

# Software, Rice Database, Technical Indicators

BUSI 722: Data-Driven Finance II

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# Review: CAPM & Fama-French Factors

The Capital Asset Pricing Model says that the expected excess return of any asset is proportional to the market's expected excess return:

$$\mathbb{E}[r_i] - r_f = \beta_i(\mathbb{E}[r_m] - r_f)$$

- $r_i$  = return on asset  $i$
- $r_f$  = risk-free rate
- $r_m$  = return on the market portfolio
- $\beta_i = \frac{\text{Cov}(r_i, r_m)}{\text{Var}(r_m)}$

Run a time-series regression for each asset  $i$ :

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_{it}$$

- The CAPM is equivalent to saying  $\alpha_i = 0$  for every asset.
- If  $\alpha_i > 0$ : the asset earns more than the CAPM predicts — it is “underpriced.”
- If  $\alpha_i < 0$ : the asset earns less than the CAPM predicts — it is “overpriced.”

Testing the CAPM = testing whether alphas are jointly zero.

# The Size Effect

**Small stocks have historically earned higher average returns than large stocks,** even after adjusting for beta.

- Sort stocks into portfolios by market capitalization
- Small-stock portfolios earn positive CAPM alphas
- Large-stock portfolios earn negative CAPM alphas
- This is evidence against the CAPM

Size is measured by market capitalization = price  $\times$  shares outstanding.

Value stocks (high book-to-market) have historically outperformed growth stocks (low book-to-market), even after adjusting for beta.

- Book-to-market = book equity / market equity
- High B/M (“value”) stocks: positive CAPM alphas
- Low B/M (“growth”) stocks: negative CAPM alphas
- This is further evidence against the CAPM

## Fama-French Three-Factor Model (1993)

Fama and French proposed replacing the CAPM with a three-factor model:

$$\mathbb{E}[r_i] - r_f = \beta_i^{\text{MKT}} \cdot \text{MKT} + \beta_i^{\text{SMB}} \cdot \text{SMB} + \beta_i^{\text{HML}} \cdot \text{HML}$$

- **MKT** =  $r_m - r_f$ : market excess return
- **SMB** (Small Minus Big): return on small stocks minus return on large stocks
- **HML** (High Minus Low): return on high B/M stocks minus return on low B/M stocks

# Interpreting the Three-Factor Model

The three-factor model says that expected returns are explained by exposures to three sources of risk.

- The model “works” if alphas are zero when we regress excess returns on the three factors:

$$r_{it} - r_{ft} = \alpha_i + \beta_i^{\text{MKT}} \text{MKT}_t + \beta_i^{\text{SMB}} \text{SMB}_t + \beta_i^{\text{HML}} \text{HML}_t + \varepsilon_{it}$$

- The size and value effects that produced nonzero CAPM alphas are captured by SMB and HML.
- But ... other anomalies (momentum, profitability, investment) still produce nonzero alphas.

# Setup: Claude Pro & Claude Code

## 1. Sign up for Claude Pro:

1. Visit [claude.ai](https://claude.ai)
2. Click “Sign Up” or “Get Started”
3. Create account using email or Google/Apple sign-in
4. After signing in, click “Upgrade to Pro” in the sidebar
5. Choose the monthly payment plan
6. Complete payment information

## 2. [YouTube Video](#)

## Mac – Install Claude Code

### Step 1: Install Node.js

- Using Homebrew: `brew install node`
- Or download installer from [nodejs.org](https://nodejs.org)

### Step 2: Install Claude Code

- Run: `npm install -g @anthropic-ai/claude-code`

### Step 3: Verify Installation

- Run: `claude doctor`

# Windows – Install Claude Code

## Step 1: Install Node.js

- Download and install from [nodejs.org](https://nodejs.org)
- Choose the LTS (Long Term Support) version

## Step 2: Install Git for Windows

- Download from [git-scm.com/download/win](https://git-scm.com/download/win)
- During installation, select “Git Bash” (default option)

## Step 3: Install Claude Code

# Install Python & Create Virtual Environment

## Install Python:

- Tell Claude Code: “Install Python 3.13 and add it to the path.”
- Tell Claude Code: “Upgrade pip”

## Create Virtual Environment:

- Tell Claude Code: “Create a virtual environment using Python 3.13 in my current directory.”

## Install packages in the virtual environment:

# VS Code & Database Setup

# Install and Open VS Code

- Install VS Code: [code.visualstudio.com](https://code.visualstudio.com)
- Launch VS Code
- File → Open Folder → navigate to your course folder
- Install extensions: Python, Jupyter, Claude Code, Data Wrangler, Rainbow CSV
- View → Command Palette → “Python: Select Interpreter” → choose venv

## Launch Claude Code in VS Code

- If you see the orange Claude icon in the top toolbar, click it.
- If not, create a new file (File → New Text File) and you should see it.
- Or View → Command Palette and enter “Claude Code: Open in New Tab.”

Test: Ask Claude Code: What is the sum of the first 1,000 integers?

- Database Guide: <https://portal-guide.rice-business.org>
- Visit [data-portal.rice-business.org](https://data-portal.rice-business.org) to get an access token
- The data portal is an AI agent that uses ChatGPT to generate SQL and query the database

## Create .env File:

- Tell Claude Code to create a `.env` file
- Add: `RICE_ACCESS_TOKEN=your_token_here`

# Database Tables

Three tables are relevant for price-based analysis:

- SEP (prices): *ticker*, *date*, *close* (split-adjusted), *closeadj* (adjusted for splits, dividends, and spinoffs), *volume*
- DAILY (valuation metrics): *ticker*, *date*, *marketcap* (USD millions), *pb*, *pe*, *ps*
- TICKERS (company info): *ticker*, *sector*, *industry*, *scalemarketcap*

Full documentation at <https://portal-guide.rice-business.org>

# Querying the Data Portal

Ask Claude Code to query the database directly.

## Example prompts:

- “Query the SEP table for end-of-month close and closeadj for all stocks from 2018 through 2024.”
- “Query the DAILY table for end-of-month marketcap for all stocks from 2018 through 2024.”
- “Query the TICKERS table for sector and industry for all tickers.”

Claude writes Python code that sends HTTP requests to the API, using your access token from the `.env` file.

# Computing Returns

Monthly returns are computed from *closeadj* (the fully adjusted price):

$$r_t = \frac{\text{closeadj}_t}{\text{closeadj}_{t-1}} - 1$$

- Use *closeadj*, not *close*: it accounts for dividends and spinoffs, so the return includes total return.
- *close* (split-adjusted only) is useful for computing moving averages and chart prices.
- Group by ticker when computing returns – never mix prices across stocks.

# Computing Momentum

Momentum is the cumulative return from month  $t-13$  to month  $t-2$ :

$$\text{momentum}_t = \frac{\text{closeadj}_{t-2}}{\text{closeadj}_{t-13}} - 1$$

- Skips the most recent month ( $t-1$ ): short-term reversal contaminates the signal.
- Requires 13 months of price history, so the first 12 months are **NaN**.
- **Lagged return** (the prior month's return) is a separate signal that captures short-term reversal.

# Moving Averages

Moving averages smooth out price noise and reveal trends.

- **Short MA** (3-month):  $MA_3 = \frac{1}{3} \sum_{j=0}^2 \text{close}_{t-j}$ . Tracks recent price action.
- **Long MA** (12-month):  $MA_{12} = \frac{1}{12} \sum_{j=0}^{11} \text{close}_{t-j}$ . Captures the longer-term trend.
- **MA Ratio**:  $\text{close}/MA_{12}$ . A stock trading above its long MA (ratio  $> 1$ ) is in an uptrend.
- **Golden Cross**:  $MA_3 > MA_{12}$ . A classic trend-following signal.

Compute moving averages from *close* (split-adjusted), grouped by ticker.

## Assigning Quantiles Each Month

Each month, sort stocks into groups (deciles, quintiles, etc.) by a signal:

```
# Assign momentum deciles (1 = lowest, 10 = highest)
df["mom_decile"] = df.groupby("month")["momentum"].transform(
    lambda x: pd.qcut(x, 10, labels=False, duplicates="drop") + 1
)

# Assign size quintiles (1 = smallest, 5 = largest)
df["size_q"] = df.groupby("month")["marketcap"].transform(
    lambda x: pd.qcut(x, 5, labels=False, duplicates="drop") + 1
)
```

- `groupby("month")` ensures sorting is cross-sectional (within each month).
- `pd.qcut` assigns equal-count groups; `labels=False` gives integers starting at 0.

## Computing Equal-Weighted Portfolio Returns

Compute the mean return of each group each month, then average across months:

```
# Mean return by decile and month
decile_monthly = df.groupby(["month", "mom_decile"])["return"] \
                  .mean().reset_index()

# Time-series average across all months
decile_avg = decile_monthly.groupby("mom_decile")["return"].mean()

print(decile_avg)
```

- The first *groupby* computes the equal-weighted portfolio return each month.
- The second *groupby* averages across months to get the expected return of each portfolio.
- A monotone pattern (D1 low, D10 high) indicates the signal has predictive

Claude should automatically save data as parquet files. This is a compact, fast format.

To view the data, ask Claude to:

- **“Convert the file to Excel.”** Then open as usual.
- **“Convert the file to csv.”** Then double-click in VS Code File Explorer.
- **“Read the data in a Jupyter notebook.”** Then work with the data in Python.