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**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 multiplier 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.

**Keywords:** Fiscal multiplier, structural VAR, meta-analysis
**JEL codes:** E62, C32

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# 1 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 (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 (see e.g. Auerbach and Gorodnichenko, 2017; Caldara and Kamps, 2017; Leeper et al., 2017; Brinca et al., 2016; Gechert et al., 2016).

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 asymmetry of fiscal multipliers in different business cycle phases. Our contribution aims at assessing how the size and accuracy of fiscal multipliers obtained using structural VAR (SVAR) models depend on the different methodological choices that need to be made when specifying such models. 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 standard 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 accuracy of the multipliers depends on the particular characteristics of the modelling framework.

Rusnák (2011) and Gechert (2015) present meta-analyses on the literature of 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, the 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 systematic reviews of the literature. Such aspects are omitted from the published meta-analyses for several reasons. On the one hand, 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 estimates of fiscal multipliers. On the other hand, some of these characteristics are often considered innocuous by the authors of the studies 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 ESA 95 (rather than ESA 2010) tend to be significantly larger. Our results indicate that data composition for government spending and government revenue play a role as well. 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 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 has also an effect on fiscal multiplier estimates, with the evidence presented supporting the existance of larger multipliers since the beginning of the current decade.

The rest of the paper is organized as follows. Section 2 presents the methodology of the analysis in detail, section 3 interprets the empirical results, as well as an array of sensitivity checks. Section 4 concludes.

## 2 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,

$$A(L)Y_t = u_t, \tag{1}$$

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 $A_j$, $j = 1, \ldots p$ 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 $\varepsilon_t$. Pre-multiplying equation (1) with a convenient matrix $A_0$ results on the structural form of the VAR model,

$$B(L)Y_t = B\varepsilon_t, \tag{2}$$

where $B(L) = A_0 A(L)$ and

$$A_0 u_t = B\varepsilon_t \tag{3}$$

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

Various identification methods can be used to retrieve the structural shocks in $\varepsilon_t$. 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 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 multipliers and tax cut multipliers can be computed. In line with recent literature (e.g. Ilzetzki et al., 2013; Caggiano et al., 2015; Gechert and Rannenberg, 2014), we concentrate on discounted cumulative multipliers, defined as

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

where $i$ is the (average) interest rate, $y_t$ is output at time $t$, $g_t$ denotes government expenditures at time $t$ 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. The superscript at $m$ denotes the type of multiplier, $m^s$ being the spending multiplier. Tax cut multipliers $m^\tau$ 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.

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 pre-processing 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 a 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, for example interests and subsidies. Crespo Cuaresma et al. (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 on 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 pre-processing

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 method 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 is 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. Among others, the literature uses for example dummies to account for military buildups and for selling Universal Mobile Telecommunications System licenses. Due to the large number of estimated models, we use an automatized approach of outlier detection to assign dummies. In particular, the time series of government spending and taxes are checked for outliers using seven different tests (based on the adjusted boxplot, the generalized ESD procedure, Grubbs' procedure, the moving window filtering algorithm, the modified $Z$-score method, and the interquartile range test). 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 $\Sigma_u$, (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 three-variable VAR model, equation (3) takes the form

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

where $g$ denotes government expenditures, $y$ output, and $\tau$ 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-covariance matrix $\Sigma_u$ 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

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

The Cholesky decomposition of the variance-covariance matrix of the reduced-form residuals $\Sigma_u = PP'$ yields a lower triangular matrix $P$. If $\Sigma_\varepsilon$ 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 $\varepsilon_t$. Sticking to the example of a three-variable VAR, equation (3) takes the form

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

where the specific output elasticity of government revenue ($\alpha_{\tau y} = 1.85$) is adopted from Perotti (2004). In a five-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.[1]

The sign restriction approach imposes conditions directly on the shape of the impulse response functions corresponding to the VAR model. Mountford and Uhlig (2009) or 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), modern approaches employ an algorithm based on rotation matrices (see e.g. Canova and Pappa, 2007; Rubio-Ramírez et al., 2010; Arias et al., 2014). 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.

## 3 The methodological determinants of differences in fiscal multipliers

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.[2] 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 and model selection criteria are computed for all estimated models. In addition, residual autocorrelation is tested using the Ljung-Box Q test. We order all our models by selection criterion and Ljung-Box statistics and concentrate exclusively on the 10% best models according to this ordering. By making this choice for 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.

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 percentile ranges we employ a regression similar to the one used in meta-analysis (Stanley and Jarrell, 2005, eq. 3),

$$m = \alpha + \beta_c D_c + \beta_m D_m + \nu, \tag{8}$$

where $m$ is a vector containing all multipliers (or alternatively, the percentile range), $D_c$ 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 $\nu$ is a vector error

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

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

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

**Table 1:** Descriptive statistics of multiplier medians and percentile ranges in the sub-group of "best" models, $N = 2{,}540{,}877$.

term. The 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 $m^s_{median}$ or $m^\tau_{median}$ and with the standard least squares method for regressions of multiplier ranges $m^s_{16-84pr}$ or $m^\tau_{16-84pr}$. The results of the estimations are reported in Tables 3–8.[3]

The results are reported for the full set of countries as well as for two sub-groups of economies, with the aim of investigating possible differences in the relationship between modelling choices and multiplier size within the standard western European union countries as compared to eastern European economies.[4] 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.

| **Baseline specification** | **Alternative specification/s** |
|---|---|
| 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, 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. |
| Computation of inflation rate (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. |

**Table 2:** Baseline and alternative settings for regression models

[3] We do not report the coefficient estimates for the country fixed effects $\beta_c$ in equation (8), but they are available from the authors upon request.

[4] See Appendix for the identities of the countries in each group.

| Predictor | All | West | East |
|---|---|---|---|
| (a) Variable definitions and data source | | | |
| Nominal variables deflated by HICP | 0.122*** (48.4) | 0.010*** (2.9) | 0.107*** (26.6) |
| ESA 95 used | 0.119*** (48.6) | 0.092*** (28.3) | 0.083*** (20.7) |
| Revenues following Crespo Cuaresma et al. (2011) | 0.112*** (29.1) | 0.126*** (24.5) | 0.065*** (9.7) |
| Revenues following Muir and Weber (2013) | 0.021*** (5.6) | 0.096*** (19.5) | −0.144*** (21.7) |
| Spending following Crespo Cuaresma et al. (2011) | −0.035*** (7.6) | 0.118*** (19.3) | 0.026*** (3.5) |
| Spending following Muir and Weber (2013) | 0.025*** (5.9) | 0.138*** (25.6) | −0.010 (1.4) |
| Total spending less interest | 0.041*** (12.2) | 0.079*** (17.8) | 0.108*** (17.8) |
| (b) Data preprocessing | | | |
| Fiscal data is smoothed with moving average of length 5 | −0.045*** (10.8) | −0.027*** (4.9) | −0.028*** (4.0) |
| Fiscal data and GDP is smoothed with moving average of length 5 | −0.041*** (8.3) | −0.120*** (16.6) | 0.148*** (19.1) |
| (c) Structural identification | | | |
| 3-variable VAR identified with sign restrictions | −0.080*** (14.5) | 0.183*** (21.7) | −0.290*** (36.2) |
| 3-variable VAR identified with elasticities from Crespo Cuaresma et al. (2011) | 0.003 (0.7) | 0.031*** (6.1) | −0.061*** (10.3) |
| 5-variable VAR identified with Cholesky decomposition | 0.113*** (27.4) | 0.046*** (9.1) | 0.147*** (18.3) |
| 5-variable VAR identified with sign restrictions | 0.320*** (30.1) | −0.061*** (4.6) | 0.836*** (45.9) |
| 5-variable VAR identified with elasticities from Caldara and Kamps (2008) | −0.058*** (4.5) | −0.130*** (9.6) | 0.518*** (14.8) |
| 5-variable VAR identified with elasticities from Crespo Cuaresma et al. (2011) | −0.176*** (11.0) | −0.309*** (18.3) | 0.471*** (10.9) |
| (d) VAR specification and sample | | | |
| No dummies for possible outliers in the fiscal time series | 0.004 (1.2) | −0.034*** (7.1) | 0.078*** (11.6) |
| Constant + time trend in the VAR | −0.123*** (49.4) | −0.174*** (52.7) | 0.062*** (14.4) |
| VAR with 1 lag | −0.103*** (16.4) | −0.133*** (16.1) | −0.061*** (5.4) |
| VAR with 2 lags | −0.094*** (16.7) | −0.160*** (21.6) | −0.047*** (4.5) |
| Time sample ends in 2008, before the onset of the Great Recession | −0.105*** (33.1) | 0.039*** (9.3) | −0.302*** (51.2) |
| Time sample ends in 2010, typically in a trough of the Great Recession | −0.146*** (40.8) | −0.218*** (46.3) | −0.178*** (25.6) |
| Observations | 420,986 | 218,791 | 132,054 |
| Number of regressors in model | 61 | 45 | 39 |
| $R^2$ | 0.47 | 0.30 | 0.46 |

Notes: ***, **, * denotes significance at 1, 5, 10% level, respectively. Absolute value of $t$-statistic in parenthesis. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications, not reported.

**Table 3:** Determinants of spending multiplier $m^s_{median}$: Regression results

| Predictor | All | West | East |
|---|---|---|---|
| Variable definitions and data source: 5-variable VAR | | | |
| Deflator inflation, year-on-year | $0.051^{***}$ (35.6) | $-0.022^{***}$ (10.9) | $0.111^{***}$ (61.0) |
| HICP inflation, year-on-year | $0.007^{***}$ (4.2) | $-0.011^{***}$ (4.9) | $0.061^{***}$ (30.5) |
| HICP inflation, quarter-on-quarter, annualized | $0.049^{***}$ (40.5) | $0.024^{***}$ (15.0) | $0.082^{***}$ (46.6) |
| 3-month interbank rate | $-0.246^{***}$ (129.5) | $0.014^{***}$ (5.0) | $-0.494^{***}$ (202.0) |
| 6-month interbank rate | $-0.259^{***}$ (139.0) | $-0.012^{***}$ (4.4) | $-0.466^{***}$ (196.0) |
| 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: ***, **, * denotes significance at 1, 5, 10% level, respectively. Absolute value of $t$-statistic in parenthesis. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications, not reported.

**Table 4:** Determinants of spending multiplier $m^s_{median}$, selected results for VAR models based on 5 variables

Table 3 presents the results based on the median of spending multiplier $m^s_{median}$ at horizon $T = 4$. We only present in our tables the results for covariates with significant coefficient estimates.[5] 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 choice of interest rate 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 size. 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. If the researcher instead follows the definition of revenue in Crespo Cuaresma et al. (2011) or defines spending as total spending less interest, 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 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 the 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, 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 crisis years indicate that spending multipliers have become

[5]The full set of estimates is available from the authors upon request.

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. Gechert et al., 2016; Auerbach and Gorodnichenko, 2012).

Table 4 presents the results for alternative choices of inflation and interest rate variables. Since these two time series only enter VAR specifications which contain five variables, we restrict our sample to fiscal multipliers obtained in these specifications. A standard set of predictors was used, but we only report the estimates corresponding to the choice of data on inflation and interest rates. A significant increase in the size of the spending multiplier when HICP (instead of a deflator) is used to calculate inflation can be observed in our exercise, with important differences across subsamples of countries. Using interbank rates in the multiplier estimation tends to decreases 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 which maturity the interest rate used has.

Although some of the values of the effects to the multiplier estimates found in Table 3 a 4 and discussed above may seem small, the difference becomes more pronounced if several modelling choices are considered. To illustrate this, we can define two sets of sensible methodological choices and report the difference in the estimate of the spending multiplier.[6] For example, let us define a scenario where the econometrician uses data based on ESA 2010, defines revenue as total revenues less interest, transfers, and social contributions and spending as total spending less transfers and social contributions, uses a VAR(1) with 3 variables employing Cholesky ordering for identification, and uses quarter-on-quarter deflator inflation. Compared to a scenario with ESA 95, revenue defined as in Crespo Cuaresma et al. (2011), spending as total spending less interest, a 5-variable VAR(4) with Cholesky decomposition, and using quarter-on-quarter HICP inflation, the spending multiplier at the 4-quarter ahead horizon would be larger on average by $0.537$.

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 for the tax cut multiplier. The definition of spending, as well as that of revenues, appears important, and the smoothing of the data prior to estimation also leads to changes in the estimate of the multiplier. 5-variable specifications lead to a higher multiplier and the elasticities used in the BP identification scheme matter significantly. The results for the parameter estimates attached to the dummies that deal with sub-sample stability reveal varied results when different time-spans are considered. If the estimation period ends before the onset of the Great Recession, the tax cut multipliers tend to be higher, while if the time period ends close to the trough of the recession, the multipliers tend to be lower. This contrasts with the results obtained for the spending multiplier, which significantly implied 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 the interest rate used do not affect the tax cut multiplier substantially, with small effects found for all methodological differences studied, which are in addition homogeneous across subsamples.

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 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 percentile range at horizon $T = 4$.[7] The choice of whether to deflate nominal variables with a GDP deflator or HICP plays a significant role when it comes to the

[6]In order to illustrate only robust results, we do not utilize choices that only lead to a change in the multipliers in a subset of countries.

[7]The results for the percentile range of the tax cut multiplier are very similar to those for the spending multiplier and are not reported but available from the authors upon request.

| **Predictor** | **All** | **West** | **East** |
|---|---|---|---|
| (a) Variable definitions and data source | | | |
| Nominal variables deflated by HICP | $-0.024^{***}$ (22.3) | $-0.037^{***}$ (28.8) | $0.005^{**}$ (2.2) |
| ESA 95 used | $0.005^{***}$ (4.7) | $0.016^{***}$ (12.7) | $-0.037^{***}$ (15.6) |
| Revenues following Crespo Cuaresma et al. (2011) | $0.058^{***}$ (27.0) | $0.044^{***}$ (17.4) | $0.189^{***}$ (33.5) |
| Revenues following Muir and Weber (2013) | $0.151^{***}$ (73.4) | $0.106^{***}$ (43.7) | $0.333^{***}$ (63.0) |
| Spending following Crespo Cuaresma et al. (2011) | $-0.072^{***}$ (38.4) | $-0.073^{***}$ (31.5) | $-0.098^{***}$ (25.1) |
| Spending following Muir and Weber (2013) | $-0.062^{***}$ (33.7) | $-0.059^{***}$ (26.6) | $-0.088^{***}$ (21.9) |
| Total spending less interest | $0.033^{***}$ (23.2) | $0.028^{***}$ (16.5) | $0.055^{***}$ (17.6) |
| (b) Data preprocessing | | | |
| Fiscal data is smoothed with moving average of length 5 | $-0.134^{***}$ (77.3) | $-0.142^{***}$ (69.6) | $-0.103^{***}$ (25.5) |
| Fiscal data and GDP is smoothed with moving average of length 5 | $0.030^{***}$ (12.7) | $-0.002$ (0.7) | $0.123^{***}$ (25.3) |
| (c) Structural identification | | | |
| 3-variable VAR identified with sign restrictions | $0.176^{***}$ (32.1) | $0.199^{***}$ (25.1) | $0.153^{***}$ (17.3) |
| 3-variable VAR identified with elasticities from Crespo Cuaresma et al. (2011) | $-0.161^{***}$ (75.6) | $-0.126^{***}$ (46.5) | $-0.257^{***}$ (58.3) |
| 5-variable VAR identified with Cholesky decomposition | $0.160^{***}$ (93.8) | $0.158^{***}$ (77.3) | $0.268^{***}$ (68.4) |
| 5-variable VAR identified with sign restrictions | $0.007$ (1.4) | $0.050^{***}$ (9.1) | $-0.028^{**}$ (2.4) |
| 5-variable VAR identified with elasticities from Caldara and Kamps (2008) | $0.040^{***}$ (6.0) | $0.061^{***}$ (8.6) | $0.051^{**}$ (2.3) |
| 5-variable VAR identified with elasticities from Crespo Cuaresma et al. (2011) | $0.165^{***}$ (80.1) | $0.166^{***}$ (67.7) | $0.253^{***}$ (55.2) |
| (d) VAR specification and sample | | | |
| No dummies for possible outliers in the fiscal time series | $-0.014^{***}$ (10.5) | $-0.005^{***}$ (3.1) | $0.018^{***}$ (6.4) |
| Constant + time trend in the VAR | $-0.012^{***}$ (11.1) | $-0.025^{***}$ (19.1) | $0.001$ (0.5) |
| VAR with 1 lag | $0.024^{***}$ (7.1) | $0.016^{***}$ (3.9) | $0.069^{***}$ (9.8) |
| VAR with 2 lags | $0.008^{***}$ (2.7) | $-0.002$ (0.5) | $0.103^{***}$ (15.8) |
| Time sample ends in 2008, before the onset of the Great Recession | $0.132^{***}$ (87.6) | $0.132^{***}$ (77.4) | $0.366^{***}$ (88.2) |
| Time sample ends in 2010, typically in a trough of the Great Recession | $-0.098^{***}$ (70.9) | $-0.082^{***}$ (48.3) | $-0.031^{***}$ (10.4) |
| Observations | 420,986 | 218,791 | 132,054 |
| Number of regressors in model | 61 | 45 | 39 |
| $R^2$ | 0.62 | 0.53 | 0.69 |

Notes: ***, **, * denotes significance at 1, 5, 10% level, respectively. Absolute value of $t$-statistic in parenthesis. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications, not reported.

**Table 5:** Determinants of tax cut multiplier $m^{\tau}_{median}$: Regression results

| Predictor | All | West | East |
|---|---|---|---|
| Variable definitions and data source: 5-variable VAR | | | |
| Deflator inflation, year-on-year | $-0.016^{***}$ (38.7) | $-0.015^{***}$ (27.0) | $-0.013^{***}$ (19.0) |
| HICP inflation, year-on-year | $-0.020^{***}$ (42.8) | $-0.029^{***}$ (45.3) | $-0.012^{***}$ (17.1) |
| HICP inflation, quarter-on-quarter, annualized | $-0.019^{***}$ (49.6) | $-0.024^{***}$ (51.3) | $-0.005^{***}$ (7.1) |
| 3-month interbank rate | $0.038^{***}$ (64.8) | $0.019^{***}$ (22.3) | $0.047^{***}$ (54.2) |
| 6-month interbank rate | $0.040^{***}$ (68.1) | $0.015^{***}$ (17.8) | $0.052^{***}$ (60.1) |
| 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: ***, **, * denotes significance at 1, 5, 10% level, respectively. Absolute value of $t$-statistic in parenthesis. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications, not reported.

**Table 6:** Determinants of tax cut multiplier $m^s_{median}$, selected results for VAR models based on 5 variables

precision of multiplier estimates. Using HICP reduces the percentile range of the estimate of the spending multiplier, giving an estimate with higher precision. The effect is much more pronounced for the eastern European subsample. 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) increases the percentile range 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 with $MA(5)$, 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 accuracy of the multiplier estimate. As for subsample stability, the results for the spending multiplier indicate that post-crisis estimates are associated with less precision multipliers. On the other hand, the time sample that ends during the Great Recession tends to produce estimates which are characterized by lower accuracy. The tax cut multipliers (not reported here) tend to have similar results except when eastern European countries are considered.

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

We conducted several robustness checks, varying the horizon used to compute the discounted cumulative multipliers and changing the procedure for model selection. Qualitatively, the estimation results for horizons below $T = 4$ are 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).[8]

The importance of verification and model selection measures is tested by relaxing the requirements mentioned earlier. The tested alternatives exhibit a higher number of results compared to the baseline, because the most strict criteria was imposed on the baseline in order to work with only the best results. These 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

[8] Detailed results are available from the authors upon request.

| Predictor | All | West | East |
|---|---|---|---|
| (a) Variable definitions and data source | | | |
| ESA 95 used | $-0.969^{***}$ (37.3) | 0.007 (0.2) | $-2.537^{***}$ (41.3) |
| (b) Data preprocessing | | | |
| Revenues following Crespo Cuaresma et al. (2011) | $-0.748^{***}$ (17.9) | $-0.749^{***}$ (17.4) | $-0.113$ (1.1) |
| Revenues following Muir and Weber (2013) | $-1.013^{***}$ (24.4) | $-0.794^{***}$ (18.6) | $-0.699^{***}$ (6.6) |
| Spending following Crespo Cuaresma et al. (2011) | $2.286^{***}$ (56.3) | $2.370^{***}$ (54.2) | $1.975^{***}$ (20.5) |
| Spending following Muir and Weber (2013) | $1.638^{***}$ (40.9) | $1.453^{***}$ (34.1) | $1.428^{***}$ (14.9) |
| Total spending less interest | $-1.299^{***}$ (32.9) | $-1.352^{***}$ (32.3) | $-1.484^{***}$ (15.4) |
| Fiscal data is smoothed with moving average of length 5 | $0.847^{***}$ (23.4) | $0.727^{***}$ (19.0) | $0.854^{***}$ (9.4) |
| Fiscal data and GDP is smoothed with moving average of length 5 | $0.193^{***}$ (3.3) | 0.084 (1.2) | $-0.180$ (1.3) |
| (c) Structural identification | | | |
| 3-variable VAR identified with sign restrictions | $4.752^{***}$ (83.2) | $5.172^{***}$ (79.1) | $4.168^{***}$ (31.8) |
| 3-variable VAR identified with elasticities from Crespo Cuaresma et al. (2011) | $-0.024$ (0.4) | $-0.013$ (0.2) | $-0.108$ (0.8) |
| 5-variable VAR identified with Cholesky decomposition | $0.281^{***}$ (4.7) | $0.457^{***}$ (7.1) | 0.055 (0.4) |
| 5-variable VAR identified with sign restrictions | $4.676^{***}$ (77.3) | $4.855^{***}$ (75.6) | $4.661^{***}$ (31.0) |
| 5-variable VAR identified with elasticities from Caldara and Kamps (2008) | $7.612^{***}$ (126.2) | $6.989^{***}$ (109.0) | $9.841^{***}$ (65.7) |
| 5-variable VAR identified with elasticities from Crespo Cuaresma et al. (2011) | $10.585^{***}$ (175.6) | $8.821^{***}$ (137.6) | $14.930^{***}$ (99.7) |
| No dummies for possible outliers in the fiscal time series | 0.028 (0.7) | $-0.156^{***}$ (3.9) | $0.387^{***}$ (4.5) |
| (d) VAR specification and sample | | | |
| Constant + time trend in the VAR | $-0.875^{***}$ (33.6) | $-0.523^{***}$ (18.7) | $-1.581^{***}$ (25.3) |
| VAR with 1 lag | $-0.697^{***}$ (9.4) | $-0.987^{***}$ (12.4) | $-0.640^{***}$ (3.6) |
| VAR with 2 lags | $-0.867^{***}$ (12.8) | $-1.322^{***}$ (18.4) | $-0.373^{**}$ (2.3) |
| Time sample ends in 2008, before the onset of the Great Recession | $-1.595^{***}$ (45.6) | $-1.402^{***}$ (39.0) | $-0.992^{***}$ (10.2) |
| Time sample ends in 2010, typically in a trough of the Great Recession | $0.432^{***}$ (13.5) | $0.800^{***}$ (22.7) | $0.615^{***}$ (7.9) |
| Observations | 420,986 | 218,791 | 132,054 |
| Number of regressors in model | 61 | 45 | 39 |
| $R^2$ | 0.27 | 0.28 | 0.30 |

Notes: ***, **, * denotes significance at 1, 5, 10% level, respectively. Absolute value of $t$-statistic in parenthesis. Country fixed effects in all specifications, not reported.

**Table 7:** Determinants of spending multiplier ranges $m^s_{16-84pr}$: Regression results

| Predictor | All | West | East |
|---|---|---|---|
| Variable definitions and data source: 5-variable VAR | | | |
| Deflator inflation, year-on-year | $-0.070^{***}$ (3.5) | $-0.211^{***}$ (8.8) | $-0.253^{***}$ (7.1) |
| HICP inflation, year-on-year | $0.637^{***}$ (29.1) | $0.694^{***}$ (26.2) | $0.522^{***}$ (13.7) |
| HICP inflation, quarter-on-quarter, annualized | $0.305^{***}$ (17.8) | $0.197^{***}$ (10.2) | $0.413^{***}$ (12.7) |
| 3-month interbank rate | $-0.699^{***}$ (24.5) | $-0.392^{***}$ (10.6) | $-0.939^{***}$ (20.1) |
| 6-month interbank rate | $-0.802^{***}$ (28.8) | $-0.444^{***}$ (12.1) | $-0.883^{***}$ (19.9) |
| 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: ***, **, * denotes significance at 1, 5, 10% level, respectively. Absolute value of $t$-statistic in parenthesis. Estimation by WLS with inverse variance as weight. Country fixed effects in all specifications, not reported.

**Table 8:** Determinants of spending multiplier ranges $m^s_{16-84pr}$, Notes: see Table 7

that the multipliers are assumed to fulfil. The results of the baseline regressions are not significantly affected by estimating them with these expanded samples.[9]

## 4 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 two different seemingly innocuous modelling and methodological choices. 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. We also find that the identification strategy used to isolate structural shocks matters in some cases. If 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 rates, the value of the spending multiplier tends to be larger. This 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 sub-sample instability when comparing western European economies to their eastern Europeans counterparts, as well as when comparing multipliers estimated with data which include the financial crisis to those that do not.

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.

[9] Detailed results on this robustness check are available from the authors upon request.

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# Appendix

## Countries in sample and subsamples

| Sample | Countries (ISO 3166-1 alpha-2 codes) |
|---|---|
| All countries | AT, BE, BG, CH, CY, CZ, DE, DK, EE, EL, ES, FI, FR, HR, HU, IE, IS, IT, LT, LU, LV, MT, NL, NO, PL, PT, RO, SE, SI, SK, UK |
| Western EU | AT, BE, DE, DK, EL, ES, FI, FR, IE, IT, NL, PT, SE, SI, UK |
| Eastern EU | BG, CZ, EE, HU, LT, LV, PL, RO, SK |