



Spoor A3a1:

Stamp Duties Forecasting Models Based on Intra-Annual Data

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Stamp Duties Forecasting Models Based on Intra-Annual Data

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Abstract. This paper addresses the issue of providing timely forecasts for disaggregated fiscal data. In the aftermath of the 2008-2009 crisis governments have become increasingly aware of the importance to generate trustworthy, time-consistent budget forecasts. Recently, several papers (Onorante et.al., 2008; Pedragal & Perez, 2010; Hallet et.al., 2012. Ghysels & Ozkan, 2012) showed that using intra-annual data can increase forecasting performance. In addition, these models can provide governments with “early warning signals”. A second strand of literature (Lütkepohl, 2010; Asimakopulos et.al., 2013) recognizes that aggregating the forecasts for different expenditure and revenue components reduces the forecast error of the resulting budget deficit. Unfortunately, little evidence is available concerning the best models for specific revenue categories like stamp duties or inheritance taxes.

In this paper we contribute to the literature by modeling the regional revenues of stamp duties using quarterly and monthly data covering the time period 1994-2013. More than 60 models were tested, including a-theoretical AR and (E(G))ARCH models, and more theory driven DL, ADL, VAR, VEC models. In addition, combination forecasts were produced. Forecast horizons vary from one month ahead to 2 years ahead; model selection is based on the Aikake Information Criteria and on theoretical arguments, stemming from housing models. Performance evaluation is based on MPE, MAPE and RMSPE of both in-sample as well as out-of-sample forecasts..

In general, multivariate models show lower in-sample forecasting errors than univariate models. Based on the out-of-sample performance, theory driven models outperform the least complex models for shorter forecasting horizons. However, with forecasts heading for 2 years the outperformance of the more advanced models is less convincing. In addition, the results reveal that combination forecasts strongly enhance the accuracy of stamp duties revenues forecasting models. In general, the results are in line with the findings of Favero & Marcellino (2005) : simple forecasting models and combined forecasts outperform more complicated specifications.

Keywords: Time-series models, forecasting, combination forecast, tax revenues, government budget

JEL-Classification: C22, C32, C51, C52, C53, H68, H72

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1 Introduction

Each Spring, Euro area Member States submit their Stability Programs (SP) to the EC and the Council of the EU. This part of the preventive arm of the Stability and Growth Pact has become a central tool for the implementation of the European fiscal surveillance framework. The main function of the SP is to allow the EC to assess whether Member States succeed in reaching their medium-term budgetary objectives (MTOs), and if not, whether they are implementing adjusting policies to reach the targeted deficit and debt levels.

Though the EU- Member States have been formulating SP for more than 15 years, recent legislation has urged them to invest even more in tools and methods to strengthen fiscal surveillance. Directive 2011/85/UE of the EU Council explicitly demands the fiscal plans to be based on the most realistic macroeconomic and budgetary forecasts possible (EC,2011; ESM Treaty, 2012). It requires a study of the main fiscal variables based on different assumptions relating to growth and interest rates. The Directive forces to adopt minimum standards with regard to accounting, statistics, forecasting, numerical fiscal rules, medium-term budgetary frameworks and transparency. Since May 30 2013 the Two Pack-regulations wants EU-Member States to apply these standards not only to the Spring SP, but also to the draft of the next year's budgetary plan which has to be transferred to the EC mid-October.

In addition, due to the trend towards increasing fiscal decentralization across most of the EU countries, more attention is given to the budgetary outcomes of the subnational governments (Eyraud & Badia, 2013; European Commission, 2012). Whereas the efficacy of the SP used to be mainly the responsibility of a country's central government, the EU-Six Pack regulation now explicitly asks for designing fiscal rules for subnational authorities (Van Hecke, 2013). This regulation especially affects Belgium, which is generally acknowledged to show one of the most far-reaching levels of decentralization in the EU. Six constitutional reforms gradually transformed the Belgian unitary State into a federal state made up of three tiers of subnational government (regions and communities; provinces; municipalities). The 2001 State reform resulted in a considerable increase in the tax autonomy of the regions. In 2014 these governments had full taxing powers concerning property taxes, traffic taxes, stamp duties, inheritance and gift taxes and a few minor taxes. For the Flemish region, these regional taxes amount up to 19.7% of the region's revenues in 2014 (Rekenhof, 2014). As such, to safeguard the general budgetary targets, these revenues deserve to be monitored carefully .

Yet, with the exception of the property taxes, these regional taxes are still collected by the federal government agencies. Consequently, the Flemish government receives its tax projections from the federal government. Due to lacking information, the regional government is not able to determine underlying trends and determinants. However, starting from January 1 2015 the Flemish government shall take over the tax collec-

tion for the stamp duties and the inheritance taxes. It therefore felt the need to invest in developing forecasting models for both these taxes.

In this paper we model the regional revenues of stamp duties using quarterly and monthly data covering the time period 1994-2013. More than 60 models were tested, including a-theoretical AR and (E(G))ARCH models, and more theory driven DL, ADL, VAR, VEC models. In addition, combination forecasts were generated. For each of the models forecast horizons vary from one month ahead to 2 years ahead, offering now casts next to medium term forecasts. Model selection is based on the Aikake Information Criteria and on theoretical arguments, stemming from housing models. MPE, MAPE and RMSE of both in-sample as well as out-of-sample forecasts were produced to evaluate the models.

The paper is organized as follows: in the next section we discuss forecasting models for tax revenues; section 3 briefly presents the Flemish stamp duties legislation; section 4 discusses the additional data used in the forecasting models; section 5 is the methodological section; section 6 presents the results and section 7 provides conclusions.

2 Forecasting Tax Revenues

As the purpose of this paper is to provide timely prospects for the Flemish stamp duties revenues, the literature on relevant forecasting models was screened. A general observation is that fiscal forecasts predominantly apply to deficits, total expenditures and total revenues (Favero & Marcellino, 2005; Onorante et.al., 2010; Pedregal & Perez, 2010; Ghysels & Ozkan, 2012; Aspergis & Cooray, 2013). Silvestrini et.al. (2008); Buettner & Kauder (2010) and Asimakopoulos et.al. (2013) test forecasting models for more detailed revenue categories, but at the most disaggregated level, taxes are still clustered into 4 broad groups (e.g. income taxes, sales taxes, corporate taxes and other less important taxes). No specific models were found regarding stamp duties revenues.

Buettner & Kauder (2010) reviewed the revenue forecasting methodology used by 14 OECD countries, including Belgium. Corporate taxes and income taxes are mostly estimated in an indirect way, i.e. based on macroeconomic aggregates like GDP, national income or income from entrepreneurial activity. In Belgium, Austria and Canada the forecasts of the macroeconomic aggregates are exogenous, but in countries like the UK or the Netherlands they are part of macroeconomic recursive models. These iterative models are also used by the IMF, OECD, ECB, EC, CBO. Fiscal variables are simultaneously determined with economic growth, inflation and other macroeconomic tax base determinants. In these models revenue projections $E_t(R_{t+j})$ in year t at horizon j are based on two main determinants: how do tax revenues react when the tax base TB changes and what will be the effect of policy measures or specific shocks (P):

$$E_t(R_{t+j}) = \varepsilon_{t-x} E_t(TB_{t+j}) + P_{t+j}$$

$$E_t(TB_{t+j}) = \alpha_{1,t-x} TB_t + \alpha_{2,t-x} P_t$$

Whereas the tax elasticity (ε_{t-x}) is currently generated by means of macroeconomic simulations, through regression analysis or derived from the detailed information on the distribution of income and revenue, policy outcomes are far more dependent on the judgment of the analyst (Leal et al. 2007). These elasticity models are usually built with yearly or quarterly national account data and provide forecasts for the government in general, rather than for the underlying government levels.

Though these macroeconomic models are useful to generate medium term prospects, policy makers also need forecasting models on a much more detailed level and for much shorter time horizons. In the case of the Flemish government for instance, revenue forecasts for the regional taxes are needed. These should enable policymakers to prepare the year $t+1$ budget prognosis asked for by the EC mid-October in year t . Next, forecasts for 1 to 2 years ahead are necessary to monitor how the regional governments fit in the MTO of the SP.

For excise taxes, or taxes only weakly related to the macroeconomic aggregates, trend extrapolation based on tax revenues of former years and vector-autoregressive (VAR) models seems to be the dominant practice (Buettner & Kauder, 2010).

Regarding forecasting performance, Favero & Marcellino (2005) conclude that the outcome of simple time series models and pooled forecasts outperform more complicated specifications. More specifically, they compare the Random Mean Squared Error (RMSE) of 8 models (autoregressive moving average models (ARMA), one and two lag VAR, single country structural models, multiple country structural models, pooled forecasts based on the mean and the median of the forecast of all models, Random Walk model (RW)). The analysis applies for France, Germany, Italy and Spain and is based on OECD-data collected at semi-annual frequency, for the period 1981-2001. The one step ahead forecasts of the total receipts show that the RW model generally performs the best. Except for Spain the two lag VAR model produces the largest RMSE. Comparable results are presented for the two step ahead forecasts.

Buettner & Kauder (2010) test the performance of the models used in 14 OECD countries to forecast 4 groups of tax revenues. They find the largest mean forecast errors for Canada and the Netherlands. The forecast errors for Belgium are higher than average, but estimates still are quite accurate, according to the standard deviation. Ten out of fourteen countries show negative means, indicating underestimation. The analysis further reveals that forecasting precision is significantly influenced by how far ahead tax prospects (= time span) are generated and by the number of taxes in the tax system. Precision increases in case the forecasts are calculated by an independent agency instead of the Ministry of Finance. The interactions for tax type and time span, reveal that especially corporate taxes become more hard to forecast when the analysis is meant to generate prospects for longer periods ahead. Using endogenous macroeco-

conomic models only significantly decreases the dispersion of the forecast errors in case of the corporate taxes.

When forecasting specific tax revenues for policymaking purposes, the following additional issues are important. First, overprediction is much more harmful than underprediction. A lot of studies confirm conservative forecasting strategies, pointing to the forecaster's loss-aversion (Kroll, 2011). Yet, Bretschneider and Schroeder (1988), Gentry (1989), Feenberg, Gentry, Gilroy, and Rosen (1989), Rogers and Joyce (1996) argue that the political and administrative costs associated with overestimating are greater than for underestimating tax revenues. Systematic overprediction is an important criterion when choosing the appropriate models to avoid the structural derailment of the budget.

Second, for policymaking purposes, models are needed, that allow for timely corrective actions (Vlaams Parlement, 2013). To provide governments with "early warning signals", models should be tested using intra-annual data rather than annual ESA95 Economic Accounts data. Recently, several papers (Onorante et.al., 2008; Pedragal & Perez, 2010; Hallet et.al., 2012 and Ghysels & Ozkan, 2012) address the performance of models using intra-annual data. Pedragal & Perez (2010) tested the performance of 4 moving sum models and 4 flow models mixing annual and quarterly ESA95 data with monthly cash accounts on a dataset covering 1984-2007 subsets of EU countries. Next to the cash deficit, aggregate indicators of total revenues or expenditures were targeted by the models. Comparison of the models' RMSE with that of a quarterly (QRW) and an annual random walk (ARW) model showed that all models with intra-annual updating outperform the ARW and show superior outcomes than the QRW model. The moving sum models and the flow models produce fairly similar results. Onorante et al. (2010) construct a state space model, bringing together 2 different models. The first one is an Error Correction Model (ECM) to explain annual fiscal indicators (deficit, total revenues, total expenditures all expressed as % of GDP); the second one is an appropriate model for the intra-annual indicator variables. As such the annual forecasts produced by this model are based on recent observations that enter the dataset from the moment they are available. Next to this model an AR1 model and a two-step mixed model are tested and compared to the ARW model using data for 8 EU countries using data for the period 2004-2007. The results indicate that the mixed data models generally dominate the ARW and AR1 model for the three budgetary indicators. The same conclusions hold for the estimations concerning the Belgian total revenues.

Finally, post-2009 forecasting models must somehow cope with the shifts in the underlying macroeconomic parameters due to the great recession (Ng & Wright, 2013). They should identify transitory from permanent tax base affecting events and indicate whether revenues are returning to the previous trend or not.

3 The Flemish Stamp Duties

Stamp duties represent the Flemish region's most important regional tax. According to the Flemish Budget this tax was expected to yield €1,952 billion in 2013, or 37.6% of total revenues out of regional taxes. The tax is levied on different types of transactions, but the taxes collected at the moment of the acquisition of property are generating most of the revenues. Stamp duties were transferred from the federal government in 1989 but only from 2001, the Flemish government was in charge of the tax base as well as the tax rate and the corresponding revenues. Since 2001 the Flemish government on several occasions launched stamp duties reforms. In 2002 the tax rate was reduced from 12.5% to 10 % for regular sales of property and from 6% to 5% for sales of property characterized by an imputed rent inferior to €745. From 2001 and onwards, citizens were allowed to compensate the stamp duties paid in the past up to €12500, when buying the next property. At the same moment, tax base reductions were introduced for property meant to be a family's principal place to live. In 2007 the government increased these tax base reductions from €12500 to €15000. Since 2009 citizens were given an extra tax base reduction on top of the existing ones in case the home was financed by means of a mortgage. Figure 1 illustrates the increasing trend in the revenues for the period 2004-2008; the financial crisis impact is mostly observed in 2009, but since 2010 the trend has recovered its previous path.

Although the stamp duties are a regional tax, up to now, fiscal revenues were projected by the federal Ministry of Finance. A specific tax elasticity was used for 8 tax categories, among which the stamp duties. Revenues forecasts were derived from the underlying trend of a small set of exogenous macroeconomic variables (Lenoir & Valenduc, 2006).

4 Data

For the purpose of comparison, estimations are invariably based on data covering the 20 year period 1994-2013, though for some of the variables longer time series are available. We work with a set of disaggregated monthly and quarterly data of fiscal and macro-economic variables.

More specifically, the fiscal data on Stamp Duties (SD) were made available by the Finance Federal Public Service. All other series are part of the database of the National Bank of Belgium. We transform the data by taking the logarithm of the Stamp Duties, GDP, Saving Deposits (SDP) and the value of stocks held by individual investors (STOCKS). Moreover, we make use of consumer confidence (CONF), mortgage rates (IR), and unemployment rates (UR). Furthermore, we interpolate GDP, saving deposits and the value of stocks held by individual investors for the analysis to obtain monthly data as these series are only available on a quarterly basis.

Out-of-sample forecasts are generated based on both monthly and quarterly data for the evaluation period 2007-2013. For the models estimated with monthly data 24 step ahead forecasts were generated. When using the quarterly data 8 step ahead are computed. In addition, higher frequency forecasts are also aggregated to quarterly and yearly data when examining the performance of the models.

5 Methodology

Several types of models were explored. First a-theoretical univariate AR and (E(G))ARCH time series models were estimated. Based on that outcome, more theory driven multivariate ADL, VAR and VEC models were tested. In addition, models with lagged macro-economic variables and without autoregressive terms were computed. Due to the logarithmic transformation of the variables, the coefficients of these models can be interpreted as the elasticity of the explanatory variables such as GDP on the stamp duties revenues. We therefore refer to these models as the “elasticity models”. Following Stock & Watson (2004) combination forecasts were generated to further increase forecasting accuracy. Furthermore, conform the recommendation of Stock and Watson simple weights such as average for combination of the forecasts were adopted (Stock & Watson, 2004, p. 428).

Model selection was based on the in-sample performance which was indicated by the Akaike Information Criteria (AIC), the mean percentage error (MPE), the mean absolute percentage error (MAPE), and the root mean squared percentage error (RMSPE). The same set of evaluation criteria are applied to identify the out-of-sample performance of the models. The MPE error is informative about the over- or underestimation of the forecasts over the complete evaluation period 2007-2013. Especially, overestimation is very precarious in a budgeting context. The MAPE shows how much the forecast deviate in absolute terms from the realized revenues. Contrary to the MPE, there can be no cancelling out of under- and overestimations. Finally, the RMSPE is reported. This measure more strongly penalizes large deviations, which is desirable when forecasting tax revenues.

While using both monthly and quarterly data, the performance of the models can be compared using different frequencies for the models. The maximum lag length is limited to three years, corresponding to 12 lags for quarterly data, or 36 lags for monthly data. When performing out-of-sample forecasts with the ADL and Elasticity models, additional estimations of the future values of the macro-economic variables in the models are needed. When GDP is included, the data come from the GDP “Spring” and “Autumn” forecast of the European Commission. Other series were extended based on the most effective AR model, in accordance with the AIC.

A three step procedure was followed to come up with the best performing models. The method is illustrated using quarterly data. First, the model is selected with the appropriate number of lags following the AIC. In fact, this process is iterated when an

extra variable is added, and this is done for all different techniques. This results in 60 different models chosen on the goodness of the fit and parsimoniousness. Second, out-of-sample forecast are performed for the evaluation period 2007q1-2013q4, going from one period ahead forecast, up to a forecasting horizon of two years. The starting point is the estimation sample covering the period 1994q1 up to 2004q4; this is gradually expanded with one quarter at a time. Per model, out-of-sample forecast from all different horizons (t-1,t-2,...,t-8) for every period in the evaluation sample were generated. As a result, the average deviation of the forecasted and realized revenues for the period 2007q1 to 2013q4 was calculated, and this was done for all different forecasting horizons separately. Third, the forecasts were then aggregated on an annual basis and the model with the lowest RMSPE was selected for a horizon of one year (short term) and two year (medium term) per technique. This results in a selection of 10 models using six different techniques. In addition, a combination forecasts based on the best performing models to predict the tax revenues is set up.

6 Empirical Results

Table 1 and 2 show the empirical results for the forecasted stamp duties revenues using respectively quarterly and monthly data. Both tables show, for the different types of models, the root mean squared percentage error (RMSPE), the mean absolute percentage error (MAPE) and the mean percentage error (MPE) for the out-of-sample forecasting period and the in-sample period. The first 2 criteria calculate the average forecast accuracy, the latter the average level of over- or underestimation of the forecasts. For the out-of-sample forecast period a distinction was made between 1-year ahead forecasts (Step 1) and 2-year ahead forecasts (Step 2). The 1-year and 2-year ahead forecasts are calculated by aggregating quarterly and monthly forecasts into yearly forecasts. See Section 5 for detailed explanations on how the forecasting models are selected.

Looking at the individual forecasting models in Table 1 (model 1 to 10), ADL models perform the best based on the RMSPE measure. Only the simple autoregressive model with one lag seems to slightly outperform the best performing ADL model for the 2-year ahead forecasts. ARCH models and the more advanced multivariate models (especially VEC) perform badly with RMSPE measures up to 2-3 times as high as the best performing model, especially for the 1-year ahead forecasts. We further see that out of sample forecast accuracy deteriorates substantially for the medium term forecast horizon (2nd year). If we look at the last three rows of the table, we see that combination forecasts generally improve the forecast accuracy for both horizons. More specific, combining all models delivers the highest accuracy for the medium term forecast horizon. Combining all AR, ADL and ELAST models improves the short-term forecast accuracy. A possible explanation is that combination forecasts offer 'diversification gains' as negative and positive forecast errors are averaged out (see,

among others, Timmermann, 2006)¹. In general, the results are in line with findings of Favero & Marcellino (2005) that simple forecasting models and combined forecasts outperform more complicated specifications.

The results based on the MAPE measure are more or less consistent with the results based on the RMSPE measure, though the outperformance of the combination forecasts is more outspoken. The latter confirms that combining individual forecasts result in less dispersed forecasts. We further see that the elasticity models substantially improve in performance (relative to using the RMPSE measure), which suggests that elasticity models generate less extreme forecasts².

It is also instructive to look at the MPE measure as it gives us an indication whether the forecasting model systematically over predicts (positive MPE) or under predicts (negative MPE) stamp duties. VEC models generally over predict stamp duties which is undesirable from a policy point of view. Mean pricing errors are close to zero for the combination forecasts. Also for AR models the MPE is rather low. (EG)ARCH models and ADL models generally under predict the stamp duties and hence are more conservative.

Finally, the results for the in-sample forecasts are in line with the results for the out-of-sample forecasts. ADL models and combination forecast perform the best.

In general, we can conclude that the combination forecasts outperform in terms of forecasting accuracy. An additional advantage of the combination forecasts is that they slightly underestimatethe stamp duties, which is desirable for policymaking purposes. VEC models perform the worst, especially as they greatly over predict stamp duties.

Table 2 shows the empirical results for forecasting stamp duties using monthly data. The results are more or less consistent with the results of Table 1. Striking is the good performance of the simple AR model (4 lags) for both the short and medium term forecast horizon. This model even outperforms the combination forecasts. Adding economic variables to this AR model (ADL model) doesn't improve the forecast accuracy. On the contrary, for the medium term forecast horizon, forecast errors are up to 3 times higher. This might be due to the fact that the ADL models need forecasts of economic variables as input. This potentially is adding noise to the model. The AR model is also conservative as it generally underestimates stamp duties (see MPE). In sum, this results in the conclusion that simple a-theoretical models outperform theory driven models and more complex models when forecasting stamp duties using higher frequency data.

¹ Another reason is that individual forecasts are affected differently by structural breaks (note that we have a structural break in 2005 due to federal fiscal reforms, see section 3). Some models will not adapt quickly enough to account for structural breaks. Combination forecasts account for that and the instability of individual forecasting models (e.g. Timmermann, 2006; Stock and Watson, 2003).

² Note that using the MAPE measure high forecast errors (in positive and negative sense) are given less weight.

7 Conclusions

New EU regulation urged EU Member states to invest even more in reliable and timely forecasts. In addition more strain is put on subnational governments to control the underlying determinants affecting revenues and expenditures. This is of particular importance for the Belgian regional governments. As a result of the 6 consecutive State reforms, these regional governments are facing considerable taxing powers. However, up to now, specific tax revenue forecasting models are lacking. Consequently, policymakers are not able to make reliable prognoses concerning the effects of fiscal shocks or policy measures.

In this paper we evaluate models for the forecasting of one of the most important Flemish taxes, i.e. stamp duties, using quarterly or monthly data. For the purpose of comparison, estimations are based on data covering the period 1994-2013. Several types of models were explored. First a-theoretical univariate AR and (E(G))ARCH time series models were estimated. Based on that outcome, more theory driven multivariate ADL, VAR and VEC models were tested. In addition, models with lagged macro-economic variables and without autoregressive terms were computed.

The models based on quarterly data reveal that the combination forecasts outperform the outcome of the other models tested. In addition, using monthly data, simple AR model (4 lags) show impressive performance for both the short and medium term forecast horizon. This models even outperform the combination forecasts. Our findings are in line with the results of Favero & Marcellino (2005) who show that simple forecasting models and combined forecasts outperform more complicated specifications.

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Table 1. Forecasting Performance for Quarterly Data

This table reports for different types of models the root mean squared percentage error (RMSPE), the mean absolute percentage error (MAPE) and the mean percentage error (MPE) for the out-of-sample forecasting period and the in-sample period. For the out-of-sample forecast period we make a distinction between 1-year ahead forecasts (Step 1) and 2-year ahead forecasts (Step 2). The 1-year and 2-year ahead forecasts are calculated by aggregating quarterly forecasts into yearly forecasts. In-sample error measures are calculated on the disaggregated ‘quarterly’ forecasts. The selection of models is explained in Section 5. The column “specifications model” shows which variables are used to forecast. Between brackets we report the lags that are included in the model.

Model	Technique	Specifications model	Out-of-sample						In-sample		
			RMSPE		MAPE		MPE		RMSPE	MAPE	MPE
			1 Step	2 Step	1 Step	2 Step	1 Step	2 Step	Quarterly		
1	AR	AR(1)	5.28%	8.30%	4.58%	7.43%	2.59%	-0.35%	7.18%	5.81%	-1.07%
2	AR	AR(1,3,10)	4.33%	9.64%	3.82%	7.41%	0.57%	-0.42%	6.61%	5.26%	-0.90%
3	(EG)ARCH	ARCH(1)	9.31%	11.51%	8.73%	10.68%	-6.07%	-8.35%	21.69%	14.75%	8.06%
4	ADL	AR(1,3),GDP(1,3,4),CONF(9)	3.13%	9.68%	2.88%	7.86%	-1.41%	0.18%	5.41%	4.16%	0.25%
5	ADL	AR(1,3),GDP(1,3,4),CONF(4,9)	3.69%	8.34%	2.96%	7.26%	-2.66%	-4.22%	5.79%	4.41%	-1.42%
6	VAR	VAR(1,2,4),GDP,IR	6.20%	9.35%	5.17%	6.66%	0.94%	3.72%	5.54%	4.26%	0.15%
7	VEC	SDP(1-6)	8.09%	12.84%	6.54%	10.96%	6.39%	10.24%	21.38%	17.33%	1.88%
8	VEC	STOCKS(1-7)	7.58%	14.37%	6.74%	9.27%	1.42%	4.86%	15.79%	12.55%	0.17%
9	ELAST.	GDP(1),CONF(9)	3.47%	9.70%	2.87%	7.65%	0.03%	1.44%	6.17%	5.04%	0.19%
10	ELAST.	GDP(1),CONF(9),IR(2),UR(3)	4.39%	8.48%	3.50%	7.54%	-2.51%	-4.88%	5.43%	4.54%	0.15%
11	Comb. FC	All models	3.61%	7.91%	3.24%	5.77%	0.03%	0.41%	6.97%	5.40%	0.75%
12	Comb. FC	All AR, ADL and ELAST.	3.00%	8.32%	2.66%	6.73%	-0.39%	-1.07%	5.48%	4.38%	-0.47%
13	Comb. FC	ALL ADL and ELAST.	3.15%	8.29%	2.50%	6.84%	-1.38%	-1.41%	5.26%	4.22%	-0.21%

Table 2. Forecasting Performance for Monthly Data

This table reports for different types of models the root mean squared percentage error (RMSPE), the mean absolute percentage error (MAPE) and the mean percentage error (MPE) for the out-of-sample forecasting period and the in-sample period. For the out-of-sample forecast period we make a distinction between 1-year ahead forecasts (Step 1) and 2-year ahead forecasts (Step 2). The 1-year and 2-year ahead forecasts are calculated by aggregating monthly forecasts into yearly forecasts. In-sample error measures are calculated on the disaggregated 'monthly' forecasts. The selection of models is explained in Section 5. The column "specifications model" shows which variables are used to forecast. Between brackets we report the lags that are included in the model.

Model	Technique	Specifications model	Out-of-sample						In-sample		
			RMSPE		MAPE		MPE		RMSPE	MAPE	MPE
			1 Step	2 Step	1 Step	2 Step	1 Step	2 Step	Monthly		
1	AR	AR(1-4)	2.53%	3.04%	2.11%	2.55%	-0.59%	-2.46%	10.55%	6.85%	-0.44%
2	(EG)ARCH	ARCH(1)	9.45%	12.32%	8.77%	11.50%	-5.95%	-8.63%	24.48%	16.48%	9.30%
3	ADL	AR(1,2,3,7,8,9),GDP(2,5)	3.63%	9.87%	3.32%	7.99%	-2.45%	-0.09%	9.59%	6.21%	0.48%
4	ADL	Model 3 + CONF(26),IR(4),UR(23)	4.29%	8.10%	3.54%	7.17%	-2.99%	-2.85%	8.98%	5.93%	0.52%
5	VAR	VAR(12),GDP,UR	5.13%	10.88%	4.37%	6.73%	1.41%	3.94%	11.03%	7.03%	0.51%
6	VEC	SDP(1-12)	6.97%	8.89%	4.06%	6.71%	3.91%	6.65%	31.73%	22.57%	3.52%
7	VEC	STOCKS(1-12)	3.69%	14.59%	2.92%	12.09%	1.20%	1.87%	31.75%	22.59%	3.50%
8	ELAST.	GDP(2),CONF(12),IR(12),UR(12)	4.35%	8.56%	3.67%	7.32%	-3.52%	-3.72%	10.26%	7.00%	0.46%
9	Comb. FC	All models	3.09%	7.50%	2.90%	5.98%	-1.12%	-0.66%	13.28%	8.46%	2.23%
10	Comb. FC	All AR, ADL and ELAST.	3.04%	6.73%	2.56%	5.69%	-2.39%	-2.28%	9.46%	6.09%	0.26%
11	Comb. FC	ALL ADL and ELAST.	3.69%	8.58%	3.17%	7.13%	-2.99%	-2.22%	9.37%	6.13%	0.49%

Fig. 1. Evolution Flemish stamp duties revenues (1994q1-2013q4) (in millions €)

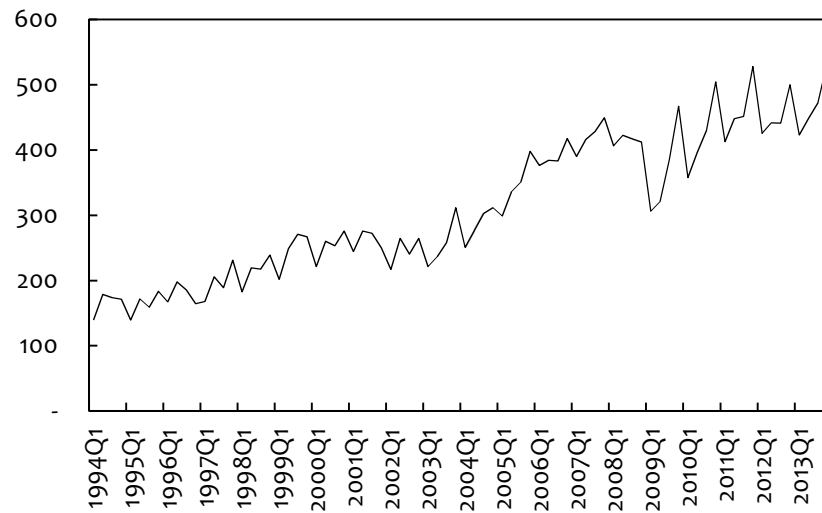


Fig. 2. Out-of-Sample Mean Average Percentage Errors for Quarterly Data

The figure shows the magnitude of the MAPE on different forecasting horizons. We see that the error rises when the forecasting horizon enlarges. Some models exhibit steeper rises of the forecasting error meaning that these models are less suited for longer forecasting horizons.

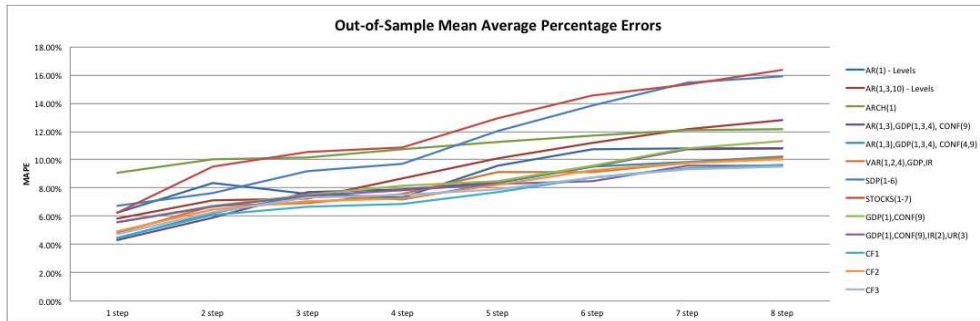
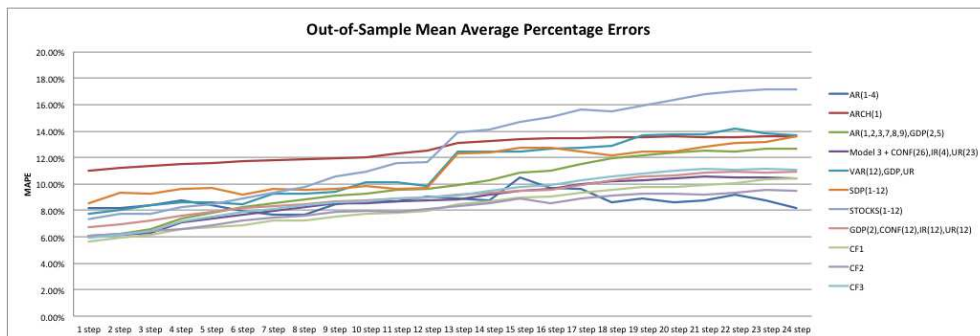
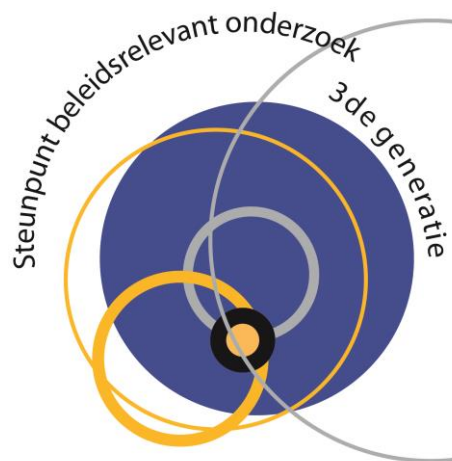


Fig. 3. Out-of-Sample Mean Average Percentage Errors for Monthly Data





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