The value of external information: including leading indicators in sales forecasting

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Business problem

A global tire manufacturer wants to improve its tactical sales forecasting with external data, obtaining insight in the main relevant leading indicators.
Motivation long-term forecasting

- Global supply chains need long-term forecasting for decision making (procurement, production scheduling and capacity planning)
- External data is often available (public & expert sources)
- Incorporating field knowledge via judgement: inconsistent & bias
- Combining univariate and exogenous information (Huang et al., 2014) (Leitner et al., 2011)

Belief in external leading indicators

National economic conjuncture is a leading for tire sales:

\[\text{Economic Growth} \uparrow \Rightarrow \text{Road Transport} \uparrow \Rightarrow \text{Tire Production} \uparrow\]
Leading Indicator Example: Tires for passenger cars (US)

The amount of newly registered cars (blue) is a leading indicator to the sudden drop (bold) in car tire sales (US) during the economic crisis of 2009-2010.
Insight in case study data
Methodology: the curses of leading indicators

Curse of dimensionality
- Short fat data problem
- $p > n$: much more predictors than training sample

Curse of optimal leading effect
- Leading indicators exhibit leading information in advance
- $pl \gg n$: detecting optimal lead expands dimensionality

Curse of missing future information
- Indicators only exhibit information up to a certain point in time
- Clear need for unconditional forecasting
Methodology: LASSO regression

Least Absolute Shrinkage Selection Operator (Tibshirani, 1996)

\[
\sum_{i=1}^{n} \left( y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j|
\]

Advantages (Bai and Ng, 2008) (Li and Chen, 2014) (Iturbide, 2013)

- Works with \( p > n \)
- Shrinking coefficients
- Variable selection

Model problems
- Include univariate information
- Choosing and optimising Lambda
Methodology: LASSO regression

LASSO shrinks coefficients to zero and selects predictors
Methodology

Forecast horizon | 1 | 5 | 12
--- | --- | --- | ---
Lags | 1-12 | 5-12 | 12
Number of variables | 814,212 | 542,808 | 67,851
Forecasting results

LASSO can improve on company benchmark and ETS, but deteriorates over long horizons

<table>
<thead>
<tr>
<th>Model</th>
<th>MAPE</th>
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</thead>
<tbody>
<tr>
<td>Naive</td>
<td>17.2</td>
</tr>
<tr>
<td>Holt-Winters</td>
<td>18.6</td>
</tr>
<tr>
<td>Exponential Smoothing (ETS)</td>
<td>15.3</td>
</tr>
<tr>
<td>LASSO</td>
<td>15.2</td>
</tr>
<tr>
<td>Oracle LASSO</td>
<td>13.8</td>
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Final model contains:
- Relevant indicators
- Leading effect
- 8-15 variables