Less is more: Granularity of information, estimation errors and optimal portfolios

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Introduction (1/2)

- **Markowitz (1952) →** Mean-variance (MV) optimization maximizes Sharpe-ratio
  - Seminal paper that marks the birth of modern finance theory
  - Hardly implemented in practice because of **poor out-of-sample performance**

- **Michaud (1989) →** MV-optimization tends to maximize estimation error
  - MV-optimization allocates more (less) to assets with:
    - High (low) expected returns
    - Low variance
    - Low correlation
  - These assets also tend to be the ones with the highest estimation error

Introduction (2/2)

- **DeMiguel, Garlappi and Uppal (2009):**
  - Intention of reducing the impact of estimation errors with limited success
  - Estimating reliable parameter inputs based on historical data is notoriously difficult

- **Allen, Lizieri and Satchell (2019):**
  - Parameter inputs based on historical data are not reliable
  - Forecasts based on established predictor variables can be used as input for MV-optimization to improve out-of-sample performance

Motivation & Research Gap & Research Question

Lessons learned:

1. Using **no asset-specific information** (i.e. equally-weighting) when building portfolios has more economic value than relying on forecasts based on historical data.
2. Investors can use **forecasted returns** as approximations for expected returns and thereby improve the out-of-sample performance of MV-optimized portfolios.

Research gap:

Is there an **optimal level of information** at which the impact of estimation errors is small relative to the performance gain that comes from incorporating forecasts in a portfolio optimization?

Research question:

How does sequentially reducing the informational content of forecasted expected returns affect the performance of mean-variance optimized portfolios?

Data

– Fama-French industry portfolios (i.e. 5, 10, 12 and 49 industries)

– Predictor variables (PV) for equity premium (EP):

  > Variance risk premium of Zhou (2018)

  > Popular predictor variables of Welch and Goyal (2008)

  > Aggregated short interest of Rapach, Ringgenberg and Zhou (2016)

  > Cross-sectional moments of Maio (2016) and Stöckl and Kaiser (2016)

  > Parameter uncertainty of Stöckl (2017)

Methodology (1/2)

Forecasts:

1. Simple → sample means and covariances based on historical data (e.g. past 60 monthly returns)

2. Sophisticated → predicting individual returns using Hasler and Martineau (2020):

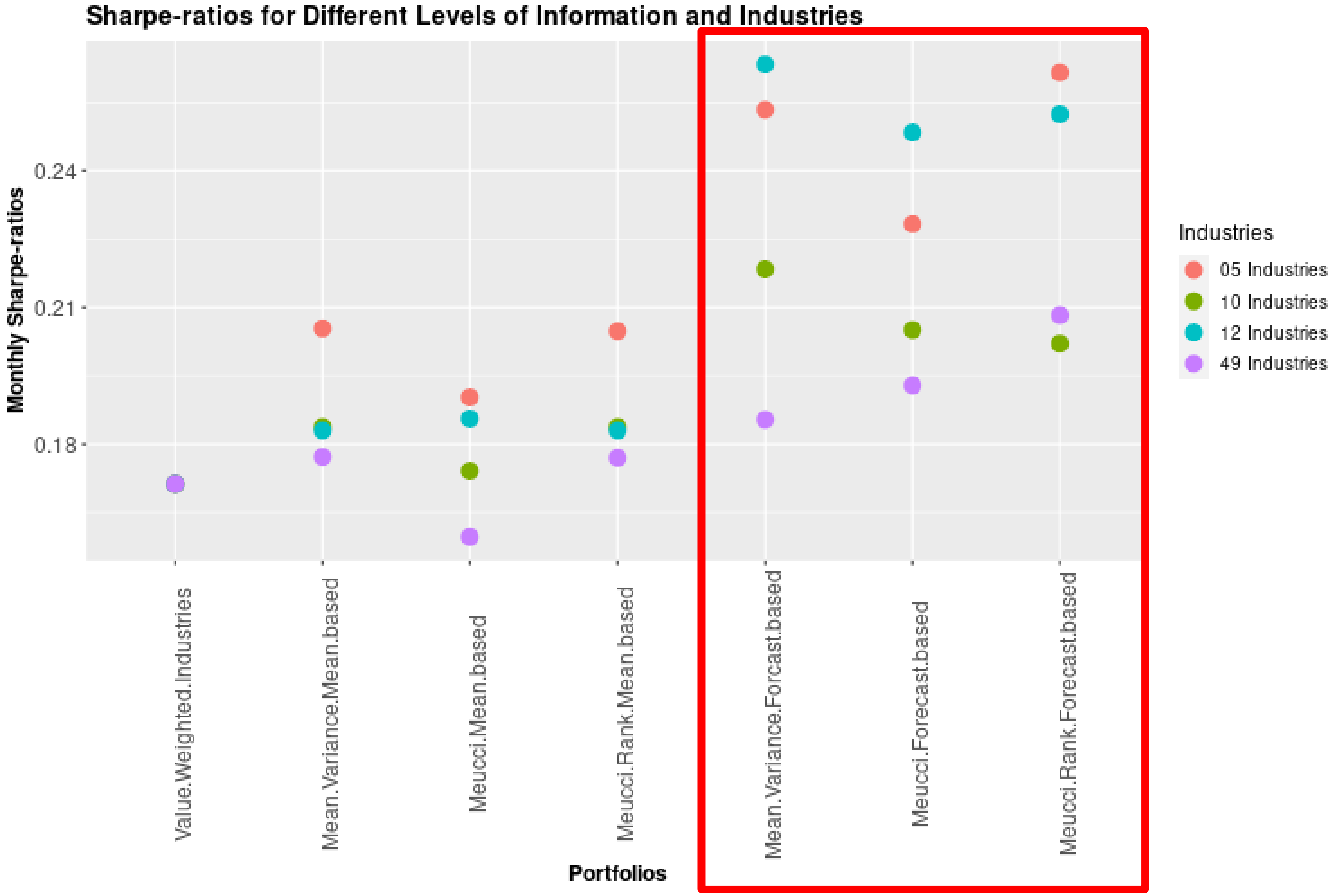
$$\mathbb{E}_t[r_{M,t+1}] = c_1 + c_2 * PV_t + \varepsilon_{t+1} \qquad (1)$$

$$\mathbb{E}_t[r_{i,t+1}] = \beta_{i,t}\mathbb{E}_t[r_{M,t+1}] \qquad (2)$$

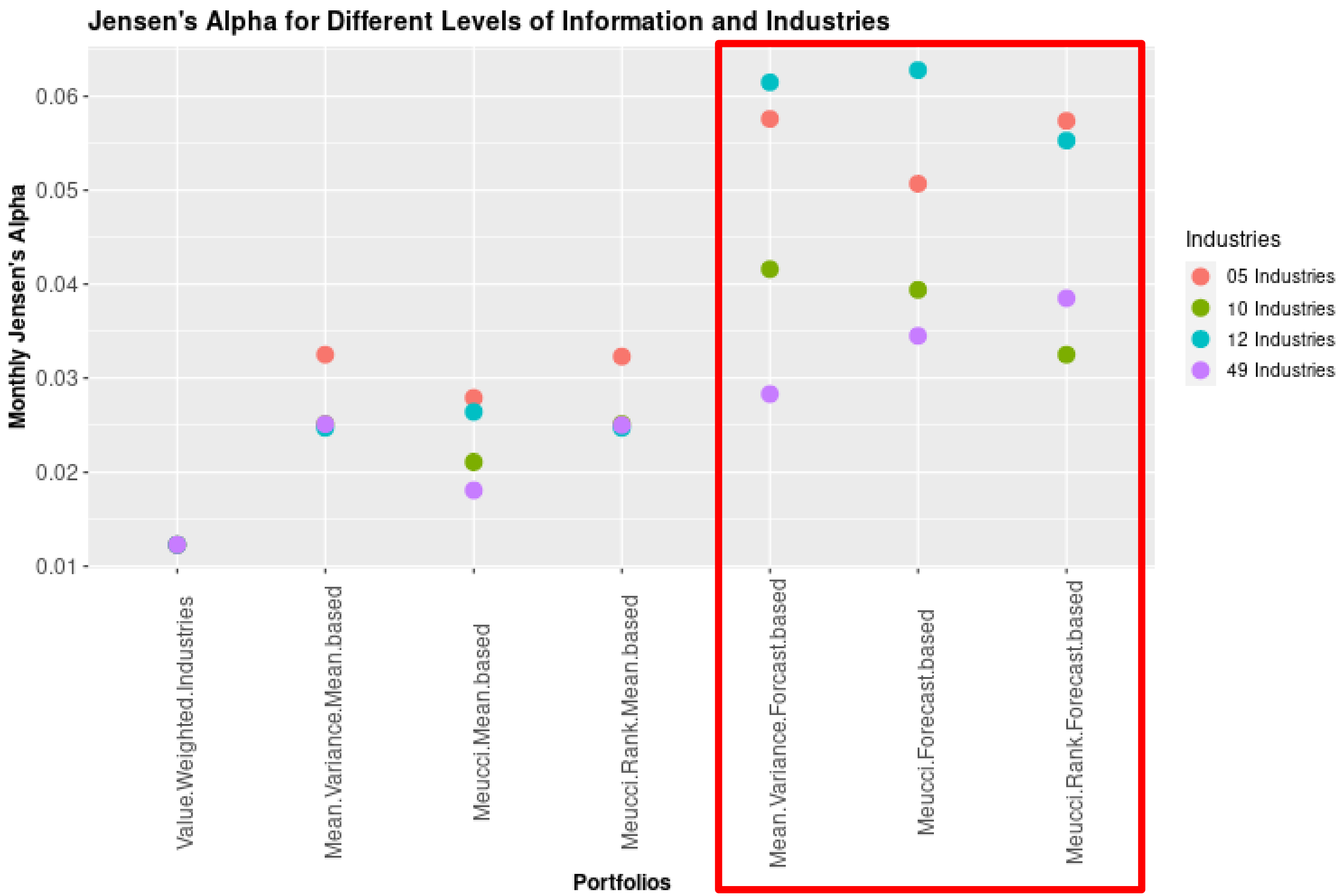
Methodology (2/2)

- Building portfolios:
  - Approach 1 – **full information:**
    - **Simple and sophisticated return forecasts** are used for optimization
    - “Fully Flexible Views” approach is used as in Meucci (2008)
  - Approach 2 – **ranking information:**
    - **Only use ranking information** obtained from return forecasts
    - “Fully Flexible Views” approach is used as in Meucci (2008)
  - Approach 3 – **group ranking information:**
    - **Only use group ranking** (i.e. top or bottom half of forecasts)
    - “Fully Flexible Views” approach is used as in Meucci (2008)
- Standard mean-variance approach is used as benchmark model

Preliminary Results – Sharpe-ratio



Preliminary Results - Alpha



Preliminary Findings

1. **Sophisticated forecasts** rather than simple forecasts of expected returns perform **better** for all optimization approaches and industries

2. **Reducing informational** content generally **improves** performance in both types of forecasts

3. **Reducing informational** is especially beneficial when estimation errors are expected to be **larger** (i.e. broader cross-section → 49 industry portfolios)

Thank you for your attention.

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