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Estimating Fiscal Multipliers for Austria
New Evidence from 2,520 VAR and FAVAR Models

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Abstract

This thesis estimates fiscal multipliers for Austria using a large number of structural VAR and FAVAR models. Motivated by recent economic crises and the renewed importance of fiscal policy, it addresses the question of how government spending and taxation affect real GDP under modeling uncertainty. Building on the methodology of Čapek et al. (2022), 2,520 different model specifications are constructed, varying in terms of (FA)VAR specification, identification strategy, fiscal data definition, deflators, deterministics, and lag length. Three identification approaches are applied – Cholesky ordering, the Blanchard-Perotti method, and sign restrictions – and robustness is assessed using model averaging and forecast-based model selection. The results show that government spending has consistently strong and positive effects on output across all horizons with short- and medium-run multipliers exceeding unity on average. In contrast, tax multipliers are generally small, model-sensitive, and centered around zero, particularly in the most reliable models. Budget-neutral fiscal expansions also yield positive effects, underscoring the potential for output-stimulating, revenue-backed public investment. In addition to providing updated and robust evidence on the effectiveness of fiscal policy in Austria, this thesis contributes to the empirical literature by explicitly addressing model uncertainty and demonstrating how different modeling choices affect multiplier estimates.

Zusammenfassung

Diese Arbeit schätzt Fiskalmultiplikatoren für Österreich mithilfe verschiedener struktureller VAR- und FAVAR-Modelle. Angesichts jüngster wirtschaftlicher Krisen und der wieder gestiegenen Bedeutung der Fiskalpolitik wird untersucht, wie sich Staatsausgaben und Steuereinnahmen unter Modellunsicherheit auf das reale BIP auswirken. Aufbauend auf der Methodik von Čapek et al. (2022) werden 2.520 verschiedene Modellspezifikationen konstruiert, die hinsichtlich der (FA)VAR-Spezifikation, der Identifikationsstrategie, der Definition fiskalischer Variablen, der Deflatoren, deterministischer Komponenten und der Anzahl der Lags variieren. Es werden drei Identifikationsmethoden angewandt – die Cholesky-Zerlegung, die Blanchard-Perotti-Methode und Sign Restrictions – und die Robustheit wird mithilfe von Modellmittelung und prognosebasierter Auswahl der zuverlässigsten Modellspezifikationen sichergestellt. Die Ergebnisse zeigen, dass Staatsausgaben über alle Zeithorizonte hinweg durchgängig starke und positive Effekte auf das reale BIP haben, wobei die kurzfristigen und mittelfristigen Multiplikatoren im Durchschnitt über eins liegen. Im Gegensatz dazu sind Steuermultiplikatoren im Allgemeinen gering, modellabhängig und im Mittel nahe null – insbesondere in den zuverlässigsten Modellspezifikationen. Budgetneutrale fiskalische Expansionen führen ebenfalls zu positiven Effekten und unterstreichen damit das Potenzial einnahmengestützter öffentlicher Investitionen zur Wachstumsförderung. Die Ergebnisse liefern nicht nur robuste und neue Evidenz zur Wirksamkeit der Fiskalpolitik zur Wachstumsförderung in Österreich, sondern berücksichtigen Modellunsicherheit explizit und zeigen auf, wie unterschiedliche Modellannahmen die Schätzung von Fiskalmultiplikatoren beeinflussen.

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1 Introduction

The relationship between government spending, taxation, and real GDP is central to effective economic policymaking. It has gained renewed relevance in the aftermath of the 2008-09 global financial crisis and, more recently, in the wake of the COVID-19 pandemic and the war in Ukraine. In these periods of crisis, fiscal policy has taken an important role for economic stabilization, especially in situations where monetary policy is constrained – such as by the zero lower bound of interest rates or by rigid institutional settings.

In Austria, the scope for fiscal policy is shaped by a threefold challenge: Firstly, there is an urgent need to promote economic growth after three years of recession. Secondly, it is necessary to invest in long-term priorities such as infrastructure and climate policy – and also social transformations require fiscal measures (Piketty, 2015, pp. 30-32). Thirdly, however, persistent fiscal deficits have raised concerns about fiscal sustainability. For example, the Austrian Fiscal Advisory Council has repeatedly raised concerns about the risk of high deficits (see, for example, Fiskalrat (2025)). Nonetheless, as Dullien et al. (2021, p. 700) argue, to the extent that public investment raises output, it can ultimately generate additional tax revenues and thereby possibly finance itself. Beyond the (normative) debate over how to balance the need for renewed public infrastructure with concerns about debt sustainability, the broader tension between promoting economic growth and maintaining fiscal discipline raises key (positive) empirical questions: Can public spending – whether financed through compensatory taxation or debt – effectively stimulate economic output? Under what conditions might it even enhance debt sustainability? And are tax-based measures more effective than spending-based ones in delivering fiscal stimuli?

At the heart of this discussion lies the concept of fiscal multipliers, defined as the change in real GDP resulting from a one-unit change in government spending or tax revenues. Spending and tax multipliers serve as key indicators of policy effectiveness. Knowledge of their size influences not only fiscal decisions and budgetary planning but is also essential for producing accurate growth forecasts (Blanchard and Leigh, 2013, p. 118) – making reliable estimates of fiscal multipliers critically important for effective economic policymaking. Nevertheless, economic theories offer different expectations about fiscal multipliers, typically ranging from -0.5 to 2 for spending and -1.5 to 0.5 for tax changes. *Keynesian* theory predicts large positive spending multipliers, especially during recessions, due to shortfalls in private demand, particularly in consumption and investments. In contrast, *neoclassical* theory, assuming rational agents with perfect foresight, predicts small or even negative multipliers due to crowding-out effects and Ricardian equivalence. *New Keynesian* models, which add nominal rigidities to a neoclassical macro framework, generally support moderate multipliers in the short and medium run and highlight fiscal effectiveness when monetary policy is constrained. Arguing that fiscal interventions may lead to inflationary pressures or

crowding-out of private investment, *monetarist* views emphasize monetary over fiscal tools, often downplaying size and reliability of fiscal impacts. Among heterodox approaches, *Post-Keynesian* economics sees fiscal policy as central, with multipliers potentially large and persistent due to financial instability and demand-driven dynamics. These contrasting theoretical views highlight the importance of empirical estimation to guide fiscal policy.

Fiscal multiplier estimates generally fall into two categories: model-based and empirical. Model-based approaches, such as dynamic stochastic general equilibrium (DSGE) models, rely heavily on the theoretical framework in which they are embedded. Their fiscal multiplier estimates are therefore closely tied to structural assumptions about market structure, agent behavior, and preferences. These models offer internal consistency and allow for rich counterfactual analysis, but their results can be highly sensitive to the underlying theoretical choices. By contrast, empirical approaches are more data-driven and impose fewer theoretical restrictions. Nevertheless, they are not theory-free: their identification strategies often draw on theoretical insights to isolate exogenous fiscal shocks. A landmark contribution in this tradition is [Blanchard and Perotti \(2002\)](#), who use output, price, and spending elasticities for identification. Another key example is the narrative approach by [Romer and Romer \(2010\)](#), which relies on official budget documents and long-run time series to distinguish exogenous tax changes from endogenous responses.

Despite their relevance, however, there is no consensus even on the directional effect of the fiscal multipliers ([Perotti, 2004](#), p. 1) – and their estimates vary widely: There is no time-invariant, universally valid fiscal multiplier ([Gechert, 2017](#), p. 6). This heterogeneity has been documented in both country-specific and cross-country studies as well as in meta-analyses [Gechert \(2015\)](#); [Hlaváček and Ismayilov \(2022\)](#). Firstly, these variations are due to data limitations. Secondly, seemingly minor modeling decisions even within one class of models – such as the choice of the identification strategy, data definitions, the choice of deflators, lag length and deterministics – can substantially alter the resulting fiscal multiplier estimates [Čapek and Crespo Cuaresma \(2020\)](#). This highlights the importance of addressing *model uncertainty* when estimating fiscal multipliers: No single model can capture the full complexity of an economy, and results based on narrow specifications risk being misleading. Finally, this heterogeneity is due to structural country-specific characteristics such as the degree of development, openness to trade, exchange rate flexibility, the amount of outstanding debt [Ilzetzi et al. \(2013\)](#), the phase of the business cycle [Gechert and Rannenberg \(2018\)](#), the rigidity of prices and wages, interest rate stickiness, liquidity constraints, membership in a currency union, and the structure of the tax and transfer system ([Holler and Schuster, 2019](#), 9-11). Taken together, this suggests that we cannot simply use available estimates based on, for example, U.S. data and make inferences on Austria. Furthermore, we need to be aware that the size of multipliers changes over time and needs to be reassessed frequently.

In addition to these practical issues in the estimation, empirical work on fiscal multipliers in Austria (and other developed European small open economies with similar macroeconomic characteristics and, therefore, multipliers) has been limited. Whereas some authors have covered single countries using empirical methods (see, for example, [Jemec et al. \(2011\)](#) for Slovenia, [Ravn and Spange \(2014\)](#) for Denmark, or [Resende and Naik \(2025\)](#) for Estonia), other estimations have been based on panel studies for several countries with similar characteristics (see, for example, [Ilzetzki et al. \(2013\)](#)). In addition, there have been Austria-specific estimations employing model-based calculations (see, for example, [Barrell et al. \(2012\)](#); [Breuss et al. \(2009\)](#); [Schuster \(2019\)](#)). However, a comprehensive, purely empirical estimate that accounts for model uncertainty has been missing – until recently: [Čapek et al. \(2022\)](#) provide the first extensive, Austria-specific empirical estimation of fiscal multipliers using a large-scale ensemble of structural VAR and FAVAR models. Their approach systematically varies identification strategies, data definitions, and model structures. They report a mean present-value spending multiplier of 0.68 (peak 0.85) and tax multipliers of –1.12 (present value) and –0.54 (peak) in the short run. Notably, they find that multipliers are higher in models with better forecasting performance.

In re-estimating the fiscal multipliers based on more recent data and considering further time horizons, this study aims to gain new insights gained from, among others, the COVID pandemic, the war in Ukraine, the energy crisis, and the current recession. Following [Čapek et al. \(2022\)](#), which serves as the methodological and empirical baseline, the fiscal multipliers are estimated using a large number of different structural (FA)VAR models – amounting to 2,520 specifications in total. This is done in light of model uncertainty (i.e., arbitrary assumptions regarding, for example, identification, lags, trends, deflators, and fiscal definitions) and data limitations (i.e., there are only 96 observations per variable). Robustness is pursued through several measures: Firstly, 500 repetitions are conducted and the median impulse responses – and thus multipliers – are calculated for each of the 2,520 model specifications. Secondly, results are averaged across all specifications instead of relying on any single, arbitrary model. Thirdly, the results for those models that fit the data best are reported separately. In this study, the best models are selected based on mean average error (MAE) of out-of-sample forecasts, although applying alternative model performance criteria does not alter the overall findings.

This approach differs from previous literature in several ways: Firstly, a more extensive dataset is employed, expanding the existing database by one third compared to the benchmark analysis in [Čapek et al. \(2022\)](#). This extension includes more recent episodes, such as the economic disruptions caused by the COVID-19 pandemic and the energy crisis associated with the war in Ukraine. Secondly, the analysis reports multipliers not only for the short run, but also for the immediate (impact) and medium-run effects. Thirdly, several minor issues in [Čapek et al. \(2022\)](#) are corrected. Finally, the analysis places greater emphasis on transparency regarding modeling choices.

This transparency is essential not only for interpreting the results accurately, but also for enabling meaningful comparisons in future meta-analyses.

The analysis provides updated and robust evidence on the macroeconomic effects of fiscal policy in Austria, explicitly accounting for model uncertainty. Government spending consistently boosts output across all horizons, with average present value multipliers rising from 0.76 at impact (0.33 in the best-performing models) to 1.22 (0.67) in the short run and 1.82 (1.52) in the medium run. These results reflect both demand effects and indirect multiplier dynamics, indicating strong and persistent crowding-in. In contrast, tax multipliers are small, dispersed, and model-sensitive, averaging -0.04 at impact (-0.06 in the best models) and ranging from -0.96 to 0.10 in the medium run – suggesting modest and often temporary contractionary effects. Importantly, budget-neutral fiscal expansions, i.e., spending increases financed by taxes, continue to yield positive output effects in most models, including the most reliable ones. This indicates that the trade-off between public spending and debt sustainability can be softened through tax-financed expenditure. Overall, the results confirm that fiscal policy – especially through spending – remains a powerful instrument for macroeconomic stabilization and growth in Austria.

The structure of the study is as follows: Chapter 2 introduces the concept of fiscal multipliers, including their formal definitions, types, and relevance for fiscal policy. Chapter 3 presents the overall estimation strategy, describing the SVAR and FAVAR models, identification methods, and the range of model specifications considered. Chapter 4 outlines the data sources, transformations, and fiscal variable definitions used in the analysis. Chapter 5 provides the formal econometric setup and explains how structural shocks are identified. Chapter 6 presents the main results, including fiscal multiplier estimates, their robustness across model variants, and economic interpretation. Chapter 7 concludes.

2 Definitions

Fiscal multipliers measure the effect that discretionary – as opposed to automatic – fiscal policy has on the real GDP. In other words, they indicate by how many units the real GDP changes in response to a one unit change in government spending or taxation. On the one hand, fiscal multipliers can be divided into spending multipliers and tax multipliers. On the other hand, they can be divided into, most importantly, present value multipliers and peak multipliers. Each of these measures is important in different political and economics contexts.

The peak multiplier measures the maximum effect of a fiscal impulse during time period H . In accordance with Čapek et al. (2022), we set $H = 8$ to capture the business cycle dynamics of the multipliers.

$$m_{spending}^{peak} = \frac{\max_{t=0,\dots,H}\{y_t\}}{\max_{t=0,\dots,H}\{g_t\}} \times \frac{1}{g/y} \quad (1)$$

$$m_{tax}^{peak} = \frac{\max_{t=0,\dots,H}\{y_t\}}{\max_{t=0,\dots,H}\{\tau_t\}} \times \frac{1}{\tau/y}$$

Whereas m denotes the respective fiscal multipliers, y_t is the impulse response (in logs) of output to a fiscal shock at time t . Whereas g_t is the impulse response of government spending (in logs), τ_t is the response of taxation (in logs). The scaling factors g/y and τ/y denote the average share of government expenditures and taxation in the real GDP. The peak multiplier is important when the goal is to assess the maximum short-term impact of fiscal policy, such as during economic crises. As it indicates when and how strongly a fiscal measure will boost output, it is especially relevant for timing-sensitive intervention.

The present value multiplier captures the overall impact of fiscal stimulus over a given period T . This impact is discounted by the interest rate, which is set to annually 4 percent (such that $i = 0.01$).

$$m_{spending}^{npv} = \frac{\sum_{t=0}^T (1+i)^{-t} y_t}{\sum_{t=0}^T (1+i)^{-t} g_t} \times \frac{1}{g/y} \quad (2)$$

$$m_{tax}^{npv} = \frac{\sum_{t=0}^T (1+i)^{-t} y_t}{\sum_{t=0}^T (1+i)^{-t} \tau_t} \times \frac{1}{\tau/y}$$

Opposed to the peak multiplier, the present value multiplier is particularly useful when the objective of fiscal policy is to stabilize the business cycle in the short to medium run. Moreover, it serves as a crucial metric for structural policy planning with a long-term focus. Against this background, it is therefore distinguished between present value multipliers for the direct impact as well as the short and medium run. Whereas the impact is defined as the quarter following the fiscal stimulus (i.e., $T = 1$), the short run covers the first year (i.e., $T = 4$) and the medium run extends up to five years (i.e., $T = 20$). This study does not, however, cover the long run for two reasons. For one, there are data limitations in that many fiscal data in Austria are available only until 2001; for another, (FA)VAR models assume that the effects of fiscal shocks disappear relatively quickly ([Holler and Schuster, 2019](#), p. 12), making long-run multipliers less reliable. It is important to note that there are many other ways to define fiscal multipliers. However, since many studies do not specify which type of multiplier they use, caution is needed when comparing their results ([Holler and Schuster, 2019](#), pp. 3-4) – a problem that is especially relevant for meta studies, however.

Discretionary fiscal policies influence aggregate demand through both direct and indirect channels. The *direct* effect primarily involves the impact on real GDP resulting from adjustments in government spending and taxation. In contrast, the *indirect* effect encompasses changes in the behavior of economic agents in response to fiscal shocks, with its sign varying across different

economic theories and models – while it is assumed to be positive in Keynesian models, it tends to be negative in neoclassic frameworks. The fiscal multiplier is obtained by adding the direct and indirect effects of a fiscal policy measure ([Holler and Schuster, 2019](#), p. 4).

3 Methodology

3.1 VAR and FAVAR models

This study employs different vector autoregressive (VAR) as well as factor-augmented vector autoregressive (FAVAR) models. The idea of a *VAR model* is that each variable is explained by its own past values as well as the past values of all the other model variables up to some fixed maximum lag order. In this sense, VAR models differ from univariate times series models such as ARIMA, which model a single variable based solely on its own past values and its past forecast errors – without accounting for interactions with other variables. For instance, the most extensive VAR model in our analysis regresses GDP growth on itself as well as government expenditure, government revenue, inflation, and interest rate, using up to four lags for each variable. *FAVAR models*, in addition, account for the fact that each variable might also be explained by unobserved factors that capture patterns from a large number of additional time series. The FAVAR models in this study incorporate either one or two latent factors estimated from a set of 26 alternative macroeconomic and financial indicators. Taking account of the direct and indirect effects of fiscal policy mentioned above, the aim of FAVAR models is to account for the anticipation of fiscal shocks: Since economic agents adjust their behavior in anticipation of pre-announced fiscal policy changes, fiscal foresight needs to be modeled [Ramey \(2011\)](#) and – if ignored – would lead to an underestimation of the fiscal multipliers ([Fragetta and Gasteiger, 2014](#), p. 686).

The factors employed in the FAVAR specifications are estimated by principal components using the following 26 variables: domestic credit to households, loans from MFIs to non-MFIs, capital and reserves, loans to MFIs, home improvement expectations, capacity utilization, manufacturing orders, consumer confidence index, economic sentiment index, industrial production index, real effective exchange rate, EMU convergence bond yields, employment (age 15–64), employment (total), employment (machine operators), employment (service and sales), hours worked (machine operators), gross fixed capital formation, household consumption, government consumption, exports, imports, price index, liabilities (currency and deposit), liabilities (loans), and unemployment. Tables [5](#) and [7](#) provide more details.

Both the VAR and FAVAR models are structural, which means that they are specified in a way that allow to separate economically meaningful shocks from mere statistical noise. While reduced-form (FA)VAR models are useful for capturing the statistical relationships in the data and for making

Methodological choice	Dimension	Variants
Estimation method	Model	VAR models (3 to 5 variables) and FAVAR models (3 variables and 1-2 factors)
	Identification strategy	Cholesky decomposition, Blanchard-Perotti (VARs only), sign restrictions
Data	Fiscal data definition	7 variants (see table 2)
	Deflating index	GDP deflator, HICP (0 and 4 lags)
	Deterministics	Constant only, constant and linear time trend
	Lags	1 to 4 lags

Table 1: The methodological choices that were considered in this study. Taken together, they amount to 2,520 different model specifications.

forecasts (Kilian and Lütkepohl, 2017, 2), a structural specification is essential for making causal inferences and, thus, economically interpreting the effects of the respective shocks.

3.2 Model Specifications

In order to estimate the fiscal multipliers, this study employs 2,520 different specifications of structural VAR and FAVAR models. These model specifications capture differences arising from (i) the choice of estimation method, (ii) the dataset employed, and (iii) additional technical aspects. Table 1 provides an overview of the different modeling choices. As regards the estimation method, this study sets up VAR models with three to five variables and FAVAR models with three variables plus one or two factors. Furthermore, identification of the structural shocks is achieved through the Cholesky decomposition, the Blanchard-Perotti method (for VARs only), and sign restrictions. As regards data, this study employs different definitions to calculate government spending and revenues and calculates the real from nominal values using different inflation indices. In addition, the different specifications reflect further technical choices regarding the number of factors in the FAVAR models, the use of linear time trends, and the number of lags.

As Čapek and Crespo Cuaresma (2020) have argued, such apparently minor modeling choices can substantially influence both the magnitude and the precision of the estimates. Alongside Čapek et al. (2022), this study therefore combines these specifications in order to account for this modeling uncertainty: After running 500 repetitions and calculating the median multipliers for each specification, the results are averaged across all specifications and the results of the best models in terms of forecasting are reported separately.

Table 2 provides an overview of the different definitions used for government expenditure and revenue data. It outlines the various fiscal data variants used in this study, each with specific adjustments to the baseline composition. On the expenditure side, the baseline includes compensation of employees, intermediate consumption, and gross capital formation, which may be adjusted for social benefits in-kind or acquisitions of assets. On the revenue side, the baseline consists of taxes on production, imports, income, and wealth, and is incrementally adjusted across variants to include social contributions, social benefits, subsidies, capital taxes, capital transfers, and other revenues. While this study mainly sticks to these definitions for means of comparability, Čapek et al. (2022, p. 52) provide some further reasons.

Variant	Expenditure	Revenue
core/tax tiny	compensation of employees, intermediate consumption, and gross capital formation ("baseline")	taxes on production, imports, income, and wealth ("baseline")
core/tax small net soc.t		baseline adjusted for social contributions (by employers only) and social benefits
core/net tax small		baseline adjusted for social contributions, social benefits, and subsidies
corefix+soc.t.kind/tax mid	baseline (but only gross fixed capital) adjusted for social benefits (in-kind only)	baseline adjusted for social contributions, and capital taxes
corefix+soc.t.kind/net tax mid		baseline adjusted for social contributions, social benefits (monetary only), capital taxes, and subsidies
corefix+soc.t.kind/net tax large		baseline adjusted for social contributions, benefits (monetary only), subsidies, capital taxes, and other revenues and expenditures
core/net tax all	baseline adjusted for acquisitions of assets	baseline adjusted for social contributions, benefits, subsidies, capital transfers, and other revenues and expenditures

Table 2: Overview of the different government expenditure and revenue definitions employed in this study. This closely follows Čapek et al. (2022, p.419).

4 Data

The primary data source is Eurostat, supplemented by data from the European Central Bank. The dataset comprises quarterly observations from 2001 to 2024, yielding 96 data points per variable¹. The following transformations of the original data were made: If only monthly data were available, they were transformed into quarterly values. For series expressed in monetary units, the data was aggregated by summing over the three months. For index-based data, the quarterly average was computed. In the case of the HICP, quarterly values were calculated as $HICP_q = (1 + HICP_{m1})(1 + HICP_{m2})(1 + HICP_{m3}) - 1$. Furthermore, if seasonally adjusted data were not readily available, the respective time series and the autocorrelation functions (ACFs) were plotted in order to visually detect seasonality, supplemented by economic intuition. In case of seasonality, it was removed using X13-ARIMA. In addition, all fiscal data as well as the GDP were logarithmized. Finally, a first-difference transformation was applied to all source series used for factor extraction – except for flow variables – in order to ensure (trend) stationarity.

Tables 5 and 6 in the Appendix provide an overview of the data series used in the VAR and FAVAR specifications, including their source and the transformation steps that were applied in the data cleaning process. Table 7, in addition, presents the descriptive statistics of the seasonally adjusted data that were used as variables, factors, or the further computation of fiscal variables. Additional insight is provided by Figure 1, which traces the time series of the same spending and revenue aggregates. It confirms that these variants do not merely differ conceptually, but also exhibit substantial and persistent differences in both level and volatility.

5 Econometric Model

5.1 Formal VAR and FAVAR Models

Following [Stock and Watson \(2016, p. 477\)](#) but using the notation of [Kilian and Lütkepohl \(2017\)](#), the structural FAVAR can be written as follows:

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix}_{\substack{n \times 1 \\ m \times 1}} = \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{\Lambda}^Y & \mathbf{\Lambda}^F \end{pmatrix}_{\substack{n \times n & n \times r \\ m \times n & m \times r}} \begin{pmatrix} \tilde{F}_t \\ F_t \end{pmatrix}_{\substack{n \times 1 \\ r \times 1}} + \begin{pmatrix} 0 \\ e_t \end{pmatrix}_{\substack{n \times 1 \\ m \times 1}} \quad (3)$$

$$\mathbf{A}(L)_{(n+r) \times (n+r)} \begin{pmatrix} \tilde{F}_t \\ F_t \end{pmatrix}_{\substack{n \times 1 \\ r \times 1}} = \begin{pmatrix} \mathbf{I} \\ \mathbf{0} \end{pmatrix}_{\substack{(n+q) \times (n+q) \\ (r-q) \times (n+q)}} \begin{pmatrix} u_t \\ \end{pmatrix}_{(n+q) \times 1} \quad (4)$$

¹Earlier fiscal data are not available. As the factors were first-differenced, this study actually employed non-fiscal data from the fourth quarter in 2000 as well, still yielding 96 observation, however.



Figure 1: Time series of the public spending and revenue data for the different definitions from table 2, deflated by HICP.

$$\begin{matrix} \mathbf{B} \\ (n+q) \times (n+q) \end{matrix} \begin{matrix} u_t \\ (n+q) \times 1 \end{matrix} = \begin{matrix} \mathbf{C} \\ (n+q) \times (n+q) \end{matrix} \begin{matrix} w_t \\ (n+q) \times 1 \end{matrix} \quad (5)$$

Whereas equation (3) is the *measurement* equation, equation (4) is the reduced-form *transition* equation, and equation (5) is the structural *identification* equation. The lag polynomial $\mathbf{A}(L)$ is defined as $\mathbf{A}(L) = \mathbf{I} - \mathbf{A}_1 L - \dots - \mathbf{A}_p L^p$, where $\mathbf{A}_l$ are the coefficient matrices for lags $l = 1, \dots, p$. The variables in Y_t for time $t = 0, \dots, T$ include the real GDP, government spending, taxation, and, only in VAR specifications with four or five variables, inflation and the interest rate. They are assumed to be measured without any error by the observed factors $\tilde{F}_t$. The variables in X_t relate to other macroeconomic and financial variables as well as other variables related to labor markets,

production and sectoral developments that are included in the FAVAR specifications. They are assumed to be measured with an idiosyncratic error e_t and depend on the observed factors $\tilde{F}_t$ and the unobserved factors F_t , with Λ^Y and Λ^F depicting the respective factor loadings. The unobserved factors F_t are estimated as principal components. After estimating the reduced-form VAR or FAVAR models, the matrices B and C are selected using identification strategies, allowing the (economically meaningful) structural shocks w_t to be retrieved from the (purely statistical) reduced-form shocks u_t .

Notably, if $r = 0$, we have no unobserved factors F_t and the FAVAR model collapses to the structural VAR model with the following reduced-form transition and structural identification equations:

$$\begin{aligned} \tilde{F}_t &= \sum_{i=1}^p \mathbf{A}_i \tilde{F}_{t-i} + u_t \\ \mathbf{B} u_t &= \mathbf{C} w_t \end{aligned}$$

$n \times 1 \quad n \times n \quad n \times 1 \quad n \times 1 \quad n \times n \quad n \times 1 \quad n \times n \quad n \times 1$

5.2 Identification Strategy

Because the structural shocks w_t , i.e., the exogenous discretionary fiscal impulses, are not directly observable, they need to be identified from the reduced-form shocks u_t which comprise all discretionary and automatic fiscal impulses. This is done in equation 5. It is important to highlight that the structural shocks are not directly associated with the respective model variables. They have, thus, no natural unit of measurement and need to be standardized. Unfortunately, economists disagree about how to perform the identification due to the possibility of reverse causality: fiscal policy variables may influence real GDP, but real GDP developments may simultaneously influence fiscal policy decisions through, among others, rule-based policy responses. In order to estimate w_t , this study therefore uses three different identification strategies: the Cholesky decomposition, the Blanchard-Perotti method, and the sign restriction approach. As soon as the coefficients of the respective reduced-form VAR and FAVAR models are estimated and the structural shocks w_t are identified from the reduced-form shocks u_t , the impulse response functions (IRFs) are calculated and used as input for the calculation of the multipliers in equations 1 and 2. Given that even minor variations in the identification strategy can substantially influence the estimated magnitude of the multipliers, a detailed and transparent account of each approach is provided in the following sections.

5.2.1 Cholesky Decomposition

The Cholesky decomposition, introduced into fiscal analysis by (Fatás and Mihov, 2001, pp. 6-8), identifies a fiscal shock based on assumptions about the timing of responses among variables.

Specifically, it assumes that some variables do not respond contemporaneously to shocks in other variables. The core idea is to order the variables such that the first variable can contemporaneously affect all others, the second can affect only those that follow it in the ordering, and so on, with the last variable not affecting any others within the same period. The specific ordering reflects economic assumptions about the relative speed in which the variables respond to each other.

Following Čapek et al. (2022), the basic three-variable VAR specification orders government spending first, followed by real GDP, and then taxes. Economically, this means that, within the same quarter, (i) government spending does not respond to shocks in GDP or inflation, (ii) real GDP may react to changes in government spending, but not to changes in inflation, and (iii) inflation can respond to changes in both spending and real GDP. In VAR specifications with four variables, the ordering is spending, real GDP, inflation, and tax, and in VAR specifications with five variables, it is spending, real GDP, inflation, taxes and interest rate.

Under the Cholesky decomposition, the identification equation 5 simplifies to $w_t = Bu_t$. In the three-variable VAR specification where g_t denotes government spending, y_t real GDP per capita, and τ_t taxation, therefore, the following transition and identification equations hold:

$$\begin{bmatrix} g_t \\ y_t \\ \tau_t \end{bmatrix} = \sum_{i=1}^p \begin{bmatrix} a_i^{gg} & a_i^{gy} & a_i^{g\tau} \\ a_i^{yg} & a_i^{yy} & a_i^{y\tau} \\ a_i^{\tau g} & a_i^{\tau y} & a_i^{\tau\tau} \end{bmatrix} \begin{bmatrix} g_{t-i} \\ y_{t-i} \\ \tau_{t-i} \end{bmatrix} + \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^\tau \end{bmatrix} \quad (4')$$

$$\begin{bmatrix} 1 & 0 & 0 \\ b_{21} & 1 & 0 \\ b_{31} & b_{32} & 1 \end{bmatrix} \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^\tau \end{bmatrix} = \begin{bmatrix} w_t^g \\ w_t^y \\ w_t^\tau \end{bmatrix} \quad (5')$$

5.2.2 Blanchard-Perotti identification

The Blanchard-Perotti identification strategy imposes numerical restrictions on the reduced-form and structural shocks that are based on economic argumentation. This study follows Blanchard and Perotti (2002) for three-variable models and Perotti (2004) for specifications with four or five variables and is applied to VAR models only.

As regards the structural impact matrices B and C in the three-variable VAR case, the economic restrictions imposed by Blanchard and Perotti (2002, p. 1333-1336) are used. As regards the elasticities, which quantify the responsiveness of fiscal variables to economic conditions, this study follows Čapek et al. (2022, p. 7) and assumes the output elasticity of government revenue to be 1.66 (which means that $b_{32} = -1.66$), the price elasticity of revenue to be 0.78, and the price elasticity of spending to be -0.5. Opposed to Blanchard and Perotti (2002, 1336), they seem to implicitly

assume that spending decisions always come first and taxes only respond. Considering the basic VAR specification with three variables, the Blanchard-Perotti identification equation is

$$\begin{bmatrix} 1 & 0 & 0 \\ b_{21} & 1 & b_{23} \\ 0 & -1.66 & 1 \end{bmatrix} \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^\tau \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ c_{31} & 0 & 1 \end{bmatrix} \begin{bmatrix} w_t^g \\ w_t^y \\ w_t^\tau \end{bmatrix} \quad (5'')$$

5.2.3 Sign restriction approach

In contrast to approaches that impose exact numerical constraints on the structural matrices $\mathbf{B}$ and $\mathbf{C}$, the sign restriction approach identifies the structural shocks w_t from the reduced-form shocks u_t by imposing economically motivated sign restrictions on the impulse responses over a fixed time horizon. As a result, this procedure allows for an identification of structural shocks based on qualitative economic theory, while avoiding strong quantitative assumptions.

In general, this study follows the procedure outlined by Kilian and Lütkepohl (2017, p.424-425; 427-428). Along with Uhlig (2005), Mountford and Uhlig (2009) and Rubio-Ramírez et al. (2010), the sign restriction strategy is implemented using a Bayesian framework. This means that, after estimating the reduced-form (FA)VAR model, the parameters in the transition equation 4 — i.e., the coefficients $\mathbf{A}$ and the variance-covariance matrix Σ — are treated as random instead of fixed. For clarity and reproducibility, the procedure is presented below in its logical order:

1. **ESTIMATE THE REDUCED-FORM (FA)VAR:** Estimate the reduced-form model from equation 4 to obtain the coefficient matrices $\hat{\mathbf{A}}_1, \dots, \hat{\mathbf{A}}_p$ and the covariance matrix $\hat{\Sigma}_u = \mathbb{E}[u_t u_t']$.
2. **CALCULATE THE LOWER TRIANGULAR $\mathbf{P}$:** Calculate the (unique) initial orthogonal matrix $\mathbf{P}$ by performing a Cholesky decomposition of the error covariance matrix $\hat{\Sigma}_u = \mathbf{P}\mathbf{P}'$. (The Cholesky decomposition is used only as a convenient tool to orthogonalize the reduced-form shocks, but not to impose an economic ordering. Any solution for $\mathbf{P}$ such that $\hat{\Sigma}_u = \mathbf{P}\mathbf{P}'$ works.)
3. **CALCULATE THE MA COEFFICIENTS $\hat{\Phi}_h$:** Calculate the moving average coefficients of the reduced-form VAR $\hat{\Phi}_h$ for $h = 0, \dots, H$.
4. **CALCULATE THE INITIAL IRFS $\Psi_h^{initial}$:** Calculate the initial IRFs $\Psi_h^{initial} = \hat{\Phi}_h \mathbf{P}$ for $h = 0, \dots, H$.
5. **GENERATE THE ROTATION MATRIX $\mathbf{Q}$:** Draw a random matrix $\mathbf{W} \in \mathbb{R}^{n \times n}$, where each element is independently sampled from a standard normal distribution, i.e., $\mathbf{W} \sim \mathcal{N}(0, 1)$. As $\mathbf{W} = \mathbf{Q}\mathbf{R}$, apply the QR decomposition to $\mathbf{W}$ to obtain an orthonormal rotation matrix $\mathbf{Q}$ with $\mathbf{Q}\mathbf{Q}' = \mathbf{I}$.
6. **IF $\mathbf{R}$ HAS NEGATIVE DIAGONAL ELEMENTS, PERFORM A SIGN NORMALIZATION:** Perform a sign normalization on $\mathbf{R}$ by reversing all signs of the i^{th} column of $\mathbf{Q}$ if the i^{th} diagonal element of $\mathbf{R}$ is negative. (Note that, as we are not interested in $\mathbf{R}$, it suffices if we adjust $\mathbf{Q}$.)

7. CALCULATE A CANDIDATE STRUCTURAL IMPACT MATRIX C^* : Calculate a candidate structural impact matrix $C^* = PQ$ and the candidate structural shocks $w_t^* = C^* u_t$. (As $C^* C^{*'} = PQQ'P' = PP' = \hat{\Sigma}_u$, the candidate structural impact matrix defines a possible rotation of the orthogonal shocks. Again, the candidate structural shocks implied by C^* are not yet structural and can, thus, not yet be interpreted economically.)
8. CALCULATE THE IRF OF THE CANDIDATE STRUCTURAL IMPACT MATRIX Ψ_h : Rotate the initial IRF in order to obtain the IRF of the respective candidate structural impact matrix, i.e., $\Psi_h = \Psi_h^{initial} Q = \hat{\Phi}_h PQ = \hat{\Phi}_h C^*$.
9. TEST AGAINST THE SIGN RESTRICTIONS: Test whether the rotated IRF satisfies the imposed sign restrictions.
10. IF APPROPRIATE, CHANGE THE SIGN: If all impulse responses to a given shock have the opposite sign of the imposed restriction, flip the sign of the corresponding column of Q . (As the resulting Q now satisfies the imposed sign restriction and remains a valid orthogonal matrix, this procedure is computationally more efficient than discarding the initial draw.)
11. SAVE THE ACCEPTED DRAWS: Save only the draws for which the relevant sign restriction is satisfied.
12. REPEAT STEPS 5-11: Repeat this procedure until a sufficiently large number of accepted draws has been obtained - in this case, this number was set to 500.
13. SUMMARIZE: Summarize the results by computing the median of the IRFs across all accepted draws.

The following sign restrictions are imposed to distinguish between the different types of shocks: Firstly, a *business cycle shock* is identified iff the impulse responses of GDP and taxes are positive for at least four quarters following the shock. Secondly, a *tax shock* occurs iff the impulse response of taxes is positive for at least four quarters, and the conditions for a business cycle shock are not met. Finally, a *government spending shock* is defined analogously – government expenditure must exhibit a positive impulse response for at least four quarters, again without fulfilling the conditions of a business cycle shock.

5.3 Robustness of the Estimates and Assumptions

This study estimates the fiscal effects using empirical methods, as opposed to macroeconomic models such as Dynamic Structural General Equilibrium (DSGE) and Real Business Cycle (RBC) frameworks or large-scale macroeconomic simulations. Structural VAR and FAVAR models have established themselves as a widely used methodological framework in empirical macroeconomic

time series analysis (Kilian and Lütkepohl, 2017, p. xvii). On the one hand, compared to model-based approaches, empirical methods such as structural VAR and FAVAR models offer greater flexibility and impose fewer theoretical assumptions. Whereas DSGE and RBC models rely heavily on structural assumptions about agent behavior, preferences, and market mechanisms, empirical approaches are more data-driven. Their results are typically less sensitive to specific theoretical frameworks and better suited for capturing real-world dynamics — especially when those dynamics are uncertain or evolving. That said, empirical methods are not theory-free: they still require identification strategies, which often draw on economic theory to isolate exogenous fiscal shocks. On the other hand, compared to other empirical approaches, structural VAR and FAVAR models often achieve a good empirical fit while relying on relatively few identification assumptions (Kilian and Lütkepohl, 2017, p. 4). In particular, FAVAR models offer an important advantage: they incorporate a broad range of both observed and unobserved factors, which enhances their ability to approximate the true data-generating process. This is especially valuable in settings with limited data availability — such as Austria, where the macroeconomic time series used in this study contain only 96 observations per variable.

Furthermore, the identification strategies employed in this study — namely, the Cholesky decomposition, the Blanchard-Perotti method, and the sign restriction approach — are considered appropriate, as they are well-established in the empirical macroeconomic literature. In addition, each method is grounded in economic theory and allows for a transparent decomposition of fiscal shocks. By employing recursive timing assumptions, structural elasticities, and economically motivated sign restrictions, they allow to achieve identification from multiple complementary perspectives.

To produce interpretable and robust estimates of fiscal multipliers, several assumptions underpin the modeling approach used in this thesis. Firstly, it is assumed that seasonal patterns have been eliminated and that the data are, therefore, stationary or, in models that contain a linear trend, trend-stationary. Secondly, structural identification of fiscal shocks requires economic assumptions. These include timing restrictions, sign restrictions imposed on impulse responses, and elasticity assumptions based on economic theory and institutional knowledge. These assumptions vary by identification strategy and are central to interpreting the estimated responses as causal effects.

Importantly, however, no single specification is assumed to be correct. Instead, a large and diverse set of models is estimated, varying systematically in lag length, variable inclusion, trend specification, and identification method. This approach directly addresses model uncertainty — acknowledging that different modeling choices can lead to different results — and assumes that the model space is sufficiently rich to approximate the true data-generating process. In the tradi-

tion of Popperian falsificationism, this study treats each model specification as a provisional hypothesis that needs to be subject to empirical testing in order to be "temporarily non-falsified". By averaging across all models and highlighting those with the strongest out-of-sample forecasting performance, this strategy aims to produce fiscal multiplier estimates that are not only empirically grounded but also robust to specification choices. This broad modeling framework is a crucial component in ensuring the reliability and robustness of the final results.

For each model specification, the positive definiteness of the residual covariance matrices was checked to ensure the validity of the (FA)VAR estimation. Models that did not satisfy this condition were discarded. In addition, a variety of model selection criteria were calculated — the Akaike Information Criterion (AIC), the Hannan–Quinn Criterion (HQC), and the Schwarz Information Criterion (SIC), as well as Lagrange Multiplier (LM) and Portmanteau test statistics. Finally, the last four observations were used to generate one-step-ahead out-of-sample forecasts of the real GDP, enabling an assessment of the predictive accuracy of the respective models. These forecast evaluation metrics include mean squared error (MSE), mean average error (MAE), directional accuracy (DA), and directional value (DV). Based on these results, a separate set of multipliers was calculated from the subset of models with the highest predictive accuracy. While results for all model selection criteria and forecast evaluation metrics are not reported in this study — with a focus instead on MSE and MAE — the overall findings are very similar.

6 Results

6.1 All Model Specifications

Table 3 presents the estimated fiscal multipliers for Austria, and Figure 2 displays the corresponding kernel density plots for government spending and tax multipliers at impact, in the short run, and in the medium run. Overall, government spending multipliers are positive across most specifications and horizons, while tax multipliers are smaller in magnitude, more dispersed, and exhibit greater sensitivity to model selection.

At impact, the average present value spending multiplier is 0.76 across all models and 0.33 among the best-performing models in terms of out-of-sample forecast accuracy. In the short run, the mean multiplier increases to 1.22 in the full sample and 0.67 among the best 40% of models. By the medium run, the average spending multiplier rises further to 1.82 for all models and 1.52 for the best-performing subset. Peak spending multipliers average 1.36 in the full sample and 0.74 among the best models. The full sample includes some negative estimates and shows broader dispersion, with minimum values as low as -3.62 at impact. In contrast, the distribution of multipliers among the best-performing models is tighter and centered around moderate positive values. Across all

horizons, the distribution of spending multipliers is right-skewed, and in the full sample, it exhibits signs of bimodality, especially at impact and in the short run. The data also show that, in many specifications, the largest output responses occur in the medium run.

Tax multipliers are generally smaller in absolute value and more variable than spending multipliers. At impact, the mean tax multiplier is -0.05 across all models and -0.06 among the best-performing models. In the short run, the mean is -0.31 for the full sample and -0.04 for the best subset. By the medium run, the mean tax multiplier is -0.96 across all models and 0.10 among the best models. One specification in the full sample yields a multiplier of -15.77 , contributing to a wide range of values in the medium run. Peak tax multipliers average -0.34 in the full sample and -0.19 in the best-performing models. The kernel densities for tax multipliers show broad, flat distributions with substantial mass near zero, particularly in the best models, where the medium-run distribution becomes tightly centered around zero. Compared to the full sample, the best-performing models exhibit substantially reduced dispersion and tighter clustering of values across all horizons.

Government spending and tax multipliers also differ in scale. On average, spending multipliers are substantially larger than tax multipliers across all horizons and model subsets. This contrast in both size and distributional characteristics is consistent throughout the full model ensemble and the subset of models with the strongest forecasting performance.

These findings align broadly with existing estimates for Austria. Most importantly, Čapek et al. (2022, p. 421) report short-run present value spending multipliers of 0.94 across all models and 0.87 among the best-performing ones, based on Austrian data up to 2018. The present short-run estimates of 1.22 (full sample) and 0.67 (best models) fall within a comparable range. For tax policy, Čapek et al. report a mean short-run multiplier of -0.76 , whereas the current results are -0.31 across all models and approximately zero among the best-fitting models. A comparison with Schuster (2019, p. 15), who estimates present value multipliers using a macroeconomic model for Austria, shows similar directional patterns. Schuster reports a spending multiplier of 0.80 at impact, 0.83 in the short run, and 0.74 in the medium run. The current estimates — 0.76 , 1.22 , and 1.82 — are similar at impact but considerably higher in the short and medium term. For tax multipliers, Schuster finds -0.38 at impact, -0.84 in the short run, and -1.08 in the medium run, which are broadly comparable to the present estimates of -0.04 , -0.31 , and -0.96 .

6.2 Model Sensitivity

This section examines the sensitivity of fiscal multiplier estimates to the key modeling choices depicted in Table 1. Specifically, it explores how the different (FA)VAR specifications, identifications

Multiplier type	min	16-th p.	mean	median	84-th. p	max
Spending						
Peak	0.05	0.45	1.36	1.34	2.08	7.17
— best 40%	0.06	0.31	0.74	0.57	1.29	2.71
Present value, impact	-3.62	0.04	0.76	0.58	1.60	9.44
— best 40%	-3.32	0.02	0.33	0.23	0.67	3.09
Present value, short run	-1.50	0.40	1.22	1.12	2.01	6.39
— best 40%	-1.07	0.25	0.67	0.56	1.15	2.95
Present value, medium run	-2.86	1.13	1.82	1.72	2.64	5.34
— best 40%	-1.76	1.01	1.52	1.43	2.11	3.86
Tax						
Peak	-1.46	-0.65	-0.34	-0.30	-0.01	0.44
— best 40%	-1.14	-0.44	-0.19	-0.11	0.00	0.35
Present value, impact	-1.05	-0.33	-0.04	-0.05	0.26	1.19
— best 40%	-0.90	-0.32	-0.06	0.01	0.13	1.19
Present value, short run	-3.96	-0.89	-0.31	-0.21	0.28	1.86
— best 40%	-2.68	-0.42	-0.04	0.05	0.37	1.86
Present value, medium run	-15.77	-3.15	-0.96	-0.71	0.94	19.96
— best 40%	-11.01	-1.14	0.10	0.26	1.18	17.00

Table 3: Estimates of the different fiscal multipliers in the short, medium and long run.

strategies, fiscal variable definitions, deflation methods, and trend assumptions affect the magnitude and shape of estimated spending and tax multipliers.

6.2.1 (FA)VAR Specifications and Identification Strategy

Figure 3 presents box plots of the different spending and tax present value multipliers across the different VAR and FAVAR specifications and identification methods. To analyze systematic differences, several alternative arrangements of the box plots — such as ordering them by median values and dispersion — were examined, based on the key dimensions model type, number of variables, and identification method. While these alternative visualizations are omitted for brevity, they enabled an assessment of whether certain specifications systematically produce higher or lower multipliers, both within and across different time horizons. (i) For model type, the results show that spending multipliers do not differ systematically between VAR and FAVAR models across any horizon. In the case of tax multipliers, however, FAVAR models tend to produce larger multipliers in absolute terms at impact and in the short run. (ii) With respect to the number of included variables, no clear relationship emerges. For both spending and tax multipliers, models with more variables do not consistently yield higher or lower multipliers within any time horizon. (iii) More consis-

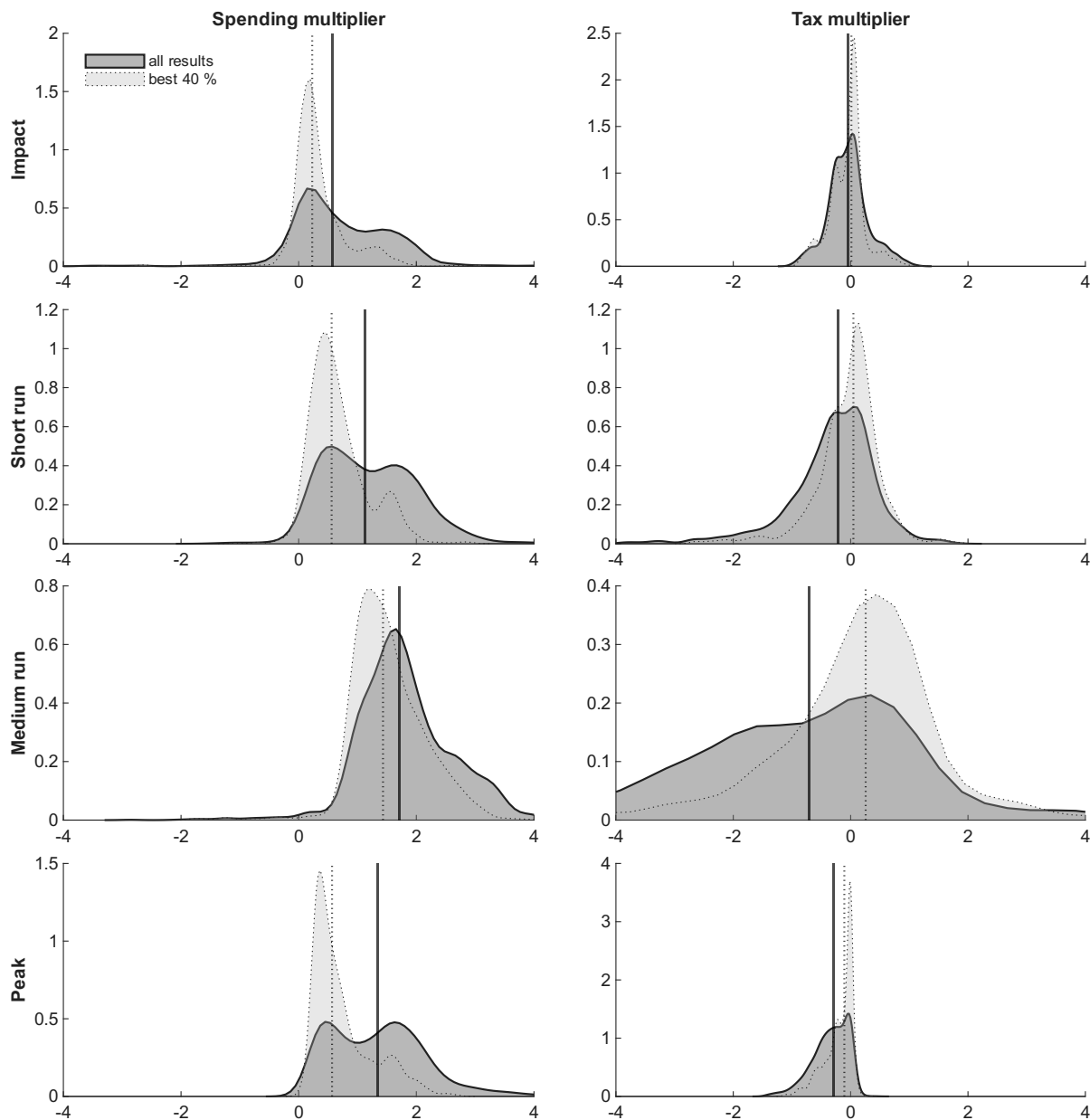


Figure 2: Kernel density plots of the spending and tax multipliers for all model specifications and those with the best predictive performance as measured in terms of mean average error (MAE) of out-of-sample predictions. The vertical lines depict the respective medians.

tent patterns are observed across identification strategies. For spending multipliers, models using Cholesky decomposition yield higher values at impact and in the short run. Sign-restricted models produce lower short-run multipliers but higher values in the medium run. The Blanchard-Perotti method typically lies between these two across all horizons. For tax multipliers, Cholesky-based models again produce larger absolute values at impact and in the short run, while sign restrictions lead to higher absolute multipliers in the medium run. In contrast, Blanchard-Perotti models stand

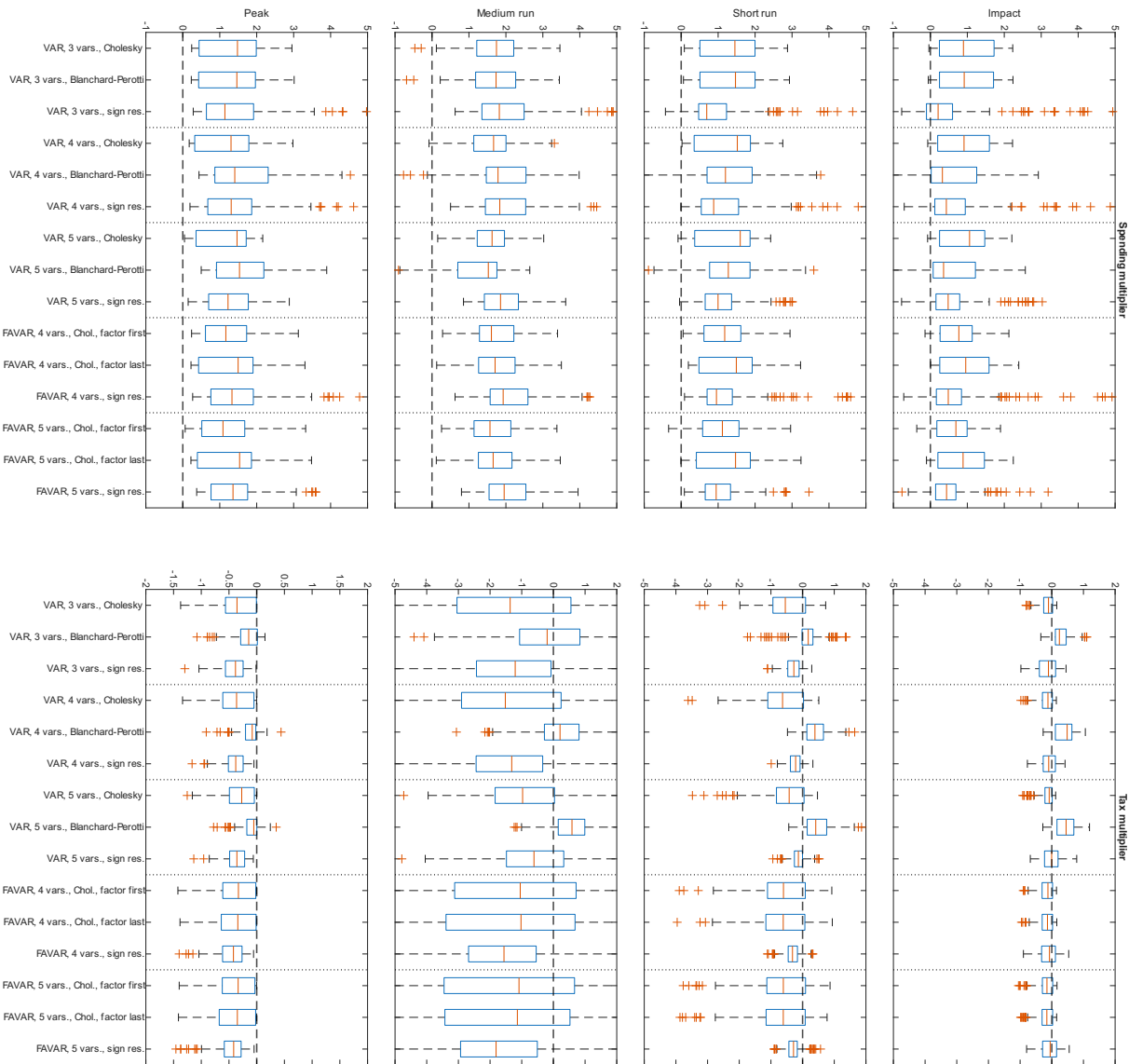


Figure 3: Box plots of the different spending and tax multiplier estimations for each (FA)VAR specification and identification method.

out: across nearly all horizons and VAR specifications, they produce positive median tax multipliers, which runs counter to standard economic expectations. As these results are not confirmed by other identification methods, this raises concerns about the robustness of the Blanchard-Perotti approach in this context.

Notably, Čapek et al. (2022, p. 426) do not report such positive tax multipliers under the Blanchard-Perotti scheme. Furthermore, they find that models with only three variables or using Cholesky identification tend to yield lower multipliers, a pattern that is not replicated here. Instead, the current findings show that spending multipliers identified through sign restrictions tend to be lower

Fiscal data definition	Count		Percentage	
	total	best 40%	total	best 40%
core/tax tiny	360	141	14.3	14.0
core/tax small net soc.t.	360	147	14.3	14.6
core/net tax small	360	120	14.3	11.9
corefix+soc.t.kind/tax mid	360	165	14.3	16.4
corefix+soc.t.kind/net tax mid	360	165	14.3	16.4
corefix+soc.t.kind/net tax large	360	150	14.3	14.9
core/net tax all	360	120	14.3	11.9

Table 4: Forecasting performance of the different fiscal data definitions

at impact and in the short run, but become higher in the medium run. Notably, unlike this study, the authors do not identify structural shocks using sign restrictions in the VAR3 model. Taken together, these findings reinforce the importance of accounting for model uncertainty. Multiplier estimates, especially for tax policy, are highly sensitive to seemingly minor modeling choices, confirming concerns raised by Čapek and Crespo Cuaresma (2020). The substantial variation across horizons, specifications, and identification methods underlines the necessity of robustness checks and the use of large model ensembles when evaluating the effects of fiscal policy. At the same time, the results corroborate earlier findings that spending multipliers are predominantly positive and often exceed one, particularly in the medium run, while tax multipliers are generally negative but closer to zero. Overall, spending multipliers tend to be larger in absolute terms across specifications and horizons, further supporting the asymmetry in fiscal policy effects.

6.2.2 Fiscal Accounting Choices

Figure 4 presents density plots of the spending and tax multipliers across various model specifications, each defined by a different combination of government spending and revenue concepts as outlined in Table 2. As previously described, the expenditure baseline includes compensation of employees, intermediate consumption, and gross capital formation, which may be adjusted for social benefits in-kind or acquisitions of assets. On the revenue side, the baseline consists of taxes on production, imports, income, and wealth, and is incrementally adjusted across variants to include social contributions, social benefits, subsidies, capital taxes, capital transfers, and other revenues. Again, the overall patterns in the model sensitivity to fiscal data definitions reinforce the main findings: Government spending multipliers are consistently positive across all definitions and horizons, tend to increase over time, and generally exhibit right-skewed distributions. In contrast, tax multipliers are centered around zero across all horizons and fiscal concepts, but display greater dispersion—particularly in the medium run—and tend to be left-skewed. These results also confirm that multiplier estimates, especially for tax policy, are highly sensitive to modeling choices, in

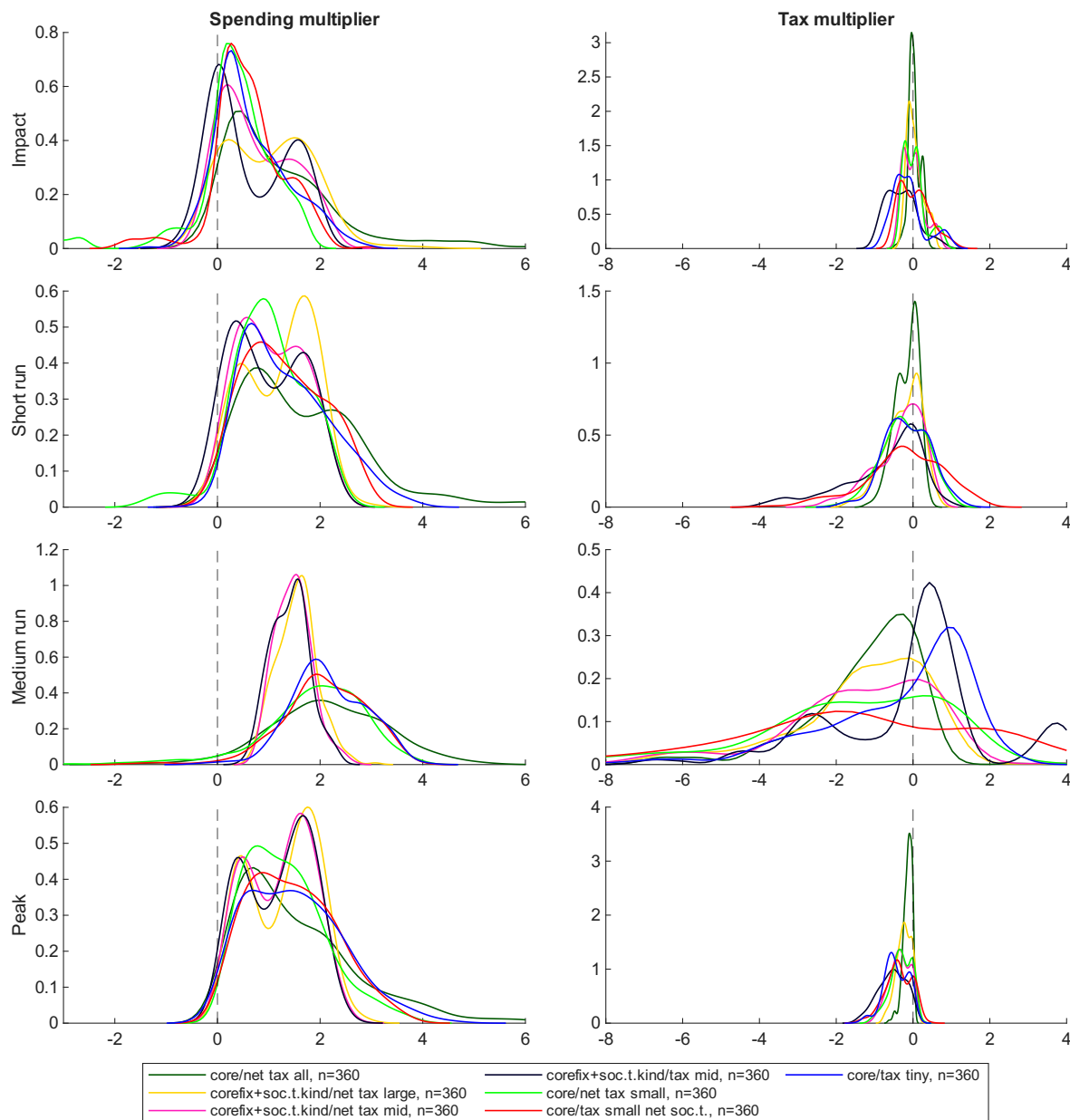


Figure 4: Density plots of the different spending and tax multiplier estimations for the different definitions of the fiscal variables.

line with concerns raised by Čapek and Crespo Cuaresma (2020).

However, the results presented here differ notably from those of Čapek et al. (2022, pp. 424–426) in important ways. While they find that most empirical distributions are relatively smooth and unimodal, my findings frequently exhibit bimodal densities. This pattern suggests that the definitions of government spending and revenues interact with the identification strategies: Depending on how what the fiscal variables include, the Cholesky decomposition, the Blanchard-Perotti method and the sign restriction approach identify different structural shocks – leading to distinct clusters

of multiplier estimates. This view also fits well to the observation that some identification methods systematically lead to higher multiplier estimates, depending on the type of multiplier and horizon, however. Moreover, whereas Čapek et al. (2022) highlight a reduction in dispersion under certain data compositions (such as the inclusion of monetary social transfers), I find no consistent relationship between the breadth of fiscal variable definitions and either the central tendency or the dispersion of the estimated multipliers.

That said, the model selection patterns in Table 4 offer additional insights: definitions involving mid-level adjustments, such as "corefix+soc.t.kind/tax mid" and "corefix+soc.t.kind/net tax mid", are overrepresented among the best-performing models. Conversely, the broadest net tax definitions (for example, "core/net tax small" and "core/net tax all") appear less frequently among the best-performing models, suggesting reduced empirical reliability. Baseline-like variants (for example, "core/tax tiny") perform close to their expected share. These results differ from Čapek et al. (2022, p. 424), where the definitions closer to the baseline are overrepresented. As no single specification dominates in general, these results reinforce the importance of model averaging and transparency when evaluating fiscal policy effects.

6.2.3 Deflation and Deterministic Trends

Figures 5 and 6 show how spending multiplier estimates vary depending on the choice of deflator and the inclusion of a deterministic time trend. The figures display kernel density estimates of present value spending multipliers across the impact horizon and the short and medium run, comparing all models to the best-performing 40% based on out-of-sample prediction accuracy. As with earlier findings, government spending multipliers are consistently positive across all horizons and specifications, tend to increase over time, and generally exhibit right-skewed distributions. The choice of deflator, however, has a substantial effect on the magnitude and shape of the estimated multipliers. Using the GDP deflator yields relatively conservative and tightly distributed results, with impact medians of about 0.25, short-run medians just above 0.5, medium-run values around 1.4, and peak multipliers near 0.5 – even among the best-performing models. In contrast, deflating GDP with the HICP results in considerably larger multipliers. With zero lags, the best-performing models show medians rising from roughly 0.9 at impact to 1.5 in the short run and peaking at 1.6 in the medium run. With four lags, the trajectory moves from 1.6 at impact to 1.8 in the short run, and peaks at 1.9 in the medium run. These HICP-deflated variants also exhibit frequent bimodal distributions among the best-performing models, suggesting interaction between price deflation and the identification of fiscal shocks.

Notably, however, models that are based on the GDP deflator dominate in the subset containing the best-performing models, constituting for 78% of them. HICP-based models appear in only 21%, and models based on HICP with four lags in just 1% of the top group – raising concerns that HICP deflation may overstate multiplier estimates and should be treated with caution. This is broadly

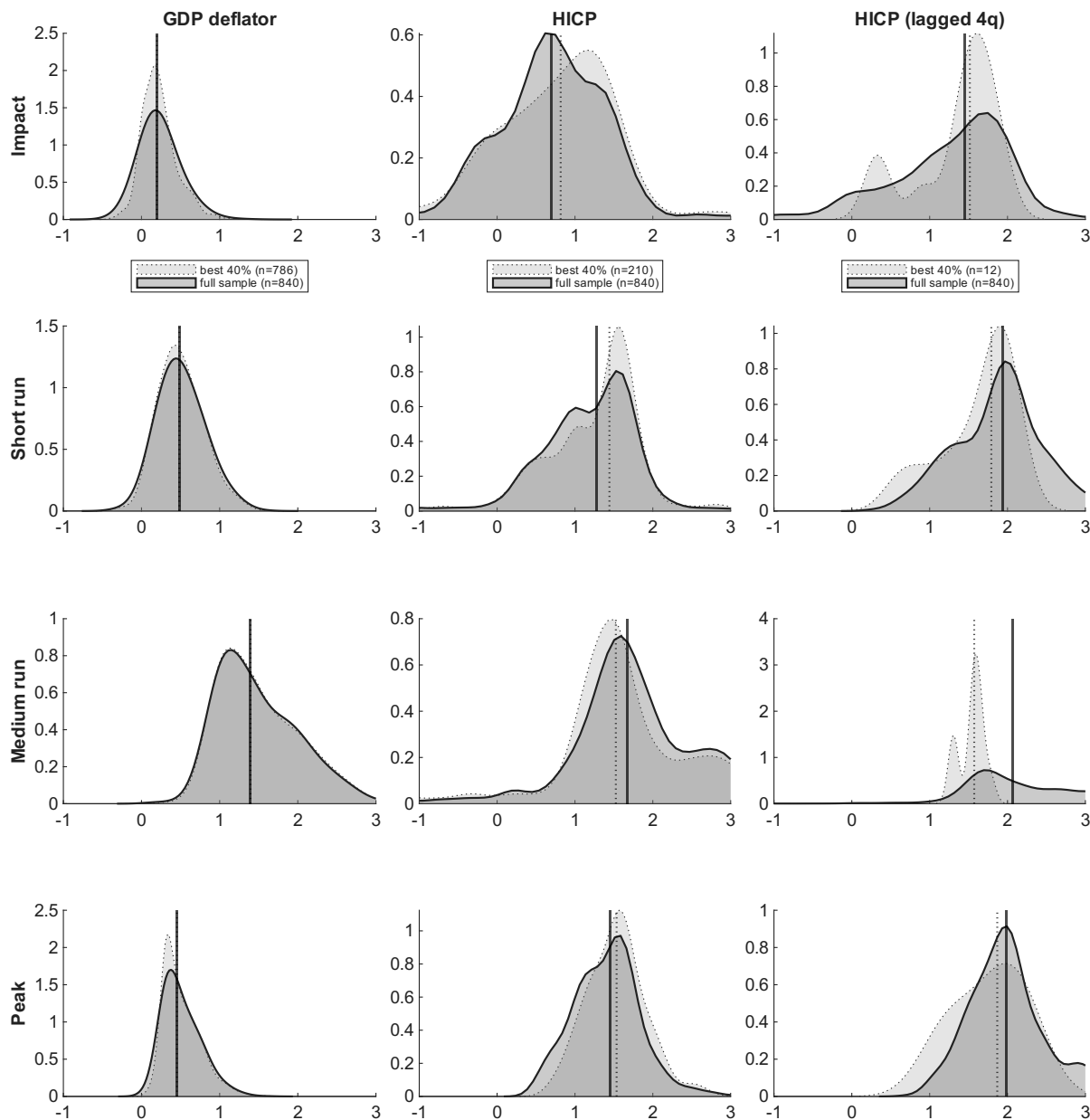


Figure 5: Kernel density plots of the present value spending multipliers for all model specifications and those with the best predictive performance as measured in terms of mean average error (MAE) of out-of-sample predictions, separated for different deflation indices. The vertical lines depict the respective medians.

consistent with findings by Čapek et al. (2022, pp. 422 - 424), who also observe that the GDP deflator tends to yield larger multipliers when predictive performance is taken into account. In their results, among models with high forecast accuracy, the GDP deflator accounts for 48%, while HICP and HICP with four lags account for 12% and 40%, respectively. Thus, while both studies acknowledge the influence of the deflator, the present analysis finds a more pronounced performance ad-

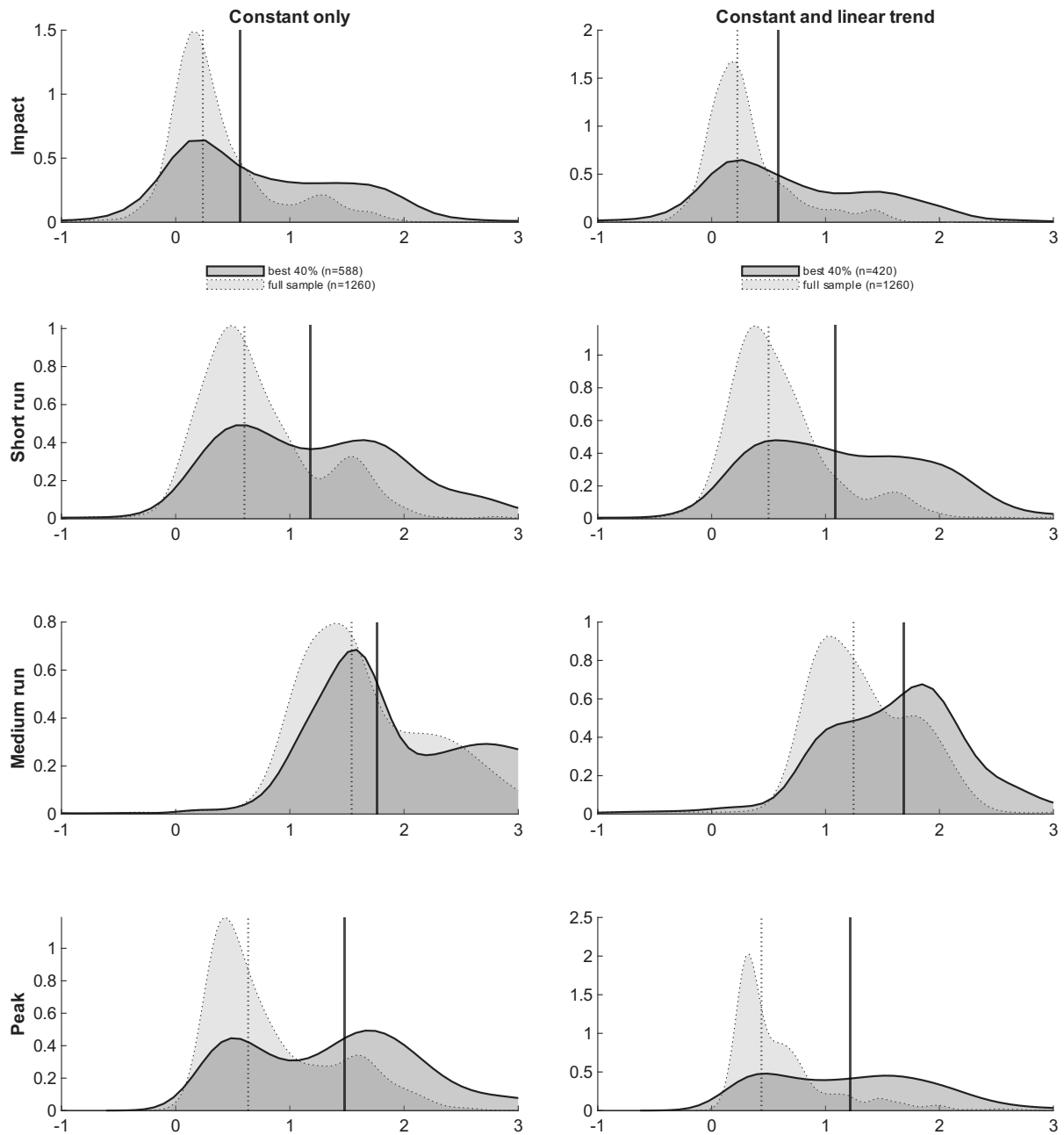


Figure 6: Kernel density plots of the present value spending multipliers for all model specifications and those with the best predictive performance as measured in terms of mean average error (MAE) of out-of-sample predictions, separated for the existence of a linear trend in the model. The vertical lines depict the respective medians.

vantage – and statistical dominance – of models using the GDP deflator.

Regarding deterministic trends, the inclusion of a linear trend does not significantly affect multiplier magnitudes in this study. Models with and without a trend yield broadly similar distributions,

and among the best-performing specifications, those without a trend constitute around 60%. This stands in contrast to Čapek et al. (2022), who find that 64% of their best-performing models include a trend, with only 36% excluding it. Moreover, the authors emphasize that omitting a trend may lead to underestimated multipliers due to unaddressed non-stationarity, whereas my findings suggest no such systematic bias. Once again, these differences underscore the importance of accounting for model uncertainty and validating empirical results across a broad range of plausible specifications.

6.3 Economic Interpretation

The estimated fiscal multipliers quantify the discretionary effect of government spending and taxation on Austria's real GDP across different time horizons. The results show that spending multipliers are consistently positive and even exceed unity in the short and medium run. Specifically, a short-run present value spending multiplier of 1.22 (0.67 in the best-performing models) implies that an additional euro of public expenditure yields more than a one-euro increase in real output over the first year. Over the medium run, these effects grow further to 1.82 (1.52 in the best-performing models), suggesting persistent stimulus effects – especially from investment-related spending. These findings indicate that fiscal spending stimulates immediate demand through direct effects and also fosters additional output through indirect effects, such as income generation and multiplier feedback loops.

Tax multipliers, by contrast, are smaller, more dispersed, and more sensitive to model specification. The short-run present value tax multiplier is 0.31, approaching zero in the best-performing subset of models. By the medium run, tax effects remain modest in the aggregate (−0.96) but even turn slightly positive (0.10) in the most reliable specifications. This asymmetry highlights a key finding of the analysis: tax increases may have only limited and temporary contractionary effects, especially when they are used to finance productive public spending. In this context, the interpretation of tax multipliers must consider not only the direct drag on demand, but also possible indirect positive effects.

There is no evidence that tax cuts work faster or more efficiently than spending increases. A critical implication is that budget-neutral fiscal expansions can be output-enhancing. The combination of strong spending multipliers and weak tax multipliers implies that raising taxes to fund additional government spending can still produce a net increase in output. This holds across most models and is particularly robust among those models that best fit the data. In light of Austria's institutional and fiscal constraints, these findings provide empirical support for tax-financed public spending as a means to stimulate economic growth. Although this positive analysis does not resolve the normative question of how best to balance the competing priorities of public investment,

social transfer payments, and debt sustainability, it does offer evidence that this trade-off can be mitigated by tax-funding the public expenditures.

This study's findings also reaffirm the importance of model uncertainty in estimating fiscal multipliers. While spending effects are robust across a wide range of VAR and FAVAR specifications, tax multipliers are more susceptible to variation in identification strategy, deflation method, and fiscal variable definitions. For instance, FAVAR models tend to yield larger absolute tax multipliers in the short run, but spending effects are largely invariant to model type. Identification strategies likewise matter: Cholesky-based models produce higher multipliers at impact, while sign-restricted approaches show stronger medium-run effects. As no single specification consistently dominates, model averaging remains crucial to ensure robustness and guard against overreliance on any individual configuration.

The choice of deflator also plays a non-trivial role. Models using the GDP deflator – overrepresented among the best-performing subset – tend to yield more moderate and reliable spending multipliers than those based on the HICP, which often generate inflated and bimodal distributions. These patterns suggest that deflation methods can interact with identification strategies, influencing the timing and magnitude of estimated responses. Similarly, while the inclusion of deterministic trends does not systematically affect results in this study, differences from prior work reinforce the necessity of transparency in modeling choices.

From a theoretical standpoint, these findings provide strong empirical support for Keynesian and New Keynesian predictions, particularly in a context of constrained monetary policy, as in recent Austrian economic episodes. By contrast, the results are inconsistent with neoclassical or monetarist expectations of small or negative multipliers, which rely on crowding-out effects or Ricardian equivalence.

In summary, this study finds that discretionary fiscal policy – especially on the spending side – can be an effective macroeconomic stabilization tool in Austria, even under strict budgetary constraints. The asymmetry in multiplier magnitudes between spending and tax changes suggests that the composition of fiscal policy matters at least as much as its size. Given Austria's structural challenges and current economic context, these insights offer a valuable empirical foundation for designing strategic, growth-oriented fiscal interventions that are both economically effective and institutionally feasible.

7 Conclusion

This study set out to provide a robust and updated estimation of fiscal multipliers for Austria, a task motivated by the renewed relevance of fiscal policy in the conflict between stimulating economic growth, necessary investments and social transformations on the one hand and the necessity of fiscal sustainability on the other hand – a balance that requires sound empirical evidence on the effectiveness of government spending and taxation.

By building on the framework of Čapek et al. (2022) and significantly extending it in terms of dataset size, time coverage, and transparency, this thesis delivers new insights into the macroeconomic effects of fiscal interventions. Using a comprehensive set of 2,520 structural (FA)VAR model specifications, it addresses the issue of model uncertainty in the estimation of fiscal multipliers. Furthermore, the inclusion of more recent data including the COVID-19 pandemic and the war in Ukraine, enhances the relevance of the results for current policy debates. In doing so, the study makes an important contribution to a literature that has remained surprisingly sparse for Austria.

The key findings are clear and consistent. Government spending has a strong and positive effect on output across all time horizons, with medium-run multipliers frequently exceeding unity. This effect is robust across a wide array of model specifications and remains evident even under stricter model selection criteria based on forecast performance. The robustness of these spending effects, particularly across different VAR and FAVAR models, identification strategies, and deflation techniques, lends strong empirical support to the Keynesian prediction that public expenditure can effectively stimulate demand, even under fiscal or monetary constraints. In contrast, tax multipliers are smaller, more sensitive to model assumptions, and centered around zero in the most reliable models. This provides a strong argument in favor of tax-funded public spending as a means to stimulate economic growth.

Moreover, the findings on model specifications are less clear than those reported in Čapek et al. (2022). Their conclusions regarding the performance of various (FA)VAR specifications, identification strategies, fiscal data definitions, deflators, and time trends are not replicated when using the updated time span and horizons. For example, Cholesky-based identification tends to produce higher impact multipliers, while sign-restriction methods yield more persistent effects, particularly for spending shocks. FAVAR models amplify short-run tax responses, though spending responses remain remarkably stable. The GDP deflator, dominant among best-performing models, yields more moderate and consistent estimates than the HICP. These differences further underscore the importance of modeling choices and the role of model averaging in deriving credible policy conclusions.

Future research could build on this foundation in several ways. Firstly, more work is needed to

examine the state-dependence of fiscal multipliers, particularly whether their magnitude varies across phases of the business cycle or under monetary constraints. Secondly, a disaggregated analysis of different types of spending and taxation could help uncover the mechanisms driving the heterogeneous effects observed. These include, for example, different types of investment, consumption and transfer spending, or a range of tax instruments such as progressive personal income taxes, corporate income taxes, value-added taxes, and taxes on wealth or capital holdings. Thirdly, expanding the empirical framework to include interactions between fiscal and monetary policy would allow for a more holistic understanding of macroeconomic stabilization in Austria. Finally, future studies may explore long-run effects and potential structural shifts by applying non-linear or time-varying (FA)VAR models, should data availability improve.

In sum, this thesis underscores the effectiveness of government spending as a policy instrument for stabilizing and stimulating the Austrian economy. It reaffirms the importance of data-driven fiscal policy under uncertainty and provides a strong empirical foundation for designing budget-neutral yet output-enhancing public investment strategies. As policymakers navigate a complex and evolving economic landscape, such evidence-based guidance will remain essential.

Dataset and Code

The thesis has been submitted together with the dataset, along with the accompanying R and MATLAB code. All materials are also available for access [here](#).

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Appendix

Variable	Source	Reference
Nominal GDP	Eurostat	namq_10_gdp B1GQ SCA Q CP_MEUR
HICP	Eurostat	prc_hicp_midx CP00 M I15
GDP deflator	Eurostat	namq_10_gdp B1GQ CLV_I15 SCA
Inflation	ECB	ICP.M.U2.Y.000000.3.MOR
Interest rate	Eurostat	irt_lt_mcby_q MCBY Q
Compensation of employees (D1PAY)	Eurostat	gov_10q_ggnfa D1PAY NSA S13 Q MIO_EUR
Taxes on production and imports (D2REC)	Eurostat	gov_10q_ggnfa D2REC NSA S13 Q MIO_EUR
Total subsidies (D3PAY)	Eurostat	gov_10q_ggnfa D3PAY NSA S13 Q MIO_EUR
Income and wealth taxes (D5REC)	Eurostat	gov_10q_ggnfa D5REC NSA S13 Q MIO_EUR
Employer social contributions (D611REC)	Eurostat	gov_10q_ggnfa D611REC NSA S13 Q MIO_EUR
Household social contributions (D613REC)	Eurostat	gov_10q_ggnfa D613REC NSA S13 Q MIO_EUR
Net social contributions (D61REC)	Eurostat	gov_10q_ggnfa D61REC NSA S13 Q MIO_EUR
Social benefits (not in-kind) (D62PAY)	Eurostat	gov_10q_ggnfa D62PAY NSA S13 Q MIO_EUR
Social benefits (in-kind) (D632PAY)	Eurostat	gov_10q_ggnfa D632PAY NSA S13 Q MIO_EUR
Other expenditures (D7PAY)	Eurostat	gov_10q_ggnfa D7PAY NSA S13 Q MIO_EUR
Other revenues (D7REC)	Eurostat	gov_10q_ggnfa D7REC NSA S13 Q MIO_EUR
Capital taxes (D91REC)	Eurostat	gov_10q_ggnfa D91REC NSA S13 Q MIO_EUR
Capital transfers (expenditure) (D9PAY)	Eurostat	gov_10q_ggnfa D9PAY NSA S13 Q MIO_EUR
Capital transfers (revenue) (D9REC)	Eurostat	gov_10q_ggnfa D9REC NSA S13 Q MIO_EUR
Acquisition of non-financial assets (NP)	Eurostat	gov_10q_ggnfa NP NSA S13 Q MIO_EUR
Intermediate consumption (P2)	Eurostat	gov_10q_ggnfa P2 NSA S13 Q MIO_EUR
Gross capital formation (P5)	Eurostat	gov_10q_ggnfa P5 NSA S13 Q MIO_EUR
Gross fixed capital formation (P51G)	Eurostat	gov_10q_ggnfa P51G NSA S13 Q MIO_EUR
Domestic credit to households	ECB	BSI.M.AT.N.A.A25.A.1.U6.2250.Z01.E
Loans from MFIs to non-MFIs	ECB	BSI.Q.AT.N.A.A20.A.1.U6.2000.EUR.E
Capital and reserves	ECB	BSI.M.AT.N.A.L60.X.4.Z5.0000.Z01.E
Loans to MFIs	ECB	BSI.M.AT.N.A.A20.A.4.U6.1000.Z01.E
Home improvement expectations	Eurostat	ei_bsco_q BS-HI-NY SA Q BAL
Capacity utilization	Eurostat	ei_bsin_q_r2 BS-ICU-PC SA Q
Manufacturing orders	Eurostat	ei_bsin_q_r2 BS-INO-BAL SA Q
Consumer confidence index	Eurostat	ei_bssi_m_r2 BS-CSMCI-BAL SA M
Economic sentiment index	Eurostat	ei_bssi_m_r2 BS-ESI-I SA M
Industrial production index	Eurostat	ei_isbr_m IS-IP F-CC1 M RT12-CA
Real effective exchange rate	Eurostat	ert_eff_ic_q REER_EA19_CPI Q I15
Employment (age 15–64)	Eurostat	lfsi_emp_q / lfsi_emp_q_h ACT SA Y15-64 T Q THS_PER
Employment (total)	Eurostat	lfsi_emp_q / lfsi_emp_q_h EMP_LFS Y15-64 T Q THS_PER
Employment (machine operators)	Eurostat	lfsq_egais OC8 EMP Y15-64 T Q
Employment (service and sales)	Eurostat	lfsq_egais OC5 EMP Y15-64 T Q
Hours worked (machine operators)	Eurostat	lfsq_ewhuis OC8 EMP Y15-64 T Q HR
Gross fixed capital formation	Eurostat	namq_10_gdp P51G CLV10_MEUR SCA
Household consumption	Eurostat	namq_10_gdp P31_S14 CLV10_MEUR SCA
Government consumption	Eurostat	namq_10_gdp P32_S13 CLV10_MEUR SCA
Exports	Eurostat	namq_10_gdp P6 CLV10_MEUR SCA
Imports	Eurostat	namq_10_gdp P7 CLV10_MEUR SCA
Price index	Eurostat	namq_10_gdp B1GQ PD10_EUR SCA
Liabilities (currency and deposit)	Eurostat	nasq_10_f_bs LIAB S1 F1 Q MIO_EUR
Liabilities (loans)	Eurostat	nasq_10_f_bs LIAB S1 F4 Q MIO_EUR
Unemployment	Eurostat	une_rt_q / une_rt_q_h Y15-74 T SA THS_PER Q

Table 5: Data sources and references

Data series	Monthly to Quarterly	Seasonal Adjustment	Logarithmation	First Difference
Nominal GDP	no	initially SCA	yes	no
HICP	yes	no seasonal pattern detected	no	no
GDP deflator	no	initially SCA	no	no
Inflation	yes	initially SCA	no	no
EMU convergence bond yields	no	no seasonal pattern detected	no	no
Compensation of employees (D1PAY)	no	X13-ARIMA	yes	no
Taxes on production and imports (D2REC)	no	X13-ARIMA	yes	no
Total subsidies (D3PAY)	no	no seasonal pattern detected	yes	no
Income and wealth taxes (D5REC)	no	X13-ARIMA	yes	no
Employer social contributions (D611REC)	no	X13-ARIMA	yes	no
Household social contributions (D613REC)	no	X13-ARIMA	yes	no
Net social contributions (D61REC)	no	X13-ARIMA	yes	no
Social benefits (not in-kind) (D62PAY)	no	X13-ARIMA	yes	no
Social benefits (in-kind) (D632PAY)	no	X13-ARIMA	yes	no
Other expenditures (D7PAY)	no	no seasonal pattern detected	yes	no
Other revenues (D7REC)	no	no seasonal pattern detected	yes	no
Capital taxes (D91REC)	no	no seasonal pattern detected	yes	no
Capital transfers (expenditure) (D9PAY)	no	no seasonal pattern detected	yes	no
Capital transfers (revenue) (D9REC)	no	no seasonal pattern detected	yes	no
Acquisition of non-financial assets (NP)	no	no seasonal pattern detected	yes	no
Intermediate consumption (P2)	no	X13-ARIMA	yes	no
Gross capital formation (P5)	no	X13-ARIMA	yes	no
Gross fixed capital formation (P51G)	no	X13-ARIMA	yes	no
Domestic credit to households	yes	no seasonal pattern detected	yes	yes
Loans from MFIs to non-MFIs	no	no seasonal pattern detected	yes	yes
Capital and reserves	yes	no seasonal pattern detected	no	no
Loans to MFIs	yes	no seasonal pattern detected	no	no
Home improvement expectations	no	initially SA	no	yes
Capacity utilization	no	initially SA	yes	yes
Manufacturing orders	no	initially SA	no	yes
Consumer confidence index	yes	initially SA	no	yes
Economic sentiment index	yes	initially SA	yes	yes
Industrial production index	yes	initially CA	no	yes
Real effective exchange rate	no	no seasonal pattern detected	yes	yes
EMU convergence bond yields	no	no seasonal pattern detected	no	yes
Employment (age 15–64)	no	initially SA	yes	yes
Employment (total)	no	initially SA	yes	yes
Employment (machine operators)	no	no seasonal pattern detected	yes	yes
Employment (service and sales)	no	no seasonal pattern detected	yes	yes
Hours worked (machine operators)	no	no seasonal pattern detected	yes	yes
Gross fixed capital formation	no	initially SCA	yes	yes
Household consumption	no	initially SCA	yes	yes
Government consumption	no	initially SCA	yes	yes
Exports	no	initially SCA	yes	yes
Imports	no	initially SCA	yes	yes
Price index	no	initially SCA	yes	yes
Liabilities (currency and deposit)	no	no seasonal pattern detected	yes	yes
Liabilities (loans)	no	no seasonal pattern detected	yes	yes
Unemployment	no	initially SA	yes	yes

Table 6: Data transformation

Statistic	N	Mean	St. Dev.	Min	Max
Nominal GDP	96	82,261.530	18,870.030	54,412.200	121,199.900
GDP deflator	96	98.177	8.965	82.176	113.558
HICP	96	97.553	15.588	76.167	135.183
Inflation	96	0.717	1.137	−0.676	8.996
Interest rate	96	2.513	1.708	−0.410	5.310
Compensation of employees (D1PAY)	96	8,941.903	2,033.437	5,875.120	14,325.040
Taxes on production and imports (D2REC)	96	11,750.550	2,513.542	7,938.599	17,027.660
Total subsidies (D3PAY)	96	1,683.355	1,281.959	834.000	7,974.000
Income and wealth taxes (D5REC)	96	11,073.250	2,797.414	7,420.938	17,968.400
Employer social contributions (611REC)	96	5,638.214	1,492.644	3,633.467	9,272.040
Household social contributions (D613REC)	96	6,537.728	1,702.646	4,180.812	10,593.790
Net social contributions (D61REC)	96	12,680.170	3,112.925	8,490.870	20,270.390
Social benefits (not in-kind) (D62PAY)	96	15,420.560	3,723.401	10,187.050	25,076.150
Social benefits (in-kind) (D632PAY)	96	3,178.872	1,101.866	1,621.419	5,799.364
Other expenditures (D7PAY)	96	2,519.343	1,091.855	832.300	5,984.000
Other revenues (D7REC)	96	764.990	318.822	159.200	1,705.600
Capital taxes (D91REC)	96	30.723	72.173	0.200	676.400
Capital transfers (expenditure) (D9PAY)	96	1,028.771	976.055	270.400	8,248.300
Capital transfers (revenue) (D9REC)	96	197.776	168.003	46.800	1,232.000
Acquisition of non-financial assets (NP)	96	11.860	62.155	−249.300	214.700
Intermediate consumption (P2)	96	5,366.703	1,537.001	2,957.317	8,717.346
Gross capital formation (P5)	96	2,661.303	962.626	1,304.148	6,374.796
Gross fixed capital formation (P51G)	96	2,608.347	860.121	1,335.116	4,895.402
Domestic credit to households	96	50,789.100	9,160.547	27,405.000	59,493.330
Loans from MFIs to non-MFIs	96	287,753.400	73,720.980	179,089	427,096
Capital and reserves	96	410.073	703.114	−1,613.333	2,794.667
Loans to MFIs	96	300.838	3,951.359	−12,290.000	23,536.920
Home improvement expectations	96	−30.852	7.260	−49.400	−18.400
Capacity utilization	96	85.039	2.846	73.000	88.800
Manufacturing orders	96	6.622	18.042	−43.000	43.900
Consumer confidence index	96	−10.107	6.701	−32.600	2.333
Economic sentiment index	96	99.549	9.748	69.700	119.800
Industrial production index	92	2.475	5.322	−12.867	19.967
Real effective exchange rate	96	99.629	2.578	96.485	105.823
EMU convergence bond yields	96	2.513	1.708	−0.410	5.310
Employment (age 15–64)	96	4,245.417	256.311	3,823	4,645
Employment (total)	96	4,019.646	230.740	3,643	4,404
Employment (machine operators)	96	240.224	22.427	198.900	299.600
Employment (service and sales)	96	651.987	103.825	461.200	780.600
Hours worked (machine operators)	96	40.327	1.124	38.600	42.600
Gross fixed capital formation	96	19,689.230	5,138.492	12,883.900	29,852.300
Household consumption	96	37,948.460	2,387.464	33,257.900	41,675.900
Government consumption	96	5,904.282	379.642	5,119.100	6,729.400
Exports	96	41,391.570	8,474.982	27,054.500	56,964.200
Imports	96	38,894.960	7,745.655	26,326.100	53,577.800
Price index	96	106.757	15.180	85.147	142.876
Liabilities (currency and deposit)	96	1,837.344	1,932.192	185	7,223
Liabilities (loans)	96	538,356.400	131,807.800	320,495	767,442
Unemployment	96	226.375	41.369	131	324

Table 7: Descriptive statistics of the seasonally adjusted but level data

Variant	Expenditure	Revenue
core/tax tiny		D2REC + D5REC
core/tax small net soc.t	D1PAY + P2 + P5	D2REC + D5REC + D611REC - D62PAY - D632PAY
core/net tax small		D2REC + D5REC + D61REC - D62PAY - D632PAY - D3PAY
corefix+soc.t.kind/tax mid		D2REC + D5REC + D611REC + D613REC + D91REC
corefix+soc.t.kind/net tax mid	D1PAY + P2 + P51G + D632PAY	D2REC + D5REC + D611REC + D613REC + D91REC - D3PAY - D62PAY
corefix+soc.t.kind/net tax large		D2REC + D5REC + D611REC + D613REC + D7REC + D91REC - D3PAY - D62PAY - D7PAY
core+ass/net tax all	D1PAY + P2 + P5 + NP	D2REC + D5REC + D61REC + D7REC + D9REC - D62PAY - D632PAY - D3PAY - D7PAY - D9PAY

Table 8: Government Expenditure and Revenue Composition. See Tables 5 and 7 for the respective components and Figure 1 for the time series.