

Automatic Statistical Forecasting of Univariate Time Series

Use in Supply Chain Management
(SCM) and Comparison of
Three Implementations

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Outline

- Demand Planning / Statistical Forecasting in the Food Industry
- ForecastPRO
- State-Space Model of Exponential Smoothing
- *SAP Advanced Planning and Optimization (APO)*
- Comparison / Conclusions

Make-to-Stock

The Food Industry uses the *Make-to-Stock* approach: due to industrial constraints, we need to manufacture our products in advance, and we cannot wait for the order of the customer.

Therefore, foreseeing future orders is paramount. We need to make sure that we have the

- right product,
- at the right location,
- at the right moment in time,
- with the right amount.

Demand Planning Process

At Nestlé, this planning process is known as *Consensus Demand Planning*.

The outcome of this process is a quantity per product, location and week (short term) / months (mid-term, up to 18 months), agreed upon by Sales, Marketing, Supply Chain and Finance functions, within the context of:

- high number of products
- high innovation/renovation rate
- need to forecast customer orders, and not real consumer demand
- promotion driven business (need to capture consequences of internal trade and marketing activities)
- many categories depend on weather situation

SAP APO Screen

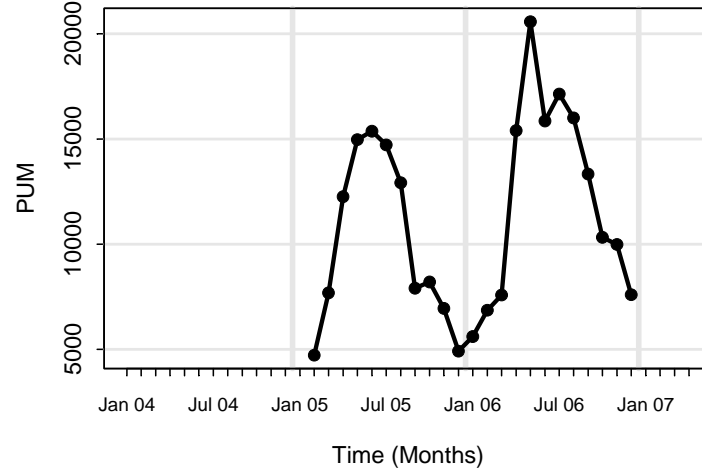
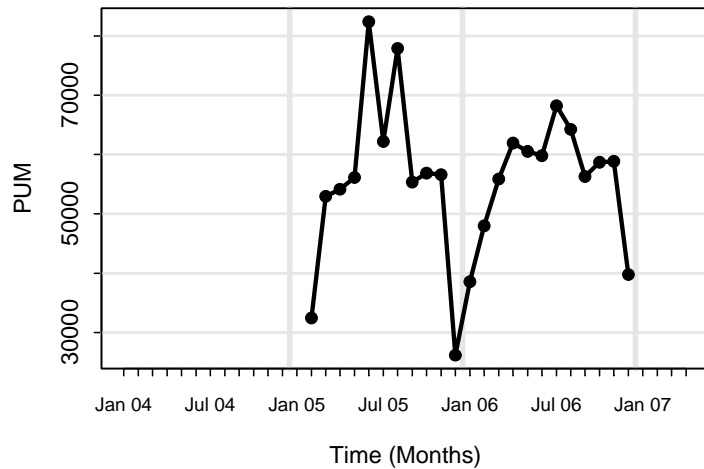
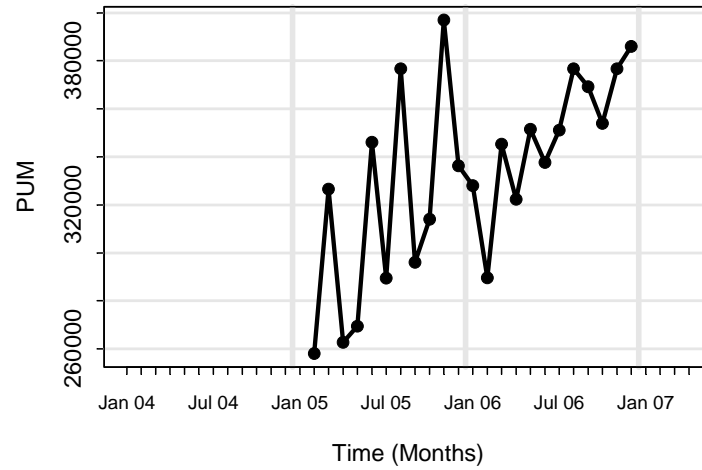
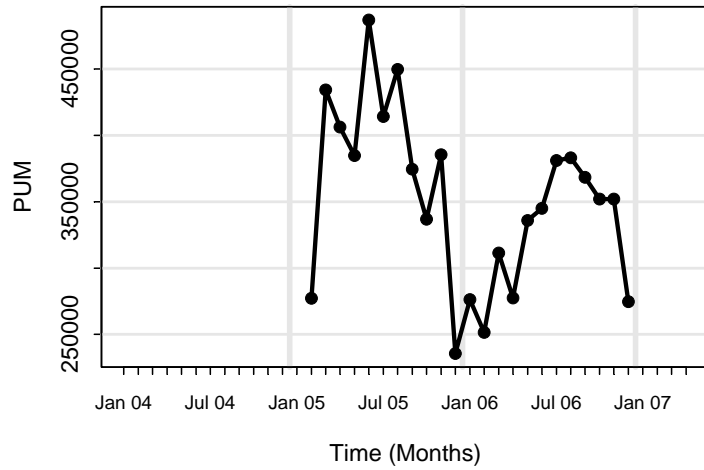
Planning Book: [Live] MAIN PLANNING BOOK / WEEKLY VIEW

	Unit	W 38.2007	W 39.2007	W 40.2007	W 41.2007	W 42.2007	W 43.2007	W 44.2007	W 45.2007
Dispatches	PUM	3'901	6'037						
Order Quantity	PUM	4'325	6'038	3'460		184	78		
Statistical (Base) Forecast	PUM	5'543	5'544	4'821	4'820	4'821	4'820	4'909	5'040
Baseline	PUM	5'543	4'650	3'946	3'946	3'945	3'946	3'994	4'068
Uplift	PUM	96	119		973	430	886		650
Uplift Adjustment	PUM	96	119		973	430	886		650
Final Consensus DP	PUM	5'639	4'769	3'946	4'919	4'375	4'832	3'994	4'718

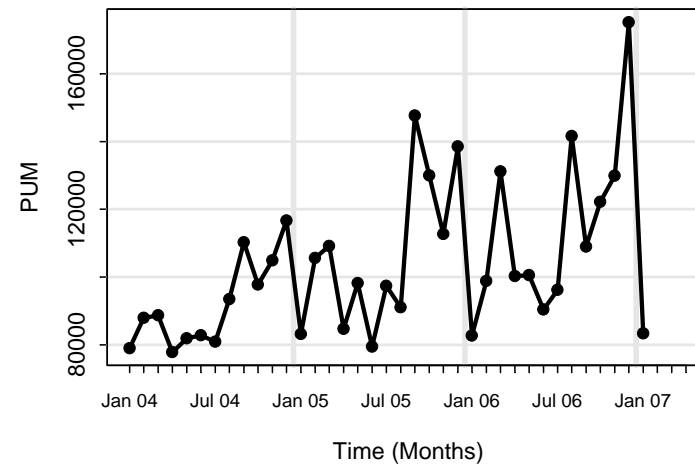
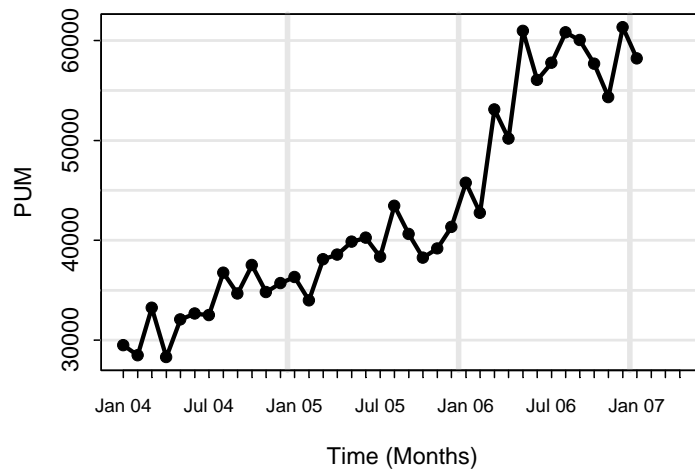
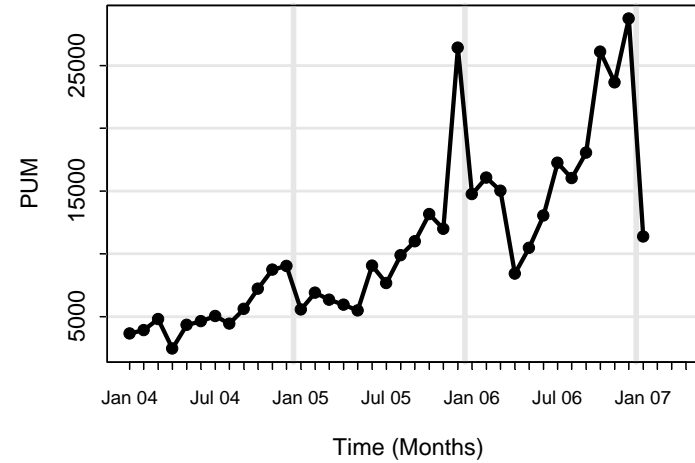
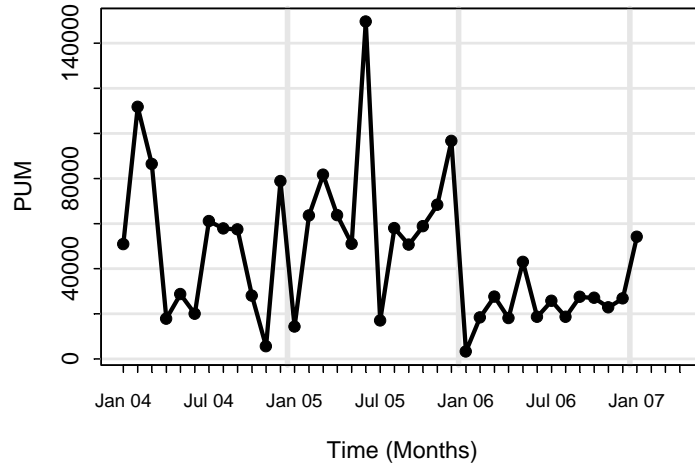
This is part of the screen used by a Demand Planner. He/She sees historical data, and can input/calculate future planned orders, per product, location and/or customer.

The Planner can also use *Statistical Forecasting* algorithms available in this SAP Module.

Examples of Time Series



Examples of Time Series



ForecastPRO

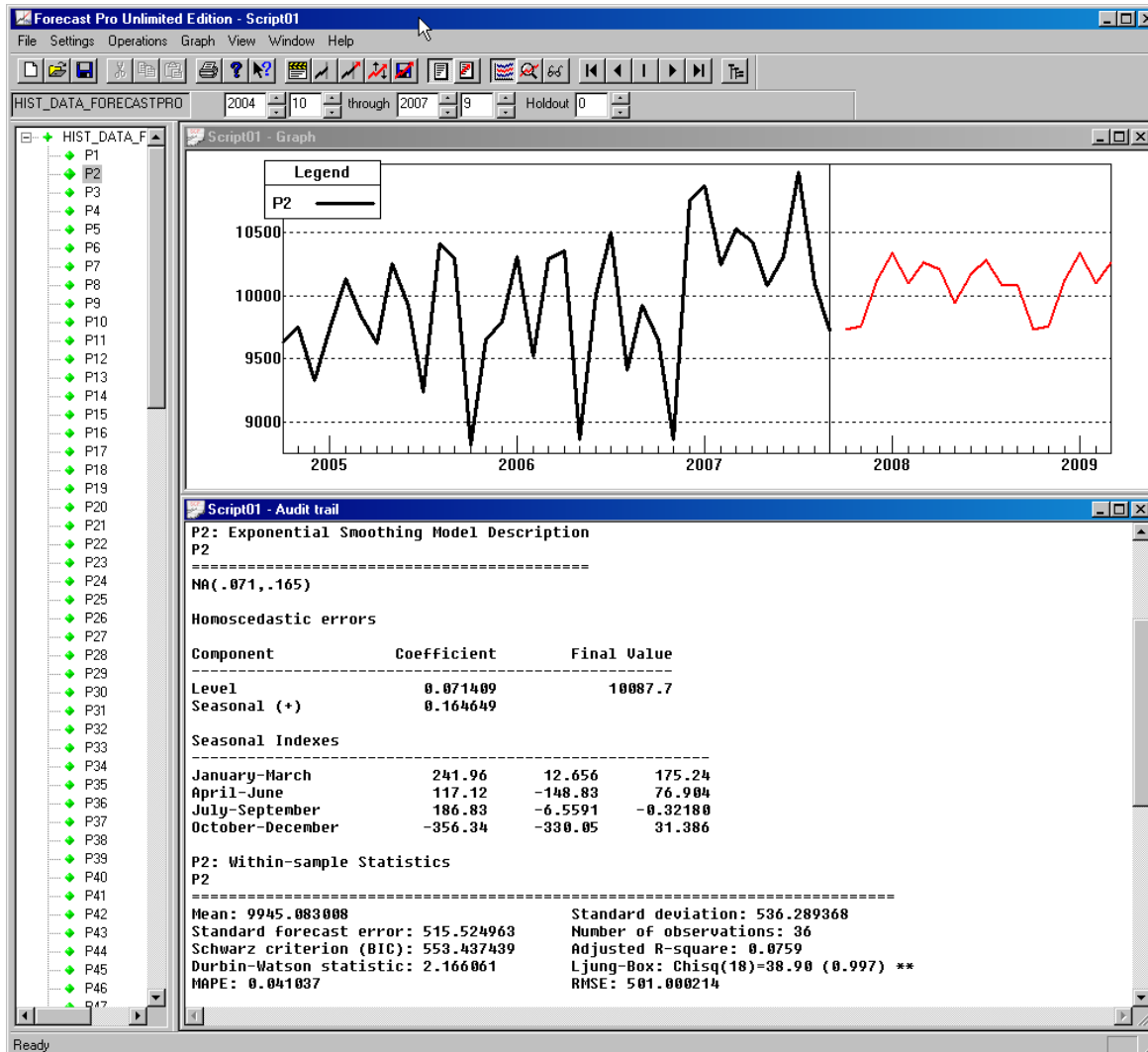


ForecastPRO is a renowned, best-of-breed statistical forecasting software. It has a proven track record, notably in the famous "M3 Forecasting Competition".

Its *Expert Selection* forecasting methods uses *Exponential Smoothing* and *ARIMA* type algorithms. It can be run as a full black-box type method.

Advanced users can also choose themselves the family of method and the smoothing parameters.

Layout of ForecastPRO



State Space Model of Exponential Smoothing

www.RobHyndman.info

This brand new approach is developed by Rob Hyndman, Monash University, Melbourne.

Rob Hyndman is co-author of "Business Forecasting: Methods and Applications" by Makridakis et al., and the lead author of a forthcoming book on Exponential Smoothing.

Hyndman has developed a new framework for *Exponential Smoothing* based on *State-Space Models*. This allowed him to develop a much more robust approach to parameter fitting, and using Akaike type error measurements to estimate the "best" models.

His algorithm can also be run fully automatically. It is available in the package 'forecast' for R.

ETS() in R

```
> x.ts
      Jan  Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct  Nov  Dec
2004
2005 8010 10016 9736 9656 9124 9389 9128 10064 9854 9436 9121 8990
2006 10089 9236 9660 9628 8659 8503 9417 9994 8729 8746 9333 8649
2007 9148 8287 9317 9213 9262 8726 8654 8849 9539
> x.ets <- ets(x.ts)
> x.ets
ETS(M,M,N)

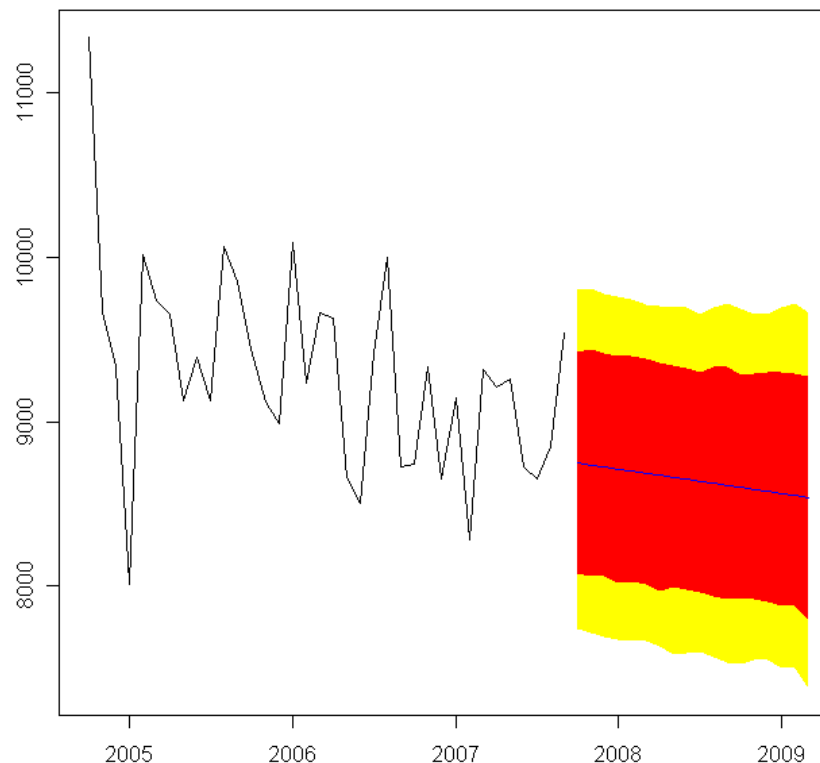
Call:
ets(y = x.ts)

Smoothing parameters:
  alpha = 0.01
  beta  = 0.01

Initial states:
  l = 9863.2379
  b = 0.9965

sigma: 0.0606
AIC:   591.9277
AICc:  593.218
BIC:   598.2618
> forecast(x.ets,h=18)
      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Oct 2007  8749.078 8076.056 9468.787 7697.493 9828.300
Nov 2007  8736.517 8080.797 9406.716 7698.910 9748.150
Dec 2007  8723.973 8044.222 9410.581 7690.806 9795.340
Jan 2008  8711.448 8014.593 9389.144 7694.054 9719.676
Feb 2008  8698.941 8015.549 9377.469 7643.466 9698.905
Mar 2008  8686.452 8000.297 9342.348 7609.226 9717.750
Apr 2008  8673.981 8006.143 9357.990 7671.909 9699.004
May 2008  8661.528 7979.596 9338.303 7599.730 9669.771
Jun 2008  8649.092 7961.689 9328.927 7639.438 9705.380
Jul 2008  8636.675 7966.255 9331.372 7594.205 9698.840
Aug 2008  8624.275 7929.004 9324.538 7562.499 9691.458
Sep 2008  8611.893 7941.915 9318.171 7575.280 9678.965
Oct 2008  8599.529 7904.413 9310.827 7533.724 9657.084
Nov 2008  8587.182 7866.665 9272.525 7539.509 9642.586
Dec 2008  8574.854 7878.827 9264.928 7527.169 9671.179
Jan 2009  8562.543 7853.625 9272.497 7484.743 9657.017
Feb 2009  8550.250 7833.811 9262.454 7469.180 9665.408
Mar 2009  8537.974 7799.030 9287.598 7439.766 9679.611
> █
```

Forecasts from ETS(M,M,N)



SAP APO DP



SAP is one of the biggest business software providers. Nestlé supports its processes and best practices with SAP modules, in all kinds of areas, like Finance, Sales, Human Resources, Manufacturing, but also *Supply Chain Management* (SCM).

The main module for SCM is called APO (Advanced Planning and Optimization). A sub-module is related to Demand Planning. It contains statistical forecasting algorithms, essentially based on *Exponential Smoothing* and *Linear Regression*.

APO DP has a fully automated method as well, but its architecture is quite different compared to Hyndman's approach or the one from ForecastPRO.

Logic of APO's Automatic Method

APO uses three statistical tests to define the methods to be estimated.

The trend test is based on the *Confidence Interval* of the estimated slope of a linear regression. The seasonal test is based on the autocorrelation coefficient for the period of the data (e.g. 12 month seasonality). The white noise test is the *Box-Ljung Portmanteu* test, using the χ^2 distribution.

Trend Test	Seasonal Test	White Noise Test	Constant	Trend	Season, No Trend	Season and Trend	Linear Regression	Seasonal Linear Regression
-	-	-	X					
+	-	-	X	X			X	
-	+	-	X		X			
+	+	-	X	X		X	X	X
-	-	+	X					
+	-	+	X					
-	+	+	X					
+	+	+	X					

Overview of Methods



www.RobHyndman.info



Best-of-breed statistical forecasting software.

Internally developed expert selection algorithm, without any detailed documentation.

Proven track record in forecast competitions.

Easy to use.

Extremely fast !

Brand new approach, "only" available in R. Based on a solid statistical foundation, using modern model selection criteria.

Algorithm documented in details.

Seems to compare well in the classic M3 competition.

Execution is slow, but easy to use and to parametrize.

Simple and straightforward implementation of exponential smoothing, with an automatic method based on statistical tests.

Well documented, not as fast as ForecastPRO, but faster than the state-space model.

Has not been tested in forecasting competitions.

Well integrated in a business software for Demand Planning.

Simulation Study

In order to study the quality of the forecasts of these three methods, and also how differently they behave, we have simulated time series.

We vary 3 types of seasonality and 5 types of trend. This results in an experimental design of 15 combinations. For each combination, we generated 10 samples (different random numbers).

Simulation Results (I)

To measure the quality of the forecasts, we compare the estimates of the 3 methods with the "true" future. We then compute an error rate:

$$Error = 100 \cdot \frac{|Forecast - Truth|}{Truth}$$

We simply sum the next 3 months. Here are the average scores for each method:

APO	FPRO	Hyndman
13.983	13.053	10.508

Hyndman's method seems to slightly outperform the two other methods.

Simulation Results (II)

, , **No Season**

	No Trend	Upwards	Downwards	Shift	Exponential
APO	5.5	7.4	10.0	13.1	15.9
FPRO	4.0	5.6	12.2	9.5	13.7
Hyndman	2.6	5.1	7.6	7.9	13.1

, , **Summer-Winter**

	No Trend	Upwards	Downwards	Shift	Exponential
APO	9.9	14.2	13.7	16.1	31.5
FPRO	8.1	13.6	13.4	10.6	28.8
Hyndman	8.2	10.5	11.4	17.2	14.6

, , **Easter-Christmas**

	No Trend	Upwards	Downwards	Shift	Exponential
APO	10.6	8.7	12.7	10.8	29.6
FPRO	10.9	9.7	16.1	16.0	23.6
Hyndman	8.3	7.8	9.4	10.2	23.6

Interpretation

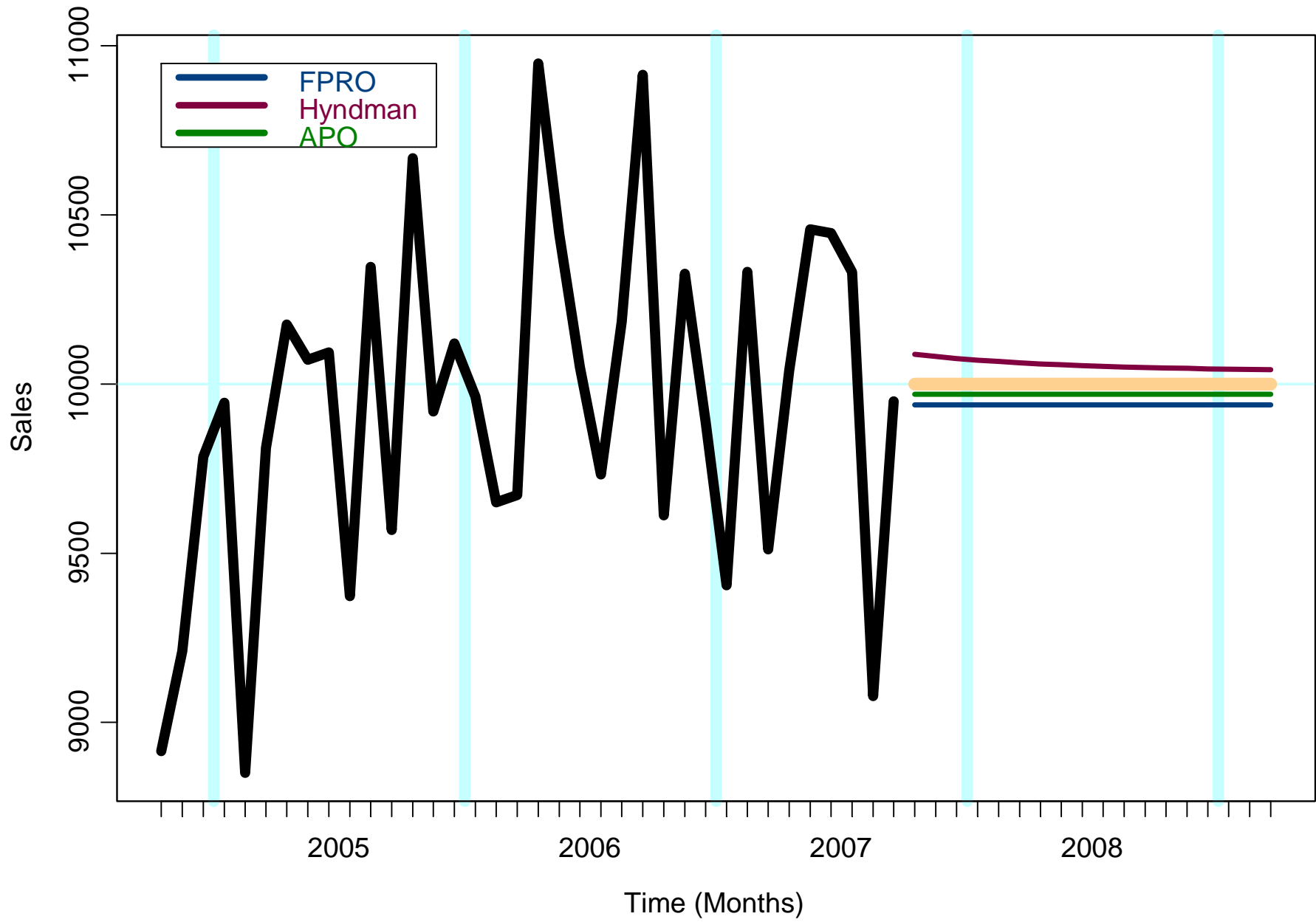
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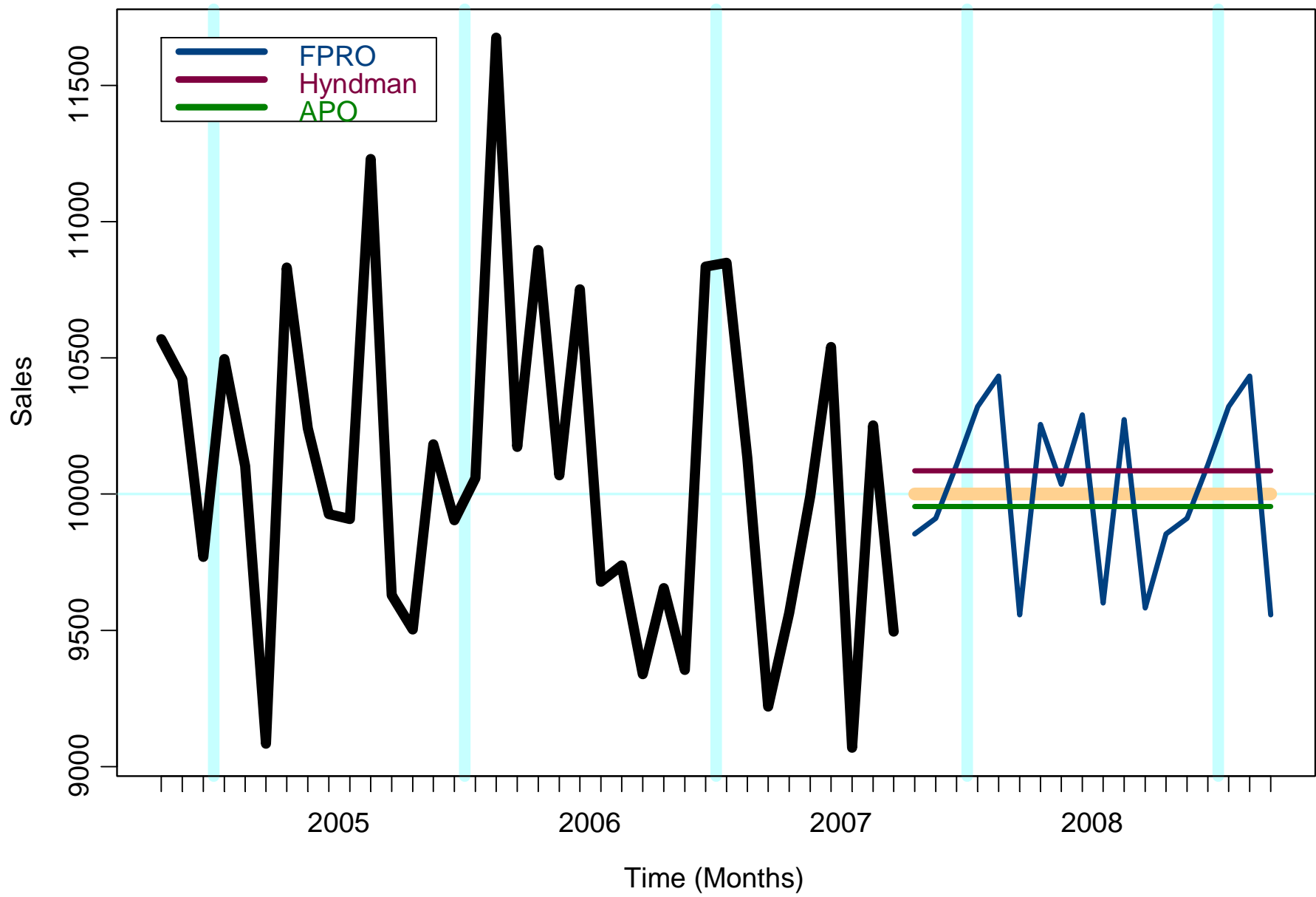
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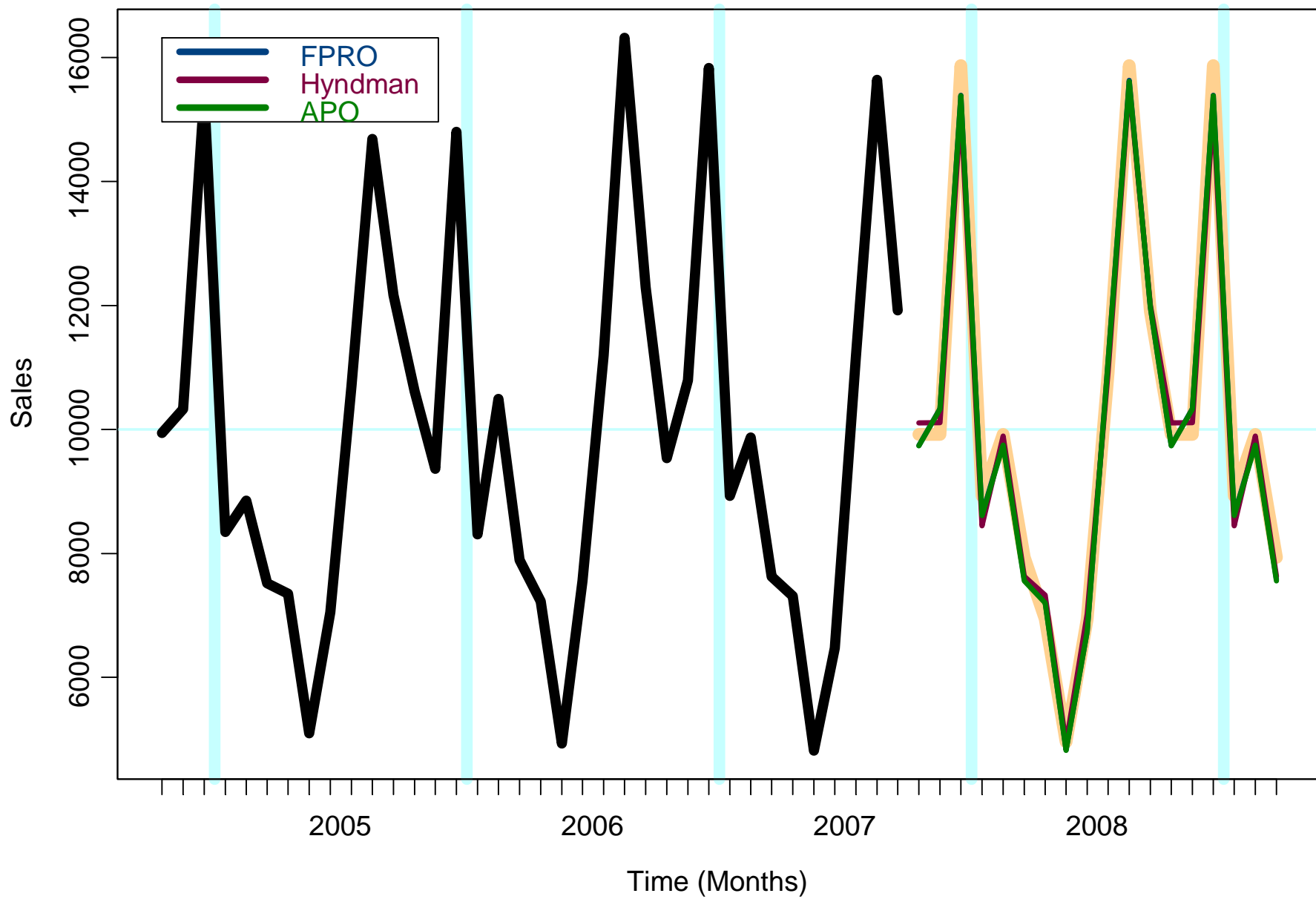
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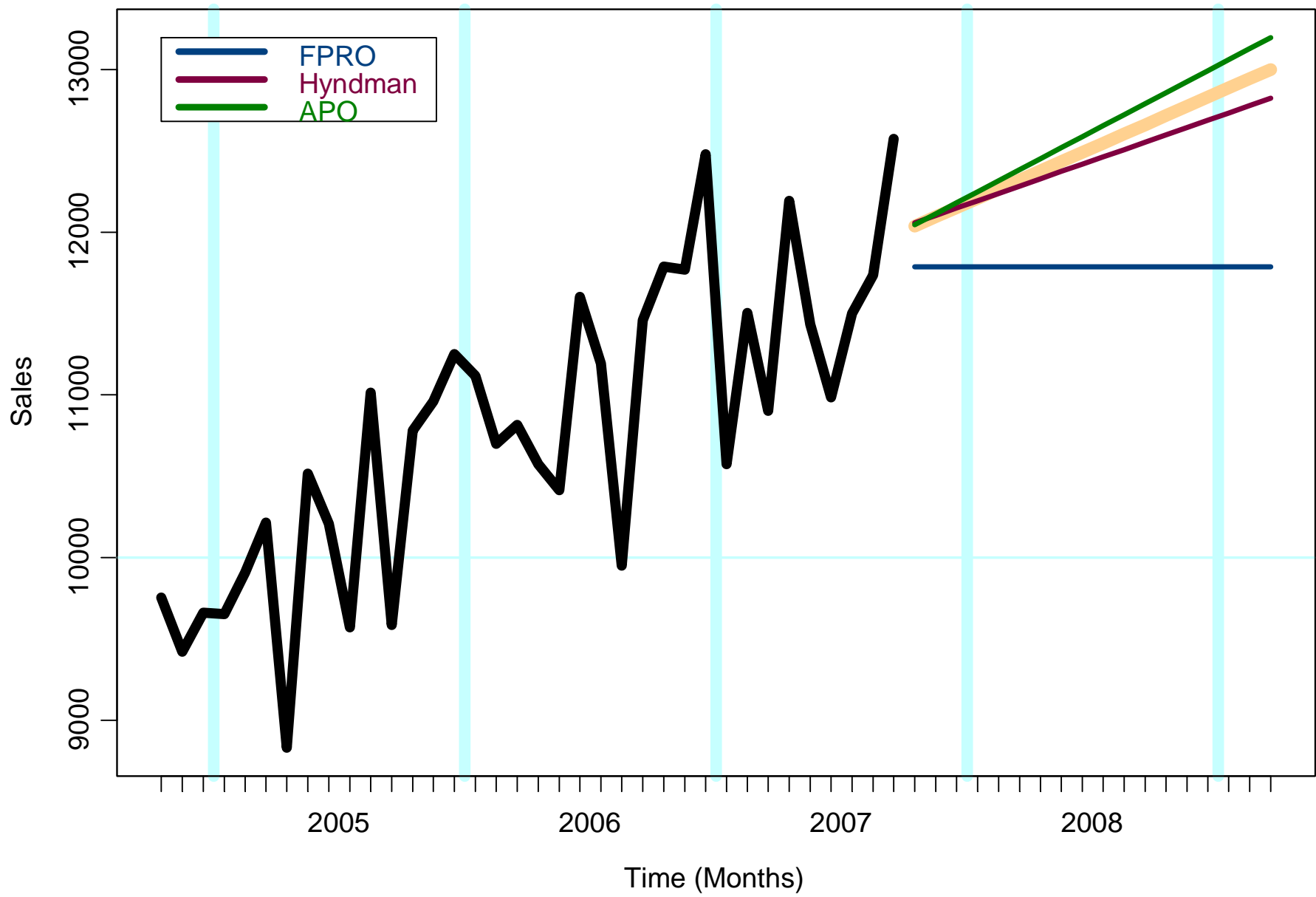
Hyndman's method seems to perform consistently better, particularly for time series with trend components.

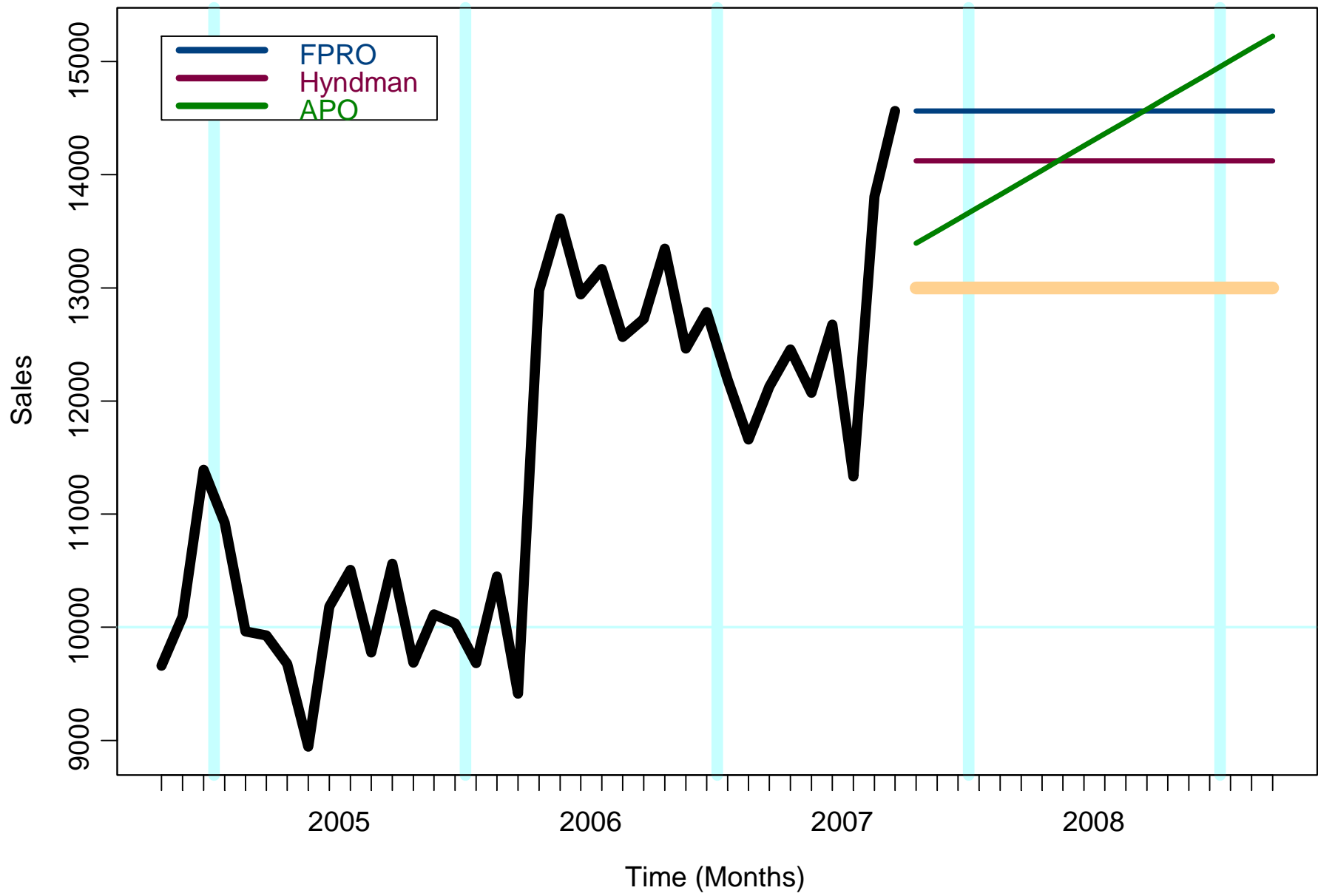
APO and ForecastPRO do have similar results on average, but their performance varies with different trend patterns.

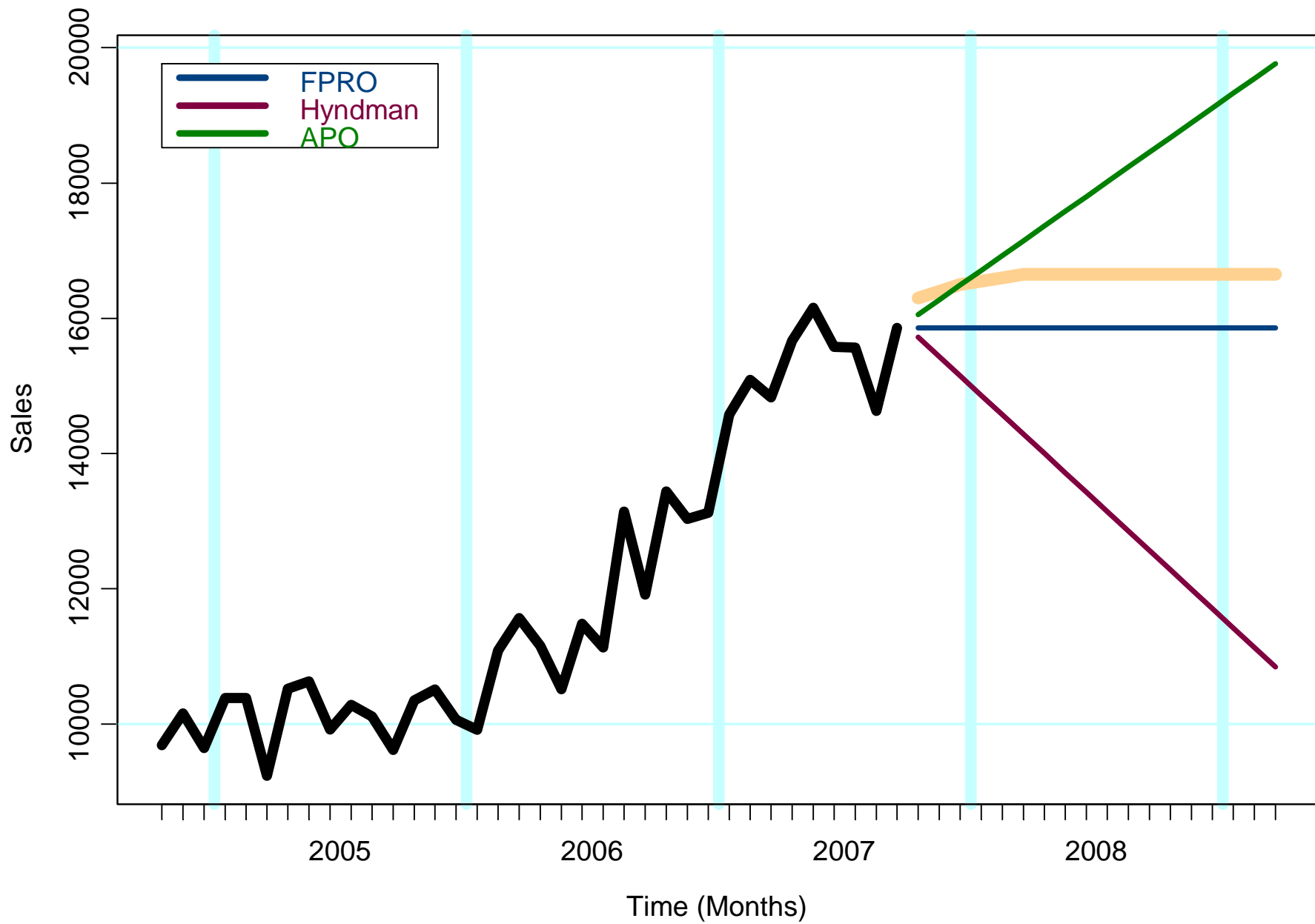






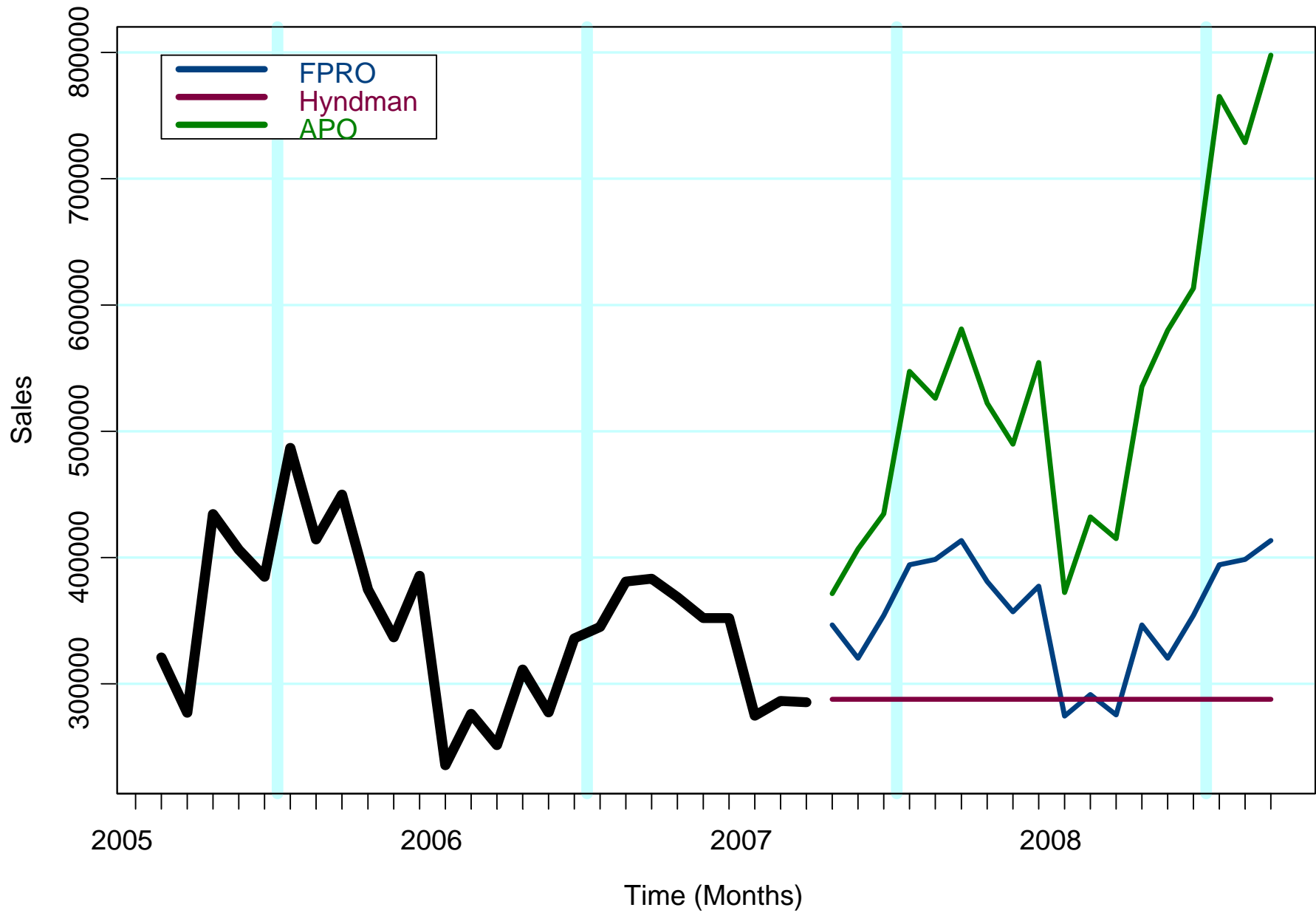


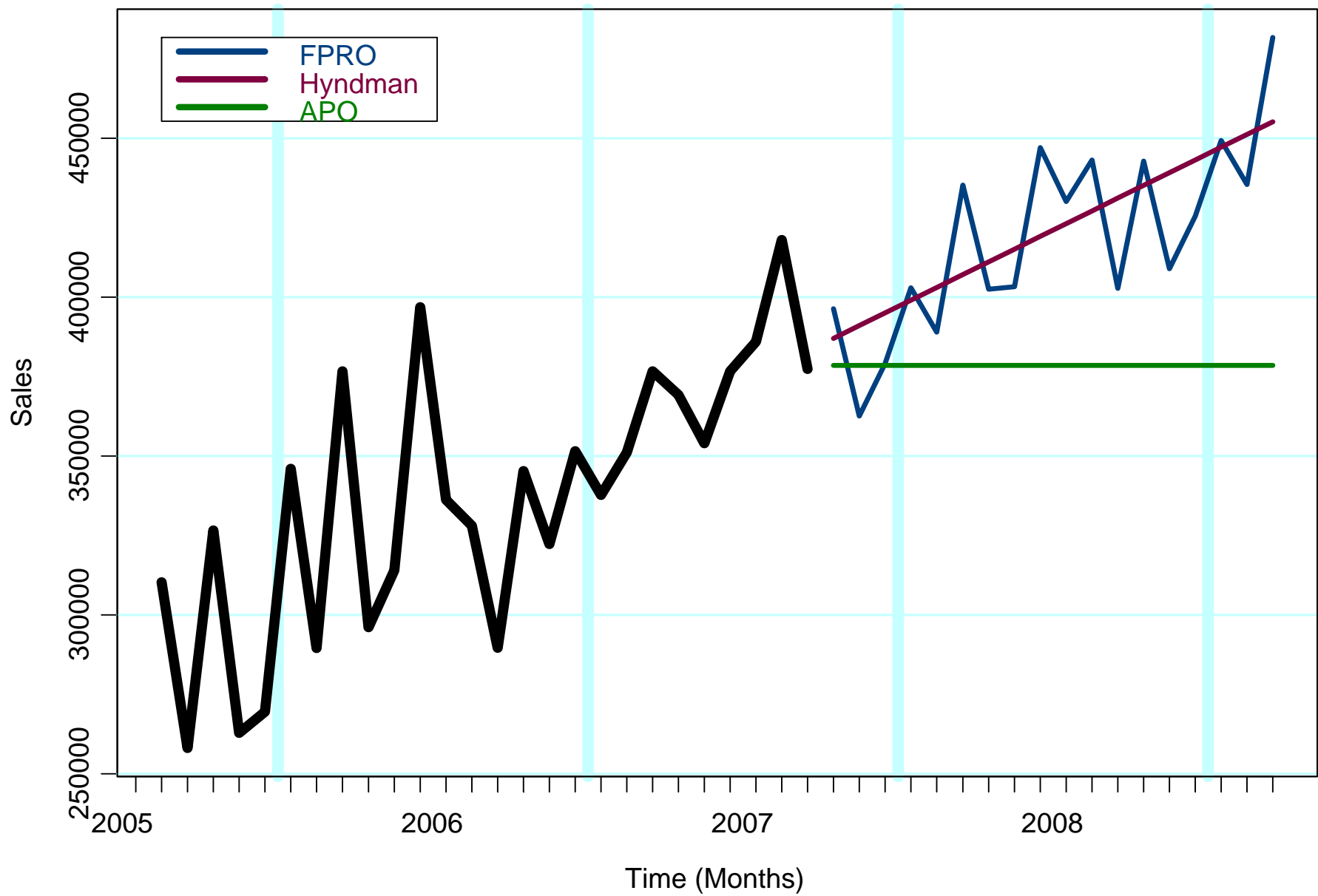


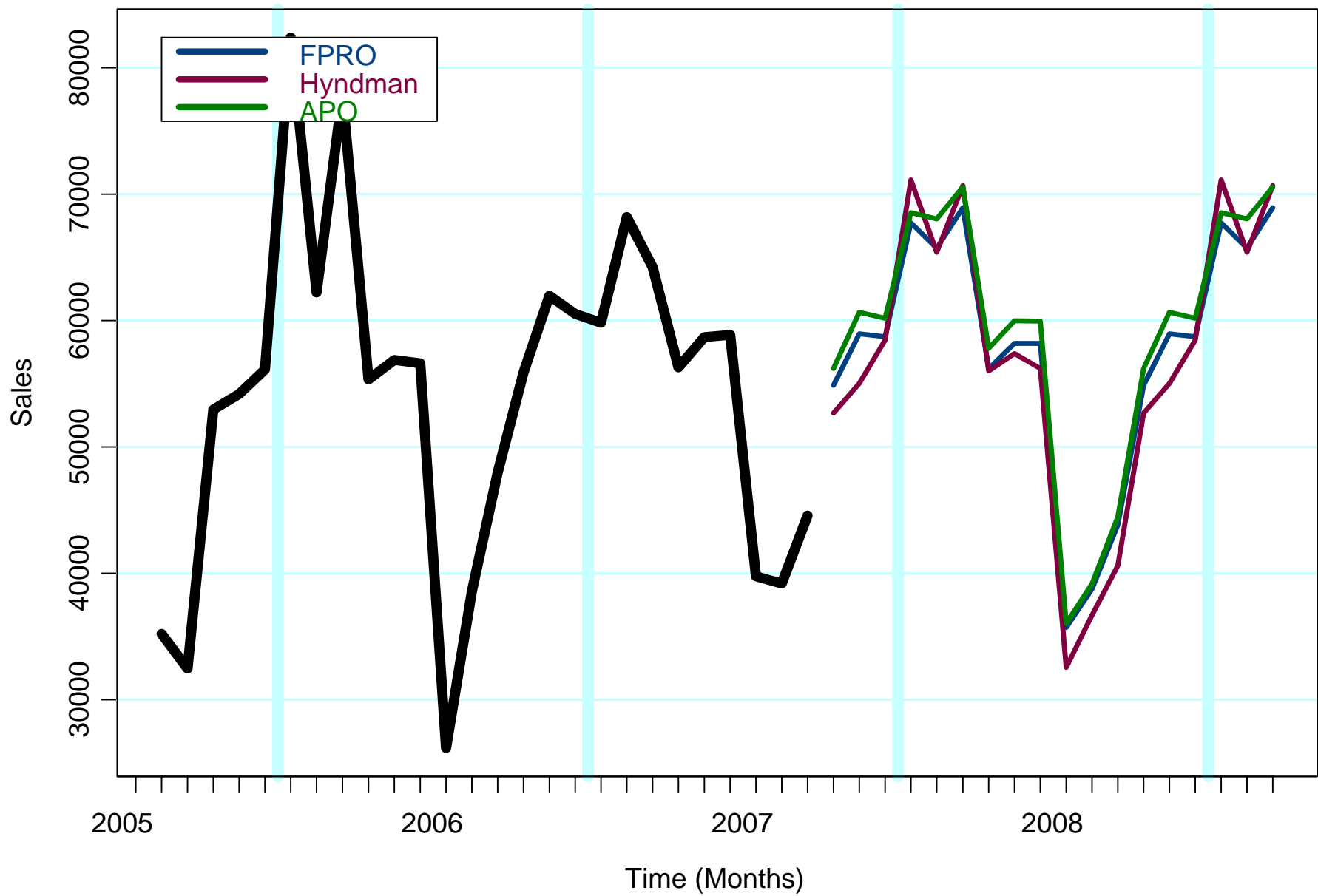


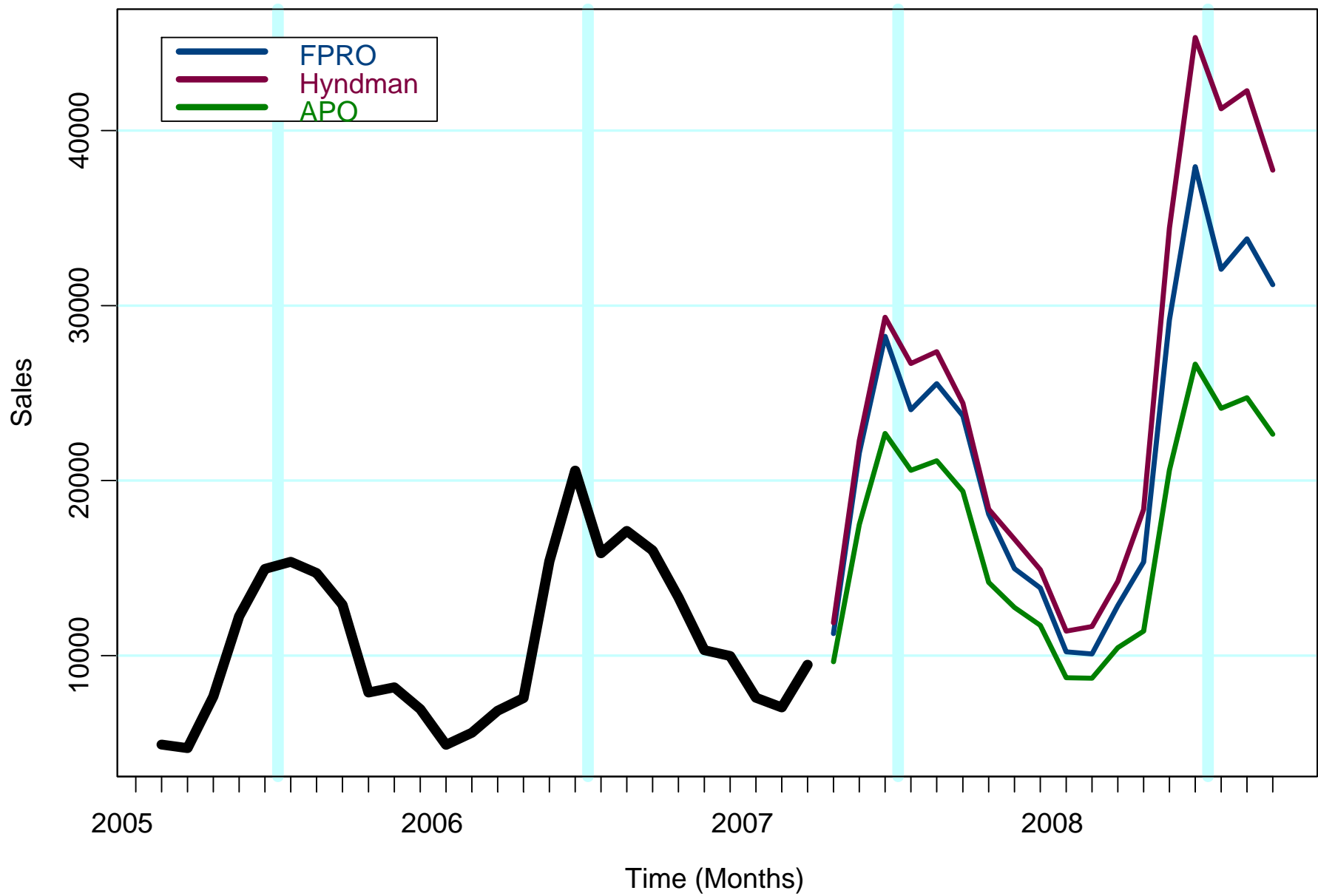
Real Data

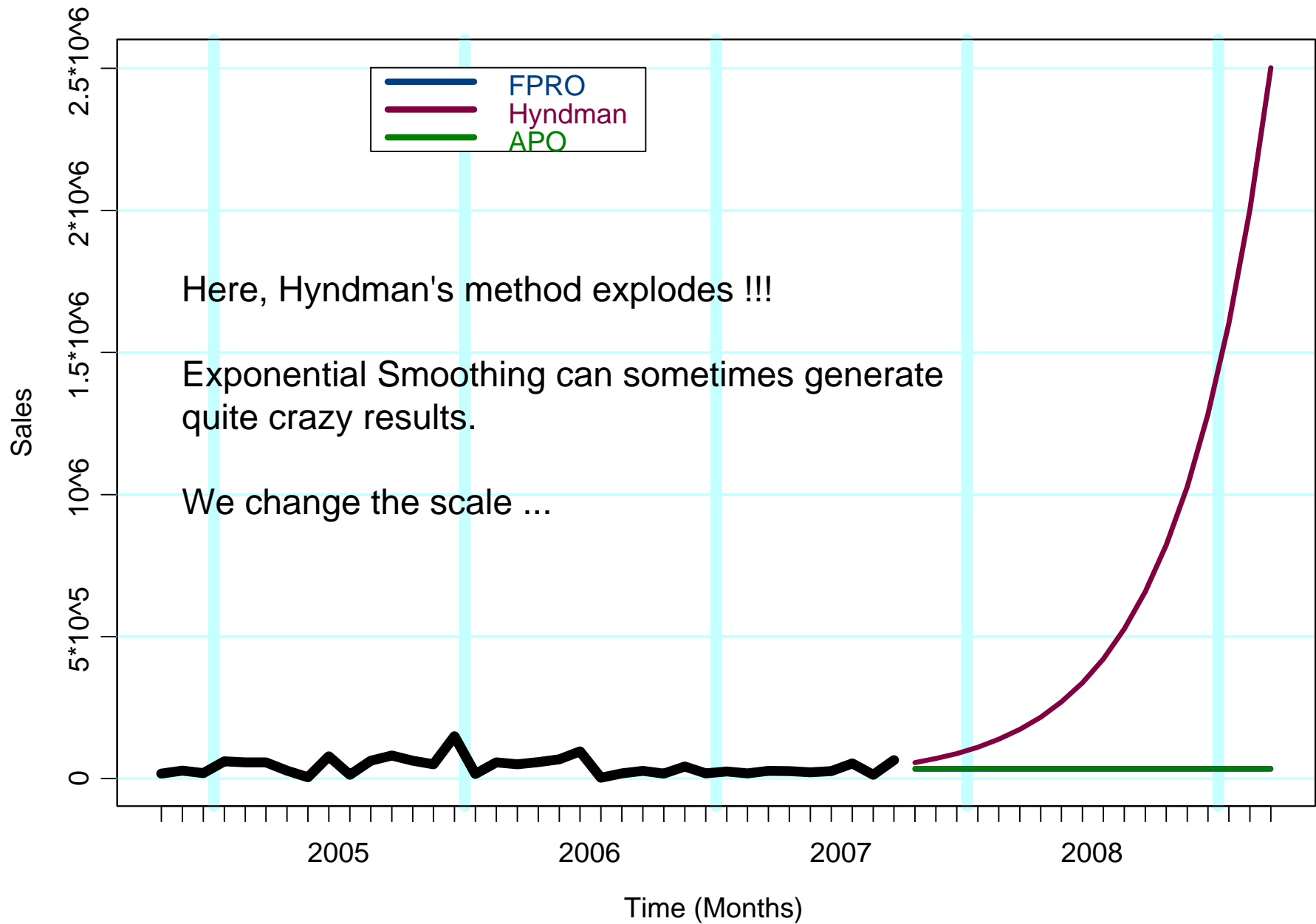
We now show the results of the same forecasting methods on the set of real time series presented earlier.

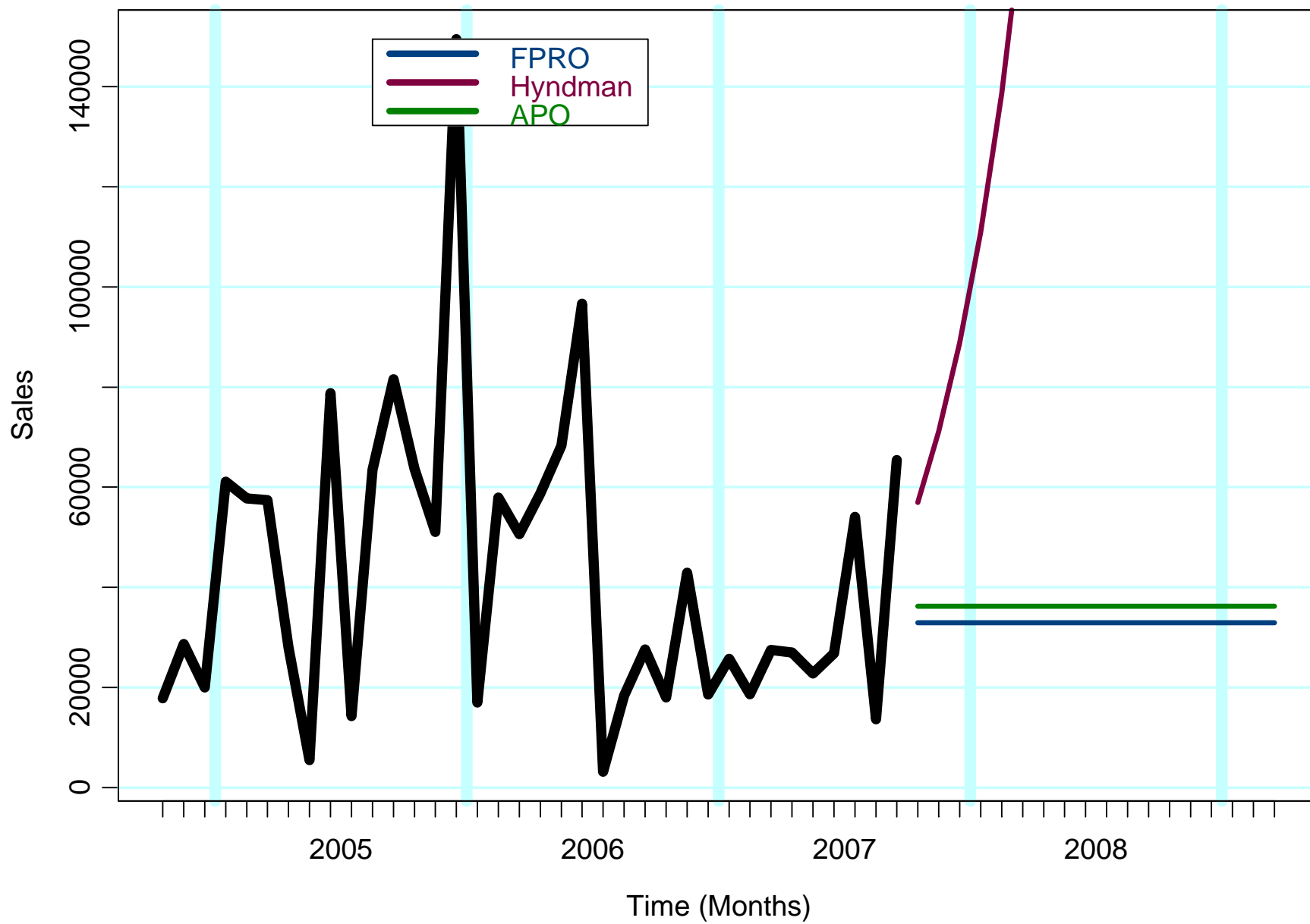


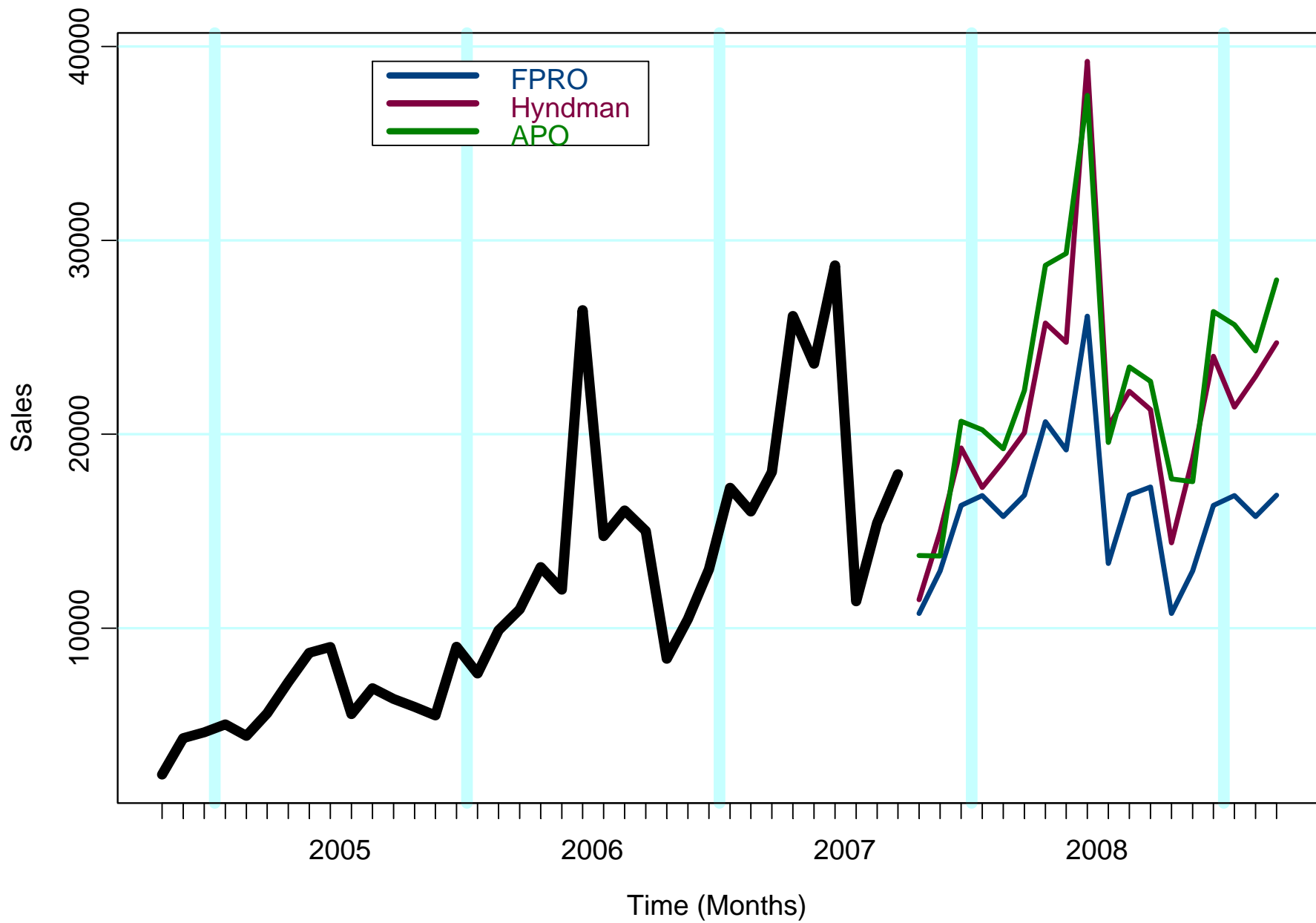


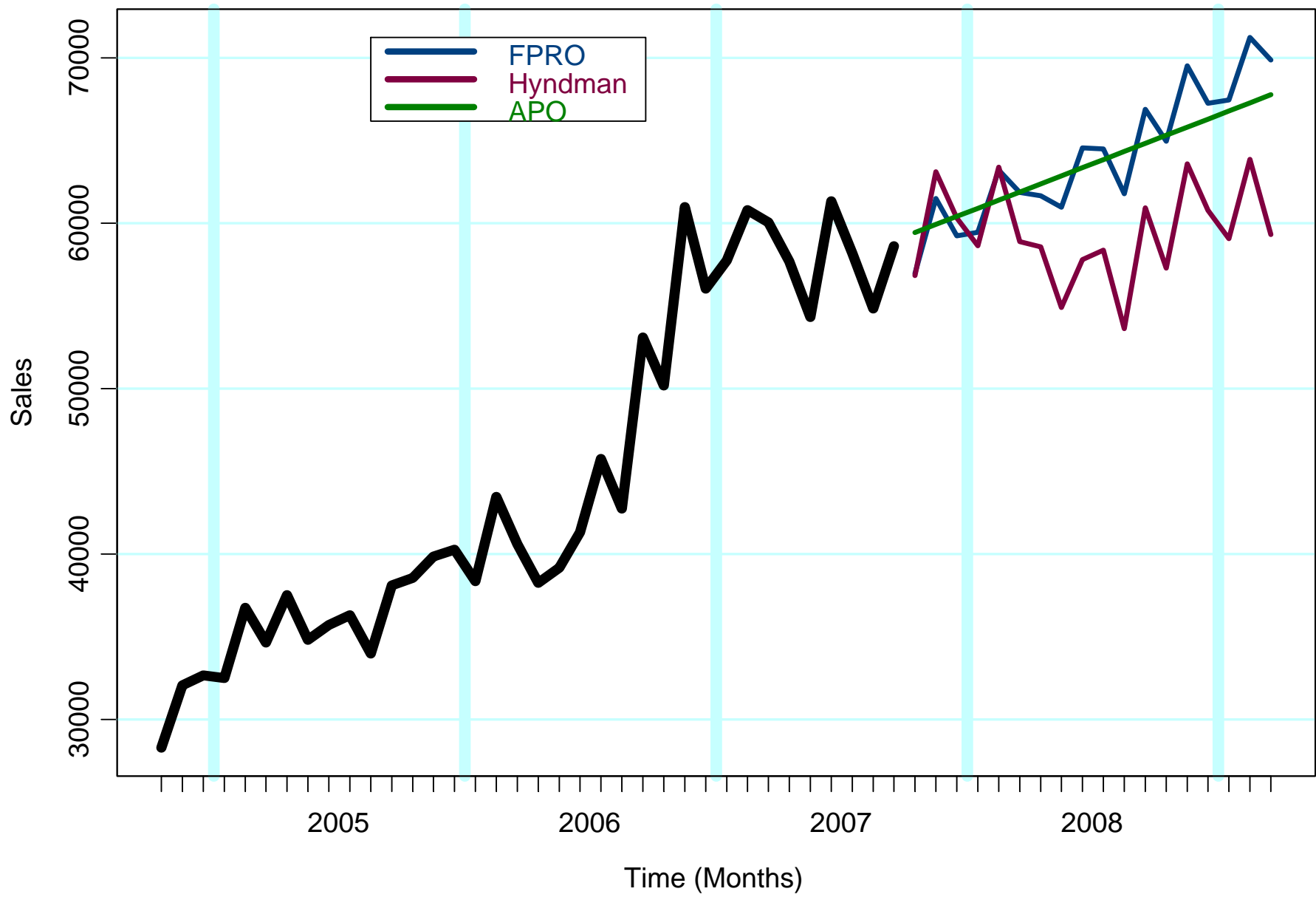


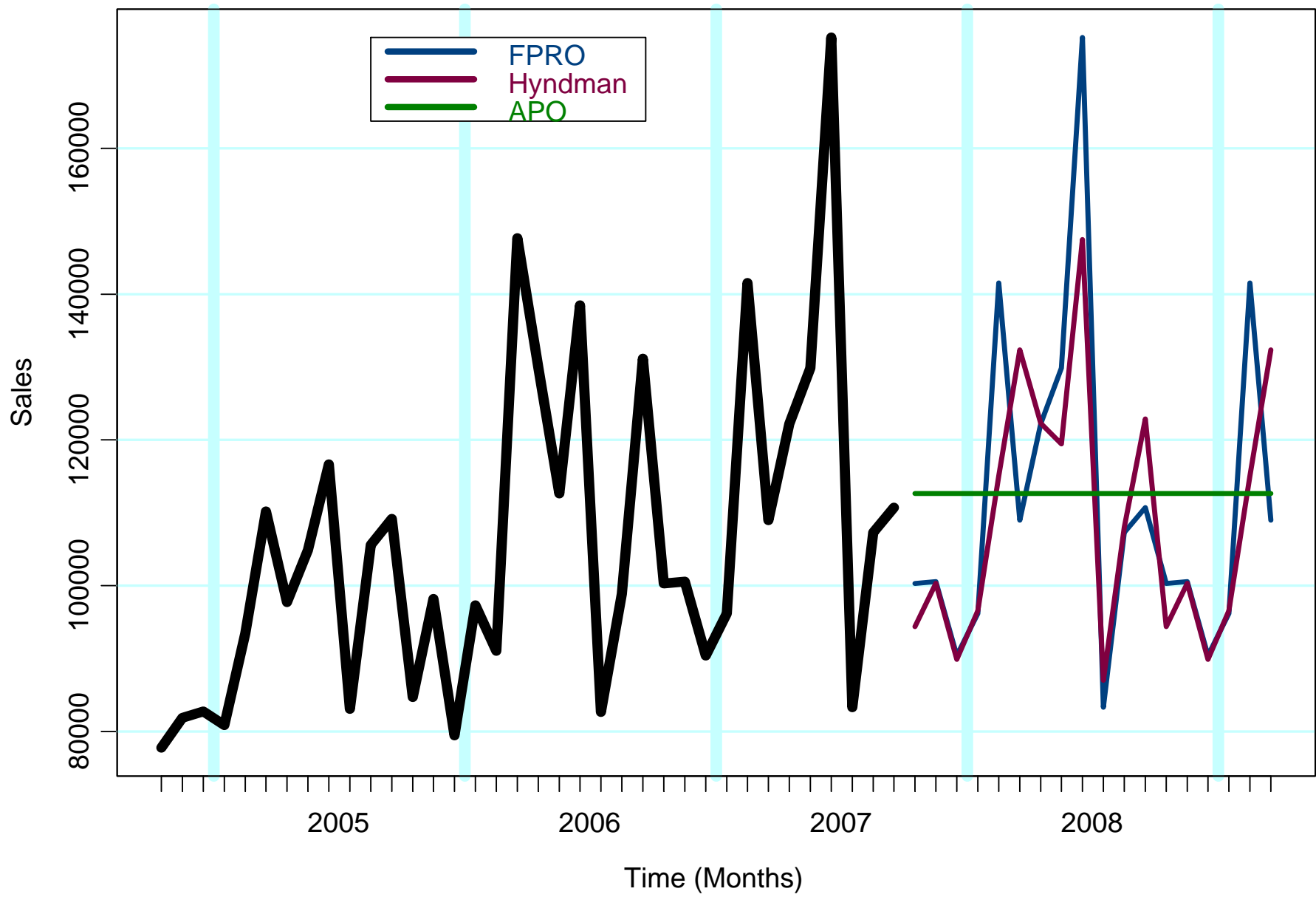












Conclusions

The different methods behave in a fairly similar way, and with good results for the simulated data.

The more simplistic algorithm of APO also compares favorably with the more advanced approach of ForecastPRO and with Hyndman's method, which has a more solid statistical foundation. For noisy time series, more simple approaches sometimes work even better.

We can thus continue to improve and promote the use of the automatic forecasting method in APO, and follow-up the next developments in the area of state-space models for exponential smoothing.