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Abstract

Although a forecasting model has very good statistical properties and the mean of the residuals equals zero, it can produce systematic errors during a short period. In the case of regular publications, forecasters want to prevent such a persistence of errors over several periods. For this reason, a safeguard model can be used to inform the forecaster when there is a risk that the standard model (i.e. the best specified model on average) leads to persistent errors over several months or quarters.

This paper explains why and how such a safeguard model has been built in order to improve the forecasts of French GDP at the current quarter horizon (nowcasts), which are officially published by the French central bank. The official benchmark model for GDP nowcasts is an aggregated model that relies exclusively on survey in the manufacturing industry. In the long run, this model still has the best performances. On the contrary, the safeguard model is a disaggregated model which features equations for the valued added of 6 sectors. From this example, we provide general remarks on the advantages of disaggregation as well as how such safeguard models can be used in practice.

Keywords: GDP nowcasting; Aggregation; Mixed-frequency data.

JEL classification: C52, C53, E37.

Résumé

Un modèle de prévision peut avoir de bonnes propriétés statistiques et présenter des erreurs de prévisions en moyenne nulles. Toutefois, des séries d'erreurs de même signe peuvent apparaître sur des périodes courtes. Lorsque ce modèle sert de base à une publication régulière de prévisions de croissance de l'activité, le prévisionniste souhaiterait éviter que de telles séries apparaissent. Pour cette raison, un modèle « garde-fou » peut être utilisé pour alerter le prévisionniste lorsque son modèle de référence (à savoir le modèle le mieux spécifié en moyenne sur longue période) conduit à des erreurs persistantes sur plusieurs trimestres.

Cet article présente les motivations et les principes méthodologiques qui ont conduit au développement d'un modèle garde-fou dans le but d'améliorer les prévisions du PIB français pour le trimestre en cours (publiées mensuellement par la Banque de France). Le modèle de référence utilisé pour prévoir la croissance du PIB est un modèle agrégé qui repose exclusivement sur l'enquête mensuelle de conjoncture dans l'industrie. Sur longue période, les performances de ce modèle en termes de prévision sont difficiles à battre. À l'inverse, le modèle garde-fou est un modèle désagrégé prévoyant la croissance de la valeur ajoutée dans les six branches principales de l'économie. Grâce à cet exemple, nous formulons des remarques générales sur les mérites comparés de la désagrégation pour prévoir l'évolution d'un agrégat, puis nous présentons la façon dont un modèle garde-fou peut être utilisé en pratique pour améliorer la prévision de croissance.

Mots-clés : Prévisions du PIB ; Agrégation ; Données à fréquence-mixte.

Codes JEL : C52, C53, E37.

Non-technical summary

First estimates of quarterly GDP growth rates are now released by the French national statistical institute (INSEE) with a 30 days delay. Before the release, it is important that central banks might rely on relevant monthly information to form an overview on current economic conditions in the second largest economy in the euro area.

Since January 2000, the Banque de France publishes its own short term forecasts every month in the Overview of the Banque de France monthly business survey (EMC, *Enquête Mensuelle de Conjoncture*). The so-called Monthly Index of Business Activity (MIBA) aims at predicting the quarterly growth rate of France's GDP at the current quarter horizon (nowcasting). The new version of this model (Mogliani et al. 2014) is based exclusively on information stemming from the EMC in manufacturing industry: the rationale behind this is that the business cycle in the manufacturing industry is on average closely correlated to the business cycle in the whole economy.

If this assumption is true most of the time, some periods have witnessed a decoupling between economic sectors, leading to sometimes persistent MIBA forecast errors. In particular, from late 2013 until the end of 2014, MIBA forecasts overestimated GDP growth due to a disconnection between manufacturing and the construction sector. A new model called PRISME (in French, *Prévision Intégrée Sectorielle Mensuelle*) has been launched in the summer of 2014 to develop a "safeguard" to the MIBA model by identifying quarters when such a decoupling between sectors is observed. This new model produces an alternative forecast by aggregating sectorial forecasts for the six major economic activities (market services, manufacturing, construction, energy, non-market services and agriculture).

This working paper presents the basic features of the PRISME model as well as its intrinsic value as a safeguard to the MIBA model. The methodological approach adopted to specify the PRISME model was aimed at selecting variables in a parsimonious, pragmatic and meaningful way, which contrasts with the use of a large number of data series as in dynamic factor models (Giannone and Reichlin 2008; Banbura and Rünstler 2011; Banbura, Giannone and Reichlin 2010). Our approach is similar to the methodology carried on in Hahn and Skudelny (2008) who predict Euro area GDP growth with a bottom up approach on the production side, whereas our selection procedure is related to the “general-to-specific" approach (GETS) popularized by Krolzig and Hendry (2001).

Out-of-sample results show that PRISME’s sectorial equations perform relatively well compared to naive benchmarks and “Miba-like” equations. Going to the aggregate level, PRISME is able to forecast GDP growth more accurately than dynamic factor models we use as benchmarks. From an empirical, out-of-sample perspective, this supports the disaggregation approach embedded in the PRISME model. However, PRISME is not better than MIBA to predict the quarterly change in GDP on average over the long run (2007-2015). More precisely, PRISME gives more accurate forecasts when first hard indicators (i.e. industrial production, turnover indexes...) are available or when value added drops outside the manufacturing sector. In this regard, PRISME is a valuable tool to alert on a possible decoupling between sectors and thus allows correcting the MIBA forecast if necessary. It has also the advantage to give a more detailed analysis of forecast errors at the time of publication of GDP.

The paper also explores the pros and cons of disaggregation when forecasting the GDP aggregate. The econometric literature distinguishes three kinds of "aggregation problems". The first one refers to the possible difference between the parameters of the macro equation and the average of the corresponding micro parameters (Orcutt, Watts and Edwards 1968, Imbs et al. 2005, Mayoral 2013). The second one relates to the possible correlation of the errors resulting from simultaneously estimated equations. Each equation can be estimated separately with OLS but they cannot be estimated simultaneously: a SUR estimator has to be used instead of OLS (Zellner 1962). The third problem refers to the choice between the direct prediction of an aggregate variable or the sum of the predictions of its components (Grunfeld, Griliches 1960, Pesaran, Pierse, Kumar 1989, Hendry & Hubrich 2010). This choice cannot be based solely upon theoretical reasons when the data generating process driving the underlying macroeconomic variable is not perfectly known. Thus, it remains a very empirical question whether aggregating forecasts of an aggregate's subcomponents is better than forecasting directly the aggregate of interest (Hubrich 2005). We compare the PRISME model with some aggregate challengers and show that the former performs well in forecasting GDP using a supply-side disaggregation method.

1. Introduction

First estimates of quarterly GDP growth rates are released by the French national statistical institute (INSEE) with a 45 days delay[2]. Before this release, it is important that central banks might rely on relevant monthly information to form an overview on current economic conditions and to set up the appropriate monetary stance. Useful information usually includes quantitative indicators like industrial production or other "soft" indicators such as survey data which are the timeliest monthly indicators. Since January 2000, the Banque de France publishes its own short term forecasts every month in the Overview of the Banque de France monthly business survey (EMC, *Enquête Mensuelle de Conjoncture*). The so-called Monthly Index of Business Activity (MIBA) aims at predicting the quarterly growth rate of France's GDP at the current quarter horizon (nowcasting).

The new version of this model (Mogliani et al. 2014) is based exclusively on information stemming from the EMC in manufacturing industry. The rationale behind this model is that the business cycle in the manufacturing industry is on average closely correlated to the business cycle in the whole economy. Manufacturing industry accounts only for a small part of the total value added in France (11.2% in 2014) and its contribution to total VA growth is modest since 1995 (its contribution explaining on average 11.3% of total VA growth rate). However it represents a higher direct contribution to the volatility of total VA growth rate (22.8%)[3], which is the most important for a business cycle analysis. Moreover, the rationale for using information on manufacturing industry is that all other sectors of the economy consume manufacturing goods. Thus, changes in the manufacturing sector activity well reflect the variations in the activity of other sectors. Last but not least, it is often recognized that surveys in manufacturing industry provide more reliable information than their counterparts in the services sector[4], so models based on the first surveys can be more efficient to predict macroeconomic aggregates and even GDP.

If the assumption of a very close correlation between manufacturing and the economy as a whole is true most of the time, some periods have witnessed a decoupling between economic sectors, leading to temporary (as in the case of energy) or more persistent (as in the case of construction) MIBA forecast errors. Indeed, since late 2013 until the end of 2014, MIBA forecasts overestimated GDP growth due to a disconnection between manufacturing and the construction sector. As shown in Mogliani (2014), residuals of the MIBA model have the needed properties (normality, absence of autocorrelation) that make a prolonged period of systematic positive or negative forecast errors rather unlikely. However, if one or two sectors of the economy diverge from the manufacturing sector during several quarters, the MIBA model might produce short series of systematically positive or negative forecast errors.

The PRISME model (in French, *Prévision Intégrée Sectorielle Mensuelle*) was launched in the summer of 2014 to develop a "safeguard" to the MIBA model by providing an alternative forecast of GDP growth obtained from the aggregation of forecasts for the six major economic activities (market

[2] This delay will be reduced to 30 days starting from GDP first estimate for 2015q4.

[3] See Gregoir and Laroque (1992) for the decomposition of the growth rate and the volatility of an aggregate with respect to its main components. The contribution of each sub-component to the aggregate's volatility is simply equal to the covariance between the two divided by the variance of the aggregate. Thereafter we will refer to this ratio as the direct contribution to aggregate volatility.

[4] See for example Combes et al. (2014) which recalls the weak performance of models based on surveys only for forecasting activity in the services sector.

services, manufacturing, construction, energy, non-market services, agriculture). This working paper aims at presenting the basic features of this model but also its intrinsic value as a safeguard to the MIBA model. Out-of-sample results show that PRISME is not better than MIBA to predict the quarterly change in GDP on average over the long run (2007-2014). However, PRISME gives more accurate forecasts when first quantitative data are available or when a drop in value added – persistent or transitory – appears outside the manufacturing sector. In this regard, PRISME is a valuable tool to alert on a possible decoupling between sectors and thus allows correcting the MIBA forecast if necessary. It has also the advantage to give a more detailed analysis of forecast errors at the time of publication of GDP[5].

The pros and cons of disaggregation

The PRISME model performs a breakdown of the French economy total value added (VA) into its main components. If such a disaggregation is obviously welcome from an analytical point of view, some issues arise for the forecaster who wants to reaggregate such information to produce an aggregate forecast of total VA or GDP[6]. The econometric literature distinguishes three kinds of "aggregation problems". The first one refers to the possible difference between the parameters of the macro equation and the average of the corresponding micro parameters (Orcutt, Watts and Edwards 1968, Imbs et al. 2005, Mayoral 2013). The second one relates to the possible correlation of the errors resulting from simultaneously estimated equations. Each equation can be estimated separately with OLS but they cannot be estimated simultaneously: a SUR estimator has to be used instead of OLS (Zellner 1962). The third problem refers to the choice between the direct prediction of an aggregate variable or the sum of the predictions of its components (Grunfeld, Griliches 1960, Pesaran, Pierse, Kumar 1989, Hendry & Hubrich 2010).

Theoretical work on the third problem does not provide clear solutions once we relax the assumption that the data generating process is perfectly known. The discussion then relies first on whether disaggregating increases misspecifications or not, and, second, on whether forecast errors of the disaggregated components might cancel out each other (which depend on how unexpected shocks affect forecast errors). Grunfeld & Griliches (1960) propose the first test to compare aggregated and disaggregated models. Their test simply compares the variance of the residuals of the macro equation to the variance of the sum of the residuals of the micro equations. However this test is valid only for in-sample predictions as the more robust test of Pesaran, Pierse, Kumar (1989). As long as the composition of the aggregate (i.e the share of each component) or the coefficients in each “micro” equation change over time, the in-sample criteria cannot be used to assess the out-of-sample performances of the models (Pesaran, Pierse, Kumar 1989). Thus, it remains a very empirical question whether aggregating forecasts of an aggregate’s subcomponents is better than forecasting directly the aggregate of interest (Hubrich 2005, Hendry & Hubrich 2010). This issue of disaggregation will be largely discussed when presenting the model and comparing it with its aggregate challengers.

[5] Another advantage of the PRISME model is that it proceeds to a disaggregation on the supply-side. Most of the disaggregated models aimed at predicting GDP components in the short run focus on the demand side (private consumption, investment etc.). But as showed by Gregoir and Laroque (1992), demand components such as business investment or changes in inventories – which are rather difficult to predict – contribute much more to the overall GDP volatility than suggested by their share in final demand.

[6] The difference between GDP and total VA will be further discussed in Section 4. For now we make no distinction between both aggregates.

The paper is organized as follows. Section 2 introduces the PRISME model and explains the methodological approach that led to its specification. Section 3 considers the aggregation issue from a theoretical perspective and conducts some in-sample aggregation tests. Section 4 presents the out-of-sample evaluation of the model and compares PRISME to its natural benchmark (the MIBA model) and to other models. Section 5 shed some light on the operational benefit of working with PRISME in a complementary fashion with the MIBA model. Section 6 concludes.

2. Main features of the PRISME model

The PRISME model performs a forecast of total value added (VA) by aggregating forecasts of the six major economic activities (market services, manufacturing, construction, energy, non-market services and agriculture).

There are three versions of the PRISME model, each corresponding to one of the three months of the quarter, with an information set that is progressively expanded. Indeed when building up the PRISME model, we had to mimic the timing of the MIBA forecasts, which are published on the 6th working day of each month. Thus, for each year's first quarter for instance, three forecasts are made and published on the 6th working day of February, March and April respectively. In the following, M1 will refer to the PRISME version of the model with data available up to the 1st publication of the MIBA forecast (M2 and M3 will refer to the versions with data available up to the 2nd and 3rd publications of the MIBA forecast, respectively).

Before presenting the equations of the PRISME model and assessing the relevance of a disaggregated approach to forecast aggregate VA, we first introduce the methodological approach that leads to characterize the equations for the six major economic activities.

On the steps leading to the model

The methodological approach adopted to specify the PRISME model was aimed at selecting variables in a parsimonious, pragmatic and meaningful way.

Our parsimonious approach contrasts with the use of a large number of data series as if the information content of each of these series was indeed useful for forecasting the variable of interest. Since a number of years, the use of dynamic factor models (DFMs) – which consists in summarizing the information of the many data releases with a few common factors – has been considered as a promising area for forecasting macroeconomic aggregates. If DFMs present the clear advantage of reducing the dimensionality of the information data set without much loss of information, they also have their own drawbacks. Too much information is not always good from a forecasting perspective. Boivin & Ng (2006) show for instance that putting together highly correlated series into a single variable can reduce the efficiency of the factor estimates. In contrast, given an initial dataset summarized in a few number of common factors, introducing a new time series that is weakly correlated with the other lowers the size of the average component and also reduces estimates' efficiency. One alternative could be to adjust the number of factors but it seems that there is no universal criterion to choose the appropriate number (Breitung (2005)).

DFMs have not performed so well in the recent period to predict GDP growth in France or other euro area countries and have displayed a systematic upward bias[7]. This rather unsatisfactory performance could be due to the presence in the factors of variables not necessarily relevant for forecasting global GDP growth. By contrast to this approach, we aimed at selecting only a few variables that are easily interpretable and really helpful in predicting activity in each economic sector[8].

Our approach to specify the model is quite similar to the methodology carried on in Hahn and Skudelny (2008) who predict Euro area GDP growth with a bottom up approach on the production side. This selection procedure is also related to the “general-to-specific" approach (GETS) popularized by Krolzig and Hendry (2001). A simple algorithm is used in a first step to select variables from a large set of survey (“soft”) data and quantitative variables (industrial production, household consumption of goods, turnover and sales in services, HICP) on the basis of in-sample performance.

More specifically, the algorithm first regresses the dependent variable (quarterly VA growth rate in a specific sector) on a constant only. It then selects from an expanded set of preselected variables a first variable having the highest correlation with the residual calculated in the previous step. The algorithm then regresses the dependent variable on this first variable and a constant. These two steps are repeated several times until a maximum number of variables is reached (usually not more than five). Fixing a maximum number of variables enables us to avoid overfitting and “data mining”. Moreover, it is known that an equation with too many variables, although fitting the dependent variable very well, behaves poorly when an out-of-sample forecast evaluation is implemented.

The second step is our expert judgment, which leads to exclude variables that enter with the wrong theoretical sign in the equations. Finally an out-of-sample analysis is carried on to select variables that are not necessarily the most highly correlated with the dependent variable– although their regression coefficient remains significant – but help to improve forecast accuracy. This for instance leads to introducing industrial production in the market services equation (see below).

There is one main difference in our approach with Hahn et al. (2008), i.e. the constraint we impose on the selection of variables to maintain consistency and continuity between equations for the different months. More precisely, we aim at using as much as possible the same variables to predict the VA growth rate in one specific sector. This has the valuable advantage to easily interpreting the forecast revisions over the months. Moreover, variables in M1 equations will be more forward looking (e.g. balances of opinion on expected activity) whereas variables in M2 and M3 equations will be more backward looking (e.g. balances of opinion on past production or deliveries for soft data, carry-overs of industrial production or services turnover for hard data).

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[7] See section 4 for the comparison of the PRISME model with a set of DFM benchmarks.

[8] By this way we end up with a set of 6 equations for the 6 major economic activities. An alternative approach would have been to use a factor model with a block structure where some factors are common to all activities, while other factors are sector-specific. Examples of such models can be found in Kose et al. (2003) who carry out an analysis of the international business cycle by using regional, country-specific and global factors or in Reis and Watson (2010) who estimate a measure of “pure” inflation. However this methodology is not suitable in our framework because our goal is not to find the best cross-correlations both between and within sectors but to select explanatory variables that help to predict each sector’s value added in a complementary fashion before proceeding to the aggregation of forecasts.

On the way to deal with the mixed frequency issue

Following the approach implemented in the MIBA model, we use the *blocking* approach to deal with missing values. This approach consists in using only the information available every month at the time of each monthly forecasting exercise[9]. More precisely, monthly data are split into three quarterly series: one with the observations from the first months (m1) of each quarter (January, April, July and October), another one (m2) with the observations from the second months (February, May, August and November), and a last one (m3) with the remaining observations from the third months (March, June, September and December). For example, for a Q1 forecast made a few days after the end of February, coincident m1 and m2 series for survey data are available, while m3 series can only be used with a lag of at least one quarter[10]. However we sometimes depart from the MIBA model by using quarterly or two-month averages for survey data instead of individual monthly time series.

The next subsection presents the equations of the PRISME model, one for each month of the quarter (thereafter called M1, M2 and M3 equations), for the six major economic activities. Equations are estimated by simple OLS. For each equation we present the selected variables, coefficients and goodness of fit as well as usual residuals' tests (heteroskedasticity, normality, serial correlation). The problem of error cross section dependence, which can potentially be solved by SURE estimators (seemingly unrelated regressions equations) will be tackled in section 3.

Specifications of the PRISME model

Intuitively, the quality of a disaggregated model to forecast the growth rate of an aggregate should depend, among other things, on the quality of the equations related to economic sectors that explain the most part of the aggregate's volatility. As mentioned in the introduction, the direct contribution of manufacturing to the volatility of total value added is almost double its weight in total VA (manufacturing VA / total VA ratio). We can also compute the total (direct + indirect) contribution of each sector to the volatility (variance) of total value added by simply computing the R^2 of an OLS regression of total VA growth rate on the growth rate in each sector. This allows to taking into account the correlations among the different economic activities. Table 1 shows that market services are the main contributor (direct and total contribution) to total VA's volatility, but the relative contribution of manufacturing with respect to market services is clearly higher than suggested by its relative weight in total VA. Construction also emerges as an important contributor to total VA added. Equations for these three sectors (market services, manufacturing and construction) should therefore be the cornerstones of any model aiming at forecasting the growth rate of total VA.

Table 1: Contributions of the 6 major economic activities to the volatility of total value added

[9] An alternative method was to fill missing values by forecasting explanatory variables (e.g., through autoregressive models). However, this method has the main drawback of having to forecast explanatory variables which may be at the expense of the forecast accuracy of the dependent variable.

[10] The *blocking* approach is somehow equivalent to a MIDAS type approach where coefficients are freely estimated.

	Weight * (%)	Direct contribution to total VA volatility** (%)	Total contribution to total VA volatility*** (R^2)
Market services	54.6	63.9	0.93
Non-market services	23.0	0.2	0.00
Manufacturing	11.7	22.8	0.70
Construction	6.3	8.6	0.39
Energy	2.6	3.5	0.11
Agriculture	1.8	1.0	0.01

* VA branch / VA tot in real terms; ** cov(VA branch, VA tot) / var(VA tot)
** R^2 of the OLS regression (qoq % growth rates) : VA tot = c + beta*VA branch

Market services

Forecasting the VA growth rate in market services in the short run presents several challenges despite the relatively low volatility of this sector. The main difficulty is the relatively narrow set and low quality of data for market services, in particular monthly quantitative data. Indeed the only quantitative data that is published for market services on a monthly basis is turnover data, which is not available in volume terms (except for trade). As regards survey variables, market services show a high degree of heterogeneity and the scope of surveys does not necessarily cover this diversity. Surveys in services can even be less informative than surveys in the manufacturing industry to predict the VA growth rate in market services[11].

This explains why the 3rd month equation (m3) contains two variables related to the manufacturing sector[12]: one balance of opinion from the BDF survey in manufacturing (quarterly average of the change in production) as well as the carry-over of manufacturing production after the 1st month of the quarter. The equation also contains a quantitative variable related to business services (turnover index). One can think of this variable as containing some specific information not provided by manufacturing surveys or hard data, as the subsector of business services uses relatively few inputs from the industry compared to other services subsectors like trade or transport activities. Moreover, as noted by Bouton and Erkel-Rousse (2002), the change in market services activity is often highly correlated to business services[13].

In line with these findings, the M2 equation also contains two balances of opinion from the BDF manufacturing survey: one backward looking variable (2-months average of the change in past

[11] Bouton and Erkel-Rousse (2002) show that surveys in services do have a predictive content for the growth of GDP subcomponents and GDP itself, but their approach is very different from ours since they use a VAR model with business climate indicators whereas we use univariate equations with balances of opinion as raw data. Moreover they don't proceed to an out-of-sample forecasting exercise to test the predictive content of their survey variables.

[12] The usefulness of manufacturing data to forecast activity in market service is also linked to the way in which French quarterly national accounts are constructed. In particular, industrial production is not only one of the main indicators used to compute the balance of goods, but it also determines the value added in services through intermediate consumption.

[13] By using the same method as in table 1, we find that business services are indeed the main contributor (direct and total contribution) to the volatility of market services value added.

production) and one forward looking variable (3-months moving average of the change in total orders). It also includes the carry-over of manufacturing production at the beginning of the quarter. Anticipating the out-of-sample exercise of section 4, it is worth mentioning that no survey variable in market services was found to lower the root mean square error (RMSE) over the sample period considered (2007q1-2015q2), once manufacturing surveys are included in the equation.

Variables in the M1 equation are the same as in M2 except that they are delayed by one month according to the *blocking* approach. Manufacturing production does not appear in this equation as only two months of data for the preceding quarter are available.

	M1	M2	M3
Constant	0.26 [0.00]	0.20 [0.00]	0.11 [0.01]
BDF manufacturing survey			
- change in production:			
quarter T average			0.07 [0.00]
M1 and M2 average		0.02 [0.09]	
M1	0.02 [0.02]		
- change in orders			
M2 3-month moving average		0.02 [0.05]	
M1 3-month moving average	0.03 [0.00]		
Manufacturing IP			
carry-over after M1			0.09 [0.00]
carry-over after M3(-1)		0.13 [0.01]	
Business services turnover (carry-over after M1)			0.05 [0.01]
Estimation sample	81q2 – 15q2	90q2 – 15q2	95q2 – 15q2
Adjusted R^2	0.48	0.61	0.81
Standard error	0.41	0.35	0.26
Normality	5.75 [0.06]	2.00 [0.37]	1.04 [0.59]
AR(4)	2.97 [0.02]	3.66 [0.01]	1.18 [0.33]
Heteroscedasticity	5.45 [0.01]	3.50 [0.02]	0.51 [0.68]

P-values in brackets. "Normality" denotes the Bera-Jarque test for residual normal distribution. AR(4) denotes the Breusch-Godfrey test for residual serial correlation up to order p = 4. "Heteroscedasticity" is the Breusch-Pagan-Godfrey test for heteroscedasticity.

Manufacturing

The most useful variables for predicting the VA growth rate in manufacturing are manufacturing production and variables related to the change in production in manufacturing business surveys (INSEE and BDF). Some dummy variables are included in the specifications when the VA growth rate in manufacturing shows sudden peaks and troughs that are difficult to explain with its usual determinants.

	M1	M2	M3
Constant	-0.28 [0.02]	-0.30 [0.01]	-0.06 [0.58]
Manufacturing IP			
carry-over after M1			0.42 [0.00]
carry-over after M3(-1)		0.43 [0.00]	
qoq growth rate (lagged)		-0.20 [0.01]	-0.15 [0.01]
carry-over after M2(-1)	-0.16 [0.01]		
BDF manufacturing survey			
- change in production:			
quarter T average			0.08 [0.00]
M1 and M2 average		0.12 [0.00]	
- expected change in production (M1)	0.07 [0.00]		
- change in orders (M1)	0.04 [0.00]		
Insee manufacturing survey			
- personal production expectations (in difference)	0.03 [0.05]		
Dummies			
- 93q3	1.91 [0.02]	2.87 [0.00]	
- 07q4			-2.11 [0.00]
- 09q1	-3.09 [0.00]	-2.13 [0.01]	
Estimation sample	90q3 – 15q2	90q3 – 15q2	90q3 – 15q2
Adjusted R²	0.54	0.62	0.63
Standard error	0.76	0.69	0.68
Normality	0.91 [0.63]	0.77 [0.68]	0.00 [1.00]
AR(4)	0.37 [0.83]	0.58 [0.68]	1.63 [0.17]
Heteroscedasticity	0.61 [0.72]	0.50 [0.78]	1.60 [0.18]

P-values in brackets. "Normality" denotes the Bera-Jarque test for residual normal distribution. AR(4) denotes the Breusch-Godfrey test for residual serial correlation up to order p = 4. "Heteroscedasticity" is the Breusch-Pagan-Godfrey test for heteroscedasticity.

Construction

The main characteristic of the construction sector is that it is divided in two separate activities which may vary differently: civil engineering (public works) and housing construction. Housing construction is itself divided in two main activities: construction of new housing per se and renovation of existing dwellings.

Hard data such as housing starts cover a rather small part of the value added of the whole construction sector. Furthermore, housing starts or building permits do not provide information about the value of the building which is constructed, nor on the necessary time to build it. They may also suffer from a high cancellation rate and these data are often revised by a significant amount. Thus, in the French case, housing starts or permits have proven to be very imprecise predictors of the valued of added of the construction sector or of residential investment.

There are monthly surveys on building activities conducted by Banque de France and INSEE but they actually have a weak predictive power of the variation of the value added of the construction sector. Such a weakness might be explained by the fact that the monthly surveys exclude small businesses (firms with less than 11 employees) which are difficult to survey. But since the housing construction sector is known to be mainly composed of small firms, the limited scope of the survey may create an important bias. In particular, renovation of existing dwelling is almost essentially done by very small firms. Construction of new dwellings may involve bigger firms but also usually rely on small ones.

Hence, we use a quarterly survey conducted by INSEE on the small business (less than 11 employees) in the housing construction sector ("artisanat du bâtiment"). This variable provides a better proxy for the activity in housing construction than any other available variable.

Regarding civil engineering, there were much fewer options since only quarterly surveys are available. Both Banque de France and INSEE publish one. We have selected the Banque de France's one which has a slightly better predictive power. We also considered using hard data such as those issued by the *Federation nationale des travaux publics* (FNTP). Unfortunately, these data are available quite late in the quarter (only one month of data is published before the 3rd and last forecast of our benchmark MIBA model) so we preferred not to take them into account.

To sum up, the specification adopted for predicting the growth rate of the value added of construction includes the lagged dependent variable and two surveys of opinion both coming from quarterly surveys: the expected activity in the building crafts sector on the one hand (INSEE) and the expected activity in public works on the other hand (BDF).

Both surveys are available for the M1 equation, which is why equations for the three monthly forecasting exercises are the same. The M1 equation includes predicted lagged VA growth rate since quarterly national accounts of the previous quarter are not yet published at this time.

	M1-M2-M3
Constant	-0.01 [0.91]
Lagged dependent variable (Q-1)	0.44 [0.00]
Insee building crafts quaterly survey	
Expected activity (Q)	0.02 [0.00]
BDF public works quaterly survey	
Expected activity (Q-1)	0.01 [0.02]
Estimation sample	96q3 – 15q2
Adjusted R^2	0.69
Standard error	0.58
Normality	0.16 [0.92]
AR(4)	1.79 [0.14]
Heteroscedasticity	0.83 [0.48]

P-values in brackets. "Normality" denotes the Bera-Jarque test for residual normal distribution. AR(4) denotes the Breusch-Godfrey test for residual serial correlation up to order p = 4. "Heteroscedasticity" is the Breusch-Pagan-Godfrey test for

Energy

The production cycle in the energy sector is quite atypical as it is related to some specific variables such as weather conditions and changes in energy prices. Preselected variables for forecasting energy VA include household consumption in energy goods, energy industrial production, electricity consumption (households and firms) which are available in real time and energy HICP.

The most important indicator that emerged for forecasting purposes is households' energy consumption. For months when this indicator is not yet available, electricity consumption data is a good advanced indicator of household consumption. This indicator is also assumed to capture some reaction to the change in weather conditions. Finally, lagged energy price inflation is negatively correlated with the energy VA growth rate.

Estimations showed a systematic upward bias in the period between Q4 2007 and Q3 2009 which corresponds to a marked decline in energy VA not fully captured by cyclical indicators. Consequently a dummy variable for this period is included in the specifications.

It should be noted that the M2 equation differs when the 3rd quarter is considered. In fact, households' energy consumption for July and August together is released at the end of September; therefore its carry-over after M1 is not available for the M2 forecast of Q3 at the beginning of this month. The carry-over at the beginning of the quarter as well as the carry-over of electricity consumption after M2 are then used instead of the variables employed for the three other quarters.

	M1	M2	M2 Q3	M3
Constant	0.51 [0.00]	0.47 [0.00]	0.16 [0.40]	0.46 [0.00]
Households' energy consumption				
carry-over after M2				0.41 [0.00]
carry-over after M1		0.37 [0.00]		
carry-over after M3(-1)	0.13 [0.14]		0.16 [0.09]	
Electricity consumption (households and firms)				
mom growth rate (M3)				0.07 [0.20]
mom growth rate (M2)		0.15 [0.00]		
carry-over after M2			0.21 [0.00]	
carry-over after M1	0.20 [0.00]			
HICP energy (Q-1)	-0.13 [0.05]	-0.14 [0.03]	-0.10 [0.21]	-0.16 [0.01]
Dummy 07q4-09q3				
Estimation sample	96q2 – 15q2	96q1 – 15q2	96q1 – 15q2	96q1 – 15q2
Adjusted R²	0.37	0.50	0.20	0.50
Standard error	1.45	1.35	1.64	1.35
Normality	0.56 [0.75]	1.38 [0.50]	1.07 [0.59]	1.01 [0.60]
AR(4)	1.53 [0.20]	2.94 [0.03]	2.56 [0.05]	2.76 [0.03]
Heteroscedasticity	1.01 [0.41]	1.12 [0.35]	2.03 [0.12]	2.10 [0.09]

P-values in brackets. "Normality" denotes the Bera-Jarque test for residual normal distribution. AR(4) denotes the Breusch-Godfrey test for residual serial correlation up to order p = 4. "Heteroscedasticity" is the Breusch-Pagan-Godfrey test for heteroscedasticity.

Non-market services

Non-market services correspond to a diverse set of activities – in general public – for which there is no specific leading indicator. Several regressors were tested in the regressions, some of which related to market services. We also tried a "MIBA-like" specification with MIBA variables explaining the VA growth rate. Finally no specification was found to do better than a simple AR model in which we define the optimal lag order by Schwarz criterion.

	M1-M2-M3
Constant	0.19 [0.00]
Lagged dependent variable	
Q-1	0.18 [0.03]
Q-2	0.25 [0.00]
Estimation sample	80q4 – 15q2
Adjusted R²	0.10
Standard error	0.28
Normality	7.90 [0.02]
AR(4)	0.26 [0.90]
Heteroscedasticity	6.92 [0.00]

P-values in brackets. "Normality" denotes the Bera-Jarque test for residual normal distribution. AR(4) denotes the Breusch-Godfrey test for residual serial correlation up to order p = 4. "Heteroscedasticity" is the Breusch-Pagan-Godfrey test for

Agriculture

Unlike non -market services, some leading indicators can be tested in a forecasting equation (surveys in agri-food industry, agricultural commodity prices) but no one was found to help predicting VA growth rate in agriculture. Finally we chose to retain an autoregressive process with a five-lag order that performs quite well in forecasting VA growth rate for this sector. As for the building sector, the M1 equation includes predicted lagged VA growth rate for the previous quarter.

	M1-M2-M3
Constant	0.21 [0.01]
Lagged dependent variable	
Q-1	1.06 [0.00]
Q-2	-0.12 [0.32]
Q-3	-0.45 [0.00]
Q-4	-0.13 [0.29]
Q-5	0.22 [0.01]
Estimation sample	80q4 – 15q2
Adjusted R^2	0.89
Standard error	0.85
Normality	0.85 [0.65]
AR(4)	9.28 [0.00]
Heteroscedasticity	1.19 [0.32]

P-values in brackets. "Normality" denotes the Bera-Jarque test for residual normal distribution. AR(4) denotes the Breusch-Godfrey test for residual serial correlation up to order p = 4. "Heteroscedasticity" is the Breusch-Pagan-Godfrey test for

Residuals' tests of the estimated equations for each sector show that their statistical properties are broadly satisfactory. In general, we cannot reject the null hypothesis of absence of autocorrelation (up to order 4), as well as homoskedasticity and normality, with some exceptions. Normality and homoskedasticity are rejected for non-market services equations, while homoskedasticity and absence of serial correlation are rejected for M1 and M2 equations in market services.

3. PRISME and the aggregation issue

Once we have an equation for each of the six major economic activities, it is easy to obtain a forecast of total VA growth rate by aggregating forecasts from our six equations. However the relevance of this disaggregated approach is not guaranteed. As we saw in the introduction, there are three kinds of aggregation problems that can potentially cast doubt on the need for disaggregation.

PRISME is not concerned with the first problem that occurs when the parameters of the macro equation differ from the average of the corresponding micro parameters, since explanatory variables in PRISME differ for each "micro" equation. But the two other aggregation problems may arise. On the one hand, errors in PRISME equations can be contemporaneously correlated. On the other hand, it can be more efficient to predict directly an aggregate variable than summing the predictions of its components.

Error Cross section independence in PRISME

A first look at correlations between in-sample residuals (see table 2) of M3 equations show that errors may be correlated across equations. In particular the correlation between manufacturing and market services residuals is positive and significantly different from zero, showing that errors may not compensate each other when aggregating forecasts for these sectors.

Table 2: Correlations between in-sample residuals in the PRISME model

	DSM	DIM	FZ	DE	DSN	AZ
DSM	1.00					

DIM	0.28	1.00				
	0.02	-----				
FZ	0.19	0.17	1.00			
	0.11	0.15	-----			
DE	0.17	-0.08	-0.06	1.00		
	0.14	0.49	0.60	-----		
DSN	0.01	0.01	0.01	0.04	1.00	
	0.90	0.94	0.94	0.76	-----	
AZ	0.07	-0.20	0.12	-0.05	-0.03	1.00
	0.57	0.08	0.29	0.64	0.81	-----

Correlation between in-sample residuals on the first line. P-values on the second line.
DSM: Market services; DIM: Manufacturing; FZ: Building; DE: Energy; DSN: Non-market services; AZ: Agriculture

To test formally the null hypothesis of independence of residuals across sectors, we can use the following test proposed by Pesaran (2008):

$$\mathrm{CD} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$$

where $\hat{\rho}_{ij}$ is the estimated correlation coefficient between residuals in sectors *i* and *j* equations

For *T* sufficiently large, the statistic above converges to a standard normal distribution.

According to this test, we cannot reject the null hypothesis of independence across residuals for the M3 equations (p-value=0.15). However we do reject the null hypothesis of independence across residuals at a 1% critical level for the M1 and M2 equations. A usual approach to deal with error cross section dependence is to estimate SURE estimators. Therefore we reestimate the parameters of the PRISME model, accounting for heteroskedasticity and contemporaneous correlation in the errors across equations. We find that coefficients and standard errors are not very different from OLS estimations. Therefore we can conclude that estimation results presented in the previous section are robust to the correction of error cross section dependence.

Positive correlations between residuals (e.g. between residuals in the manufacturing and market services equations) is something difficult to avoid when using a disaggregated approach like PRISME. The positive sign of these correlations means that some part of a common co-movement between variables is not taken into account in the different equations. An alternative approach to deal with cross-correlations would be to estimate a factor model which captures the common business cycle driving activity in different sectors. Section 4 shows that this approach is not necessarily better than a disaggregated model like PRISME to forecast GDP growth.

It is worth noting that the correlation between residuals for the two main economic activities – manufacturing and market services – decreases in M3 when we introduce in these equations the first hard data available. In particular, manufacturing production enters both manufacturing and market equations. This variable surely helps to better predict the common cycle component between these two sectors, reducing the “common” part of the residuals relative to their idiosyncratic part, thus reducing the positive correlation between total residuals for these two sectors.

In-sample aggregation tests

The third aggregation problem is a very practical one: is it more efficient to predict directly an aggregate variable than summing the predictions of its components? Here again there is no obvious answer to that question. To compare in-sample predictions of disaggregated models like PRISME and aggregated models, we can first use the prediction criterion for aggregation proposed by Grunfeld & Griliches (1960) which simply compares the variance of the residuals of the "macro" equation (in our case, the direct equation for total VA) to the variance of the weighted sum of the residuals of the "micro" equations (in our case, equations for the six economic activities).

In this context, it seems interesting to compare four models, two of which being derived from our natural benchmark, the MIBA model, the other two derived from the PRISME model: *i)* a simple "aggregated MIBA"[14] model that predicts directly total VA growth with MIBA variables (BDF manufacturing survey's variables and lagged growth rate of GDP first estimate); *ii)* a "disaggregated MIBA" model that predicts VA in each sector with the same MIBA variables before aggregating these forecasts to predict total VA; *iii)* an "aggregated PRISME" model with all the PRISME variables stacked into one single equation to predict total VA growth; *iv)* the PRISME model. The comparison of *i)* and *ii)* on the one hand and the comparison of *iii)* and *iv)* on the other hand allow us to infer directly the benefit (or loss) of using VA components forecast to predict the aggregate. Model *iii)* is similar to the benchmark model that will be introduced in the next section when we will compare PRISME to dynamic factor models.

More specifically, if we write down the equations for *i)* and *ii):*

i) $$VA_{a,t} = a + b_a X_{Miba,t} + c_a Pibprem_{t-1} + e_{a,t} \qquad (1)$$

ii) $$VA_{i,t} = a_i + b_i X_{Miba,t} + c_i Pibprem_{t-1} + e_{i,t}, \;\; i = DSM, DIM, FZ, DE, DSN, AZ \qquad (2)$$

Or if we write down the equations for *iii)* and *iv):*

iii) $$VA_{a,t} = a + b_a X_{Prisme,t} + e_{a,t} \qquad (3)$$

iv) $$VA_{i,t} = a_i + b_i X_{Prisme,i,t} + e_{i,t}, \;\; i = DSM, DIM, FZ, DE, DSN, AZ \qquad (4)$$

the Grunfeld & Griliches (1960) test says that the disaggregate model should be chosen if

$$\sigma_a^2 > \sigma_d^2$$

With $\sigma_a^2 = var(e_{a,t})$, $\sigma_d^2 = var(e_{d,t})$ and $e_{d,t} = \sum_i w_i \, e_{i,t}$ where w_i is the weight of each sector in total VA.

Variances are shown in table 3. According to the Grunfeld & Griliches prediction criterion for aggregation, the aggregated models should be preferred to their disaggregated counterparts. The results are less clear for the MIBA model, for which the test values of MIBA and disaggregated MIBA are very similar. However, the aggregated PRISME model contains a lot of variables that are non-significant when we put all together the PRISME variables in one single equation. This raises the

[14] Note that this aggregated MIBA model differs from our MIBA benchmark model since the latter predicts directly the first estimate of GDP growth rate.

question of the credibility of the aggregated PRISME model as a benchmark for PRISME in this specific context. If we compare the "true" (disaggregated) PRISME model to the "true" (aggregated) MIBA model, results are better for PRISME in M3. For M2, the results provided by PRISME are similar to those of the MIBA model, while for M1 the variance of the sum of the residuals of the PRISME equations is clearly higher than the variance of the aggregate residuals of the MIBA model. These results should however be interpreted with caution as the Grunfeld & Griliches criterion was not designed to test a disaggregated model like PRISME where equations differ both between themselves and with the aggregate equation.

Table 3: Results of the Grunfeld & Griliches test for MIBA and PRISME models

	Aggregated Miba	Disaggregated Miba	Aggregated Prisme	Prisme
M1	0.072	0.072	0.052	0.088
M2	0.061	0.062	0.046	0.065
M3	0.055	0.058	0.032	0.042

To conclude this section, we must keep in mind that in-sample performance criteria such as Grunfeld & Griliches (1960) or more refined aggregation tests like Pesaran, Pierse, Kumar (1989), tell us nothing about the out-of-sample forecast accuracy of PRISME, although it already brings some insights on the features of the disaggregation approach embedded in this model. As noted in the introduction, it remains a very empirical question whether aggregating forecasts of disaggregates is better than forecasting directly the aggregate of interest. The next section deals with out-of-sample empirics.

4. Forecasting performances of the PRISME model

This section presents results on forecast accuracy of the PRISME model. All the forecasts analyzed in this section are pseudo real-time out-of-sample forecasts (see box 1) from 2007q1 to 2015q2 (34 observations). Equations are estimated recursively on the whole sample available at the time of the forecasting exercise.

4.1 Forecast accuracy of sectorial equations

As previously explained, the PRISME model is a disaggregated model where the value added growth rates of the six major economic activities are forecasted separately. The first step to analyze the forecasting performance of PRISME is logically to look at forecast accuracy for each sector.

We retain two benchmarks to assess the quality of one given sector's forecasts. The first one, called "MIBA-like" model[15], is the regression of the value added growth rate for each sector on the variables used in the MIBA equation (BDF manufacturing survey's variables and lagged growth rate of GDP first estimate). As the PRISME model is designed to highlight and correct a potential disconnection between MIBA variables (related to the manufacturing sector) and the activity in a given sector, it seems logical to define, through the "MIBA-like" model, a forecast for each sector

[15] The "disaggregated MIBA" model presented in section 3 was the collection of these "MIBA-like" models for each sector.

consistent with MIBA variables. The second benchmark is the naive AR model, where the number of lags is selected before each forecasting exercise with the Schwarz information criteria.

Box 1: Real-time or pseudo real-time data and forecasts

The best way to judge the quality of the model is to compute *ex post* forecasts that should have been made in real-time conditions. This implies knowing the exact information set available at each monthly forecasting exercise, called vintage data. However, PRISME uses a large dataset and the sample for which vintage data are available for all variables is too small. Thus, we consider data series available in September 2015 and define for each quarter a pseudo vintage dataset[16], which corresponds to the September 2015 dataset truncated at the date of the forecasting exercise for this quarter. The pseudo vintage dataset for each quarter includes all revisions made from this quarter until September 2015. Accordingly, pseudo real-time forecast accuracy of PRISME and benchmarks models will be defined relatively to pseudo vintage data of dependent variables (quarterly growth rates of GDP and sectorial value added).

However, our benchmark MIBA model is designed to forecast the first estimate of the GDP growth rate. For this benchmark only, forecast accuracy will be compared relatively to both vintage (first estimate) and pseudo vintage (last estimate) data of the GDP growth rate.

Table 4 reports forecast accuracy of the PRISME model for each monthly forecasting exercise in terms of mean absolute forecast error (MAE) and root mean square forecast errors (RMSE) in percent, both in absolute terms and relative to the standard deviation of each dependent variable. This table also presents the ratios of PRISME's MAE and RMSE over those of the benchmark models (MIBA-like and AR models).

[16] More precisely, we define three pseudo vintage datasets for each quarter, each one corresponding to the month of the forecasting exercise (M1, M2 or M3).

Table 4: Forecast accuracy (absolute and relative to benchmarks) of PRISME's sectorial equations

	DSM	DIM	FZ	DE	DSN	AZ
	MAE PRISME					
M1	0.28	0.76	0.62	1.15	0.09	0.97
M2	0.28	0.65	0.49	1.28	0.09	0.61
M3	0.17	0.68	0.49	1.16	0.09	0.61
	RMSE PRISME					
M1	0.40	1.03	0.80	1.48	0.12	1.18
M2	0.35	0.83	0.64	1.63	0.12	0.77
M3	0.22	0.86	0.64	1.48	0.12	0.77
	Standard deviation of the dependent variable					
SE	0.65	1.43	0.92	1.85	0.11	1.77
Ratios RMSE / SE						
M1	0.61	0.72	0.87	0.80	1.05	0.67
M2	0.53	0.58	0.70	0.88	1.06	0.44
M3	0.34	0.61	0.70	0.80	1.06	0.44

DSM : Market services; DIM : Manufacturing; FZ: Building; DE: Energy; DSN: Non-market services; AZ: Agriculture

	DSM	DIM	FZ	DE	DSN	AZ
Ratios / AR	MAE					
M1	0.60	0.65	0.83	0.68	0.97	1.04
M2	0.68	0.58	0.93	0.77	0.97	0.96
M3	0.40	0.60	0.93	0.70	0.97	0.96
	RMSE					
M1	0.58	0.64	0.89	0.75	0.99	1.04
M2	0.59	0.56	0.99	0.81	0.99	0.96
M3	0.38	0.58	0.99	0.73	0.99	0.96

	DSM	DIM	FZ	DE	DSN	AZ
Ratios / MIBA	MAE					
M1	0.84	0.91	0.84	0.71	0.99	0.61
M2	0.86	0.83	0.70	0.86	1.02	0.38
M3	0.62	0.90	0.69	0.85	1.02	0.35
	RMSE					
M1	0.95	0.94	0.94	0.77	0.99	0.60
M2	0.84	0.83	0.76	0.90	1.07	0.38
M3	0.58	0.88	0.76	0.90	1.07	0.36

Market services

The contribution of market services to GDP growth and GDP growth volatility is the most important although the latter contribution is smaller in relative terms because of the relatively low volatility of the VA growth rate in market services compared to the other sectors. Results for this sector can be seen as broadly satisfactory: the improvement of PRISME's forecast accuracy over time is noticeable, as the RMSE declines from 0.40 in M1 to 0.35 in M2 and to 0.22 in M3. Moreover, the ratio of RMSE on standard deviation is at 34% only in M3, the lowest value among all sectors. PRISME's equations outperform significantly the two benchmark models, except the MIBA-like model in M1 for which the difference is less significant. In M3, the superiority of PRISME is particularly obvious, with a forecast accuracy gain in terms of RMSE of 42% compared to MIBA-like and 62% compared to the AR model.

Manufacturing

In manufacturing, PRISME's RMSEs throughout the monthly forecasting exercises do not change as much as for market services: 1.03 in M1, 0.83 in M2 and 0.86 in M3. Intuitively, manufacturing should be the sector where the MIBA-like model is the more efficient, given that most MIBA variables are related to deliveries in manufacturing. Still the gain in forecast accuracy of PRISME is between 6% and 17% compared to MIBA-like. The naive AR model performs poorly in forecasting VA growth rate in manufacturing, with RMSEs higher than standard deviation.

Construction

The standard deviation of VA growth rate in construction is 0.92. PRISME's RMSEs go from 0.80 in M1 to 0.64 in M3. The gain in forecast accuracy compared to MIBA-like is only 6% in M1 but reaches 24% in M3. These results confirm our prior insights that the disconnection between this specific sector and the whole economic cycle can be particularly important on the one hand, but that PRISME forecast can correct this on the other hand. As the VA growth rate is strongly persistent, the benchmark AR model has also good forecasting performances, comparable to PRISME's ones.

Energy

Energy is the most volatile economic sector: the standard deviation of the quarterly growth rate is 1.85. The two benchmark models have poor forecasting performances. RMSEs of AR models are higher than the standard deviation of the dependent variable. RMSEs of MIBA-like are also higher in M1, slightly better in M2 and M3 (RMSE of 1.81 and 1.65 respectively). PRISME's forecasting errors are also quite high (RMSEs between 1.5 and 1.6). Surprisingly, forecast accuracy is worse in M2 than in M1. In M3, the gain in forecast accuracy compared to MIBA-like stands at 10%. Given the volatility of the sector, PRISME's performance is satisfactory albeit weak in absolute terms.

Non-market services

VA in market services is relatively inert (standard deviation of 0.11). The PRISME equation follows an AR process and is then very close to the naive AR model. The coefficients of the MIBA-like model are not significantly different from zero; so MIBA-like in this case almost reduces to a constant. Finally, the three models produce very close forecasts and RMSEs are comparable to the standard deviation, which mean that none are efficient to predict the VA growth rate in this sector.

Agriculture

The forecasting equation is an autoregressive process. Logically, PRISME's forecast accuracy is very close to the one of the naive AR model. The RMSE stands at 1.2 for the first month and 0.8 for the two next months, less than half of the dependent variable's standard deviation (1.8). The gain in forecast accuracy is noticeable compared to MIBA-like: from 40% in M1 to 64% in M3.

Before turning to the aggregate's forecast, it is worth summing up the main results for the sectorial equations:

- The forecast accuracy of the PRISME sectorial equations is generally high compared to naïve benchmarks.
- Results for PRISME are clearly better in market services relative to our MIBA-like benchmark when first hard data is available (3rd month forecasts). Results are only marginally better for the 1st and 2nd month's equations when forecasts rely mainly on manufacturing surveys. In manufacturing, the gain in forecast accuracy of PRISME compared to MIBA-like is the most sizeable for the 2nd month forecasts.
- Results are also more favorable for PRISME in the construction and energy sectors.

4.2 Forecast accuracy of aggregate's forecasts

Beyond the quality of each sectorial equation, PRISME is expected to help for forecasting the GDP growth rate during the MIBA forecasting exercises. By construction, PRISME can only forecast the growth rate of total value added, but does not predict the growth rate of the "residual" made of net taxes on products and errors related to summing chain-linked volumes. The latter represents a very small part of GDP growth volatility, whereas the contribution to forecast errors of net taxes on products can sometimes be non-negligible. But the difficulty to forecast such an item prevents us to add an extra equation in the PRISME model. Thus, our growth forecast for this item is implicitly the same as for total value added, which seems a plausible assumption. Even though the forecast accuracy of PRISME is computed in reference to the GDP growth rate, we should remind that this model should be judged on its ability to forecast correctly the aggregate (total) value added.

We have retained five benchmarks models to be compared to PRISME. The first one is the MIBA model. Comparing these two models is an obvious step since PRISME has been built as a "safeguard" of MIBA. The second benchmark is the OPTIM model, which adds to the MIBA variables (*Banque de France* manufacturing survey) other "soft" manufacturing data (balances of opinion from the Insee survey in industry) as well as "hard" manufacturing production data when available. The third benchmark is a simple AR model. The number of lags is selected before each forecasting exercise with the Schwarz information criteria. The last two benchmarks are dynamic factors models, which are often used by institutions for nowcasting[17].

The first DFM only integrates the PRISME variables from every sectorial equation. The goal of this benchmark is to evaluate the disaggregated structure of PRISME, i.e. to check whether PRISME's information set is more efficiently used through disaggregated equations than through a factor model that "bridges" the information content of all PRISME variables with projected GDP growth. This model is called thereafter DFM1. The dynamic factors are computed on monthly variables which are expected to correspond to series of quarterly growth rates. Quarterly variables are transformed in monthly data by filling the value of the third month with the quarterly value (the first and second months stay unfilled). Monthly variables are also transformed to be consistent with a quarterly growth rate. For example, variables from Banque de France's surveys are consistent with monthly growth rates (evolution of production over the last month), therefore the new series are weighted moving averages of original series:

$$\tilde{x}_t = \frac{1}{3}x_t + \frac{2}{3}x_{t-1} + x_{t-2} + \frac{2}{3}x_{t-3} + \frac{1}{3}x_{t-4} \qquad (5)$$

Dynamic factors follow an autoregressive process and the idiosyncratic part of each variable is a white noise. Factors are estimated through a Kalman filter by the maximum of likelihood method. We test sixteen different specifications: the number of factors and the number of lag for each factor vary between one and four. We retain the specification that minimizes the root mean squared error.

[17] The comparison of PRISME with another important class of models, i.e. *bridge* models with extrapolation of explanatory variables, will be made in future work.

The second DFM benchmark is a state-of-the-art DFM following the methodology of Giannone and Reichlin (2008)[18] and thereafter called DFM2. Their approach consists in summarizing all the available information contained in numerous monthly time series in few common factors. They assume a certain factor structure for their monthly indicators, which basically sums up to the number of static and dynamic factors as well as the number of lags in state equations. They obtain the GDP growth nowcast as a linear function of the expected common factors. They also deal with missing data at the end of the sample by combining principal components with Kalman filtering techniques. Although the model does not allow for cross-sectional and serial correlation of the idiosyncratic component, the model's consistency is ensured under the assumption that this component becomes negligible as the cross-sectional dimension increases. This explains why the model needs large-scale information sets to produce consistent parameter estimates. In our case we choose to include in addition to PRISME variables a much larger set of data (110 variables) which is rather similar to the dataset used by the ECB to predict French GDP growth[19]. Variables are also transformed according to (5). As for the 1st DFM, the number of factors and lags in state equations is chosen so that we obtain the lowest RMSE over the sample considered.

As explained in box 1, the comparison between PRISME and the benchmarks is based on pseudo real time forecast from 2007q1 to 2015q2, except for the comparison between PRISME and MIBA that will also be based on pure real time forecasts from 2011q2 to 2015q2.

Comparison with MIBA and OPTIM: Pseudo real time forecasts

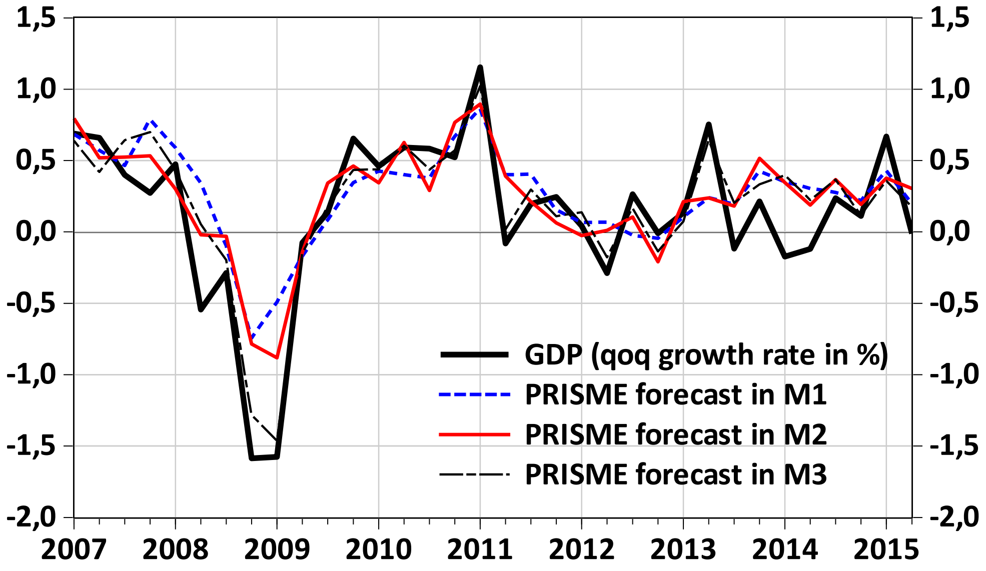
The RMSE of PRISME stands at 0.37 in M1, then 0.31 in M2 and 0.22 in M3 (see table 5). RMSE in M3 is 61% lower than the standard deviation of the GDP growth rate. The rapid decrease of RMSE between M1 and M2 on one hand and M3 on the other hand reflects the availability of hard data (in particular industrial production) in the 3rd month of nowcasting. A lot of papers (for example Banbura and Rünstler (2011); Banbura, Giannone and Reichlin (2010)) show indeed that the contribution of surveys to nowcast accuracy almost vanishes by the time hard information becomes available.

The improvement of PRISME forecast accuracy between M1 and M3 is particularly obvious during the Great Recession (see chart 1). After this crisis, GDP growth rates of high amplitude (e.g. 2011q1 and 2013q2) are better anticipated by the M3 equation. However, all PRISME forecasts present a systematic upward bias from 2013q3 to 2014q3. This series of negative forecast errors might be due to the presence of residuals' serial correlation in some of the PRISME specifications. However, the absence of autocorrelation of residuals is broadly not rejected as shown in section 3. Moreover, by taking into account the deterioration of activity in the construction sector, PRISME is able to reduce at least some of the cumulated forecast errors made by our benchmark MIBA model during that period (see section 5).

[18] *Nowcasting: The Real-Time Informational Content of Macroeconomic Data*, Journal of Monetary Economics, 2008

[19] Variables are listed in the annex.

Chart 1: GDP growth rate and PRISME's forecasts



Forecast accuracy of MIBA is almost stable across the different months. The RMSE stands at 0.37 in M1, 0.36 in M2 and 0.35 in M3. In M1, MIBA is insignificantly more accurate than PRISME (PRISME's RMSE is 2% higher) but from M2 onward PRISME performs better with a gain in forecast accuracy of 12% in M2 and 36% in M3.

Unlike PRISME in M3, MIBA forecasts are often not able to capture extreme variations, for example during the Great Recession or in 2013Q2, which explains most of the gain in forecast accuracy of PRISME compared to MIBA. MIBA's forecasts also suffer from a systematic overestimation of the GDP growth rate from 2013q3 to 2014q3.

We also compare PRISME to the OPTIM model. The latter is a useful benchmark in the sense that it incorporates both manufacturing survey data (*Banque de France* and Insee surveys) as well as "hard" data (manufacturing production) when first data is available during the quarter. It allows us to control if the forecast accuracy gain of PRISME is only due to the presence of manufacturing production – a variable which is crucial to construct quarterly national accounts first estimates – in the manufacturing and market services equations. Table 5 shows that OPTIM makes better than MIBA for the M3 forecast thanks to the carry-over variable of manufacturing production after 1st month. For M1 and M2, forecasting performances of both models are quite similar, showing that Insee survey variables don't help to improve forecast accuracy of MIBA beyond *Banque de France* survey variables. For M3, PRISME does better than the OPTIM model, making it clear that the use of other variables from different sectors, as well as the disaggregated structure of the PRISME model help to improve forecast accuracy for this particular month.

Table 5: Forecast accuracy (absolute and compared to MIBA/OPTIM) of PRISME relative to GDP growth

	MAE	RMSE	
PRISME			*% of SD**
M1	0.27	0.37	0.66
M2	0.26	0.31	0.56
M3	0.17	0.22	0.39
MIBA			
M1	0.28	0.37	0.65
M2	0.27	0.36	0.63
M3	0.25	0.35	0.62
Ratio PRISME / MIBA			
M1	0.97	1.02	
M2	0.95	0.88	
M3	0.68	0.64	

	MAE	RMSE	
PRISME			*% of SD**
M1	0.27	0.37	0.66
M2	0.26	0.31	0.56
M3	0.17	0.22	0.39
OPTIM			
M1	0.28	0.37	0.65
M2	0.28	0.36	0.64
M3	0.22	0.28	0.50
Ratio PRISME / OPTIM			
M1	0.95	1.02	
M2	0.93	0.87	
M3	0.77	0.79	

*Standard deviation of GDP growth, 2007q1-2015q2 (0.57)

SD 0.565563

Comparison with MIBA: Real time forecasts

For PRISME and MIBA models, data vintages are available since 2011q2. Thus we can compare the real time forecast of those models over the 2011q2-2015q2 period. Results are shown in table 6. It confirms that PRISME forecast accuracy is better for the M3 forecasting exercise where first quantitative data are available. For M1 and M2, results are more in favor of MIBA compared to the pseudo real-time results.

Table 6: Forecast accuracy (absolute and compared to MIBA) of PRISME relative to GDP growth 1st estimate (real time forecasts)

	MAE	RMSE	
PRISME			*% of SD**
M1	0.21	0.23	1.00
M2	0.19	0.23	0.99
M3	0.14	0.18	0.78
MIBA			
M1	0.18	0.19	0.83
M2	0.17	0.21	0.90
M3	0.16	0.20	0.85
Ratio PRISME / MIBA			
M1	1.17	1.21	
M2	1.11	1.10	
M3	0.86	0.91	

*Standard deviation of GDP growth 1st estimate, 2011q2-2015q2 (0.23)

Comparison with DFMs

The 1st DFM benchmark model is a small-scale DFM that includes all PRISME variables and nothing else. The comparison of PRISME with this model aims at showing the benefits of PRISME coming from its disaggregated structure compared to a factor model's direct approach to forecast GDP growth. Results are shown in table 7. PRISME's forecast accuracy is higher for M2 and M3 while forecasting performances are quite similar for the M1 equation. It should be noted that the factor model's accuracy does not change much over the monthly forecasting exercises.

The 2nd DFM benchmark model is a large-scale DFM that includes an extended set of variables (survey and quantitative data, financial and monetary variables). Despite its comprehensive information content, this model performs significantly worse than the PRISME model over the 2007q1 – 2015q2 period for all months considered. Unlike the 1st DFM, the forecasting performance of this benchmark improves however across the three forecasting exercises. It is worth noticing that its forecast accuracy relative to the 1st benchmark is only better for M3. This result emphasizes the relatively better forecasting performance of a small-scale model in our specific context[20].

Table 7: Forecast accuracy (absolute and compared to DFMs) of PRISME relative to GDP growth

DFM1

	MAE	RMSE	
PRISME			*% of SD**
M1	0.27	0.37	0.66
M2	0.26	0.31	0.56
M3	0.17	0.22	0.39
DFM1			
M1	0.27	0.39	0.68
M2	0.27	0.37	0.65
M3	0.27	0.36	0.63
Ratio PRISME / DFM1			
M1	0.99	0.97	
M2	0.96	0.86	
M3	0.63	0.62	

*Standard deviation of GDP growth, 2007q1-2015q2 (0.57)

DFM2

	MAE	RMSE	
PRISME			*% of SD**
M1	0.27	0.37	0.66
M2	0.26	0.31	0.56
M3	0.17	0.22	0.39
DFM2			
M1	0.31	0.43	0.75
M2	0.29	0.36	0.64
M3	0.22	0.30	0.53
Ratio PRISME / DFM2			
M1	0.87	0.88	
M2	0.88	0.86	
M3	0.75	0.75	

*Standard deviation of GDP growth, 2007q1-2015q2 (0.57)

Some main results emerge from this section:

- PRISME's sectorial equations perform relatively well compared to naive benchmarks and "Miba-like" equations.
- Going to the aggregate level, PRISME is able to forecast GDP growth more accurately than our DFM benchmarks. From an empirical, out-of-sample perspective, this supports the disaggregation approach embedded in the PRISME model.
- Out-of-sample results relative to our central benchmark – the MIBA model – are mixed. PRISME performs better when first quantitative date are available (M3 equations). For the 2nd month forecasting exercise, PRISME performs relatively better with pseudo real time data but it performs worse with real time data over a shorter evaluation period. At the beginning of the quarter (M1 equations), results are more in favor of the MIBA model.

[20] Some recent papers confirm that small-scale factor models often outperform the forecast obtained from large-scale ones. See for instance Banbura and Modugno (2010) or Burriel and Garcia-Belmonte (2013).

5. The true advantage of using PRISME as a complement to an aggregated model

As shown in the previous section, the gain of the PRISME model in terms of forecast accuracy compared to our central benchmark (MIBA) is established only when first quantitative data (manufacturing production, business services turnover) become available. If we consider instead the 2nd month of one particular quarter, e.g., when nowcast relies only on partial information (mainly soft data), then forecasting GDP growth is subject to high uncertainty, and it seems hard to distinguish between PRISME and MIBA models if we just consider mean squared errors over a long period of time (2007-2015 in our out-of-sample exercise). The reason behind is that it is hard to find leading indicators beyond the manufacturing surveys used in MIBA that bring extra-information on the whole business cycle.

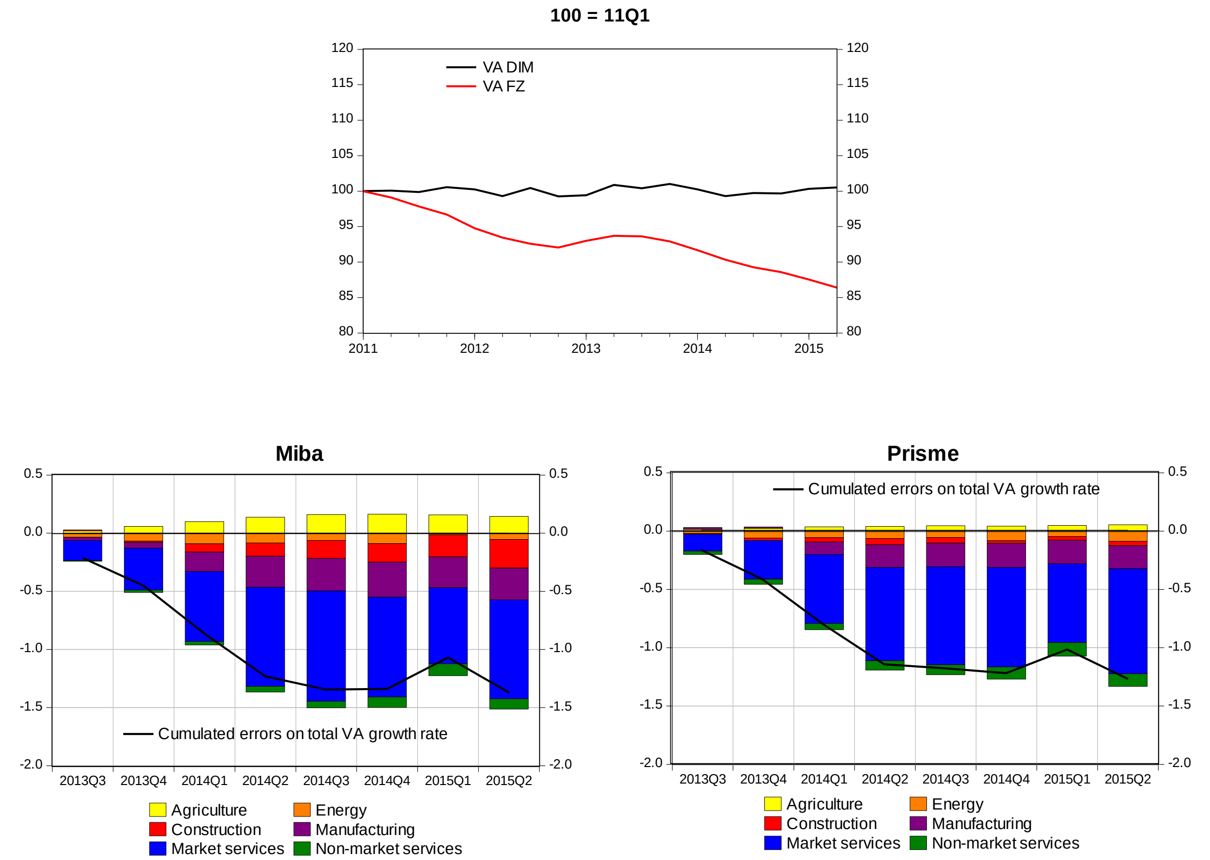
These preliminary statements highlight the fact that PRISME is not devoted to replace the MIBA model as the main tool at Banque de France to nowcast GDP, at least in the short run. The MIBA model seems hard to be outperformed for nowcasting with data available after two months. But PRISME has still a specific usefulness if we consider the forecasting exercise in a more operational sense.

The need for a safeguard model was formalized more than one year ago when the MIBA model made five consecutive negative forecast errors from 2013q3 to 2014q3. Although standard properties of MIBA residuals (normality and non-auto correlation) were not questioned, it became clear that cumulated forecast errors could appear during some short periods of time if a decoupling between some sectors and the MIBA reference – the manufacturing sector – occurred. A new safeguard model was therefore needed to prevent such a transitory accumulation of forecasting errors of the same sign. Construction in particular was the most credible candidate to explain why MIBA systematically overestimated GDP growth during several consecutive quarters.

To sum up, PRISME was made up not to systemically beat the MIBA model in terms of forecast accuracy, but to be used as an operational backup to our central benchmark. To illustrate this operational background, our focus in this section is the construction sector for which the advantages of a safeguard model like PRISME is notably obvious. To do so, instead of considering forecast errors for each quarter, we look at cumulated forecast errors to find evidence of transitory periods when the divergence between activity in construction and manufacturing leads to several consecutive forecasts errors of the same sign (typically negative).

As regards the construction sector, a 1st period starting in 2011 and ending in2015 is considered, when a disconnection between manufacturing activity and construction is clearly visible (see chart 2). During this period the deep downturn in construction is due to a combination of adverse factors (decrease in housing demand, budget cuts on public spending in infrastructures). The gap is increasing in 2011 and 2012, stabilizes in 2013 before increasing further from late 2013 until 2015q2. A pseudo vintage analysis can be made on this last sub-period, in order to underline the contribution of the construction sector to cumulated forecast errors of the PRISME and the MIBA models. This is done for M2 equations for which the pseudo real time analysis over a longer period (2007-2015) showed that the gain of the PRISME model in terms of RMSE compared to the MIBA model was not clearly apparent. The results appear in chart 2, where an important portion of cumulated forecast error of the MIBA model over the last eight quarters appears to be due to the contribution of construction. Conversely, the manufacturing and market services contributions to cumulated errors are similar for the PRISME and MIBA models, reminding us that the M2 equations for these two models are not so different, resulting in a limited forecast relative performance of PRISME compared to MIBA.

Chart 2: Contributions to cumulated forecast errors

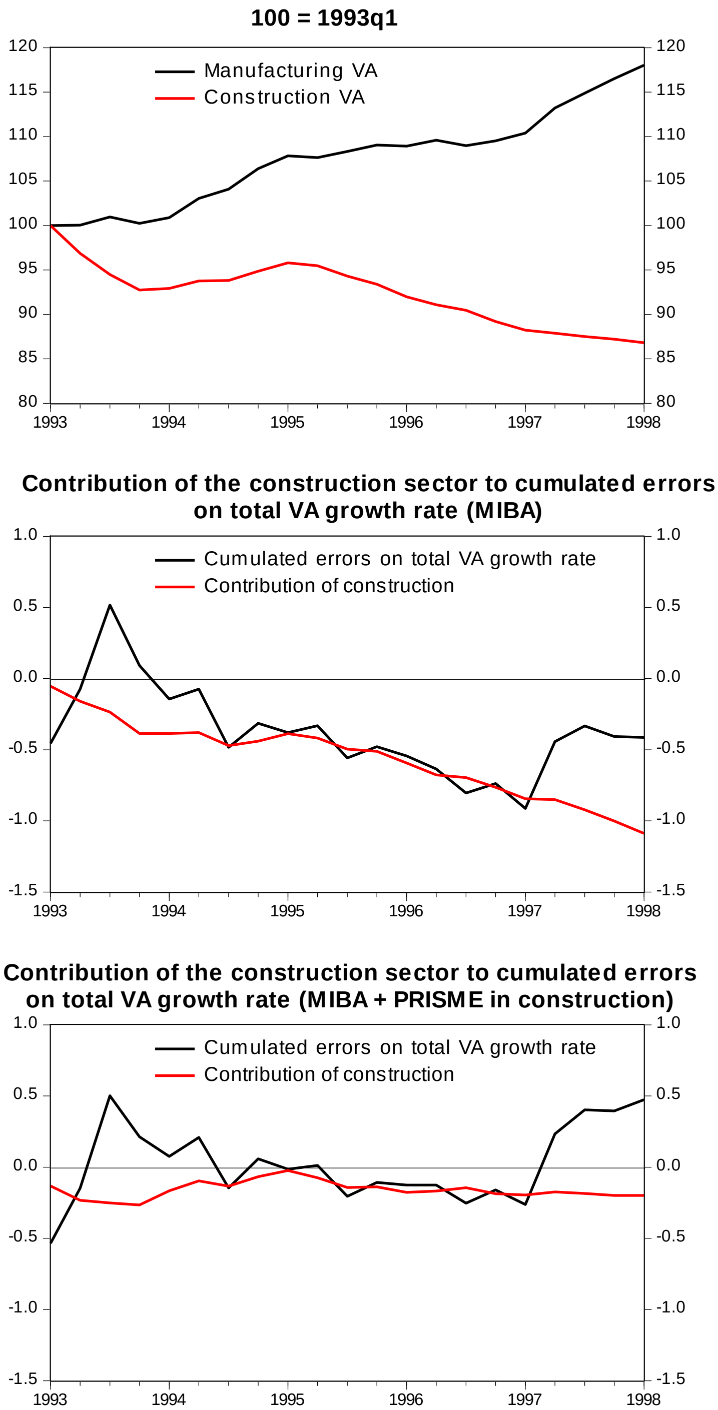


The second period when the operational gain of using PRISME appears more dramatically is the 1993-1998 period. During this period a deep contraction of activity in the construction sector took place, although barely interrupted by a short recovery in 1994. Whereas the real estate crisis of 1993 had already seriously undermined this sector, other factors continued to drag on construction activity until late 1997: threat of unemployment and high interest rates on the households' side, companies reorienting investment spending at the expense of building expenditure, public debt reduction during the transition to the euro. The consequence here is also an extended period of decoupling between the manufacturing and construction sectors (see Chart 3).

The pseudo vintage analysis is not feasible for this period since some data used in the PRISME model are only available since 95q1. However we can proceed to an in-sample comparison of two disaggregated models, one being the now familiar disaggregated MIBA model, the other being exactly the same model but with the PRISME equation in construction. This enables us to isolate the gain from forecasting activity in construction with the PRISME equation when this sector diverges from manufacturing.

Results in chart 3 are striking: while the two models present similar patterns for the shape of cumulated errors on total Value Added, the “pure” MIBA model shows an increasing optimistic bias that is almost entirely due to the contribution of the construction sector.

Chart 3: Contributions of the construction sector to cumulated forecast errors



6. Conclusion

This working paper presents the methodology and the equations of the new model PRISME used as a safeguard of the Banque de France MIBA model to forecast quarterly GDP growth. The development of a disaggregated model began when it became clear that an aggregated model based solely on surveys in the manufacturing sector like the MIBA one was not able to foresee a possible disconnect between different sectors (e.g. market services, construction…). It could therefore produce errors of the same sign for several consecutive quarters. The PRISME model that emerges from this work does not outperform MIBA over a long period in terms of forecast accuracy. It is nevertheless a useful complement to our central model especially over the recent period where there is a significant disconnect between activity in the construction sector and in manufacturing industry.

Thanks to its disaggregated approach, PRISME is also able to identify the supply side contributions of the different sectors to GDP forecast errors. Beyond this analytical benefit, PRISME's disaggregated approach seems validated by its out-of-sample forecasting performance compared to other aggregated models like Dynamic Factor Models.

Several work streams on PRISME will be of special importance. The improvement of the model is not yet finalized and will probably never be. Forecast accuracy of a particular model – in absolute terms or compared to other forecasting tools – varies substantially according to the period considered. The PRISME model will also be monitored on a regular basis as new data comes in. A special effort should be made to improve PRISME's forecasting equations in market services. Although the business cycle in this sector is linked for some part to the manufacturing cycle and is thus partially captured by the MIBA model, market services have still their own determinants that are not well captured by the specific indicators we have in hand. Finally, the contribution of the PRISME model to forecasting GDP growth could be compared to other types of forecasting models, including the D€stiny model of the Bank of Spain[21] or the new short term ECB model.

[21] See Burriel and Garcia-Belmonte (2013).

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Annex: variables used in the large scale dynamic factor model (section 4)

Variable	Publication lag	Transformation
Industrial production (excluding construction)	m-2	dlog
Industrial production (Total)	m-2	dlog
Industrial production (MIG - Intermediate goods)	m-2	dlog
Industrial production (MIG – Energy, except D and E)	m-2	dlog
Industrial production (MIG - Capital goods)	m-2	dlog
Industrial production (MIG - Durable consumer goods)	m-2	dlog
Industrial production (MIG - Non-durable consumer goods)	m-2	dlog
Industrial production (Manufacturing)	m-2	dlog
Industrial production (Manufacture of paper and paper products)	m-2	dlog
Industrial production (Manufacture of chemicals and chemical products)	m-2	dlog
Industrial production (Manufacture of rubber and plastic products)	m-2	dlog
Industrial production (Manufacture of basic metals)	m-2	dlog
Industrial production (Manufacture of electrical equipment)	m-2	dlog
Industrial production (Manufacture of machinery and equipment n.e.c.)	m-2	dlog
Industrial production (Electricity, gas, steam and air conditioning supply)	m-2	dlog
Industrial production (Mining and quarrying; manufacturing except MIG energy)	m-2	dlog
Industrial production (Construction)	m-2	dlog
Turnover, Transportation and storage	m-2	dlog
Turnover, Accommodation and food service activities	m-2	dlog
Turnover, Information and communication	m-2	dlog
Turnover, Professional, scientific and technical activities	m-2	dlog
Turnover, Administrative and support service activities r	m-2	dlog
Sales of motor vehicles; sale and repair of motorcycles	m-2	dlog
Retail trade, except of motor vehicles and motorcycles	m-1	dlog
Households goods consumption, food	m-1	dlog
Households goods consumption, cars	m-1	dlog
Households goods consumption, durable goods	m-1	dlog
Households goods consumption, energy	m-1	dlog
Households goods consumption, equipment	m-1	dlog
Households goods consumption, residential equipment	m-1	dlog
Households goods consumption, engineered goods	m-1	dlog
Households goods consumption, other engineered goods	m-1	dlog
Households goods consumption, manufactured goods	m-1	dlog
Households goods consumption, textile	m-1	dlog
Households goods consumption, total	m-1	dlog
Electricity consumption	m	dlog
Exports, value, customs data	m-2	dlog
Imports, value, customs data	m-2	dlog
Unemployment rate	m-1	dlevel
Job-seekers (A category)	m-1	dlog
Job-seekers (A B C categories)	m-1	dlog
Temporary work	m-2	dlog
BDF monthly survey in industry, order book (weeks of activity)	m	level
BDF monthly survey in industry, order book (level)	m	level
BDF monthly survey in industry, change in total orders	m	level

Variable	Publication lag	Transformation
BDF monthly survey in industry, change in foreign orders	m	level
BDF monthly survey in industry, change in labor force	m	level
BDF monthly survey in industry, change in deliveries	m	level
BDF monthly survey in industry, change in production	m	level
BDF monthly survey in industry, change in inventories	m	level
BDF monthly survey in industry, expected change in labor force	m	level
BDF monthly survey in industry, expected change in production	m	level
BDF monthly survey in industry, expected change in prices	m	level
BDF monthly survey in industry, expected change in inventories	m	level
BDF monthly survey in industry, capacity utilization rate	m	level
Insee household survey, major purchases opportunity	m	dlevel
EC Industry survey - industrial confidence indicator	m	dlevel
EC Industry survey - production trend observed in recent months	m	dlevel
EC Industry survey - assessment of order-book levels	m	dlevel
EC Industry survey - assessment of export order-book levels	m	dlevel
EC Industry survey - assessment of stocks of finished products	m	dlevel
EC Industry survey - production expectations for the months ahead	m	dlevel
EC Industry survey - selling price expectations for the months ahead	m	dlevel
EC Industry survey - employment expectations for the months ahead	m	dlevel
EC Consumer survey - consumer confidence indicator	m	dlevel
EC Consumer survey - general economic situation over last 12 months	m	dlevel
EC Consumer survey - general economic situation over next 12 months	m	dlevel
EC Consumer survey - price trends over last 12 months	m	dlevel
EC Consumer survey - price trends over next 12 months	m	dlevel
EC Consumer survey - unemployment expectations over next 12 months	m	dlevel
EC Retail trade survey - retail confidence indicator	m	dlevel
EC Retail trade survey - present business situation	m	dlevel
EC Retail trade survey - assessment of stocks	m	dlevel
EC Retail trade survey - expected business situation	m	dlevel
EC Retail trade survey - employment expectations	m	dlevel
EC Construction survey - construction confidence Indicator	m	dlevel
EC Construction survey - trend of activity compared with preceding months	m	dlevel
EC Construction survey - assessment of order books	m	dlevel
EC Construction survey - employment expectations for the months ahead	m	dlevel
EC Construction survey - price expectations for the months ahead	m	dlevel
Insee quarterly survey in building craftworks (expected activity)	m	level
BDF quarterly survey in public works (expected activity)	m	level
Euro Area - industrial production (total)	m-2	dlog
Euro Area - new orders for manufacturing	m-2	dlog
Euro Area - retail trade, except of fuels, motor vehicles and motorcycles	m-1	dlog
Euro Area - car registrations	m-1	dlog
Euro Area – unemployment rate	m-1	dlevel
Euro Area - EC Industry survey - ESI	m	dlevel
Euro Area - EC Consumer survey - consumer confidence indicator	m	dlevel
Euro Area - EC Industry survey - production expectations for the months ahead	m	dlevel
Euro area - loans excluding reverse repos, total maturity	m-1	dlog
Euro area - monetary aggregate M1	m-1	dlog
Euro area - monetary aggregate M2	m-1	dlog
Euro area - monetary aggregate M3	m-1	dlog

Variable	Publication lag	Transformation
United States – industrial production excl. construction	m-1	dlog
United States – retail sales	m-1	dlog
United States – civilian employment	m-1	dlog
United States – unemployment	m-1	dlevel
United States – Production expectations in manufacturing	m	dlevel
United States – consumer expectations	m	dlevel
United States - M2	m-1	dlog
United States – Treasury 10 years bonds rate	m	dlevel
United States – 3 months Treasury bill rate	m	dlevel
France - 10 years Government bond yield	m	dlevel
Euribor 3-month	m	dlevel
Gold price	m	d12log
Gold price	m	d12log
Crude oil price	m	d12log
World market prices of raw materials	m	d12log
World market prices of raw materials, total excluding energy	m	d12log
Nominal effective exchange rate	m	dlog

Note: dlog, dlevel and d12log stand for the first difference of the log, the first difference of the levels and the first difference of the yearly growth rates of the series, respectively.

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