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Abstract

We generate observable expectations about fiscal variables through laboratory experiments using real world data from several European countries as stimuli. We compare a VAR model of expectations for data which is presented in a fiscal frame with one for neutrally presented data. We measure the degree to which participants use fiscal data for their forecasts. Agents' expectations are found neither to be consistent with rational nor with purely adaptive expectations but, instead, follow an augmented-adaptive scheme. Methodological implications of the present approach for experiments in macroeconomics are also discussed.

Keywords: Experiments, fiscal policy, expectations, causality, cointegration, panel data.

JEL classification: C91, D89, E62, H31.

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1 Introduction

Expectations on fiscal variables are crucial to understand the effect of fiscal policy on the private sector. Little is however known on the actual way people form expectations on fiscal variables. While many models are based on the hypothesis of rational expectations, empirical evidence is limited and indirect; this is partly due to the unobservability of expectations.

The standard approach is to empirically investigate predicted relations between observable variables, like relationships between fiscal variables and components of output, and from there to infer the effect which unobservables might have played. Examples of this approach range from classical tests of the Ricardian equivalence (see Seater, 1993, for a review), to more recent analyses of the so called 'anti-Keynesian' (i.e. expansionary) effects of fiscal adjustments (Giavazzi, Jappelli, and Pagano, 2000).

A problem in this approach, however, is that the identification of the effects of expectations is model-dependent, and model comparison is very hard. Moreover many unobserved correlated factors are typically at play in data collected from real economies. This makes identification of the effects of expectations quite difficult, because "economists cannot observe all the data that economic agents do" (Seater, 1993, p. 164).

The latter limitation is also relevant for expectation measures derived from opinion surveys[1]. Moreover surveys suffer from lack of economic incentives to reveal true opinions, so that for various reasons respondents "may express judgements that are different from the ones they choose to act upon" (Pesaran, 1987, p. 209).

A third approach is to measure expectations in a controlled experiment. Expectations experiments have been conducted since as early as the sixties in a wide range of economic contexts. They have looked at price expectations (Fisher, 1962 and Schmalensee, 1977), expectations about artificially constructed time series (Hey, 1994), expectations on monetary policies (e.g. Marimon and Sunder, 1993, and Bernasconi and Kirchkamp, 2000), or even fiscal policy (Swenson, 1997).

While the experimental approach allows to implement the *ceteris paribus* condition as none of the other two (and correct for the lack of incentives of the survey approach), it typically suffers from the critique that the stimuli are given in situations that are far from the real economic world, thus questioning the validity of the connection between the lab and the real economy.

In this paper, we study the process of forming expectations on fiscal

[1] For example, surveys conducted by Grun (1991) and Allers, de Haan, and de Kam (1998) found widespread evidence of misinformation on the conduct of government fiscal policy.

policy. We combine field and lab data to control information that subjects observe, while still giving them data taken from the real world [2].

The approach innovates on existing literature in various respects. We list here few areas in which the paper gives original contributions.

First of all, stimuli are represented by annual time series of fiscal variables from 15 OECD countries. Unlike in previous experiments, they refer to bivariate, not univariate, times series, namely taxes and public expenditures. This allows us to include a richer set of models in our comparison and to extend the analysis to augmented adaptive models. Stimuli are given sequentially. We recorded 1581 different time series of realized expectations.

We check the internal validity of the experimental set-up by way of a control group of participants who form expectations without knowing the fiscal origin of the times series and we discuss the extent of the external validity of the experiment.

Given the type of stimuli-response data of this experiment, we need new techniques to model both parts of the data. We develop a modeling strategy which is consistent both with current practice in macro-econometrics and micro-econometrics. We assume that the joint data generating process (DGP) of stimuli and expectations data is a VAR; we next show how natural assumptions arising from the experimental design imply specific restrictions. Two subsystems are derived, one for the field data and one for the agents' expectations; we then discuss various possible econometric relationships between the subsystems. Various econometric results in the area are collected and we show how to analyse the field data first and subsequently the expectation data. The analysis allows for non-stationary behaviour both of field and expectation variables.

Many macroeconomic investigations use cointegration techniques and Granger causality tests to investigate the sustainability of fiscal policy and the type of causality between taxes and public expenditure (see, e.g., Trehan and Walsh, 1991 and Ahmed and Rogers, 1995, as classical references; Garcia and Henin, 1999, as a more recent example); the present two stage approach contains this analysis as the first step.

The approach encompasses many micro-models for the formation of expectations in the second step. We find that a major component of the process depends on past forecast errors. Generally subjects fail to perceive the fiscal properties which we estimate in the field.

The evidence neither supports the 'rational expectation hypothesis', nor a purely adaptive scheme; rather, expectations fall within a class of so called

[2] The experiments of Fisher (1962) and Schmalensee (1977) used real price data, though the focus there was on purely statistical, rather than economic meaning of data.

‘augmented-adaptive models’, introduced in the early eighties by various authors, see Pesaran (1987). These models then become the starting point for a growing literature of ‘bounded rationality’ (Sargent, 1993) and ‘adaptive learning’ in self referential economies (see Evans and Honkapohja, 2001, for a comprehensive survey).

The VAR approach we take to analyse the data excludes non-linear behaviour in the DGP. This may be disputable, since discretionary interventions and exogenous shifts may introduce non linearities in fiscal policy (as for example documented for the US by Bohn, 1998, and Sarno, 2001). The latter case is of interest since it may also generate specific anti-Keynesian effects of fiscal policy (see e.g. the models surveyed in Giavazzi, Jappelli, and Pagano, 2000, and the empirical investigation conducted therein).

We test for nonlinearity and find that the VAR specification is robust against it.

The paper is organised as follows. Section 2 presents the setup of the experiment and dicusses issues of internal and external validity. Section 3 develops the econometric approach to analyse both the stimulus and the expectations data. Section 4 discusses the empirical specification of the field and lab models. Inference results are presented in Section 5. The last section summarises and discusses the implications of the present approach for experiments in macroeconomics.

2 Experimental setup

The experiment has a time-structure, $t = 1, \ldots, n$; the setup nests a simple (two-periods) representative agent small economy. Participants are exposed to graphical representations of time series of fiscal variables, taken from various European countries. The stimuli refer to gross total taxes T_t, total public expenditure (inclusive of interest payments) G_t, public debt B_t, and change in the debt level $\Delta B_t = B_t - B_{t-1}$ at time t, all expressed as yearly percentage of GDP. Here and in the following Δ is the time difference. In this paper we focus on the relationship and the direction of perceived causality between taxes and expenditure, namely vector $x_t := (T_t, G_t)$.

Agents do not know which country and which period the series refer to. Utility in the experiment is derived from consumption over two subsequent periods:

$$u_t = \prod_{i=t}^{t+1} \gamma C_i + (1-\gamma) G_i \qquad \text{with } \gamma = 0.75 \tag{1}$$

subject to the budget constraint

$$\sum_{i=t}^{t+1} \underbrace{(1 - C_i - T_i)}_{\text{savings}} \cdot (1+r)^{i-t} = 0 \qquad \text{with } r = 0.1\,. \tag{2}$$

Agents receive initial information on the first seven values of stimuli; for most countries the first available year was 1970. Let $t-1$ be the last available year and $X_{t-1} := (x_1, \ldots, x_{t-1})'$ the available information; for each subsequent year t agents forecast taxes and/or public expenditure.

Three experimental treatments were performed: in one of the treatments participants forecast both T_t and G_t (see figure 1), in a second treatment participants forecast T_t only (see figure 2). The third treatment is a control treatment that is designed similarly to the first (T_t and G_t) treatment. The only difference is that participants are not informed about the economic content of the variables. Variables are simply called A, B, and C (see figure 3). Everything else is as in the original T_t and G_t treatment. We call this treatment the 'neutral' treatment. Agents express forecasts clicking with the mouse directly into the diagrams. Instructions can be found in appendix B. Forecasts are indicated as $T_t^{E_i}$ and $G_t^{E_i}$, where i indicates agent i and E stands for expectation. Let $y_{i,t}$ indicate all the forecast of agent i that refer to time t; in the T_t and G_t treatment $y_{i,t} := (T_t^{E_i}, G_t^{E_i})'$ while $y_{i,t} := T_t^{E_i}$ in the T_t only treatment.

The time series of the stimuli are updated recursively in each period after forecasts are made, so that subjects learn about realization of the stimuli as the economy moves on. More specifically, given subjects' forecasts $y_{i,t}$ for year t, the computer determines an optimal consumption level C_{t-1} for the current period given eq. (1) and (2). In period t, $x_t := (T_t, G_t)'$ become available and are communicated to the participant. The computer uses equation (2) to determine C_t and then uses equation (1) to calculate the participant's utility for period $t-1$. The participant's per minute wage is

$$w = 0.66 \cdot (u_t/u_t^*)^\eta \text{ where } \eta = \begin{cases} 12000 \text{ in the } T_t \text{ and } G_t \text{ treatment} \\ 15000 \text{ in the } T_t \text{ only treatment} \end{cases} \tag{3}$$

where u_t^* is the utility the participant would obtain with forecasting the true values. This transformation from utilities into wages is monotonic and, hence, does not affect the maximisation problem of the individual. The transformation, however, creates steeper incentives to make good forecasts.

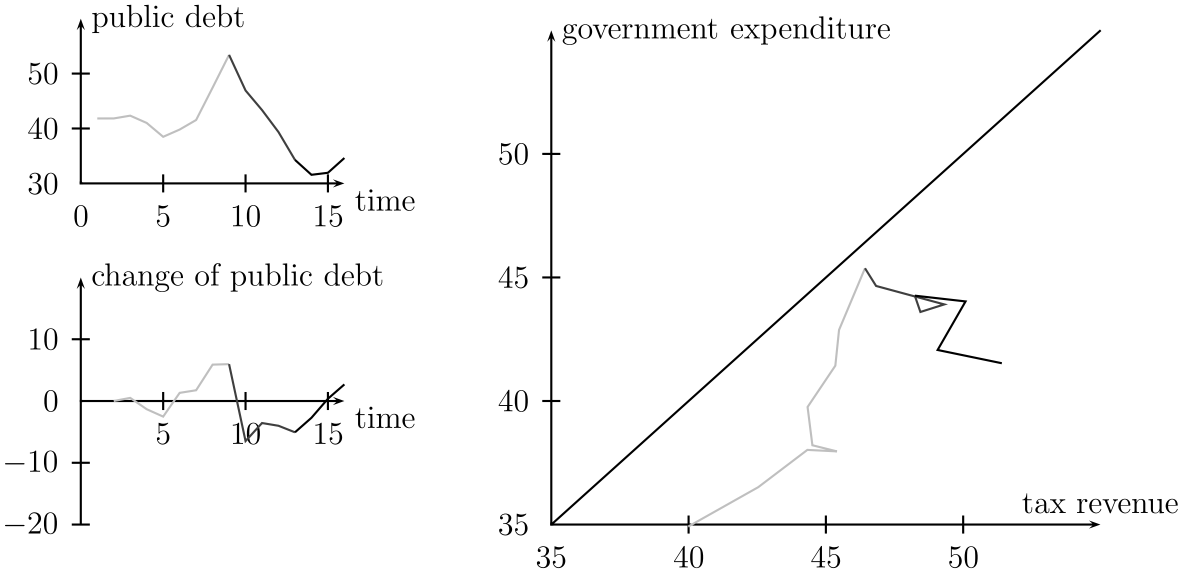
Participants are payed this wage up to two minutes for each forecast. If a participant needs more time to complete a forecast only the first two minutes are paid[3].

[3]We have introduced this payment scheme to simultaneously encourage participants to

		number of participants		
Country	Sample period	T_t and G_t	T_t only	neutral
Austria	1970-1998	34	14	28
Belgium	1970-1998	52	20	48
Denmark	1971-1995	43	14	43
Finland	1970-1998	33	12	24
France	1977-1998	29	10	31
Germany	1970-1998	14	13	5
Greece	1975-1998	26	13	22
Ireland	1970-1995	45	21	44
Italy	1970-1998	35	16	29
Netherlands	1970-1998	32	9	23
Norway	1970-1998	32	14	26
Portugal	1970-1998	25	13	23
Spain	1970-1998	30	11	24
Sweden	1970-1998	53	16	41
United Kingdom	1970-1995	27	15	19
non-economists (54)		23	5	26
economists (116)		53	20	43
Total (170)		76	25	69

Table 1: Summary of the experimental treatments

Since participants made forecasts for more than one country the total number is not the sum of the number of participants in all countries.



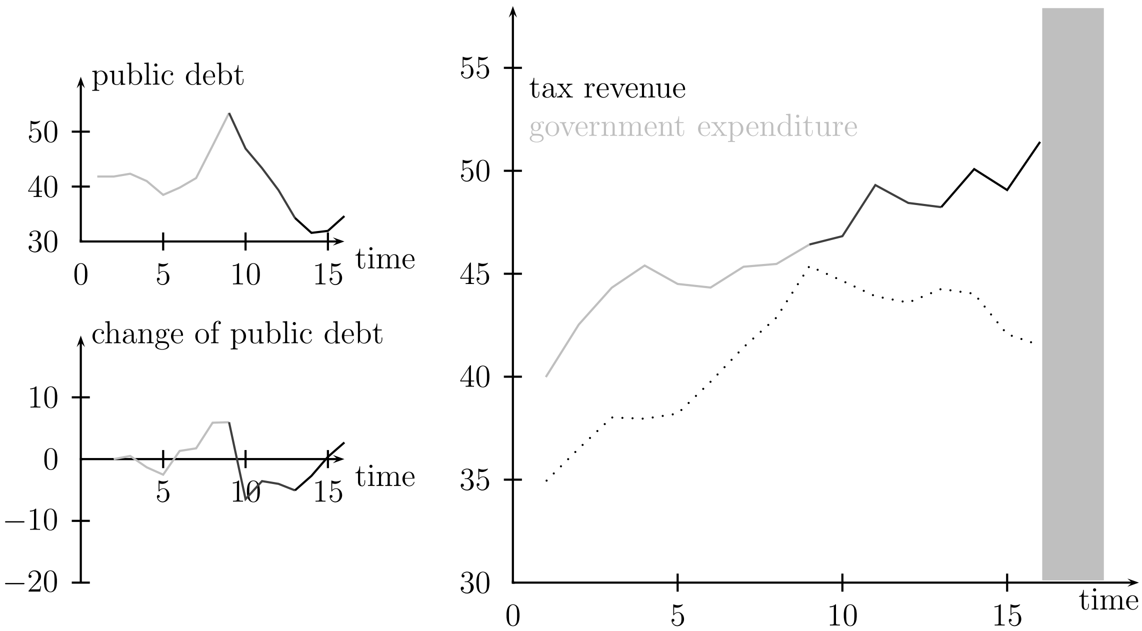
Values are given as percentage of GDP.Gray lines indicate past, black lines indicate recent years.

Figure 1: T_t and G_t treatment

Different agents participated in the three treatments. 76 took part in the T_t and G_t treatment, 25 in the T_t only treatment, and 69 in the neutral treatment. Of these participants 116 were students in economics or business (we will call them economists), 54 were from a different field (natural sciences, languages, law, and social sciences; we will call them non-economists). Each agent made predictions for several countries within each treatment. Stimulus data were from 15 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden and UK[4]. Table 1 summarises the parameters of the treatments with the number of participants in the various conditions. For the majority of countries the sample period of stimulus data was 1970-98; few exceptions (Denmark, France, Greece, Ireland and UK) are due to limits in the availability of the fiscal time series. For all countries, expectations recording started from the seventh year of the stimulus (which was then 1977 for most countries). A representation of the stimulus data for the different countries is shown in figure 4 and figure 5.

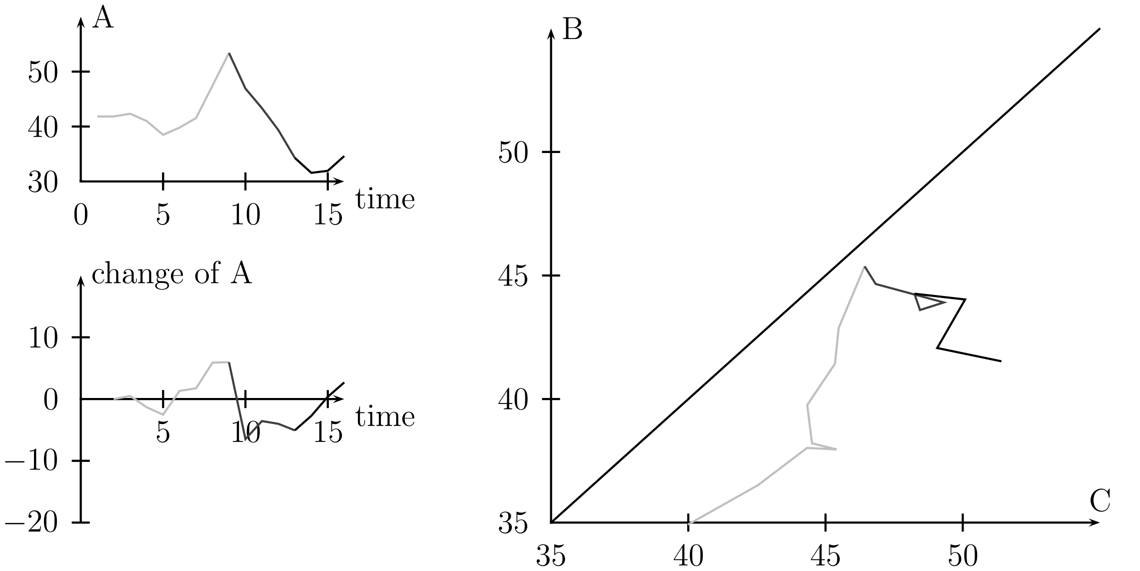
think about their forecasts, but also to remain active.

[4]All stimulus data used in the experiment were taken from the OECD (2000) database "Fiscal Positions and Business Cycle".



Values are given as percentage of GDP. Gray lines indicate past, black lines indicate recent years.

FIGURE 2: T_t only treatment



Gray lines indicate past, black lines indicate recent periods.

FIGURE 3: neutral treatment

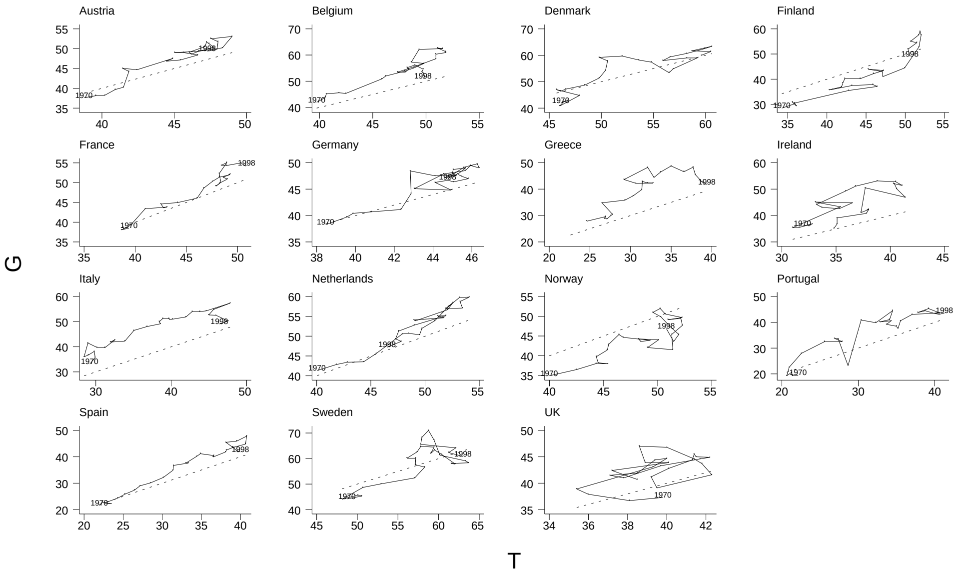


FIGURE 4: Stimulus data (as G over T)

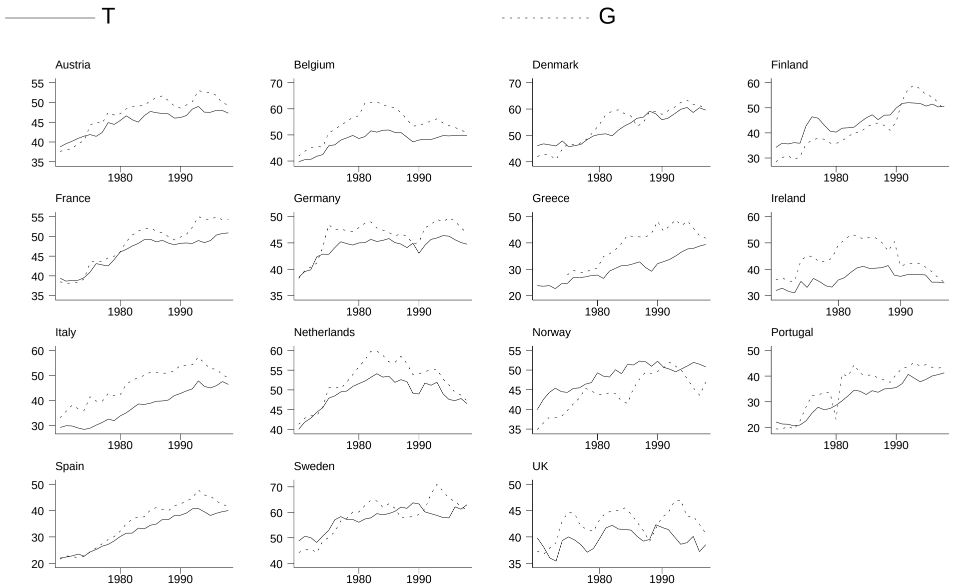


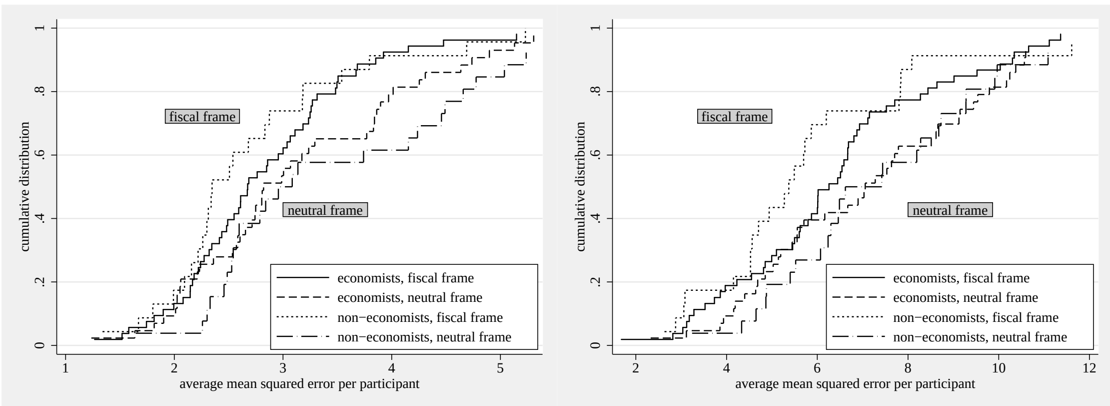
FIGURE 5: Stimulus data (as G and T over t)

The experiment were carried out in the experimental laboratory of the SFB 504 in Mannheim between November 2000 and December 2002. Experimental sessions were conducted individually. All 170 participants spent about 2 hours in the laboratory. They made, on average, 136 forecasts (between 28 and 309), and completed on average one forecast every 39 seconds. Instructions given to participants are reported in appendix B.

2.1 Internal validity

Can we trust our setup? Are participants understanding and are they using the economic context, or are they simply extrapolating the data without economic consideration. To answer this question we compare the T_t and G_t treatment with the neutral treatment. If participants understand and make use of the economic context we should expect that forecasts are better in the fiscal frame than in the neutral frame. Furthermore, if special economic skills are necessary to make forecasts we should expect that participants from the economists group make better forecasts than the non-economists.

In figure 6 we show the cumulative distribution of the mean squared error of the forecasts for tax revenue. The solid line shows the distribution



average of $(T - T^E)^2$ average of $(G - G^E)^2$

FIGURE 6: Forecast errors in the fiscal and neutral treatments

for economists in the fiscal frame. The dashed line shows the distribution for economists in the neutral frame. Indeed, mean squared errors of forecasts are smaller in the fiscal frame than in the neutral frame, i.e. participants in the experiments seem to be able to make use of the economic context of the information. The dotted line shows the distribution for non-economists in the fiscal frame. Again their forecast errors are smaller than the errors of non-economists in the neutral frame (dashed-and-dotted line). While there is a stark difference between the fiscal frame and the neutral frame there is no obvious difference between the economists and the non-economists.

To test this more formally we explain the mean squared errors as a function of a dummy d_{e} that is one for economists and zero otherwise, and a dummy d_{n} that is one in the neutral treatment and zero otherwise.

$$(T - T^E)^2 = \beta_{\mathrm{e}}^T d_{\mathrm{e}} + \beta_{\mathrm{n}}^T d_{\mathrm{n}} + c + \epsilon \tag{4}$$

$$(G - G^E)^2 = \beta_{\mathrm{e}}^G d_{\mathrm{e}} + \beta_{\mathrm{n}}^G d_{\mathrm{n}} + c + \epsilon \tag{5}$$

Results of the robust regression that treats each participant as an independent observation are shown in table 2. In both equations we have β_{n} positive and significantly different from zero. β_{e} is not significantly different from zero.

estimation of equation 4 (145 independent observations)						
$(T - T^E)^2$	β	σ	t	$P > \lvert t \rvert$	95% Conf.	Interval
β_{n}	.5586159	.2216946	2.52	0.013	.12042	.9968119
β_{e}	−.0226633	.2255656	−0.10	0.920	−.4685105	.423184
c	2.791348	.1996356	13.98	0.000	2.396754	3.185943
estimation of equation 5 (145 independent observations)						
$(G - G^E)^2$	β	σ	t	$P > \lvert t \rvert$	95% Conf.	Interval
β_{n}	1.071765	.4808198	2.23	0.027	.1213885	2.022141
β_{e}	.0039117	.5156949	0.01	0.994	−1.015398	1.023221
c	6.366691	.5207256	12.23	0.000	5.337437	7.395944

Table 2: Test for internal validity

All standard deviations are calculated using a robust regression method taking into account correlations of observations for each participant.

Given that β_{n} is significant and positive in both equations we conclude that we have obtained internal validity in our experiment. We also see that students from economics and related fields do not have a significant advantage in the experiment.

2.2 External validity

It is unlikely that consumers form expectations on fiscal policy only on the basis of spending and taxes. Expectations might be affected by the composition of the government, the date of the next election, economic development, foreign policy, natural disasters, to name only a few. Why are we neglecting all these factors?

Indeed, neglecting these factors and concentrating only on a few would be more problematic if our expectations were formed in the field and not in the lab. In the field we would not know whether a change in expectations is due to a change in the fiscal policy or due to some other factor. Isolating all these factors in the field can be a very hard task, a task that can be simplified in the laboratory. It is a strength, not a weakness, of laboratory experiments that we can concentrate on a small number of factors. In this paper we look only at taxation and government expenditure. We do not tell participants about political parties, elections, etc., to make sure that their expectations can not be tainted by these variables. Changes in our participants' expectations can in the lab only be the result of the information we provide them.

Putting our participants in such a simple world means that they may not form particularly precise expectations. This, however, is not a problem, since we are not interested in a comparison of the expectation and the realisation. What we want to know is how the expectation process works and how past fiscal variables affect expectations. For this reason, past values of fiscal variables are the only information available in the experiment.

A vast empirical literature on fiscal policy also use the time series we provide to subjects in the experiment, to analyse the fiscal conduct of countries and to derive judgements regarding the sustainability of their fiscal policies and the direction of causality between fiscal variables. In the remaining body of the paper, we develop an empirical model of stimuli and of expectation data, which coherently ties the present experiment to such econometric practice. Through it we discuss the meaning and implication of general expectation schemes (rational, adaptive, augmented adaptive), consider and estimate properties of field data and check how these features are perceived by subjects in the experiment.

3 A VAR model for the experiment

This section discusses the joint modelling of the stimuli and of expectation data. In order to simplify the analysis we specify a model on each single country separately. This choice corresponds to a limited information context in simultaneous systems of equations. In a complete system, i.e. one containing all country-specific subsystems, one could envisage several effects (variance components) associated with each individual, which are now discarded in the analysis.

While the limited information context leaves room for improvement in efficiency for estimation and testing, it delivers more robust inference, i.e. consistent estimates even under misspecification of some other country specific subsystem. This appears highly desirable.

Each individual i provides forecasts $y_{i,t}$ on the basis of the knowledge of the history of stimuli $X_{t-1} := (x_1, \ldots, x_{t-1})'$, where $x_t = (T_t, G_t)'$. Let m indicate the number of individuals, $i = 1, \ldots, m$. Recall that $y_{i,t} = (T_t^{E_i}, G_t^{E_i})'$ in the T_t and G_t treatment and $y_{i,t} = T_t^{E_i}$ in the T_t only treatment. Let $z_{i,t} := (y'_{i,t}, x'_t)'$ be the data vector involved in the prediction for agent i at time t. Let $Z_{i,t-1}$ indicate the history of $z^j_{i,s}$ up to time $t-1$, $Z_{i,t-1} := (z_{i,1}, \ldots, z_{i,t-1})'$, which represents the relevant information set available to individual i in the expectation formation for the next period.

Consider also the vector $w_t := (y'_t, x'_t)' := (y'_{1,t}, y'_{2,t} \ldots y'_{m,t},\ x'_t)'$ containing all predictions performed by all agents at time $t-1$ along with the variables to be predicted. The prediction variables are grouped in the vector $y_t := (y'_{1,t}, y'_{2,t} \ldots, y'_{m,t})'$. Let also $W_{t-1} := (w'_1, \ldots, w'_{t-1})'$ indicate the complete history of stimuli and predictions of all agents. We next state restrictions on the DGP of the joint process $\{w_t\}_{t=1}^{\infty}$ that are consistent with the experimental setup.

3.1 Assumptions

Given the sequential structure of the experiment, we decompose the probability measure of the stochastic process $\{w_t\}_{t=1}^{\infty}$ sequentially, as in Engle, Hendry, and Richard (1983), into the product of $\mathcal{L}(w_t|W_{t-1})$. Here and in the following $\mathcal{L}(\cdot|W_{t-1})$ indicates conditional probability given W_{t-1}. This allows to define the DGP of the process by its transition probabilities.

We assume that the DGP for w_t can be taken to be a Vector Autoregressive process (VAR), $A(L)w_t = \mu + \epsilon_t$ where ϵ_t are i.i.d. $N(0, \Omega)$ across t and $A(L) = \sum_{\ell=0}^{k} A_\ell L^\ell$ is the autoregressive polynomial in the lag operator L, $A_0 := I$, the identity matrix. This assumption is summarised as follows.

Assumption 1 *The law of w_t conditional on W_{t-1}, $\mathcal{L}(w_t|W_{t-1})$ is Gaussian with moments*

$$E(\Delta w_t|W_{t-1}) = \mu + \Pi w_{t-1} + \sum_{\ell=0}^{k-1} \Gamma_\ell \Delta w_{t-\ell} \qquad V(w_t|W_{t-1}) = \Omega.$$

where $\Pi := -A(1)$, $\Gamma_\ell := -\sum_{i=\ell+1}^{k} A_i$, and μ is a vector of constants.

Several remarks are in order here. First of all, assumption 1 states that the DGP of the variables observed in the field x_t is nested within a VAR assumption for w_t. It should be noted that this excludes non-linear behaviour in x_t, which (as anticipated in the introduction) is viewed as disputable by some (see e.g., Bohn, 1998, Giavazzi, Jappelli, and Pagano, 2000, and references therein). We consider the issue of nonlinearity in some details in Section 5.3.

The assumption of normality may appear also restrictive. It is adopted here for convenience and can be dropped when one resorts to time-asymptotics. We note, however, that for moderate temporal sample size this assumption is hard to test and reject.

Mostly important, we emphasise that most panel data models do not start with a VAR as a reference model, but rather directly from a collection of single equations, one of each individual. This is not advisable in the present context, for various reasons. Firstly, w_t contains the stimuli, which are likely to have obvious interactions. As suggested above, the econometric analysis of the stimuli is just as important as the one of the responses, and hence a multivariate approach for the modelling of x_t is mandatory. Moreover, the present VAR approach allows to view the links between the information set $Z_{i,t-1}$ and the prediction $y_{i,t}$ directly as parameters of the joint model and it includes the univariate standard regression model as a special case.

Obviously, starting with a VAR as reference model, while very general, leaves room for too many parameters; in the present case, it also permits variables in the field to be influenced by data in the experiment, an issue which we address in the next assumption.

Assumption 2 *The DGP of the stimuli x_t conditional on W_{t-1} does not depend on past prediction variables y_s for any $s = 1, \dots t-1$, i.e. $\mathcal{L}(\Delta x_t | W_{t-1}) = \mathcal{L}(\Delta x_t | X_{t-1})$.*

Under assumption 2, y_t does not Granger-cause x_t (see e.g. Engle, Hendry, and Richard, 1983). This assumption makes sense in this experimental setting, where the stimuli were generated by natural experiments well before the lab experiment was performed.

In the following, blocks of the Π, Γ_ℓ and Ω matrices corresponding to the various components of w_t are indicated with the subscripts $1, \dots, m$, x conformably with $w_t := (y'_{1,t}, y'_{2,t} \dots, y'_{m,t}, x'_t)'$. In the following the subscript y is used to group the first m blocks of prediction variables together: $\Gamma_{\ell,1x}$ is e.g. the block of coefficients of $x_{t-\ell}$ in the expression for $E(\Delta y_{1,t} | W_{t-1})$, while Π_{xy} is the block of coefficients of $(\Delta y'_{1,t-1}, \dots \Delta y'_{m,t-1})'$ in the expression for $E(\Delta x_t | W_{t-1})$[5].

[5]Note that the conditional expectation operator $E(\cdot | W_{t-1})$ and the prediction performed by the agents do not necessarily coincide.

Under Assumption 1, it is well known that Assumption 2 holds if and only if $\Pi_{xy} = 0$ and $\Gamma_{\ell,xy} = 0$ for all $\ell = 1, .., k-1$. This translates Assumption 2 into a parametric restriction, which is later exploited in model specification.

We next wish to incorporate information on the relation among the prediction variables $y_{i,t}$ across agents. Given the experimental setup, it is natural to assume that forecasts are independent across agents, given the public information available.

Assumption 3 *Let j be different from i;*

a) the DGP of the forecast $\mathcal{L}(\Delta y_{i,t}|W_{t-1})$ does not depend on the forecast made by other agents, i.e. on $y_{j,s}$ for any time in the past $s = 1, \ldots t-1$.

b) Moreover $\Delta y_{i,t}$ and $\Delta y_{j,t}$ are independent conditionally on W_{t-1}.

This assumption formalises the experimental setup where individual forecasts are performed independently of each other. Under Assumption 1, observe that Assumption 3a holds if and only if $\Pi_{yy} = \mathrm{diag}(\Pi_{11}, \ldots, \Pi_{mm})$, $\Gamma_{\ell,yy} = \mathrm{diag}(\Gamma_{\ell,11}, \ldots, \Gamma_{\ell,mm})$ for all $\ell = 1, .., k-1$; while Assumption 3b holds if and only if $\Omega_{yy} = \mathrm{diag}(\Omega_{11}, \ldots, \Omega_{mm})$. Again this translates Assumption 3 into parametric restrictions, which are later exploited in model specification.

The structure implied by the three Assumptions above can be used to derive two sub-systems, a field system for the stimuli x_t, and a lab system for the prediction variables y_t. This is done in the following Proposition.

Proposition 4 *Let Assumption 1 and 2 hold; then*

- *the field sub-system DGP for x_t, $\mathcal{L}(\Delta x_t|W_{t-1}) = \mathcal{L}(\Delta x_t|X_{t-1})$, is Gaussian with variance matrix Ω_{xx} and mean*

$$E(\Delta x_t|X_{t-1}) = \mu_x + \Pi_{xx} x_{t-1} + \sum_{\ell=1}^{k-1} \Gamma_{\ell,xx} \Delta x_{t-\ell}. \tag{6}$$

- *If moreover Assumption 3 holds, the lab sub-system DGP for y_t given the past, $\mathcal{L}(\Delta y_t|W_{t-1})$, is Gaussian with independent components, i.e. $\mathcal{L}(\Delta y_t|W_{t-1})$ can be decomposed in the product of $\mathcal{L}(\Delta y_{i,t}|W_{t-1})$ for $i = 1, \ldots, m$, where $\mathcal{L}(\Delta y_{i,t}|W_{t-1}) = \mathcal{L}(\Delta y_{i,t}|Z_{i,t-1})$ is Gaussian with variance Ω_{ii} and conditional mean*

$$\begin{aligned} E(\Delta y_{i,t}|W_{t-1}) &= E(\Delta y_{i,t}|Z_{i,t-1}) = \\ &= \mu_i + (\Pi_{ii} : \Pi_{ix}) z_{i,t-1} + \sum_{\ell=1}^{k-1} (\Gamma_{\ell,ii} : \Gamma_{\ell,ix}) \Delta z_{i,t-\ell}. \end{aligned} \tag{7}$$

  and $\Omega_{yy} = \mathrm{diag}(\Omega_{11}, \ldots, \Omega_{mm})$. Recall that $z_{i,t} := (y'_{i,t}, x'_t)'$.

Proof. The results hold by standard properties of the Gaussian distribution. ■

The Proposition clarifies that the model nests a marginal VAR for x_t, which will be the basis for the analysis of stimuli data. Moreover, y_t is a VARX where the stimuli x_t act as exogenous variables.

Two important issues here concern the process of expectations forming and the properties of fiscal variables, namely cointegration and causality, as occurring in the field and as perceived in the lab. These are analysed in the following subsections.

3.2 Expectation schemes

The restricted VAR discussed in the previous section has implications regarding the formation of expectations. In this section we illustrate rational, adaptive and augmented-adaptive expectations within the present context.

We start from rational expectations. The optimisation problem given trough equations (1) and (2) implies a quadratic loss function. For a quadratic loss function and a given information set the optimal predictor is given by conditional expectations (Muth, 1961). Expectations are called rational if they coincide with the ones formed under the DGP (see e.g. Pesaran, 1987). One can then calculate rational expectations by computing the conditional expectations of x_t given the relevant information set.

The implied specific form of rational expectations is repeated in the following proposition.

Proposition 5 (Rational expectations) *Let Assumptions 1 and 2 hold; the rational expectation on Δx_t given any of the information sets X_{t-1}, W_{t-1}, Z^i_{t-1} is given by*

$$\begin{aligned} g(X_{t-1}) \;&:=\; E(\Delta x_t|W_{t-1}) = E(\Delta x_t|X_{t-1}) = E(\Delta x_{t+1}|Z_{i,t-1}) = \\ &\qquad \mu_x + \Pi_{xx}x_{t-1} + \sum_{\ell=1}^{k-1}\Gamma_{\ell,xx}\Delta x_{t-\ell}. \end{aligned}$$

Proof. Under Assumption 2, the information contained in W_{t-1} or $Z_{i,t-1}$ in excess of the past history of x (X_{t-1}) is irrelevant, so that the various conditional expectations coincide. The marginal DGP for x_t is Gaussian with the above conditional expectations (see eq. (6) in Proposition 4). ■

Let a superscript 1 indicate the first component of a vector; $y^1_{i,t}$, the first component in $y_{i,t}$, is a representative expectation variable, and assume that $y^1_{i,t}$ represents a forecast of x^1_t, the first component in x_t. The form of the rational expectations on proposition 5 provides the yardstick to measure the degree of rationality present in actual forecasts. In particular, for rational expectations to hold one expects to find $E(\Delta y_{i,t}^1|Z_{i,t-1}) = g^1(X_{t-1})$, i.e. that the observed expectations are rational *on average*. If observed expectations were *exactly* rational one would expect $\Delta y_{i,t} = g(X_{t-1})$ almost surely; we here allow for some idiosyncratic error in the observed expectations, and take $E(\Delta y_{i,t}^1|Z_{i,t-1}) = g^1(X_{t-1})$ as a test of rational expectations. Deviations from this equality are taken as departure from rationality of expectations.

One alternative formation process of expectations is the adaptive scheme, as originated in the 1950s by the works of Cagan (1956), Friedman (1957) and Nerlove (1958). We employ here the following definition.

Definition 6 (Adaptive expectations) *An adaptive scheme is any* bivariate *transfer function of the form*

$$E(\Delta y_{i,t}^1|Z_{i,t-1}) = a(L)y_{i,t-1}^1 + b(L)x_t^1 + c$$

where $a(L)$ and $b(L)$ are finite scalar polynomials of the lag operator L, and c is a constant.

We emphasise the bivariate nature of the adaptive scheme[6]: in particular, under adaptive expectations, one would expect that only past values of the forecasted variable x_t^1 and of its forecast $y_{i,t}^1$ enter in the expectation process for $y_{i,t}^1$. In most of the previous experiments studying expectation formation, subjects had to forecast a univariate time series (as for example in Schmalensee, 1977 or Hey, 1994). They generally found support for adaptive expectations (though not necessarily of the first order, e.g Hey, 1994). In the present experiment, if other variables enter in the estimated equation for $\Delta y_{i,t}^1$, this is evidence against a purely adaptive scheme and in favour of a more general class of models known as augmented-adaptive (Pesaran, 1987).

Definition 7 (Augmented-adaptive expectations) *An augmented-adaptive scheme is any* multivariate *transfer function of the form*

$$E(\Delta y_{i,t}^1|Z_{i,t-1}) = C(L)z_{i,t-1} + c$$

where $C(L) := \sum_{\ell=1}^{p} C_\ell L^\ell$ is a finite order matrix polynomial of the lag operator L, and c is a constant, $z_{i,t} := (y_{i,t}', x_t')'$.

Augmented-adaptive schemes are interesting because they nest both rational and simple adaptive schemes; therefore they offer the natural setting to test for both types of expectations processes.

[6] See Pesaran (1987) for many variations nested within this general definition.

They are also sometimes referred to as ‘boundedly rational’ learning models (Sargent, 1993). In particular, they emphasise the use that an important stream of literature makes of these schemes to study the actual transition dynamics of economies driven by the way people form expectations, like for example in the classical cobweb economy or in the more recent literature on general equilibrium self-referential economy (as e.g. reviewed in Evans and Honkapohja, 2001). A question of interest in the latter context is whether ‘boundedly rational’ learning models can bring convergence to rational expectations equilibria, as also studied experimentally in various investigations [7]. In the partial equilibrium approach of the present experiment, the question of convergence is clearly of a lesser interest.

The next section discusses cointegration and causality restrictions on the subsystems (6), (7).

3.3 Properties of data: cointegration and causality

In the following, we enquire the possibility of cointegration (CI) in the vector w_t under Assumptions 1 and 2, and state the expected long run properties of stimuli and predictions. The integration properties of the series do not interfere with the analysis of the degree of rationality of expectations, but rather offer additional opportunities in the study of expectation formation.

The following proposition states CI restrictions, and focuses on the Equilibrium Correction Mechanisms (ECM) (see Hendry, 1995) of the two subsystems.

Proposition 8 *Let w_t be at most $I(1)$ with CI rank equal to r; this implies $\Pi = \alpha\beta'$, with α and β full column rank matrices with rank r. Under Assumptions 1, 2, the CI space β and the adjustment coefficients α can be represented as follows*

$$\begin{aligned} \alpha\beta' &= \begin{pmatrix} \alpha_{y1} \\ 0 \end{pmatrix} \beta'_{1w} + \alpha_{w2} \begin{pmatrix} 0 & \beta'_{2x} \end{pmatrix} \\ &= \begin{pmatrix} \alpha_{y1} & \alpha_{y2} \\ 0 & \alpha_{x2} \end{pmatrix} \begin{pmatrix} \beta'_{1y} & \beta'_{1x} \\ 0 & \beta'_{2x} \end{pmatrix} = \begin{pmatrix} \alpha_{y1}\beta'_{1y} & \alpha_{y1}\beta'_{1x} + \alpha_{y2}\beta'_{2x} \\ 0 & \alpha_{x2}\beta'_{2x} \end{pmatrix}, \end{aligned} \tag{8}$$

where the 2 blocks of columns in α and β have full rank equal to r_1, r_2, and $r = r_1 + r_2$. Hence

- *the ECM terms in the autonomous VAR system for x_t are $\alpha_{x2}\beta'_{2x}x_t$, while the ones that appear in the VARX subsystem for y_t are $\alpha_{y1}\beta'_{1w}w_t + \alpha_{y2}\beta'_{2x}x_t$;*

[7] See, e.g., (Marimon and Sunder, 1993), and Bernasconi and Kirchkamp, 2000 for a more recent study.

- *the CI rank of the autonomous VAR system x_t is equal to r_2;*

- *under Assumptions 3 $\alpha_{y1}\beta'_{1y}$ has a block-diagonal structure of the form $\alpha_{y1} = \mathrm{diag}(\alpha_{11}, \ldots, \alpha_{mm})$, $\beta_{y1} = \mathrm{diag}(\beta_{11}, \ldots, \beta_{mm})$.*

Proof. Mosconi and Giannini (1992) prove (8), see also Johansen (1995), section 5.6. Note that we exclude I(2) behaviour. Under Assumptions 3 one has that $\Pi_{yy} = \mathrm{diag}(\Pi_{11}, \ldots, \Pi_{mm})$, which can be decomposed into $\alpha_{y1}\beta'_{1y}$ with block-diagonal structure of the form $\alpha_{y1} = \mathrm{diag}(\alpha_{11}, \ldots, \alpha_{mm})$, $\beta_{y1} = \mathrm{diag}(\beta_{11}, \ldots, \beta_{mm})$ where $\Pi_{ii} = \alpha_{ii}\beta'_{ii}$. ■

Proposition 8 clarifies that the analysis of the autonomous VAR for the stimuli allows to make inference on part of the cointegrating space, the one spanned by β_{x2}. We observe that the structure of the restricted joint VAR allows the expectation variables to possibly respond to the disequilibrium errors $\beta'_{2x}x_t$ in any way, including the one characterising the ECM in the field, with coefficients α_{x2}. This behaviour would be consistent with rational expectations.

The ECM of the expectation variables possibly contains r_1 additional CI vectors. One such CI vector could be of the form $y^1_{i,t} - x^1_t$, i.e. could describe the expectation error. Adjustment to this expectation error is expected in an adaptive scheme.

The comparison of the field and expectation sub-systems allows to evaluate the presence and direction of causality, both in the real-world data and in their perception by the agents in the expectations data. Significant coefficients on taxes within the equation for spending are taken as evidence of causality from taxes to spending, and vice versa.

In the next section we illustrate in greater details the type of cointegrating and causal relationships which may be expected between and within the two models. We do it while summarising the various steps of the econometric analysis performed on the data.

4 Empirical specification and inference

The econometric specification described in the previous sections allows to perform the empirical analysis in two stages: the first one on the field sub-system, the second one on the expectation data.

4.1 Specification of the field model (stimuli)

Visual inspection and evidence in the literature suggest that the stimuli data $x_t := (T_t, G_t)'$ are integrated of order 1, I(1). Because x_t contains the ratio of taxes and expenditure to total GDP, $x_t := (T_t, G_t)'$, we expect the system x_t not to contain a linear trend.

A natural parametrisation of the sub-system is then

$$\Delta x_t = \alpha_{x2}(\beta_{2x}' x_{t-1} + \rho) + \sum_{\ell=1}^{k-1} \Gamma_{\ell,xx} \Delta x_{t-\ell} + \epsilon_{xt}, \tag{9}$$

where $\mu_x = \alpha_{x2} \cdot \rho$ has been assumed to exclude linear trends (see Johansen, 1995).

Versions of this basic model have been analysed quite extensively in the empirical time series analysis on fiscal policy. Two issues have been considered with particular attention: the sustainability of fiscal policy and the direction of causality between fiscal variables.

Since Trehan and Walsh (1991) and Hakio and Rush (1991), a classical method to address the first issue investigates cointegration between taxes and public expenditure inclusive of interest payments: in short, cointegration tests of sustainability are based on the idea that solvency requires the budget deficit to be stationary[8]. We follow a standard procedure to test for cointegration.

We start determining the lags order k of the field VAR: for each country, we begin with $k = 5$ and then restrict the order eliminating lags which are not statistical significant and checking for absence of correlation in the residuals. The Johansen (1995) procedure is used to test for the rank r_2 of the system, and possibly to estimate the cointegrating vector β_{2x}. We use the LR trace test for $H_0 : r_2 = 0$ versus $H_1 : r_2 = 1$, and exclude the case of a stationary system $r_2 = 2$, where both taxes and expenditure are stationary in levels. This assumption is justified by previous studies and informal inspection of the graphs of the series; see figure 4 and 5 with stimulus data in Section 2.

We rely on standard n-asymptotic tables, despite the limited time span of the data set. This reflects the unavailability of finite sample size quantiles, and it is also consistent with the inference agents could possibly perform in the experiment.

[8] Quintos (1995) clarifies that stationarity is in fact a strong solvency condition. In particular, he shows that the No Ponzi Game on public deficits is satisfied when the budget is integrated of order one and therefore distinguishes between strong and weak forms of solvency (on this, see also Bergman, 2001). We also note that, empirically, it has been proved difficult to accept sustainability in most countries (see references in Bohn, 1998, for the US; and see, e.g., Manasse, 1996, and the results section below for international evidence). Recently, Bohn (1998), and Sarno (2001) have adopted econometric approach which allow for nonlinearity in the adjustment process of fiscal policy; and have reach results supporting sustainability.

For the countries for which $r_2 = 1$, we estimate the CI vector in the form $\beta_{2x}' x_t = T_t + \gamma G_t$ imposing the normalisation to 1 of the coefficient of taxes, and testing whether the corresponding spending parameter $\gamma = -1$. The ML estimate $\widehat{\gamma}$ of γ is later used in the analysis of the lab sub-system[9].

The second empirical issue analysed within equation (9) concerns the direction of causality between taxes and public expenditure. This is also a classical theme in public finance. We recall four basic hypotheses. The first is that taxes cause spending; this has for example been advocated by the Leviathan State writers (Buchanan, 1977; Buchanan and Wagner, 1978), and as an implication of improvements in the technological capacity of raising revenues (Friedman, 1978). The opposite view that expenditure proceeds taxes is rooted in the theory of fiscal illusion, dating back to the nineteenth century 'Italian School of Public Finance' (Buchanan, 1960); it is also implied by Barro's models of exogenous public spending (Barro, 1974, 1979). Bidirectional causality may follow when taxes and expenditure are simultaneously determined according to the standard economic calculus of weighting the marginal costs and the marginal benefits of public services (Musgrave, 1966; Meltzer and Richard, 1981). Lack of causality may finally arise when taxes and public expenditure are decided upon by distinct institutional authorities (Hoover and Sheffrin, 1992).

Tests of the presence and direction of causality can be based on the field sub-model (9). In particular, when the series in $x_t := (T_t, G_t)'$ are cointegrated, we know that at least one between T_t and G_t adjusts to disequilibrium with respect to the long run relation. The four cases above corresponds to vector α_{x2} of the forms $(0, *)'$, $(*, 0)'$, $(*, *)'$ and $(0, 0)'$ (with $*$ indicating a non-zero coefficient), and provide tests of Granger long-run causality. Similarly short run-causality can be simply checked looking for significant off-diagonal coefficients in the matrices $\Gamma_{\ell,xx}$. Mixed results have been obtained regarding causality, see, e.g. recently, Garcia and Henin (1999) and Payne (1998).

Again here, we emphasise that in the present paper we are *not* interested in testing for causality (or for sustainability of fiscal policy) per se; but we are interested in whether and how properties of fiscal policy found in the stimuli are perceived in the lab-subsystems of expectations variables.

[9]Note that the generated regressor bias has no effect on the n-asymptotics for the lab sub-system, because $\widehat{\gamma}$ is superconsistent, $\widehat{\gamma} - \gamma = O_p(n^{-1})$ compared to the $n^{1/2}$ consistency of the parameters of stationary variables.

4.2 Specification of the lab model (expectations)

Under assumptions 1, 2, and 3, the lab sub-system can be decomposed into m individual sub-systems of the form

$$\Delta y_{i,t} = \mu_i+\alpha_{i1}\beta_{1z_i}' \begin{pmatrix} y_{i,t-1} \\ x_{t-1} \end{pmatrix}+\alpha_{i2}(\beta_{2x}'x_{t-1})+\sum_{\ell=1}^{k-1}(\Gamma_{\ell,ii}:\Gamma_{\ell,ix}) \begin{pmatrix} \Delta y_{i,t-\ell} \\ \Delta x_{t-\ell} \end{pmatrix}+\epsilon_{yt}, \tag{10}$$

where $y_{i,t} := (T_t^{E_i}, G_t^{E_i})'$ in the T_t and G_t treatment or $y_{i,t} := T_t^{E_i}$ in the T_t only treatment, and $x_t := (T_t, G_t)'$. In the following we illustrate the inference procedure only for $y_{i,t} := (T_t^{E_i}, G_t^{E_i})'$, with obvious modifications for the T_t only treatment. Equation (10) shows how the expectation variables may react to the field disequilibrium error $\beta_{2x}'x_{t-1}$, which is labelled ${}_{\text{ECM}}TG$. Additional CI relations may exist through the term $\alpha_{i1}\beta_{1z_i}'$ which is a 2×4 matrix of rank $r_{1i}\leq 2$.

Inference on the number of additional CI vectors r_{1i} can be performed for fixed values of the ECM term ${}_{\text{ECM}}TG$ obtained in the marginal field system[10]. In this paper we take a different and simpler approach. The hypothesis of adaptive behaviour in the formation of expectation suggests to calculate the expectation errors $(T_t^{E_i} - T_t,\ G_t^{E_i} - G_t)'$ as a possible choice of extra CI relations $\beta_{1z_i}'(y_{i,t-1}',\ x_{t-1}')'$. Because these extra relations do not contain any parameter to be estimated, it is simple to inspect the implied time-series of the forecast errors in order to infer if they are stationary or I(1). This can be done visually or through univariate unit root tests. Both the tests and the graphical analysis[11] suggest that the forecast errors are stationary.

This leads us to conclude that the sub-system (10) could be rewritten as follows

$$\begin{pmatrix} \Delta T_t^{E_i} \\ \Delta G_t^{E_i} \end{pmatrix} = \mu_i + \alpha_i \begin{pmatrix} T_{t-1}^{E_i} - T_{t-1} \\ G_{t-1}^{E_i} - G_{t-1} \\ T_{t-1} + \widehat{\gamma} G_{t-1} \end{pmatrix} + \sum_{\ell=1}^{k-1}(\Gamma_{\ell,ii}:\Gamma_{\ell,ix}) \begin{pmatrix} \Delta y_{i,t-\ell} \\ \Delta x_{t-\ell} \end{pmatrix} + \widehat{\varepsilon}_{yt}, \tag{11}$$

where $\alpha_i := (\alpha_{i1} : \alpha_{i2})$ is the adjustment coefficient, $\widehat{\varepsilon}_{yt} := \varepsilon_{yt} - \alpha_{i2}(\widehat{\gamma} - \gamma)G_{t-1}$. Eq. (11) involves only stationary variables and delivers standard $n^{1/2}$ asymptotics for $(\mu_i, \alpha_i, \Gamma_{\ell,ii}, \Gamma_{\ell,ix}, \Omega_{ii})$ (see Johansen, 1995, chapter 13.5).

[10] Paruolo (2001) has derived the asymptotics of LR trace test for CI rank when some CI relation are known. These results are not directly applicable here because the ECM term ${}_{\text{ECM}}TG$ has been estimated in the field sub-system and because (10) is a sub-system.

[11] Both are not reported for brevity.

The analysis of eq. (11) permits to discriminate among the different expectation formation processes detailed in Section 3.2. In particular, if subject i has rational expectations, one would expect the equations for $\Delta y_{i,t}$ to collapse to the specification of the marginal system Δx_t. This can be checked by testing if the coefficients of the variables that are present in (11) and not in (9) are equal to zero.

Of specific interest is to investigate whether and how the long-run adjustment in the conditional model α_{i2} relate to the one in the marginal model α_{x2}, since this coefficient indicates if agents perceive and adjust to the actual cointegration characteristics in the data.

However if expectations are adaptive, one would expect only Δx_t^1 to enter the equation for $\Delta y_{i,t}^1$, where a superscript 1 indicates one stimulus variable and the corresponding forecast. If other variables appear in the equation for $\Delta y_{i,t}^1$, this is consistent with an augmented-adaptive scheme. Again this can be tested via zero restrictions on coefficients.

Finally, questions of perceived causality between taxes and public expenditure can be addressed by inspection of parameters in (11), which nest causality links from $x_{t-\ell}$ and $y_{i,t-\ell}$ to $y_{i,t}$. In particular the off-diagonal elements in the $\Gamma_{\ell,ix}$ matrices and the α_{i2} coefficients determine the direction of causality from the field to the lab, while the off-diagonal elements in the $\Gamma_{\ell,ii}$ matrices and the α_{i1} coefficients regulate the ones from the past expectations on present expectations. Causal links in αs pertain adjustment to the long run equilibrium and are termed 'long run causality' links, while the ones in Γs are called 'short run causality' links.

The individual lab sub-systems (11) may be estimated one at the time or jointly. Joint estimation under some homogeneity restrictions allows to exploit the panel dimension of the data to increase efficiency. In the empirical analysis we first of all assume all individual-specific parameters to be equal across agents $(\mu_i, \alpha_i, \Gamma_{\ell,ii}, \Gamma_{\ell,ix}, \Omega_{ii}) = (\mu_*, \alpha_*, \Gamma_{\ell,*}, \Gamma_{\ell,*x}, \Omega_{**})$, obtaining the maximal reduction in the number of parameters. We estimate for each country a model of a representative-agent's expectations, which we compare with the corresponding country field model. This comparison will primarily focus on the expectations obtained from the experiment conducted under the fiscal frame. Next we will compare results from different treatments, including experiments conducted under the neutral frame. There we will also reconsider the homogeneity condition imposed through the representative agent assumption and we will perform alternative estimations at more disaggregated levels.

5 Empirical evidence

5.1 Analysis on the level of countries

Cointegration in the field: The result of the cointegration analysis of the stimulus data is given in table 3. We find that two lags (that is, models with one lagged difference, the VAR order is $k = 2$) are enough to characterise the dynamic structure of the series for most of the countries considered in the experiments. For 9 countries (Austria, Finland, Germany, Italy, Netherlands, Norway, Portugal, Sweden and UK), we find that taxes and public expenditures are cointegrated; for 6 (Belgium, Denmark, France, Greece, Ireland and Spain) we find that they are not. Among the former and consistently with the general evidence reported in the literature (see, e.g. Manasse, 1996), we found that the condition for stationarity of the budget $\widehat{\gamma} = -1$ is rejected for most countries. In fact, it is accepted only for Italy, somehow surprisingly given that Italy is notoriously considered a country with very easy public spending[12].

Causality in the field and in the lab: Table 4 summarises the main findings of the inference on both the field and the lab systems in the two experimental treatments under the fiscal frame. The complete parameter estimates are available in appendix A, other evidence on the estimates will be provided below.

Parameters reported in the table 4 are significant at a 5% level at least[13]. In considering the results, recall that in the T_t only treatment, in which agents forecast taxes, expectations on $G_t^{E_i}$ are not available. Thus, inference results on the lab system for the T_t only treatment is limited to the equation for $\Delta y_t^1 = \Delta T_{t+1}^{Ei}$.

The first part of the table reports, for the field and for the lab, the coefficients of responses to the field error correction term $\beta_{2x}'(T_t, G_t)'$ (also indicated with ${}_{\mathrm{ECM}}TG$). Consider first the field evidence (the first column in the table). Among the nine countries for which cointegration between taxes and expenditure was found, expenditure is long-run adjusting to taxes in four cases (Austria, Norway, Sweden and UK); taxes are adjusting to expenditure in others four (Finland, Germany, Italy and Netherlands); and in one country (Portugal) there is bidirectional adjustment.

[12]Notice, however, that the hypothesis of no-cointegration for Italy was rejected only marginally with a p-value of 0.09.

[13]All models presented below have been selected performing a computerised strategy, which started to drop coefficients with higher p-values. We have checked that the selected models are robust to alternative procedures

Table 3: Results of cointegration analysis on stimulus data

Country (sample period)	VAR order	$H_0(r_2 = 0)$ *versus* $H_1(r_2 = 1)$	Rank	Cointegrating Vector (β'_{2x}, ρ)	Test of the homogeneity condition $\widehat{\gamma} = -1$
Austria (1970-98)	$k = 3$	42.5***	$r = 1$	$(1; -0.739; -10.385)$	-13.23***
Belgium (1970-98)	$k = 2$	9.05	$r = 0$		
Denmark (1971-95)	$k = 2$	15.92	$r = 0$		
Finland (1970-98)	$k = 5$	27.99***	$r = 1$	$(1; -0.565; -21.436)$	-28.29***
France (1970-98)	$k = 2$	15.92	$r = 0$		
Germany (1976-98)	$k = 2$	19.40*	$r = 1$	$(1; -0.572; -17.863)$	-4.32**
Greece (1970-98)	$k = 2$	14.37	$r = 0$		
Ireland (1970-98)	$k = 2$	16.67	$r = 0$		
Italy (1970-98)	$k = 4$	18.19*	$r = 1$	$(1; -0.892; 0)$	-1.72
Netherlands (1970-98)	$k = 2$	20.47**	$r = 1$	$(1; -0.606; -17.630)$	-13.51***
Norway (1970-98)	$k = 2$	18.42*	$r = 1$	$(1; -1.051; 0)$	-3.52**
Portugal (1970-98)	$k = 3$	49.12***	$r = 1$	$(1; -1.177; 13.667)$	-2.09*
Spain (1970-98)	$k = 2$	16.10	$r = 0$		
Sweden (1970-98)	$k = 2$	18.18*	$r = 1$	$(1 : -0.950; 0)$	-2.13*
UK (1970-98)	$k = 2$	23.42**	$r = 1$	$(1; -0.922; 0)$	-9.18***

Legend: *, **, *** denote rejection at, in the order, 10%, 5%, 1% significance level.

	Vectors of responses to ${}_{\mathrm{ECM}}TG$: $T_t+\widehat{\gamma}G_t$			Vectors of responses to $({}_{\mathrm{ECM}}T^{E}T,\ {}_{\mathrm{ECM}}G^{E}G)'$: $\beta'_{w1}\cdot(y_{t-1},\ x_{t-1})'$		Direction of short run causality inferred from $\Gamma_{l,xx}$ and $\Gamma_{\ell,ix}$		
	Field α_{x2}	T_t and G_t treatment α_{i2}	T_t only treatment α_{i2}	T_t and G_t treatment α_{i1}	T_t only treatment α_{i1}	Field	T_t and G_t treatment	T_t only treatment
Austria	(0,1.308)	(0,0)	(0,*)	((-0.921,0), (0.084,-0.695))	((-0.863,*) ,*)	$T \leftrightarrow G$		$T \leftarrow G$
Belgium				((-0.838,0), (0,-0.656))	((-0.810,*) ,*)	$T \leftarrow G$	$T \leftrightarrow G$	$T \leftarrow G$
Denmark				((-0.885,0.138), (0.096,-0.622))	((-0.872,*) ,*)		$T \leftrightarrow G$	$T \leftarrow G$
Finland	(-0.953,0)	(-0.145,0)	(-0.164,*)	((-0.923,0.171), (0,-0.512))	((-0.825,*) ,*)	$T \leftarrow G$	$T \leftrightarrow G$	$T \leftarrow G$
France				((-0.709,-0.124), (0,-0.849))	((-0.655,*) ,*)	$T \leftarrow G$	$T \leftrightarrow G$	$T \leftarrow G$
Germany	(-1.007,0)	(0,0)	(0.165,*)	((-0.842,0), (0,-0.695))	((-0.961,*) ,*)		$T \rightarrow G$	$T \leftarrow G$
Greece				((-0.915,0), (0,-0.717))	((-1.058,*) ,*)		$T \leftarrow G$	$T \leftarrow G$
Ireland				((-0.739,0), (-0.141,-0.799))	((-0.676,*) ,*)		$T \rightarrow G$	$T \leftarrow G$
Italy	(-0.155,0)	(-0.072,-0.084)	(-0.034,*)	((-0.771,0.074), (0,-0.744))	((-0.864,*) ,*)		$T \rightarrow G$	
Netherlands	(-0.623,0)	(0,0)	(0,*)	((-0.736,0), (0,-0.800))	((-0.809,*) ,*)		$T \leftarrow G$	$T \leftarrow G$
Norway	(0,0.308)	(0,0.083)	(0,*)	((-0.732,0), (0.166,-0.751))	((-0.731,*) ,*)	$T \rightarrow G$	$T \rightarrow G$	$T \leftarrow G$
Portugal	(0.290,0.670)	(0,0.175)	(0,*)	((-0.744,0), (0.240,-0.633))	((-0.758,*) ,*)	$T \leftrightarrow G$	$T \leftrightarrow G$	$T \leftarrow G$
Spain				((-0.732,0), (0,-0.657))	((-0.548,*) ,*)		$T \rightarrow G$	$T \leftarrow G$
Sweden	(0,0.280)	(-0.034,0.086)	(0,*)	((-0.692,0), (0.111,-0.743))	((-0.670,*) ,*)	$T \rightarrow G$	$T \leftarrow G$	$T \leftarrow G$
United-Kingdom	(0,0.435)	(0,0)	(0,*)	((-0.883,0), (0.175,-0.780))	((-0.675,*) ,*)		$T \rightarrow G$	$T \leftarrow G$

TABLE 4: Summary of inference results

Results from the experiments show that subjects don't perceive the CI characteristics of the field data. In both experimental treatments the lab responses α_{i2} to ${}_{\mathrm{ECM}}TG$ are often not significantly different from zero and even when they are, α_{i2} are in any case quite small[14]

In the rightmost part of table 4 we show the results of tests on Granger causality in the field as it can be inferred from inspection of the off-diagonal coefficients of the matrix $\Gamma_{l,xx}$ from equation 11, and compare them with tests of perceived causality in the lab as inferred from the off-diagonal coefficients of matrix $\Gamma_{\ell,ix}$.

Here also results speak strongly against subjects correctly perceiving the properties of field stimuli data. Field evidence in particular shows that in eight countries, causality runs in neither direction[15], in three countries causality runs from expenditure to taxes; in two countries it runs from taxes to expenditure[16]; and in other two causality is bidirectional[17].

Lab results are not consistent with the directions of causality in the field. In the T_t and G_t treatment only in one case (Portugal) the causality matches the causality from the field data[18]. In the T_t only treatment the causality from the field is consistent with the one in the lab in six cases[19] and not consistent in the remaining nine.

Expectation schemes: The middle part of table 4 shows the estimates of the vector α_{y1} describing how individuals react in the long run to errors in the process of expectations forming $\beta'_{1z_i}(y'_{i,t-1}, x'_{t-1})' = (T_t^{E_i} - T_{t-1}, G_t^{E_i} - G_{t-1})'$ (also denoted $({}_{\mathrm{ECM}}T^ET, {}_{\mathrm{ECM}}G^EG)'$). The results supports the importance of

[14] In greater details, in the T_t and G_t treatment, in which subjects forecasted both taxes and expenditure, we find that in 4 countries (Austria, Germany, Netherlands, UK) subjects fail to perceive any long run adjustment; in one country (Finland), they perceive some low adjustment of taxes to expenditure, in two (Norway and Portugal) of expenditure to taxes, and in other two (Italy and Sweden) a bi-directional long run adjustment. In the T_t only treatment, we don't know how participants perceive the dynamics of the series of public expenditure; on the other hand, we see that out of the six countries in which adjustment in the field was from expenditure to taxes, only in the case of Finland and Italy participants seem to perceive some small adjustment in the right direction, while for Germany the coefficient of the long run adjustment has the wrong sign.

[15] The countries were causality in the field runs in neither direction in the are Denmark, Germany, Greece, Ireland, Italy, Netherlands, Spain, UK.

[16] These countries are Norway and Sweden.

[17] Bidirectional causality is found in Austria and Portugal in the field data.

[18] For one country (Austria), subjects don't perceive any causality in the T_t and G_t treatment while we estimate a bidirectional causality in the field. For the remaining 14 countries we estimate a causality with the lab data which is matched by the field causality only in the case of Portugal.

[19] These countries are Austria, Belgium, Finland, France, Italy, Portugal.

adaptive expectations. In the T_t and G_t treatment we find the coefficients for ${}_{\mathrm{ECM}}T^ET$ in the equation for $\Delta T_t^{E_i}$, and the coefficients on ${}_{\mathrm{ECM}}G^EG$ in the equation for $\Delta G_t^{E_i}$ to be positive and close to 1. The same holds in the T_t only treatment for the coefficients for ${}_{\mathrm{ECM}}T^ET$ in the equation for $\Delta T_t^{E_i}$[20] We also see that in both experimental treatments the estimated parameters are typically less than 1. (This is also confirmed by formal t-tests conducted on the parameters). Conversely, we should note that in the T_t and G_t treatment, the off-diagonal diagonal of α_{i1} are in most cases equal to or very close to zero. In other words, subjects do not adjust expectations for taxes to errors in the expectations on expenditure, and vice versa.

Taken as a whole, the aggregate evidence from table 4 thus indicates that subjects are far from a model of rational expectations; their behaviour seems rather to follow adaptive expectations, but possibly not quite a purely adaptive model. While the results suggest that participants assume some causality, this causality changes over countries. (As we will see this causality differs also among participants and, for each participant, it differs even from country to country). We take this to be a weak evidence for model of augmented-adaptive expectations.

To obtain further evidence on the issue, in figure 7 we compare the distributions of the coefficients for the two fiscal treatments summarised in table 4 with similar aggregate estimates obtained from the experiments conducted under the neutral frame. The left column of diagrams figure 7 shows estimated coefficients for $\Delta T_t^{E_i}$, the right column of diagrams shows the coefficients for $\Delta G_t^{E_i}$. We see some difference among treatments, but also a good deal of similarity.

Coefficients of responses to the field error correction term ${}_{\mathrm{ECM}}TG$ are zero or close to zero for all treatments and for both equations for $\Delta T_t^{E_i}$ and $\Delta G_t^{E_i}$.

The distributions of the adjustment coefficients to the error terms $({}_{\mathrm{ECM}}T^ET, {}_{\mathrm{ECM}}G^EG)'$) confirm that in all treatments subjects follow in the aggregate a model of adaptive expectation, with on-diagonal coefficients close but generally lower than one, while off-diagonal coefficients are basically zero. That is, subjects don't adjust adaptively across variables. There is, however, a small but clear difference between the treatments, in particular regarding the equation for $\Delta G_t^{E_i}$, for which subjects in the (control) neutral treatment show greater adjustment coefficients than subjects in the fiscal (T_t and G_t) treatment. One could say that the economic context reduces the amount of adaptive behaviour.

The next graphs of the figure report the distribution of the coefficients

[20]In the T_t only treatment subjects do not form expectations on G, hence, we can not measure the other coefficients.

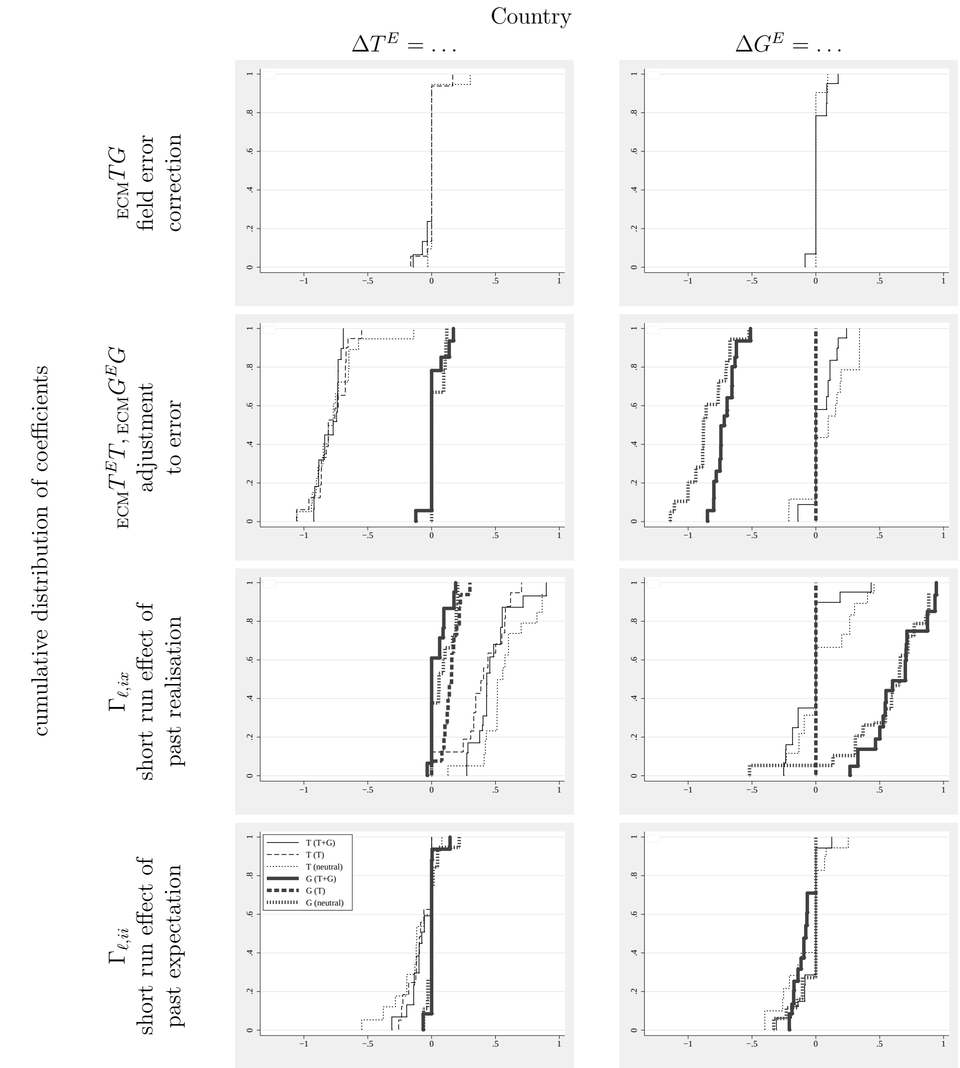


FIGURE 7: Results of estimating equation (11) for each country

Graphs show the distribution of the estimated coefficients of equation (11). We impose the restriction that all individuals in one of our three treatments use the same model. The distribution in the $T + G$ treatment is always shown as a solid line, the distribution in the T treatment as a dashed line, and the distribution in the neutral treatment is shown as a dotted line. Distributions of coefficients for ${}_{\text{ECM}}T$, ΔT, and ΔT^E are shown as thin lines, distributions of coefficients for ${}_{\text{ECM}}G$, ΔG, and ΔG^E are shown as thick lines.

of matrices $\Gamma_{\ell,ix}$ summed over lags[21]. In both equations, the diagonal coefficients (hence the own-effects of $\Delta T_{t-\ell}$ on $\Delta T_t^{E_i}$ and of $\Delta G_{t-\ell}$ on $\Delta G_t^{E_i}$) are larger than the off-diagonal terms, which corroborates the view that perception of Granger causality in the T_t and G_t treatment is neither systematic nor strong. A noteworthy exception is perceived causality from expenditure to taxes in T_t only treatment which is often significant and positive, which we view as support to include short run causalities for this treatment in table 4.

The last two diagrams show the coefficients from matrix $\Gamma_{\ell,ii}$, summed-up over lags, which refer to the short run effects of past expectations on present expectations. The results show a moderate tendency of subjects smoothing out peaks in past expectations, as these (diagonal) effects are negative, but generally close to zero.

5.2 Analysis on the level of individuals

The results discussed in section 5.1 have been estimated assuming all individual-specific parameters to be equal across agents within each country. This restriction may be natural when all individual behaviour satisfies rational expectations. In the discussion of the estimates on the level of countries we have seen that subjects in aggregate violate rational expectations. Still, there may be some subjects behaving differently or more rational than others. In addition, it is possible that responses given by the same participants for different countries are correlated. In such a case, correlated responses by few participants may influence the patterns of aggregate results (since the sample sizes of participants in the various treatments are in any case limited).

To investigate this possibility we have also estimated equation (11) separately for each individual in each country. The results are shown in figure 8. The results do not alter the general picture from the homogeneous case (figure 7). Rather, the results confirm the strong inclination toward adaptive expectations of most subjects, as well some other features of the data presented for the aggregate case.

In figure 9 we show for the various treatments the cumulative distributions of the coefficients of the lab sub-systems (11) assuming that they are equal for each participant over all countries (though they may differ among participants)[22].

[21] Looking at sums of coefficients to aggregate coefficients for different lags is crude, but it is also simple and effective. We get a very similar picture if we take only the first lag. The other lags are typically much smaller (by a factor of at least 10).

[22] We should note that there may be other ways to impose a structure on individual

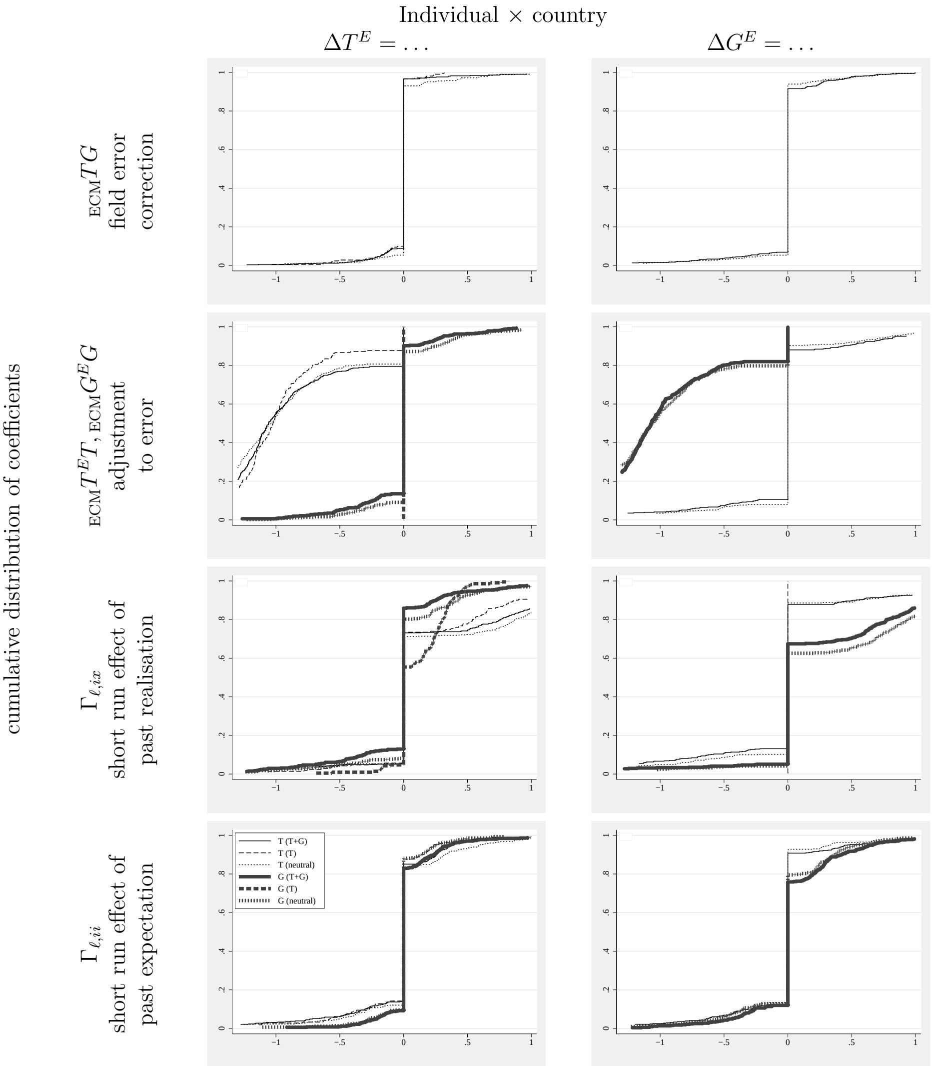


FIGURE 8: Results of estimating equation (11) separately for each individual and each country

Graphs show the distribution of the estimated coefficients of equation (11). Individuals may use different models for each country. The distribution in the $T + G$ treatment is always shown as a solid line, the distribution in the T treatment as a dashed line, and the distribution in the neutral treatment is shown as a dotted line. Distributions of coefficients for $_{\mathrm{ECM}}T$, ΔT, and ΔT^E are shown as thin lines, distributions of coefficients for $_{\mathrm{ECM}}G$, ΔG, and ΔG^E are shown as thick lines.

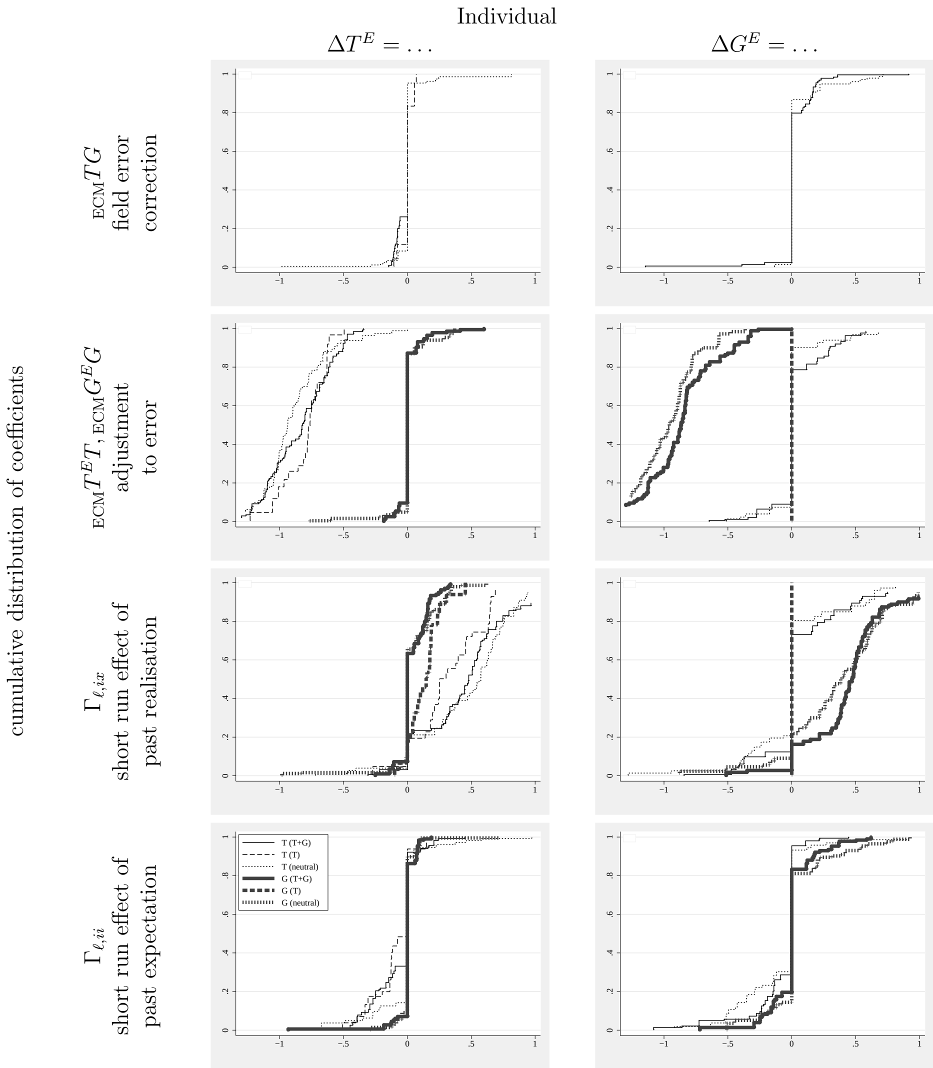


FIGURE 9: Results of estimating equation (11) for each individual

Graphs show the distribution of the estimated coefficients of equation (11). We impose the restriction that each individual uses the same model for all countries. The distribution in the $T+G$ treatment is always shown as a solid line, the distribution in the T treatment as a dashed line, and the distribution in the neutral treatment is shown as a dotted line. Distributions of coefficients for ${}_{\text{ECM}}T$, ΔT, and ΔT^E are shown as thin lines, distributions of coefficients for ${}_{\text{ECM}}G$, ΔG, and ΔG^E are shown as thick lines.

The graphs look similar to those obtained for the coefficients estimated in the representative agent set-up, with the few differences among the treatments. In particular, the response estimates to vectors $({}_{\text{ECM}}T^E T, {}_{\text{ECM}}G^E G)')$ confirm that the (own) adjustments coefficients are grater than 0.5 and less than 1 for most subjects in all treatments. They also verify, though, that the coefficients in the neutral treatments are systematically greater than in the fiscal treatments, and here also in the equation for expected taxes. The data also confirm the general weak evidence on Granger causality from the off-diagonal elements of matrix $\Gamma_{\ell,ix}$, but less so in results from the T_t only treatment.

5.3 Misspecification tests for nonlinearity and anti-Keynesian effects

The VAR approach pursued in the previous sections works under the maintained hypothesis of a linear process for the time series considered. As intuition and some current literature has documented (see Bohn, 1998, and Sarno, 2001), this hypothesis may conflict with the fact that fiscal policy is subject to various possible structural shifts and discretionary interventions, which may introduce nonlinearity in fiscal policy.

We have controlled for misspecification biases due to nonlinearity in the field systems by way of standard RESET tests. We haven't found evidence of misspecification for the spans of data given as stimulus to subjects in the experiment.

When the field systems are correctly specified, still, the conduct of fiscal policy might change at some point in time. As emphasised by some recent literature a large intervention on the fiscal variables, perhaps addressed to correct disequilibrium in the public budget, may be perceived by the public as to imply lower taxation in the future, and therefore generate an expansion in economic activity, rather than a contraction as predicted by a standard Keynesian perspective.

Proposed originally by the Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung 1981, this view has been made popular by Giavazzi and Pagano (1990), who brought to the attention of the profession the astonishing expansionary fiscal consolidations occurred in the mid 1980s in Denmark and Ireland. Various subsequent literature has been developed on the circumstances and conditions under which nonlinear effects of fiscal policy are more or less likely to occur.

behaviour over different countries. In this exercise we are keeping the structure of equation (11) to facilitate the comparison with our previous results.

Taking a pragmatic approach on the issue, Giavazzi, Jappelli, and Pagano (2000) have defined periods of 'large and persistent' fiscal contractions and fiscal expansions as situations in which, for at least two consecutive years, the budget balance as a percentage of GDP increase or decrease, respectively, by at least 1.5 point per year. Looking at two panels of OECD and non-OECD data, the study reports widespread evidence of nonlinear effects of fiscal policy.

However, as noted in the introduction, a problem with this approach is that a link between the observed nonlinear effects of fiscal policy and the role of expectations can be inferred, but not really tested.

We control for the possibility of nonlinear effects in the present experiment introducing dummies in the equation (11) for expected taxes. Two dummies are introduced on the intercept: one (d_{CONTR}) activated in periods of "sizeable and persistent" fiscal contractions, and the other (d_{EXP}) activated in periods of "sizeable and persistent" fiscal expansions. According to the view, we should expect the coefficients on d_{CONTR} to be negative and that on d_{EXP} to be positive[23].

Table 5 reports the periods in which the two dummies were activated, with the related evidence. (A fuller account of the evidence can be found in appendix A).

We counted 11 episodes of fiscal expansions (in 10 countries, with Sweden counting for two), and 10 episodes of fiscal contractions (in 7 countries, with Ireland counting for two and Sweden for three). In the majority of cases the dummies are not significant, in some they are inconsistent with theory. The evidence thus rejects the hypothesis of nonlinear responses of expectations to 'large and persistent' changes in fiscal policy *per se*.

6 Conclusion

In a famous taxonomy of the goal which may be pursued in the laboratory, Roth (1987) suggests three categories to classify experiments in economics: the first is "speaking to theorists", the second is "searching for facts and meaning", the third is "whispering in the ears of princes". The experiment described in the previous pages has especially pursued the second goal in a field — that of expectations on fiscal policy —, in which very little is actually known, though much is assumed through the hypothesis of rational expectations.

[23]This would in particular signal a negative and positive change in the drift of agents' expectations following periods of "large and persistent" fiscal contraction and fiscal expansion, respectively.

	Vectors of responses to ${}_{\mathrm{ECM}}TG$: $T_t+\widehat{\gamma}G_t$		Vectors of responses to $({}_{\mathrm{ECM}}T^ET,\, {}_{\mathrm{ECM}}G^EG)'$: $\beta_{w1}' \cdot (y_{t-1},\, x_{t-1})'$		Direction of short run causality inferred from $\Gamma_{l,xx}$ and $\Gamma_{\ell,ix}$		Fiscal Expansions coefficients of d_{EXP}			Fiscal Contractions coefficients of d_{CONTR}		
	T_t and G_t treatment α_{i2}	T_t only treatment α_{i2}	T_t and G_t treatment α_{i1}	T_t only treatment α_{i1}	T_t and G_t treatment	T_t only treatment	Episodes	T_t and G_t treatment	T_t only treatment	Episodes	T_t and G_t treatment	T_t only treatment
Austria	(0,0)	(0,*)	((-0.921,0), (0.084,-0.695))	((-0.863,*) ,*)		$T \leftarrow G$						
Belgium			((-0.838,0), (0,-0.656))	((-0.780,*) ,*)	$T \leftrightarrow G$	$T \leftarrow G$	80, 81	0	-0.303			
Denmark			((-0.885,0.138), (0.096,-0.622))	((-0.872,*) ,*)	$T \leftrightarrow G$	$T \leftarrow G$	74, 75, 80, 81, 82	0	0	83, 84, 85, 86	0	0
Finland	(-0.238,0)	(-0.164,*)	((-0.932,0.210), (0,-0.512))	((-0.825,*) ,*)	$T \leftrightarrow G$	$T \leftarrow G$	91, 92, 93	0.623	0	75, 76, 88, 89	0	0
France			((-0.712,0), (0,-0.849))	((-0.655,*) ,*)	$T \leftrightarrow G$	$T \leftarrow G$	92, 93	0.466	0			
Germany	(0,0)	(0.165,*)	((-0.842,0), (0,-0.695))	((-0.961,*) ,*)	$T \rightarrow G$	$T \leftarrow G$	74, 75	0	0			
Greece			((-0.915,-0.067), (0,-0.717))	((-1.058,*) ,*)		$T \leftarrow G$	88, 89, 90	0	0	96, 97	0	0
Ireland			((-0.739,0), (-0.141,-0.799))	((-0.676,*) ,*)	$T \rightarrow G$	$T \leftarrow G$	74, 75, 78, 79, 80	0	0	83, 84, 87, 88	0	0
Italy	(-0.072,-0.084)	(-0.034,*)	((-0.771,0.074), (0,-0.744))	((-0.864,*) ,*)	$T \rightarrow G$		71, 72	0	0			
Netherlands	(0,0)	(0,*)	((-0.736,0), (0,-0.800))	((-0.809,*) ,*)	$T \leftarrow G$	$T \leftarrow G$						
Norway	(0,0.083)	(0,*)	((-0.736,0), (0.166,-0.751))	((-0.731,*) ,*)	$T \rightarrow G$	$T \leftarrow G$	91, 92	0.324	0	94, 95, 96	0	0
Portugal	(0,0.175)	(0,*)	((-0.744,0), (0.240,-0.633))	((-0.758,*) ,*)	$T \leftrightarrow G$	$T \leftarrow G$	74, 75, 76	0	0			
Spain			((-0.712,0), (0,-0.657))	((-0.548,*) ,*)	$T \leftrightarrow G$	$T \leftarrow G$	81, 82	0	0	96, 97	0.312	0
Sweden	(-0.034,0.086)	(0,*)	((-0.715,0), (0.111,-0.743))	((-0.673,*) ,*)		$T \leftarrow G$	78, 79, 91, 92, 93	0.575	0	83, 84, 86, 87, 94, 95, 96	0	0.238
United-Kingdom	(0,0)	(0,*)	((-0.883,0), (0.175,-0.780))	((-0.897,*) ,*)	$T \rightarrow G$		72, 73, 92, 93	0	0.791			

Table 5: Evidence on expectations in episodes of "large and persistent" fiscal adjustments

We attempt to take a first step in studying the reliability of this hypothesis and the process people use to form expectations on fiscal variables more generally. It is clear that in the real world expectations on fiscal policy depend on a long list of political, institutional, and cultural conditions. Yet, we have conducted an experiment in which participants receive as stimuli only real world data on fiscal variables and where they form expectations on the basis of that information alone. We have taken this approach to control the environment of the stimulus data as the very essence of laboratory experiments.

Though such a simple environment is not the most precise model of a process of fiscal expectations, in providing only a limited set of information, and in leaving out announcements, contracts between countries, etc., we want come close in the experiment to standard models used by economists and econometricians to study and analyse the properties of fiscal policy. Consistently, we follow an econometric approach for the process of formation of expectations, which coherently arises from the data generating process of the field stimuli; we have distinguished between long-run and short-run effects, both of the stimuli and of past expectations.

We found that subjects behave adaptively, though they do not adjust perfectly to past expectation errors, not even in the long run. We found that subjects follow an augmented-adaptive model, which hasn't however revealed a general pattern of behaviour regarding causal relationships between fiscal variables. Indeed, we have found little difference in the models estimated for subjects giving expectations when they knew that the stimulus data concerned real fiscal variables, and the control group which didn't know. Still, we have seen less noise and more accuracy in the expectations of participants in the fiscal frame than in the neutral frame, which we have taken as a sign of a better understanding of the experimental task and of the internal validity of the experimental set-up.

For subjects in the fiscal frame, we have also tested whether their expectations respond nonlinearly to large discretionary changes in fiscal policy; but we haven't found this behaviour. Once again, this does not necessarily mean that nonlinear effects of fiscal policy may not be relevant in the field, however, it means that if nonlinear effects occur, they might not be simply imputed to general characteristics of fiscal policy *per se*, but may need other catalysing factors, which may be political events, announcements, perhaps news from the press or media broadcasting.

A possible next step would be to include some of these factors in a richer experimental setup, which gives information on political events or announcements from historical records, as additional stimulus data. Likewise, experiments giving more information on the country or the period of stimulus data or the composition of the public budget may provide a way to test models of an increasing degree of closeness to the real world, while maintaining control on subjects' information sets.

From a methodological perspective, the main novelty of the present approach is the idea of using field and laboratory data complementarily. Experimental economics has grown substantially over the last two or three decades, as it is now a well-acknowledged method through which decision theorists, game theorists and microeconomists have tested and refined theoretical models in their respective fields of interest.

Relatively few experiments have instead been conducted in the field of macroeconomics. The reason, probably, is that macroeconomists deal with real world questions to a much greater degree than other economists, in the belief that laboratory experiments cannot really answer such type of questions. Olivier Blanchard argues in this context: "When an engineer wants to find out how the temperature affects material's conductivity, she builds an experiment in which she changes the temperature, makes sure that everything else remains the same, and looks at the change in conductivity. But macroeconomists who want to find out, for example, how changes in the money supply affect aggregate activity cannot perform such controlled experiments; they cannot make the world stop while they ask the central bank to change the money supply" (Blanchard, 1997).

The approach pursued in this paper suggests that it is not necessary to make the whole world stop to test macroeconomic models experimentally. Instead, by using real world data as stimulus for subjects in the experiments it may be possible to start collecting pieces of evidence that may help us understanding which forces and variables are more relevant when individuals take macroeconomic actions.

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A Detailed results of the estimation

	without dummies							with dummies for contr. and exp.				
	field		T_t and G_t		T_t only	neutral		T_t and G_t		T_t only	neutral	
	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG
Austria												
ECM	·	1.31	·	·	·	·	·	·	·	·	·	·
$_{\text{ECM}}T$	·	·	-.921	.084	-.863	-.89	.155	-.921	.084	-.863	-.89	.155
ΔT^E_{t-1}	·	·	·	·	-.06	·	-.115	·	·	-.06	·	-.115
ΔT_{t-1}	-.562	-.751	.275	·	.247	.411	·	.275	·	.247	.411	·
$_{\text{ECM}}G$	·	·	·	-.695	·	·	-.94	·	-.695	·	·	-.94
ΔG^E_{t-1}	·	·	·	-.07	·	·	·	·	-.07	·	·	·
ΔG_{t-1}	·	.355	·	.713	.225	·	.77	·	.713	.225	·	.77
ΔG_{t-2}	.318	.705	·	·	·	·	·	·	·	·	·	·
Belgium												
$_{\text{ECM}}T$	·	·	-.838	·	-.81	-.77	.097	-.838	·	-.78	-.752	.097
ΔT^E_{t-1}	·	·	-.085	·	-.067	-.1	·	-.085	·	-.081	-.119	·
ΔT^E_{t-2}	·	·	-.056	·	-.052	-.094	·	-.056	·	-.06	-.1	·
ΔT_{t-1}	·	·	.43	-.139	.33	.602	·	.43	-.139	.313	.546	·
$_{\text{ECM}}G$	·	·	·	-.656	·	.095	-.673	·	-.656	·	.095	-.673
ΔG^E_{t-1}	·	·	·	-.067	·	-.063	-.105	·	-.067	·	-.052	-.105
ΔG_{t-1}	.261	.372	.096	.874	.217	.205	.884	.096	.874	.264	.268	.884
d_{EXP}	·	·	·	·	·	·	·	·	·	-.303	-.422	·
Denmark												
$_{\text{ECM}}T$	·	·	-.885	.096	-.872	-.647	.342	-.885	.212	-.872	-.647	.297
ΔT^E_{t-1}	·	·	-.057	-.087	·	-.121	-.294	-.057	-.162	·	-.121	-.279
ΔT^E_{t-2}	·	·	·	·	·	·	-.105	·	-.062	·	·	-.076
ΔT_{t-1}	·	·	.456	·	.386	.865	.265	.456	.328	.386	.569	.587
$_{\text{ECM}}G$	·	·	.138	-.622	·	·	-1	.138	-.691	·	·	-.949
ΔG^E_{t-1}	·	·	-.066	-.146	·	-.037	·	-.066	-.121	·	·	-.063
ΔG^E_{t-2}	·	·	·	-.062	·	.048	·	·	·	·	.035	·
ΔG_{t-1}	·	·	.175	.933	.128	.058	.721	.175	.757	.128	.246	.517
d_{EXP}	·	·	·	·	·	·	·	·	·	·	-.993	.784
d_{CONTR}	·	·	·	·	·	·	·	·	-.605	·	.92	-1.43
Finland												

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	without dummies							with dummies for contr. and exp.				
	field		T_t and G_t		T_t only	neutral		T_t and G_t		T_t only	neutral	
	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG
ECM	-.953	·	-.145	·	-.164	·	·	-.238	·	-.164	·	-.216
$_{\text{ECM}}T$	·	·	-.923	·	-.825	-.935	·	-.932	·	-.825	-.935	·
ΔT^E_{t-1}	·	·	·	·	·	·	.12	·	·	·	·	.124
ΔT^E_{t-2}	·	·	·	·	·	·	.133	·	·	·	·	.148
ΔT_{t-1}	.847	·	.486	·	.55	.514	·	.627	.18	.55	.514	·
ΔT_{t-2}	.514	·	·	·	·	·	·	.13	·	·	·	·
ΔT_{t-3}	·	·	·	·	·	·	·	.139	·	·	·	·
ΔT_{t-4}	.528	·	·	-.252	·	·	·	·	-.267	·	·	·
$_{\text{ECM}}G$	·	·	.171	-.512	·	·	-.879	.21	-.573	·	·	-.894
ΔG^E_{t-1}	·	·	·	-.079	·	·	·	-.057	·	·	·	·
ΔG_{t-1}	·	.872	.067	.943	.097	·	.538	·	.791	.097	·	.653
ΔG_{t-2}	-.666	-.468	·	·	·	·	·	·	·	·	·	·
ΔG_{t-3}	·	·	-.101	·	·	·	·	-.177	·	·	·	·
ΔG_{t-4}	-.309	·	·	·	·	·	-.168	·	·	·	·	-.199
d_{EXP}	·	·	·	·	·	·	·	.623	·	·	·	-1.24
d_{CONTR}	·	·	·	·	·	·	·	·	·	·	·	.889
France												
$_{\text{ECM}}T$	·	·	-.709	·	-.655	-.902	-.212	-.712	·	-.655	-.901	-.198
ΔT^E_{t-2}	·	·	·	.125	·	.08	.068	·	.092	·	·	·
ΔT_{t-1}	·	·	.432	·	.501	.421	-.252	.493	·	.501	.608	·
$_{\text{ECM}}G$	·	·	-.124	-.849	·	·	-.859	·	-.817	·	·	-.869
ΔG^E_{t-1}	·	·	-.052	-.116	·	·	·	-.108	-.138	·	·	·
ΔG^E_{t-2}	·	·	.056	·	·	·	·	·	·	·	·	·
ΔG_{t-1}	.358	.444	·	.527	.172	.092	.545	·	.435	.172	-.188	.243
d_{EXP}	·	·	·	·	·	·	·	.466	.506	·	.829	.771
Germany												
ECM	-1.01	·	·	·	.165	·	·	·	·	.165	·	·
$_{\text{ECM}}T$	·	·	-.842	·	-.961	-.853	·	-.842	·	-.961	-.853	·
ΔT^E_{t-2}	·	·	·	-.14	·	·	·	·	-.14	·	·	·
ΔT_{t-1}	·	·	.398	-.234	·	.516	·	.398	-.234	·	.516	·
$_{\text{ECM}}G$	·	·	·	-.695	·	·	-.939	·	-.695	·	·	-.939
ΔG_{t-1}	·	·	·	.709	.3	·	.459	·	.709	.3	·	.459
Greece												
$_{\text{ECM}}T$	·	·	-.915	·	-1.06	-1.05	.191	-.915	·	-1.06	-.757	.191
ΔT^E_{t-1}	·	·	·	·	-.118	·	·	·	·	-.118	-.228	·
ΔT^E_{t-2}	·	·	·	·	-.106	·	·	·	·	-.106	-.143	·
ΔT_{t-1}	·	·	.275	·	·	.128	·	.283	·	·	.317	·
$_{\text{ECM}}G$	·	·	·	-.717	·	·	-1.14	-.067	-.717	·	·	-1.14

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	without dummies							with dummies for contr. and exp.				
	field		T_t and G_t		T_t only	neutral		T_t and G_t		T_t only	neutral	
	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG
ΔG^E_{t-1}	·	·	·	-.109	·	·	·	·	-.109	·	·	·
ΔG^E_{t-2}	·	·	·	-.078	·	·	·	·	-.078	·	·	·
ΔG_{t-1}	·	·	.09	.601	.122	·	.134	·	.601	.122	·	.134
d_{EXP}	·	·	·	·	·	·	·	·	·	·	-.944	·
Ireland												
${}_{\text{ECM}}T$	·	·	-.739	-.141	-.676	-.849	·	-.739	·	-.676	-.836	·
ΔT^E_{t-1}	·	·	·	·	-.097	·	·	·	·	-.097	·	·
ΔT_{t-1}	·	·	.54	-.183	.345	.512	-.132	.54	·	.345	.671	·
${}_{\text{ECM}}G$	·	·	·	-.799	·	.112	-.886	·	-.813	·	.111	-.881
ΔG^E_{t-2}	·	·	·	·	·	.047	·	·	·	·	.06	.065
ΔG_{t-1}	·	·	·	.329	.158	.193	.309	·	.25	.158	.202	.272
d_{EXP}	·	·	·	·	·	·	·	·	·	·	-1.55	-1.76
d_{CONTR}	·	·	·	·	·	·	·	·	-1.42	·	-.845	-1.95
Italy												
ECM	-.155	·	-.072	-.084	-.034	·	·	-.072	-.084	-.034	·	·
${}_{\text{ECM}}T$	·	·	-.771	·	-.864	-.651	.197	-.771	·	-.864	-.651	.197
ΔT^E_{t-1}	·	·	-.223	·	·	-.22	-.207	-.223	·	·	-.22	-.207
ΔT^E_{t-2}	·	·	-.088	·	·	-.158	·	-.088	·	·	-.158	·
ΔT_{t-1}	·	·	.573	-.237	.441	.574	·	.573	-.237	.441	.574	·
ΔT_{t-2}	·	·	.324	·	·	·	.203	.324	·	·	·	.203
${}_{\text{ECM}}G$	·	·	.074	-.744	·	·	-.764	.074	-.744	·	·	-.764
ΔG^E_{t-1}	·	·	·	-.112	·	·	·	·	-.112	·	·	·
ΔG^E_{t-2}	·	·	·	-.062	·	·	·	·	-.062	·	·	·
ΔG_{t-1}	·	·	·	.543	·	·	.593	·	.543	·	·	.593
ΔG_{t-2}	·	·	·	·	·	.164	·	·	·	·	.164	·
ΔG_{t-3}	·	.587	·	·	·	·	·	·	·	·	·	·
Netherlands												
ECM	-.622	·	·	·	·	.303	·	·	·	·	.303	·
${}_{\text{ECM}}T$	·	·	-.736	·	-.809	-.14	.341	-.736	·	-.809	-.14	.341
ΔT^E_{t-1}	·	·	-.146	·	-.123	-.426	-.143	-.146	·	-.123	-.426	-.143
ΔT^E_{t-2}	·	·	-.049	·	·	-.121	·	-.049	·	·	-.121	·
ΔT_{t-1}	·	·	.376	·	.306	1.05	.404	.376	·	.306	1.05	.404
${}_{\text{ECM}}G$	·	·	·	-.8	·	·	-.761	·	-.8	·	·	-.761
ΔG^E_{t-1}	·	·	.071	·	·	.147	·	.071	·	·	.147	·
ΔG^E_{t-2}	·	·	.073	·	·	.069	·	.073	·	·	.069	·
ΔG_{t-1}	.368	.478	·	.501	.174	·	.598	·	.501	.174	·	.598
Norway												
ECM	·	.308	·	.083	·	·	·	·	.083	·	·	.093

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	without dummies							with dummies for contr. and exp.				
	field		T_t and G_t		T_t only	neutral		T_t and G_t		T_t only	neutral	
	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG
$\text{ECM}T$	·	·	-.732	.166	-.731	-.728	.34	-.736	.166	-.731	-.797	.391
ΔT^E_{t-1}	·	·	-.08	-.162	·	-.06	-.153	-.073	-.162	·	·	-.221
ΔT^E_{t-2}	·	·	-.056	-.147	·	·	-.108	-.055	-.147	·	·	-.163
ΔT_{t-1}	·	-.461	.431	·	.407	.557	.303	.453	·	.407	.54	.296
$\text{ECM}G$	·	·	·	-.751	·	.119	-.705	·	-.751	·	.126	-.727
ΔG^E_{t-1}	·	·	·	-.14	·	·	-.205	·	-.14	·	·	-.173
ΔG^E_{t-2}	·	·	·	·	·	·	-.125	·	·	·	·	-.094
ΔG_{t-1}	·	.489	·	.549	.156	.105	.661	·	.549	.156	.102	.626
d_{EXP}	·	·	·	·	·	·	·	.324	·	·	.449	.725
Portugal												
ECM	.288	.666	·	.175	·	·	·	·	.175	·	·	·
$\text{ECM}T$	·	·	-.744	.24	-.758	-.753	·	-.744	.24	-.758	-.753	·
ΔT^E_{t-1}	·	·	-.098	·	-.18	-.131	·	-.098	·	-.18	-.131	·
ΔT_{t-1}	·	-.591	.402	.433	.409	.701	.456	.402	.433	.409	.701	.456
ΔT_{t-2}	-.436	-.481	·	·	.168	·	·	·	·	.168	·	·
$\text{ECM}G$	·	·	·	-.633	·	·	-1.11	·	-.633	·	·	-1.11
ΔG^E_{t-1}	·	·	·	-.171	·	·	·	·	-.171	·	·	·
ΔG^E_{t-2}	·	·	·	·	·	-.032	·	·	·	·	-.032	·
ΔG_{t-1}	.297	.375	.124	.267	.08	.055	-.3	.124	.267	.08	.055	-.3
ΔG_{t-2}	.168	.374	.064	·	·	·	-.22	.064	·	·	·	-.22
Spain												
$\text{ECM}T$	·	·	-.732	·	-.548	-.572	.165	-.712	·	-.548	-.572	.187
ΔT^E_{t-1}	·	·	-.077	-.099	-.18	-.205	-.162	-.096	-.099	-.18	-.205	-.128
ΔT^E_{t-2}	·	·	·	-.093	-.078	-.078	-.09	·	-.093	-.078	-.078	·
ΔT_{t-1}	·	·	.716	·	.704	.825	·	.724	·	.704	.825	·
$\text{ECM}G$	·	·	·	-.657	·	.107	-.524	·	-.657	·	.107	-.559
ΔG^E_{t-1}	·	·	·	·	·	·	-.152	.039	·	·	·	-.132
ΔG^E_{t-2}	·	·	·	·	·	·	-.079	·	·	·	·	-.06
ΔG_{t-1}	·	·	·	.706	.197	.19	1.06	·	.706	.197	.19	1.07
d_{CONTR}	·	·	·	·	·	·	·	.312	·	·	·	.767
Sweden												
ECM	·	.276	-.034	.086	·	-.03	.093	-.034	.086	·	-.03	.087
$\text{ECM}T$	·	·	-.692	.111	-.67	-.808	·	-.715	.111	-.673	-.808	·
ΔT^E_{t-1}	·	·	-.099	·	-.086	-.116	·	-.076	·	-.076	-.116	·
ΔT_{t-1}	·	-.553	.553	·	.573	.515	-.091	.573	·	.564	.515	-.151
$\text{ECM}G$	·	·	·	-.743	·	·	-.881	·	-.743	·	·	-.878
ΔG^E_{t-1}	·	·	·	-.094	·	·	·	·	-.094	·	·	·
ΔG^E_{t-2}	·	·	·	·	·	-.029	·	·	·	·	-.029	·

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	without dummies							with dummies for contr. and exp.				
	field		T_t and G_t		T_t only	neutral		T_t and G_t		T_t only	neutral	
	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG	ΔT	ΔG	ΔT	ΔT	ΔG
ΔG_{t-1}	·	.423	.063	.701	.104	·	.654	·	.701	.139	·	.716
d_{EXP}	·	·	·	·	·	·	·	.575	·	·	·	-.67
d_{CONTR}	·	·	·	·	·	·	·	·	·	.238	·	·
United-Kingdom												
ECM	·	.435	·	·	·	·	·	·	·	·	·	·
$_{\text{ECM}}T$	·	·	-.883	.175	-.675	-.942	-.21	-.883	.175	-.897	-.942	-.21
ΔT^E_{t-1}	·	·	·	-.085	-.159	·	·	·	-.085	·	·	·
ΔT^E_{t-2}	·	·	·	·	-.076	·	.08	·	·	·	·	.08
ΔT_{t-1}	·	·	.284	.19	.618	.429	-.23	.284	.19	.507	.429	-.23
$_{\text{ECM}}G$	·	·	·	-.78	·	·	-.699	·	-.78	·	·	-.699
ΔG^E_{t-1}	·	·	·	·	·	·	-.146	·	·	·	·	-.146
ΔG_{t-1}	·	.385	·	.467	.139	·	.86	·	.467	·	·	.86
d_{EXP}	·	·	·	·	·	·	·	·	·	.791	·	·

B Instructions to the experiment

The experiment was conducted in German. In this section you find a translation of the instructions:

1. Please read the instructions carefully. Only if you have understood them well you can successfully participate in the experiment and gain money.

2. **Thereafter** fill in the questionnaire at the screen.

Welcome to the strategy experiment

Welcome to the strategy experiment

This strategy experiment is financed by the University of Mannheim and the German research council.

The instructions are simple, and if you carefully pay attention to it and decide deliberately, you will win a considerable amount of money, which is disbursed to you at the end of the game.

The payment is dependent on your success. In the experiment you forecast the development of public expenditures and taxation in several European countries. For that purpose there are past data about budget debt, annual change of budget debt, government expenditure and taxes made available for you. Dependent on the quality of your forecast you receive a payment for each period.

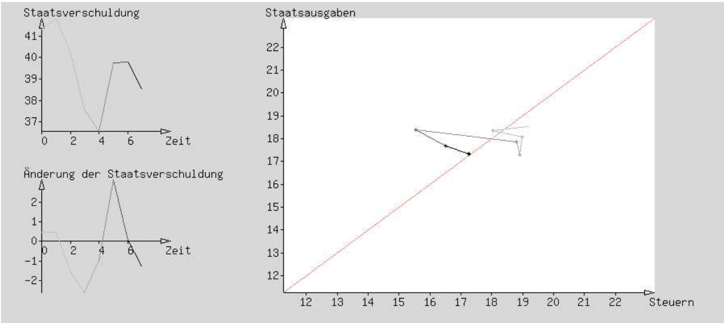
Please note that we do not have any interest in paying less money than you are entitled to. We must return all the money, which we do not disburse to you, to the German research council.

Please note that we will not deceive you in this experiment. Everything you read in these instructions is correct. You may take this for granted, but actually there are occasionally experiments in psychology, where experiment participants are deceived about parts of the experiment. This is not the case in economic experiments like this. In the beginning we explain exactly the rules to you, and we will also adhere to them.

Rules

You will play several rounds in turns. In each round it is your task to forecast the development of two variables. These variables refer to the development of government expenditure and taxes in several European states between 1950 and 2000. Which states you play in each case will be specified randomly and is not made known to you. These data are shown graphically.

Top of the screen

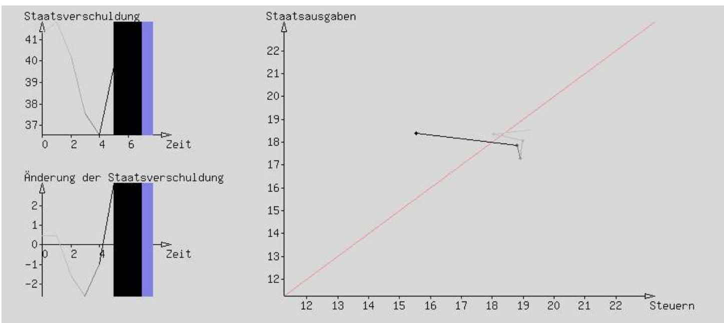


On the left you can see the development of the budget debt and annual change of budget debt, each in per cent of the gross national product. The horizontal axis shows time in years. You may use this data to obtain a reference point how government expenditure and taxes will change in the future. Current periods are shown in black, past periods are shown in gray.

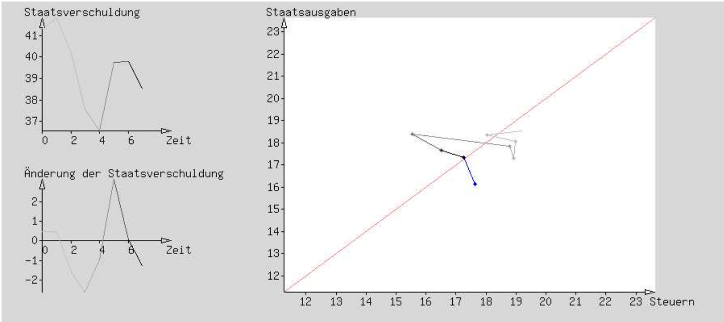
On the right you can see the government expenditure and taxes, again as percentage share of the gross national product. The vertical axis shows government expenditure, the horizontal axis shows taxes. Government expenditure is higher than taxes above the red diagonal; below, government expenditure is lower than taxes. Past periods are shown in a lighter shade of gray than current periods.

Partial representation of the past development You can present yourself also only one part of the past periods to get a better overview.

In order to do so click on the diagrams budget debt and annual change of budget debt. In these diagrams the range to the right of your click is covered black. Also in the diagram of government expenditure and taxes the covered periods are not shown. Each click onto the black range of the diagrams budget debt and annual change of budget debt uncovers one period after another. A click on the blue range uncovers all periods.



Forecasts In order to make a forecast about the development of government expenditure and taxes, click onto the white range. Your forecast is shown in blue.



If you are content with your forecast, please confirm it by clicking on confirm forecast. If you want to correct your forecast, please click on delete forecast.

Payment Given your forecast the computer determines a consumption decision, which would be optimal for a person who lives in the period. From your consumption-decisions you derive a certain utility. This utility is compared with the utility you would have obtained if you had forecasted the true future development of taxes and government expenditure.

You receive a wage of 0.45€ per minute for a correct forecast. Worse forecasts result in smaller wages.

It is worth to spend some time to make a good forecast. Example: You need 2 minutes in order to make a very good forecast and therefore receive wages of 0.45€ per minute. Your income in the 2 minutes is thus 0.90€.

Another person, who makes forecasts for e.g. 4 periods in these 2 minutes, which are not so good, may only receive a wage of 0.10€ per minute for each forecast. The income of this person in the 2 minutes is thus only 0.20€.

You should settle your forecast within 2 minutes. If you need more time for a forecast, you are paid only for the first 2 minutes.

A warning on the left side will remind you, as soon as you need more than 2 minutes.

Furthermore you get a list about the income of your past forecasts on the left side.

Duration of the experiment The experiment takes 90 minutes, regardless whether you made many or few forecasts in this time. That requires, however, that you take yourself at least 20 seconds time for each forecast on the average. If you take yourself less time, you are finished with the experiment sooner, but earn fewer money, accordingly.

Should you have any questions, you now have the opportunity to ask them. In addition, you can ask questions at any time during the experiment.

Appendix to the instructions

To determine your payoff we use the following model. **It is not necessary to understand this model to participate successfully in the experiment.** The model is shown only in case you want to control us.

In two subsequent periods you consume c_0 and c_1 and pay taxes t_0, t_1. You save the remaining part:

$$s_i = 1 - c_i - t_i \tag{12}$$

Your total income in each period is $Y = 1$ (note that all values are relative to the gross domestic product Y).

We call government expenditure g_i. Then your utility in two subsequent periods is

$$u = \sum_{i=0}^{1} \gamma c_i + (1 - \gamma) g_i \tag{13}$$

In your case $\gamma = 0.75$.

Your budget restriction is

$$\sum_{i=0}^{1} s_i \cdot (1 + r)^i = 0 \tag{14}$$

with an interest rate $r = 0.1$.

Based on your forecast for t_1 and g_1 we determine your optimal consumption c_0.

In the next period t_1 und g_1 are realised. Your actual consumption c_1, and, hence, your utility u, follows from the budget restriction. This utility is compared with the utility u^* that you could have obtained with the correct forecast for t_1 and g_1. Your wage is $(u/u^*)^\eta$. In your case $\eta = 12000$. This normalisation does not change your utility maximisation problem.