

Forecasting the Equity Risk Premium: Predictability versus Profitability

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September 29, 2016

Motivation

- Forecasting next month's ERP, using a univariate linear regression framework
- Long list of macroeconomic predictors:
T-bill rate (Fama & Schwert, JFE-1977), dividend yield (Fama & French, JFE-1988), D/P (Campbell & Shiller, RFS-1988), term spread (Keim & Stambaugh, JFE-1986), volatility (French, Schwert & Stambaugh, JFE-1987), B/M (Kothari & Shanken, JFE-1997), inflation (Fama & Schwert, JFE-1977), default spread (Fama, JFE-1986), corporate issuing activity (Baker & Wurgler, JF-2000), consumption-surplus ratio (Campbell & Cochrane, JPE-1999), consumption-wealth ratio (Lettau & Ludvigson, JF-2001)
- Broadly speaking, these have “good” in-sample forecasting power.
- Out-of-sample, they struggle to beat historical average (Goyal and Welch, RFS-2008)
- Significant implications for asset allocation decisions

Motivation

- Following **Goyal and Welch (RFS-2008)**, two streams of literature have emerged:
 - Devise/identify “better” forecasting variables:
 - output gap (**Cooper & Priestley, RFS-2009**), VRP (**Bollerslev et al. RFS-2009**), 52-week high vs. historical high (**Li & Yu, JFE-2012**), aggregate ICC (**Li, Ng & Swaminathan, JFE-2013**), technical indicators (**Neely, Rapach, Tu & Zhou MS-2014**), economic growth (**Mller & Rangvid, JFE-2015**), investor sentiment (**Huang, Jiang, Tu & Zhou, RFS-2015**), mean-reversion (**Huang, Jiang, Tu & Zhou, WP-2015**), short interest (**Rapach, Ringgenberg & Zhou, JFE-2015**)
 - Refine the forecasting model - **OUR FOCUS!**
- **Campbell & Thompson (RFS-2008)** and **Pettenuzzo, Timmermann & Valkanov (JFE-2014)** introduce **economic constraints** to generate non-negative ERP forecasts
- **Argument:** positive ERP forecast justifies equity investing.
- Research questions:
 - How do constrained models perform in months/periods of **negative ERP realisations**?
 - How do constrained models perform in periods of **high volatility**?
 - What are the **asset allocation implications** from using constrained ERP models?
 - What are the implications of real-life **investment constraints**?

Main Findings - Contributions

- Out-of-sample forecasting performance: the constrained models ...
 - ...outperform OLS across the entire sample period (1947-2013)
 - ...outperform OLS during periods of positive ERP realisations
 - ...outperform OLS during expansionary periods
 - ...underperform OLS during periods of negative ERP realisations
 - ...underperform OLS during recessionary periods
 - ...underperform OLS during periods of high volatility
- Asset allocation implications:
 - Constrained models generate CER gains and losses against OLS as above.
 - Any economic benefits of the constrained models diminish for conservative investors.
 - Short-sale constraints or even a minimum required investment is equivalent to a constrained model.
 - No-leverage constraints become more often binding for constrained models and therefore reduce any economic benefit during up markets.
- Our findings have important implications for designing new ERP forecasting models.

Out-of-sample ERP Forecasting Models

- Traditional linear regression forecasting model:

$$OLS : \hat{r}_{t+1|t}^{OLS} = \hat{\alpha} + \hat{\beta} \cdot x_t$$

where $\hat{\alpha}$ and $\hat{\beta}$ are estimated using information up to time t :

$$r_{\tau+1} = \alpha + \beta \cdot x_{\tau} + \epsilon_{\tau+1}, \quad \tau = 1, \dots, t-1$$

- Campbell & Thompson (RFS-2008, CT) truncation model:

$$CT : \hat{r}_{t+1|t}^{CT} = \max(\hat{\alpha} + \hat{\beta} \cdot x_t, 0)$$

- Pettenuzzo, Timmermann & Valkanov (JFE-2014, PTV) Bayesian model:

$$PTV : \hat{r}_{t+1|t}^{PTV} = \bar{\alpha} + \bar{\beta} \cdot x_t$$

where $\bar{\alpha}$ and $\bar{\beta}$ are the averages of all pairs of values (α, β) that belong to a set \mathcal{A}_t :

$$\mathcal{A}_t = \{(\alpha, \beta) : \alpha + \beta \cdot x_{\tau} \geq 0, \quad \forall \tau = 1, \dots, t\}$$

Data

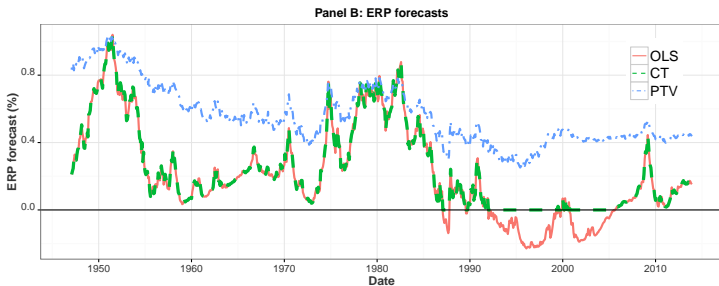
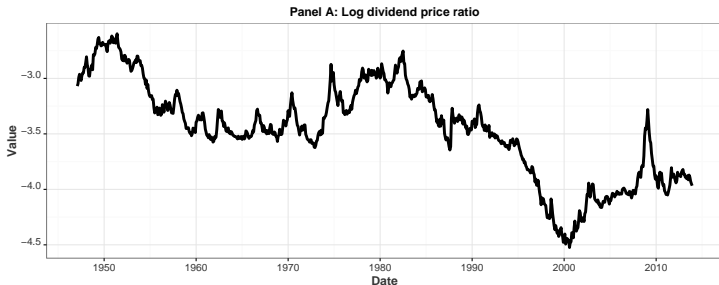
- Equity Risk Premium (ERP):
 - S&P500 monthly excess total (i.e. including dividends) logarithmic return
 - Source: CRSP

- Forecasting variables:
 - Log dividend-price ratio
 - Source: webpage of Amit Goyal

- Sample period:
 - Full sample: January 1927 - December 2013
 - Training period: 20 years
 - Out-of-sample: January 1947 - December 2013 (804 months)

| <i>Sample: Jan. 1927 - Dec. 2013</i> | Mean | St.Dev | Skewness | Kurtosis | AC(1) |
|--------------------------------------|-------|--------|----------|----------|-------|
| Annualised Log Excess Returns in % | 5.90 | 19.15 | -0.42 | 10.58 | 0.09 |
| Dividend Price Ratio (d/p) | -3.35 | 0.46 | -0.32 | 2.84 | 0.99 |

January 1927 – December 2013 - Out-of-sample ERP forecasts (initial training period: 20 years)



Evaluating OOS forecasting accuracy

Estimate the **Difference in the Cumulative Sum of Squared Errors (DCSSE)** between a benchmark model and the model of interest (Goyal & Welch, MS-2003):

- Typical benchmark - Historical Average (HA):

$$DCSSE_{HA} = \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{HA} \right)^2 - \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{Model} \right)^2$$

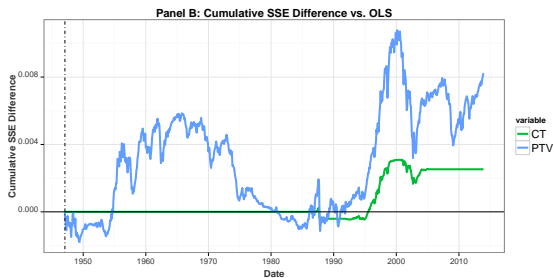
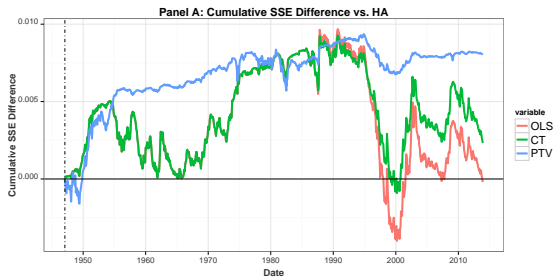
where $Model = \{OLS, CT, PTV\}$; $\tau = t_{OOS}$: first OOS forecast; T : end of sample.

- **Upward** movement: model is **more accurate** than HA
 - **Downward** movement: model is **less accurate** than HA
 - **Flat**: the model and the HA are equally good (or bad)
- Our focus is against OLS:

$$DCSSE_{OLS} = \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{OLS} \right)^2 - \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{Model} \right)^2$$

where $Model = \{CT, PTV\}$.

Forecasting accuracy against the historical average & OLS



Forecasting accuracy against OLS

- Proportional decrease in MSFE between the model of interest and the benchmark (OLS):

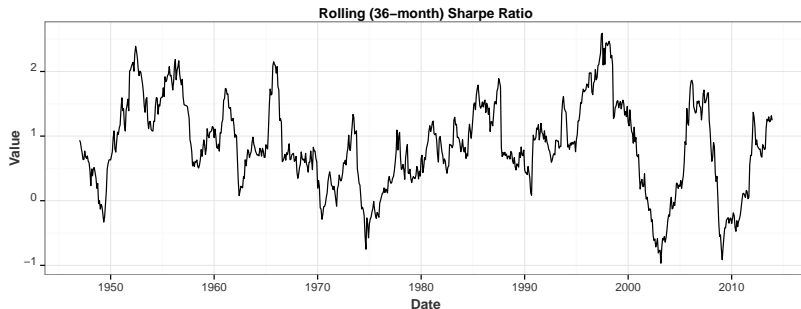
$$R_{OOS,OLS}^2 = 1 - \frac{MSFE_{Model}}{MSFE_{OLS}} = 1 - \frac{\sum_{\tau=t_{OOS}}^T (r_{\tau} - \hat{r}_{\tau|\tau-1}^{Model})^2}{\sum_{\tau=t_{OOS}}^T (r_{\tau} - \hat{r}_{\tau|\tau-1}^{OLS})^2}$$

where $Model = \{CT, PTV\}$.

| OOS Period: Jan. 1947 - Dec. 2013 | | d/p |
|--|----------|----------|
| | # months | 804 |
| RMSFE x 100 | OLS | 4.227 |
| | CT | 4.223 |
| | PTV | 4.215 |
| $R_{OOS,OLS}^2$ | CT | 0.18%** |
| | PTV | 0.57%*** |
| % of months with smaller error vs. OLS | CT | 13.20% |
| | PTV | 55.54% |

- The constrained models generally **outperform** the unconstrained OLS model.

36-month rolling Sharpe ratio of S&P500



- The constrained models outperform the OLS model during strong market rallies
- However, they underperform during volatile periods of negative ERP realisations
- We focus on **regime dependent** analysis:
 - Return dependent analysis (up versus down)
 - Volatility dependent analysis (high versus low volatility)

Up versus Down markets

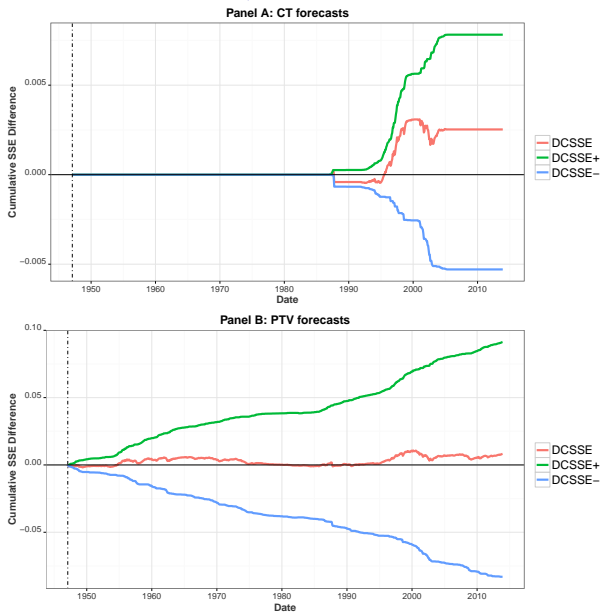
Split $DCSSE_{OLS}$ calculation separately for months with positive and negative EPR realisations:

$$DCSSE_{OLS}^+ = \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{OLS} \right)^2 \cdot \mathcal{I}_{r_{\tau} \geq 0} - \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{Model} \right)^2 \cdot \mathcal{I}_{r_{\tau} \geq 0}$$

$$DCSSE_{OLS}^- = \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{OLS} \right)^2 \cdot \mathcal{I}_{r_{\tau} < 0} - \sum_{\tau=t_{OOS}}^T \left(r_{\tau} - \hat{r}_{\tau|\tau-1}^{Model} \right)^2 \cdot \mathcal{I}_{r_{\tau} < 0}$$

where $\mathcal{I}_{r_{\tau} \geq 0}$ and $\mathcal{I}_{r_{\tau} < 0}$ denote indicator functions for positive and negative ERP realisations.

Up versus Down markets: using D/P ratio



Up versus Down markets: the statistics

| | | All | Down | Up |
|---|----------|----------|---------|-----------|
| | # months | 804 | 328 | 476 |
| RMSFE × 100 | OLS | 4.227 | 4.746 | 3.828 |
| | CT | 4.223 | 4.763 | 3.806 |
| | PTV | 4.215 | 5.005 | 3.568 |
| $R_{OOS,OLS}^2$ | CT | 0.18%** | -0.72% | 1.12%*** |
| | PTV | 0.57%*** | -11.25% | 13.12%*** |
| % of months with smaller error vs. OLS | CT | 13.20% | 0.30% | 22.11% |
| | PTV | 55.54% | 1.52% | 92.84% |

Up versus Down markets: further statistics

| | | NL | NS | PS | PL |
|--|----------|--------|---------|-----------|-----------|
| | # months | 164 | 164 | 238 | 238 |
| ERP realisations | min | -25.0% | -2.4% | 0.0% | 2.9% |
| | max | -2.4% | 0.0% | 2.9% | 15.0% |
| RMSFE x 100 | OLS | 6.512 | 1.625 | 1.476 | 5.213 |
| | CT | 6.533 | 1.638 | 1.451 | 5.188 |
| | PTV | 6.813 | 1.921 | 1.187 | 4.909 |
| $R_{OOS,OLS}^2$ | CT | -0.66% | -1.64% | 3.37%*** | 0.94%*** |
| | PTV | -9.47% | -39.71% | 35.33%*** | 11.33%*** |
| % of months with smaller error vs. OLS | CT | 0.00% | 0.61% | 23.95% | 20.25% |
| | PTV | 2.44% | 0.61% | 88.24% | 97.47% |

Recessions versus Expansions

- Split the OOS period in recessionary and expansionary months based on NBER:
- Split the OOS period in months of low volatility, medium volatility and high volatility:
 - Based on S&P500 monthly realised volatility (sum of squared daily returns)
 - Low-medium breakpoint: 9.71%
 - Medium-high breakpoint: 13.92%

| | | Business Cycles | | Volatility Regimes | | |
|--|----------|-----------------|----------|--------------------|----------|--------|
| | | Rec | Exp | Low | Med | High |
| | # months | 122 | 682 | 268 | 268 | 268 |
| RMSFE x 100 | OLS | 5.774 | 3.885 | 2.848 | 3.609 | 5.696 |
| | CT | 5.777 | 3.879 | 2.838 | 3.602 | 5.697 |
| | PTV | 5.855 | 3.848 | 2.702 | 3.587 | 5.753 |
| $R^2_{OOS,OLS}$ | CT | -0.13% | 0.30%*** | 0.70%*** | 0.39%*** | -0.04% |
| | PTV | -2.82% | 1.92%*** | 9.98%*** | 1.23%** | -2.04% |
| % of months with smaller error vs. OLS | CT | 2.46% | 15.12% | 11.19% | 13.11% | 15.30% |
| | PTV | 43.44% | 57.71% | 66.04% | 54.68% | 45.90% |

Asset Allocation Implications

A risk-averse investor allocates between the equity market and a risk-free asset:

- Mean-variance preferences suggest an equity allocation of:

$$w_t = \frac{1}{\gamma} \cdot \frac{\hat{r}_{t+1|t}}{\hat{\sigma}_{t+1|t}^2}$$

- γ : relative risk aversion
 - $\hat{r}_{t+1|t}$: OOS ERP forecast based on a forecasting model
 - $\hat{\sigma}_{t+1|t}^2$: ERP forecast variance; assume a rolling five-year historical estimate
- Typically the equity weighted is **constrained** (the very big majority of papers...):

$$w_t = \max \left\{ \min \left[\frac{1}{\gamma} \cdot \frac{\hat{r}_{t+1|t}}{\hat{\sigma}_{t+1|t}^2}, w_{max} \right], w_{min} \right\}$$

- Baseline scenario: $\gamma = 3$, $w_{min} = -0.5$ and $w_{max} = 1$ (i.e. no leverage)

Asset Allocation Implications

- Portfolio return:

$$r_{p,t+1} = w_t \cdot r_{t+1} + r_{f,t+1}$$

- r_{t+1} : next month's equity excess return
- $r_{f,t+1}$: risk-free rate prevailing at the end of month t

- Economic benefit of ERP forecasting models is measured by CER:

$$CER = \hat{\mu}_P - \frac{\gamma}{2} \cdot \hat{\sigma}_P^2$$

- $\hat{\mu}_P$: average annual portfolio return over the OOS period
- $\hat{\sigma}_P^2$: annual portfolio variance over the OOS period
- CER can be interpreted as the **annual fee** that the investor would be willing to pay to have access to the respective ERP forecast and therefore to exploit it.
- Relative economic benefit of constrained models vs. OLS:

$$CER_{gain\ vs.\ OLS} = CER_{Model} - CER_{OLS}$$

where $Model = \{CT, PTV\}$.

CER Gains

| Baseline parameter values: $\gamma = 3$, $w_{min} = -0.5$, $w_{max} = 1$ | | | |
|--|----------|------------|--------------|
| Forecast Model | CER gain | Volatility | Sharpe ratio |
| Panel A: Overall | | | |
| CT | 0.52% | 8.82% | 0.79 |
| PTV | 1.80% | 12.86% | 0.74 |
| Panel B: Down markets | | | |
| CT | -1.66% | 7.38% | -1.84 |
| PTV | -19.02% | 9.56% | -3.18 |
| Panel C: Up markets | | | |
| CT | 2.16% | 7.28% | 2.91 |
| PTV | 18.02% | 7.82% | 4.76 |
| Panel D: Recessions | | | |
| CT | -0.33% | 15.76% | 0.06 |
| PTV | -6.70% | 18.88% | -0.20 |
| Panel E: Expansions | | | |
| CT | 0.67% | 6.86% | 1.17 |
| PTV | 3.34% | 11.34% | 1.05 |

Sensitivity Analysis

Maximum and minimum weights:

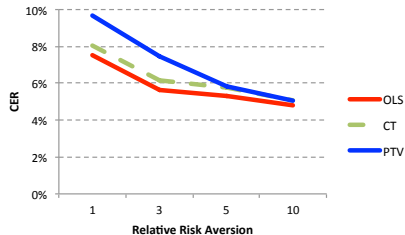
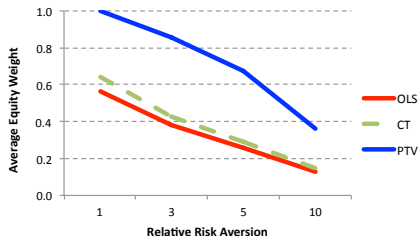
- Campbell & Thompson (RFS-2008), Goyal & Welch (RFS-2008), Rapach, Strauss & Zhou (RFS-2010), Neely, Rapach, Tu & Zhou (MS-2014), Huang, Jiang, Tu, & Zhou (RFS-2015): $w_{min} = 0$ and $w_{max} = 1.5$
- Huang, Jiang, Tu & Zhou (WP-2015): $w_{min} = -0.5$ and $w_{max} = 1$
- Rapach, Ringgenberg & Zhou (JFE-2015): $w_{min} = -0.5$ and $w_{max} = 1.5$
- Ferreira & Santa-Clara (JFE-2011), Pettenuzzo et al. (JFE-2014): no restrictions

The typical level of **relative risk aversion** that is used in these studies is $\gamma = 3$, except:

- Ferreira & Santa-Clara (JFE-2011) use $\gamma = 2$
- Pettenuzzo, Timmermann & Valkanov (JFE-2014) present results for $\gamma = 2, 5, 10$
- Huang, Jiang, Tu & Zhou (RFS-2015) present results for $\gamma = 1, 3, 5$

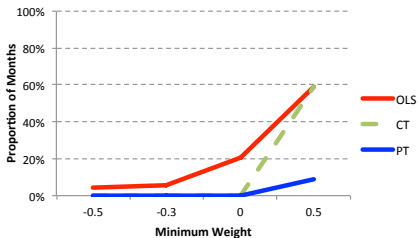
The effect of risk aversion

- Assume $w_{min} = -0.5$ and $w_{max} = 1$
- Average equity weight & CER for different levels of γ (1, 3, 5, 10):



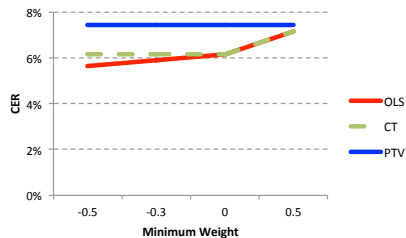
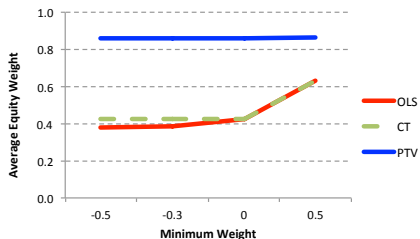
The effect of minimum weight and short selling

- Assume $\gamma = 3$ and $w_{max} = 1$.
- Different levels of the w_{min} :
 - -0.5 (allow short selling of up to 50% of the total wealth)
 - -0.3 (allow short selling of up to 30% of the total wealth)
 - 0 (allow no short selling)
 - 0.5 (require minimum equity investment of at least 50% of the total wealth)
- Minimum weight constraint becoming binding:



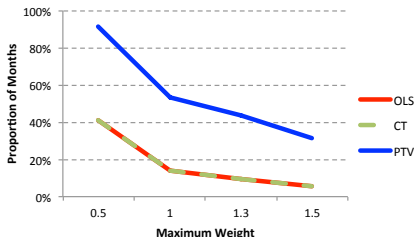
The effect of minimum weight and short selling

- Average equity weight & CER for different levels of w_{min} :



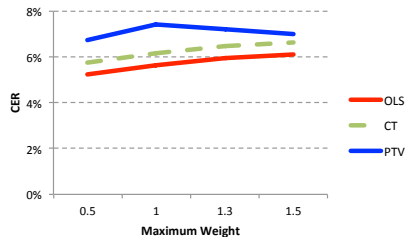
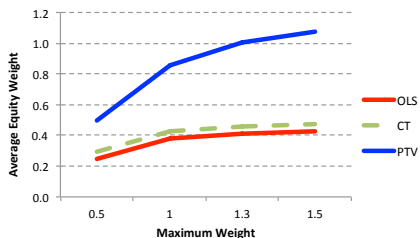
The effect of maximum weight and leverage

- Assume $\gamma = 3$ and $w_{min} = -0.5$.
- Different levels of the w_{max} :
 - 0.5 (constrain the portfolio against an all-equity possibility)
 - 1 (allow no leverage)
 - 1.3 (allow leverage of 30% of the total wealth)
 - 1.5 (allow leverage of 50% of the total wealth)
- Maximum weight constraint becoming binding:



The effect of maximum weight and leverage

- Average equity weight & CER for different levels of w_{max} :



Conclusions and Future Research

To summarise:

- Our findings expose an important pitfall of constrained ERP forecasting models
- Constrained ERP forecasting models generally outperform
- However, they struggle when it matters the most...
- ... negative ERP realisations, recessions, high-volatility periods
- Important asset allocation implications for actual dynamic portfolio decisions
- Conservative and short-sale / leverage constrained investors cannot benefit generally from constrained models

Future research:

- New ERP models should incorporate regime dependence
- The first attempt towards this: Huang, Jiang, Tu, & Zhou (WP-2015)
- Suggestion: dynamic combination of unconstrained and constrained models
- New forecasting variables: e.g. option implied metrics

Appendix

