

We just estimated twenty million fiscal multipliers*

JAN ČAPEK† and JESÚS CRESPO CUARESMA‡,§,¶,††

†Faculty of Economics and Administration, Masaryk University, Lipová 41a, 602 00 Brno, Czech Republic (e-mail: jan.capek@econ.muni.cz)

‡Department of Economics, Vienna University of Economics and Business, Welthandelsplatz 1, 1020 Vienna, Austria (e-mail: jcrespo@wu.ac.at)

§International Institute of Applied System Analysis (IIASA),

¶Wittgenstein Center for Demography and Global Human Capital (IIASA, VID/OEAW, WU),

††Austrian Institute of Economic Research (WIFO)

Abstract

We analyse the role played by data and specification choices as determinants of the size of the fiscal multipliers obtained using structural vector autoregressive models. The results, based on over twenty million fiscal multipliers estimated for European countries, indicate that 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, or whether data are smoothed prior to estimation. The cumulative effects of such arguably innocuous methodological choices can lead to a change in the spending multipliers of as much as 0.4 points.

I. Introduction

The estimation of fiscal multipliers (the ratio of the change in output to an exogenous change in government spending or taxes) is a central element for the evaluation of the macroeconomic effects of fiscal policy. Fiscal multipliers can be communicated and compared easily across different countries and time periods and the precision of their estimation contributes significantly to the quality of GDP growth predictions (Blanchard and Leigh, 2013). Since the work of Fatás and Mihov (2001) and the seminal contribution by Blanchard and Perotti (2002), empirical estimates of fiscal multipliers tend to rely on vector autoregressive

JEL Classification numbers: E62, C32

*The authors thank the editor, Jonathan Temple, an anonymous referee and participants in research seminars at the Norwegian School of Economics, the University of Innsbruck, the University of Sankt Gallen, the Paris Lodron University of Salzburg, the Bank of Lithuania and ifo Munich, as well as participants in the Austrian Economic Association Meeting 2019 in Graz, the XXI Applied Economics Meeting in Alcalá de Henares and the Slovak Economic Association Meeting 2017 in Košice for helpful comments on an earlier draft of the paper. Financial support from the Czech Science Foundation, Grant 17-14263S, is gratefully acknowledged. Computational resources were provided by the CESNET LM2015042 and the CERIT Scientific Cloud LM2015085, provided under the programme ‘Projects of Large Research, Development, and Innovations Infrastructures’.

(VAR) models, with the current literature still demonstrating a widespread interest in the computation of such measures and the use of credible identification techniques to ensure the exogeneity of fiscal shocks in the framework of the estimation method. While the long time series available for the US allow for the use of narrative methods to identify exogenous shocks (Ramey, 2011) or the assessment of different regimes (Auerbach and Gorodnichenko, 2012), estimates based on shorter time series for European, Latin American, or African countries still rely on less sophisticated methods (Estevão and Samaké, 2013; Muir and Weber, 2013; Petrevski, Bogoev and Tevdovski, 2015).¹ Existing fiscal multiplier estimates (even using the same broad methodology, country, and time period) are notoriously heterogeneous. Some reasons for the differences across estimates have already been addressed in the literature, which has emphasized the role of institutional settings or the asymmetry of fiscal multipliers in different business cycle phases.

Our contribution aims to assess how the size and precision of fiscal multipliers obtained using structural VAR (SVAR) models depend on the different methodological choices that need to be made when specifying them. Rather than working on the results from the existing empirical literature on fiscal multipliers, we obtain the multiplier estimates ourselves, changing the data source and model settings in order to explore the determinants of the size and precision of the estimated multipliers. Using data for European countries, we estimate SVAR models that mimic different settings used in the empirical literature with respect to the particular specification of the model, data transformations and identification strategies. Making use of the estimated SVAR models, we obtain fiscal multipliers and assess how the size and precision of the multipliers depend on the particular characteristics of the modelling framework. Admittedly, the shorter time series available for European countries as compared to the US constrains the choice of modelling tools, but the literature which deals with the estimation of fiscal multipliers has used modelling tools such as those entertained here for countries with even shorter time series. A systematic investigation of the role of methodological choices on the size of fiscal multipliers for SVAR models appears thus justified for countries for which relatively short spans of data are available.²

Gechert (2015) and Rusnák (2011) present meta-analyses of the literature on fiscal multipliers that share some common ground with the research question posed in this piece. These contributions assess, among other aspects, the influence of the identification strategy for structural shocks, the effect of the number of variables in the VAR, the horizon at which the multiplier is reported, and the effect of sample size. However, a systematic analysis of the role played by data composition, data transformations, the methodology of fiscal data collection or the specific formulation of the reduced-form VAR model is absent in the existing literature, either in meta-analysis pieces like Gechert (2015) and Rusnák (2011), or in more systematic empirical approaches like Caldara and Kamps (2008). There are several reasons for the missing evidence. From the meta-analysis perspective, there are so many possible combinations of these characteristics that there are simply not enough studies yet to have been able to cover the variability needed to identify their effects on the

¹ See e.g. Ramey (2016) for a modern review of the methods used for the identification of exogenous fiscal shocks.

² Canova and Pappa (2007), Estevão and Samaké (2013), Muir and Weber (2013), Perotti (2004), and Petrevski *et al.* (2015) are examples of studies reporting fiscal multipliers estimated on time series of 24–56 observations.

estimates of fiscal multipliers. In addition, from the perspective of the practitioner, some of these characteristics are often considered innocuous and do not tend to be reported in the published pieces.

Our results indicate that many seemingly inconsequential choices affect the value of the estimated multipliers as well as the precision with which they are estimated. For example, spending multipliers obtained using HICP to deflate nominal variables (instead of a GDP deflator) and following the European System of National and Regional Accounts (ESA) 95 rather than ESA 2010 tend to be significantly larger (by 0.122 and 0.119, respectively). The results demonstrate that data composition for government spending and government revenue play a role as well, leading to changes in the estimated multiplier by as much as 0.126 for spending in a group of western European countries and 0.189 for tax cut multipliers in a group of eastern European countries. We show that the way data are transformed prior to estimation also affects the size of the multiplier estimates, as well as the choice of identification strategy and the number of variables in the VAR model. Furthermore, the effect of some of these modelling choices appears different in western versus eastern European economies and in spending versus tax multipliers. The inclusion of data corresponding to the financial crisis period also has an effect on fiscal multiplier estimates, with the evidence presented supporting the existence of larger spending multipliers since the beginning of the current decade. In eastern European countries, this increase can be as much as 0.3, whereas the results for western European countries show an increase of 0.2.

Apparently unimportant methodological choices can lead to sizeable differences in multiplier estimates. Changing the source of the data, the deflator and the definition of government revenues and spending, for instance, leads to spending multiplier estimates that differ by 0.4 on average, irrespective of the identification scheme used to extract structural shocks. An implication of our analysis is that, when structural VARs are used to estimate fiscal multipliers, it is important for researchers to document their choices in detail, even for aspects of the research design that may seem innocuous.

The rest of the paper is organized as follows. Section II presents the methodology of the analysis in detail, section III reports the results for the determinants of differences in estimates of the fiscal multipliers and section IV analyses the determinants of differences in their precision. Section V concludes.

II. Estimating fiscal multipliers: The SVAR framework

Ever since the work of Blanchard and Perotti (2002), methodological frameworks that build upon SVAR specifications have become the workhorse for the estimation of fiscal multipliers. Abstracting from further deterministic terms, the estimation of the fiscal multiplier is based on the following reduced-form VAR model,

$$A(L)Y_t = u_t, \quad (1)$$

where Y_t is a K -dimensional vector containing output, fiscal variables and other covariates, $A(L) \equiv I_K - \sum_{j=1}^p A_j L^j$ denotes the autoregressive lag polynomial, where $A_j, j = 1, \dots, p$ are $K \times K$ matrices and u_t is a vector of potentially correlated error terms with a variance-covariance matrix given by $\Sigma_u \equiv E(u_t u_t')$. In order to obtain the fiscal multiplier, we need to recover structural uncorrelated shocks ε_t . Pre-multiplying equation (1) with a convenient

matrix A_0 results in the structural form of the VAR model,

$$B(L)Y_t = B\varepsilon_t, \quad (2)$$

where $B(L) = A_0A(L)$ and

$$A_0u_t = B\varepsilon_t \quad (3)$$

describes the relation between the reduced-form errors u_t and structural disturbances ε_t . With a proper choice of A_0 and B , ε_t has a diagonal covariance matrix Σ_ε and the structural shocks are uncorrelated with one another.

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 through a recursive identification scheme based on lags in the implementation of fiscal policy, while more recent methods (Rubio-Ramírez, Waggoner and Zha, 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 multipliers and tax cut multipliers can be computed. In line with recent literature (e.g. Ilzetzki, Mendoza and Végh, 2013; Gechert and Rannenberg, 2014; Caggiano *et al.*, 2015), we concentrate on discounted cumulative multipliers, defined as

$$m^s = \frac{\sum_{t=0}^T (1+i)^{-t} \Delta y_t}{\sum_{t=0}^T (1+i)^{-t} \Delta g_t}, \quad (4)$$

where i is the (average) interest rate, which we set to 1% per quarter for our computation,³ y_t is output at time t , g_t denotes government expenditures at time t , Δ denotes the deviation from the respective baseline, and T is the horizon at which the multiplier is computed. Unless otherwise stated, the multipliers are reported for $T = 4$ in the context of data at quarterly frequency.⁴ The superscript on m denotes the type of multiplier, m^s being the spending multiplier. Tax cut multipliers m^τ are calculated similarly, only with an increase in (net) taxes $\Delta\tau_t$ in the denominator of equation (4) and a switched sign in the reaction of output, $-\Delta y_t$, in the numerator.

As compared to log-level models, first-differenced VAR specifications are rarely used in the literature on the estimation of fiscal multipliers after the contribution by Blanchard and Perotti (2002) and are not included in our analysis. Blanchard and Perotti (2002) report significant differences between the log-level and first difference settings and aim at accounting for time-varying drift terms by subtracting a changing mean, constructed as the geometric average of past first differences, with a decay parameter equal to 2.5% per quarter. Due to the lack of direct comparability between the standard SVAR models in log levels and the VAR models in first differences after accounting for this particular adjustment, we decided to exclude them from the exercise.

³The interest rate corresponds to 4% *per annum* and means that the corresponding discount factor in the quarterly frequency is 0.99. While we concentrate on discounted cumulative multipliers in our analysis, results for different definitions of the fiscal multiplier for selected countries do not lead to qualitatively different conclusions.

⁴The results for horizons below $T = 4$ are qualitatively similar to those found for the one year horizon, although the effects of data and methodology tend to be weaker, a conclusion that is expected from a theoretical point of view and confirms the results in Gechert (2015).

Fiscal multipliers estimated in SVAR frameworks are the outcome of numerous data, modelling, and methodological choices. These choices can be separated into several categories: (i) the group of macroeconomic variables included in the SVAR model, (ii) the definition of the government spending and tax variables, as well as other macroeconomic covariates, (iii) the existence of data preprocessing related to smoothing of certain variables, (iv) the specification of the VAR model in terms of the inclusion of deterministic terms and the choice of lag length, and (v) the identification strategy for structural shocks. Below we describe the various data transformation and modelling choices used in the existing literature, which will be addressed in our empirical analysis.

Macroeconomic variables in the VAR model

The most used specifications in the empirical literature on the estimation of fiscal multipliers are VAR models with three variables (government expenditures, government revenues, and output), following the model put forward by Blanchard and Perotti (2002), and VAR models with five variables (the former three plus inflation and interest rate) following for instance the work of Perotti (2004). Although some other papers have enriched these basic settings with additional variables, we stick to these variable choices when assessing the effect of covariate choices on fiscal multipliers.

Definition and source of fiscal and other macroeconomic variables

Prior to the estimation of the model, the variables measuring government spending and/or revenues need to be defined based on their expected effect on output. Some contributions in the literature of fiscal multipliers adjust government spending and/or revenue for components that are not under direct control of the government. This adjustment mainly concerns automatic stabilizers such as social transfers but may also involve other components, like interest payments and subsidies. Crespo Cuaresma, Eller and Mehrotra (2011) and Muir and Weber (2013) offer a comprehensive treatment of the construction of fiscal variables for use in SVAR models.

Existing studies based on European countries also differ in the source of the fiscal data. Recent studies tend to use variables based on the European System of Accounts 2010 (ESA 2010), whereas older papers follow the ESA 95 methodology. Similarly, inflation is calculated employing the GDP deflator in some studies, while others compute it based on changes in the harmonized index of consumer prices (HICP). In addition, one finds inflation definitions based on year-on-year changes as well as on quarter-on-quarter rates of change. The maturity used for the interest rate also differs across studies, as does the source employed to retrieve the interest rate data.

Data preprocessing

The standard data source for the macroeconomic variables used in studies about fiscal multipliers in European economies, Eurostat, does not publish seasonally adjusted quarterly government data and only provides nominal values. Authors using these figures to obtain fiscal multipliers typically use seasonal adjustment procedures based on the TRAMO/

SEATS or X11 methods prior to the analysis. However, some studies also apply data smoothing with moving averages for seasonal adjustment (Klyviene and Karmelavičius, 2012) or for reasons related to the potential existence of outliers (Crespo Cuaresma *et al.*, 2011). Depending on the study, the published nominal data are deflated using a GDP deflator or a consumer price index.

Specification of the VAR model: deterministic terms and lag length

The specific form of the model given by equation (1) which is actually estimated varies across studies when it comes to the deterministic terms and lag length. While some models use deterministic linear time trends in addition to the intercept, others stick to a basic specification with the intercept term only. Furthermore, some studies add dummy variables that control for specific time periods of non-systematic behaviour like military buildup periods or for selling Universal Mobile Telecommunications System licenses. Due to the large number of estimated models, we use an automated approach to outlier detection to assign dummies. In particular, the time series of government spending and taxes are checked for outliers using seven different tests.⁵ If five or more tests identify an outlier, a dummy that identifies it is added as a deterministic term to equation (1) when specifying it. In our analysis, since the frequency of the data is quarterly, the lag length of the VAR model is allowed to be one to four lags.

Identification strategy for structural shocks

The bulk of the literature on the estimation of fiscal responses based on SVAR models relies on three identification strategies to retrieve structural shocks: (i) recursive identification based on the Cholesky decomposition of the variance–covariance matrix of the reduced-form VAR shocks Σ_u , (ii) imposing restrictions on the A_0 and B matrices in equation (3) based on the elasticities of government purchases and taxes to output, in the spirit of Blanchard and Perotti (2002) (BP) and (iii) identification based on sign restrictions.

In shock identification designs based on recursive schemes, the order in which the variables enter the VAR model is the only aspect that matters to identify the shocks. The shock ordered first is assumed not to react contemporaneously to any other shocks in the system. The second shock reacts only to the first shock, while the last shock reacts contemporaneously to all shocks in the system. For a standard 3-variable VAR model, equation (3) takes the form

$$\begin{bmatrix} 1 & 0 & 0 \\ -\alpha_{yg} & 1 & 0 \\ -\alpha_{\tau g} & -\alpha_{\tau y} & 1 \end{bmatrix} \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^\tau \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^g \\ \varepsilon_t^y \\ \varepsilon_t^\tau \end{bmatrix}, \quad (5)$$

where g denotes government expenditures, y output, and τ taxes. Therefore, for the case of recursive identification, $B = I$ and A_0 is a lower triangular matrix. Consequently, A_0^{-1} is also lower triangular, which implies that the Cholesky decomposition of the variance-

⁵The tests are based on the adjusted boxplot (Brys, Hubert and Rousseeuw, 2005), Grubbs' procedure (Grubbs, 1969), the moving window filtering algorithm (Brownlees and Gallo, 2006), the generalized ESD procedure, the modified Z-score method, and the interquartile range test (see Iglewicz and Hoaglin, 1993, for the last three methods).

covariance matrix Σ_u can be used for identification. Solving equation (3) for u_t , substituting to $\Sigma_u = E(u_t u_t')$, and setting $B = I$ results in

$$\Sigma_u = A_0^{-1} \Sigma_\varepsilon (A_0^{-1})'. \quad (6)$$

The Cholesky decomposition of the variance-covariance matrix of the reduced-form residuals $\Sigma_u = PP'$ yields a lower triangular matrix P . If Σ_ε is not normalized, its Cholesky decomposition $\Sigma_\varepsilon = DD'$ provides the diagonal matrix D with the standard deviations of the structural shocks on the main diagonal. Following these two decompositions, $P = A_0^{-1}D$, which implies that A_0^{-1} is known once we account for (possible) non-unit standard deviations of the structural shocks stored in D .

The structural identification approach introduced in Blanchard and Perotti (2002) has been extremely influential in the modern literature on fiscal multipliers. It relies on institutional information about tax and transfer systems and about the timing of tax collections in order to identify the structural shocks ε_t . Sticking to the example of a 3-variable VAR, equation (3) takes the form

$$\begin{bmatrix} 1 & 0 & 0 \\ -\alpha_{yg} & 1 & -\alpha_{y\tau} \\ 0 & -1.85 & 1 \end{bmatrix} \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^\tau \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \beta_{\tau g} & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^g \\ \varepsilon_t^y \\ \varepsilon_t^\tau \end{bmatrix}, \quad (7)$$

where the specific output elasticity of government revenue ($\alpha_{\tau y} = 1.85$) is adopted from Perotti (2004). In a 5-variable setting that includes inflation and the interest rate as additional variables, other elasticity values need to be fixed in order for the system (7) to be identified. Several variations of elasticity values found in Caldara and Kamps (2008) and Crespo Cuaresma *et al.* (2011) are used in the empirical analysis presented below. Generally, in the Blanchard and Perotti (2002) approach, A_0 is not lower triangular and B is not an identity matrix. In the typical setting, the concentrated log-likelihood corresponding to the VAR model can be maximized with respect to the free parameters in A_0 and B , yielding the estimates of these matrices.⁶

The sign restriction approach imposes conditions directly on the shape of the impulse response functions corresponding to the VAR model. Mountford and Uhlig (2009) and Caldara and Kamps (2008) propose restrictions that imply that business cycle shocks are identified by the positive reaction of both taxes and output, tax cut shocks are identified by the negative reaction of taxes and spending shocks by the positive reaction of spending. All of these restrictions are assumed to hold for four quarters. While one strand of literature follows the penalty function approach introduced in Uhlig (2005) and Mountford and Uhlig (2009), recent approaches employ an algorithm based on rotation matrices (see e.g. Canova and Pappa, 2007; Rubio-Ramírez *et al.*, 2010; Arias, Rubio-Ramírez and Waggoner, 2018). The algorithm used in our implementation of this identification strategy makes use of the so-called QR-factorization and relies on 300 solutions that fulfil the required sign restrictions.

⁶ Alternatively, some authors use a two-step procedure, starting with the estimation of cyclically adjusted taxes and government expenditures.

III. Fiscal multipliers: Methodological determinants

Using all possible combinations of the methodological choices described above, we estimate SVAR models for all the EU-28 economies as well as for Switzerland, Norway and Iceland. The data, with quarterly frequency, are sourced from Eurostat and typically span the period 1999–2014 (subject to availability). For each model, we simulate 300 multipliers based on the distribution of the estimate and work with the median multiplier m_{median} as well as with the range between 16th and 84th percentiles $m_{16-84pr}$, which will serve as a measure of uncertainty.⁷ The total number of estimated fiscal multipliers is therefore 26,373,098 for each one of the horizons evaluated.

We concentrate on analysing the fiscal multipliers obtained from models that (i) are stable, (ii) are among the best models according to information criteria, and (iii) are among the models least burdened by residual autocorrelation. An estimated model is considered stable if the maximum eigenvalue modulus of the VAR is below unity. Model selection criteria are computed for all estimated models and residual autocorrelation is tested using the Ljung–Box Q test. We order all our models by selection criteria using the Schwarz, Akaike and Hannan–Quinn criteria as well as Ljung–Box statistics and concentrate exclusively on the 10% best models according to this ordering. In particular, we record for each model the share of Q -tests which do not imply a rejection of the null hypothesis of autocorrelation for all variables at lags 4, 8 and 20 and the number of times the model is chosen as a best model within the class of comparable VAR specifications using the three selection criteria mentioned above. We select the top 10% models in these two dimensions.

By concentrating on a selected group of specifications in the baseline setting, we favour economic interpretation over the completeness of the set of all possible multipliers obtained by combining modelling options. Such a selection appears in line with the typical workflow for estimating multipliers in empirical studies. We also evaluate the importance of verification and model selection measures by relaxing the requirements (i)–(iii) and thus increasing the number of multipliers used for analysis.⁸ The results of the baseline regressions are not significantly affected by estimating them with these expanded samples.

Table 1 shows the descriptive statistics of the median multipliers, as well as of the 16th–84th percentile range for the selected models (2,540,877 of them). The vast majority of the estimated multipliers have sensible values. The spending multipliers m^s seem generally higher in absolute value than the tax cut multipliers and less precisely estimated. The minimum number of observations used to estimate them is 27, while the most common number of observations is 43.

In order to quantify the effect of methodological choices on the multiplier values and dispersion of the estimates, we employ a meta-regression (Stanley and Jarrell, 2005, eq. 3):

$$m = \alpha + \beta_c D_c + \beta_m D_m + v, \quad (8)$$

⁷In sign restriction identification schemes, the 300 solutions are the actual draws. Other identification approaches rely on bootstrapping to compute the 300 draws.

⁸These alternative settings expand the number of observations of our baseline regression models ($N = 2,540,877$), to $N = 8,688,247$; $14,221,717$; $22,972,983$; and $25,015,940$, depending on the set of conditions that the multipliers are assumed to fulfil. The online Appendix S1 presents the results for the regression based on the broad set of 22,972,983 multipliers.

TABLE 1

Descriptive statistics of multiplier medians and percentiles in the subgroup of 'best' models,
 $N = 2,540,877$

	Minimum	5-th p.	16-th p.	Median	84-th p.	95-th p.	Maximum
m_{median}^s	-115.53	-3.82	-1.67	0.07	1.97	4.61	112.21
m_{median}^τ	-72.14	-2.63	-1.31	-0.33	0.21	0.91	118.67
$m_{16-84pr}^s$	0.05	0.92	1.60	4.06	11.61	24.72	740.41
$m_{16-84pr}^\tau$	0.02	0.23	0.42	1.33	4.23	9.02	458.78
Observations	27	32	34	43	58	69	136

where m is a vector containing all multipliers (or alternatively, the dispersion measure), D_c is a matrix whose columns are dummies identifying the different countries, D_m is a matrix that collects dummies related to data transformations, modelling details and structural identification procedures, and v is a vector error term. The meta-regression model given by equation (8) is estimated using weighted least squares (WLS) with weights given by the inverse of the variance of the estimates for models where the dependent variable is m_{median}^s or m_{median}^τ and with the standard least squares method for meta-regressions of multiplier ranges $m_{16-84pr}^s$ or $m_{16-84pr}^\tau$. The results of the estimations are reported in Tables 3–8. Since the main aim of our study is to quantify the role of methodological choices as a determinant of differences in the size of the estimated fiscal multiplier, we do not report the coefficient estimates for the country fixed effects β_c in equation (8) in the tables.⁹

The results are reported for the full set of countries as well as for two subgroups of economies, with the aim of investigating possible differences in the relationship between modelling choices and multiplier size within the core countries that joined the European Union prior to 2004 as compared to the eastern European economies that have formed part of the EU since 2004 and used to be centrally planned economies (see Appendix A for the identity of the countries in each group). In the spirit of Ilzetzi *et al.* (2013), we try to construct both groups in a way that ensures a higher degree of homogeneity in economic structure within the country groups than when assessing the full group of European economies for which data are available.

Since the predictors are only dummies, the coefficients have the simple interpretation of a change in the multiplier for deviations from the baseline setting. In the specification used, the baseline setting is chosen on the basis of corresponding to the most common case in the existing literature. Table 2 lists the baseline setting and various alternative settings investigated.

Table 3 presents the results for the effects of variable definitions, data source, VAR specification and identification based on the median of spending multiplier m_{median}^s at horizon $T = 4$.¹⁰ In this setting, we entertain fiscal multipliers based on a single choice of inflation and interest rates (the benchmark one) for the 5-variable VAR models. We assess the potential differences in fiscal multipliers based on the different choices of interest rate

⁹The estimates of the country fixed effects are available in the online Appendix S1.

¹⁰We only present in our tables coefficient estimates for selected regressors, the online Appendix S1 contains the results for the full set of estimates.

TABLE 2

Baseline and alternative settings for regression models

<i>Baseline specification</i>	<i>Alternative specification/s</i>
Nominal variables deflated by GDP deflator	Nominal variables deflated by HICP
European System of Accounts (ESA) 2010	Older ESA 95
Revenues definition: total revenues less interest payments, transfers, and social contributions	Several different revenues definitions
Spending definition: total spending less transfers and social contributions	Several different spending definitions
No smoothing of data	Fiscal data (and GDP) smoothed using MA(3) or MA(5)
Identification of a 3-variable VAR with Cholesky ordering	Identification of 3- and 5-variable VARs with Cholesky, sign restrictions, and BP with various elasticities
Outliers in fiscal time series detected and shift/jump dummies added	Possible outliers in the fiscal time series ignored
Constant but no trend in the VAR	Constant + time trend in the VAR
VAR with 4 lags	VAR with 1, 2, or 3 lags
Full time sample	Time sample ends in 2008 or 2010
Inflation rate based on GDP deflator (quarter-on-quarter, annualized)	Deflator inflation computed year-on-year and HICP inflation computed as both q-o-q and y-o-y
Interest rate: Maastricht criterion bond yields (long term)	3-month and 6-month interbank rates

and inflation measures in 5-variable VARs in an additional regression model whose results are presented in Table 4.

We start by discussing the results that appear significant and robust to the choice of country groups. Data source and methodological choices have significant effects on the size of the estimated multipliers which can be very important in magnitude. If the nominal variables are not deflated with a GDP deflator but with the HICP index, the estimated spending multiplier increases on average by 0.122. If the European System of Accounts (ESA) 95 is used, this leads to a median value of the multiplier that is higher on average by 0.119. The definition of revenues and spending used to calculate the multipliers also appears to affect the size of the multiplier. The baseline for these data composition choices (see Table 2) is similar: for both series, we subtract transfers and social contributions. In the case of revenues, we also subtract interest payments. If the researcher instead follows the definition of revenues in Crespo Cuaresma *et al.* (2011) or defines spending as total spending less interest payments, the value of the multiplier is on average higher by 0.112 or 0.041, respectively. The smoothing of fiscal data with a moving average filter, in addition, leads on average to a significant but small decrease in the estimated multiplier.

Turning to the effects of the structural shock identification strategies, here the results show strong variation with respect to the choice of country groups. The sign restrictions approach for both 3-variable and 5-variable VAR and the Blanchard and Perotti (2002) approach lead to very different results for a group of western economies as compared to eastern European countries. Also, the 5-variable approach, which includes the interest rate and inflation, generally leads to higher multiplier values than the 3-variable approach,

TABLE 3
Determinants of spending multiplier m^s_{median} : Regression results

<i>Predictor</i>	<i>Country subgroup</i>		
	<i>All</i>	<i>West</i>	<i>East</i>
<i>(a) Variable definitions, data source & transformations</i>			
Nominal variables deflated by HICP	0.122*** (0.0025)	0.010*** (0.0034)	0.107*** (0.0040)
ESA 95 used	0.119*** (0.0024)	0.092*** (0.0033)	0.083*** (0.0040)
Revenues following Crespo Cuaresma <i>et al.</i> (2011)	0.112*** (0.0039)	0.126*** (0.0052)	0.065*** (0.0067)
Total spending less interest payments	0.041*** (0.0034)	0.079*** (0.0044)	0.108*** (0.0060)
Fiscal data smoothed with moving average of length 5	−0.045*** (0.0041)	−0.027*** (0.0056)	−0.028*** (0.0070)
<i>(b) Structural identification</i>			
5-variable VAR identified with Cholesky decomposition	0.113*** (0.0041)	0.046*** (0.0050)	0.147*** (0.0080)
5-variable VAR identified with sign restrictions	0.320*** (0.0106)	−0.061*** (0.0132)	0.836*** (0.0182)
5-variable VAR identified with BP (elasticities from Caldara and Kamps, 2008)	−0.058*** (0.0129)	−0.130*** (0.0136)	0.518*** (0.0349)
5-variable VAR identified with BP (elasticities from Crespo Cuaresma <i>et al.</i> , 2011)	−0.176*** (0.0160)	−0.309*** (0.0169)	0.471*** (0.0431)
<i>(c) VAR specification and sample</i>			
Constant + time trend in the VAR	−0.123*** (0.0025)	−0.174*** (0.0033)	0.062*** (0.0043)
VAR with 1 lag	−0.103*** (0.0063)	−0.133*** (0.0083)	−0.061*** (0.0114)
VAR with 2 lags	−0.094*** (0.0057)	−0.160*** (0.0074)	−0.047*** (0.0106)
Sample ends in 2008	−0.105*** (0.0032)	0.039*** (0.0042)	−0.302*** (0.0059)
Sample ends in 2010	−0.146*** (0.0036)	−0.218*** (0.0047)	−0.178*** (0.0069)
Observations	420,986	218,791	132,054
Number of regressors in model	61	45	39
R^2	0.47	0.30	0.46

Notes: Estimates correspond to the specification in equation (8). Dependent variable is the estimated multiplier. All covariates are dummy variables, baseline specification given in Table 2. ‘All’: all countries in the sample, ‘West’: western European countries, ‘East’: eastern European countries. ***, **, * denotes significance at 1%, 5%, 10% level, respectively. Standard errors in parentheses. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications. Parameter estimates reported if significant in at least one of the country group samples.

although this result depends on the choice of calibrated elasticities. Identifying shocks by means of Cholesky ordering using the 5-variable specification instead of the 3-variable specification, for instance, leads to an average increase of 0.113 in the estimated multiplier. The results also show that using fewer lags than four in the VAR specification leads to a decrease in the estimated multiplier. The results for estimates based on data prior to the

TABLE 4

Determinants of spending multiplier m_{median}^s , selected results for VAR models based on five variables

Predictor	Country subgroup		
	All	West	East
<i>Variable definitions and data source: 5-variable VAR</i>			
Deflator inflation, year-on-year	0.051*** (0.0014)	-0.022*** (0.0021)	0.111*** (0.0018)
HICP inflation, year-on-year	0.007*** (0.0016)	-0.011*** (0.0023)	0.061*** (0.0020)
HICP inflation, quarter-on-quarter, annualized	0.049*** (0.0012)	0.024*** (0.0016)	0.082*** (0.0018)
3-month interbank rate	-0.246*** (0.0019)	0.014*** (0.0027)	-0.494*** (0.0024)
6-month interbank rate	-0.259*** (0.0019)	-0.012*** (0.0027)	-0.466*** (0.0024)
Observations	2,318,268	1,137,774	990,406
Number of regressors in model	60	48	41
R^2	0.41	0.30	0.63

Notes: Estimates correspond to the specification in equation (8). Dependent variable is the estimated multiplier. All covariates are dummy variables, baseline specification given in Table 2. 'All': all countries in the sample, 'West': western European countries, 'East': eastern European countries. ***, **, * denotes significance at 1%, 5%, 10% level, respectively. Standard errors in parentheses. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications. Only parameter estimates for the dummies corresponding to the 5-variable VAR reported.

crisis years indicate that spending multipliers have become on average larger in the second decade of the 21st century, lending support to the hypothesis that fiscal multipliers are larger in recessions than in expansions, and were particularly large in the aftermath of the financial crisis (see e.g. Auerbach and Gorodnichenko, 2012; Gechert, Hallett and Rannenberg, 2016).

Table 4 presents the results for alternative choices of inflation and interest rate variables. Since these two variables only enter VAR specifications which contain five variables, we restrict our sample to fiscal multipliers obtained in these specifications. A standard set of predictors similar to those in the specifications reported in Table 3 was used, but we only report the estimates corresponding to the choice of data on inflation and interest rates. A robust but quantitatively small increase in the size of the spending multiplier when HICP (instead of the GDP deflator) is used to calculate inflation can be observed in our exercise, with important differences across subgroups of countries. Using interbank rates in the multiplier estimation tends to decrease the estimate of the spending multiplier by almost 0.5 in eastern European countries, while the effect for western Europe is clearly smaller in absolute value and its direction depends on the maturity of the interest rate.

Although some of the values of the effects found in Tables 3 and 4 and discussed above may seem small, the joint effect of different modelling choices can lead to sizeable cumulative effects. To illustrate this, we can define two sets of sensible methodological choices that differ only in what may appear to be 'innocuous' methodological choices

and report the difference in the estimate of the spending multiplier.¹¹ For example, starting from the baseline specification (see Table 2) we define a scenario where the econometrician uses data based on ESA 2010, defines revenue as total revenues less interest payments, transfers, and social contributions, defines spending as total spending less transfers and social contributions, and deflates nominal variables by the GDP deflator. Compared to a scenario with ESA 95, revenue defined as in Crespo Cuaresma *et al.* (2011), spending defined as total spending less interest payments, and nominal variables deflated by HICP, the spending multiplier at the 4-quarter ahead horizon would be larger on average by 0.394.

Table 5 shows the estimation results for tax cut multipliers in the same structure as in Table 3. The absolute value of the parameter estimates for tax cut multipliers is generally smaller than that of their spending counterparts, which is in line with the smaller variability found in tax cut multipliers (see Table 1). The data composition definitions play a major role as determinants of differences in the size of tax cut multipliers. Switching from the baseline revenue composition to the one introduced in Crespo Cuaresma *et al.* (2011), or from the baseline spending composition to total spending less interest payments, both increase the estimate of the tax cut multiplier. Note that the same qualitative results (which are robust across country groups) are obtained for the spending multiplier. Smoothing the fiscal data decreases the estimate of the tax cut multiplier on average by 0.134. In general, higher tax cut multipliers are obtained if specifications based on VAR models with five variables are used. Specifically, the multiplier increases by 0.160 after adding inflation and the interest rate to the baseline setting. The results for the parameter estimates attached to the dummies that identify subsample stability reveal varied results when different spans of time are considered in the sample. If the estimation period ends before the onset of the Great Recession, the tax cut multipliers tend to be higher (by 0.132), while if the time period ends close to the trough of the recession, the multipliers tend to be lower (by -0.098). This contrasts with the results obtained for the spending multiplier, which imply lower fiscal multipliers when using data prior to the crisis. Table 6 shows that, unlike in the case of spending multipliers in Table 4, the effects of changing the method of inflation calculation or the interest rate used do not affect the tax cut multiplier substantially, with small effects found for all methodological differences studied.

The results in Tables 3–6 unveil magnitudes of the effect of methodological changes which differ strongly across multiplier type. There are also several results that are common for both spending and tax cut multipliers and also robust to country group selection. As an example of the size of such effects, the use of the revenue definition adopted from Crespo Cuaresma *et al.* (2011) and total spending less interest payments increases both the spending and tax cut multiplier. On the other hand, smoothing fiscal data decreases both the spending multiplier (by 0.045) and tax cut multiplier (by 0.134). While using the Cholesky identification strategy, introducing inflation and the interest rate to the original three variables in the VAR increases the spending multiplier by 0.113 and the tax cut multiplier by 0.160.

¹¹ In order to illustrate only robust results across European economies, we do not employ choices that lead to a significant change in the multipliers in only a subset of countries.

TABLE 5
Determinants of tax cut multiplier m_{median}^{τ} : Regression results

Predictor	Country subgroup		
	All	West	East
<i>(a) Variable definitions, data source & transformations</i>			
Nominal variables deflated by HICP	−0.024*** (0.0011)	−0.037*** (0.0013)	0.005** (0.0023)
ESA 95 used	0.005*** (0.0011)	0.016*** (0.0013)	−0.037*** (0.0024)
Revenues following Crespo Cuaresma <i>et al.</i> (2011)	0.058*** (0.0022)	0.044*** (0.0025)	0.189*** (0.0056)
Total spending less interest payments	0.033*** (0.0014)	0.028*** (0.0017)	0.055*** (0.0031)
Fiscal data is smoothed with moving average of length 5	−0.134*** (0.0017)	−0.142*** (0.0020)	−0.103*** (0.0041)
<i>(b) Structural identification</i>			
5-variable VAR identified with Cholesky decomposition	0.160*** (0.0017)	0.158*** (0.0020)	0.268*** (0.0039)
5-variable VAR identified with sign restrictions	0.007 (0.0048)	0.050*** (0.0055)	−0.028** (0.0117)
5-variable VAR identified with BP (elasticities from Caldara and Kamps, 2008)	0.040*** (0.0066)	0.061*** (0.0071)	0.051** (0.0225)
5-variable VAR identified with BP (elasticities from Crespo Cuaresma <i>et al.</i> , 2011)	0.165*** (0.0021)	0.166*** (0.0024)	0.253*** (0.0046)
<i>(c) VAR specification and sample</i>			
Constant + time trend in the VAR	−0.012*** (0.0011)	−0.025*** (0.0013)	0.001 (0.0023)
VAR with 1 lag	0.024*** (0.0034)	0.016*** (0.0042)	0.069*** (0.0071)
VAR with 2 lags	0.008*** (0.0031)	−0.002 (0.0039)	0.103*** (0.0065)
Time sample ends in 2008	0.132*** (0.0015)	0.132*** (0.0017)	0.366*** (0.0042)
Time sample ends in 2010	−0.098*** (0.0014)	−0.082*** (0.0017)	−0.031*** (0.0030)
Observations	420,986	218,791	132,054
Number of regressors in model	61	45	39
R^2	0.62	0.53	0.69

Notes: Estimates correspond to the specification in equation (8). Dependent variable is the estimated multiplier. All covariates are dummy variables, baseline specification given in Table 2. ‘All’: all countries in the sample, ‘West’: western European countries, ‘East’: eastern European countries. ***, **, * denotes significance at 1%, 5%, 10% level, respectively. Standard errors in parentheses. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications. Parameter estimates reported if significant in at least one of the country group samples.

IV. The determinants of multiplier precision

Data, modelling, and methodological choices do not only affect the point estimates of the multipliers, but also their precision. Some of the methodological choices lead to a more precise estimate of the multiplier, whereas others increase the dispersion of multiplier

TABLE 6

Determinants of tax cut multiplier m_{median}^T , selected results for VAR models based on five variables

<i>Predictor</i>	<i>Country subgroup</i>		
	<i>All</i>	<i>West</i>	<i>East</i>
<i>Variable definitions and data source: 5-variable VAR</i>			
Deflator inflation, year-on-year	−0.016 (0.0004)	−0.015*** (0.0005)	−0.013*** (0.0007)
HICP inflation, year-on-year	−0.020*** (0.0005)	−0.029*** (0.0006)	−0.012*** (0.0007)
HICP inflation, quarter-on-quarter, annualized	−0.019 (0.0004)	−0.024*** (0.0005)	−0.005*** (0.0006)
3-month interbank rate	0.038*** (0.0006)	0.019*** (0.0008)	0.047*** (0.0009)
6-month interbank rate	0.040*** (0.0006)	0.015*** (0.0008)	0.052*** (0.0009)
Observations	2,318,268	1,137,774	990,406
Number of regressors in model	60	48	41
R^2	0.58	0.52	0.67

Notes: Estimates correspond to the specification in equation (8). Dependent variable is the estimated multiplier. All covariates are dummy variables, baseline specification given in Table 2. ‘All’: all countries in the sample, ‘West’: western European countries, ‘East’: eastern European countries. ***, **, * denotes significance at 1%, 5%, 10% level, respectively. Standard errors in parentheses. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications. Only parameter estimates for the dummies corresponding to the 5-variable VAR reported.

estimates around their median. Table 7 reports the estimation results of a regression model such as the one in equation (8) addressing the determinants of the spending multiplier dispersion (18th–84th percentile range) at horizon $T = 4$.¹² The choice of whether to deflate nominal variables with a GDP deflator or HICP plays a significant role when it comes to the precision of multiplier estimates. Using HICP reduces the dispersion of the estimate of the spending multiplier, giving an estimate with higher precision. The effect is much more pronounced for the eastern European country group. A similar effect is also found for the methodological choice of ESA 95, however, this effect does not appear to exist for Western EU countries.

As for the effect of the definitions of fiscal variables, spending variables that follow Muir and Weber (2013) and Crespo Cuaresma *et al.* (2011) increase the dispersion of both spending and tax cut multiplier estimates. The results for the data smoothing choice delivers mixed results, except for the case where only fiscal time series are smoothed, which increases the dispersion of the estimates of spending multiplier. Identification strategies affect the dispersion significantly: sign restriction estimates increase the dispersion considerably, as does the Blanchard and Perotti (2002) approach applied to a 5-variable VAR. Our results indicate that including a time trend in the formulation of the VAR increases the precision of the spending multiplier estimate. As for subsample stability, the results for

¹²The results for the dispersion of the tax cut multiplier can be found in the online Appendix S1.

TABLE 7
Determinants of spending multiplier ranges $m_{16-84pr}^s$: Regression results

Predictor	Country subgroup		
	All	West	East
<i>(a) Variable definitions, data source & transformations</i>			
Nominal variables deflated by HICP	-0.555*** (0.0256)	-0.228*** (0.0274)	-2.030*** (0.0611)
ESA 95 used	-0.969*** (0.0260)	0.007 (0.0276)	-2.537*** (0.0614)
Revenues following Crespo Cuaresma <i>et al.</i> (2011)	-0.748*** (0.0418)	-0.749*** (0.0431)	-0.113 (0.1068)
Total spending less interest payments	-1.299*** (0.0395)	-1.352*** (0.0418)	-1.484*** (0.0962)
Fiscal data is smoothed with moving average of length 5	0.847*** (0.0362)	0.727*** (0.0382)	0.854*** (0.0909)
<i>(b) Structural identification</i>			
5-variable VAR identified with Cholesky decomposition	0.281*** (0.0603)	0.457*** (0.0641)	0.055 (0.1497)
5-variable VAR identified with sign restrictions	4.676*** (0.0605)	4.855*** (0.0642)	4.661*** (0.1502)
5-variable VAR identified with BP (elasticities from Caldara and Kamps, 2008)	7.612*** (0.0603)	6.989*** (0.0641)	9.841*** (0.1497)
5-variable VAR identified with BP (elasticities from Crespo Cuaresma <i>et al.</i> , 2011)	10.585*** (0.0603)	8.821*** (0.0641)	14.930*** (0.1497)
<i>(c) VAR specification and sample</i>			
Constant + time trend in the VAR	-0.875*** (0.0260)	-0.523*** (0.0280)	-1.581*** (0.0625)
VAR with 1 lag	-0.697*** (0.0740)	-0.987*** (0.0797)	-0.640*** (0.1791)
VAR with 2 lags	-0.867*** (0.0677)	-1.322*** (0.0720)	-0.373** (0.1652)
Time sample ends in 2008	-1.595*** (0.0350)	-1.402*** (0.0359)	-0.992*** (0.0969)
Time sample ends in 2010	0.432*** (0.0320)	0.800*** (0.0352)	0.615*** (0.0776)
Observations	420,986	218,791	132,054
Number of regressors in model	61	45	39
R^2	0.27	0.28	0.30

Notes: Dependent variable is the dispersion (16th–84th percentile range) of the estimated multipliers. All covariates are dummy variables, baseline specification given in Table 2. ‘All’: all countries in the sample, ‘West’: western European countries, ‘East’: eastern European countries. ***, **, * denotes significance at 1%, 5%, 10% level, respectively. Standard errors in parentheses. Country fixed effects in all specifications. Parameter estimates reported if significant in at least one of the country group samples.

the spending multiplier indicate that postcrisis estimates are associated with less precisely estimated multipliers. On the other hand, the time sample that ends during the Great Recession tends to produce estimates which are characterized by lower dispersion. Tax cut multipliers (see the online Appendix S1) tend to provide similar results for the full sample, although the estimates for eastern European countries differ across multiplier types.

TABLE 8

Determinants of spending multiplier ranges $m_{16-84pr}^s$, selected results for VAR models based on five variables

<i>Predictor</i>	<i>Country subgroup</i>		
	<i>All</i>	<i>West</i>	<i>East</i>
<i>Variable definitions and data source: 5-variable VAR</i>			
Deflator inflation, year-on-year	−0.070*** (0.0202)	−0.211*** (0.0241)	−0.253 (0.0354)
HICP inflation, year-on-year	0.637*** (0.0219)	0.694*** (0.0265)	0.522*** (0.0382)
HICP inflation, quarter-on-quarter, annualized	0.305*** (0.0172)	0.197*** (0.0193)	0.413*** (0.0324)
3-month interbank rate	−0.699*** (0.0286)	−0.392*** (0.0369)	−0.939*** (0.0468)
6-month interbank rate	−0.802*** (0.0279)	−0.444*** (0.0367)	−0.883*** (0.0444)
Observations	2,318,268	1,137,774	990,406
Number of regressors in model	60	48	41
R^2	0.26	0.25	0.28

Notes: Dependent variable is the dispersion (16th–84th percentile range) of the estimated multipliers. All covariates are dummy variables, baseline specification given in Table 2. ‘All’: all countries in the sample, ‘West’: western European countries, ‘East’: eastern European countries. ***, **, * denotes significance at 1%, 5%, 10% level, respectively. Standard errors in parentheses. Country fixed effects in all specifications. Only parameter estimates for the dummies corresponding to the 5-variable VAR reported.

The results in Table 8 indicate that using HICP inflation instead of GDP deflator inflation increases the dispersion of spending multipliers. Similarly, using long-term bond yields instead of interbank rates increases the dispersion of spending (and partially also tax cut) multipliers.

V. Conclusions

This paper addresses how (sometimes seemingly unimportant) data, modelling, and methodological choices can affect the estimates of fiscal multipliers obtained from SVAR models. Both spending and tax cut multipliers are sensitive to specific choices regarding the composition of government spending and revenues. The particular definition of government revenues or spending, as well as specific ways of treating the data prior to estimation, can be very influential for both spending and tax cut multipliers.

The spending multiplier is sensitive to different, seemingly innocuous, modelling and methodological choices. In particular, using HICP to deflate nominal variables (rather than a GDP deflator) and using data based on ESA 95 (instead of ESA 2010), for instance, increases the estimate of the spending multiplier by 0.122 and 0.119, respectively. We also find that the identification strategy used to isolate structural shocks matters in some cases. In cases that a causal ordering based on Cholesky decompositions or sign restriction identification are used to identify fiscal shocks in VAR models that contain inflation and

the interest rate, the value of the spending multiplier tends to be larger (by 0.113 and 0.320, respectively). This qualitative result holds also for the tax cut multiplier in the case of Cholesky-based identification, which is also strongly affected by the particular values of the elasticities used when implementing the Blanchard and Perotti (2002) approach. Data choices and identification strategies are also found to have important effects on the precision of multiplier estimates. The results also point to significant heterogeneity across country groupings when comparing western European economies to their eastern European counterparts, as well as when comparing multipliers estimated with data which include the global financial crisis to those that do not. The most pronounced difference between the results for eastern and western European countries are obtained for spending multipliers estimated with models that contain inflation and the interest rate. Investigating the variation in identification strategies for such models in eastern European countries, the change in spending multiplier reaches 0.836, whereas for the western European country group, the change with respect to the baseline is negative and as low as -0.309 for these specifications.

Our analysis provides ample evidence of important quantitative effects of modelling choices on fiscal multiplier estimates. Given the central role that fiscal multipliers play in the design and evaluation of macroeconomic policy, the results of our study call for a rigorous assessment of specification uncertainty when multipliers based on estimates from SVAR models are used. Further research on how to address such uncertainty, for example, using model averaging techniques, appears necessary to advance our knowledge of the effect of fiscal shocks on the real economy.

Appendix A. Countries in full sample and country groupings

Sample	Country codes	Country names
All countries	AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MT, NL, NO, PL, PT, RO, SE, SI, SK	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Ireland, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovenia, Slovakia, Spain, Sweden, Switzerland, United Kingdom
Western EU	AT, BE, DE, DK, ES, FI, FR, GB, GR, IE, IT, NL, PT, SE, SI	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Netherlands, Portugal, Slovenia, Spain, Sweden, United Kingdom
Eastern EU	BG, CZ, EE, HU, LT, LV, PL, RO, SK	Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia

Final Manuscript Received: October 2019

References

Arias, J., Rubio-Ramírez, J. F. and Waggoner, D. F. (2018). 'Inference based on SVARs identified with sign and zero restrictions: theory and applications', *Econometrica*, Vol. 86, pp. 685–720.

- Auerbach, A. J. and Gorodnichenko, Y. (2012). ‘Measuring the output responses to fiscal policy’, *American Economic Journal: Economic Policy*, Vol. 4, pp. 1–27.
- Blanchard, O. J. and Leigh, D. (2013). ‘Growth forecast errors and fiscal multipliers’, *American Economic Review*, Vol. 103, pp. 117–120.
- Blanchard, O. and Perotti, R. (2002). ‘An empirical characterization of the dynamic effects of changes in government spending and taxes on output’, *Quarterly Journal of Economics*, Vol. 117, pp. 1329–1368.
- Brownlees, C. T. and Gallo, G. M. (2006). ‘Financial econometric analysis at ultra-high frequency: data handling concerns’, *Computational Statistics and Data Analysis*, Vol. 51, pp. 2232–2245.
- Brys, G., Hubert, M. and Rousseeuw, P. (2005). ‘A robustification of independent component analysis’, *Journal of Chemometrics: A Journal of the Chemometrics Society*, Vol. 19, pp. 364–375.
- Caggiano, G., Castelnuovo, E., Colombo, V. and Nodari, G. (2015). ‘Estimating fiscal multipliers: news from a non-linear world’, *The Economic Journal*, Vol. 125, pp. 746–776.
- Caldara, D. and Kamps, C. (2008). *What are the Effects of Fiscal Shocks? A VAR-Based Comparative Analysis*, Technical report, ECB Working Paper No. 877.
- Canova, F. and Pappa, E. (2007). ‘Price differentials in monetary unions: the role of fiscal shocks’, *The Economic Journal*, Vol. 117, pp. 713–737.
- Crespo Cuaresma, J., Eller, M. and Mehrotra, A. (2011). ‘The economic transmission of fiscal policy shocks from western to eastern Europe’, *BOFIT Discussion Papers*, Vol. 2011, pp. 3.
- Estevão, M. M. M. and Samaké, I. (2013). *The Economic Effects of Fiscal Consolidation with Debt Feedback*, No. 13-136, International Monetary Fund.
- Fatás, A. and Mihov, I. (2001). *The Effects of Fiscal Policy on Consumption and Employment: Theory and Evidence*, Technical report, CEPR Discussion Paper No. 2760.
- Gechert, S. (2015). ‘What fiscal policy is most effective? A meta-regression analysis’, *Oxford Economic Papers*, Vol. 67, 553–580.
- Gechert, S. and Rannenberg, A. (2014). *Are Fiscal Multipliers Regime-Dependent? A Meta Regression Analysis*, Technical report September.
- Gechert, S., Hallett, A. H. and Rannenberg, A. (2016). ‘Fiscal multipliers in downturns and the effects of euro area consolidation’, *Applied Economics Letters*, Vol. 23, pp. 1138–1140.
- Grubbs, F. E. (1969). ‘Procedures for detecting outlying observations in samples’, *Technometrics*, Vol. 11, pp. 1–21.
- Iglewicz, B. and Hoaglin, D. (1993). ‘How to detect and handle outliers’, ASQC basic references in quality control, Mykytka E. F. (ed.), Vol. 16, Milwaukee, ASQC Quality Press, pp. 87.
- Ilzetki, E., Mendoza, E. G. and Végh, C. A. (2013). ‘How big (small?) are fiscal multipliers?’, *Journal of Monetary Economics*, Vol. 60, pp. 239–254.
- Klyviene, V. and Karmelavičius, J. (2012). ‘Svar analysis of the impacts of corporate taxation on the macro-economy of lithuania’, *Ekonomika/Economics*, Vol. 91, pp. 107–124.
- Mountford, A. and Uhlig, H. (2009). ‘What are the effects of fiscal policy shocks?’, *Journal of Applied Econometrics*, Vol. 24, pp. 960–992.
- Muir, D. and Weber, A. (2013). *Fiscal Multipliers in Bulgaria: Low But Still Relevant*, Technical report, IMF Working Paper No. 13/49.
- Perotti, R. (2004). *Estimating the Effects of Fiscal Policy in OECD Countries*, Technical report December, IGER Working Paper No. 276.
- Petrevski, G., Bogoev, J. and Tevdovski, D. (2015). ‘Fiscal and monetary policy effects in three south eastern european economies’, *Empirical Economics*, Vol. 50, pp. 415–441.
- Ramey, V. A. (2011). ‘Identifying government spending shocks: It’s all in the timing’, *Quarterly Journal of Economics*, Vol. 126, pp. 1–50.
- Ramey, V. A. (2016). ‘Macroeconomic shocks and their propagation’, in J. B. Taylor and H. Uhlig (eds.), *Handbook of Macroeconomics*, Vol. 2, Amsterdam: Elsevier, pp. 71–162.
- Rubio-Ramírez, J. F., Waggoner, D. F. and Zha, T. (2010). ‘Structural vector autoregressions: Theory of identification and algorithms for inference’, *The Review of Economic Studies*, Vol. 77, pp. 665–696.
- Rusnák, M. (2011). *Why Do Government Spending Multipliers Differ? A Meta-Analysis*, Mimeo. Prague: CERGE-EI.

Stanley, T. D. and Jarrell, S. B. (2005). 'Meta-regression analysis: A quantitative method of literature surveys', *Journal of Economic Surveys*, Vol. 19, pp. 299–308.

Uhlig, H. (2005). 'What are the effects of monetary policy on output? Results from an agnostic identification procedure', *Journal of Monetary Economics*, Vol. 52, pp. 381–419.

Supporting Information

Additional supporting information may be found in the online version of this article:

Appendix S1. Additional regression results.