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Revenue elasticities in euro area countries

An analysis of long-run and short-run dynamics

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Abstract

Revenue elasticities play a key role in forecasting, monitoring and analysing public finances under the European fiscal framework, which largely builds on cyclically adjusted indicators. This paper investigates whether there is evidence for dynamic – instead of the currently used static – elasticities in euro area countries. Applying country-specific error correction models we reveal important differences across countries. For a majority of euro area Member States we find evidence for dynamic revenue elasticities. We show that the application of such dynamic elasticities could substantially reduce forecast errors in several countries – with the evidence being stronger based on ex-post than based on real-time data.

Keywords: EU fiscal surveillance; revenue elasticities; error correction models; tax forecasts; real-time data

JEL codes: E62; H68

Non-technical summary

Revenue elasticities measure the reaction of public revenues to changes in their base. They play a key role in forecasting, monitoring and analysing public finances. They are at the core of cyclical adjustment methods of public finances and are therefore especially important under the European fiscal framework, which largely builds on cyclically adjusted indicators. This paper investigates whether there is evidence for dynamic – instead of the frequently used static – elasticities in euro area countries. While static elasticities assume that revenues only react to changes in their base in the contemporaneous period, dynamic elasticities allow for time lags in the reaction of revenues to changes in their base and hence also for a variation between the short-run and long-run revenue elasticities.

Based on country-specific error correction models we find evidence for dynamic revenue elasticities in a majority of euro area Member States (12 out of the 18 countries analysed). Relationships between macroeconomic and public revenue developments are found to be strongly dynamic in Spain, Greece, Luxembourg, Malta and Cyprus. A second group of countries with smaller, but nevertheless significant dynamics in the relationship between GDP and public revenues includes Estonia, Belgium, Austria and Italy. Only small differences between short- and long-term elasticities and hence very limited dynamics are found for Slovenia, Finland and Latvia. In quantitative terms, the difference between the short-run and the long-run revenue elasticity varies between 0.7 (in the case of Spain) and 0.1 (as in the case of Latvia). For six countries (France, Ireland, Germany, Portugal, the Netherlands and Slovakia) however, we find no evidence for dynamic revenue elasticities. Relying on static revenue elasticities for cyclical adjustment is likely to lead to systematic biases especially for those countries for which we found large differences between short- and long-run elasticities (i.e. Spain, Greece, Luxembourg, Malta and Cyprus).

Our analyses reveal that adjustment patterns between short- and long-run elasticities also differ strongly across countries and need to be taken into account for forecasting and cyclical adjustment of public finances. In a majority of those countries with evidence for dynamic revenue elasticities (Greece, Luxembourg, Malta, Estonia, Belgium, Austria, Italy, Slovenia and Finland), the short-run elasticity is found to be below the long-run elasticity leading to an “undershooting” of revenues after a shock in aggregate income. For three countries (Cyprus, Spain and Latvia) short-run elasticities are significantly higher than long-run elasticities – leading to an overshooting of revenues in the short run.

A comprehensive out-of-sample forecast evaluation based on an ex-post dataset shows that applying the identified dynamic elasticities (instead the frequently applied static ones) reduces revenue forecast errors for all euro area Member States except for Italy. For three of the five countries with strongly dynamic revenue elasticities (Cyprus, Greece and Luxembourg) the forecast evaluation shows that a dynamic model performs significantly better than a model with static elasticities. Moreover, the dynamic models consistently outperform benchmark random walk forecasts in all euro area countries. Based on real-time data, random walk benchmark forecasts turn out to be generally harder to beat and there is less evidence for the superiority of dynamic over static elasticities for current year forecasting.

Taken together our findings indicate that the dynamic revenue elasticities derived by us could in several countries help to improve cyclical adjustment methods and could also help to substantially reduce forecast errors – with the evidence being substantially stronger based on ex-post than on real-time data.

"Taxes grow without rain."

— Proverb.

1 Introduction

Revenue elasticities play a key role in forecasting, monitoring and analysing public finances. Notably there are three main applications of these elasticities: i) revenue forecasts often rely on elasticities to calculate the expected revenues based on macroeconomic predictions, ii) revenue elasticities are a core element of cyclical adjustment methods to calculate the structural balance, which is a decisive indicator for the European budgetary surveillance framework in form of the Stability and Growth Pact (SGP), and iii) revenue elasticities are employed by analytical studies (for example of fiscal multipliers) to decompose the working of automatic stabilisers and discretionary revenue shocks.[1]

The revenue elasticities applied in fiscal policy analyses are usually static in the sense that changes in the base influence tax revenues only in the contemporaneous period. However, this assumption might be overly restrictive as the relationship between revenue bases and revenues might in fact be more dynamic: changes in the base might affect revenues beyond the contemporaneous period and short-run reactions of revenues to cyclical fluctuations might differ from long-run reactions to structural economic changes.[2]

If the reactions of revenues were indeed not restricted to the period of the shock, purely static revenue elasticities would be misspecified. This could have impacts on all three main applications of revenue elasticities. First, not taking into account dynamic revenue-base relationships could imply systematic errors in revenue forecasts. Second, the calculation of the structural balance as a key indicator for fiscal surveillance could be distorted if dynamic revenue-base elasticities exist, but are not taken into account in cyclical adjustment. Finally, the decomposition of revenue developments into automatic stabilisers and discretionary shocks might not be accurate if it relies on static elasticities, while elasticities might in fact be dynamic.

Against this background this paper evaluates empirically, whether there is evidence for dynamic revenue elasticities and whether such dynamic elasticities could indeed help to reduce revenue forecast errors. Such dynamic elasticities could then be applied for example in modelling country-specific revenue forecasts, in cyclical adjustment methods or to identify fiscal policy shocks in analytical studies.

In this paper we apply country-specific dynamic error correction models (ECM) to estimate short- and long-run revenue elasticities and the adjustment path between them. In order to evaluate the potential benefits of applying dynamic elasticities, we estimate whether they would systematically reduce forecast errors when compared to a common benchmark as well as when compared to the static elasticities currently applied under the European fiscal framework. These estimations are performed based on ex-post as well as based on real-time data.

The paper is structured as follows. In section 2 we briefly review the existing literature. Section 3 reviews concepts of revenue elasticities and the role of revenue elasticities in the European fiscal framework. It

[1] One important application is the so-called Blanchard-Perotti approach. For a discussion see, for example, Caldara and Kamps (2012), Baum and Koester (2011) or Priesmeier (2014). See Dolls et al. (2015) for an overview on automatic stabilization in the euro area under the framework of the Stability and Growth Pact.
[2] For details see the discussion in section 2.

also displays descriptive statistics and discusses the role of discretionary revenue measures for calculating revenue elasticities. Data and the methodology applied in this paper are described in section 4. Section 5 presents the results of our estimations and section 6 evaluates the impact of dynamic tax elasticities on forecast performance. Section 7 concludes.

2 Literature review

Despite the important role of revenue elasticities for fiscal forecasting, surveillance and analysis, the analytical literature on the topic is relatively thin. Mourre, Astarita and Princen (2014) is one important recent contribution that presents the methodology currently applied by the European Commission and derives new values of frequently applied budgetary semi-elasticities to quantify the effects of macroeconomic developments on public budget deficits. Technically, the semi-elasticities applied by the European Commission are based on revenue and expenditure elasticities, which have been recently re-estimated and revised by the OECD (2014). These elasticities are static in the sense that they focus only on the contemporaneous reaction of revenues to changes in the base.[3]

However, the concept of static revenue elasticities needs to rely on far-reaching assumptions. First, it assumes that changes in a revenue base affect only revenues in the contemporaneous and not also in later periods. Second, it assumes implicitly that revenues react in the same way to cyclical short-run fluctuations as to structural long-run developments of the economy. In contrast, a dynamic concept would allow for lagged effects of economic changes on revenues and could distinguish between short-run and long-run revenue elasticities.

In such a dynamic approach the long-run tax revenue elasticity measures how the growth of revenues depends on the long-run growth of their bases, i.e. on the growth rates of the revenue bases adjusted for any short-run fluctuations. This long-run revenue elasticity should normally be linked to the progressivity of revenues with respect to their base.[4] In contrast, a short-run elasticity measures how short-run fluctuations in the revenue bases – resulting especially from the business cycle – affect revenue developments. Differences between short- and long-run revenue elasticities can result, for example, from loss carry-forward regulations in profit taxes or lags in tax collection, which lead to a delayed adjustment of tax revenues to tax base changes.[5] Furthermore cyclical changes in consumption spending might affect the composition of spending on differently taxed categories of goods in a different way than long-run changes – which would then lead to differences in the short- and the long-run consumption tax revenue elasticities.[6]

One important advantage of the dynamic approach is that it allows for differences between short- and long-run elasticities, but does not require or impose them. In case there is no evidence for dynamic

[3] See Price, Dang and Guillemette (2014). For a discussion of the recent update, see also European Commission (2014): Public Finances in EMU 2014 – part II.3. The aggregate tax revenue elasticity is calculated as a weighted sum of two rather static components (corporation tax elasticity, indirect tax elasticity) and two static components (personal income tax and social contributions elasticity and non-tax revenue elasticity). We therefore refer to the aggregate tax revenue elasticity with respect to the output gap as static (see section 3.2 for further details).

[4] As we cannot neutralize the effects of discretionary policy changes on revenues due to a lack of data, progressivity could result not only from a progressive rate structure but also from discretionary changes in the rates of proportional taxes over time.

[5] Additionally there might be an influence of factors like asset prices (see e.g. Morris and Schuknecht, 2007) or tax compliance.

[6] See also the discussion of determinants for short- and long-term elasticities in Belinga, Benedek, de Mooij and Norregaard (2014) pp. 4 ff.

elasticities, the dynamic analysis can be expected to just reveal identical values for short- and the long-term revenue elasticities.

In the literature, the potential dynamics of revenue elasticities were first taken into account by Sobel and Holcombe (1996). They apply error correction models to evaluate the dynamic properties of the elasticities of different categories of taxes in US states. Bruce, Fox and Tuttle (2006) expand their approach by allowing also for dynamic revenue responses to tax base changes depending on the relationship between current and expected tax base growth. Such state-dependent as well as state-independent long- and short-run dimensions of tax revenue changes with respect to their bases are evaluated for the Netherlands by Wolswijk (2009) and by Bettendorf and van Limbergen (2013). Fricke and Suessmuth (2014) apply this dynamic and non-linear approach to the effects of changes in GDP on tax revenues for several Latin American countries. Dynamic elasticities of tax revenues are estimated for Germany by Koester and Priesmeier (2012) and for the Czech Republic by Havranek, Irsova and Schwarz (2015). Recent papers that are closely related to our work are Mourre and Princen (2015), who estimate dynamic elasticities for an EU country pool and Belinga, Benedek, de Mooij and Norregaard (2014) who estimate short- and long-run tax buoyancy in OECD countries.[7]

3 Revenue elasticities: role, definition, pattern and treatment of discretionary measures

3.1 Role of revenue elasticities in the European fiscal framework

Elasticities quantify the effect of changes in a base (e.g. GDP or a disaggregated tax base like consumption expenditures) on revenues. Thereby they link macroeconomic and fiscal developments.

A first important role of elasticities in the European fiscal framework is therefore related to forecasting. Economic forecasts – as, for example, the economic forecasts done by the European Commission – often employ revenue elasticities to quantify the effects of macroeconomic developments on fiscal revenues and ultimately the deficit.

A second role of elasticities relates to the cyclical adjustment of fiscal balances especially in form of the structural balances (defined as the cyclically adjusted balance net of one-off and temporary measures). As the business cycle has the strongest impact on the budget balance via its effects on revenues, revenue elasticities play a decisive role for this cyclical adjustment. Hence, a misspecification of revenue elasticities could therefore not only distort economic forecasts but also introduce – via the cyclical adjustment method applied – a bias in the values of the structural balance.

Such a misspecification could not only hinder a sound analysis of public finances. As the structural budget balance plays a decisive role under the Stability and Growth Pact (SGP), it could also have direct implications for fiscal surveillance. One example would be the assessment, whether a country has delivered a required improvement of the structural balance under the Excessive Deficit Procedure.[8]

[7] In the literature different definitions of tax elasticity and tax buoyancy exist. Some papers use both terms synonymously, while others argue that tax buoyancy reflects overall developments of tax revenues with respect to an economic base, while tax elasticities need to be derived based on a dataset that is corrected for the effects of discretionary revenue measures. In this paper we use both terms synonymously.
[8] See for the details of assessing “effective action” under the SGP European Commission (2014): Public Finances in EMU 2014 – part II.2. Revenue elasticities play a decisive role in this assessment not only via the calculation

3.2 Elasticity definition

The most recent literature refers to three different concepts of revenue elasticities (see Princen et al. (2013)):

- *the elasticity of tax revenues with respect to their specific tax bases:* this concept is applied e.g. by Koester and Priesmeier (2012) for Germany, by Wolswijk (2009) and Bettendorf and van Limbergen (2013) for the Netherlands and by Bouthevillain et al. (2001) for the euro area and the EU15;
- *the elasticity of revenues with respect to the output gap:* such output gap elasticities are calculated by the OECD (2014), and then applied in the cyclical adjustment methodology of the European Commission (see Mourre, Astarita and Princen (2014));[9]
- *the elasticity of revenues with respect to GDP:* such elasticities are estimated for example by Barrios and Fargnoli (2010) for 13 EU Member States. Within the EU fiscal framework, the OECD elasticities mentioned above are applied to nominal GDP growth in order to calculate revenue wind- or shortfalls.[10]

In this paper we choose to apply the third of the concepts described above for the following reasons: *First,* we want to contribute a cross-country analysis on dynamic revenue elasticities to the literature, which so far does not exist. In a first step, it seems reasonable to focus such an analysis on the aggregate development of revenues and therefore also on an aggregate base. *Second,* GDP has the advantage over the output gap, that it is an observable and readily available. The output gap on the other hand is an unobservable, which is usually derived from a complex production function methodology and is frequently revised quite substantially. If we would base our analysis on the output gap as a measure for developments of the tax base, we would have no possibility to identify whether the results could not also be driven by a bias in the output gap calculation. *Third,* studies that are closely related to ours find that the concept of deriving tax elasticities with respect to GDP growth turns in practice out to be close to the concept of deriving elasticities with respect to changes in the output gap (which is applied by the OECD - see e.g. Princen et al. 2013, p.11). *Finally*, we are also interested in the surveillance implications of possible misspecifications of revenue elasticities. The fact that the European Commission applies elasticities to nominal GDP growth in order to correct the structural effort under the excessive

of the structural balance, but also because the structural balance is adjusted ex post for revenue wind- and shortfalls, which are diagnosed based on standard revenue elasticities.

[9] Following OECD approach, this elasticity can be decomposed into the product of two main elements: the responsibility of revenues to their base and the responsibility of the base to the economic cycle, i.e. the output gap. With respect to corporation and indirect taxes, the derived “effective” tax-to-base elasticity builds on a (three-year) average of the short- and long-term elasticities, i.e. on tracing the effect of a base-change through an ECM for three years. As the application of this (average) elasticity in practice does only take the contemporaneous effects of changes in base on revenues into account, we refer to the effective elasticity as static. The base-to-output gap elasticity builds only on the short-term relation estimated in another ECM. W.r.t. personal income taxes and social security contributions, the tax-to-base elasticity is derived from average earnings data, which relate per capita income tax paid to incomes along a distribution scale (measured in multiples of average earnings) and we therefore refer to it as static. The base-to-output gap elasticity builds only on the short-term relation estimated in an ECM. The non-tax revenues are considered not to be related to the cycle and thus a static elasticity is applied. Finally, the aggregate tax revenue-to-output gap elasticity is derived as the weighted sum of the product of tax-to-base and base-to-output gap elasticities estimated by the OECD (2014) for each tax category. The OECD weights each tax category with its share in GDP, whereas the European Commission refers to the average (2002-2011) share of each tax category in total revenues. Hence, the aggregate tax elasticity is a weighted sum of two rather static components (corporation taxes, indirect taxes) and two static short-term components (personal income tax and social contributions elasticity and non-tax revenue elasticity). Against this background we classify the aggregate tax revenue elasticity with respect to the output gap being static.

[10] See footnote 8 for details.

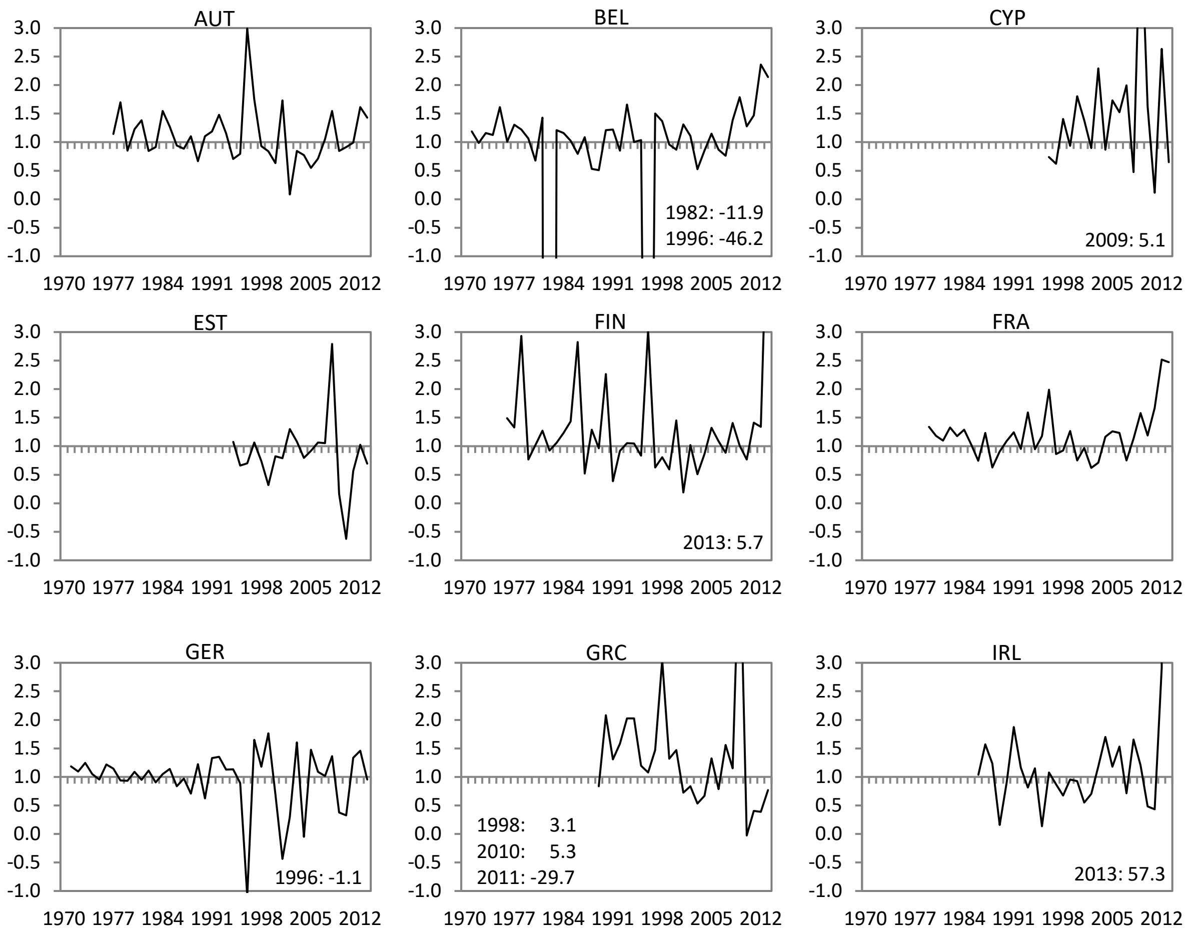
deficit procedure for revenue wind- and shortfalls (see also section 3.1 for details) is another reason for us to focus on the elasticity of revenues with respect to GDP.

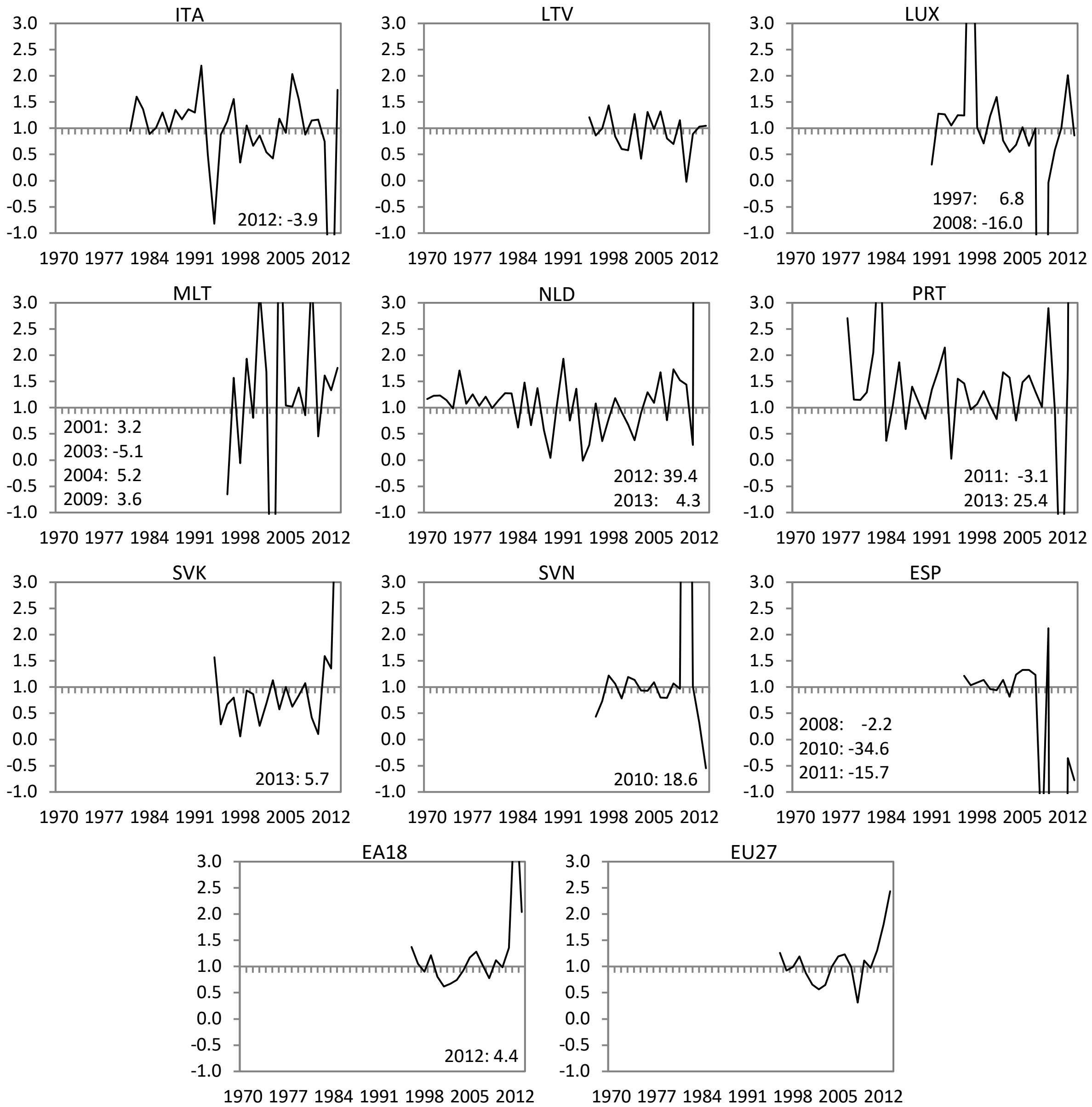
3.3 Patterns of gross elasticities over time

An aggregate revenue-base elasticity links changes of GDP to changes in aggregate tax revenues. If the elasticity is static and changes in GDP only affect the contemporaneous relationship between GDP and revenues, data on the ratio of the growth rates of revenues over the growth rates of GDP can give a first indication of the size of the elasticity as well as its potential stability over time. This ratio is called the deterministic gross revenue elasticity. Figure 1 displays the development of this elasticity over time for each of the EA18 Member states as well as the EA18 and the EU27 aggregates.

The panels of figure 1 can be interpreted as follows: First, the gross elasticities all fluctuate around one and show no increasing or decreasing trends. This can be seen as indication for a general benchmark around unity for the gross elasticity in the long run. Second, the deterministic short-run elasticities do generally not follow a common pattern across all Member States. Countries with a larger number of observed gross elasticities above one may tend to have long-run elasticities larger than one (as Cyprus, Greece, Malta and Portugal). Countries with a majority of observations below the benchmark may tend to have long-run elasticities lower than one (Slovakia and Latvia). Third, the short-run realizations turn out to be very volatile and even change their sign in some cases.

Figure 1: Gross revenue elasticities for EA18 countries, EA18 and EU27 (1970-2013). Values of elasticities outside the scale applied are indicated on each chart.





The main question of this paper is whether this observed volatility of the deterministic gross elasticities points to the need to take more dynamic interactions between GDP and public revenues into account and whether applying such dynamic elasticities could indeed systematically reduce the amount of revenue wind- and shortfalls, which cannot be explained.

3.4 Discretionary revenue measures

One can argue that the observed volatility of the deterministic gross elasticities (see subsection 3.3) is likely to be also linked to the effects of discretionary tax measures. This would call for a correction of revenue developments for the effects of discretionary revenue measures, i.e. the calculation a net elasticity. Indeed, such a correction is conceptually desirable and has led some authors build their estimations on "policy-neutral" datasets, i.e. tax revenue data is adjusted for tax reform effects (see, e.g.

Wolswijk (2009), Koester and Priesmeier (2012), or Mourre and Princen (2015)).[11] For this paper, which covers long time series and a large number of countries, the construction of such policy-neutral datasets is however impossible because of a lack of data. In the AMECO database of the European Commission, for example, consistent estimates for DRMs of all euro area Member States are only available from 2010 onwards. In our view, this however does not question the general validity of the design of our study for two reasons: First, the majority of recent studies finds that discretionary revenue measures (DRMs) do not seem to explain significant parts of the observable large fluctuations in unadjusted (gross) elasticities of revenues to their base (i.e. the correlation between the gross elasticities and adjusted (net) series is very high; for details see e.g. Princen et al. (2013)). This is also confirmed by Barrios and Fargnoli (2010) who find that the effect of discretionary measures on total taxes tends to be relatively small. In this context the available data for recent years (2011-14) indicates that DRMs amount on average to only 1.3 percent of revenues in EU countries (1.4% in euro area countries). Second, the link between discretionary revenue measures and the economic cycle seems to be rather weak as demonstrated in Princen et al. (2013). The largest part of DRMs would therefore be identified as non-systematic part of the revenue to base relations. This would usually be captured in the non-systematic residuals of the estimation equation, independently on whether a static or a dynamic model is applied.

4 Data and Methodology

4.1 Data

We base our estimations on annual data of public revenues and nominal GDP for all EA18 Member States and the aggregates of EA18 and EU27. For each case we refer to the longest available time series in the annual macroeconomic database of the European Commission (AMECO).[12] Overall revenues are defined as total current revenues of general government. The main elements of current revenues are taxes on production and imports, current taxes on income and wealth, and social contributions. Flows inside the general government sector (i.e. transfers between the sub-sectors of general government) are consolidated.

To evaluate the effects of dynamic elasticities on forecast errors in a sophisticated manner, we compiled also a database of the real-time values of our variables for all analysed countries covering forecast vintages dating back till 2000 (for details see section 6).

4.2 Methodology - estimation of dynamic revenue elasticities

In order to estimate dynamic tax elasticities, we use a two-step regression method, which was recently applied for the estimation of tax elasticities e.g. by Wolswijk (2009), Koester and Priesmeier (2012) and Mourre and Princen (2015). This method allows us to separately analyse long- and short-run elasticities as well as the adjustment process between these two stages.

[11] The most comprehensive multi-country studies based on policy-neutral dataset are Mourre and Princen (2015) including pooled data for EU28 Member States for 12 time series observations (2001-2013) and Princen et al. (2013) including pooled data for 20 of 27 EU Member States from 2001 to 2012.
[12] The Netherlands provide the longest ex-post data set (1969-2013). For some Member States as well as for the EA18 and EU27 aggregate data starts only in 1995. See table A.1 for further details.

A stable long-run or equilibrium relation between revenues and their base requires a cointegrating relationship between the two (Sobel and Holcombe, 1996). Generally, there is a strong theoretical presumption of such long-run relationship between tax revenues and the aggregate tax base. This is based on the fact that there is only “limited possibility to avoid taxation if the taxable event that increases the tax base occurs” (Wolswijk (2009), p.4). For a vast majority of euro area countries the existence of such long-run relationships is indeed confirmed in cointegration tests.[13] Only for Germany, Malta and Portugal the presumption is rejected at a 5% level of significance for each version the deterministic benchmark specification. However, for these countries, there is some evidence for a stable long-run relationship based on specifications without a constant restricted to the cointegrating relation. The long-run equilibrium for each country i can be expressed by the static contemporaneous log level relation between revenues $\left(rev_{t,i}\right)$ and their base in log levels $\left(gdp_{t,i}\right)$ controlling for a constant, structural breaks (level shifts) where necessary and stationary equilibrium errors $\left(ec_{t,i}^{rev}\right)$. The corresponding elasticity measures the revenue response to a 1% change in aggregate income of the economy. In a first estimation step, this long-run relation is estimated by dynamic OLS (DOLS).[14]

The immediate effect of changes in the base on revenues is captured by the contemporaneous relation of growth rates (first differences of log levels) and measured by the corresponding elasticity $\beta_{1,i}$. However, it is not the only channel at work in the short run. Whenever there is a difference between the direct short-run response of tax revenues and the identified long-run relationship, temporary deviations from the stable equilibrium relationship can occur. These are captured in the stationary equilibrium errors $\left(ec_{t,i}^{rev}\right)$. For example, a contemporaneous revenue response to GDP changes that is higher than the long-run response would generate higher than equilibrium revenues and thus create a positive equilibrium error (*overshooting*). As these deviations can only be transitory they have to be corrected over time. This second channel is captured by loading the lagged equilibrium errors into the model for short-run tax revenue dynamics. The corresponding loading parameter $\beta_{2,i}$ measures the adjustment. In addition, the autoregressive character of macroeconomic aggregates such as revenues and GDP could require autoregressive components. Strong evidence for serial correlation in a rather static model is usually a good indicator of misspecified dynamics. A lagged dependent variable included via the corresponding parameter $\beta_{3,i}$ is an appropriate solution to capture such somewhat “richer” dynamics.[15]

All elements are included in the following error correction model (ECM), with equilibrium deviations from the first stage (corrected for the nuisance terms required in the DOLS estimation) as error correction term, a constant $\left(\alpha_{0,i}\right)$, and, where necessary, a country-specific structural break term $\left(\alpha_{sb,i}sb_{t,i}\right)$,

$$\Delta rev_{t,i} = \alpha_{0,i} + \alpha_{sb,i}sb_{t,i} + \beta_{1,i}\Delta gdp_{t,i} + \beta_{2,i}ec_{t-1,i}^{rev} + \beta_{3,i}\Delta rev_{t-1,i} + \varepsilon_{t,i} \quad (1).$$

[13] Detailed results of cointegration tests can be found in table A.2 in the appendix A. We apply to the Johansen system-based approach in order to take into account possible endogeneities between the variables. In the benchmark specification of the long-run relationship we include a constant restricted to the cointegration equation and test versions with and without an additional endogenous lag.
[14] See e.g. Stock and Watson (1993). We regress revenue on contemporaneous GDP in log levels and additionally on leads and lags of the first differences of GDP, a constant and – where necessary – additional structural breaks. Particularly in small samples this estimator has proved superior to standard OLS or Johansen estimates as it is not only able to accommodate higher orders of integration, but also to tackle the problem of endogeneity among the regressors, and serial correlation issues. Where necessary, we apply also the correction approach of the standard errors developed by Newey and West to account for serial correlation and heteroscedasticity.
[15] Accordingly, we include the lagged annual growth rate of revenues in an alternative specification for each Member State, EA18 and EU27.

In a second estimation step, the short-run elasticities are estimated by ordinary least squares (OLS). The adequacy of the country-specific models, i.e. the iid hypothesis of the residuals, is evaluated in diagnostic checks (Table A.1 in appendix A presents the results for the two-step regressions).

An intuitive way to illustrate a dynamic relation between public revenues and GDP developments is tracing the effects of exogenous shocks in GDP on aggregated revenues. Therefore, in a last step, we simulate and bootstrap the estimated models and compute the corresponding impulse-response functions and their confidence intervals.[16] Results for all EA18 Member States are presented in the next section.

5 Results – dynamics of tax systems in euro area countries

A dynamic approach to revenue elasticities allows for the analysis of three dimensions of a tax system: i) the degree of progressivity indicated by the long-run elasticity, ii) the degree of volatility indicated by the difference between the long- and the short-run elasticity and iii) the adjustment pattern.

The degree of progressivity of a country's tax system can be defined by the deviation of the estimated long-run elasticity from a unitary benchmark, which would be consistent with a constant revenue to GDP ratio in the long term. Long-run elasticities of one imply proportional tax systems, elasticities larger than one indicate progressive, elasticities lower than one degressive tax systems.[17] The degree of volatility of a country's tax system can be explained by the absolute difference between the short- and long-run revenue elasticity. The third dimension, the type of adjustment pattern, is indicated by the direction of the short-run deviation from the long-run elasticity. Either revenues are *overshooting* or *undershooting* their long-run equilibria in the short-run – which implies that systematic negative or positive corrections are necessary in order to converge to the long-run equilibrium subsequently.

Impulse response functions derived from the error correction models reflect the degree of progressivity as well as of volatility of a tax system. They are also a suitable instrument to map the adjustment pattern in form of a potential over- or undershooting. In this section we show and discuss the responses of revenues over a horizon of 10 periods after a one percentage point shock in aggregated income.[18] We group countries by type of adjustment pattern: we start with countries for which an overshooting (short-run higher than long-run elasticity) is observed, then discuss countries in which revenues are in the short run undershooting (short-run lower than long-run elasticity) and finally turn to countries with no dynamic reaction (short-run equals long-run elasticity). Inside the three groups we order countries from high to low degrees of volatility. The impulse response functions are based for each country on the ECM with the best fit, i.e. the ECM for which the iid hypothesis is not rejected and which has the lowest value for the Akaike information criterion (AIC).

[16] We apply parametric bootstrapping and repeat the sampling process 2000 times.
[17] As we cannot neutralize the effects of discretionary policy changes on revenues due to a lack of data, progressivity could result not only from a progressive rate structure but also from discretionary changes in the rates of proportional taxes over time.
[18] Additional information on the progressivity and volatility of the countries' tax systems is displayed in appendix B.

For 12 countries of our sample of euro area Member States (Spain, Greece, Luxembourg, Malta, Cyprus, Estonia, Belgium, Austria, Italy, Slovenia, Finland and Latvia) we find significant deviations between short- and long-run elasticities (see figures 2 and 3 below).

Overshooting revenue responses

For three (Spain, Cyprus and Latvia) of these 12 countries, tax revenues contemporaneously *overshoot* their equilibrium level after a positive shock in aggregate income (see figure 2, overshooting in Latvia only significant within the weaker 68% confidence intervals). The most pronounced case is Spain. Within the same year of the one percentage point (1 pp) shock in aggregate income revenues increase very strongly by 1.80 pp – substantially above the nearly proportional long-run equilibrium elasticity of 1.06. This contemporaneous overshooting indicates a very high degree of volatility. Within the following year, revenues decrease and their levels adjust completely to their new steady state values. In Cyprus and Latvia the observed overshooting is less strong while the adjustment to the new steady state proceeds within a similar timeframe as in Spain.

Figure 2: Countries with overshooting revenue responses

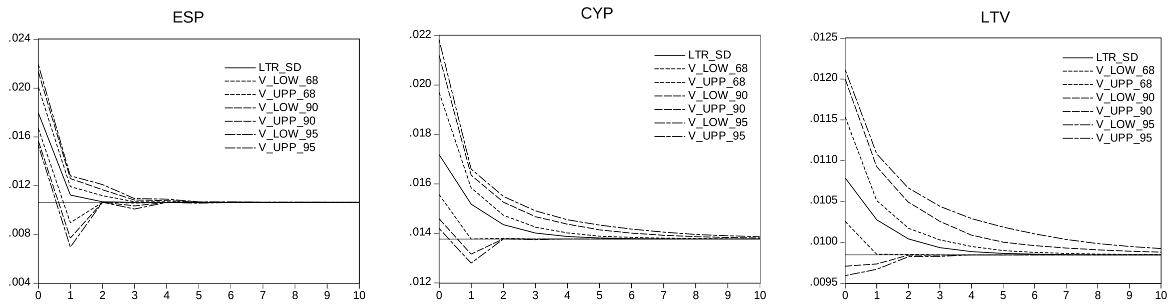
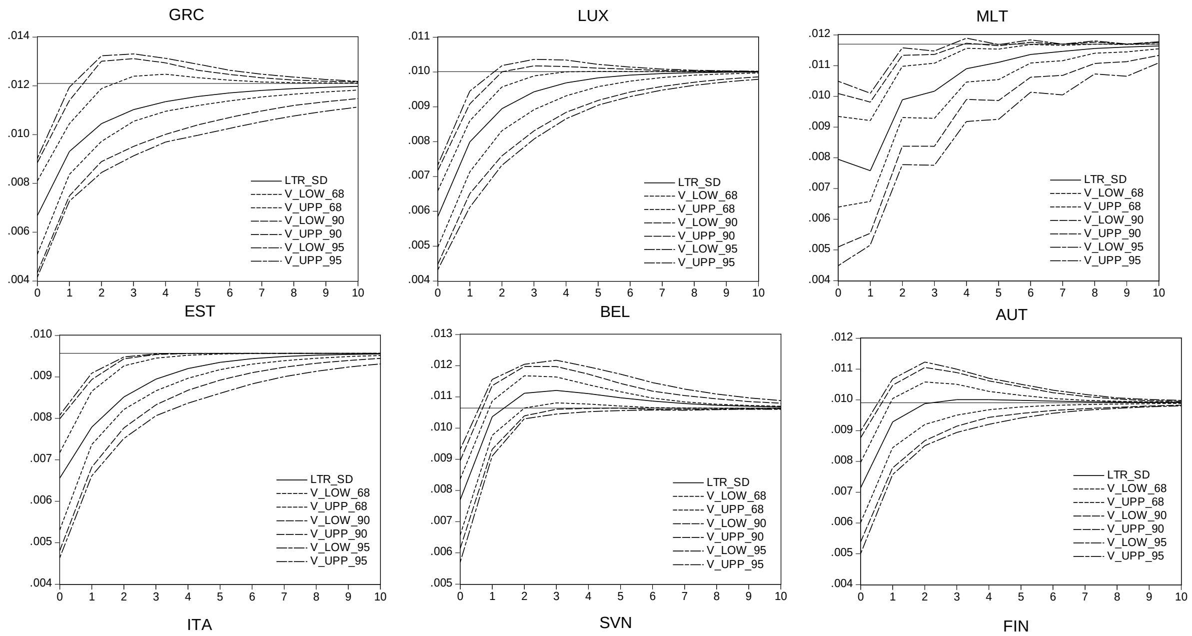


Figure 3: Countries with undershooting revenue responses



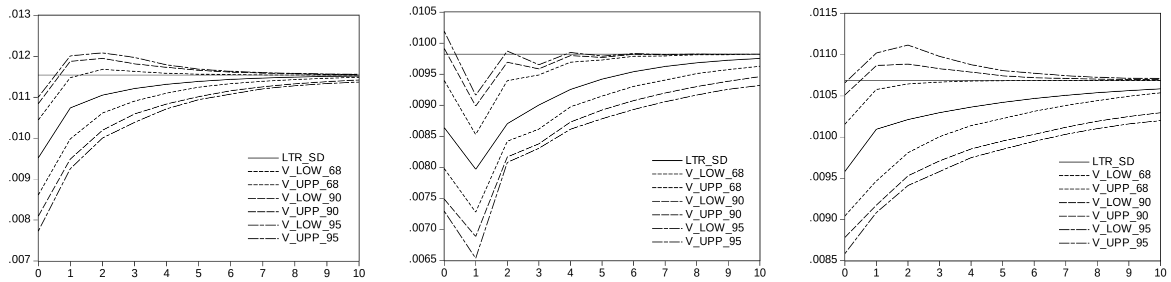
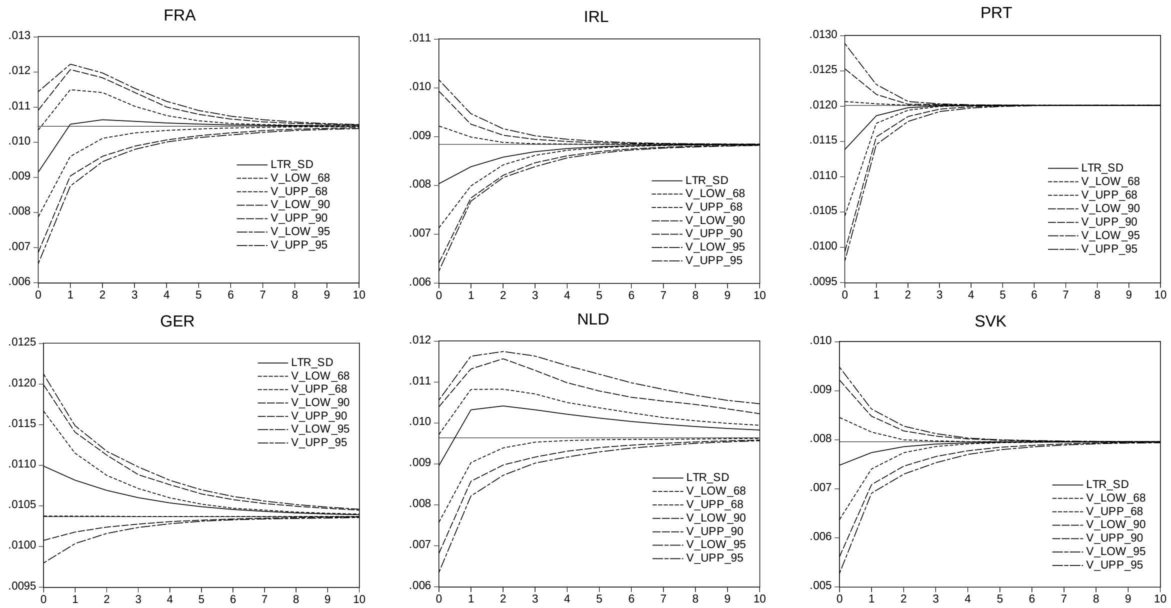


Figure 4: Countries with no significant dynamics in revenue responses



Undershooting revenue responses

For nine countries (Greece, Luxembourg, Malta, Estonia, Belgium, Austria, Italy, Slovenia and Finland) revenues contemporaneously *undershoot* their equilibrium level after a positive shock in aggregate income (see figure 3). The most pronounced case is Greece. Within the same year, a one percentage point (1 pp) shock in aggregate income increases revenues by only 0.67 pp. The contemporaneous reaction of revenues therefore significantly undershoots the progressive long-run equilibrium value of 1.21 pp. In the following periods after the shock, revenues increase rather slowly and reach their new equilibrium level within the second year. For the remaining countries the difference between short- and long-run responses decreases (as indicated by the ordering of the charts in figure 3) from 0.41 pp for Luxembourg to 0.11 pp for Finland. With 0.59 pp Luxembourg shows the lowest immediate tax response to changes in income and the proportional equilibrium value of 1.00 pp is reached within the third year after the shock. Malta and Estonia show very similar shapes. In the remaining countries – except for Slovenia - we observe faster adjustments and revenues reach the new equilibrium mostly already in the first period after the shock.

Static revenue responses

For six countries in our sample, namely France, Ireland, Portugal, Germany, the Netherlands and Slovakia no significant deviations between short- and long-run elasticities are found.[19] For Portugal, France and, to a lesser extent, also for Germany long-run revenue elasticities are found to be larger than unity. Ireland and Slovakia are the only countries with equilibrium elasticities below unity, indicating a rather degressive overall structure of their revenue systems.

Explaining differences in country-specific dynamics

Our results indicate that the dynamic reactions of revenues to changes in their macroeconomic base differ strongly across countries w.r.t. the degree of progressivity indicated by the long-run elasticity, the degree of volatility indicated by the difference between the long-run and the short-run elasticity and the adjustment pattern. In Cyprus, for example, we find a high long-run elasticity of 1.4 while the long-run elasticity in Slovakia equals only 0.8. In Spain, revenues overshoot substantially before converging to their long-term equilibrium, while we observe in Luxembourg a substantial undershooting directly after the shock.

These different reactions could result from a broad variety of factors. They might be linked to national differences in the composition of tax revenues, as for example corporate income taxes are likely to react far stronger in the short-run than social security contributions.[20] But not only the composition but as well the progressivity of the rate structure (e.g. in personal income or corporate income taxes) could play an important role – with more progressive rate structures leading to a higher elasticity in the respective tax category. Along similar lines, the composition of income growth could play an important role. If, for example, the wage-share in aggregate income is decreasing, the contribution from the generally more progressive personal income tax becomes less important. This could lead to a reduction of the respective revenue elasticity. Additionally the structure of the labour market and the economy might play an important role. In countries with more rigid wages and tighter employment protection, personal income tax and social security revenues are likely to react in the short run less strongly to economic shocks than in very flexible economies. Other important economic factors could be the degree of trade openness, the role of foreign or internal demand shocks or the importance of different sectors in an economy. The sensitivity of revenues can also depend on tax compliance. If negative income shocks increase credit constraints of economic subjects, tax compliance may fall and revenues might decline by more than income in the short term.

A thorough analysis of the economic determinants of the observed cross-national differences would hence require a broad analytical approach studying national tax and revenue systems in great detail, which goes far beyond the scope of this paper.

6 Revenue forecast evaluation

Section 5 presented evidence pointing to a potentially important role for dynamic revenue elasticities in several countries of our sample. Building on these findings we evaluate in this section, whether applying the identified dynamic elasticities could help to improve revenue forecasting. To this end, we apply “one-

[19] Estimates for the EA18 and EU27 aggregates show constant and close to proportional revenue elasticities. However, as the iid hypothesis is rejected with respect to autocorrelation for the underlying ECMs and the loading parameter are not found to be significant we do not present the impulse response functions for the EA 18 and EU 27 aggregates.
[20] See e.g. the analysis of elasticities by revenue category in Belinga, Benedek, de Mooij and Norregaard (2014).

step-ahead forecasts" for the current year to evaluate:[21] (i) whether the dynamic elasticities are able to outperform common benchmark forecasts; and (ii), whether they perform better than the static tax revenue elasticities applied for example by the European Commission.[22] For each country we refer to the dynamic model with the best fit, i.e. the model for which the iid hypothesis is not rejected and the value for the Akaike information criterion (AIC) is the lowest.

The accuracy of the forecasts is evaluated based on a relative approach, which reflects the current standard in the literature on time series models: we compare the performance of each forecast to that of a benchmark forecast, namely a random walk. An advantage of such relative evaluation procedures is that they generally reduce biases stemming from country-specific trends and outliers, and, therefore, make forecasts more comparable across countries. We refer to the mean absolute forecast errors (MAFE) as measure for accuracy to evaluate the performances of the different models for each country.[23] Finally, we subject differences in the accuracy measure to a statistical analysis by testing the null hypothesis of equal forecast accuracy of the different models based on the approach of Diebold and Mariano (1995).[24]

Initially we base our analyses on ex-post data from the annual macroeconomic database of the European Commission (AMECO). We focus on a sample from 1997-2013, a period for which data is available for all countries included. Testing forecast accuracy should ideally be based on real-time data, which could deviate substantially from ex-post data.[25] Therefore we also perform our analysis based on real-time data, which is taken from different vintages of the AMECO database. For a given year t we use real-time data that was available at the beginning of the year, i.e. data from the Spring Forecast of the European Commission in year t.[26] Forecast errors are then calculated as deviations from ex-post realizations. As real-time data is not available for all countries and all years, we had to exclude the early years and base the evaluation for real-time data on a sample covering only 2000 to 2013.

6.1 Results based on ex-post data

We start our revenue forecast evaluations with ex-post data (1997-2013). Table 1 reports mean absolute forecast errors (MAFE) in levels for the random walk. The figures presented for the static and dynamic

[21] The literature sometimes refers to current-year forecasts as "nowcasts".

[22] It has to be kept in mind that OECD revenue elasticities are computed with respect to the output gap, while our estimates are elasticities to GDP growth. However, differences resulting from these different bases are in general minor. In appendix C.1 the new (2014) and old (2005) OECD estimates and the elasticities underlying revenue projections for 2015 (Autumn Forecast 2014) and 2016 (Autumn Forecast 2015) of the European Commission are presented.

[23] The mean absolute forecast error is less sensitive to large deviations than e.g. the mean squared error. Moreover it is a rather intuitive measure and thus has become a standard in forecast evaluation.

[24] In a simple version, the Diebold and Mariano test is performed by regressing the difference of the loss functions (based on absolute errors) on a constant. To correct for heteroscedasticity and autocorrelation we use the HAC covariance matrix estimates obtained via the modified Bartlett kernel in line with Newey and West (1987), where the truncation lag is set automatically as proposed by Newey and West (1994).

[25] In some cases, the use of real-time data can be problematic. Cimadomo (2011) finds real-time data are eventually more vulnerable to creative accounting and fiscal gimmickry by governments and national statistical agencies, with the goal of meeting, for example, the SGP requirements in real time. In this context, it is often shown that the presence of strong fiscal rules and institutions tends to be associated with more accurate releases of fiscal data and fiscal projections by governments.

[26] Referring to the Spring Forecast of the current year is a rather conservative choice as in spring the available information for the fiscal "nowcast" of tax revenues of the current year is already relatively close to the ex-post realization compared to e.g. the ex-ante information available in the Autumn or Spring forecast of year t-1.

models are ratios of the corresponding random walk error. Hence, a ratio below unity indicates that the forecast performance of a given model is better than what could be expected using a random walk (RW).

In all 18 cases the mean absolute forecast errors of the dynamic model are lower than the errors of the RW forecast. In 17 of 18 cases (94%), they are lower than the RW forecast errors and the errors resulting from an approach applying static elasticities. Only for Italy, the static model generates lower errors than the dynamic one. On average the ECM mean absolute errors amount to only 41% of the RW errors, whereas the average of the errors of the static approach equals 53%. These findings could be seen as indication that applying the dynamic revenue elasticities estimated by us could indeed tend to reduce revenue forecast errors in most countries. In a next step, we test the significance of the differences statistically.

Table 1: Relative forecast accuracy (ex-post data)

Ex-post	**RW** MAFE	**Static** MAFE (ratio of RW MAFE)	**ECM**
AUT	0.025	0.439 **	**0.373** ***
BEL	0.018	0.605	**0.517** *
CYP	0.065	0.525 ***	**0.392** *** °
ESP	0.034	0.609 *	**0.501** *
EST	0.050	0.675 *	**0.432** ***
FIN	0.041	0.362 **	**0.326** **
FRA	0.022	0.475 *	**0.453** *
GER	0.024	0.539 ***	**0.512** ***
GRC	0.033	0.810	**0.495** °°
IRL	0.050	0.538 *	**0.451** *
ITA	0.034	**0.431** **	0.460 **
LTV	0.095	0.302 **	**0.247** **
LUX	0.027	0.913	**0.408** ** °°
MLT	0.055	0.523 *	**0.283** *
NLD	0.032	0.524	**0.503** *
PRT	0.041	0.521 **	**0.379** *** °°
SVK	0.065	0.462 ***	**0.404** ***
SVN	0.032	0.323 **	**0.259** ***

Note: RW model MAFEs are reported in levels while other presented figures are ratios of MAFE from a given model to the corresponding MAFE from a RW model. A ratio unity indicates that the MAFE for a given model is lower than the corresponding one from a RW model. Symbols ***, ** and * indicate the rejection of the null of the DM test, which states that the given MAFE is not significantly different from the corresponding MAFE from a RW model, at 1%, 5% and 10% significance levels, respectively.
Symbols °°°, °° and ° indicate the rejection of the null of the DM test, which states that the given MAFE from the ECM is not significantly different from the corresponding MAFE from the static model, at 1%, 5% and 10% significance levels, respectively.
Smallest MAFE is bold.
ITA: 1.08 is used as static elasticity.

On a 5% level of significance, the dynamic model performs significantly better than the RW for 11 (61%) out of 18 countries, whereas this does only hold for the static model in 9 (50%) out of 18 countries. In addition, for three countries (Greece, Luxembourg, Portugal), the dynamic model performs significantly more accurately than the RW and the static approach (on a 10% level this does also hold for Cyprus).

Overall the results based on ex-post data show that the random walk performs relatively poorly in forecasting revenues. Both alternative specifications seem superior to the RW - with a better overall performance of dynamic models. However, only for Greece, Luxembourg, Portugal and – to a lesser extent – also for Cyprus our analysis finds that the dynamic models significantly outperform static models.

Table 2: Relative forecast accuracy (real-time data)

Real-time	**RW** MAFE	**Static** MAFE (ratio of RW MAFE)	**ECM**	
AUT	0.023	**0.392** **	0.419 **	
BEL	0.020	**0.530**	0.593	
CYP	0.081	0.784	**0.754**	
ESP	0.035	**0.869**	1.327	
EST	0.047	**0.717** **	0.862	
FIN	0.047	0.425 **	**0.402** ***	
FRA	0.020	0.671	**0.597**	
GER	0.024	0.681	**0.523** **	°°
GRC	0.031	**0.558** *	0.596 *	
IRL	0.044	0.753	**0.749**	
ITA	0.027	0.653	**0.581** *	
LTV	0.103	0.673	**0.575**	°
LUX	0.032	**0.715** *	0.719	
MLT	0.034	**0.537** *	1.273	
NLD	0.032	0.676	**0.633**	
PRT	0.046	**0.619** **	1.133	
SVK	0.059	**0.584** ***	1.168	°°
SVN	0.030	**0.378** *	0.464	

Note: RW model MAFEs are reported in levels while other presented figures are ratios of MAFE from a given model to the corresponding MAFE from a RW model. A ratio unity indicates that the MAFE for a given model is lower than the corresponding one from a RW model.
Symbols ***, ** and * indicate the rejection of the null of the DM test, which states that the given MAFE is not significantly different from the corresponding MAFE from a RW model, at 1%, 5% and 10% significance levels, respectively.
Symbols °°°, °° and ° indicate the rejection of the null of the DM test, which states that the given MAFE from the ECM is not significantly different from the corresponding MAFE from the static model, at 1%, 5% and 10% significance levels, respectively.
Smallest MAFE is bold.
CYP, MLT, SVN: real-time data only available from SF2005 on.
EST: real-time data only available from SF2001 on.
LTV, SVK: real-time data only available from SF2003 on.
ITA: 1.08 is used as static elasticity.

6.2 Results based on real-time data

Table 2 presents the results of the tax revenue forecast evaluations for *real-time* data (2000-2013) based on mean absolute forecast errors (MAFE). For real-time data the forecast errors of the dynamic model are lower than the RW errors in 14 of 18 cases (78%). However, in only eight of those cases (44% of the total of 18 cases), the dynamic approach generates lower forecast errors than the static approach. On average the mean absolute forecast errors of the dynamic model amount to 74% of the RW errors, whereas the average of the errors of the static elasticity approach is only 62%. Hence it is less clear based on real-time data whether applying the dynamic revenues elasticities derived by us could indeed help to reduce revenue forecast errors. Furthermore the dynamic model significantly outperforms the

RW in only three (17%) out of the 18 countries analysed on a 5% level of significance, whereas the static model generates significantly lower errors in five cases (28%) out of the 18 countries analysed. In only two cases there are significant differences between the errors of the dynamic and the static model. For Slovakia, the static model performs significantly better than the dynamic approach (and the RW), whereas for Germany the dynamic model performs significantly better than the static model (and the RW). On a 10% level, this is also the case for Latvia. These results of the real-time data analysis also show that the benchmark random walk forecasts are generally harder to beat compared to an analysis based on ex-post data.

While the descriptive statistics show for the static as well as the dynamic approach smaller forecast errors than for the RW approach, we are in most cases (67%) not able to reject the null of equal forecast accuracy of the models (with a slightly stronger performance of the static models).

7 Conclusion

Based on country-specific error correction models we find evidence that dynamic revenue elasticities explain revenue developments significantly better than static elasticities in a majority of euro area Member States (12 out of the 18 countries analysed).[27] Dynamic relationships are most pronounced in Spain, Greece, Luxembourg, Malta and Cyprus. A second group of countries with somewhat less pronounced, but nevertheless still significant dynamics in the relationship between economic developments and public revenues includes Estonia, Belgium, Austria and Italy. Dynamic relationships exist but seem to play no strong role in Slovenia, Finland and Latvia. The differences between the short-run and the long-run elasticities (which are measures of the "volatility of a tax system") range from 0.7 (in the case of Spain) to 0.1 (as in the case of Latvia). In France, Ireland, Germany, Portugal, the Netherlands and Slovakia there is no evidence that tax elasticities are not static.

Especially for those countries with large differences between short- and long-run elasticities (i.e. Spain, Greece, Luxembourg, Malta and Cyprus), cyclical adjustment based on static tax elasticities is likely to be systematically biased.

Adjustment patterns between short- and long-run elasticities also differ strongly across countries. In nine of those 12 countries with evidence for dynamic revenue elasticities (Spain, Greece, Luxembourg, Malta, Cyprus, Estonia, Belgium, Austria, Italy, Slovenia, Finland and Latvia) the short-run elasticity is found below the long-run elasticity – leading to an undershooting of revenues after a shock in aggregate income in the short term. In Cyprus, Spain and Latvia on the other hand, short-run elasticities are significantly higher than long-run elasticities leading to an overshooting of revenues in the short term.

A comprehensive out-of-sample forecast evaluation based on an ex-post dataset leads to two findings: applying the identified dynamic elasticities (instead the frequently applied static ones) reduces revenue forecast errors for all euro area Member States except for Italy. For three of the five countries for which strongly dynamic elasticities are identified, the forecast evaluation shows that the dynamic model performs significantly better than static elasticities (Cyprus, Greece and Luxembourg). Moreover, the dynamic models are able to consistently outperform benchmark random walk forecasts in the euro area countries. Using real-time data, benchmark random walk forecasts are generally harder to beat and there is less evidence for the superiority of dynamic over static elasticities for current year forecasting.

[27] For Latvia this holds only within the 68% confidence intervals.

Taken together our findings indicate that the effects of applying dynamic revenue elasticities differ strongly by country, but could in several countries improve cyclical adjustment methods as well as revenue forecast performances – with the evidence being substantially stronger based on ex-post than based on real-time data.

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Appendices

A. Results: estimates, diagnostic checks and cointegration tests

Table A.1 (continued): Elasticities of total current revenues

Country	FIN(1)	FIN(2)	FRA (1)	FRA (2)	GER (1)	GER (2)	IRL(1)	IRL(2)	ITA (1)	ITA (2)
Sample (unadj.)	1975-2013	1975-2013	1978-2013	1978-2013	1970-2013	1970-2013	1985-2013	1985-2013	1980-2013	1980-2013
long run	*DOLS(NW)*		*DOLS(NW)*		*DOLS(NW)*		*DOLS(NW)*		*DOLS(NW)*	
gdp_t	**1.07** ***		**1.05** ***		**1.04** ***		**0.88** ***		**1.15** ***	
	0.02 °°°		*0.02* °°		*0.01* °°°		*0.01* °°°		*0.03* °°°	
c_{LR}	-0.94 ***		-1.03 ***		-1.09 ***		-0.49 ***		-1.90 ***	
	0.08		*0.15*		*0.10*		*0.05*		*0.17*	
short run	*OLS*	*OLS*	*OLS*	*OLS(NW)*	*OLS*	*OLS*	*OLS(NW)*	*OLS*	*OLS*	*OLS*
Δgdp_t	**0.96** ***	**0.99** ***	**0.88** ***	**1.00** ***	**1.07** ***	**1.10** ***	**0.82** ***	**0.80** ***	**0.95** ***	**0.97** ***
	0.06	*0.06*	*0.11*	*0.10*	*0.07*	*0.05* °	*0.12*	*0.10* °°	*0.09*	*0.08*
Δrev_{t-1}	0.03		0.12		0.04		-0.02		0.07	
	0.05		*0.08*		*0.05*		*0.09*		*0.08*	
ec^{rev}_{t-1}	**-0.17** *	**-0.22** **	**-0.25** *	**-0.32** ***	**-0.31** ***	**-0.28** ***	**-0.42** **	**-0.43** **	**-0.28** **	**-0.28** ***
	0.09	*0.09*	*0.13*	*0.09*	*0.11*	*0.10*	*0.19*	*0.18*	*0.10*	*0.10*
c_{SR}	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00
	0.01	*0.01*	*0.00*	*0.01*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.71*
ecm diagnostics										
R^2(adj)	0.91	0.91	0.82	0.86	0.92	0.93	0.77	0.78	0.88	0.87
LM ($\chi^2(1)$)	0.88	0.52	0.20	*0.04*	0.23	0.43	*0.02*	0.16	0.30	0.68
LM ($\chi^2(2)$)	0.59	0.81	0.07	*0.03*	0.45	0.67	*0.02*	0.37	0.42	0.90
BPG	0.99	0.66	0.54	0.57	0.59	0.96	0.42	0.18	0.89	0.77
JB	0.79	0.99	0.71	0.72	0.29	0.22	0.95	0.95	0.45	0.35
AIC	-4.40	-4.27	-5.75	-5.74	-5.29	-5.35	-3.93	-4.05	-4.71	-4.70

Note: Std. errors in italics. *, **, *** denote statistical significance at the 10%, 5% and 1% level against the hypothesis that the coefficient equals zero. °,°°, °°° denote statistical significance at the 10%, 5% and 1% level against the hypothesis of the single linear restriction that the coefficient equals one (Wald-test). Whenever there is evidence for serial correlation or heteroskedasticity in the residuals (at the 5% level of significance), the variance-covariance matrices are corrected with the Newey-West (NW) or White (W) approach to generate more reliable standard errors. *Long-run:* w use up to 1 lag and 1 lead of first differences of the DOLS regressors (estimates are not presented). *Short-run:* p-values are shown for ecm diagnostics. We use the Breusch-Godfrey Lagrange Multiplier (LM) approach instead of the Durbin-Watson test to test for serial correlation in the estimated residuals, as it allows to test for higher than AR(1) orders and is applicable in case of lagged dependent variables (Null: no serial correlation up to lag order 1 and 2). We use the Breusch-Pagan-Godfrey Lagrange Multiplier (LM) approach to test for the null hypothesis of no heteroskedasticity in the residuals against heteroskedasticity in the residuals explained by the independent variables of the regression. A Jarque-Bera test ist performed on the null of normality. In addtition the adjusted R^2 and the Akaike information criterion (AIC) is shown. *PRT:* The slight decoupling of revenues from GDP developments in 2013 is related to some noise in the model with additional endogenous lag (no normality). Therefore, we cut the sample in 2012 in 1a. *SVK:* According to large outliers in the first and in the last year of the original sample (1993-2013), we refer to 1994-2012 as sample range. *GRC:* Equation 1a and 2a include a financial crisis impulse in 2009. *GER:* A reunifiaction shift in 1991 was found insignificant in the long-run equation.

Table A.1 (continued): Elasticities of total current revenues

Country	LTV(1)	LTV(2)	LUX(1)	LUX(2)	MLT(1)	MLT(2)	NLD (1)	NLD (2)	SVK(1)	SVK(2)
Sample (unadj.)	1994-2013	1994-2013	1990-2013	1990-2013	1995-2013	1995-2013	1969-2013	1969-2013	1994-2012	1994-2012
long run	*DOLS*		*DOLS(NW)*		*DOLS*		*DOLS(NW)*		*DOLS*	
gdp_t	**0.98 *****		**1.00 *****		**1.17 *****		**0.96 *****		**0.80 *****	
	0.02		*0.02*		*0.04* °°°		*0.06*		*0.01* °°°	
c_{LR}	-1.06 ***		-0.83 ***		-1.26 ***		-0.49		-0.28 ***	
	0.05		*0.07*		*0.08*		*0.37*		*0.05*	
short run	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
Δgdp_t	**1.08 *****	**1.08 *****	**0.59 *****	**0.53 *****	**0.80 *****	**0.72 *****	**0.90 *****	**1.02 *****	**0.75 *****	**0.75 *****
	0.09	*0.08*	*0.08*	*0.10* °°°	*0.17*	*0.23*	*0.11*	*0.08*	*0.13* °°	*0.12* °°
Δrev_{t-1}	0.01		0.12		**-0.30 ****		0.14		0.01	
	0.09		*0.11*		*0.12*		*0.09*		*0.11*	
ec^{rev}_{t-1}	**-0.60 ****	**-0.54 ****	**-0.35 *****	**-0.38 *****	**-0.53 *****	**-0.70 *****	**-0.14 ****	**-0.13 ****	**-0.54**	**-0.54 ***
	0.27	*0.23*	*0.11*	*0.12*	*0.16*	*0.21*	*0.05*	*0.05*	*0.31*	*0.30*
c_{SR}	0.01	0.01	0.01	0.02	0.02	-0.01	0.14	-0.01	-0.01	-0.01
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.02*	*-0.01*	*0.01*	*0.01*	*0.01*
ecm diagnostics										
R^2(adj)	0.91	0.91	0.75	0.61	0.73	0.59	0.85	0.84	0.82	0.83
LM ($\chi^2(1)$)	0.54	0.64	0.96	0.36	0.14	0.35	0.31	0.99	0.51	0.68
LM ($\chi^2(2)$)	0.63	0.66	0.65	0.54	0.23	0.08	0.48	0.60	0.48	0.58
BPG	0.68	0.40	0.47	0.11	0.86	0.48	0.36	0.31	0.97	0.99
JB	0.54	0.71	0.88	0.25	0.18	0.25	0.86	0.97	0.48	0.48
AIC	-3.77	-3.87	-5.09	-4.70	-4.40	-3.84	-4.54	-4.54	-4.10	-4.23

Note: Std. errors in italics. *, **, *** denote statistical significance at the 10%, 5% and 1% level against the hypothesis that the coefficient equals zero. °,°°, °°° denote statistical significance at the 10%, 5% and 1% level against the hypothesis of the single linear restriction that the coefficient equals one (Wald-test). Whenever there is evidence for serial correlation or heteroskedasticity in the residuals (at the 5% level of significance), the variance-covariance matrices are corrected with the Newey-West (NW) or White (W) approach to generate more reliable standard errors. *Long-run:* w use up to 1 lag and 1 lead of first differences of the DOLS regressors (estimates are not presented). *Short-run:* p-values are shown for ecm diagnostics. We use the Breusch-Godfrey Lagrange Multiplier (LM) approach instead of the Durbin-Watson test to test for serial correlation in the estimated residuals, as it allows to test for higher than AR(1) orders and is applicable in case of lagged dependent variables (Null: no serial correlation up to lag order 1 and 2). We use the Breusch-Pagan-Godfrey Lagrange Multiplier (LM) approach to test for the null hypothesis of no heteroskedasticity in the residuals against heteroskedasticity in the residuals explained by the independent variables of the regression. A Jarque-Bera test ist performed on the null of normality. In addtition the adjusted R^2 and the Akaike information criterion (AIC) is shown. *PRT:* The slight decoupling of revenues from GDP developments in 2013 is related to some noise in the model with additional endogenous lag (no normality). Therefore, we cut the sample in 2012 in 1a. *SVK:* According to large outliers in the first and in the last year of the original sample (1993-2013), we refer to 1994-2012 as sample range. *GRC:* Equation 1a and 2a include a financial crisis impulse in 2009. *GER:* A reunifiaction shift in 1991 was found insignificant in the long-run equation.

Table A.1 (continued): Elasticities of total current revenues

Country	**SVN(1)**	**SVN(2)**	**EA18(1)**	**EA18(2)**	**EU27(1)**	**EU27(2)**	**PRT(1)**	**PRT(2)**	**PRT(1a)**
Sample (unadj.)	1995-2013	1995-2013	1995-2013	1995-2013	1995-2013	1995-2013	1977-2013	1977-2013	1977-2012
long-run	*DOLS*		*DOLS(NW)*		*DOLS(NW)*		*DOLS(NW)*		*DOLS(NW)*
$\mathbf{gdp_t}$	**0.98** ***		**0.95** ***		**0.97** ***		**1.20** ***		**1.20** ***
	0.02		*0.02* °°		*0.01* °°		*0.01* °°°		*0.01* °°°
c_{LR}	-0.78 ***		-0.36 *		-0.55 ***		-1.95 ***		-1.95 ***
	0.07		*0.18*		*0.13*		*0.05*		*0.05*
short run	*OLS*	*OLS*	*OLS(NW)*	*OLS(NW)*	*OLS(NW)*	*OLS(NW)*	*OLS*	*OLS*	*OLS(NW)*
$\Delta\mathbf{gdp_t}$	**0.86** ***	**0.83** ***	**0.92** ***	**0.95** ***	**1.00** ***	**1.03** ***	**1.04** ***	**1.14** ***	**1.07** ***
	0.08 °	*0.08* °°	*0.16*	*0.14*	*0.07*	*0.06*	*0.09*	*0.09*	*0.08*
Δrev_{t-1}	-0.13		0.03		0.04		0.08		**0.12** ***
	0.09		*0.05*		*0.03*		*0.06*		*0.03*
$\mathbf{ec^{rev}_{t-1}}$	**-0.35** *	**-0.36** *	**-0.02**	**-0.06**	**-0.16**	**-0.15**	**-0.84** ***	**-0.77** ***	**-0.82** ***
	0.19	*0.20*	*0.20*	*0.20*	*0.21*	*0.20*	*0.20*	*0.20*	*0.15*
c_{SR}	0.01 *	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.01	*0.00*	*0.01*	*0.01*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*
ecm diagnostics									
R^2(adj)	0.91	0.88	0.76	0.77	0.90	0.90	0.89	0.89	0.92
LM ($\chi^2(1)$)	0.15	0.79	*0.00*	*0.01*	*0.00*	*0.00*	0.46	0.09	0.88
LM ($\chi^2(2)$)	0.25	0.83	*0.01*	*0.02*	*0.01*	*0.01*	0.07	0.22	*0.02*
BPG	0.73	0.42	0.95	0.92	0.89	0.79	0.73	0.75	0.21
JB	0.38	0.54	0.69	0.64	0.75	0.70	*0.01*	0.30	0.53
AIC	-5.84	-5.70	-5.96	-6.04	-6.12	-6.21	-4.28	-4.20	-4.60

Note: Std. errors in italics. *, **, *** denote statistical significance at the 10%, 5% and 1% level against the hypothesis that the coefficient equals zero. °,°°, °°° denote statistical significance at the 10%, 5% and 1% level against the hypothesis of the single linear restriction that the coefficient equals one (Wald-test). Whenever there is evidence for serial correlation or heteroskedasticity in the residuals (at the 5% level of significance), the variance-covariance matrices are corrected with the Newey-West (NW) or White (W) approach to generate more reliable standard errors. *Long-run:* w use up to 1 lag and 1 lead of first differences of the DOLS regressors (estimates are not presented). *Short-run:* p-values are shown for ecm diagnostics. We use the Breusch-Godfrey Lagrange Multiplier (LM) approach instead of the Durbin-Watson test to test for serial correlation in the estimated residuals, as it allows to test for higher than AR(1) orders and is applicable in case of lagged dependent variables (Null: no serial correlation up to lag order 1 and 2). We use the Breusch-Pagan-Godfrey Lagrange Multiplier (LM) approach to test for the null hypothesis of no heteroskedasticity in the residuals against heteroskedasticity in the residuals explained by the independent variables of the regression. A Jarque-Bera test ist performed on the null of normality. In addtition the adjusted R^2 and the Akaike information criterion (AIC) is shown. *PRT:* The slight decoupling of revenues from GDP developments in 2013 is related to some noise in the model with additional endogenous lag (no normality). Therefore, we cut the sample in 2012 in 1a. *SVK:* According to large outliers in the first and in the last year of the original sample (1993-2013), we refer to 1994-2012 as sample range. *GRC:* Equation 1a and 2a include a financial crisis impulse in 2009. *GER:* A reunifiaction shift in 1991 was found insignificant in the long-run equation.

Table A.1 (continued): Elasticities of total current revenues

Country	**GRC(1)**	**GRC(2)**	**GRC(1a)**	**GRC(2a)**
Sample (unadj.)	1988-2013	1988-2013	1988-2013	1988-2013
long run	*DOLS(NW)*		*DOLS(NW)*	
gdp_t	**1.21** ***		**1.21** ***	
	0.05 °°°		*0.05* °°°	
c_{LR}	-2.02 ***		-2.02 ***	
	0.25		*0.25*	
short run	*OLS*	*OLS*	*OLS*	*OLS*
Δgdp_t	**0.76** ***	**0.86** ***	**0.67** ***	**0.80** ***
	0.17	*0.12*	*0.14* °°	*0.10* °
Δrev_{t-1}	0.20		**0.25** *	
	0.17		*0.14*	
ec^{rev}_{t-1}	**-0.13**	**-0.11**	**-0.17** **	**-0.15** *
	0.09	*0.09*	*0.08*	*0.08*
c_{SR}	0.01	0.02 **	0.02 *	0.02 ***
	0.01	*0.01*	*0.01*	0.01
i2009			-0.08 ***	-0.08 **
			0.03	*0.03*
ecm diagnostics				
R^2(adj)	0.71	0.69	0.81	0.77
LM (χ^2(1))	0.16	0.16	0.55	0.13
LM (χ^2(2))	0.24	0.24	0.21	0.05
BPG	0.74	0.55	0.50	0.40
JB	0.33	0.61	0.86	0.81
AIC	-4.09	-4.09	-4.44	-4.32

Note: Std. errors in italics. *, **, *** denote statistical significance at the 10%, 5% and 1% level against the hypothesis that the coefficient equals zero. °,°°, °°° denote statistical significance at the 10%, 5% and 1% level against the hypothesis of the single linear restriction that the coefficient equals one (Wald-test). Whenever there is evidence for serial correlation or heteroskedasticity in the residuals (at the 5% level of significance), the variance-covariance matrices are corrected with the Newey-West (NW) or White (W) approach to generate more reliable standard errors. *Long-run:* we use up to 1 lag and 1 lead of first differences of the DOLS regressors (estimates are not presented). *Short-run:* p values are shown for ecm diagnostics. We use the Breusch-Godfrey Lagrange Multiplier (LM) approach instead of the Durbin-Watson test to test for serial correlation in the estimated residuals, as it allows to test for higher than AR(1) orders and is applicable in case of lagged dependent variables (Null: no serial correlation up to lag order 1 and 2). We use the Breusch-Pagan-Godfrey Lagrange Multiplier (LM) approach to test for the null hypothesis of no heteroskedasticity in the residuals against heteroskedasticity in the residuals explained by the independent variables of the regression. A Jarque-Bera test ist performed on the null of normality. In addtition the adjusted R^2 and the Akaike information criterion (AIC) is shown. *PRT:* The slight decoupling of revenues from GDP developments in 2013 is related to some noise in the model with additional endogenous lag (no normality). Therefore, we cut the sample in 2012 in 1a. *SVK:* According to large outliers in the first and in the last year of the original sample (1993-2013), we refer to 1994-2012 as sample range. *GRC:* Equation 1a and 2a include a financial crisis impulse in 2009. *GER:* A reunifiaction shift in 1991 was found insignificant in the long-run equation.

Table A.2. Johansen System Cointegration Test (rank test)

	Sample (adj.)	CE	Lags	Null	Trace statistic
AUT	1978-2013	restricted constant	1	None	2,747 ***
				At most 1	6,281
	1977-2013	restricted constant	0	None	1,030 ***
				At most 1	7,799 *
BEL	1972-2013	restricted constant	1	None	2,664 ***
				At most 1	6,309
	1971-2013	restricted constant	0	None	9,591 ***
				At most 1	4,323
CYP	1997-2013	restricted constant	1	None	1,413
				At most 1	3,326
	1996-2013	restricted constant	0	None	3,265 ***
				At most 1	3,662
ESP	1997-2013	restricted constant	1	None	1,320
				At most 1	3,450
	1996-2013	restricted constant	0	None	4,889 ***
				At most 1	4,952
EST	1995-2013	restricted constant	1	None	1,884 *
				At most 1	4,449
	1994-2013	restricted constant	0	None	4,037 ***
				At most 1	3,977
FIN	1977-2013	restricted constant	1	None	1,359
				At most 1	4,632
	1976-2013	restricted constant	0	None	3,247 ***
				At most 1	2,719
FRA	1980-2013	restricted constant	1	None	2,253 **
				At most 1	5,438
	1979-2013	restricted constant	0	None	9,604 ***
				At most 1	6,324
GER	1972-2013	restricted constant	1	None	3,301 ***
				At most 1	9,338 **
	1971-2013	restricted constant	0	None	9,177 ***
				At most 1	9,369 **
	1972-2013	none	1	None	2,549 ***
				At most 1	1,918
	1971-2013	none	0	None	8,394 ***
				At most 1	1,747
GRC	1990-2013	restricted constant	1	None	2,256 **
				At most 1	5,013
	1989-2013	restricted constant	0	None	4,176 ***
				At most 1	1,388
IRL	1987-2013	restricted constant	1	None	1,959 *
				At most 1	4,047
	1986-2013	restricted constant	0	None	3,293 ***
				At most 1	5,126
ITA	1982-2013	restricted constant	1	None	1,856 *
				At most 1	3,036
	1981-2013	restricted constant	0	None	4,848 ***
				At most 1	3,686
LTV	1996-2013	restricted constant	1	None	1,478
				At most 1	6,771
	1995-2013	restricted constant	0	None	2,674 ***
				At most 1	5,437

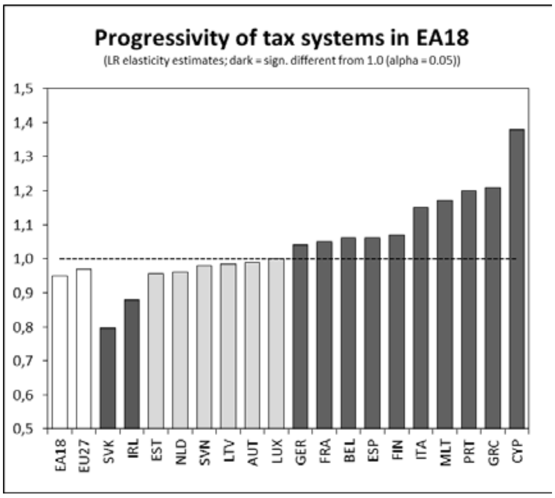
Note: ***, **, *denotes rejection of the null hypothesis at the 0.01, 0.05, 0.10 level of significance. MacKinnon, Haug, and Michelis (1999) p-values.

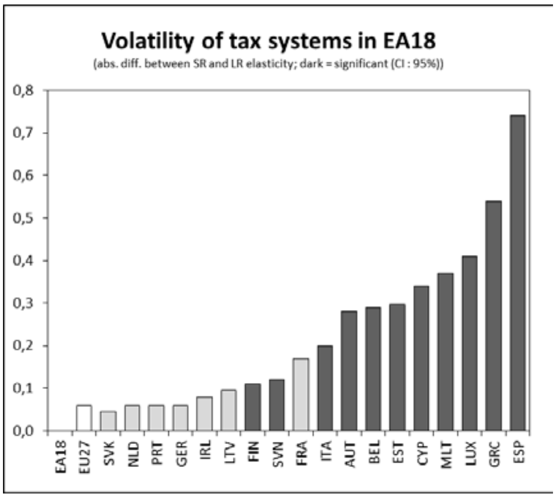
Table A.2 (continued) Johansen System Cointegration Test (rank test)

	Sample (adj.)	CE	Lags	Null	Trace statistic
LUX	1992-2013	restricted constant	1	None	2,250 **
				At most 1	7,375
	1991-2013	restricted constant	0	None	4,803 ***
				At most 1	5,529
MLT	1997-2013	restricted constant	1	None	1,855 *
				At most 1	3,150
	1996-2013	restricted constant	0	None	3,794 ***
				At most 1	1,203 **
	1997-2013	none	1	None	1,443 **
				At most 1	0,103
	1996-2013	none	0	None	2,517 ***
				At most 1	0,264
NLD	1971-2013	restricted constant	1	None	3,374 ***
				At most 1	7,390
	1970-2013	restricted constant	0	None	1,017 ***
				At most 1	6,623
PRT	1979-2013	restricted constant	1	None	2,894 ***
				At most 1	1,317 ***
	1978-2013	restricted constant	0	None	5,408 ***
				At most 1	1,286 ***
	1979-2013	none	1	None	1,575 **
				At most 1	0,000
	1978-2013	none	0	None	3,629 ***
				At most 1	0,260
SVK	1995-2013	restricted constant	1	None	1,933 *
				At most 1	7,584 *
	1994-2013	restricted constant	0	None	3,027 ***
				At most 1	2,719
SVN	1997-2013	restricted constant	1	None	1,970 *
				At most 1	7,742 *
	1996-2013	restricted constant	0	None	2,726 ***
				At most 1	5,463
EA18	1997-2013	restricted constant	1	None	1,577
				At most 1	5,368
	1996-2013	restricted constant	0	None	2,773 ***
				At most 1	1,304
EU27	1997-2013	restricted constant	1	None	2,029 **
				At most 1	6,590
	1996-2013	restricted constant	0	None	2,401 **
				At most 1	1,241

Note: ***, **, *denotes rejection of the null hypothesis at the 0.01, 0.05, 0.10 level of significance. MacKinnon, Haug, and Michelis (1999) p-values.

B. Progressivity and volatility of tax systems





C. Elasticities underlying revenue projections in euro area countries

Table C.1: Aggregate tax elasticities underlying revenue projections

Country	OECD / European Commission		EC AF(2014)	EC AF(2015)
	new (2014)*	old (2005)		
CYP	1.18	0.95		
NLD	1.15	0.88	1.3	0.6
EST	1.10	0.74	1.4	0.8
ITA**	1.08	1.09	1.5	0.8
IRL	1.05	1.00	0.4	0.7
BEL	1.03	0.94	1.0	1.0
ESP	1.03	1.00	1.1	1.1
MLT	1.02	0.86	1.2	0.1
AUT	1.02	0.87	1.1	1.0
LUX	1.01	1.06	1.0	1.0
FRA	1.00	0.89	1.1	1.0
SVN	0.99	0.91	0.1	-0.1
SVK	0.99	0.77	1.0	-0.6
GER	0.98	0.89	1.0	1.0
PRT	0.95	0.92	0.6	
GRC	0.94	1.00		
FIN	0.94	0.75	0.8	1.1
LTV	0.92	0.73	1.0	0.8
EA18***	1.02	0.90	1.0	0.9

*Notes:*Calculations follow the methodology in Mourre et al. (2013). The aggregate tax revenue-to-output gap elasticity is derived as the weighted sum of the product of tax-to-base and base-to-output gap elasticities estimated by the OECD (2014) for each tax category. The OECD weights each tax category with its share in GDP, whereas EC refers to the average (2002-2011) share of each tax category in total revenues. The presented estimates follow the EC methodology. **Alternative estimation for ITA is 1.05. ***We calculated the mean for EA18. For the autumn forecast (2014) we refer to the EA16 elasticity. For AF(2015) Lithuania is included in EA16 and Portugal excluded. The comparison between the elasticities derived from European Commission's forecast and the OECD's elasticities should be made with care. While the first two are net elasticities to GDP growth, the latter are, strictly speaking, computed with respect to the output gap. Differences are in general minor.*

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