Do Business Tendency Surveys Help in Forecasting Employment?  
A Real-Time Evidence for Switzerland

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Plan

- Motivation
- KOF Employment Indicator (construction)
- Methodology
- Results
- Conclusion
Business Tendency Surveys (BTS)

- BTS are collected at KOF (Swiss Economic Institute)
- Questionnaires sent out to firms
  - about 11,000
  - response rate – about 60%
- Available much earlier than official statistical data are published
  - Publication lag of official employment data is two months
  - Quarterly and monthly BTS are available in the same quarter/month
- BTS allow to assess current as well as short-run future developments in different sectors of the Swiss economy prior to release of official data
- Continuous monitoring of dominating tendencies in the Swiss economy in real time
How do you assess the current employment level?
1. too high
2. adequate
3. too low

How will the number of employees change in the next three months?
1. increase
2. stay the same
3. decrease

Net balance = difference between fractions of positive and negative answers
Motivation

- Are employment-related questions in BTS useful for out-of-sample prediction of total employment?

- Aggregate information from employment related questions in BTS into one composite indicator, **KOF Employment Indicator**.

- Related literature uses BTS primary for predicting of either GDP or industrial production

- Employment related literature is scarce
  - Hartle (1958) – for Canada (negative)
  - Abberger (2007) – for Germany (affirmative)

- Our study:
  - The first exercise for Switzerland
  - Real-time data vintages, in order to replicate information flow in the past
    - Distinguishes from Abberger (2007) (last-available data)
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KOF Employment Indicator

- Covers nine branches
- Coverage gradually expanded

**Table:** KOF Employment Indicator: Changes over time

<table>
<thead>
<tr>
<th>Period</th>
<th>Sectors covered&lt;sup&gt;a&lt;/sup&gt;</th>
<th>No. of indicators</th>
<th>Coverage&lt;sup&gt;b&lt;/sup&gt; (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991Q3-1994Q1</td>
<td>IMT, GGT, GHU</td>
<td>6</td>
<td>35.2</td>
</tr>
<tr>
<td>1994Q2-1994Q3</td>
<td>IMT, GGT, GHU, DHU</td>
<td>8</td>
<td>44.0</td>
</tr>
<tr>
<td>1994Q3-1996Q1</td>
<td>IMT, GGT, GHU, DHU, BAT</td>
<td>10</td>
<td>53.4</td>
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<tr>
<td>1996Q2-2000Q1</td>
<td>IMT, GGT, GHU, DHU, BAT, AIT</td>
<td>12</td>
<td>52.6</td>
</tr>
<tr>
<td>2000Q2-2001Q2</td>
<td>IMT, GGT, GHU, DHU, BAT, AIT, BT</td>
<td>15</td>
<td>56.0</td>
</tr>
<tr>
<td>2001Q3-2006Q3</td>
<td>IMT, GGT, GHU, DHU, BAT, AIT, BT, VT</td>
<td>17</td>
<td>55.3</td>
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<tr>
<td>2006Q4-2010Q4</td>
<td>IMT, GGT, GHU, DHU, BAT, AIT, BT, VT, DLU</td>
<td>19</td>
<td>84.5</td>
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</tbody>
</table>


<sup>b</sup> Reports a share of sectoral employment covered in KOF Employment Indicator in total employment.
## KOF Employment Indicator: 19 components

<table>
<thead>
<tr>
<th>Sector</th>
<th>Label</th>
<th>Indicator</th>
<th>Weight</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing</td>
<td>IMT</td>
<td>Current employment assessment</td>
<td>50%</td>
<td>M</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>M</td>
</tr>
<tr>
<td>Hotels/restaurants</td>
<td>GGT</td>
<td>Current employment assessment</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sales expectation for next 3 months</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td>Wholesale trade</td>
<td>GHU</td>
<td>Current employment assessment</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td>Retail trade</td>
<td>DHU</td>
<td>Current employment assessment</td>
<td>50%</td>
<td>M</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td>Construction</td>
<td>BAT</td>
<td>Current business situation assessment</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td>Architects/Engineers</td>
<td>AIT</td>
<td>Current business situation assessment</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td>Banking</td>
<td>BT</td>
<td>Current employment assessment</td>
<td>50%</td>
<td>M</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>M</td>
</tr>
<tr>
<td>Insurance</td>
<td>VT</td>
<td>Current employment assessment</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td>Services</td>
<td>DLU</td>
<td>Current employment assessment</td>
<td>50%</td>
<td>Q</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Employment expectations for next 3 months</td>
<td>50%</td>
<td>Q</td>
</tr>
</tbody>
</table>

- Each sector component is weighted with a corresponding share in total employment.
Figure: KOF Employment Indicator and total employment (LTOTV) (% yoy) (mean and range adjusted)
Econometric methodology

- **Target variable**: Employment in full-time equivalent
  - Growth rate in the **current** quarter compared to the same quarter of previous year: **nowcast**
  - Growth rate in the **next** quarter compared to the same quarter of previous year: **one-quarter ahead forecast**

- **Forecasting methodology**
  - AutoRegressive (AR) univariate model: benchmark
  - AutoRegressive Distributed Lag (ARDL) models
  - Bayesian Model Averaging (BMA) approach to model selection/combination
    - Rather than trying to identify the “best” single model we combine models
    - The use of Occam’s window
  - Point- as well as density forecasts
    - Density forecasts help us assessing uncertainty around point forecasts
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Forecasting methodology

- \( Y_\tau = \Delta_4 \ln y_\tau \) – year-to-year quarterly growth rate of employment
- \( X_\tau \) – the KOF Employment Indicator for a given quarter \( \tau \)
  - Quarter in question: 2013q4 (December)
    - Official data are available until 2013q3 (released in the end of November)
    - KOF Employment Indicator is available until 2013q4
  - ARDL nowcast for the current quarter:
    \( \hat{Y}_{2013q4} = f(Y_{2013q3}, Y_{2013q2}, \ldots, X_{2013q4}, X_{2013q3}, \ldots) \)
  - ARDL one-quarter ahead forecast:
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- Nowcasts are published 2 months before official data release, one-quarter ahead forecast—5 months ahead of official release
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Forecasting methodology

- Nowcasting ARDL equation

\[ Y_\tau = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{\tau-i} + \sum_{j=0}^{q} \beta_j X_{\tau-j} + \varepsilon_\tau, \]

- Forecasting ARDL equation

\[ Y_\tau = \alpha_0 + \sum_{i=2}^{p} \alpha_i Y_{\tau-i} + \sum_{j=1}^{q} \beta_j X_{\tau-j} + \varepsilon_\tau, \]

- \( Y_\tau = \Delta_4 \ln y_\tau \) – year-on-year quarterly growth rate of employment

- \( X_\tau \) – KOF Employment Indicator for a given quarter \( \tau \)

- \( p \) – lag order of the autoregressive part

- \( q \) – lag order of \( X_\tau \)

- \( \varepsilon_\tau \sim N(0, \sigma^2) \) – an error term
Forecasting methodology: Benchmark models

- Nowcasting AR equation
  \[ Y_{\tau} = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{\tau-i} + \varepsilon_{\tau}, \]

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- \( \varepsilon_{\tau} \sim N(0, \sigma^2) \) – an error term
Bayesian Model Averaging (BMA)

- Rather than selecting a single “best” model we consider a whole range of models determined by different combinations of regressors $Y_{τ−i}$ and $X_{τ−j}$ with $i = 1, \ldots, p$ and $j = 0, \ldots, q$
- Models are ranked by their respective posterior probabilities
- Model posterior probability is computed using the Bayesian Information Criterion (BIC)
- Options for model selection/combination:
  - All possible models $K = 2^k$, $k$— a number of regressors for $k = 10$ —- $K = 2^{10} = 1024$
  - A subset of models based on Occam’s window: exclude all models that are much less (e.g. 20 times) likely than the most likely model, $K^* \approx 35$
- Forecast combination — weighted average of all model’s forecasts [by the respective posterior probability]
- Robustness of the results with respect to a choice of model
Prediction uncertainty

- Model parameters are estimated with uncertainty
  - each parameter is estimated with standard error
- Regression error term
  - unmodelled factors that influence dependent variable in (un-)systematic ways
- Uncertainty associated with the choice of a forecast model
  - BMA
- Uncertainty surrounding a point forecast is summarised in forecast density
Estimation and timing setup

- **Total sample:** 1993Q4 – 2010Q4
- **Evaluation sample:**
  - for nowcasts: 2004Q4 – 2010Q4: 25 observations
  - for forecasts: 2005Q1 – 2010Q4: 24 observations
- **Recursive estimation using a rolling window**
- **Selection of now-/forecast window size**
  - Latest update was inclusion of services sector (DLU) into the composite indicator [2006Q4] (too short)
  - Larger window size would imply more weight is put on the predictions made without DLU sector (too long)
Table: BMA: Symmetric Occam’s window (Ratio 20)

<table>
<thead>
<tr>
<th>Regressors</th>
<th>Inclusion frequency</th>
<th>Posterior distribution EV</th>
<th>SD</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 35</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incpt</td>
<td>100.0</td>
<td>0.397</td>
<td>0.131</td>
<td>0.368</td>
<td>0.535</td>
<td>0.358</td>
<td>0.447</td>
<td>...</td>
<td>0.366</td>
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<tr>
<td>$Y_{T-1}$</td>
<td>100.0</td>
<td>0.720</td>
<td>0.120</td>
<td>0.617</td>
<td>0.738</td>
<td>0.733</td>
<td>0.796</td>
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<td>0.743</td>
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<tr>
<td>$Y_{T-2}$</td>
<td>8.3</td>
<td>-0.008</td>
<td>0.053</td>
<td>.</td>
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<td>.</td>
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<tr>
<td>$Y_{T-3}$</td>
<td>10.6</td>
<td>-0.002</td>
<td>0.060</td>
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<tr>
<td>$Y_{T-4}$</td>
<td>52.4</td>
<td>-0.129</td>
<td>0.167</td>
<td>.</td>
<td>-0.282</td>
<td>-0.095</td>
<td>-0.256</td>
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<td>-0.320</td>
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<tr>
<td>$Y_{T-5}$</td>
<td>12.6</td>
<td>0.011</td>
<td>0.063</td>
<td>.</td>
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<td>.</td>
<td>...</td>
<td>0.201</td>
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<tr>
<td>$X_T$</td>
<td>100.0</td>
<td>0.045</td>
<td>0.010</td>
<td>0.052</td>
<td>0.043</td>
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<td>$X_{T-1}$</td>
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<td>$X_{T-2}$</td>
<td>8.2</td>
<td>-0.001</td>
<td>0.005</td>
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<td>...</td>
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<td>$X_{T-3}$</td>
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<td>0.000</td>
<td>0.004</td>
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<td>$X_{T-4}$</td>
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<td>-0.005</td>
<td>0.011</td>
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<td>.</td>
<td>-0.021</td>
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<td>$X_{T-5}$</td>
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<td>0.011</td>
<td>0.017</td>
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<td>0.025</td>
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<td>0.037</td>
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<tr>
<td>nVar</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>...</td>
<td>5</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>$R^2$</td>
<td>0.948</td>
<td>0.955</td>
<td>0.951</td>
<td>0.958</td>
<td>...</td>
<td>0.954</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>-122.2</td>
<td>-122.8</td>
<td>-120.9</td>
<td>-120.6</td>
<td>...</td>
<td>-116.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post. prob.</td>
<td>0.140</td>
<td>0.098</td>
<td>0.073</td>
<td>0.062</td>
<td>...</td>
<td>0.007</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Nowcast estimation results: [1999Q4-2010Q3]

- 35 models are selected in Occam’s window
- \( R^2 \approx 0.95 \) – quite high
- Highest posterior probability — 0.140
- Lowest posterior probability — 0.007
- Model 1 has the highest posterior probability:
  \[
  Y_\tau = \alpha_0 + \alpha_1 Y_{\tau-1} + \beta_0 X_\tau + \varepsilon_\tau,
  \]
- Model 1 is nested within each of Models 2-35
- Models 2-35 have one or several additional lags either of \( Y_\tau \) or \( X_\tau \)
- Contemporaneous value of the KOF Employment Indicator is present in every model:
  \textbf{Indicator is strongly informative in sample}!!!

- Out-of-sample performance?
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- Contemporaneous value of the KOF Employment Indicator is present in every model: **Indicator is strongly informative in sample!!!**
- Out-of-sample performance?
**Figure:** Nowcasts: Actual values (black), ARDL-nowcasts (blue), AR-nowcasts (red)
Figure: One-quarter ahead forecasts: Actual values (black), ARDL-nowcasts (blue), AR-nowcasts (red)
Comparison of model predictive ability

- **Point forecasts:**
  - Unconditional predictive ability test (Giacomini/White, 2006)
  - Forecast encompassing test (Harvey et al., 1998)

- **Density forecasts:**
  - Test of Mitchell/Hall (2006) based on average log scores
  - Log score — log of forecast density at the outturn
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### Unconditional predictive ability test

<table>
<thead>
<tr>
<th></th>
<th>ARDL (RMSFE)</th>
<th>AR (RMSFE)</th>
<th>ARDL/AR (Ratio)</th>
<th>GW test (P-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Nowcast</strong>&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.257</td>
<td>0.332</td>
<td>0.773</td>
<td>0.124</td>
</tr>
<tr>
<td><strong>One-step ahead forecast</strong>&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.328</td>
<td>0.649</td>
<td>0.505</td>
<td>0.007</td>
</tr>
</tbody>
</table>


<sup>c</sup> The test of equal unconditional predictive ability (Giacomini and White, 2006).
## Forecast encompassing test

<table>
<thead>
<tr>
<th></th>
<th>$H_0 : \text{ARDL encompasses AR}$ (P-value)</th>
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</tr>
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<tbody>
<tr>
<td>Nowcast$^a$</td>
<td>0.197</td>
<td>0.004</td>
</tr>
<tr>
<td>One-step ahead forecast$^b$</td>
<td>0.798</td>
<td>0.004</td>
</tr>
</tbody>
</table>


Comparison of model predictive ability

► Point forecasts:
  ► Unconditional predictive ability test (Giacomini/White, 2006)
  ► Forecast encompassing test (Harvey et al., 1998)

► Density forecasts:
  ► Test of Mitchell/Hall (2006) based on average log scores
  ► Log score — log of forecast density at the outturn (vertical line)
Density nowcast and one-step ahead forecast: 2010Q4

AR(NCST Density 2010Q4)
ARDL(NCST Density 2010Q4)

AR(FCST Density 2010Q4)
ARDL(FCST Density 2010Q4)
Density nowcast and one-step ahead forecast: Log scores

![Graph showing the comparison between AR(NCST LnS) and ARDL(NCST LnS) for 2005 to 2011. The graph plots the log scores with a y-axis range from -2 to 0.5. The x-axis represents the years from 2005 to 2011. The graph includes two lines: one red and one blue. The red line represents AR(NCST LnS), and the blue line represents ARDL(NCST LnS).]
Equal density forecast accuracy test

<table>
<thead>
<tr>
<th></th>
<th>ARDL (Average log score)</th>
<th>AR (Average log score)</th>
<th>ARDL/AR (Difference)</th>
<th>MH test (P-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nowcast&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.099</td>
<td>-0.348</td>
<td>0.249</td>
<td>0.026</td>
</tr>
<tr>
<td>One-step ahead forecast&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.371</td>
<td>-0.985</td>
<td>0.614</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<sup>c</sup> The test of equal density forecast accuracy (Mitchell and Hall, 2005).
<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>Nowcast</td>
<td>0.332</td>
<td>0.327</td>
<td>1.016</td>
<td>0.309</td>
<td>-0.348</td>
<td>-0.331</td>
<td>-0.017</td>
<td>0.139</td>
<td></td>
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</tr>
<tr>
<td>AR</td>
<td>Forecast</td>
<td>0.649</td>
<td>0.644</td>
<td>1.007</td>
<td>0.403</td>
<td>-0.985</td>
<td>-0.980</td>
<td>-0.005</td>
<td>0.723</td>
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<tr>
<td>ARDL</td>
<td>Nowcast</td>
<td>0.257</td>
<td>0.261</td>
<td>0.984</td>
<td>0.580</td>
<td>-0.099</td>
<td>-0.123</td>
<td>0.024</td>
<td>0.333</td>
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<td></td>
</tr>
<tr>
<td>ARDL</td>
<td>Forecast</td>
<td>0.328</td>
<td>0.341</td>
<td>0.961</td>
<td>0.050</td>
<td>-0.371</td>
<td>-0.385</td>
<td>0.013</td>
<td>0.403</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Prediction samples are 2004Q4–2010Q4 and 2005Q1–2010Q4 for nowcasts and forecasts, respectively.
BMA versus Single Best model (SBM)

- BMA and SBM produce very similar results both in terms of point and density forecasts.
- KOF Employment Indicator is a very good predictor of employment growth in Switzerland in the sample period in question.
- One predicted variable and one predictor: rather unusual.
- More common situation when for one predicted variable there are a (very large) number of predictors.
- Need for aggregation and combination across different predictors.
  - Aggregation of forecasts from individual models.
    - BMA is only one of many ways how to aggregate/combine forecasts.
  - Aggregation of predictors through factor models.
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  - Aggregation of predictors through factor models.
Summary

- Addition to a scarce literature on the use of business tendency surveys for predicting employment
- First study of this sort for Switzerland
- BTS for employment are useful for predicting Swiss employment
  - in-sample informative (100 % frequency: most recent values)
  - out-of-sample informative (superior to AR model)
- This holds for
  - nowcasts (2 months ahead of official release)
  - next-quarter forecasts (5 months ahead of official release)
Bayesian econometrics: Terminology

- Bayes theorem: Reverend Thomas Bayes (1701 – 1761)
- Unconditional probability: $P(A)$, $P(B)$
- Conditional probability: $P(A|B)$, $P(B|A)$
- Conjoint probability: $P(A&B)$
- Probability axiom:

\[ P(A&B) = P(A) \times P(B|A) = P(A|B) \times P(B) \]

- Bayes theorem:

\[ P(A) \times P(B|A) = P(A|B) \times P(B) \]

\[ P(B|A) = \frac{P(A|B) \times P(B)}{P(A)} \]
Bayesian econometrics: Terminology

- Bayes theorem:

\[ P(B|A) = \frac{P(A|B) \times P(B)}{P(A)} = \left[ \frac{P(A|B)}{P(A)} \right] \times P(B) \]

- \( P(B) \) - prior probability of event B

- How do our initial (prior) beliefs about probability of event B change given an additional evidence (event A)?

  - \( P(B) \Rightarrow P(B|A) \)

- \( P(B|A) \) - posterior probability of event B
Bayesian econometrics: Terminology

- Application of the Bayes theorem to regression models, $M_j, j = 1, 2, \ldots, K$

- Set prior probability: $P(M_j) = 1/K$
  - All models are equally good

- Question: How do prior beliefs change after models were taken to the data?
  - $P(M_j) \Rightarrow P(M_j|Y, X)$
  - Are there any models that are better than others?

BMA
Bayesian econometrics: Terminology

- New information based on estimation results:
  - Goodness-of-fit of a model measured by residuals (Sum of Squared Residuals, SSR)
  - Number of parameters (explanatory variables), $p$
- SSR decreases as number of explanatory variables grows
- Trade-off:
  - Minimise SSR and number of explanatory variables at the same time
- Bayesian Information Criterion (BIC):
  - $BIC = T \times \ln(SSR) + p \times \ln(T)$
- Model posterior probability:
  $$P(M_j|Y, X) = \frac{\exp\left(-\frac{1}{2}BIC_j\right)}{\sum_{j=1}^{K} \exp\left(-\frac{1}{2}BIC_j\right)}.$$
Bayesian econometrics: Example

- Two coins: Fair and Fake
- Fake coin always lands heads
- Prior belief that the coin is fake is 0.5 (event B)
  - \( P(\text{Coin is Fake}) = 0.5 \)
- Experiment:
  - If one randomly picks up a coin
  - tosses it three times
  - it lands three times heads, HHH (event A)
- Question: what is the posterior probability that the coin is fake?
  - \( P(\text{Coin is Fake}|HHH) =? \)
- Use the Bayes theorem:

\[
P(\text{Coin is Fake}|HHH) = \left[ \frac{P(HHH|\text{Coin is Fake})}{P(HHH)} \right] \times P(\text{Coin is Fake})
\]
Bayesian econometrics: Example

- Use the Bayes theorem:

\[
P(\text{Coin is Fake}|HHH) = \left[ \frac{P(HHH|\text{Coin is Fake})}{P(HHH)} \right] \times P(\text{Coin is Fake})
\]

- \(P(\text{Coin is Fair}) = 0.5\)
- \(P(\text{Coin is Fake}) = 0.5\)
- \(P(H|\text{Coin is Fair}) = 0.5\)
- \(P(H|\text{Coin is Fake}) = 1\)
- \(P(HHH|\text{Coin is Fair}) = 0.125\)
- \(P(HHH|\text{Coin is Fake}) = 1\)
- \(P(HHH)\) - unconditional probability of event A

\[
P(HHH) = P(HHH|\text{Coin is Fair}) \times P(\text{Coin is Fair}) + P(HHH|\text{Coin is Fake}) \times P(\text{Coin is Fake})
\]

- \(P(HHH) = 0.125 \times 0.5 + 1 \times 0.5 = 0.5625\)
Bayesian econometrics: Example

- Use the Bayes theorem:

\[ P(\text{Coin is Fake}|HHH) = \left[ \frac{P(HHH|\text{Coin is Fake})}{P(HHH)} \right] \times P(\text{Coin is Fake}) \]

- \( P(\text{Coin is Fair}) = 0.5 \)
- \( P(\text{Coin is Fake}) = 0.5 \)
- \( P(H|\text{Coin is Fair}) = 0.5 \)
- \( P(H|\text{Coin is Fake}) = 1 \)
- \( P(HHH|\text{Coin is Fair}) = 0.125 \)
- \( P(HHH|\text{Coin is Fake}) = 1 \)
- \( P(HHH) = 0.5625 \)

\[ P(\text{Coin is Fake}|HHH) = \left[ \frac{1}{0.5625} \right] \times 0.5 = 0.888 \]

- New evidence causes an update of the prior belief \( (P(\text{Coin is Fake}) \Rightarrow P(\text{Coin is Fake}|HHH)) \) from 0.5 to 0.888
Who is Occam?

- William of Ockham (also Occam, Hockham) (c. 1288 - c. 1348) was an English Franciscan friar and scholastic philosopher, from Ockham, a small village in Surrey, near East Horsley.

- He is considered to be one of the major figures of medieval thought and was at the centre of the major intellectual and political controversies of the XIV century.

- Most famous for *Occam’s razor*:
  - One should not multiply entities beyond necessity, i.e.
  - one should always opt for an explanation in terms of the fewest possible number of causes, factors, or variables.
Statistical tests

- A Pair of competing forecasts: \((f_{1,t}, f_{2,t})\)
- Forecast errors: \((e_{1,t}, e_{2,t})\)
- Loss differential: \(d_t = (e_{1,t})^2 - (e_{2,t})^2\)
- Under the null hypothesis of equal predictive ability:
  \[E[(e_{1,t})^2 - (e_{2,t})^2] = E[d_t] = 0\]
  - Difference in variance of forecast errors is equal to zero
- In practice:
  \[\bar{d} = \frac{1}{T} \sum_{t=1}^{P} [(e_{1,t})^2 - (e_{2,t})^2] = \frac{1}{T} \sum_{t=1}^{P} d_t, \quad (1)\]
  \[\frac{\bar{d}}{\hat{\sigma}_P / \sqrt{T}} \overset{d}{\to} N(0, 1), \quad (2)\]
  where \(\hat{\sigma}_P^2\) is a heteroskedasticity- and autocorrelation-consistent (HAC) estimator of the asymptotic variance, \(\sigma_T^2 = \text{var}(\sqrt{T} \bar{d})\).
**Statistical tests**

- Forecast encompassing test of Harvey et al. (1998)
  - Forecast $f_{1,t}$ encompasses $f_{2,t}$ if the latter forecast adds no predictive power to the former forecast.
  - Loss differential: $d_t = e_{1,t}(e_{1,t} - e_{2,t})$

- The test of equal density forecast accuracy (Mitchell/Hall, 2005)
  - $g_1(\cdot)$ and $g_2(\cdot)$ - predictive densities of the competing models
  - For a given outturn $y_t$ the corresponding log scores are $\ln g_1(y_t)$ and $\ln g_2(y_t)$
  - Loss differential: $d_t = \ln g_1(y_t) - \ln g_2(y_t)$

- The same test statistic is used for testing the null hypothesis that $E[d_t] = 0$

$$
\frac{\bar{d}}{\hat{\sigma}T/\sqrt{T}} \overset{d}{\rightarrow} N(0, 1), \quad (3)
$$