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THE PREDICTIVE CONTENT OF BUSINESS SURVEY INDICATORS:
EVIDENCE FROM SIGE

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ISBEM: An econometric model for the Italian State Budget Expenditures

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Abstract

In this paper we describe a pilot econometric model for the Italian State Budget Expenditures (ISBEM). In search for leading indicators, we consider a newly available data set of the Italian State Budget financial microdata at monthly frequency that we use to estimate and forecast annual budget data. Early work on the issue is encompassed with the provision of a dynamic multiple equations model for the budget cycle linking data coming various budget phases (i.e. appropriations, expenditures commitments and payments) and disaggregated by budget macro aggregates. The model, that consists of several "pseudo" behavioral equations and identities, can be used for simulation exercises as well as forecasting purposes.

[JEL Code: C53, E62, H50].

Keywords: Fiscal forecasting, budget state expenditures, intra annual cash data, econometric models.

***Ministry of Economy and Finance ** Bank of Italy**

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1 Introduction

The Eurozone financial crisis, involving the public debt sustainability, has alerted several European governments to strengthen their surveillance budgetary procedures also in light of the Stability and Growth Pact fulfillments. In this view, the attention of policy makers in the implementation of effective monitoring and reporting procedures for fiscal balances has steadily increased. As a result fiscal rules such as medium term budget targets, timeliness and transparency in financial reporting, were introduced to gain fiscal improvements.

The increased focus on fiscal balances after the 2007 debt crisis, has besides brought, in line with the policy measures of other OECD countries (see Robinson, 2013), to the institution of a rigorous spending review process, to the adoption of budget rules based on expenditure ceilings[1] and to an increase of tax evasion controls.

A special attention in Italy has been put on the expenditure side of budget balance items' monitoring and forecasting. In fact, while the revenues categories of State Budget (i.e. VAT) projections appear to be more stable and easier to predict since theirs amount depends on theirs elasticity to income[2], the budget expenditure components are more volatile. Indeed, budget expenditures need to be planned and authorized on yearly base by policy makers and for these reasons are more difficult to forecast. The judgmental projection procedures are in fact very complicated and often require a huge amount of information.

Due to the relevance of the state sector expenditures for policy interventions, in this paper we propose a new approach to monitor and forecast them, based on the use of intra-annual information coming from state budget monthly data. The econometric Model for the Italian State Budget Expenditures (ISBEM) that we introduce, can be used for simulation purposes as well as policy effectiveness evaluation.

Pratictionnaires commonly use judgmental models to forecast monthly expenditures in addition to simple autoregressive models for monthly state deficits. The traditional forecasts rely on rules based on past expenditure budgetary targets of governments, or deterministic projections concerning particular public sector expenditures types linked to demographic factors (i.e. pensions or instruction expenditures).

1 The building up of benchmarks for the expenditures behavior of different local level administrations to gain efficiency and to fulfill the Stability and Growth Pact requirements at local level, has also became a priority of the policy makers agenda (see Catapano et al, 2008).

2 Revenues are generally more easy to forecast with respect to taxes since they are strongly linked to income and macroeconomic parameters evolution (fiscal surveillance).

The lack of promptly available infra annual data referred to the Budget State sector concerning the expenditures evolution (in Italy as well as in the Euro Area countries) makes generally difficult to model monthly expenditures budget flows for the State sector.[3] Indeed the official infra annual data on economic accounts coming from the European System of Integrated Economic Accounts (ESA95)[4] only contains data available on quarterly bases and referred to public sector. To include higher frequency information in the estimates, Pedregal and Perez (2010) consider monthly data taken from the cash accounts of the governments together with ESA95 data using mixed frequency models.

In this paper we explore the use of intra-annual monthly financial indicators referred to State Budget expenditures (i.e. Budget items related to different State Budget phases) considering the information coming from a new Italian Government General State Accounting Department database (see Bianchi et al, 2013 for a full description of the database). Such data, are promptly available, not subject to ex post revisions and moreover allow a full comparability with the state sector budget expenditures at yearly level. With respect to Pedregal and Perez (2010) to model Budget State expenditures, we don't consider only cash data but also information concerning all the different budget phases (i.e. appropriations, expenditure commitments and payments).

In what follows we provide a full description of a multiple equation econometric model to monitor and forecast the expenditure side of Italian State budget. The model is composed of different equations linking the various budget phases (i.e. appropriations, expenditure commitments and payments) and it is sought to analyze the monthly expenditures dynamics as well as the yearly dimension of expenditures. Relying on start of year budget law appropriation, (used as a target reference value) we provide forecasts for state budget payments based on the information coming from monthly budgetary items. The model is also thought be used for simulation and projection of budget items dynamics through the use of leading indicators coming from financial accounting (Budget items).

The paper is structured as follows. Section 2 describes the data. Section 3 introduces the econometric framework, section 4 reports the empirical results of the forecast exercise. Conclusions follow.

[3] For the Euro Area, the main source of National Accounts data for General Government is in fact provided by the database AMECO Annual macroeconomic database of the European Commission's Directorate General for Economic and Financial Affairs. containing data only available at yearly frequency and referred to public sector as whole.

[4] ESA 95 items are represented a quite particular format in which public expenditures are only reported as ration to nominal GDP.

2 State Budget data

The date set used to estimate the multiple equation econometric model, contains budget expenditures data referred to different budget cycle phases such as the expenditure appropriations, expenditure commitments and cash payments. The budget cycle includes different time phases that are necessary, from an accounting point of view, to produce cash payments. These phases include the approval of appropriation expenditures at the beginning of the year, the implementation of budget over the year and the final budget report approval that usually occurs the following year by the end of June. In the model we consider the following indicators:

- **Appropriations**: they concern the expenditure stock ($x_{y,\,gen}$) authorization at the beginning of the year through the budget law approval. The appropriations can experiment possible variations during the following months of the year. Thus, the total stock of appropriations x_t^{ST} for a given year is built as follows:

$$x_t^{ST}=x_{y,\,gen}+ x_t$$

where $x_{y,gen}$ is the initial appropriation level set at time of budget law approval at the beginnings of the year Y and x_t are the additional monthly appropriations that can occur during the year.

- **Expenditure commitments:** the variable concerns the expected expenditure in a given month y_t backed by an agreement but that will be officially paid afterwards. Even in this case we will have an initial value at the beginning of the year ($y_{y,\,gen}$) and monthly values y_t.

$$y_t^{ST}=y_{y,\,gen}+ y_t$$

- **Cash data on payments** The data are available in its disaggregated components and consist in payments on commitments and unpaid commitments.

Payments on commitments indicate the part of expenditures that concern a given year and are actually paid in that year. z_t

Unpaid commitments are the part of expenditures not paid during the previous year and shifted to the current year. z^R_t

All the data used in the model are disaggregated in the three main expenditure macro-aggregates given by current, capital expenditures and financial liabilities refunds. The data span from 2003:10 to 2010:6. In order to give a better understanding of the data structure, its dimension and level of disaggregation in table 1 we report a scheme of the budget expenditures data disaggregated by macro components.

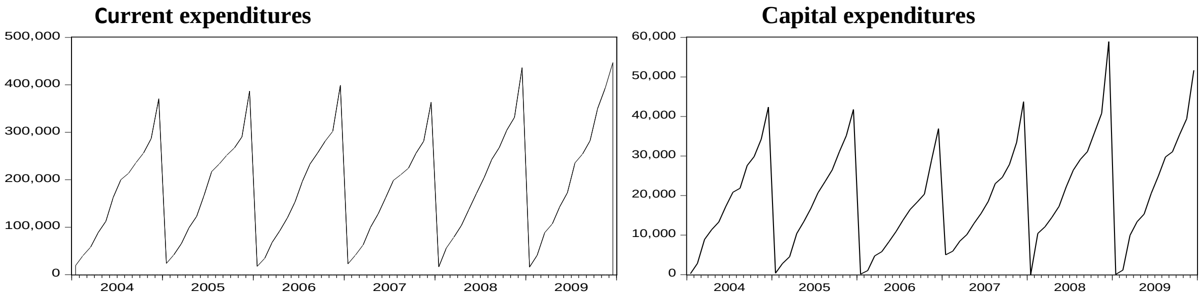
Table 1 Data set structure

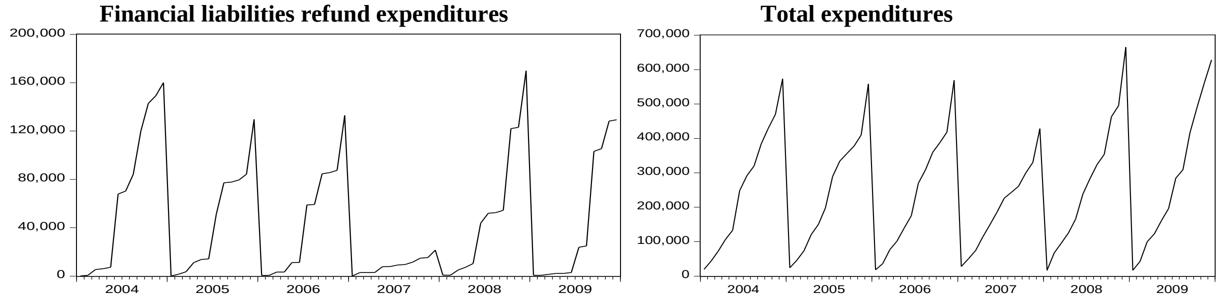
<table>
<tr><td colspan="3" rowspan="2"></td><td colspan="3">Budget Expenditure macro aggregates</td></tr>
<tr><td>current expenditures (CUEX)</td><td>capital expenditures (CAPEX)</td><td>financial liabilities refund (FLR)</td></tr>
<tr><td rowspan="4">Budget cycle items (variables)</td><td colspan="2">Appropriations (x)</td><td colspan="3" rowspan="4">stock and flows data</td></tr>
<tr><td colspan="2">Expenditure’ commitments (y)</td></tr>
<tr><td rowspan="2">Cash payments (z)</td><td>-payments on commitments</td></tr>
<tr><td>-unpaid commitments</td></tr>
</table>

The data set variables are taken by the different moments of the budget cycle and are represented by appropriations, expenditure’ commitments and cash payments. The disaggregation used concerns the expenditures at macro-aggregate’ level, namely current expenditures, capital expenditures and financial liability refund.

The dependent variable of the model that we want to forecast is given by cash payments. Cash payments Budget data are available at monthly frequency and are collected as stocks. Considering a given year t, the cash expenditures of January (the beginning of the budget year) will be equal to zero. The total expenditure at the end of the year will correspond to the cumulated sum of all the monthly expenditures. At the beginning of year t+1 the level of expenditures in January will be again equal to zero. Figure 1 reports the budget cash payments as total amount and disaggregated by macro aggregates between 2004 and 2009.

Fig. 1 Budget Monthly Expenditures (cash data). Stocks by macroaggregates and total.





Since the cumulated data on expenditures cannot be used in time series analysis, we built monthly flows data by differencing all the series within each year. The graphs of the resulting series for expenditures on commitments and unpaid commitments as whole and disaggregated by macro aggregates are reported in Figures 2 and 3. Looking at the graphs we can see that a seasonal component is present in all the series and need to be taken into account in the modeling phase.

Fig. 2 Budget Monthly Expenditures on (payments on commitments). Flows by macroaggregates and total

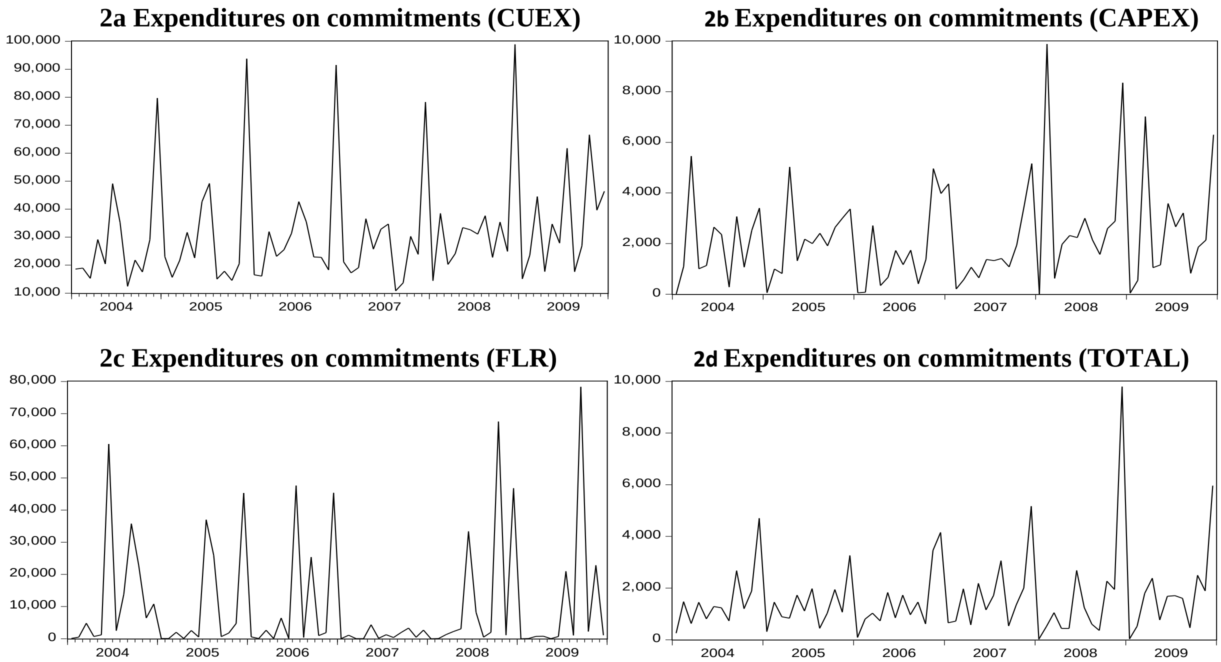
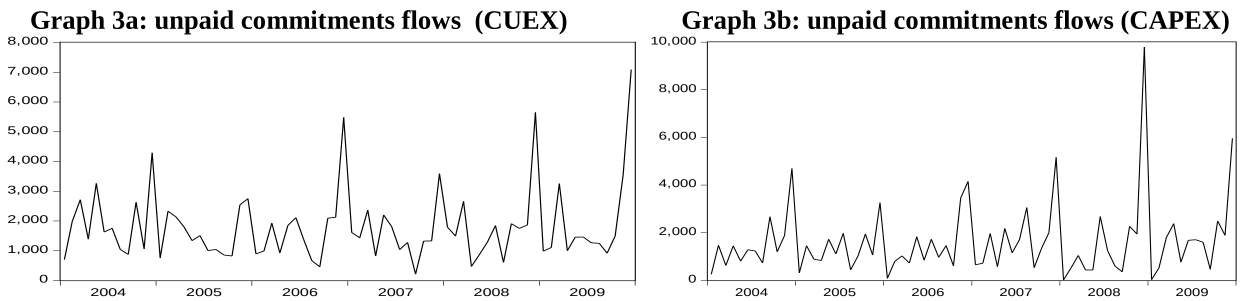
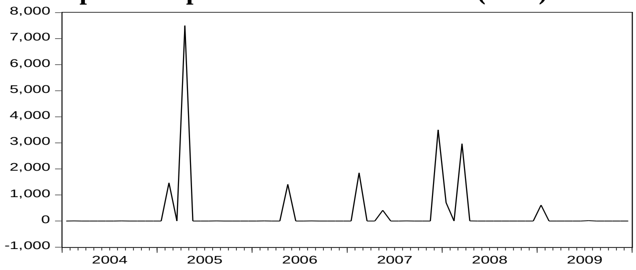


Fig. 3 Budget Monthly Expenditures (unpaid commitments). Flows by macroaggregates and total



Graph 3c: unpaid commitments flows (FLR)



Graph 3d: unpaid commitments flows (TOT)

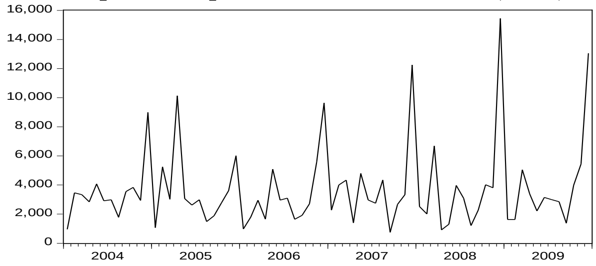
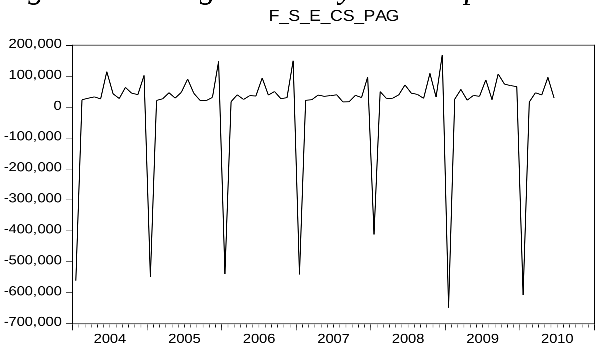
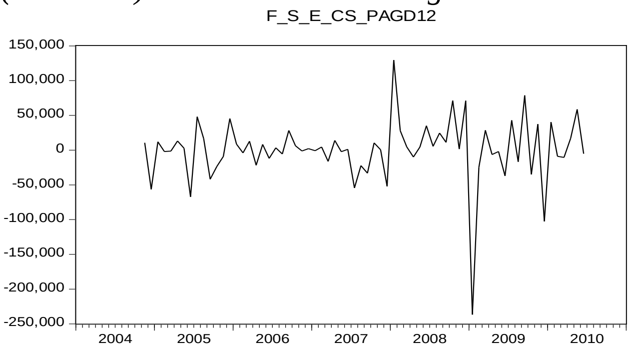


Figure 4a reports the flows of monthly cash expenditures data. Looking at the graph we can notice a strong seasonal component at the end of each month in which most payments occur. To remove such seasonal component in the econometric models we use monthly growth rates of the data. The results of such differencing are reported in Figure 4b.

Fig. 4a 4b Budget Monthly total expenditures (cash data) in levels and annual growth rate.





3 The econometric framework

In this section we describe the econometric framework used to estimate the total budget expenditures. We set up a two steps procedure starting with the forecast of expenditure commitments and ending up with the forecast of cash payments. As explained in the previous section, Commitments are conditional on initial budget appropriations (and their variations along the year). Expenditures are related to contemporary commitments and to past unpaid commitments. Our forecast strategy thus mimics the overall behavior of the budget cycle.

Since our main aim is to provide simulations[5] and early forecasts of the annual expenditures, we first estimate monthly models for the two cash expenditure components given by payments on commitments and unpaid commitments, disaggregated by expenditure macro aggregates (current expenditures, capital expenditures and financial liabilities refund) and we provide monthly forecasts until the end of the year. Secondly, we sum up monthly data available until time t and the monthly

[5] Actually it is not just a forecasting model as the impact of cutting budget appropriations can be assessed.

expenditures forecasts for the remaining months of the year, in order to obtain the annual forecast for each expenditure component in the macroaggregate. The total annual expenditure forecast will be obtained aggregating the annual forecasts over the two cash expenditure components and the three macro aggregates. For example, if we are in t=k the annual forecast will given by:

$$\sum_{i=1}^{3}\sum_{j=1}^{2}\left(\sum_{t=1}^{k} z_{i,j,t} + \sum_{t=k+1}^{12} \widehat{z_{i,j,t}}\right) \qquad (1)$$

where i represents the expenditure macroaggregate, j is the index of the expenditure component, $z_{i,j,t}$ is the actual expenditure for the i macroaggregate and the j component available until t=k and $\widehat{z_{i,j,t}}$ is the expenditure forecast for the remaining months from t=k+1 to t=12.

With respect to the majority of forecasting strategies used to predict deficits, expenditures or revenues based on the use of ARIMA models and reported in the literature, we develop a new multivariate approach based on the use of leading and coincident indicators coming from State Budget and available at monthly frequency. More in detail we estimate different models disaggregated by expenditure macro aggregates and components (payments on commitments and unpaid commitments) using as regressors data coming from the three budget cycle phases (i.e. appropriations, expenditures commitments and payments) described in the previous section.

Given the expenditure constraints provided by expenditure appropriations and commitments levels and given the accounting linkages existing between the budget cycle phases, data concerning appropriations and commitments expenditures are used in addition to past values of expenditures as regressors to explain the expenditures behavior. The corresponding forecasts for expenditures are then obtained using the actual data of such explanatory variables, if available, or their predictions. In our view we thus consider the budget data or their transformations coming from the various Budget phases as coincident or leading indicators for the total cash expenditures.

The values of budget explanatory variables used as leading indicators are in turns estimated and forecasted (if necessary) using dynamic equations. More in detail for the appropriations that (as we have seen before) represent the amounts reported in the initial budget authorization, the specifications are based on monthly ARIMA models.

For the expenditure commitments we consider dynamic monthly single equations models in which the explanatory fiscal indicators for each equation are represented by appropriations and past values of commitments. More precisely for each expenditure component we consider the following structure:

a) $\text{appropriations}_{it} = f(\text{appropriations}_{t-k})$

b) $\text{expenditure commitments}_{it} = f(\text{expenditure commitments}_{i,t-k}, \text{appropriations}_{i,t-k})$

c) $\text{expenditures}_{i,j,t} = f(\text{expenditures}_{i,j,t-k,} \text{ expenditure commitments}_{i,j,t-k})$

where i=1,2,3, j=1,2 and k=0,1,2,…12.

In this setting, our dynamic equation models, can be considered as bridge models linking the different budget phases indicators. In this context, the equations for the expenditures represent the relationship which relates the cash expenditures components to the expenditure budget indicators (i.e. appropriations and commitments).

To take into account the seasonal pattern of the data all the specifications involve differencing at seasonal frequencies of the dependent variable. The models used in the empirical exercise for the budget phases and disaggregated by macro aggregates are described below.

Appropriations

In order to model appropriations (the Budget indicator that temporally leads all the other items) we use three benchmark ARIMA models for each macro aggregate. The general form of the ARIMA models is given by:

$$\Delta^{12}x_t = c(1) + c(2) * \Delta^{12}x_{t-12} + c(3) * x_{t-12} + e_t \qquad (2)$$

where x_t = monthly appropriations, $\Delta^{12} = (1-L^{12})$ and e_t is the idiosyncratic error term.

Expenditure commitments

For the expenditure commitments we consider three different single dynamic equations for each macro aggregate:

-*current expenditures*. The model is specified according to the following equation:

$$\Delta^{12}y_t = c(1) + c(2)*\Delta^{12}y_{t-12} + c(3) * y_{t-12} + c(4)*(y_{t-1}{}^{S} / x_{t-1}{}^{ST} - y_{t-13}{}^{S} / x_{t-13}{}^{ST}) +$$
$$c(5)* [(x_{t-1} - x_{t-2}) - (x_{t-2} - x_{t-3})] + c(6)*[(y_{t-3} - z_{t-3}) / y_{t-3}{}^{S}] + c(7)*D_{2009,10} + e_t \qquad (3)$$

where y_t are the commitment expenditures in the capital expenditures macroaggregate, the fiscal indicator $y_{t-1}{}^{S} / x_{t-1}{}^{ST}$ is the ratio between the stock of commitment expenditures and the total stock $x_{t-1}{}^{ST}$ of appropriations, $D_{2009,10}$ is a dummy variable relative to October 2009. The indicator $(y_{t-3} - z_{t-3})$

gives a measure of the gap between the expenditure commitments and payments on commitments (which is supposed to capture the long run adjustment). The flow of the total stock of appropriations xt^{ST} for a given year is built as follows:

$$x_t^{ST}=x_{y,\,gen}+x_t$$

where $x_{y,gen}$ is the initial appropriation level set at time of budget law at the beginnings of the year y and x_t are the additional monthly appropriations.

-*capital expenditures*. The estimated equation is:

$$\Delta^{12}y_t = c(1) + c(2)*\Delta^{12}y_{t-12} + c(3)*(\Delta^{12}y_{t-1} - \Delta^{12}y_{t-2})+ c(4)*(y_{t-1}{}^{S} / x_{t-1}{}^{ST} - y_{t-13}{}^{S} / x_{t-13}{}^{ST})+$$
$$c(5)*(y_{t-1}/(y_{t-13} -z_{t-13})) +c(6)*D_{2008,2:3} +e_t \qquad (4)$$

where y_t are the commitment expenditures in the capital expenditures macroaggregate, $D_{2008:2,3}$ is a dummy variable that is equal to 1 in February and March 2008 and 0 otherwise.

-*financial liabilities refund*. The model is given by:

$$\Delta^{12}y_t = c(1) + c(2) * \Delta^{12}y_{t-12} + c(3) * (y_{t-1}{}^{S} / x_{t-1}{}^{ST} - y_{t-13}{}^{S} / x_{t-13}{}^{ST}) +e_t \qquad (5)$$

where y_t are the commitment expenditures in the financial liabilities refund macroaggregate, $y_{t-1}{}^{S}/x_{t-1}{}^{ST}$ is an indicator describing the part of appropriations that became expenditure commitments.

Cash Payments models

Final payments (cash data) are given by the sum of payments on commitments and unpaid commitments. Given the different behavior of payments on commitments and unpaid commitments we use two different econometric specifications.

Payments on commitments

Payments models use as regressors the leading indicators given by the expenditure commitments, appropriations as well as indicators build as transformations of the original variables.

-*current expenditures* the specification is:

$$\Delta^{12}z_t = c(1) + c(2)*\Delta^{12}y_t +\Delta^{12}z+ c(3) *\Delta^{12}z_{t-12} +c(4)*(z_{t-12})+ c(5)* y_{t-12} +c(6)*[(y_{t-1} -z_{t-1}) -(y_{t-7} -z_{t-7})] +$$
$$c(7) *\textstyle\sum_{2007:7}^{2007:12} D +c(8)*(w^{S}{}_{t-1}- w^{S}{}_{t-13}) +e_t \qquad (6)$$

where z_t are the paid commitments in the current expenditures macroaggregate,

-*capital expenditures*. The estimated equation is:

$$\Delta^{12}z_t=c(1)+c(2)*\Delta^{12}y_t+c(3)*\Delta^{12}z_{t-1}+c(4)*z_{t-12}+c(5)*y_{t-12}+c(6)*(y_{t-12}-z_{t-12})+e_t \quad (7)$$

where zt are the paid commitments in the capital expenditures macroaggregate

-*financial liabilities refund*. The estimated equation is:

$$\Delta^{12}z_t = c(1) + c(2)*\Delta^{12}z_{t-1} + c(3)*z_{t-12} + c(4)*y_{t-12} + c(5)*(y_{t-12}-z_{t-12}) + e_t \quad (8)$$

where z_t are the paid commitments in the financial liabilities refund macroaggregate.

Unpaid commitments

-*current expenditures.* The specification is:

$$\Delta^{12}z^{R}_{t} = c(1) + c(2)*z^{R}_{t-12} + c(3)*\log(trend)+c(4)*D_{2006,12}+e_t \quad (9)$$

where z^{R}_{t} are the unpaid commitments in the current expenditures macroaggregate, log(trend) is the logarithm of a linear trend, D 2006,12 is a dummy variable.

-*capital expenditures*. The estimated equation is:

$$\Delta^{12}z^{R}_{t} = c(1) + c(2)*\Delta^{12}z^{R}_{t-1} + c(3)*\Delta^{12}z^{R}_{t-4} + c(4)*{}^{12}z^{R}_{t-12} + c(5)*D_{2006,11}+ c(6)*D_{2007,08}+c(7)*D_{2008,12} + e_t \quad (10)$$

-*financial liabilities refund*. The estimated equation is:

$$\Delta^{12}z^{R}_{t} = c(1) + c(2)*\Delta^{12}z^{R}_{t-1} + c(3)*\Delta^{12}z^{R}_{t-2} + c(4)*\Delta^{12}z^{R}_{t-12} + c(5)*D_{2005,04}+e_t$$

For appropriations the ARIMA models for the three macro aggregates are specified following the general to specific modeling approach. The estimation output of the overall models is reported in appendix.

4 Empirical results

In this section we show the of the forecasts obtained with the models introduced in the previous section and we evaluate the forecast ability of these models.

4.1 Forecast comparison

In this framework we follow a bottom up approach in which we forecast some relevant disaggregated expenditures categories and we then obtain the final expenditures forecast summing up the single predictions. In order to evaluate the forecast performance of the model we compare the forecast with those obtained from a multivariate autoregressive *benchmark* that is given by univariate autoregressive equations for each budget balance expenditure aggregate.

The lag structure for the two multiple equation models considered (ISBEM and *benchmark*) are obtained estimating the models between 2004:1 and 2009:12. Starting from these specifications we perform *out of sample* forecasts for 1, 2 …6 step ahead using recursive schemes. For each forecasting step we consider a forecasting window of 24 months.

Since the current version of the model uses autoregressive equations for the budget Arrears (RS_Pag) in table 2 we report the *Root Mean Square Forecast Error* (RMSFE) of dynamic recursive forecasts for h=1, 2, 3, 4, 5 e 6 steps ahead of the single equations models related to the payments on commitments.

Table 2 RMS(F)E Recursive Estimates

Models	RMSFE h=1	RMSFE h=2	RMSFE h=3	RMSFE h=4	RMSFE h=5	RMSFE h=6
CP_Pag_t1_BM	14092	14597	15491	15157	15145	15089
CP_Pag_t2_BM	2690	2364	2021	1905	2051	2128
CP_Pag_t3_BM	24993	25442	25914	25642	26012	27198
CP_Pag_t1	11502	13075	12650	13896	13301	14178
CP_Pag_t2	2615	2453	1859	1721	1788	1674
CP_Pag_t3	20653	20542	21172	21143	21460	22884
RS_Pag_t1_BM	1189	1201	1193	1203	1179	1161
RS _Pag_t2_BM	1528	1551	1529	1532	1553	1546
RS _Pag_t3_BM	599	576	576	272	282	282
RS _Pag_t1	852	856	858	830	815	816
RS _Pag_t2	1916	1886	1880	1935	2343	2339
RS _Pag_t3_BM	599	576	576	272	282	282

The results reported in table 2 indicate that the "dynamic single equations model ISBEM produces a better forecast performance with respect to the pure benchmark autoregressive model.

To give a measure of the forecast accuracy, we report the results (table 9) of the Theil statistic defined as the ratio between the RMS(F)E of the dynamic models and the RMSFE of the benchmark:

$$\frac{\sqrt{\sum_{t=T_1}^{T_2-h}\left(Y_{t+h}^{h}-\hat{Y}_{i,t+h/h}^{h}\right)^2}}{\sqrt{\sum_{t=T_1}^{T_2-h}\left(Y_{t+h}^{h}-\hat{Y}_{0,t+h/h}^{h}\right)^2}}$$

where T1 e $T_{2\text{-}h}$ indicate the first and last dates of the out of sample estimates respectively , $\hat{Y}_{i,t+h/h}^{h}$ indicates the h step ahead forecast of the "disaggregated model and $\hat{Y}_{0,t+h/h}^{h}$ indicates the forecast obtained with the benchmark model. A value of the indicator less than 1 indicates that the augmented model as a better performance than the benchmark.

Table 3 Relative RMSFE

	h=1	h=2	h=3	h=4	h=5	h=6
CP_Pag_t1	0.816208	0.895732	0.816603	0.916804	0.878244	0.939625
CP_Pag_t2	0.97248	1.037648	0.919842	0.903412	0.87177	0.786654
CP_Pag_t3	0.826351	0.807405	0.81701	0.824546	0.825004	0.841385

Looking at the results in table 3 we find that ISBEM shows a better forecasting performance with respect to the *benchmark* for almost the forecast steps. In order to evaluate if the differences between the expenditures model forecasts and the *benchmark model forecasts* are statistically significant in what follows we report the results of Diebold Mariano test. The test is:

$$T = \frac{\overline{d_t}}{\left(cov(d_{t,}d_{t-1,})/T\right)^{1/2}} \qquad (1)$$

where $d_t = \left(e^{MOD}_{t+h/t}\right)^2 - \left(e^{BM}_{t+h/t}\right)^2$ indicates the differences between the forecasting errors obtained using the dynamic models $\left(e^{MOD}_{t+h/t}\right)$ and those obtained through the benchmark $\left(e^{BM}_{t+h/t}\right)$ model and $\overline{d_t} = \frac{1}{t_0}\sum_{t_0}^{T} d_t$.

Table 4 Diebold Mariano Test (1995) for Forecast accuracy 5% level. P value

Models	h=1	h=2	h=3	h=4	h=5	h=6
CP_Pag_t1	0.1458	0.4325	0.005	0.0019	0.0221	0.0163
CP_Pag_t2	0.7247	0.8236	0.2660	0.0006	0.3304	0.0181
CP_Pag_t3	0.0475	0.0206	0.0471	0.0394	0.0593	0.064

The test shows that for current expenditures (cp_pag_t1) an*d financial liabilities refund the* forecast obtained with the ISBEM model are significantly different from the benchmark starting from the third forecast ahead step. For capital expenditures (cp_pag_t2) however the test results do not allow to reject the null hypothesis of no differences in the forecast ability of the two models.

4.2 A comparison with the Government Judgment Based Forecasts

Official documents of the Italian Ministry of Economy and Finance (i.e. the stability law) report annual forecasts made in the first quarter of the year. These forecasts are mainly based on the analysts judgements concerning the expenditures evolutions formulated using accounting techniques and information concerning possible expenditures authorizations. In order to analyze the forecast accuracy in this section we compare the annual expenditures forecasts contained in such document with those obtained using our single equations models for the expenditures macro aggregates.

In case of annual forecast this latter is updated as soon as monthly forecasts became available. For example in case of monthly expenditures data availability until June of a given year, the model will provide the monthly forecasts for the remaining six months. The annual forecast will be then obtained summing up the forecasts of the expenditures flows for each month of the cumulated data relative to June. Once the July data becomes available a new forecast for the remaining 5 months of the will be provided and the annual forecast will be updated summing up to the cumulated expenditure data of July the monthly flows of expenditures data estimated until December. With this mechanism we update the annual expenditures forecast as soon as new monthly data became available.

In the next table we report the budget expenditure forecasts for the years 2008 and 2009 reported in the Ministry of Economy and Finance (MEF) official documents against the ISBEM forecasts.Since the estimates reported in the official documents that we consider in this excercise, are based on data available until march 2009, the ISBEM estimates reported in the table consider an information set available until those dates. The results show that, in 2009, the single equations models provide a forecast that is quite near to residuals payments with respect to RUEF forecasts both for current than capital account expenditures.

Table 5 Comparison between budget balance judgmental expenditure forecasts and ISBEM model forecasts (millions of euro).

	Balance sheet 2009	MEF Official Document April 2009	ISBEM Estimates April 2009	ISBEM Estimates September 2009
Current expenditures	469577	471912	469858	471517
Capital expenditures	53670	64142	59904	55882
Final expenditures	523247	536054	529762	527399

The comparison with the official government forecasts shows that, the use of an econometric forecast model in addition to pure judgmental techniques

Overall the forecasting exercise shows that the models augmented with financial accounting data outperform the pure autoregressive models in terms of RM(F)SE. Furthermore we find that the combination of disaggregated forecasts is able to improve the individual prediction. The comparison between the judgmental forecasts and those based on the use of econometric tools finally shows that the use of the dynamic equations models” increases the annual expenditures predictive ability.

5 Conclusions

This paper considers the possibility of using intra annual data coming from state budget into a small econometric model linking the various budget phases to forecast annual State Budget Expenditures. Relying on start of year budget law appropriation, used as a target reference value, we provide monthly forecasts for budget expenditures and we compare the results with those given by benchmark monthly ARIMA models. To evaluate the forecast ability of our models we firstly perform an out of sample forecast exercise based on recursive and rolling schemes. Secondly, we provide an evaluation of the relative performance of judgmental annual expenditures forecasts and that one obtained using intra annual data.

The forecasting performance evaluation shows that the models augmented with financial accounting data outperform the pure autoregressive models in terms of RM(F)SE. Furthermore the comparison between the judgmental forecasts and those based on the use of econometric tools shows that the use of the dynamic equations models” increases the annual expenditures predictive ability.

Our results show that the use of budget “leading indicators” coming from intra annual budget flows into a multiple equation model significantly improves annual expenditures forecast accuracy. The forecast exercise also shows that the use of disaggregated forecasts produces better results in terms of RMSFE compared to benchmark ARIMA disaggregated models.

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Appendix

Table 6 Models used for the different Budget phases.

Budget Phases:	*Flow variables*	*Stock variables*	*Macroaggregates*	*Models*
Appropriations	x_t	x^S_t	current expenditures capital expenditures financial liabilities refund	Univariate ARIMA MODEL Univariate ARIMA MODEL Univariate ARIMA MODEL
Expenditures commitments	y_t	y^S_t	current expenditures capital expenditures financial liabilities refund	Dynamic SE MODEL Dynamic SE MODEL Dynamic SE MODEL
Payments (on commitments)	z_t	z^S_t	current expenditures capital expenditures financial liabilities refund	Dynamic SE MODEL Dynamic SE MODEL Dynamic SE MODEL
Payments (on unpaid commitments)	z_{Rt}	z^S_{Rt}	current expenditures capital expenditures financial liabilities refund	Dynamic SE MODEL Dynamic SE MODEL Univariate ARIMA MODEL

Table 7 Estimated equations for appropriations ,expenditures commitments and payments. Sample estimates: 2005:1 2009:12

	Appropriations (x_t= f_s_e_cp_ti i=1,2,3)
Current Expenditures (BM)	$\Delta^{12}x_t = c(1) + c(2) *\Delta^{12}x_{t-12} + c(3) *x_{t-12}$ c(1) = 341.6564 (260.87) c(2) = -0.646(0.107) c(3) = -0.332 (0.085) Estimated S.E. = 1658.553
Capital Expenditures (BM)	$\Delta^{12}x_t = c(1) + c(2) * \Delta^{12}x_{t-12} + c(3) * x_{t-12}$ c(1) = 392.239 (146.364) c(2) = -0.21 (0.122) c(3) = -0.887 (0.151) Estimated S.E. = 1072.358
Financial liabilities refund (BM)	$\Delta^{12}x_t = c(1) + c(2) * \Delta^{12}x_{t-12} + c(3) * x_{t-12}$ c(1) = -215.857 (317.235) c(2) = -0.315 (0.071) c(3) = -0.604 (0.054) Estimated S.E. = 2145.55
	Expenditure commitments (y_t= f_s_e_cp_imp_ti i=1,2,3)
Current Expenditures	$\Delta^{12}y_t = c(1) + c(2) * \Delta^{12}y_{t-12} + c(3) * y_{t-12}+ c(4) \ (y_{t-1}{}^{S}/ x_{t-1}{}^{ST} - y_{t-13}{}^{S} / x_{t-13}{}^{ST})+ c(5)* [(x_{t-1} - x_{t-2})-(x_{t-2} - x_{t-3})]+$ $c(6)*[((y_{t-3} -z_{t-3})/ y_{t-3}{}^{S}] + c(7)* (@trend = 93)$ c(1) = 15869. 42(4183.701) c(2) = -0.44 (0.10) c(3) = -0.198 (0.074) c(4) = -202115.5 (47402.33) c(5)=-0.56 (0.1553) c(6)=- 50129.75 (18247.47) c(7)=41650.94 (9061.541) Estimated S.E. = 8704.685
Capital Expenditures	$\Delta^{12}y_t = c(1) + c(2) * \Delta^{12}y_{t-12} + c(3) *(\Delta^{12}y_{t-1} - {}^{12}y_{t-2})+ c(4) * (y_{t-3}{}^{S} / x_{t-1}{}^{ST} - y_{t-13}{}^{S} / x_{t-13}{}^{ST})+$ $c(5) *(y_{t-1} / (y_{t-13} -z_{t-13})) +c(6) * ((@trend = 73) + (@trend = 74))$ c(1) = -1641.591 (723.1604) c(2) = -0.546 (0.092) c(3) = -0.1537 (0.062) c(4) = -9869.651 (3693.876) c(5)=560.805 (242.751) c(6)=8038.578 (1226.814) Estimated S.E. = 1647.730
Financial liabilities refund	$\Delta^{12}y_t = c(1) + c(2) * \Delta^{12}y_{t-12} + c(3) * (y_{t-1}{}^{S} / x_{t-1}{}^{ST} - y_{t-13}{}^{S} / x_{t-13}{}^{ST})$ c(1) = -1887.134 (3705.134) c(2) = -0.229 (0.106) c(3) = -145940.7 (26948.67) Estimated S.E. = 26044.82

(Payments on commitments) *(z_t= f_s_e_cp_pag_ti i=1,2,3) w_t= f_s_e_cp_pag_ti/f_s_e_cp_pag_bki_ti*	
Current Expenditures	$\Delta^{12}z_t = c(1) + c(2) * \Delta^{12}y_t + \Delta^{12}z + c(3) * \Delta^{12}z_{t-12} + c(4)*(z_{t-12}) + c(5)* y_{t-12} + c(6)*[(y_{t-1} - z_{t-1}) - (y_{t-7} - z_{t-7})]$ $c(7) *(@trend>65) * (@trend<72) + c(8) * (w^S_{t-1} - w^S_{t-13})$ c(1) = 3962.6433 (2371.050) c(2) = 0.5876586 (0.0769) c(3) = -0.5015926 (0.1069) c(4) = -0.2691787 (0.1267) c(5)= 0.2180602 (0.1434) c(6)= 0.1900686 (0.06168) c(7)= -13634.327 (3542.567) c(8)=- -11875.343 (4059.898) Estimated S.E. = 6806.4895
Capital Expenditures	$\Delta^{12}z_t = c(1) + c(2)* \Delta^{12}y_t + c(3) * \Delta^{12}z_{t-1} + c(4) * z_{t-12} + c(5) * y_{t-12} + c(6) * (y_{t-12} - z_{t-12})$ c(1) = -865.24356 (504.166) c(2) = 0.5944809 (0.0639) c(3) = -0.2639903 (0.0557) c(4) = -0.6964631 (0.1136) c(5) = 0.3063876 (0.08733) c(6) = 0.2124201 (0.0699) Estimated S.E. = 1058.7385
Financial liabilities refund	$\Delta^{12}z_t = c(1) + c(2)*\Delta^{12}z_{t-1} + c(3) * z_{t-12} + c(4) * y_{t-12} + c(5) *(y_{t-12} - z_{t-12})$ c(1) = 813.90815 (4283.942) c(2) = -0.1567188 (0.0949) c(3) = -0.8572661 (0.129) c(4) = -0.1662196 (0.0893) c(5) = 0.1727683 (0.063) Estimated S.E. = 16926.021
	Arrears Expenditures (unPaid commitments) (z^R_t= f_s_e_rs _pag_ti i=1,2,3)
Current Expenditures (BM)	$\Delta^{12}z^R_t = c(1) + c(2) * z^R_{t-12} + c(3) * \log(trend) + c(4)* D_{2006,12}$ c(1) = -3314.1847 () c(2) = -0.4707 (0.) c(3) = 984.1533 (339.42) c(4) = 3326.6531 () Estimated S.E. = 856.6168
Capital Expenditures (BM)	$\Delta^{12}z^R_t = c(1) + c(2) * \Delta^{12}z^R_{t-1} + c(3) * \Delta^{12}z^R_{t-4} + c(4) * {}^{12}z^R_{t-12} + c(5) * D_{2006,11} +$ $c(6) * D_{2007,08} + c(7) * D_{2008,12}$ c(1) = 4.7840 (148.2313) c(2) = -0.109 (0.1203) c(3) = 0.0803 (0.127) c(4) = -0.5435 (0.133) c(5) = 1812.132 (1077.65) c(6) = 2384.544 (1054.8) Estimated S.E. = 1042.6201
Financial liabilities refund (BM)	$\Delta^{12}z^R_t = c(1) + c(2) * \Delta^{12}z^R_{t-1} + c(3) * \Delta^{12}z^R_{t-2} + c(4) * \Delta^{12}z^R_{t-12} + c(5) * D_{2005,04}$ c(1) = 232.427 (90.377) c(2) = -0.093 (0.052) c(3) = 0.0045 (0.052) c(4) = -1.0443 (0.076) c(5) = 7260.955 (681.279) Estimated S.E. = 670.965