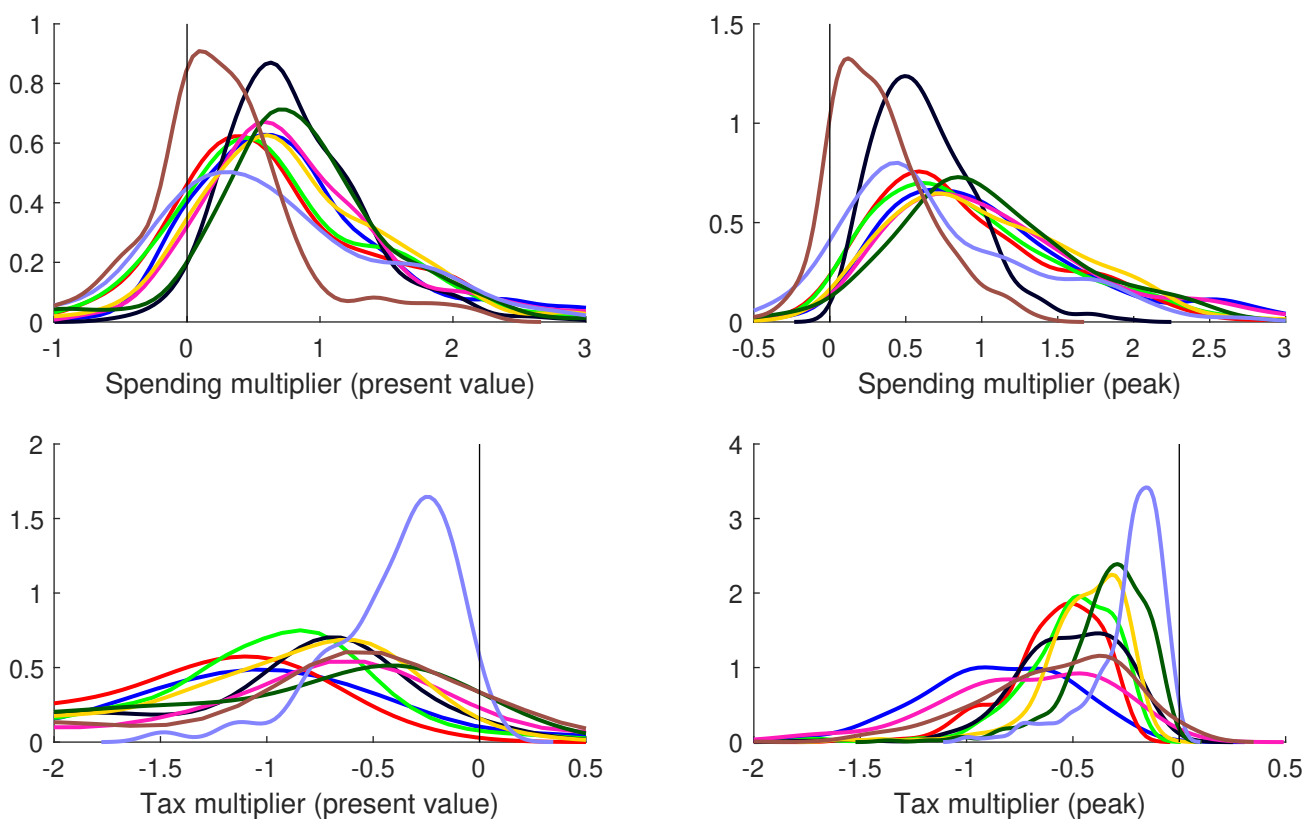
Note: Each panel displays kernel densities calculated on subsets of multipliers according to the used deflating index in the (FA)VAR equation. The darkest density corresponds to the full set of results, the lighter ones correspond to subsets of models by predictive ability (best 20%, best 40%, best 60%, best 80%).

Figure 3: Spending multiplier densities based on forecasting performance, split over used deterministic terms



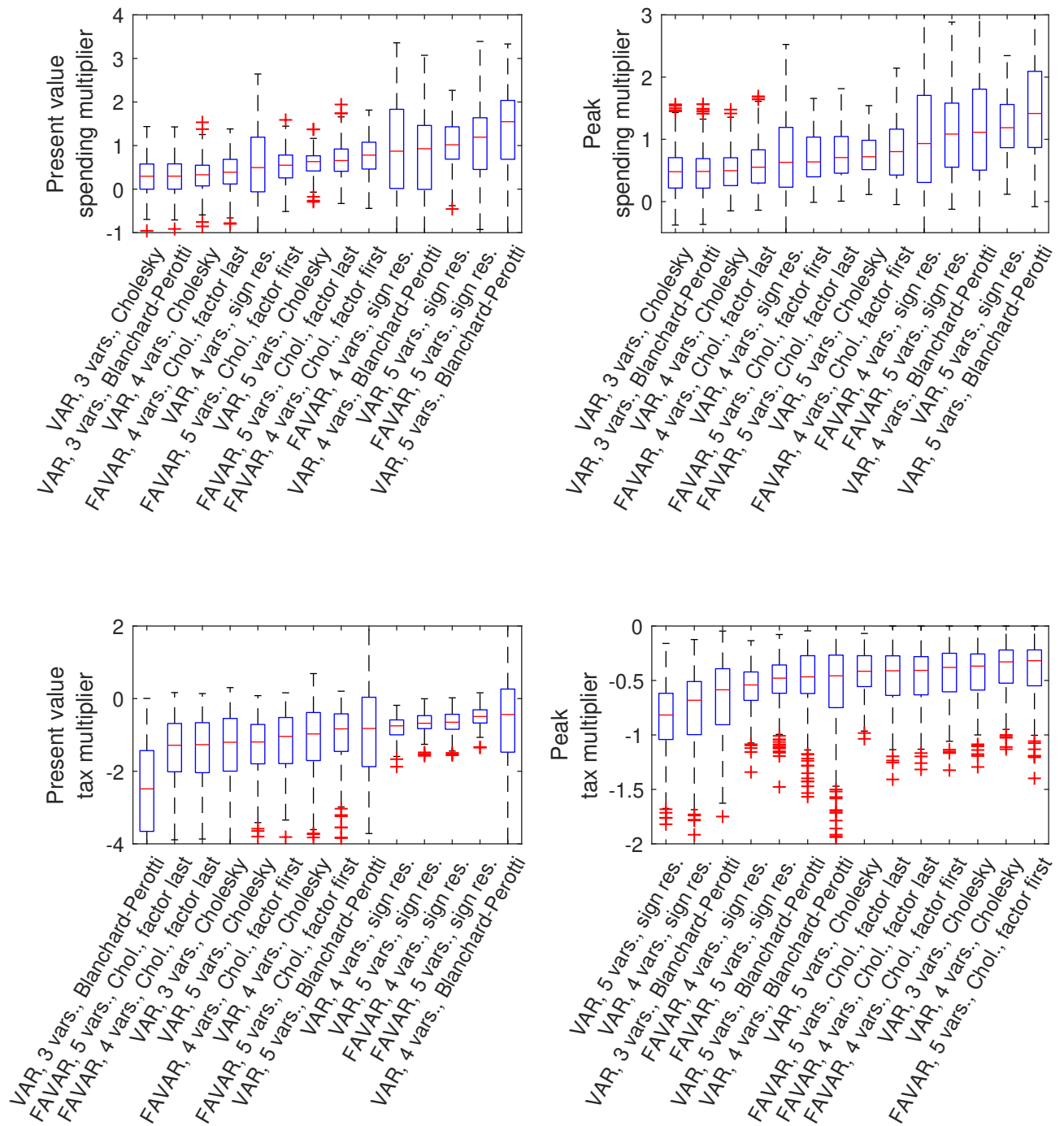
Note: See notes to Figure 2

Figure 4: Multiplier densities and data composition



Note: For the details of the data compositions, see Table 2.

Figure 5: 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.

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Appendix

A Data

Figure A.1: Government spending, deflated by GDP deflator.

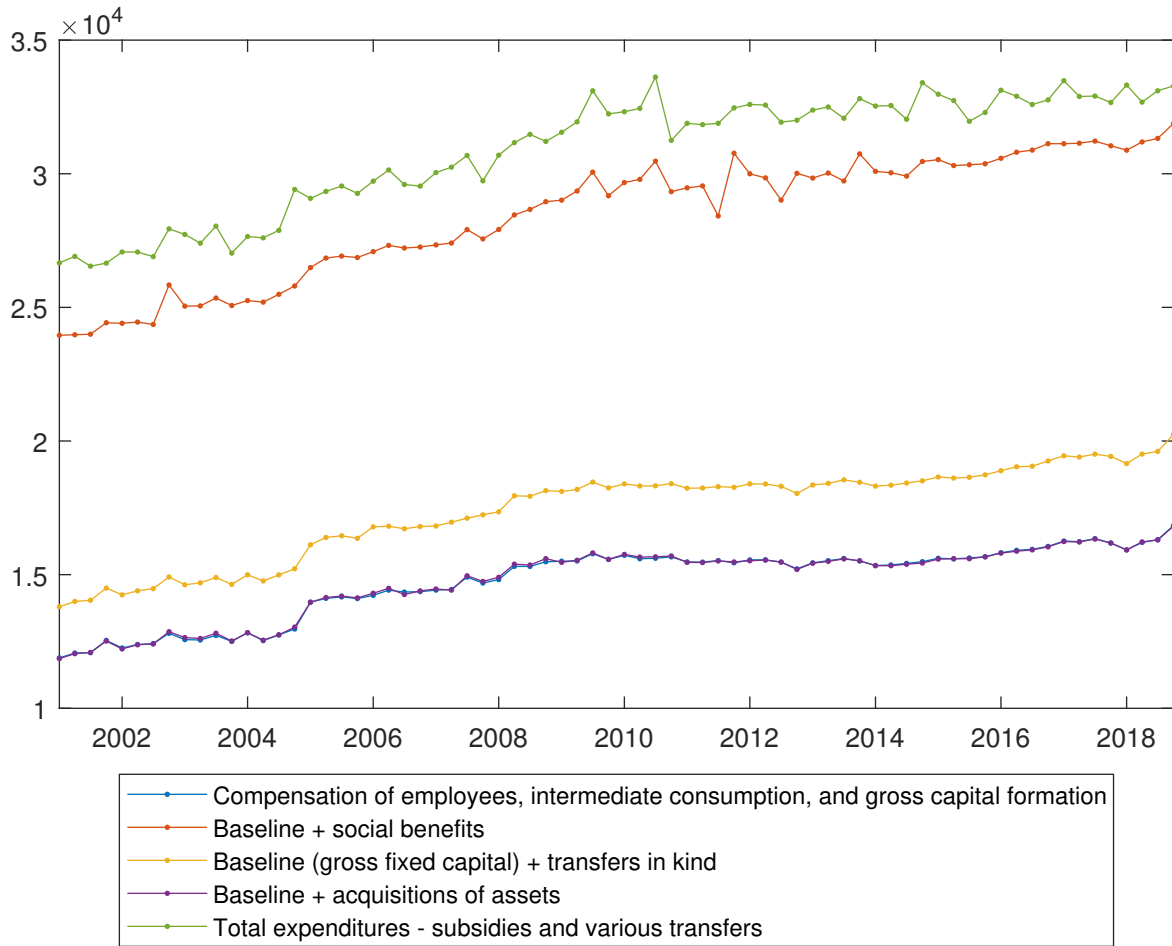


Figure A.2: Government revenue, deflated by GDP deflator.

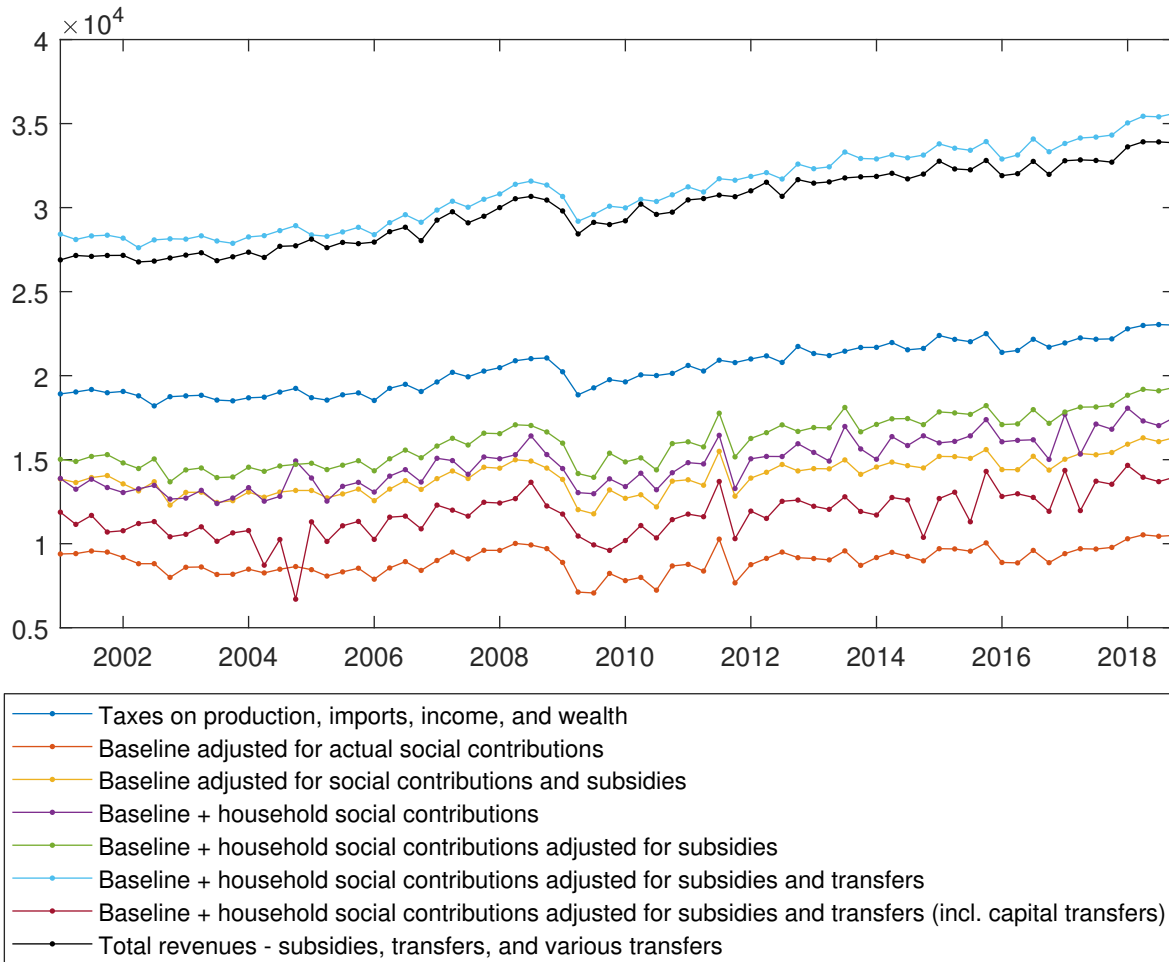


Table A.1: Time series employed for the computation of the factors

Source	Code	Series	Tr.
ECB	BSI,M,N,A,A25,A,1,U6,2250,Z01,E	Domestic credit for consumption (and other) to households (and other), currencies combined, stocks	5
ECB	BSI,Q,N,A,A20,A,1,U6,2000,EUR,E	Domestic loans from MFIs to non-MFIs, Euro	5
ECB	BSI,M,N,A,L60,X,4,Z5,0000,Z01,E	Capital and reserves, unspecified, flows	1
ECB	BSI,M,N,A,A20,A,4,U6,1000,Z01,E	Domestic loans to monetary financial institutions (MFIs), Euro, flows	1
Eurostat	ei_bscq_q/BS-HI-NY,SA,BAL	Home improvements over the next 12 months	2
Eurostat	ei_bsin_q_r2/BS-ICU-PC,SA	Current level of capacity utilization (percent)	5
Eurostat	ei_bsin_q_r2/BS-INO-BAL,SA	New orders in recent months	2
Eurostat	ei_bssi_m_r2/BS-CSMCI-BAL,SA	Consumer confidence indicator	2
Eurostat	ei_bssi_m_r2/BS-ESI-I,SA	Economic sentiment indicator	5
Eurostat	ei_isbr_m/RT12-CA,F_CC1,IS-IP	Production index	2
Eurostat	ert_eff_ic_q/REER_EA19.CPI,I10	Real effective exchange rate (deflator: consumer price index - 19 trading partners - euro area)	5
Eurostat	irt_lt_mcby_q/MCBy	EMU convergence criterion bond yields	2
Eurostat	lfsi_emp_q/THS_PER,T,ACT,Y15-64,SA	Employment - Active population age	5
Eurostat	lfsi_emp_q/ THS_PER,T,EMP_LFS,Y15-64,SA	Total employment (resident population concept - LFS)	5
Eurostat	lfsq_egais/THS,T,Y_GE15,EMP,OC8	Employed persons - Plant and machine operators and assemblers	5
Eurostat	lfsq_egais/THS,T,Y_GE15,EMP,OC5	Employed persons - Service and sales workers	5
Eurostat	lfsq_ewhuis/HR,T,TOTAL,EMP,OC8	Hours worked - Plant and machine operators and assemblers	5
Eurostat	namq_10_gdp/CLV10_MNAC,SCA,P51G	Gross fixed capital formation	5
Eurostat	namq_10_gdp/ CLV10_MNAC,SCA,P31_S14	Final consumption expenditure of households	5
Eurostat	namq_10_gdp/ CLV10_MNAC,SCA,P32_S13	Collective consumption expenditure of general government	5
Eurostat	namq_10_gdp/CLV10_MNAC,SCA,P6	Exports of goods and services	5
Eurostat	namq_10_gdp/CLV10_MNAC,SCA,P7	Imports of goods and services	5
Eurostat	namq_10_gdp/PD10_NAC,SCA,B1GQ	Price index (implicit deflator)	5
Eurostat	nasq_10_f.bs/MIO_NAC,S1,LIAB,F2	Liabilities - Currency and deposits	5
Eurostat	nasq_10_f.bs/MIO_NAC,S1,LIAB,F4	Liabilities - Loans	5
Eurostat	une_rt_q/SA,TOTAL,THS_PER,T	Unemployed	5

Note: Tr. indicates the transformation applied to the series (1 = level, 2 = first difference, 3 = logarithm, 4 = second difference, 5 = first difference of logarithm, 6 = second difference of logarithm).

Table A.2: Government spending and revenue composition

Tag	Gov't spending composition	Gov't revenues composition
core/tax tiny	D1PAY + P2 + P5	D2REC + D5REC
core/tax small net soc.t.	D1PAY + P2 + P5	D2REC + D5REC + D611REC - D62PAY - D632PAY
core/net tax small	D1PAY + P2 + P5	D2REC + D5REC + D61REC - D62PAY - D632PAY - D3PAY
core+m.soc.t./net tax small	D1PAY + P2 + P5 + D62PAY	D2REC + D5REC + D61REC - D62PAY - D632PAY - D3PAY
corefix+soc.t.kind/tax mid	D1PAY + P2 + P51G + D632PAY	D2REC + D5REC + D611REC + D613REC + D91REC
corefix+soc.t.kind/net tax mid	D1PAY + P2 + P51G + D632PAY	D2REC + D5REC + D611REC + D613REC + D91REC - D3PAY - D62PAY
corefix+soc.t.kind/net tax large	D1PAY + P2 + P51G + D632PAY	D2REC + D5REC + D611REC + D613REC + D7REC + D91REC - D3PAY - D62PAY - D7PAY
core/net tax all	D1PAY + P2 + P5 + NP	D2REC + D5REC + D61REC + D7REC + D9REC - D62PAY - D632PAY - D3PAY - D7PAY - D9PAY
top down spend./top down rev.	TE - D3PAY - D632PAY - D7PAY - D9PAY	TR - D39REC - D41REC - D611REC - D7REC - D9REC

Note: Source of data is Eurostat, the codes follow ESA2010 system.

B Subsample stability

Table B.1: Spending (present value) multiplier for different time frames

	min	16-th p.	mean	median	84-th. p	max
01-Jan-2001:01-Oct-2015	-2.94	0.36	1.01	0.92	1.70	4.10
01-Jan-2001:01-Oct-2016	-2.89	0.34	1.04	0.94	1.78	3.84
01-Jan-2001:01-Jan-2017	-2.71	0.35	1.05	0.95	1.79	3.93
01-Jan-2001:01-Apr-2017	-2.74	0.33	1.02	0.93	1.79	3.96
01-Jan-2001:01-Jul-2017	-2.84	0.29	0.99	0.90	1.76	3.88
01-Jan-2001:01-Oct-2017	-3.03	0.27	0.96	0.88	1.70	3.87
01-Jan-2001:01-Jan-2018	-4.42	-0.01	0.64	0.59	1.34	3.35
01-Jan-2001:01-Apr-2018	-4.23	0.04	0.67	0.61	1.37	4.02
01-Jan-2001:01-Jul-2018	-4.49	0.03	0.66	0.59	1.35	3.43
01-Jan-2001:01-Oct-2018	-4.52	0.05	0.68	0.60	1.39	3.39
01-Apr-2001:01-Oct-2018	-4.34	0.02	0.67	0.58	1.41	3.47
01-Jul-2001:01-Oct-2018	-4.56	-0.03	0.65	0.55	1.43	3.85
01-Oct-2001:01-Oct-2018	-4.36	-0.04	0.65	0.56	1.43	4.04
01-Jan-2002:01-Oct-2018	-4.22	-0.04	0.65	0.55	1.44	3.85
01-Apr-2002:01-Oct-2018	-3.88	-0.05	0.64	0.55	1.42	3.97
01-Jul-2002:01-Oct-2018	-3.28	-0.08	0.60	0.52	1.38	4.10
01-Jan-2003:01-Oct-2018	-4.67	-0.21	0.48	0.41	1.22	6.98
01-Jan-2004:01-Oct-2018	-9.98	-0.62	0.44	0.26	1.56	9.92

Note: Beginning-of-period notation, quarterly data (e.g. “01-Jan-2001” denotes the first quarter of 2001).

Table B.2: Spending (peak) multiplier for different time frames

	min	16-th p.	mean	median	84-th. p	max
01-Jan-2001:01-Oct-2015	-0.83	0.51	1.09	0.97	1.69	3.82
01-Jan-2001:01-Oct-2016	-0.79	0.46	1.07	0.94	1.74	3.47
01-Jan-2001:01-Jan-2017	-0.76	0.45	1.08	0.94	1.76	3.57
01-Jan-2001:01-Apr-2017	-1.17	0.44	1.07	0.93	1.75	3.65
01-Jan-2001:01-Jul-2017	-1.34	0.42	1.04	0.91	1.75	3.76
01-Jan-2001:01-Oct-2017	-1.04	0.41	1.02	0.90	1.70	3.81
01-Jan-2001:01-Jan-2018	-1.82	0.26	0.85	0.74	1.47	3.29
01-Jan-2001:01-Apr-2018	-1.67	0.28	0.86	0.75	1.48	3.40
01-Jan-2001:01-Jul-2018	-1.61	0.27	0.85	0.73	1.47	3.46
01-Jan-2001:01-Oct-2018	-1.58	0.27	0.85	0.72	1.47	3.49
01-Apr-2001:01-Oct-2018	-1.62	0.25	0.83	0.70	1.49	3.38
01-Jul-2001:01-Oct-2018	-1.61	0.22	0.83	0.69	1.51	3.44
01-Oct-2001:01-Oct-2018	-1.34	0.21	0.83	0.70	1.50	3.58
01-Jan-2002:01-Oct-2018	-1.36	0.21	0.83	0.69	1.51	3.80
01-Apr-2002:01-Oct-2018	-1.51	0.21	0.82	0.68	1.47	3.80
01-Jul-2002:01-Oct-2018	-1.46	0.18	0.80	0.67	1.45	3.79
01-Jan-2003:01-Oct-2018	-1.80	0.15	0.74	0.61	1.30	4.59
01-Jan-2004:01-Oct-2018	-2.01	0.08	0.77	0.51	1.53	7.56

Note: Beginning-of-period notation, quarterly data (e.g. “01-Jan-2001” denotes the first quarter of 2001).

Table B.3: Tax (present value) multiplier for different time frames

	min	16-th p.	mean	median	84-th. p	max
01-Jan-2001:01-Oct-2015	-8.05	-1.97	-0.99	-0.79	-0.22	9.63
01-Jan-2001:01-Oct-2016	-7.62	-1.96	-1.02	-0.80	-0.25	9.93
01-Jan-2001:01-Jan-2017	-7.86	-1.98	-1.02	-0.80	-0.25	10.86
01-Jan-2001:01-Apr-2017	-8.21	-1.99	-1.05	-0.82	-0.27	9.57
01-Jan-2001:01-Jul-2017	-8.61	-1.97	-1.07	-0.83	-0.28	9.39
01-Jan-2001:01-Oct-2017	-8.76	-1.98	-1.07	-0.84	-0.28	6.07
01-Jan-2001:01-Jan-2018	-9.12	-2.14	-1.12	-0.86	-0.27	7.84
01-Jan-2001:01-Apr-2018	-9.09	-2.10	-1.12	-0.85	-0.28	8.13
01-Jan-2001:01-Jul-2018	-8.92	-2.13	-1.12	-0.86	-0.28	7.94
01-Jan-2001:01-Oct-2018	-9.20	-2.15	-1.12	-0.85	-0.28	7.03
01-Apr-2001:01-Oct-2018	-9.35	-2.35	-1.17	-0.85	-0.24	11.84
01-Jul-2001:01-Oct-2018	-10.54	-2.62	-1.23	-0.85	-0.21	12.96
01-Oct-2001:01-Oct-2018	-11.20	-2.87	-1.23	-0.83	-0.15	11.89
01-Jan-2002:01-Oct-2018	-10.31	-2.96	-1.20	-0.81	-0.10	11.74
01-Apr-2002:01-Oct-2018	-10.02	-2.91	-1.15	-0.79	-0.06	12.33
01-Jul-2002:01-Oct-2018	-10.03	-2.87	-1.12	-0.75	-0.03	11.78
01-Jan-2003:01-Oct-2018	-9.59	-2.69	-0.97	-0.65	0.08	11.95
01-Jan-2004:01-Oct-2018	-8.98	-2.44	-0.75	-0.57	0.21	10.19

Note: Beginning-of-period notation, quarterly data (e.g. “01-Jan-2001” denotes the first quarter of 2001).

Table B.4: Tax (peak) multiplier for different time frames

	min	16-th p.	mean	median	84-th. p	max
01-Jan-2001:01-Oct-2015	-3.08	-0.86	-0.56	-0.50	-0.26	0.17
01-Jan-2001:01-Oct-2016	-3.03	-0.82	-0.52	-0.45	-0.23	0.20
01-Jan-2001:01-Jan-2017	-3.13	-0.83	-0.53	-0.46	-0.23	0.21
01-Jan-2001:01-Apr-2017	-2.94	-0.83	-0.52	-0.46	-0.23	0.20
01-Jan-2001:01-Jul-2017	-2.85	-0.84	-0.53	-0.46	-0.23	0.18
01-Jan-2001:01-Oct-2017	-2.81	-0.84	-0.53	-0.47	-0.23	0.19
01-Jan-2001:01-Jan-2018	-2.72	-0.88	-0.55	-0.48	-0.24	0.10
01-Jan-2001:01-Apr-2018	-2.74	-0.87	-0.55	-0.48	-0.24	0.10
01-Jan-2001:01-Jul-2018	-2.69	-0.86	-0.54	-0.48	-0.24	0.09
01-Jan-2001:01-Oct-2018	-2.76	-0.85	-0.54	-0.47	-0.24	0.08
01-Apr-2001:01-Oct-2018	-2.80	-0.85	-0.54	-0.46	-0.23	0.11
01-Jul-2001:01-Oct-2018	-2.75	-0.87	-0.55	-0.47	-0.23	0.03
01-Oct-2001:01-Oct-2018	-2.94	-0.89	-0.57	-0.48	-0.24	0.00
01-Jan-2002:01-Oct-2018	-2.98	-0.94	-0.58	-0.49	-0.24	0.00
01-Apr-2002:01-Oct-2018	-2.83	-0.93	-0.57	-0.48	-0.23	0.00
01-Jul-2002:01-Oct-2018	-2.79	-0.92	-0.56	-0.47	-0.23	0.00
01-Jan-2003:01-Oct-2018	-2.62	-0.88	-0.54	-0.45	-0.21	0.00
01-Jan-2004:01-Oct-2018	-2.79	-0.89	-0.54	-0.44	-0.21	0.02

Note: Beginning-of-period notation, quarterly data (e.g. “01-Jan-2001” denotes the first quarter of 2001).

C Elasticities variation

Table C.1: The changes in spending (present value) multiplier caused by the changes of the price elasticity of taxes, VAR with 4 and 5 vars.

Elasticity change	<i>n</i>	min	16-th p.	mean	median	84-th. p	max
0.5 → 0.78242	411	-0.72	-0.04	0.13	0.10	0.29	1.43
0.5 → 1	420	-1.02	-0.05	0.26	0.22	0.52	3.78
0.5 → 1.5	419	-1.34	-0.08	0.49	0.43	0.93	5.73
0.78242 → 1	406	-0.35	-0.02	0.11	0.09	0.21	2.35
0.78242 → 1.5	404	-1.03	-0.07	0.33	0.30	0.63	4.91
1 → 1.5	413	-0.68	-0.04	0.22	0.21	0.44	3.59

Table C.2: The changes in tax (present value) multiplier caused by the changes of the output elasticity of taxes, VAR with 3 vars.

Elasticity change	<i>n</i>	min	16-th p.	mean	median	84-th. p	max
0.5 → 1	216	-2.76	-1.05	-0.63	-0.51	-0.24	-0.04
0.5 → 1.6638	216	-5.07	-2.45	-1.36	-1.21	-0.57	12.56
0.5 → 2	216	-5.88	-3.23	-1.53	-1.57	-0.71	15.89
1 → 1.6638	216	-2.67	-1.44	-0.73	-0.71	-0.33	13.94
1 → 2	216	-3.77	-2.06	-0.89	-1.06	-0.51	17.26
1.6638 → 2	216	-1.13	-0.65	-0.17	-0.34	-0.12	14.82

Table C.3: The changes in tax (present value) multiplier caused by the changes of the output elasticity of taxes, VAR with 4 and 5 vars.

Elasticity change	<i>n</i>	min	16-th p.	mean	median	84-th. p	max
0.5 → 1	422	-0.73	-0.41	-0.16	-0.24	-0.03	2.31
0.5 → 1.6638	411	-1.44	-0.88	-0.29	-0.50	0.08	4.59
0.5 → 2	413	-1.75	-1.12	-0.27	-0.58	0.47	5.73
1 → 1.6638	406	-0.83	-0.52	-0.15	-0.26	0.16	3.24
1 → 2	408	-1.21	-0.75	-0.14	-0.33	0.46	5.62
1.6638 → 2	403	-0.52	-0.26	-0.04	-0.08	0.16	1.84

Table C.4: The changes in tax (present value) multiplier caused by the changes of the price elasticity of taxes, VAR with 4 and 5 vars.

Elasticity change	<i>n</i>	min	16-th p.	mean	median	84-th. p	max
0.5 → 0.78242	411	-1.76	-0.03	0.60	0.37	1.25	8.61
0.5 → 1	420	-2.66	0.01	1.13	0.78	2.10	9.17
0.5 → 1.5	419	-3.63	0.05	1.90	1.67	4.12	8.70
0.78242 → 1	406	-0.89	-0.01	0.40	0.34	0.75	3.37
0.78242 → 1.5	404	-1.87	-0.11	1.19	0.97	2.70	7.96
1 → 1.5	413	-1.31	-0.43	0.74	0.52	1.59	6.85

Table C.5: The changes in tax (peak) multiplier caused by the changes of the price elasticity of taxes, VAR with 4 and 5 vars.

Elasticity change	<i>n</i>	min	16-th p.	mean	median	84-th. p	max
0.5 → 0.78242	411	-0.34	-0.04	0.02	0.01	0.08	1.30
0.5 → 1	420	-0.54	-0.06	0.04	0.03	0.14	0.85
0.5 → 1.5	419	-1.19	-0.07	0.11	0.06	0.34	1.75
0.78242 → 1	406	-0.67	-0.02	0.02	0.01	0.07	0.59
0.78242 → 1.5	404	-1.30	-0.04	0.10	0.05	0.27	1.77
1 → 1.5	413	-1.34	-0.04	0.07	0.03	0.20	1.32