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GDP Modelling with Factor Model: An Impact of Nested Data on Forecasting Accuracy*

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Abstract

Uncertainty associated with an optimal number of macroeconomic variables to be used in factor model is challenging since there is no criteria which states what kind of data should be used, how many variables to employ and does disaggregated data improve factor model's forecasts.

The paper studies an impact of nested macroeconomic data on Latvian GDP forecasting accuracy within factor modelling framework. Nested data means disaggregated data or sub-components of aggregated variables. We employ Stock-Watson factor model in order to estimate factors and to make GDP projections two periods ahead. Root mean square error is employed as the standard tool to measure forecasting accuracy. According to this empirical study we conclude that additional information that contained in disaggregated components of macroeconomic variables could be used to enhance Latvian GDP forecasting accuracy. The efficiency gain improving forecasts is about 0.15-0.20 percentage points of year-on-year quarterly growth for the forecasting period 1 quarter ahead, but for 2 quarter ahead it's about half percentage point.

Keywords: Factor model, forecasting, nested data, RMSE.

JEL: C22, C53, E37

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1. Introduction

Seminal papers of Stock and Watson (1998, 2002a, 2002b), Forni and Reichlin (1998), Forni, Lippi, Hallin and Reichlin (2001a) put forward factor modeling framework as powerful tool to predict macroeconomic variables. Unlike the others univariate and multivariate models, factor models incorporate much macroeconomic data in the analysis. Stock and Watson (2002a) use 215 US macroeconomic variables covering the most economic sectors they may represent an economic activity and potential driving forces of an economy. Forni and Reichlin (1998) use 450 disaggregated series to understand aggregate dynamics.

Factor analysis is easy to implement by adding an additional data without any difficulty. The dataset may include as more information as more disaggregated time series are available for any additional specific sector of an economy. Since the former statement is logical to span the most sectors of the economy and to derive much variability from macroeconomic variables, whereas the latter is more uncertain and rises the question does the additional nested data brings more information to latent factors and hence enable to predict economic activity more accurate. Thus the goal of paper to study the problem of nested data and its contribution to forecasting procedures.

A literature is scarce on the issue of optimality conditions for an amount of series to include in factor models. Usually authors assume to span whole sectors of economy extracting appropriate time series as much as they concerned and judgmentally believe this is exactly right choice for their analyzing problem and relevant economy.

The paper of Boivin and Ng (2006) addresses the issue of the size and the composition of the data and its impact on factor estimates. They possess the question whether it is possible to obtain less useful factor estimates extracting them from larger datasets and argue that it is possible.

The paper of Caggiano et al. (2009) provides a comprehensive investigation on the factor modelling issues regarding number of factors, specification of the dynamics of the factors, combination of the factor-based forecasts and the choice of the dataset extracting the factors. Their empirical results point out that there are benefits of pre-screening of variables before extracting factors. For the raw of European countries pre-screening of the variables before estimating factors and then applying forecasting techniques improve forecasts substantially over the AR model benchmark. Caggiano et al. (2009) argue that the use about one fifth of original variables may yield the best results in terms of forecasts accuracy.

This paper is organizing as the following: in section 2 we describe a nature of data we use, any transformation and complexities capturing it in a model. Then the section 3 provides the model description and assumptions. Section 4 proceeds with obtained results and concludes the paper.

2. Data

We consider large dataset for Latvian economy with few additional time series of neighbor counties of Estonia and Lithuania. The data are collected on the main economic categories comprising business and consumer surveys of EU commission, industrial production, retail sales, consumer price indices, producer price indices, labour market, monetary sector, exchange rates, financial sector, foreign trade, fiscal sector and balance of payments (see Table 2). All the time series are with monthly frequency. Additional time series of Estonia and Lithuania are also included to keep dynamics of neighbor countries in common dataset making domestic factor estimates. These are real and nominal times series of industrial production, CPI components, and confidence indicators of the main groups.

The most blocs of variables may contain data with high disaggregation degree. Consider total industry sector as in Table 1. It contains 3 main sub-components: mining and quarrying, manufacturing and electricity, gas, steam and air conditioning supply. Moreover, manufacturing comprises manufacturing of food products, beverages and textiles etc. In turn, manufacturing of food products may contain even more disaggregated components. Thus total industry represented by nests of some disaggregated parts.

Table 1
Representation of nested data for industrial production

Total Industry (BCD)
Mining and quarrying (B)
Manufacturing (C)
Manufacture of food products
Processing and preserving of meat and production of meat products (10.1)
Processing and preserving of fish, crustaceans and molluscs (10.2)
...
Manufacture of other food products (10.8)
Manufacture of beverages (11)
Manufacture of textiles (13)
...
Repair and installation of machinery and equipment (33)

Source: NACE rev.2.0

On the one hand, all those parts might be considered in a factor model all together. On the other hand, we can select any level of disaggregation and apply them further in the analysis. The choice of level of disaggregation depends on researcher. The question is does the incorporation of more data is effective and gives additional information to forecasting procedure in terms of forecasting accuracy.

In the present study we consider two types of databases. The first one (N_1) is the full database comprising all about 250 variables including all the aggregates and its subcomponents of all sub-levels. The second one (N_2) is reduced-form database comprising mainly the first level aggregation. The nature of subcomponents time series is usually differs from those ones of aggregates in the sense of volatility. Going deeper in disaggregate order we may find that those time series are more volatile because more specific sectors are more vulnerable to sector-specific shocks. Thus we leave more aggregated variables in database and exclude sub-components. Therefore judgmentally we reduce the full database N_1 to the database N_2 with the sample about 50 variables. Schematically databases' composition is shown in Table 2.

Table 2

Description of the databases and number of variables representing each sector

Full Database (N_1)	Number of Variables	Reduced Database (N_2)	Number of Variables
Confidence indicators	66	Confidence indicators	24
Industry	40	Industry	4
Retail trade	30	Retail trade	1
CPI	16	CPI	4
PPI	10	PPI	1
Labour market	2	Labour market	2
Monetary sector	12	Monetary sector	7
Exchange rates	4	Exchange rates	2
Financial sector	8	Financial sector	3
Foreign trade	40	Foreign trade	2
Fiscal sector	10	Fiscal sector	2
Balance of Payments	7	Balance of Payments	2
TOTAL	245	TOTAL	54

Therefore we would like to test inclusion of disaggregated and more "noisy" series in forecasting procedure comparing two databases of different content and size.

Time span of variables is January 1996 till December 2010. All the variables are made stationary and normalized prior to factor estimation in order to neutralize differences in scale of variables (see Johnson and Wichern, 2007). The most of monthly series are subject to seasonal adjustment. Therefore all time series are seasonally adjusted by X-12-ARIMA method with specifications set by default, except interest rates and exchange rates, and those times series that already are available in seasonally adjusted form.

Data on Latvian gross domestic product (GDP) is collected on quarterly frequency. We compile real-time database in order to exclude methodology changes and GDP revisions effects on forecasting procedure (for details see Bessonovs, 2010).

Additionally the paper deals with the problem of missing values and ragged edge. Evidently, that all the monthly variables are supplied by statistical offices and respective officials with some delay or within individual schedule of publication as current month passes by. Therefore inevitably at any moment of time we observe ragged edge of data. The second problem arises as data not always is available for the desired period of time, especially at the beginning of the sample. The third, it might happen that few time series experience some breaks within the sample. These obstacles prevent us to implement factor estimation, because factor estimation techniques applied do not allow missing values.

To tackle the problems above we apply expectation-maximization (EM) mechanism introduced in Stock and Watson (2002a) in order to achieve balanced panel of data. The basic idea behind the mechanism is an assumption about expected value of missing values and iterative process of estimation of missing values by means of principal components. So far as a preliminary data transformation is made to let time series become stationary and then we normalize them with zero mean and standard deviation equals one. The expected values of missing observations are set to zero, $E(x_{ik})=0$, where $k=1, \dots, T$ is any missing value for variable i . Further factors are estimated using the balanced panel of data. Next, exploiting factor estimates and factors loadings, we recover times series. The missing values of original database are replaced by the new estimates. The iterative process is proceeded until the missing value estimates changes are negligible. The procedure could be described as the following 6 steps:

1. Get \tilde{X}_t dataset comprising original values from X_t and missing values that are set to zero;
2. Estimate initial factors $F_t^{(0)}$ as the first r principal components of dataset \tilde{X}_t ;

3. Recover \hat{X}_t by means of $\hat{F}^{t(0)}$ and $\hat{\Lambda}^{f(0)}$:

$$\hat{X}_t = \hat{\Lambda}^{f(0)'} \hat{F}_t^{(0)}$$
4. Replace $\tilde{X}_t^{(0)}$ missing values by \hat{X}_t estimates;
5. Estimate $F_t^{(1)}$ as the first K principal components of $\tilde{X}_t^{(0)}$
6. Back to step 2 using $F_t^{(1)}$ instead of $F_t^{(0)}$;

By iterating and re-estimating process we obtain stable estimates of missing values.

3. Model

Similarly as in the paper of Stock and Watson (2002a) we employ the factor model. The general form of the model we set in the paper is the following:

$$y_{t+h|t} = \alpha + \beta_i' F_{t,N} + \sum_{j=1}^p \gamma_j y_{t-j+1} + e_t \quad (1)$$

Where $y_{t+h|t}$ is scalar forecasting value for h periods ahead, $F_{t,N}$ is a $(r \times I)$ vector of factor estimates using database of N series, y_{t-j+1} is y_t j -th lag variable, α and β_i coefficients.

Let the $X_t = (X_{1t}, \dots, X_{Nt})'$ is the set of N variables at time $t=1, \dots, T$. Then the factors estimates, in turn, admit the following structure:

$$X_{it} = \lambda_i' F_t + u_{it} \quad (2)$$

Where X_{it} is i -th variable of database of N series ($i=1, \dots, N$), F_t is a $(r \times I)$ vector of factors, λ_i is $(r \times I)$ a vector of factor loadings for variable i , u_{it} is idiosyncratic error.

Concerning forecasting equation specification, note that for (1) we assume no any dynamics in factors and thus (1) is a static representation of factor model. In addition, to allow some dynamics of forecasting equation (1) we restrict $p=1$, i.e. there is one lag of dependent variable. Further (2) can be easily estimated by principal components and factors are the input for forecasting regression in (1).

As mentioned in section 2 the data frequency for monthly time series differs from GDP data and (1) cannot be estimated. To overcome that shortcoming we use (2) for monthly data, and then apply simple average function for monthly estimated factors to justify frequency basis.

4. Results and conclusions

In this section we compare the forecasting accuracy results between two databases assumed in section 2. By means of root mean square error (RMSE) we measure magnitude of forecasting error as following:

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (\hat{y}_{t+h|t} - y_{t+h})^2}$$

where $\hat{y}_{t+h|t}$ is forecasting value at time t for h periods ahead, y_{t+h} is true value. Forecasting values and true values stand for year-on-year growth rates. The number T is set to be about 1/3 of available data sample size. Respectively 2/3 of actual sample is exploited for estimation and 1/3 for out-of-sample forecasting.

Results in Table 3 compare two types of specification. First, it compares results among specified factor models with different number of factors. Second, Table 3 shows results for both types of database specification. In addition, RMSE outcome determined in terms of AR(2) model results. Thus a number below 1 assumes factor model's better performance over AR(2) model. Results suggest that on average full database tends to outperform reduced database.

Table 3

Factor model's RMSE results with respect to AR(2) model by type of database

Out-of-sample forecasting period: 2005Q4-2010Q3				
	DATABASE (N ₂)			
Horizon / Model	SW1*	SW2	SW3	SW4
+1 quarter ahead	0.73	0.74	0.76	0.70
+2 quarters ahead	0.78	0.84	0.85	0.86
	DATABASE (N ₁)			
Horizon / Model	SW1	SW2	SW3	SW4
+1 quarter ahead	0.72	0.70	0.72	0.75
+2 quarters ahead	0.78	0.77	0.78	0.79

*Number denotes number of factors used in the model.

Table 4 shows outperformance of full database over reduced one. Positive number states by how much full database outperforms another in terms of average percentage points of year-on-year growth rates, respectively negative number states deterioration.

Table 4

Comparison of RMSE of two databases by type of model

forecasting period: 2005Q4-2010Q3				
	Improvement (+) / Deterioration (-)			
	SW1	SW2	SW3	SW4
+1 quarter ahead	0.03	0.16	0.14	-0.18
+2 quarters ahead	-0.05	0.53	0.50	0.48

According to the Table 4 forecasting 1 quarter ahead the full database N_1 may outperform N_2 on about 0.15 percentage points assuming more correct model is chosen. In this case factor model with 2 factors behaves the best. Notably that for 2 quarters ahead improvement is more substantial. The model specified with 2 factors accounts half percentage point of year-on-year growth rate.

We test *ad hoc* robustness check of the results by moving out-of-sample window back. Table 5 describes and compares factor models' improvement results through the different out-of-sample periods.

Table 5

Forecasting improvement of factor models over the different out-of-sample periods

Improvement (+) / Deterioration (-)								
Out-of-sample period	+ 1 quarter ahead				+ 2 quarters ahead			
	SW1	SW2	SW3	SW4	SW1	SW2	SW3	SW4
2003Q4-2008Q3	-0.18	0.02	-0.03	0.04	-0.31	-0.04	-0.16	-0.05
2004Q1-2008Q4	-0.17	0.04	0.03	0.08	-0.29	-0.07	-0.12	-0.11
2004Q2-2009Q1	-0.18	0.15	0.12	0.04	-0.31	-0.03	0.00	-0.02
2004Q3-2009Q2	-0.22	0.14	0.14	0.05	-0.33	-0.01	0.02	0.02
2004Q4-2009Q3	-0.05	0.27	0.30	-0.10	-0.33	0.03	0.07	0.07
2005Q1-2009Q4	0.07	0.21	0.20	-0.16	-0.10	0.53	0.43	0.37
2005Q2-2010Q1	0.07	0.22	0.22	-0.16	0.01	0.61	0.59	0.49
2005Q3-2010Q2	0.02	0.15	0.12	-0.20	0.00	0.62	0.59	0.48
2005Q4-2010Q3	0.03	0.16	0.14	-0.18	-0.05	0.53	0.50	0.48

Starting with the out-of-sample time period of 2005Q4-2010Q3 we rolling back the fixed period window and counts the outcome difference between database N_1 and N_2 as previously. We find that appropriately specifying the model the constant improvement is observed forecasting 1 quarter ahead. In turn, for two quarters horizon results more ambiguous. In the early years N_1 database wasn't able to outperform N_2 and forecasts accuracy is worse. On the other hand, in the later years improvement appears to be more considerable. We note the fact that improvement of out-of-sample

periods coincide with the deep economic crisis period is challenging and might raise the hypothesis that more data still can capture more economic dynamics therefore forecasting accuracy may improve.

According to this empirical study we conclude that additional information that contained in disaggregated components of macroeconomic variables could be used to enhance Latvian GDP forecasting accuracy. The efficiency gain improving forecasts is about 0.15-0.20 percentage points of year-on-year quarterly growth for the forecasting horizon 1 quarter ahead, but for 2 quarters ahead it's about half percentage point. Robustness check shows that improvement is not constant for the different models and forecasting horizons. While one can find stable outperformance pattern of N_1 over N_2 for 1 quarter ahead forecasts, then for 2 quarters ahead there is the evidence that N_1 unable to outperform N_2 for any model in early out-of-sample periods.

Nonetheless results suggest that the use of disaggregated components does not provide the evidence of huge efficiency loss or deterioration of the results due to disaggregated data. Moreover appropriately specifying the model efficiency gain is positive.

Alternative way of research may be pursued toward finding schemes or criteria of weighting data and/or even blocs of data in order to improve forecasting accuracy by using potentially valuable disaggregated information.

References

- Bessonovs A. (2010). Agregēta un dezagregēta faktoru modeļa pieeja IKP prognožu precizitātes mērīšanā. *Latvijas Universitātes raksti*, 758 sējums. pp. 22-33.
- Boivin, J., and Ng, S. (2006). Are more data always better for factor analysis? *Journal of Econometrics*, 132:169-194.
- Caggiano, G., Kapetanios, G., and Labhard, V., (2009). Are more data always better for factor analysis? Results for the Euro Area, the six largest Euro Area countries and UK. ECB Working Paper, No. 1051.

- Forni, M. and Reichlin, L., (1998). Let's Get Real: a Factor-Analytic Approach to Disaggregated Business Cycle Dynamics, *Review of Economic Studies* 65, 453-473.
- Forni, M., Hallin, M., Lippi, M. and Reichlin, L., (2001a). Coincident and Leading Indicators for the Euro Area, *Economic Journal* 111, C82–85.
- Johnson, R., A., Wichern D., W. (2007). Applied Multivariate Statistical Analysis. Sixth edition, Pearson Prentice Hall.
- Stock, J.,H., Watson, M.W., (1998). Diffusion Indexes. NBER Working Paper No. 6702.
- Stock, J. H., Watson, M. W., (2002a). Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business & Economic Statistics*, vol. 20, No. 2.
- Stock, J. H., Watson, M. W., (2002b). Forecasting Using Principal Components from a Large Number of Predictors. *Journal of American Statistical Association*, Vol. 97, No. 460, pp. 1167-1179.

Appendix 1

Data description

Nr.	Business and consumer surveys	64	Retail confidence indicator
1	Total Confidence Indicator	65	Building confidence indicator
	Industry survey	66	Total Confidence Indicator
2	Confidence Indicator		Industry (index, 2005=100)
3	Production trend observed in recent months	67	Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply
4	Assessment of order-book levels	68	Mining and quarrying
5	Assessment of export order-book levels	69	Manufacturing
6	Assessment of stocks of finished products	70	Manufacture of food products
7	Production expectations for the months ahead	71	Processing and preserving of meat and production of meat products
8	Selling price expectations for the months ahead	72	Processing and preserving of fish, crustaceans and molluscs
9	Employment expectations for the months ahead	73	Processing and preserving of fruit and vegetables
	Services survey	74	Manufacture of dairy products
10	Confidence Indicator	75	Manufacture of bakery and farinaceous products
11	Business situation development over the past 3 months	76	Manufacture of other food products
12	Evolution of the demand over the past 3 months	77	Manufacture of beverages
13	Expectation of the demand over the next 3 months	78	Manufacture of textiles
14	Evolution of the employment over the past 3 months	79	Manufacture of wearing apparel
15	Expectations of the employment over the next 3 months	80	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and
16	Expectations of the prices over the next 3 months	81	Manufacture of paper and paper products
	Consumers survey	82	Printing and reproduction of recorded media
17	Confidence Indicator	83	Manufacture of chemicals and chemical products
18	Financial situation over last 12 months	84	Manufacture of basic pharmaceutical products and pharmaceutical preparations
19	Financial situation over next 12 months	85	Manufacture of rubber and plastic products
20	General economic situation over last 12 months	86	Manufacture of other non-metallic mineral products
21	General economic situation over next 12 months	87	Manufacture of basic metals
22	Price trends over last 12 months	88	Manufacture of fabricated metal products, except machinery and equipment
23	Price trends over next 12 months	89	Manufacture of computer, electronic and optical products
24	Unemployment expectations over next 12 months	90	Manufacture of electrical equipment
25	Major purchases at present	91	Manufacture of machinery and equipment n.e.c.
26	Major purchases over next 12 months	92	Manufacture of motor vehicles, trailers and semi-trailers
27	Savings at present	93	Manufacture of other transport equipment
28	Savings over next 12 months	94	Manufacture of furniture
29	Statement on financial situation of household	95	Other manufacturing
	Retail survey	96	Repair and installation of machinery and equipment
30	Confidence Indicator	97	Electricity, gas, steam and air conditioning supply
31	Business activity (sales) development over the past 3 months		EU Industry (index, 2005=100)
32	Volume of stock currently hold	98	Mining and quarrying
33	Orders expectations over the next 3 months	99	Manufacturing
34	Business activity expectations over the next 3 months	100	Electricity, gas, steam and air conditioning supply
35	Employment expectations over the next 3 months		EE Industry (index, 2005=100)
36	Prices expectations over the next 3 months	101	Mining and quarrying
	Building Survey	102	Manufacturing
37	Confidence Indicator	103	Electricity, gas, steam and air conditioning supply
38	Building activity development over the past 3 months		LT Industry (index, 2005=100)
39	Main factors currently limiting your building activity	104	Mining and quarrying
40	None (% s.a. - monthly question 2)	105	Manufacturing
41	Insufficient demand (% s.a. - monthly question 2)	106	Electricity, gas, steam and air conditioning supply
42	Weather conditions (% s.a. - monthly question 2)		Retail Trade (2005=100)
43	Shortage of labour force (% s.a. - monthly question 2)	107	RETAIL TRADE, TOTAL, INCLUDING AUTOMOTIVE FUEL
44	Shortage of material and/or equipment (% s.a. - monthly question 2)	108	Retail trade, total, except of automotive fuel
45	Other factors (% s.a. - monthly question 2)	109	Retail sale of automotive fuel in specialised stores
46	Financial constraints (% s.a. - monthly question 2)	110	Retail sale of food, beverages or tobacco, total ;
47	Evolution of your current overall order books	111	..retail sale in non-specialised stores with food, beverages or tobacco predominating
48	Employment expectations over the next 3 months	112	..retail sale of food, beverages and tobacco in specialised stores
	EU Business and consumer surveys	113	Retail trade of nonfood products, including automotive fuel
49	Industry confidence indicator	114	Retail trade of nonfood products, except automotive fuel
50	Services confidence indicator	115	Other retail sale in non-specialised stores
51	Consumers confidence indicator	116	Retail sale of computers, peripheral units, software telecommunications equipment in specialised stores
52	Retail confidence indicator	117	Retail sale of textiles, clothing, footwear and leather goods in specialised stores
53	Building confidence indicator	118	..retail sale of textiles in specialised stores
54	Total Confidence Indicator	119	..retail sale of clothing, footwear and leather goods in specialised stores
	EE Business and consumer surveys	120	Retail sale of audio and video equipment in specialised stores
55	Industry confidence indicator	121	Retail sale of hardware, paints and glass in specialised stores
56	Services confidence indicator	122	Retail sale of carpets, rugs, wall and floor coverings in specialised stores
57	Consumers confidence indicator	123	Retail sale of electrical household appliances in specialised stores
58	Retail confidence indicator	124	Retail sale of furniture, lighting equipment and other household articles in specialised stores
59	Building confidence indicator	125	Retail sale of music and video recordings in specialised stores
60	Total Confidence Indicator	126	Retail sale of books, newspapers and stationery in specialised stores
	LT Business and consumer surveys	127	Retail sale of sporting equipment, games and toys in specialised stores
61	Industry confidence indicator	128	Dispensing chemist in specialised stores, retail sale of medical, orthopaedic goods, cosmetic and toilet articles
62	Services confidence indicator	129	..dispensing chemist in specialised stores and retail sale of medical and orthopaedic goods in specialised stores
63	Consumers confidence indicator	130	..retail sale of cosmetic and toilet articles in specialised stores

Appendix 1

Data description

131	Retail sale of flowers, plants, seeds, fertilisers, pet animals and pet food in specialised stores	Foreign Trade (thousands of lats)
132	Retail sale of watches and jewellery and other retail sale of new goods in specialised stores	189 Exports, total
133	Retail sale of second-hand goods in stores	190 Live animals and animal products
134	Retail sale via stalls and markets	191 Vegetable products
135	Retail sale via mail order houses or via Internet	192 Fats and oils
136	Other retail sale not in stores, stalls or markets	193 Prepared foodstuffs including alcoholic and non-alcoholic beverages and tobacco products
	CPI (2005=100)	194 Mineral products
137	All-items HICP	195 Products of the chemical and allied industries
138	Food and non-alcoholic beverages	196 Plastics and articles thereof; rubber and articles thereof
139	Alcoholic beverages, tobacco and narcotics	197 Raw hides, leather, furskins and articles thereof
140	Clothing and footwear	198 Wood and articles of wood
141	Housing, water, electricity, gas and other fuels	199 Pulp of wood; paper and paperboard
142	Furnishings, household equipment and routine maintenance of the	200 Textiles and textile articles
143	Health	201 Footwear, headgear, umbrellas and other articles
144	Transport	202 Articles of stone, plaster, cement, glassware and ceramic products
145	Communications	203 Precious, semiprecious stone, precious metals, metals clad with precious metal
146	Recreation and culture	204 Base metals and articles of base metals
147	Education	205 Machinery and mechanical appliances; electrical equipment
148	Restaurants and hotels	206 Transport vehicles
149	Miscellaneous goods and services	207 Optical instruments and apparatus inc. medical; clocks and watches; musical instruments
150	EU HICP (2005=100)	208 Miscellaneous manufactured articles
151	EE HICP (2005=100)	209 Imports, total
152	LT HICP (2005=100)	210 Live animals and animal products
	Producer prices index (2005=100)	211 Vegetable products
153	Mining and quarrying	212 Fats and oils
154	Mining and quarrying; manufacturing; electricity, gas, steam and	213 Prepared foodstuffs including alcoholic and non-alcoholic beverages and tobacco products
155	Manufacturing	214 Mineral products
156	Electricity, gas, steam and air conditioning supply	215 Products of the chemical and allied industries
157	MIG - Capital goods	216 Plastics and articles thereof; rubber and articles
158	MIG - Consumer goods	217 Raw hides, leather, furskins and articles
159	MIG - Durable consumer goods	218 Wood and articles of wood
160	MIG - Intermediate goods	219 Pulp of wood; paper and paperboard
161	MIG - Non-durable consumer goods	220 Textiles and textile articles
162	MIG - Energy	221 Footwear, headgear, umbrellas and other articles
	Unemployment	222 Articles of stone, plaster, cement, glassware and ceramic products
163	Unemployment Rate (percent)	223 Precious, semiprecious stone, precious metals, metals clad with precious metal
164	Job Vacancies	224 Base metals and articles of base metals
	Monetary Statistics (millions of lats)	225 Machinery and mechanical appliances; electrical equipment
165	Money Stock M1	226 Transport vehicles
166	Money Stock M2	227 Optical instruments and apparatus inc. medical; clocks and watches; musical instruments
167	Money Stock M3	228 Miscellaneous manufactured articles
168	Currency in circulation	Fiscal Sector (thousands of lats)
169	Interest rates, lats, deposits, long-term (%)	229 Tax Revenues
170	Interest rates, lats, deposits, short-term (%)	230 Personal income Tax
171	Interest rates, lats, loans, long-term (%)	231 Enterprise Income Tax
172	Interest rates, lats, loans, short-term (%)	232 Social contributions
173	Euribor 3m (%)	233 Real Estate Tax
174	Euribor 6m (%)	234 Value added tax
175	Rigibor 3m (%)	235 Excise Tax
176	Rigibor 6m (%)	236 General government expenditure
	Exchange rates	237 Central government expenditure
177	EUR/USD	238 General government budget saldo
178	NEER - total	Balance of Payments (thousands of lats)
179	NEER - developed	239 Services Export
180	NEER - developing	240 Services Import
	Banking Statistics (millions of lats)	241 Saldo: Income
	Deposits	242 Saldo: Transfers
181	Overnight deposits	243 Saldo: Direct Investment
182	Maturity of 1-6 months	244 Saldo: Portfolio Investment
183	Maturity of 6-12 months	245 Saldo: Other Investment
184	Total deposits	
	Loans	
185	Short-term	
186	Maturity of 1-5 years	
187	Maturity of over 5 years	
188	Total loans	