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THE CYCLICALITY OF AUTOMATIC AND DISCRETIONARY FISCAL POLICY: WHAT CAN REAL-TIME DATA TELL US?

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This paper develops a new methodology for estimating both the automatic and discretionary components of fiscal policy in one reaction function using the differences between real-time and ex post data. Discretionary policy should respond to information available to the policy maker at the time (real-time data), whereas automatic fiscal policy should respond to the true state of the economy at the time (proxied by the final data). We find that the intended discretionary response of fiscal policy to the cycle is counter-cyclical. Our estimates suggest that the automatic stabilizers are at the lower end of the range found in the related literature. This new methodology reduces the risk present in the conventional CAB approach that part of the discretionary actions may be wrongly attributed to automatic stabilizers. In that sense, automatic stabilizers are typically not as strong as usually claimed. This could be of particular use in countries where insufficient data exist to estimate structural budget sensitivities directly.

Keywords: Fiscal Policy, Real-Time Data, Discretion, Automatic Stabilizers

1. INTRODUCTION

The literature on fiscal policy draws a distinction between automatic and discretionary fiscal policy. The former represents those categories of expenditure and revenues that change automatically in line with economic conditions, whereas the

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latter captures the structural state of public finances, and can only be changed via legislative actions on the part of fiscal policy makers. The size of the automatic stabilizers is an important issue with broad policy implications. The stronger the automatic stabilizers are, the less is the need for discretionary measures to stabilize output.

In the wake of the current European sovereign debt crisis, it is of particular relevance to understand to what extent the deterioration in public finances reflects the automatic workings of the tax and benefit system in response to a fall in GDP, and to what extent it reflects discretionary stimulus measures by policy makers. Moreover, given the need for fiscal consolidation in response to tensions in sovereign debt markets, quantifying the size of automatic stabilizers is of crucial importance both in forecasting the likely improvements to public finances that can be expected when growth picks up and in stripping away cyclical factors to gauge the underlying structural state of public finances.

A large body of empirical studies has estimated fiscal reaction functions in order to assess the size and cyclicality of discretionary and automatic fiscal policy (see Section 2 for a literature overview). What links these papers is the attempt to gauge the underlying fiscal position by relying on estimating the sensitivity of fiscal policy to the cycle. The cyclically adjusted primary budget balance (CAPB) is used to capture discretionary policy, whereas the remainder, sometimes termed the cyclical component, is interpreted as a measure of automatic stabilizers.

Separating out automatic and discretionary fiscal policy via a direct calculation of the CAPB has several drawbacks. First, it requires a good deal of relevant information to first compute the budgetary elasticities. Second, some elasticities are arbitrarily fixed—typically all forms of government expenditures except for unemployment compensation are assumed to have a budgetary elasticity of zero. If automatic stabilizers can also work through expenditure channels other than unemployment compensation, then conventional approaches will underestimate their true magnitude. Third, some cyclical adjustment techniques identify automatic stabilizers on the basis of their statistical correlations with the cycle. However, if discretionary policy is also correlated with the cycle, statistical measures of the CAPB may wrongly attribute this to automatic stabilizers. Fourth, empirical work that is based on CAPBs effectively assumes that the CAPB can be set directly by policy makers in the same way that a central bank can determine the interest rate. In reality, policy makers can only pass a set of expenditure and revenue plans which, if the government's projections turn out to be correct, will produce a given budget balance (and cyclically adjusted counterpart). Real-time measurement errors in estimating potential and actual output can therefore influence the observed CAPB.

This paper develops a new methodology that addresses these problems. Our approach exploits the discrepancy between real-time and ex post data to decompose the automatic and discretionary responses to the cycle within a single reaction function. Intuitively speaking, discretionary fiscal policy should respond to information available to the policy maker at the time (real-time data), whereas automatic fiscal policy should respond to the true state of the economy at the time

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(as proxied by the final data). Accordingly, the reaction of the budget balances with respect to the error in measuring the output gap in real time serves as a pure measure for discretionary fiscal policy.

Our approach has several advantages. First, discretionary fiscal policy that is correlated with the (real-time) cycle will not be counted as an automatic stabilizer, and automatic stabilizers are not arbitrarily restricted to operate only via certain channels. Second, the role of measurement errors in setting fiscal policy is explicitly accounted for. Third, the method can be implemented simply by comparing real-time with ex post data; no specific (and likely error-prone) information about the microstructure of expenditures and revenues is needed. We consider responses across both spending and revenues, and thus give an estimate of the magnitude of automatic stabilizers across the whole budget rather than just one of the two. This enables us to check how the properties of the budget deficit data match up with earlier work on the behavior of its subcomponents [see, e.g., Darby and Melitz (2008), Kalckreuth and Wolff (2011)]. Fourth, our framework forms a bridge between the standard reaction function approach and papers that identify components of fiscal policy using real-time data. That enables the results to be compared with the broader literature on how discretionary fiscal policy responds to the economic cycle.[1]

Our empirical results indicate that the estimates of automatic stabilizers are clearly at the lower boundary of the range obtained by other methodologies. Further, we find that the intended discretionary response of fiscal policy makers to the cycle is in fact countercyclical and of magnitude similar to that estimated by Momigliano and Golinelli (2006) and Cimadomo (2012), who apply the standard CAPB methodology based entirely on real-time data. This underlines the main advantage of our new reaction function: We are able to identify the magnitude of automatic and discretionary fiscal policy response within one single reaction function without having to identify—as in the standard approaches based on the CAPB—the cyclical and discretionary part of the fiscal budget up front. Our new approach is therefore less prone to identification errors and could be of particular use in countries or regions where insufficient data exist to estimate budgetary sensitivities.

The paper is organized as follows. Section 2 outlines our approach for estimating the cyclicality of discretionary and automatic components and compares it with existing techniques. Section 3 discusses econometric issues, and Section 4 reports the results of our empirical estimations. Section 5 concludes.

2. RELATED LITERATURE

A large body of empirical studies has estimated fiscal reaction functions in order to assess the stabilizing function of fiscal policy across the business cycle. In the majority of these studies, the estimates are based on ex post data. The consensus finding for the euro area is that discretionary fiscal policy is either acyclical or procyclical.[2] Taken together, these studies based on ex post data suggest that the lack of countercyclical discretionary policy appears to be robust to changes in additional control variables and the data source used.

In contrast, the small but growing number of papers estimating fiscal policy reaction functions using real-time data suggest that estimation results can differ substantially from those generated from ex post data. Forni and Momigliano (2004) estimate a reaction function using real-time data for the output gap, and Cimadomo (2012) does so using real-time data on both sides of the regression. Both find that the use of ex post data will typically lead to underestimation of the cyclical sensitivity coefficient, indicating a more procyclical fiscal stance, whereas regressions based on real-time data will contain less of an underestimate and therefore imply a countercyclical fiscal policy reaction. This provides prima facie evidence that difficulties in measuring the output gap in real time may have a role to play in explaining the apparently weak countercyclical (or even acyclical) response of fiscal policy to the cycle in conventional ex post data.[3]

Darby and Melitz (2011) have sought to identify automatic and discretionary responses using an identification strategy based on the timing of reactions to ex post data. Their proposed strategy relies on quite strong assumptions about the timing of fiscal policy decisions: discretionary fiscal policy is set in advance, takes a year to come into effect, and cannot be changed in the meantime. However, there is evidence suggesting that some discretionary measures can come into effect with an implementation lag of much less than one year[4] and that significant discretionary adjustments can and do take place within the fiscal year [Beetsma and Giuliodori (2010)]. In a similar vein, papers that control for forecasting errors when assessing the cyclicality of fiscal policy also find that these errors have a significant effect on fiscal outcomes. Buti and van den Noord (2004), Jonung and Larch (2006), and Pina and Venes (2011) all find evidence that official output forecasts may be biased to present an overly optimistic picture of the state of public finances, which suggests that aside from extra information about the output gap, fiscal plans may depart from fiscal output gaps because of manipulation of forecasts by governments. In other words, it may not be possible to distinguish discretionary from automatic fiscal responses by the speed of their reaction to cyclical or other movements in the state of the economy.[5]

3. MODELING FISCAL REACTION FUNCTIONS

In this section we describe different model specifications for examining the intentional response of budgetary policies to the economic cycle. We first present the fiscal reaction functions commonly used in the related literature, and thereafter we propose a new reaction function, which enables an identification of discretionary and automatic fiscal policy responses by exploiting real-time as well ex post data. All fiscal reaction functions presented can be derived intuitively. However, in Appendix B we show that they can also be derived from a simple model of the fiscal policy making process based on Hughes Hallett et al. (2012). Before the reaction functions are presented, some notational clarification is needed.

3.1. Notation

Actual output, Y, can be decomposed into potential output, P, plus the output gap, Q:

$$Y_t = P_t + Q_t. \tag{1}$$

For each variable, different data vintages exist. To differentiate between them, we introduce a superscript denoting the vintage. The latest available vintage of data will be referred to as the "final" vintage and is denoted by f. Accordingly, Y_t^{f} denotes the *ex post* or revised measure for time t output.[6] For other vintages, we adopt a relative notation. The information available in real time is denoted by superscript r.

The preliminary estimate of the level of output, Y_t^{r}, is subject to an error term, U_t:

$$Y_t^{\mathrm{r}} = Y_t^{\mathrm{f}} + U_t. \tag{2}$$

Similarly, the level of potential output, P_t, is measured with error in real time, V_t:[7]

$$P_t^{\mathrm{r}} = P_t^{\mathrm{f}} + V_t. \tag{3}$$

Combining (1), (2), and (3) yields

$$q_t^{\mathrm{r}} = q_t^{\mathrm{f}} + z_t, \tag{4}$$

where small letters denote the previous variables rescaled with respect to the final measure for potential GDP, P_t^{f}, and $z_t = u_t - v_t$.

3.2. Fiscal Reaction Functions

The first generation of fiscal reaction functions were of the following type:[8]

$$pb_t^{\mathrm{f}} = \alpha + \mu q_t^{\mathrm{f}} + \phi x_t^{\mathrm{f}} + \epsilon_t \tag{5}$$

$$= \alpha + (\beta + \gamma) q_t^{\mathrm{f}} + \phi x_t^{\mathrm{f}} + \epsilon_t, \tag{6}$$

where pb_t^{f} measures the total, cyclically unadjusted primary balance as a share of potential GDP, and x_t^{f} is a vector of additional control variables. This reaction function serves as a useful description of the cyclical relation between fiscal variables and economic activity. However, if the aim is to identify the discretionary response of fiscal policy makers to the cyclical stance of the economy, this function is not suitable. The reason is that the coefficient on the output gap, μ, measures jointly the automatic response to government revenues and expenditure,

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β, and the discretionary fiscal policy response, γ, as shown in equation (6). Thus, identification of the relative strength of discretionary fiscal policy is not possible.

One solution to this identification problem is to use a dependent variable that reflects only the discretionary part of the budget balance. In the existing literature it is common to use the ex post cyclically adjusted primary balance (CAPB) as the dependent variable to capture the discretionary reaction of the fiscal policy maker. This means that we subtract the cyclical component βq_t^{f} from the total, cyclically unadjusted primary balance, $\mathrm{pb}_t^{\mathrm{f}}$, in equation (6) to obtain the cyclically adjusted form,

$$\mathrm{capb}_t^{\mathrm{f}} = \mathrm{pb}_t^{\mathrm{f}} - \beta q_t^{\mathrm{f}} = \alpha + \gamma q_t^{\mathrm{f}} + \phi x_t^{\mathrm{f}} + \epsilon_t. \tag{7}$$

The coefficient on the output gap is regarded as a measure for discretionary fiscal policy. A positive value of γ indicates a systematic countercyclical fiscal policy response. However, because equation (7) relies entirely on ex post data, this reaction function does not represent the policy makers' intentions, but the realized, ex post outcome of their decisions. For an example, let's assume that policy makers believe, on basis of available information at the moment decisions have to be taken, that they are confronted with a negative output gap for the fiscal year. They might be inclined to combat this gap via an expansionary fiscal policy. If the estimate for the output gap is then subsequently revised upward to the extent that it turns positive, an analysis of fiscal policy reaction on the basis of ex post data will appear to yield a procyclical fiscal response ($\gamma > 0$), which is usually interpreted as a lax fiscal policy although that was not the intention. However, the cause of this pro-cyclical reaction is misinformation rather than malintention. Thus, as pointed out by Orphanides (2001), if the aim is to learn about policy makers' intentions, it is important to use data that was available at the time policy decisions were made, thus, in *real-time*, not ex post data.

One response is to estimate the same reaction function as described in equation (7) but to focus entirely on real-time data, because these data reflect the information that policy makers had at hand when setting fiscal policy.

Thus, taking equation (7) and conditioning on information available at time t, we obtain the following reaction function:[9]

$$\mathrm{capb}_t^{\mathrm{r}} = \alpha' + \gamma' q_t^{\mathrm{r}} + \phi' x_t^{\mathrm{r}} + \epsilon_t', \tag{8}$$

with γ' describing this time the intended discretionary fiscal policy response. This type of fiscal reaction function with the CAPB as the dependent variable is usually found in the real-time fiscal literature.[10]

However, estimating fiscal reaction functions based on the CAPB to separate out discretionary fiscal policy has a major drawback, in that the estimation results are vulnerable to mis-specifications in the size of automatic stabilizers. Let $\bar{\beta}$ denote the estimate of the automatic fiscal policy response to the economic cycle. Calculating $\bar{\beta}$ involves estimating the elasticities of various budgetary components, which may be prone to measurement error (a more detailed explanation of how

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this is done is given in Appendix A). If the estimate of the automatic fiscal policy response deviates from the true value β, then the CAPB-based reaction functions shown in equations (7) and (8) change to

$$\text{capb}_t^{\text{f}} = \alpha + (\gamma + \beta - \bar{\beta})q_t^{\text{f}} + \phi x_t^{\text{f}} + \epsilon_t \tag{9}$$

and

$$\text{capb}_t^{\text{r}} = \alpha' + (\gamma' + \beta - \bar{\beta})q_t^{\text{r}} + \phi' x_t^{\text{r}} + \epsilon_t'. \tag{10}$$

We can see that the estimated coefficients on the output gap only correctly capture discretionary policy responses if the estimated parameter for the automatic stabilizer parameter is correct, $\beta = \bar{\beta}$. If this is not the case, the coefficients on the output gap will be biased and will be an amalgam of the true discretionary response and the error in estimating automatic stabilizers, $\beta - \bar{\beta}$. Accordingly, if the automatic stabilizer is underestimated, this will lead to overestimation of the discretionary response and vice versa.

Our approach differs from the existing literature, because it does not need any prefiltering of the data to remove the cyclical, automatic components of the fiscal indicator. We are therefore free of the measurement errors found in (9) and (10). Similarly to regression (6), we use the total primary balance as the dependent variable. We distinguish discretionary from automatic fiscal policy decisions directly by exploiting the information available in real-time *and* in ex post data. The idea is that automatic fiscal policy reacts to the actual level of the output gap, whereas the discretionary fiscal policy operates in response to the perceived output gap in real time. Thus, the response of the public deficit to the error made by fiscal policy makers in estimating the output gap reflects a pure measure of the intended cyclicality of discretionary fiscal policy. Similarly, augmenting regression (6) by z_t, which according to equation (4) measures the real-time measurement error in the output gap, $q_t^{\text{r}} - q_t^{\text{f}}$, allows us to identify discretionary as well automatic fiscal policy response:

$$\text{pb}_t^{\text{f}} = \hat{\alpha} + \hat{\mu} q_t^{\text{f}} + \hat{\gamma} z_t + \hat{\phi} x_t^{\text{f}} + \epsilon_t. \tag{11}$$

Because the dependent variable is the unfiltered primary balance, the coefficient on the output gap in this regression, $\hat{\mu}$, measures the automatic and discretionary fiscal policy reactions jointly, whereas the coefficient on the real-time measurement error z_t estimates the discretionary fiscal policy response. Thus, the automatic component is given by subtracting the coefficients on z_t from the coefficient estimated on the output gap, $\hat{\beta} = \hat{\mu} - \hat{\gamma}$.

One advantage of this reaction function is that the left-hand-side variable is the ex post rather than the real-time deficit ratio. If the left-hand-side variable were a real-time value, then it would not necessarily be a true reflection of policy makers' intentions, as it could be subject to creative accounting. Expressing a reaction function with an ex post fiscal variable on the left-hand side therefore insulates our results against creative accounting on the deficit measure.

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4. ESTIMATIONS

For estimation we use the data published in successive editions of the OECD's *Economic Outlook* (EO). The OECD has published a real-time data set online, but this does not include data for fiscal variables.[11] Therefore our data set had to be compiled by taking successive issues of EO and collating them into a single file. The data set consists of the published values of GDP, the output gap, and the cyclically adjusted budget deficit series in each issue from December 1994 (Issue 56) to December 2008 (Issue 84).[12] Our sample consists of the EU-15 countries (i.e., the pre-2004-enlargement members) over the period 1994–2008.[13]

Based on equation (11), we estimate the following reaction function:

$$\mathrm{pb}_t^{\mathrm{f}} = \hat{\delta} + \hat{\mu} q_t^{\mathrm{f}} + \hat{\gamma} z_t + \hat{\phi} x_t^{\mathrm{f}} + \epsilon_t, \quad \text{(A)}$$

where ϵ_t denotes a random error term and x_t^{f} is a vector consisting of five additional explanatory variables that are commonly found to be significant in the related literature:

- debt: Measures the previous-year ($t-1$) debt-to-GDP ratio and explains the initial state of public finances [see, e.g., Bohn (1998), Gali and Perotti (2003)].
- eyear: Dummy variable taking the value of 1 in the year of parliamentary elections and zero otherwise and measuring the relevance of the electoral cycle.
- maastricht: Denotes a "Maastricht variable" similar to that developed by Forni and Momigliano (2004) to capture the effect of fiscal consolidations in the run-up to EMU. For countries with a deficit of more than 3% prior to 1998 ($b < -3$), the variable is defined as follows: $\mathrm{maastricht}_t = \frac{\mathrm{balance}_{t-1}+3}{1998-t}$.[14] The variable is set to zero for countries with previous-year deficits of less than 3%; for countries that chose not to participate in EMU; and for all countries after 1998. This variable provides a simple way to capture the fiscal consolidation needed in many EU countries in order to meet the Maastricht criteria. It uses up only one degree of freedom. A significant negative coeffient would imply a consolidation in countries whose deficit exceeds the Maastricht reference value.
- Lagged dependent variable: To account for the likely autocorrelation of budget decision resulting either from gradual adjustment to a target budget or from the serial correlation in exogenous shocks. Stability requires that the coefficient on the lagged dependent variable must be smaller than 1.
- v_t: Measures the real-time measurement error in potential output, $p_t^{\mathrm{r}} - p_t^{\mathrm{f}}$. Adding this variable to the set of regressors is motivated by our simple model of fiscal policy making presented in Appendix B.

Regression (A) delivers an estimate of the discretionary *and* the automatic fiscal policy response. A positive and significant coefficient on the measurement error of the output gap, z_t, indicates that discretionary fiscal policy is countercyclical.

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The difference between the coefficients on the output gap and z_t, $\hat{\mu} - \hat{\gamma}$, gives an estimate of the size of the automatic fiscal policy response, $\hat{\beta}$.

There is some debate over the "correct" data vintage for our real time estimations. In other words, for setting policy for year t, do policy makers use the data available at the start of the year, i.e., $(t - 1)$-vintage data? Or do they use information that becomes available to them during the course of the year, thus, t-vintage data? The fact that budgetary plans are typically drawn up and presented to national parliaments before the start of the fiscal year suggests that the appropriate information set is that which is available at time $t - 1$. On the other hand, there are considerations that may militate in favor of using data vintage t for our real-time case. Beetsma and Giuliodori (2010) find that governments do systematically depart from their $t-1$ budget plans in the face of new information. Von Kalckreuth and Wolff (2011) find evidence of "real time" fiscal responses to GDP revisions at the quarterly frequency. In other words, fiscal policy is not set in stone at the start of the year—and governments are able to make additional discretionary fiscal adjustments during the course of year t. We therefore take the time-t data as our real-time data to allow for the possibility of intrayear adjustments to fiscal policy chronicled elsewhere in the literature.

For comparison purposes, we also estimate the two alternative reaction functions based on equations (7) and (8), respectively, both relying on the CAPB as the dependent variable:

$$\mathrm{capb}_t^{\mathrm{f}} = \mathrm{pb}_t^{\mathrm{f}} - \beta y_t^{\mathrm{f}} = \delta + \gamma q_t^{\mathrm{f}} + \phi x_t^{\mathrm{f}} + \epsilon_t, \quad \text{(B)}$$

$$\mathrm{capb}_t^{\mathrm{r}} = \delta' + \gamma' q_t^{\mathrm{r}} + \phi' x_t^{\mathrm{r}} + \epsilon_t', \quad \text{(C)}$$

where the vector x_t includes the same explanatory variables as in regression (A) except the real-time measurement error v_t.[15] Regression (B) represents the conventionally used reaction function based entirely on ex post data, and the estimation results therefore do not describe fiscal policy makers' intentions but the ex post fiscal policy result. Regression (C) focuses instead on real-time data and therefore estimates fiscal policy makers' intentions. Both regressions, however, use the cyclically adjusted primary balance as the dependent variable and therefore deliver only a (probably biased) estimate of the size of discretionary fiscal policy, which is measured by the coefficient on the output gap variable.

4.1. Econometric Methodology

Because the time dimension of our data set is relatively short, we estimate each fiscal reaction function as a panel.[16] To check for stationarity, a panel unit root test [Im et al. (2003)] was performed on the variables used; see Table 1. For all variables, the null hypothesis of a unit root is rejected at the 5% significance level, and therefore we treat the data as stationary.

A necessary condition for poolability is that countries follow the same, or relatively similar, fiscal reaction functions. Therefore, we tested up front for whether

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TABLE 1. Stationarity test of variables

	p-values
capb_t^{r}	0.03
capb_t^{f}	0.00
pb_t^{f}	0.02
gap_t^{r}	0.00
gap_t^{f}	0.00
debt_t^{r}	0.00
v_t	0.00
z_t	0.00

Notes: Figures represent p-values of the unit root test proposed by Im, Peseran, and Shin, assuming individual unit root processes across countries.

the estimated slope coefficients of the three regressions (A)–(C), excluding the constant terms to allow for country fixed effects, differ between the 14 countries covered in our data set. We find that the null hypothesis of equality of slope coefficients for all countries cannot be rejected in any regression at the 5% significance level. The results of the poolability test are shown in Table 2.[17]

To capture unobserved country fixed effects, we have included country dummies in all regressions and, similarly to previous studies, we find that an F-test cannot reject their joint significance. The presence of country fixed effects and lagged dependent variables among the regressors means that ordinary least squares (OLS) and within estimations are severely biased and inconsistent unless the time dimension T is large [see Nickell (1981) and Kiviet (1995)]. Therefore, estimating the dynamic fiscal reaction function with a standard fixed-effect panel estimator—as many other studies have done—may not be appropriate.[18]

TABLE 2. Poolability test

Regression	p-value
Baseline–specification	
(A)	0.13
(B)	0.95
(C)	1.00
With maastricht and eyear	
(A)	0.90
(B)	0.92
(C)	1.00

Notes: Figures represent p-values of the F-test for equal slope coefficients across countries.

One common approach to resolving this difficulty is to remove the panel-level effects by first-differencing the estimation equation and then to apply a linear generalized method of moments (GMM) estimator.[19] A common choice in the literature is the Arellano–Bond estimator [Arellano and Bond (1991)], which uses the lags of the dependent variable to instrument the differenced dependent variable (which turns endogenous after first-differencing).[20]

However, Blundell and Bond (1998) and Alonso-Borrego and Arellano (1999) show that when the autoregressive parameter is moderately large, lagged levels of the dependent variable provide weak instruments for first differences. Given the high degree of autoregressivity in our data set,[21] the Arellano–Bond estimator would thus provide weak instruments. Furthermore, the first-difference GMM estimator only yields unbiased and consistent results if the cross-section dimension N is large.

We therefore follow Golinelli and Momigliano (2006) in using the Arellano–Bond estimator alongside the Blundell–Bond estimator (1998). The latter extends the first-difference GMM estimator proposed by Arellano and Bond (1991) by using lagged differences of the dependent variable as instruments for equations in levels, in addition to lagged levels of the dependent variable as instruments for equations in first differences [compare Arellano and Bover (1995)]. Blundell and Bond (1998) show that this "system GMM" estimation approach significantly improves on the performance of the usual first-differences GMM estimator when the autoregressive parameter is moderately high.[22] Nevertheless, we have also estimated our reaction functions with the conventional Arellano–Bond estimator as a robustness test. The results do not differ significantly between the first-difference and the system GMM estimator.

Our choice of lag length of the instrumental variables is influenced by Bun and Kiviet (2006), who showed that increasing the number of moment conditions used in dynamic panel estimates increases the bias in finite samples considerably. Further, too many instruments can significantly reduce the power of the Hansen test for overidentification. Therefore, we limit the number of available instruments by using no more than two lags of the dependent variables (in levels as well in differences) as instruments.[23]

To address the possible endogeneity of the output gap, we explicitly allow the ex post and real-time output gaps to be endogenous variables [see, e.g., Gali and Perotti (2003)]. Further, we define the debt variable to be predetermined, which means that past shocks on the budgetary variables are correlated with the current debt level, which is quite intuitive. We instrument the endogenous and predetermined variables with their first two lags and, as suggested by Forni and Momigliano (2004), with a GDP-weighted average of the output gap of all other European countries.

The validity of the GMM estimates is based on the condition of no second-order autocorrelation. Thus, in the lower part of Tables 3 and 4, we report the p-values of the Arellano–Bond test that the average autocovariance of the residuals of order two is zero. The null hypothesis of no second-order autocorrelation cannot be

TABLE 3. Estimation results for the new reaction function

	I	II	III	IV
Estimator	BB	AB	BB	AB
Gap	0.765***	0.739***	0.785***	0.800***
	(0.17)	(0.17)	(0.16)	(0.16)
v_t	−0.048	0.005	−0.026	0.019
	(0.12)	(0.08)	(0.10)	(0.07)
z_t	0.468***	0.434***	0.435***	0.441***
	(0.14)	(0.14)	(0.14)	(0.14)
debt	0.055***	0.064***	0.043***	0.039
	(0.02)	(0.03)	(0.02)	(0.03)
maastricht			−0.714***	−0.989**
			(0.20)	(0.39)
eyear			−0.417**	−0.423**
			(0.13)	(0.14)
Lagged dep variable	0.477***	0.613***	0.513***	0.642***
	(0.13)	(0.13)	(0.13)	(0.14)
Constant	−2.627**		−1.825*	
	(1.11)		(1.01)	
R^2	0.51	0.41	0.56	0.58
N	177	177	177	177
AR2	0.83	0.97	0.69	0.56
Hansen	0.31	0.51	0.21	0.38

Notes: AB denotes Arellano–Bond estimator; BB denotes Blundell–Bond estimator. Standard errors in parentheses. AR2 denotes the p-value of the Arellano–Bond test for second-order autocorrelation; Hansen shows the p-value of the Hansen test for overidentification.
*,**,*** Significance at the 10%, 5%, and 1% levels, respectively.

rejected in all four regressions. To check for misspecification of our instruments we have performed a Hansen test; the relevant p-values are also reported in the bottom line of Tables 3 and 4.

We also check for possible multicollinearity between z_t and v_t in regression (A). A simple pairwise regression of v_t on z_t yields an R^2 of 0.05 and a correlation parameter of −0.19, indicating no significant correlation between the two.[24]

4.2. Results

Table 3 shows the estimation result for our new fiscal reaction function (A). The first and third columns show the results of applying the Blundell–Bond estimator, and the second and fourth column show the results of the Arellano–Bond estimator. We first estimate a simple reaction function containing only the output gap, a lagged dependent variable, and lagged debt as explanatory variables. Thereafter, we add the two additional control variables eyear and maastricht.

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TABLE 4. Comparison with other methodologies

	(A)	(B)	(C)
Dep variable	pb_t^f	$capb_t^f$	$capb_t^r$
Output gap	y_t^f	y_t^f	y_t^r
Gap	0.785***	0.162	0.367*
	(0.16)	(0.10)	(0.17)
v_t	−0.026		
	(0.10)		
z_t	0.435**		
	(0.14)		
debt	0.043**	0.001	0.105***
	(0.02)	(0.02)	(0.01)
maastricht	−0.714***	−1.310***	−0.142
	(0.20)	(0.38)	(0.24)
eyear	−0.417**	−0.443***	−0.243
	(0.13)	(0.12)	(0.20)
Lagged dep variable	0.513***	0.781***	0.714***
	(0.13)	(0.09)	(0.16)
Constant	−1.825	0.192	−6.362
	(1.01)	(1.30)	(0.81)
R^2	0.56	0.66	0.56
N	177	177	177
AR2	0.69	0.46	0.06
Hansen	0.21	0.17	0.65

Notes: All regressions estimated with a Blundell–Bond estimator. p-values in parentheses. AR2 denotes the p-value of the Arellano–Bond test for second-order autocorrelation; Hansen denotes the p-value of the Hansen test for overidentification.
*,**,*** Significance at the 10%, 5%, and 1% levels, respectively.

The estimation results seem to be very robust to the inclusion of additional explanatory variables and the choice of the dynamic panel estimator. Our preferred specification is therefore the Blundell–Bond estimator including election and Maastricht variables [regression (III)]. The diagnostic tests also do not indicate any problems with respect to second-order autocorrelation or identification.

We find the total cyclical response of fiscal policy is 0.79. The coefficient on z_t, which measures the discretionary fiscal policy response, is highly significant and has a value around 0.44. The positive coefficient means that fiscal policy makers had intended to apply a countercyclical fiscal policy—a one-percentage-point fall in the output gap induces policy makers to loosen the budget balance by around 0.44 percentage points. The magnitude of automatic stabilizers is given by the difference between the coefficients on gap and z_t, which is 0.35 with a standard error of 0.15.[25] Estimates of automatic stabilizers are usually in the range from 0.3 to 0.5.[26] Thus, our estimate is at the lower boundary of this range, but the difference from 0.5 is marginally insignificant.[27]

The maastricht variable is negative and significant in all cases, and a t-test does not reject the null hypothesis that the value is not significantly different from minus one—the value consistent with a smooth linear adjustment of budget deficits toward the benchmark. This confirms the finding elsewhere in the literature [for example, Hughes Hallett et al. (2003), Hughes Hallett et al. (2012)] that many governments did make an additional effort to tighten fiscal policy in the run-up to EMU in order to meet the fiscal criteria for entry. The election dummy, eyear, has a significant negative coefficient, implying that fiscal policy is around 0.42 percentage points looser in an election year. In all but one regression, the debt variable is positive and significant, implying that governments do in fact tighten fiscal policy in response to rising debt ratios.

Table 4 compares our estimation results with existing approaches.[28] The first column gives the estimates using our own methodology. Regressions (B) and (C) are reaction functions using the cyclically adjusted budget balance to measure discretionary fiscal policy, equivalent to equations (7) and (8), respectively, in Section 3. For brevity, we report only the results of the Blundell–Bond estimator because the estimation results look very similar in the two cases.[29]

Regression (B) is the standard ex post reaction function, using the CAPB. The coefficient on the output gap is insignificant, which would usually be interpreted as a sign of acyclical discretionary fiscal policy. However, instead of estimating fiscal policy makers' intentions, regression (B) can be better interpreted as a measure of the actual fiscal outcome. This regression will be misspecified as a description of the policy makers' *desired* reaction, if data revisions play a role.

When we estimate the real-time CAPB reaction function (C), which regresses the real-time output gap on the real-time CAPB, we get a significant positive coefficient on the output gap, implying an intended countercyclical discretionary fiscal policy response. Insofar as the CAPB is a good measure of discretionary fiscal policy, this backs up the view that fiscal policy is more countercyclical in intention (i.e., based on real-time data) than it is in outcome. This result is in line with that of Momigliano and Golinelli (2006) and Cimadomo (2012), who also find that fiscal policy looks notably more countercyclical when assessed using real-time data than when assessed using ex post data. Compared to the results of our new reaction function shown in regression (A), however, the estimate of discretionary fiscal intervention is weaker. When we test whether the difference between regressions (A) and (C) is significant, we have to reject this hypothesis.

4.3. Robustness Tests

Although our poolability test is favorable (see Table 2), as a further robustness check we re-ran our regressions dropping one country at time to check if the results are driven by the inclusion of one country. The relevant coefficients, reported in Table 5, are very similar in both size and statistical significance across all samples.

TABLE 5. Sensitivity test

Country dropped	(A) gap_t^f	(A) z_t	(B) gap_t^f	(C) gap_t^r
Austria	0.81***	0.43***	0.14	0.50***
Belgium	0.79***	0.43***	0.15	0.48**
Germany	0.75***	0.40**	0.18	0.52***
Denmark	0.81***	0.43**	0.21*	0.44**
Spain	0.82***	0.44***	0.16	0.44***
Finland	0.75***	0.45**	0.07	0.39**
France	0.80***	0.44***	0.17	0.53***
Greece	0.80***	0.47***	0.14	0.56***
Ireland	0.79***	0.48**	0.14	0.49**
Italy	0.86***	0.49***	0.15	0.57***
Netherlands	0.73***	0.40**	0.15	0.55***
Portugal	0.94***	0.54***	0.21	0.53***
Sweden	0.78***	0.38***	0.17	0.49***
United Kingdom	0.78***	0.41**	0.16	0.51**
Min	0.73	0.38	0.07	0.39
Max	0.94	0.54	0.21	0.57

Note: Figures show the coefficients measuring fiscal reaction when the country listed in the first column is excluded from regressions.
*,**,*** Significance at the 10%, 5%, and 1% levels, respectively.

In addition, a range of other potential control variables were experimented with. Following Beetsma and Giuliodori (2010), we included a variable capturing the fiscal stance of other nations,[30] but this yielded either an insignificant or an implausibly high coefficient, depending on the precise specification used. To test for the effect of the Excessive Deficit Procedure, we constructed a variable EDP, which was equal to zero if a country's budget balance was less than −3% of GDP the previous year or if it was not a member of the eurozone at the time, and equal to the gap between the previous year's budget deficit and 3% otherwise.[31] However, this variable was not found to be significant in any of the regression specifications. In other words, breaching the 3% reference value in one year appeared to induce no extra consolidation the following year.

Lagged and led election years were also included alongside the existing electoral year dummy, with a view to capturing more sophisticated electoral budget cycle dynamics. However, when included alongside eyear, both the lag and lead of eyear were never found to be significant.

5. CONCLUSIONS

This paper outlines a new methodology for gauging the cyclicality of automatic and discretionary components of fiscal policy. Using the property that discretionary

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policy responds to real-time data, but automatic policy responds to the true state of the economy, we are able to distinguish between the two.

We estimate that for every euro fall in output, automatic stabilizers offset around 35 cents. Moreover, policy makers intend to use discretionary policy in a countercyclical way. Specifically, for every euro of negative output gap, fiscal policy expands by around 45 cents.[32] These estimates are in line with previous estimates in the related literature of the size of automatic and discretionary fiscal policy response.

Our new methodology has the advantage that the estimates of the cyclicality of both types of fiscal policy are based directly on empirical correlations between the primary balance and various measures of the output gap, rather than on imposing budgetary sensitivities a priori. Thus, this methodology reduces the risk present in the conventional CAPB approach that part of the discretionary actions may be wrongly attributed to automatic stabilizers, which would lead to an underestimation of discretionary fiscal policy and overestimation of automatic fiscal policy. Although this seems not to be a problem in our data set, it might be relevant for other countries or time periods. Our alternative technique could be of particular use in countries where insufficient data exist to estimate budgetary sensitivities using the OECD, ECB, or European Commission methodologies.

NOTES

1. In keeping with this broader literature, our focus is on identifying how policy responds to the output, as opposed to identifying how the output responds to fiscal policy.

2. See, for example, Galí and Perotti (2003), CEPII (2005), and Wyplosz (2006) using data published by the OECD, or Ballabriga and Martinez-Mongay (2003) and Balassone and Francese (2004), who found similar results using the AMECO data set. For a formal political economy model that generates a rationale for such a pro- or acyclical policy, see Talvi and Vegh (2007) or Alesina and Tabellini (2008).

3. Golinelli and Momigliano (2009) estimate a variety of fiscal reaction functions, including a specification inspired by our approach with the real-time output gap measurement error on the right hand side. However, their estimation approach is different from ours, using different lag structures for instruments, using time dummies, and employing the lagged real-time output gap rather than contemporaneous real-time output gap on the right hand side. Their results for the response of the primary balance to the output gap are somewhat different from the rest of the literature, as they find an insignificant but negative response of the primary balance to the output gap.

4. For example, Taylor (2009) notes that the U.S. tax rebates of 2001 and 2008 came into effect with "virtually no implementation lag." Similarly, measures such as the recent car scrapping incentives in Germany came into effect within the fiscal year. Some lags are even shorter—for example, in the United Kingdom, changes in excise duties on petrol, tobacco, and alcohol typically come into effect at 6 pm on the day of the budget announcement, implying an implementation lag measured in hours, not months.

5. Moreover, Darby and Melitz (2011) assume that the policy maker reacts to the lagged ex post output gap. However, this variable is not available in real time when the discretionary decision is made. In year t the data for the output gap in year $t-1$ are still very far from final; thus the real-time data may be very different from the ex post. Papers analysing data revisions find that final values are not known with any precision until many years after the event [Orphanides and van Norden (2001); Hughes Hallett et al. (2012)]. Further, it may be more plausible to assume that fiscal policy for year t is based on economic conditions for year t rather than for the previous year.

6. In this context, we mean "final" in the sense that it is the latest vintage that we have in our data set. Of course, in reality, today's data vintage will be revised in the future, but for ease of exposition, we use the term "final" to refer to the last available data vintage that we currently have.

7. Note that the terms U_t and V_t simply represent the real-time measurement error, and thus we do not assign particular statistical properties to this term.

8. See, for example, Galı and Perotti (2003), Buti and van Den Noord (2004), and Wyplosz (2006).

9. At time t, the conditional expectation of the final output gap and final capb are their real-time counterparts, q_t^{r} and $\mathrm{capb}_t^{\mathrm{r}}$, respectively.

10. Cimadomo (2012), where all variables are in real time; Forni and Momligiano, where the output gap is in real time, but the budgetary variable is in ex post form.

11. For an explanation, and for the data themselves, see http://stats.oecd.org/mei/default .asp?rev=1.

12. Some of the data were taken from a data set kindly supplied by Roel Beetsma and Massimo Giuliodori.

13. The raw data contained a small number of missing observations in the final vintage, which were proxied by taking their last reported values. For full details of the replacements made, see below. We also checked that our results are robust to dropping these observations.

Gaps in data set

Country	Variable	Vintage	Year	Action taken
Greece	Debt	Final data (EO 80)	1994	Observation dropped
Ireland	Debt	Final data (EO 80)	1994	Take latest available (EO78)
Ireland	Debt	Final data (EO 80)	1995	Take latest available (EO78)
Ireland	Debt	Final data (EO 80)	1996	Take latest available (EO78)
Ireland	Debt	Final data (EO 80)	1997	Take latest available (EO78)
Italy	Debt	Final data (EO 80)	1995	Take latest available (EO77)

14. In the case of Greece, whose convergence report was written in 2001, the formula was $\mathrm{maastricht}_t = \frac{b_{t-1}+3}{2002-t}$. Note that this variable is based on the lagged value rather than the current value of the budget balance. This ensures that maastricht is not endogenous.

15. The reason is that we focus in regression (B) entirely on ex post data and in regression (C) entirely on real-time data, with the effect that $v_t = 0$.

16. For simplicity, we drop the country index i from the variable notation.

17. Bun (2004) shows that in a dynamic panel model the classical asymptotic test procedures reject poolability too often. In other words, the p-values are too low. Thus, our estimated p-values are biased downward and should be regarded as the lower bound.

18. Galì et al. (2003), Forni et al. (2004), Annett (2006), Wyplosz (2006), and Cimadomo (2012) all followed this approach.

19. An alternative way to handle dynamic panel bias is to perform a least-squares dummy variable estimator (LSDV) and then to correct the results for the bias (Kiviet (1995). However, this approach does not address the potential endogeneity of other regressors, which is the case in our regressions.

20. See, for example, Balassone and Francese (2004), Forni and Momigliano (2004), and Debrun and Kumar (2007).

21. Regressing the real-time (ex post) cyclically adjusted budget balance on its own lag yields an autoregressive parameter of 0.89 (0.90).

22. Bun and Kiviet (2006) have analyzed the finite sample behavior of various least-squares (LS) and a range of GMM estimators (including the system GMM) in dynamic panel models with individual effects and weakly exogenous explanatory variables. They conclude that if T and N are small, standard first-order asymptotic theory is of little use in ranking the qualities of the different estimators, and that system GMM estimators are a "relatively safe choice," except when the autoregressive process of the

dependent variable is small, which is not the case in our data set. Furthermore, Hayakawa (2007) shows that system GMM estimators such as the Blundell–Bond estimator suffer less from a small sample bias than alternative first-difference GMM or level GMM estimators. The reason is that the bias of the system GMM estimator is a weighted sum of the small sample biases in opposite directions of the first - and the level-GMM estimator. The two elements of the bias of the system GMM estimator partly cancel each other out when the autoregressive coefficient on the lagged dependent variable is around 0.4, which is roughly the size of the coefficient on the lagged dependent variable in our estimates.

23. The estimation results turned out to be quite robust to the choice of the lag length of the instruments. When the maximal lag length is restricted to three and four lags of the dependent variable, the results hardly change.

24. As a similar check, z_t was regressed on the ex post output gap, and the R^2 was 0.23, again suggesting no multicollinearity problems

25. The standard error of the automatic stabilizer is calculated as $\sqrt{\mathrm{Var}(\mathrm{gap}) + \mathrm{Var}(z_t) - 2\mathrm{cov}(\mathrm{gap}, z_t)}$.

26. See, for example, Giorno et al. (1995), Kiander and Viren (2000), van den Noord (2000), Bouthevillain et al. (2001), and Barrell and Pina (2004).

27. For a one-tail test that the automatic stabilization response is less than 0.5 at the 5% significance level, we would need a covariance between the coefficients on gap and z of more than +0.0185. In fact, it was +0.011. However, this test and the estimated coefficients are rather sensitive to the time period at issue. Restricting the sample to 1993–2005, that is to before the financial crisis, the automatic response parameter was only 0.24 because the discretionary fiscal element was larger [Bernoth et al. (2008)]. That is significantly different from 0.5.

28. Note that we can only compare the estimated coefficients for the discretionary fiscal policy response, because regressions (B) and (C) do not deliver estimates for the size of automatic stabilizers.

29. A full set of results is available from the authors on request.

30. Two specifications were tried: The first was the GDP weighted average of all other countries' CAPBs; the second was the GDP weighted average of other Eurozone CAPBs for Euro members and zero for non-Eurozone countries.

31. The variable was constructed both for real-time and for final budget data.

32. Note, however, that because discretionary policy responds to the real-time output gap, the cyclicality of discretionary policy in relation to the ex post output gap is somewhat lower.

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APPENDIX A: TRADITIONAL CYCLICAL ADJUSTMENT PROCESSES

The “traditional” CAB approach used by the European Commission and OECD seeks to identify the automatic component of fiscal policy on the basis of statistical correlations between (subcomponents of) revenues and some measure of economic activity. Clearly, other methods of cyclically adjusting public finances also exist [see, for example, Deutsche Bundesbank (2000); CAB (2005)]. But because most empirical work makes use of “off the peg” CAB data from either the commission or OECD, we focus on these methods here.

The OECD approach, outlined fully in Girourard and André (2005), is as follows. Revenues are split up into four components: personal income tax, social security contributions, corporate income tax, and indirect taxes. On the expenditure side, only public spending is considered cyclically sensitive. All other expenditure and revenue categories are assumed to be fully independent of the cycle.

The cycle itself is measured using the OECD’s output gap estimate. The response of each revenue item to the cycle is obtained by combining two elasticities—the elasticity of revenue with respect to the tax base, and the elasticity of the tax base to the cycle. For unemployment, a similar calculation is performed using the elasticity of unemployment to the cycle.

The elasticity of income tax and social security revenue is typically obtained from analyzing tax legislation and income distributions, whereas the other elasticities are fixed at unity. The elasticitities of tax bases to the output gap are generally estimated econometrically. Since 2005, the OECD has explicitly incorporated lagged responses into its methodology, so that tax revenues may react with a delay to variations in economic growth.

The European Commission (2005) uses a methodology very similar to that of the OECD. It multiplies the OECD’s sensitivity parameters by its own output gap measure to obtain the cyclical component of the budget balance. Unlike the OECD, it does not consider the role of lags. (It should be noted that various factors explain the differences in approach. The Commission’s CAB figures are used in the application of the excessive deficit procedure, and therefore it is particularly important that the Commission have a transparent process that is easy to replicate. That militates in favor of a more simple and standarized approach than modeling considerations alone would imply.)

The ECB approach is laid out in Bouthevillain et al. (2001). The key point of difference from the OECD methodology is that each tax base is allowed to have its own cycle. Thus each tax base variable is HP filtered, and the deviation from trend is then taken as the cyclical measure for that particular tax base. The budgetary elasticities are then determined by a combination of two methods—derivation from tax and expenditure laws and regressing these components on a measure of the output gap.

These standard CAB techniques are subject to a number of drawbacks. First, many of the elasticities are set arbitrarily because of data limitations. For example, indirect taxes are assumed to have a unitary elasticity with respect to their tax bases. But if consumers tend to shift their consumption between higher-taxed luxury goods and lower-taxed "necessities" in response to the cycle, then the elasticity will be higher than one. On the expenditure side, only unemployment benefit is assumed to be related to the economic cycle. The operation of automatic stabilizers via other channels such as income-contingent state benefits is ruled out.

Second, to the extent that the elasticities are estimated using correlations between expenditure/revenue flows and economic activity, there is the possibility of misrecording countercyclical discretionary policy as an automatic stabilizer. If one regresses a revenue category on the output gap, then the correlation shows both the automatic effect of changes in the tax base and the discretionary effect of changes in the tax rate. The latter will then be wrongly attributed to automatic stabilizers.

Third, the CAB is often treated as if it were a variable that can be set directly by policy makers, in the same way that a central bank sets its policy interest rate. In fact, the government cannot directly set the budget balance or its cyclically adjusted counterpart. Rather, it passes a series of tax and expenditure plans, which, under certain assumptions about actual and potential output, will yield a given (cyclically adjusted) budget balance. Errors in estimating real and potential output will then show up in the ex post fiscal position of the government. Yet, in such cases, caution should be attached to interpreting such a measure as representative of the desired fiscal stance of the policy maker. An apparently weak fiscal position could represent an error in projecting the current state of the economy, rather than a conscious desire to loosen fiscal policy.

APPENDIX B: A SIMPLE ACCOUNTING FRAMEWORK FOR AUTOMATIC AND DISCRETIONARY FISCAL POLICY

In this section we outline a simple model of the fiscal policy making process, based on Hughes Hallett et al. (2012), which motivates the newly proposed fiscal reaction function presented in equation (11).

As Orphanides (2001) noted, a necessary condition for any rule that claims to characterize policy makers' intentions is that the rule must be implementable given the information they had at the time. Aside from the issue of real-time output gaps, an additional point is that policy makers cannot simply set the budget balance (or the cyclically adjusted budget

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balance) for any particular year in the way that the central bank can set its policy rate. Rather, they can pass a budget containing a mixture of discretionary actions, automatic spending/revenue items, and spending measures fixed in cash terms. If the actual GDP and/or potential output depart from their projected values, the budgetary variables will also depart from their forecast values. Accordingly, we develop here a simple model of setting the fiscal framework, which yields a fiscal policy rule that would meet Orphanides's (2001) requirement of "implementability" in real time.

A key feature of any model based on real-time data is that decisions are taken using preliminary data. Because our focus is on cyclicality, for ease of exposition we abstract here from the role of lags and from noncyclical influences on discretionary policy such as election years and EMU. The reaction functions presented in Section 3 and the empirical estimates in Section 4 do allow for a richer set of determinants of fiscal policy.

Let us assume that fiscal plans are set in real time. The projected budget balance for year t, $\mathrm{PB}_t^{\mathrm{r}}$, can be expressed as the sum of three components:

$$\mathrm{PB}_t^{\mathrm{r}} = \beta Y_t^{\mathrm{r}} + \alpha P_t^{\mathrm{r}} + \gamma (Y_t^{\mathrm{r}} - P_t^{\mathrm{r}}). \qquad \textbf{(B.1)}$$

The first category of the budget balance represents the automatic response of fiscal policy to the projected level of economic activity, βY_t^{r}. [Note that the response is to the level of output, rather than its deviation from potential. This assumption has been seen elsewhere in the literature, particularly where a separation is made between spending and revenue in fiscal plans or where the goal is to analyze the fiscal windfall arising from above-trend growth. Hughes Hallett et al. (2003), Von Hagen (2003), and Buti and van den Noord (2004) all assume that expenditures are fixed in nominal terms, and all taxes are proportional to GDP.] Thus, if ex post output is higher than projected, then the budget balance will be higher than projected. [Note that this setup for automatic stabilizers has the property that the budget balance may automatically change when output grows in line with its potential. Because tax codes are not indexed with respect to potential GDP, an identical rise in potential and actual GDP will lead to a change in the budget balance, via the automatic channel, even though the output gap is unchanged. As Masten (2008) points out, failure to account for this can also produce biased estimates of automatic stabilizers.]

The second category of the budget balance is entirely independent of the level of output and of the output gap—i.e., driven by expenditures or revenues that are fixed in cash terms. For ease of algebraic manipulation, this part is expressed as a fraction α of potential output as measured at time t. The defining property of this budgetary item is that it is fixed in cash terms and hence subsequent revisions to estimates of potential output, so that the level of GDP will not affect its cash value. These budgetary items could, in principle, be amended over the fiscal year. However, in the context of this model and the subsequent estimates, the crucial property is that any revisions to this category are independent of the level of GDP and the output gap.

The last category of the budget balance represents the government's discretionary changes to the budget balance in response to what they perceive the output gap to be at time t, $\gamma(Y_t^{\mathrm{r}} - P_t^{\mathrm{r}})$. The recent wave of fiscal stimulus measures announced by many OECD governments would fall into this category.

Thus, the coefficient β represents an automatic fiscal policy response, and the other two coefficients, α and γ, are measures of discretionary fiscal policy. The actual outturn of budget balance is thus given by

$$\mathrm{PB}_t^{\mathrm{f}} = \beta Y_t^{\mathrm{f}} + \alpha P_t^{\mathrm{r}} + \gamma (Y^{\mathrm{r}} t - P_t^{\mathrm{r}}). \tag{B.2}$$

Note that the budget balance item that is fixed in cash terms, αP_t^{r}, is still expressed in real time. This is because it is fixed in cash terms at the outset, and hence the actual outturn of actual and potential output has no effect on their value.

Substituting the measurement error equations $Y_t^{\mathrm{r}} = Y_t^{\mathrm{f}} + U_t$ and $P_t^{\mathrm{r}} = P_t^{\mathrm{f}} + V_t$ [compare equations (2) and (3) from Section 3] into (B.2) and dividing by P_t^{f}, we obtain after some rearrangements

$$\mathrm{pb}_t^{\mathrm{f}} = (\beta + \alpha) + \alpha v_t + (\beta + \gamma) q_t^{\mathrm{f}} + \gamma z_t \tag{B.3}$$

$$= \delta + \alpha v_t + (\beta + \gamma) q_t^{\mathrm{f}} + \gamma z_t, \tag{B.4}$$

where lowercase letters denote the previous variables rescaled with respect to final potential GDP P_t^{f}, $\delta = \beta + \alpha$, and $z_t = u_t - v_t$.

Thus, equation (B.4) constitutes a new fiscal reaction function, which makes it possible to identify the discretionary and automatic responses of budgetary policies to the economic cycle. The constant $(\beta + \alpha)$ gives the government's desired fiscal stance over the cycle. The coefficient on the ex post output gap, $(\beta + \gamma)$, measures the sum of automatic and discretionary components and the coefficient on the measurement error z_t, γ, is a measure of the intended cyclicality of discretionary policy. Thus, the difference between the estimated coefficient of the measurement error z_t and the output gap q_t^{f} delivers an estimate of the automatic fiscal policy response, β.

In the related literature, it is common to use the cyclically adjusted (primary) balance as the dependent variable. To express this in the context of our model, we subtract the cyclical component, βq_t^{f}, from equation (B.4) to obtain the cyclically adjusted form of the fiscal reaction function,

$$\begin{aligned} \mathrm{capb}_t^{\mathrm{f}} &= \mathrm{pb}_t^{\mathrm{f}} - \beta q_t^{\mathrm{f}} \\ &= \delta + \alpha v_t + \gamma q_t^{\mathrm{f}} + \gamma z_t, \end{aligned} \tag{B.5}$$

where the coefficient on the output gap and the coefficient on the real-time measurement error of the output gap, γ, measure the discretionary fiscal policy response the economic cycle.

By conditioning regression (B.6) on information available in real time, we obtain the fiscal reaction function based entirely on real data using the cyclically adjusted (primary) balance as the dependent variable,

$$\mathrm{capb}_t^{\mathrm{r}} = \delta + \gamma q_t^{\mathrm{r}}, \tag{B.6}$$

where the estimated coefficient on the output gap, γ, describes the discretionary fiscal policy response.