The ADP France Employment Report

Detailed Methodology:

Working in close collaboration with Moody’s Analytics, Inc. and its experienced team of labor market researchers, the ADP Research Institute® has created the monthly ADP France Employment Report® in order to estimate the employment numbers in France, align with the employment numbers published by the French National Institute of Statistics and Economic Studies (INSEE). While official nonfarm payroll employment data are published quarterly by the French National Institute of Statistics and Economic Studies (INSEE), forecasts of ADP employment changes for France will be generated and reported monthly. The ADP data contain all 16 industries reported by the INSEE each quarter.

Data Analysis:

The frequency of ADP data is monthly and the panel contains around 75,000 firms that vary in size and industry. Industry names and codes are presented in the table below.

Table 1: Industry Descriptions:

Code	Description
DE	Energy, Water and Waste
C1	Food products
C2	Coke and refined petroleum
C3	Machinery and equipment goods
C4	Transport equipment
C5	Other industrial goods
FZ	Construction
GZ	Trade
HZ	Transportation
IZ	Accommodation and food services
JZ	Information and communication
KZ	Financial services
LZ	Real estate services
MN	Business services
OQ	Non-market services
RU	Households' services

For each firm the number of active employees is reported for a specific day of the month which is defined as the date of the most recent payroll process. The time period ranges from May 2009 to July 2015. Since the data is unbalanced, interpolation is used to handle the missing observations. Once the missing observations are taken care of, the outliers are removed to smooth out monthly percentage changes. The criterion to remove the outliers is customized for different firm sizes to capture the reality and minimize the measurement error if any.

In the final stage of modeling, we take care of larger sample size fluctuations that occur in certain months. Further smoothing is needed, since, even when firm level growth rates are consistent after removing the outliers, for certain months and certain industries we can observe relatively large fluctuations in the total number of active employees. This can take the form of big spikes or drops in total industry-level employment in one or several months or a shift to a permanently higher level. These fluctuations are caused by larger than usual fluctuations in the number of firms belonging to a given industry. In order to smooth out large drops in industry-level employment we apply a moving average procedure.

After going through the above data processing steps, we aggregate the number of active employees across matched pairs for each industry and month, arriving at monthly time series which can then be used for estimations. The month-to-month percentage change is calculated for each month and each industry and they are seasonally adjusted in E-views using X13 seasonal adjustment module. Table 2 includes summary statistics by industry for resulting month-to-month seasonally adjusted percentage changes. For this reason we restrict our sample to 2012-2015.

Comparison of ADP Employment Estimates with INSEE Employment Estimates

The INSEE reports quarterly levels of employment, quarter-to-quarter absolute changes and quarter-to-quarter percentage changes for the industries listed in Table 1. Quarterly employment levels correspond to the number of persons, regardless of work duration, who are employed on the last day of a quarter. Competitive sector employment covers only metropolitan France. Quarterly data are based on the quarterly establishment survey of the Ministry of Labor (ACEMO survey), the quarterly statistics of "URSSAF" (the organization in charge of collecting employers' social contributions and EPURE and the quarterly statistics of "Pôle Emploi" (the organization in charge of collecting employers' social contributions) for temporary employment data. The flash estimate of quarterly employment, which uses only the first source and does not take into account the changes in employment in establishments with fewer than 10 employees or in new establishments, is released 45 days after the end of each quarter and only for goods-producing industries, construction and services. The first estimation using data from EPURE and containing a detailed industry breakdown is released 70 days after the end of a quarter and then data is revised 160 days after the end of such quarter.

In both ADP and INSEE data, trade and business services appear to account for largest share of total employment. In comparison with the INSEE data, ADP data account for a higher share in manufacturing sectors, information and communication, trade and financial services.

Regression and Results:

We employ vector autoregressive methodology to model and forecast monthly changes in employment. Vector autoregressive models (VAR) are widely used for analyzing multivariate time series. Typical VAR models treat all variables as endogenous following Sim's (1980) critique on the exogeneity assumption of macroeconomic models. VAR models can incorporate restrictions, including the exogeneity of some of the variables. They can also be amended to include deterministic terms and exogenous variables. VAR models are used for modeling and forecasting the dynamic behavior of economic and financial time series. They can also be used for structural inference and policy analysis. The basic VAR (p) model is defined by the following equation

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t$$

In this equation A_i are (K x K) coefficient matrices and u_t is a K dimensional white noise process with $E(u_t) = 0$ and $E(u_t u_t^T) = \sum u$. The VAR (p) model is a stationary process with time invariant mean, variance and covariance structure. Besides the lags of endogenous variables VAR model can also include exogenous regressors on the right-hand side and in this case VAR is represented by the following equation

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + B_1 X_{t-1} + \dots + B_p X_{t-p} + u_t$$

where X_t represents the vector of exogenous variables.

The coefficients of the VAR (p) process are estimated by applying OLS to each of the equations. The OLS estimator is identical to the GLS estimator if there are not restrictions in the parameters. For a normally distributed Gaussian Process $y_t \sim N(0, \sum u)$, the OLS estimator is also identical to the ML estimator. The usual statistical inference procedures can be applied if the process is stable. If there are integrated variables so that $y_t \sim I(1)$, then the process is unstable and the variables may be cointegrated. The OLS/ML method can still be applied for estimating the model parameters but the usual t-statistics and F-statistics can lead to misleading conclusions when used for hypothesis testing. VAR can also be represented in structural form if restrictions are imposed on model parameters, that is, elements of A matrix, B matrix or both matrices in the equation above.

In our setting, using VAR model allows us to incorporate spillover and feedback effects on employment among different industries and to measure the common movement of employment in different industries with backward-looking and forward-looking business cycle indicators. We start with estimating an unrestricted VAR with one lag in which endogenous variables are represented by month-to-month changes in 11 industries. We choose to aggregate employment in C1, C2, C3, C4 and C5 sectors into one sector that we call total manufacturing. The remaining industries included in our model correspond to INSEE industries listed in Table 1. For exogenous variables, business confidence indices for manufacturing and services published only on a monthly basis by INSEE together with percentage changes in quarterly employment levels published by INSEE for each industry are used. In order to employ INSEE quarterly employment data in our model that are estimated in a quarterly frequency, we convert the data to a monthly frequency using quadratic-match average conversion in E-views. The initial unrestricted VAR model used in our estimation can be written as follows;

$$PC_{tm,t} = const + a_1 PC_{tm,t-1} + a_1 PC_{tm,t-1} + a_2 PC_{de,t-1} + a_3 PC_{fz,t-1} + a_4 PC_{gz,t-1} + a_5 PC_{hz,t-1} + a_6 PC_{iz,t-1} \dots$$

$$+ a_{10} PC_{mn,t-1} + a_{11} PC_{oq,t-1} + a_{12} PC_{ru,t-1} + + a_{13} BC_{mf,t} + a_{14} BC_{serv,t} + a_{15} PC_{tminsee,t-2} + a_{16} PC_{deinsee,t-2} + a_{16} PC_{fzinsee,t-2} + a_{17} PC_{gzinsee,t-2} + a_{18} PC_{hzinsee,t-2} u_t + \cdots . + a_{18} PC_{izinsee,t-2} + \cdots a_{22} PC_{mninsee,t-2} + a_{23} PC_{oqinsee,t-2} + a_{24} PC_{ruinsee,t-2} + u_t$$

$$PC_{de,t} = const + a_1 PC_{tm,t-1} + a_1 PC_{tm,t-1} + a_2 PC_{de,t-1} + a_3 PC_{fz,t-1} + a_4 PC_{gz,t-1} + a_5 PC_{hz,t-1} + a_6 PC_{iz,t-1} \dots$$

$$+ a_{10} PC_{mn,t-1} + a_{11} PC_{oq,t-1} + a_{12} PC_{ru,t-1} + + a_{13} BC_{mf,t} + a_{14} BC_{serv,t} + a_{15} PC_{tminsee,t-2} + a_{16} PC_{deinsee,t-2} + a_{16} PC_{fzinsee,t-2} + a_{17} PC_{gzinsee,t-2} + a_{18} PC_{hzinsee,t-2} u_t + \cdots . + a_{18} PC_{izinsee,t-2} + \cdots a_{22} PC_{mninsee,t-2} + a_{23} PC_{oqinsee,t-2} + a_{24} PC_{ruinsee,t-2} + u_t$$

$$PC_{fz,t} = const + a_1 PC_{tm,t-1} + a_1 PC_{tm,t-1} + a_2 PC_{de,t-1} + a_3 PC_{fz,t-1} + a_4 PC_{gz,t-1} + a_5 PC_{hz,t-1} + a_6 PC_{iz,t-1} \dots$$

$$+ a_{10} PC_{mn,t-1} + a_{11} PC_{oq,t-1} + a_{12} PC_{ru,t-1} + + a_{13} BC_{mf,t} + a_{14} BC_{serv,t} + a_{15} PC_{tminsee,t-2} + a_{16} PC_{deinsee,t-2} + a_{16} PC_{fzinsee,t-2} + a_{17} PC_{gzinsee,t-2} + a_{18} PC_{hzinsee,t-2} u_t + \cdots . + a_{18} PC_{izinsee,t-2} + \cdots a_{22} PC_{mninsee,t-2} + a_{23} PC_{oqinsee,t-2} + a_{24} PC_{ruinsee,t-2} + u_t$$

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$$PC_{ru,t} = const + a_1 PC_{tm,t-1} + a_1 PC_{tm,t-1} + a_2 PC_{de,t-1} + a_3 PC_{fz,t-1} + a_4 PC_{gz,t-1} + a_5 PC_{hz,t-1} + a_6 PC_{iz,t-1} \dots$$

$$+ a_{10} PC_{mn,t-1} + a_{11} PC_{oq,t-1} + a_{12} PC_{ru,t-1} + + a_{13} BC_{mf,t} + a_{14} BC_{serv,t} + a_{15} PC_{tminsee,t-2} + a_{16} PC_{deinsee,t-2} + a_{16} PC_{fzinsee,t-2} + a_{17} PC_{gzinsee,t-2} + a_{18} PC_{hzinsee,t-2} u_t + \cdots . + a_{18} PC_{izinsee,t-2} + \cdots a_{22} PC_{mninsee,t-2} + a_{23} PC_{oqinsee,t-2} + a_{24} PC_{oqinsee,t-2} + u_t$$

In the model above, PC stands for percentage change. The series which have INSEE in the sub-index are percentage changes in INSEE employment for each industry. Finally, BC stands for business confidence, MF for manufacturing and SERV for services.

After the initial estimation we proceed with restricting certain coefficient estimates to zero. We impose restrictions for several reasons. Firstly, they help us to mute the effects of business confidence indices and INSEE employment data for the same industry on the estimated employment changes if those effects are going in a counterintuitive direction. Secondly, the restrictions are imposed to measure the effect of the most important drivers, namely lagged percentage change in INSEE employment for the corresponding industry and forward-looking business confidence indicator, more statistically significant and more pronounced if their coefficient estimates are insignificant in the less parsimonious and optimal specifications. Finally, statistically insignificant variables are dropped to improve the general fit of the model.

After estimating the model, the residual and stability tests are performed. An F version of the Wald statistics is used to test for joint significance of the model coefficients since it is preferable when the sample size is small. We can see that, in all of them, business confidence indices are statistically significant and have positive signs. Test results confirm that the growth of INSEE employment for a given industry with a two-period has a strong positive and statistically significant effect on ADP employment percentage for the same industry. The regressions also show that spillover effects and interaction effects among industries are also quite considerable as they can be judged from statistically significant coefficient estimates for the majority of included INSEE industry-level employment changes. Finally, chi-squared and F statistics indicate that the variables in the regression are jointly statistically significant.

<u>Results:</u>

On the charts below we plot fitted values of month-to-month percentage changes in ADP employment for selected industries together with percentage changes in INSEE employment.

Chart1. Total Employment, monthly % change, SA

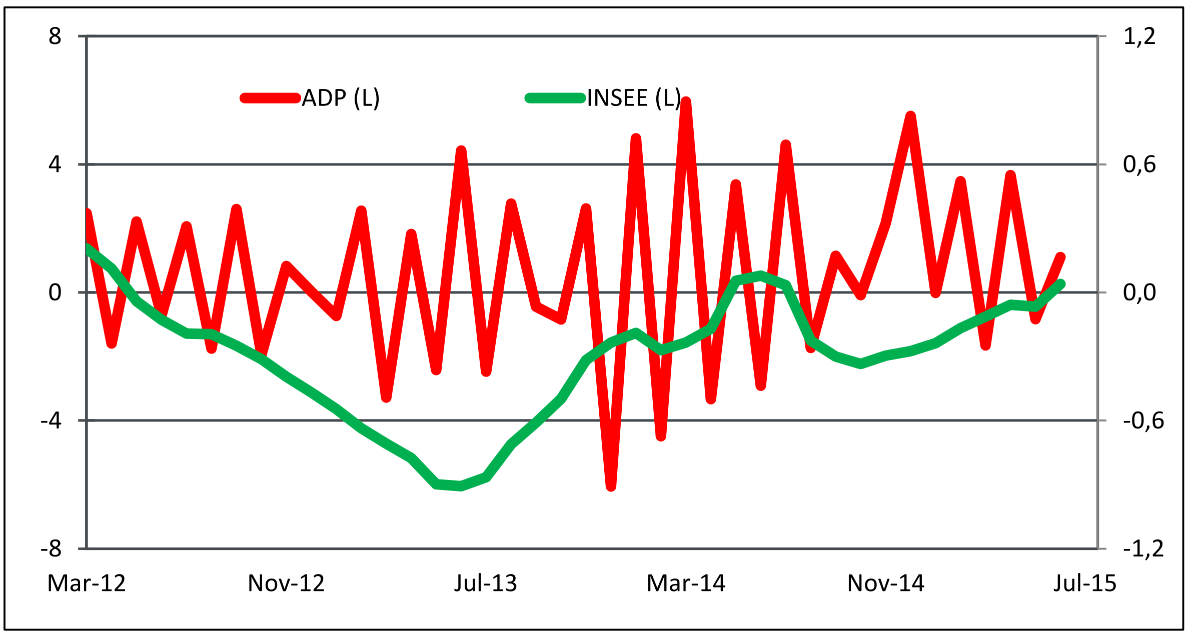

Chart2. Total Manufacturing, monthly % change, SA

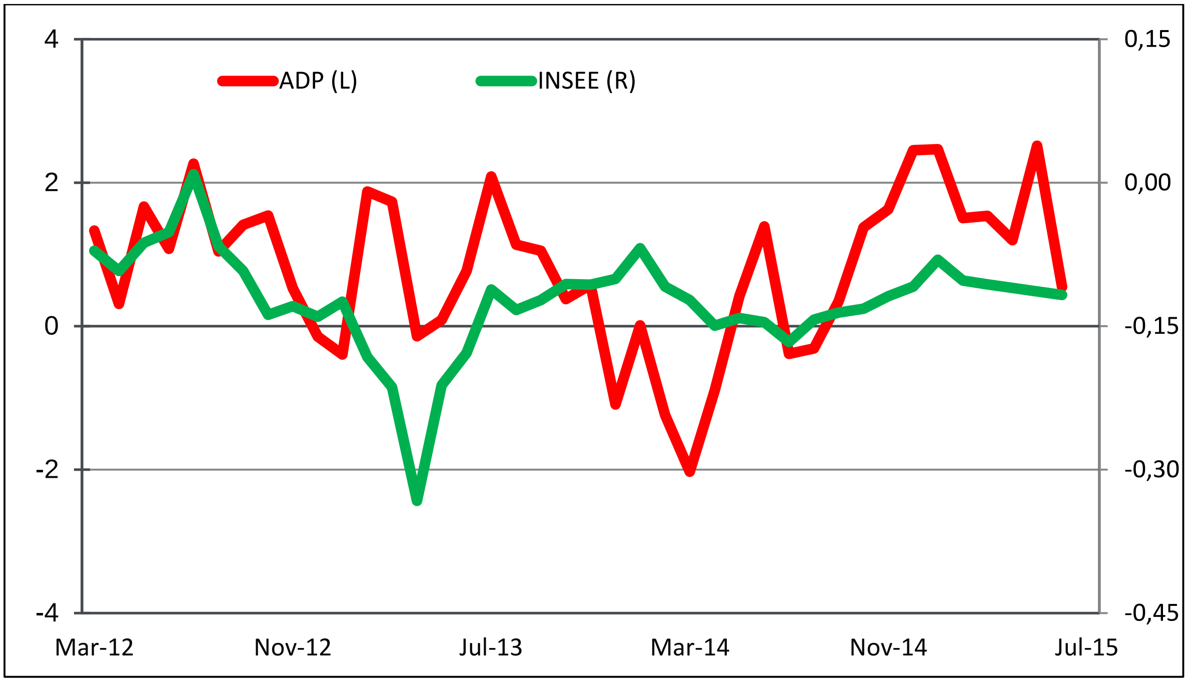

Chart3. Trade, monthly % change, SA

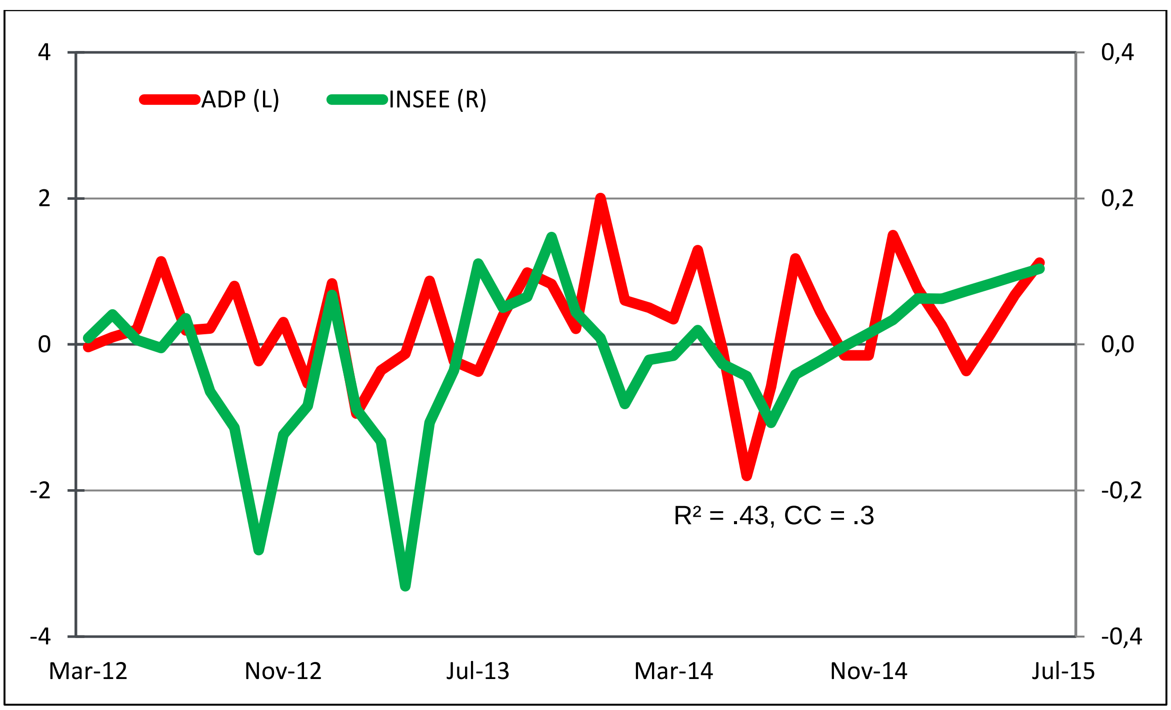

Chart4. Financial Services, monthly % change, SA

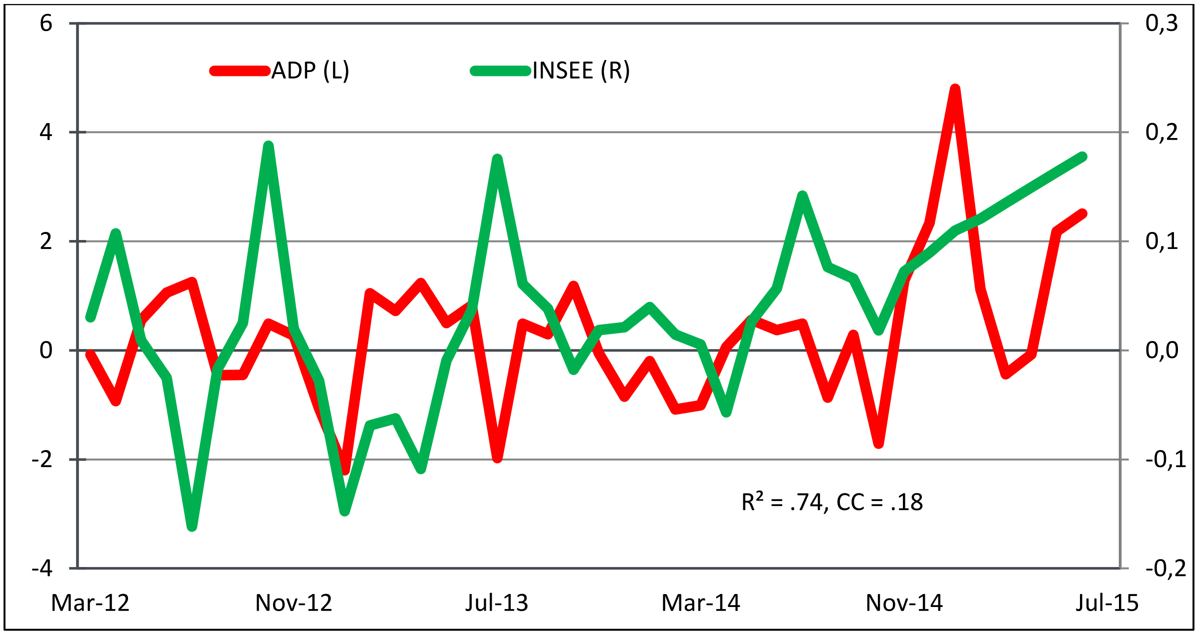

Chart5. Business Services, monthly % change, SA

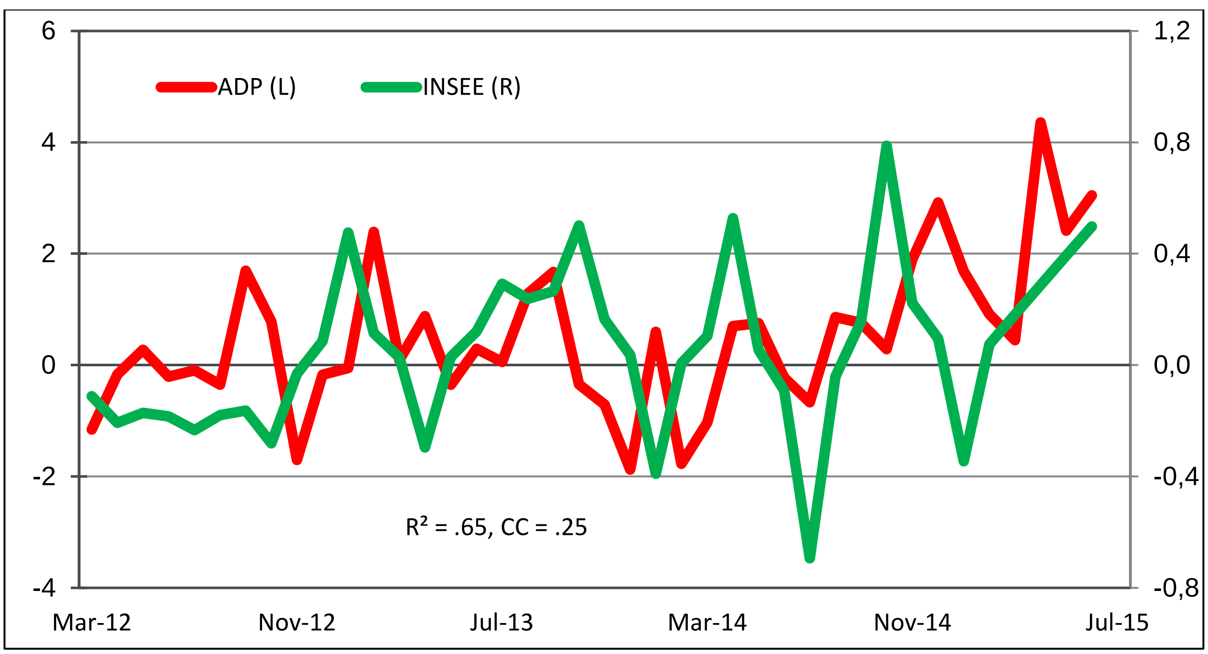

Chart6. Transportation, monthly % change, SA

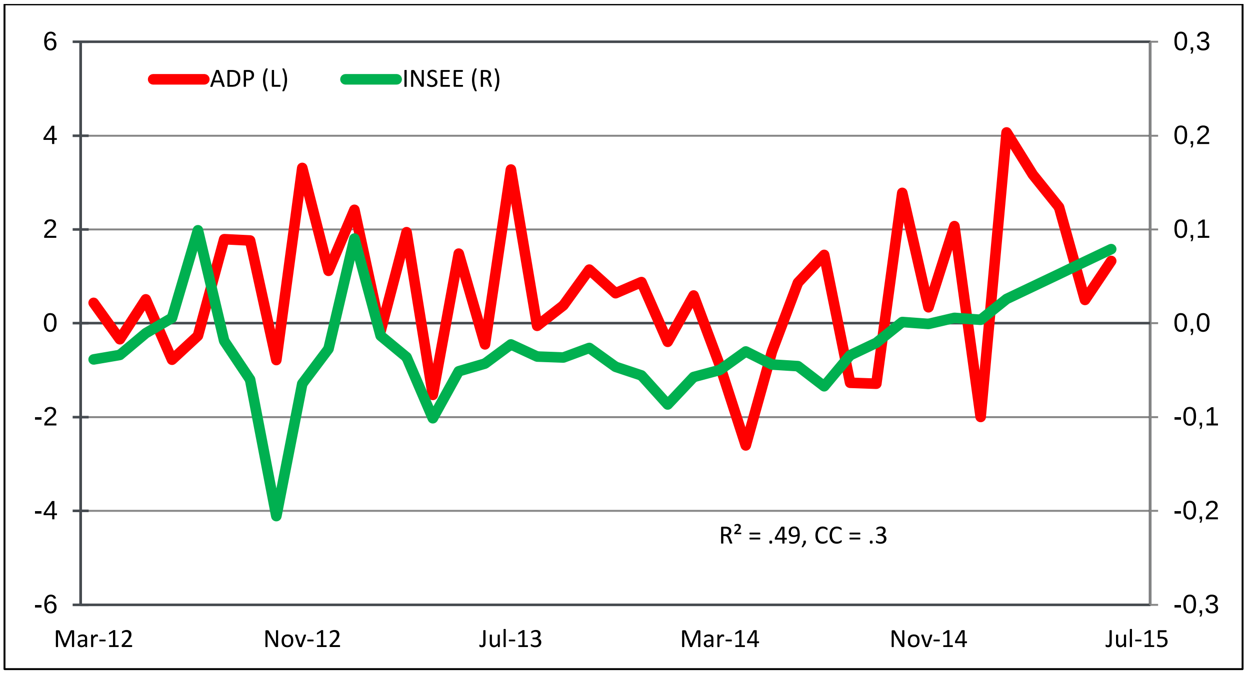

Chart7. Real Estate, monthly % change, SA