Online-Appendix

On the political economy of national tax revenue forecasts: Evidence from OECD countries

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1 Robustness checks

1.1 Robustness checks on the variables

Robustness on the macroeconomic control variable To check the validity of our results, we changed the control variable for macroeconomic output. Instead of using the forecast error of nominal GDP ($GDPERR$), we experimented with four different types of models; Table 1 presents the results of these four models. In model (1), we substituted the forecast error by the simple percentage forecast of nominal GDP ($GDPFORE$), that is provided by the OECD. Model (2) uses the estimated output gap ($OGAP$) as a proxy. In the third model we took the growth rate of nominal GDP as a control variable ($GDPGR$). Finally, we excluded GDP or any other measure in model (4).

Table 1: Estimation results – robustness on the macroeconomic control variable

Variable	(1)	(2)	(3)	(4)
ELCTY	-0.73	-0.76	-0.60	-0.78
	(0.63)	(0.67)	(0.67)	(0.67)
SCHMIDT	0.94**	0.88**	0.85*	0.93**
	(0.40)	(0.41)	(0.42)	(0.40)
RAE_LEG	-0.25**	-0.25**	-0.25**	-0.26**
	(0.11)	(0.11)	(0.10)	(0.11)
GDPFORE	0.53	–	–	–
	(0.64)			
OGAP	–	-0.42	–	–
		(0.26)		
GDPGR	–	–	-0.87**	–
			(0.39)	
c	56.67**	61.15**	64.30**	60.30**
	(24.83)	(22.78)	(24.72)	(22.62)
Other controls	YES	YES	YES	YES
C-FE	YES	YES	YES	YES
T-FE	YES	YES	YES	YES
R^2 (within)	0.47	0.47	0.49	0.46
Obs.	281	281	281	281

Note: Standard errors robust to autocorrelation and heteroscedasticity in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level.

All in all, we confirm our baseline results from the previous section with this robustness check. Left-wing incumbents produce overoptimistic tax revenue forecasts. We also still find the negative fragmentation effect. As in the baseline regression, our dummy for the election year shows no significant effect in any specification.

At this point we pick up the argumentation on the macroeconomic control variables again. In the former section we find a negative coefficient of the GDP forecast error ($GDPERR$). We argued that this may be attributed to revisions that are incorporated into the GDP figures or different information sets on which the forecasts are based on. Table 1 confirms this view. By introducing the GDP forecast, the coefficient becomes positive in model (1). However, in model (3) we find a negative and significant coefficient for the GDP growth rate, which also shows a larger magnitude compared to the coefficient for the GDP forecast. The GDP forecast, therefore, triggers the negative coefficient of $GDPERR$ in the baseline regression and might be a hint for the revision suggestion. Our main results stay robust.

Another important concern that may bias results was raised by one reviewer: an emerging simultaneity bias between the forecast errors and the tax ratio. We therefore estimated two additional models: the first model without the tax ratio and the second with a lag of one period. Both estimations yield the same results: every variable from our baseline specification shows the same sign, thus, leading to the conclusion that the described simultaneity problem does not severely bias our results.

Robustness on the political variables The next robustness checks cover the modification of the political variables. Instead of presenting another table, we will only discuss our results in a qualitative way. The substitution of our election dummy through the cut-off coded variable ($ELCTYCUT$) does not reveal any new insights. The coefficient of the cut-off variable fails to reach any level of statistical significance. All other results remain the same.

Now let us turn to the partisan variable. In a first step, we substitute the Schmidt-Index by the ideology variable of Potrafke (2009, 2010). The Potrafke-Index is related to the Schmidt-Index but coded in another way. An illustrating example is the year where the cabinet changes. This year is coded with the color of the government that stays in office for a longer time within this year. Imagine that a left-wing government is followed by a right-wing one in October. Then this year is coded as left-wing. The interpretation of the Potrafke-Index is, however, the same as for the Schmidt-Index. The resulting coefficient is positive and statistically different from zero, thus confirming our results. Substituting the Schmidt-Index with a simple ideology dummy in a second step, also confirms our results for the partisan theory. The coefficient of the ideology dummy is positive in any specification. However, the dummy marginally fails to reach statistical significance (p-value 0.143) in the full model. Obviously, the dummy is not as able to capture the complete ideological spectrum as the Schmidt- or Potrafke-Index can. Since the Schmidt-Index is highly significant in almost all other specifications, we concentrate on this variable in the following.

We substituted the two dummies for governmental fragmentation by our four other variables ($NUMCOAL$, $EFFNUMCOAL$, $SPENDMIN$, RAE_GOV). Overall, our results are confirmed, as the coefficients show the anticipated negative sign in all specifications and are mostly significant. Especially the effective number of coalition members in the government ($EFFNUMCOAL$) and the Rae-Index for governmental fragmentation (RAE_GOV) show a significant negative impact on tax revenue forecast errors.

1.2 Methodological robustness

The results for other various estimation techniques are presented in Table 2. Altogether, we present three different model outcomes. First of all, we can expand the standard two-way fixed-effects model by interaction terms between the cross-section and time dimension (FE-INT). Since an interaction of every year with every country dummy would result in a loss of all degrees of freedom, we just focus on the economic crisis by interacting the cross-section dimension with the dummy for the year 2009. Since the economic crisis hit the countries with different intensities, this may also influence national tax revenue forecast errors in different ways.

As brought forward by Goeminne *et al.* (2008), tax revenue forecast errors (and, therefore, the behavior of the forecasting institutions) might not be independent over time. So we secondly include the lagged forecast error in Equation (1); we expect a positive sign. Goeminne *et al.* (2008) state that estimating a dynamic panel data setup (DYNAM) accounts for slow adjustment processes of governments. In a dynamic panel setup, standard fixed-effects techniques lead to biased and inconsistent coefficient estimates (see Nickell, 1981). A valid set of instrumental variables is necessary to avoid such a bias. The literature recommends the usage of the two-step generalized method of moments (GMM) estimator, together with Windmeijer-corrected standard errors (see Windmeijer, 2005; Roodman, 2009a). We, however, apply the one-step GMM estimator proposed by Arellano and Bond (1991) since it is feasible in our case, whereas the two-step version is not.[1] In the end, we rewrite the model in Equation (1) in first differences and use lags of $FEPERC$ as viable instruments. The employed instruments are only valid when no autocorrelation in the error term is present. A test on autocorrelation of the residuals reveals that this validity is guaranteed in our case.

[1]The GMM estimators in the Arellano-Bond style are created for 'small-T-large-N' combinations. In our case the cross-section dimension N is small as well, so that the number of instruments rapidly reaches the number of the cross-section dimension. In the two-step procedure additional moments with higher order have to be estimated to gain the optimal weighting matrix. This is a hard task in small samples (Roodman, 2009b). We are only able to estimate a reduced model with one lag of the dependent variable and a small number of explanatory variables. To be concrete: we can only estimate a model with one lagged dependent variable, our three political variables and the tax ratio. This specification is independent from how many lags we use for instrumentation. Otherwise the variance-covariance matrix has no full rank. In that case we are not able to compare our results with the baseline specification. This seems to be no appropriate robustness check from our point of view. We, therefore, decided to use the one-step GMM estimator. First, the ready-to-use one-step estimator is robust as well as feasible and the two-step version only shows modest improvements (see Roodman, 2009a). Additionally, the simulation by Arellano and Bond (1991) reveals almost identical estimations for the one-step or two-step GMM estimators. Also a study by Judson and Owen (1999) concluded that the one-step estimator is outperforming its two-step version in small samples. Taking these findings from the literature, we rather apply the robust and asymptotically efficient one-step estimator.

Our last methodological robustness check concerns the problem of correlated error terms between countries. This phenomenon is called cross-section dependence (CSD). Whenever we do not control for potential panel correlated error terms, standard errors of the coefficients are biased. One possible explanation is the usage of similar methods between countries. As stated before, elasticity-based methods are common practice in forecasting tax revenues. If all countries use the same methodologies, then it could be the case that the forecast biases are correlated between states. We employed the test by Pesaran (2004) which reveals that cross-section correlation is present. To account for this, we applied the estimator proposed by Driscoll and Kraay (1998). This nonparametric estimator corrects the variance-covariance matrix for heteroscedasticity, auto- and panel correlation and can be used for very general forms of cross-section dependence. Since we are interested in the within variation, we decided to use the fixed-effects version of this estimator.

Table 2: Estimation results – methodological robustness

Variable	(1) FE-INT	(2) DYNAM	(3) CSD
$FEPERC_{t-1}$	–	0.24***	–
		(0.07)	
ELCTY	-0.52	-0.41	-0.52
	(0.63)	(0.67)	(0.53)
SCHMIDT	0.88*	1.09***	0.87***
	(0.44)	(0.38)	(0.24)
RAE_LEG	-0.24**	-0.18*	-0.24**
	(0.09)	(0.09)	(0.08)
c	58.44**	66.96***	58.33***
	(24.71)	(21.12)	(16.72)
Controls	YES	YES	YES
C-FE	YES	YES	YES
T-FE	YES	YES	YES
R^2 (within)	0.49	–	0.49
Obs.	281	243	281

Note: Standard errors robust to autocorrelation and heteroscedasticity in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level.

In general, our baseline results are confirmed by the various estimation techniques. We find no significant political business cycle effect. Models (1) to (3) in Table 2 clearly verify that left-wing governments overestimate tax revenue forecasts compared to right-wing incumbents. We furthermore find the negative fragmentation effect.

1.3 Interaction effects of the political variables

It is not clear how our present results vary under different political constellations, since the former estimations present average effects. The overestimation of left-wing governments, for example, could be different across the electoral cycle or could vary with one of the fragmentation variables. Such questions can easily be answered with interaction models. Speaking in a statistical way: with interaction models we can investigate whether the slope of a specific variable changes under different constellations of other variables. Thus, our baseline regression from Equation (1) is enlarged with the interaction terms $ELCTY * SCHMIDT$ and $SCHMIDT * RAE\_LEG$ separately. The following Table 3 presents the estimation results.

Table 3: Estimation results – with interaction terms

Variable	(1)	(2)
ELCTY	-1.31	-0.55
	(0.98)	(0.60)
SCHMIDT	0.81*	7.85**
	(0.40)	(3.04)
RAE_LEG	-0.24**	-0.02
	(0.10)	(0.09)
ELCTY*SCHMIDT	0.35	–
	(0.41)	
SCHMIDT*RAE_LEG	–	-0.10**
		(0.04)
c	58.84**	38.83*
	(24.23)	(18.82)
Controls	YES	YES
C-FE	YES	YES
T-FE	YES	YES
R^2 (within)	0.49	0.51
Obs.	281	281

Note: Standard errors robust to autocorrelation and heteroscedasticity in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level.

The interaction models reveal two interesting results, beside the fact that all baseline results remain untouched. First, political business cycle effects are not present, since $ELCTY$ remains insignificant, but the effect varies with the ideology of the incumbent. The interaction effect $ELCTY * SCHMIDT$ shows a positive coefficient, meaning that tax revenue forecasts are overestimated in election years if a left-wing incumbent is in charge. The coefficient is, however, not statistically different from zero. Second, the interaction between ideology and legislative fragmentation is negative and statistically significant. Thus, for a given level of the Schmidt-Index, a higher fragmentation in the parliament reduces the overestimation of the incumbent. This result confirms our former finding that overestimation decreases the more fragmented a parliament is. This is especially true if a left-wing party holds the majority in the government.

1.4 Sample composition

In order to check whether our results were driven by single countries, we begin with re-estimating Equation (1) by successively excluding each single country. In a second step, we exclude those countries which were classified by Büttner and Kauder (2010) for having the most independent forecasts. Third, we rerun our estimation by excluding the least and most fragmented countries. Finally, we estimate the effects by looking at the countries with the most independent forecasts.[2] If we exclude the most independent and most fragmented forecasts the results are - in most cases - robust to these two sub-samples. If, in a second step, we look at the results for the most independent forecasts separately, only the ideology variable is statistically significant. This, on the one hand, contradicts the view of Büttner and Kauder (2010) that independence matters for the preparation of tax revenue forecasts. On the other hand, as Büttner and Kauder (2015) find for the German case, a country where independent tax revenue forecasts have a long tradition, the government influences them via the predetermination of GDP growth or the revenue effects of tax reforms. However, it could also be the case that our inference suffers from low statistical power since we have only 51 observations left. Such questions can be further investigated in future studies.

Next to last, let us discuss the role of EU member states. The surveillance of member states via EU fiscal rules (e.g., the Stability and Growth Pact) may influence national tax revenue forecasts. To control for this potential effect we follow Pina and Venes (2011) and restrict our sample to the period from 1999 to 2012. After re- estimation, we can compare the coefficients to the baseline specification in order to check whether the effects become stronger, weaker or remain the same. To save space, we will not present a table here, but full results are available upon request from the authors. The re-estimation also yields that the election dummy has no significant impact on the tax revenue forecast error. The coefficients for ideology and legislative fragmentation, however, become larger in their magnitude and stay significant. The coefficient for the Schmidt-Index rises from 0.87 (see the table with the baseline results in the paper) to 1.11 and the coefficient for the Rae-Index from -0.27 (see the table with the baseline results in the paper) to -0.29. All control variables remain the same. Our findings go into the same direction as in Pina and Venes (2011, p. 542) as they state that "[...] the increased importance and visibility of fiscal forecasts in the SGP period made them much more vulnerable to political manipulation [...]".

Finally, we want to discuss the role of nationally adopted fiscal rules. We, therefore, add the fiscal rule index (FRI) for each single European state provided by the European Commis-

[2] To save space, we will not show the single tables here. Detailed results are, however, available upon request.

sion, Department for Economic and Financial Affairs (ECFIN), to our baseline regression. In any specification, the FRI fails to reach a meaningful level of statistical significance. While the point estimates for our political variables remain robust, they become insignificant in all specifications. This can be explained with multicollinearity issues raised by introducing the FRI into the estimation. Thus, the regression is not able to clearly distinguish the variation from the political variable from those of the FRI. The significance of our variables of interest, however, is in almost all cases not far away from reaching conventional levels of significance (p-value $SCHMIDT$: 0.12, p-value RAE_LEG: 0.24). Thus, national fiscal rules do not seem to have an influence on tax revenue forecast errors.

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