Week 10: Factor Investing & Smart Beta

Systematic Strategies in Modern FinTech

Learning Objectives

After completing this session, you will be able to:

- Explain what factors are and why they generate returns
- Distinguish between traditional and modern factor investing approaches
- Identify how robo-advisors and ETF providers implement factor strategies
- Evaluate factor portfolio performance using attribution analysis
- Understand the practical challenges of factor investing (costs, crowding, timing)
- Apply factor exposure analysis to real portfolios

The Third Prediction Problem

Remember the Three Prediction Problems from Week 3:

Problem	Target	Signal	Where We Are
Mean	Future returns	~1-2% R^2	Week 3: ARIMA rarely beats naive
Variance	Volatility	~15-40% R^2	Week 4: GARCH succeeds
Cross-Section	Which assets	~5-15% R^2	**Today: Factor models**

The cross-section is where alpha lives. Not predicting whether the market goes up, but predicting *which stocks* outperform.

This is more predictable because firm characteristics (size, value, momentum) persist longer than return patterns, and arbitrage is slower.

Part I: Understanding Factors

From CAPM to Multi-Factor Models

Traditional CAPM (1960s): - Single factor: market beta - Expected return $=$ Risk-free rate $+$ $\times$ Market risk premium - Assumes all risk explained by market exposure

Empirical reality (1970s onwards): - CAPM predictions fail systematically - Small firms outperform large firms (size effect) - Value stocks outperform growth stocks (value premium) - Winners keep winning (momentum)

Key insight: Multiple systematic factors drive returns beyond market beta

The Fama-French Revolution

Fama and French (1992) discovered persistent return patterns:

Three-Factor Model (1993): - **Market** (Rm - Rf): Overall equity risk premium - **Size** (SMB): Small minus Big : small cap premium - **Value** (HML): High minus Low : value premium (high book-to-market)

Five-Factor Model (2015) (Fama and French 2015): - Added **Profitability** (RMW): Robust minus Weak - Added **Investment** (CMA): Conservative minus Aggressive

Performance: Five-factor model explains ~95% of portfolio return variation (vs 70% for CAPM)

Beyond Fama-French: Other Factors

Momentum (Jegadeesh and Titman 1993): - Buy past winners, sell past losers - 12-month formation, 1-month skip, 1-month hold - Strongest short-term predictor

Quality (Asness, Frazzini, and Pedersen 2019): - High profitability, stable earnings, low leverage - "Boring is beautiful"

Low Volatility (Ang et al. 2006): - Low-risk stocks outperform high-risk stocks - Violates CAPM predictions

Dividend Yield, Liquidity, Carry, ...

Modern consensus: 5-7 robust factors explain most return patterns

Why Do Factors Work? Two Views

Risk-Based Explanation: - Factors represent compensation for systematic risk - Value stocks risky (distressed firms) $\rightarrow$ require higher returns - Small stocks less liquid $\rightarrow$ liquidity premium - Academic consensus view

Behavioural Explanation: - Factors exploit investor mistakes - Value premium: overreaction to bad news - Momentum: underreaction to information - Practitioner consensus view

Reality: Likely both : some factors are risk premia, others exploit biases

Academic Evidence: Do Factors Persist?

Original evidence (1993-2015): - Fama-French factors robust across decades - Global evidence (international markets) - Survived "out-of-sample" test after publication

Post-publication performance: - Value premium disappeared 2007-2020 (Arnott et al. 2021) - Size premium weakened substantially - Momentum and quality remained strong

Factor decay: Publication + crowding $\rightarrow$ reduced returns

Current state: Factors still exist, but smaller premia than historical estimates

Part II: Factor Investing in Practice

The Smart Beta Revolution

Traditional indexing: Market-cap weighted (S&P 500) - Weight by company size - Simple, low cost (0.03-0.09% fees)

Smart Beta: Alternative weighting schemes - Equal-weight, fundamental-weight, volatility-weight - Factor tilts (value, momentum, quality) - Higher fees (0.15-0.50%) but potential outperformance

Market size (2024): $2.5 trillion in smart beta ETFs globally

Value proposition: "Index returns + factor premia - modest fee increase"

Factor ETFs: Major Providers

iShares (BlackRock): - MTUM (Momentum), QUAL (Quality), VLUE (Value) - USMV (Min Volatility), SIZE (Small Cap) - Fees: 0.15-0.20%

Vanguard: - VTV (Value), VUG (Growth) - Simpler, lower-cost approach (0.04-0.07%)

Invesco: - Multi-factor combinations - Higher fees (0.25-0.39%), more active

FinTech connection: Robo-advisors increasingly offer factor tilts as client options

Robo-Advisors & Factor Strategies

Betterment: - Core portfolio: market-cap weighted - "Smart Beta" portfolio option: value + small-cap tilts - +0.10% fee for factor exposure

Wealthfront: - Automatic factor tilts in core portfolios (2016-2020) - Abandoned pure factor strategy (performance issues) - Now minimal tilts

Vanguard Personal Advisor: - No explicit factor tilts - "Market returns are hard enough to capture"

Industry trend: Moved from aggressive factor tilts (2015-2018) to modest exposures (2020+)

Factor Timing: Can You Rotate?

The idea: - Value works in some periods, momentum in others - Rotate between factors based on signals - Capture factor premia dynamically

Reality: - Factor timing extremely difficult (Harvey and Liu 2015) - Requires predicting macroeconomic regimes - Transaction costs eat potential gains

Evidence: Most factor-timing strategies underperform static multi-factor portfolios

Practitioner consensus: Diversify across factors, don't time them

Multi-Factor Portfolio Construction

Approach 1: Sequential sorts - Sort on size, then value within each size bucket - Traditional Fama-French approach

Approach 2: Composite scores - Calculate score for each factor - Rank stocks by combined score - More flexible, but requires weights

Approach 3: Optimizer - Target factor exposures as constraints - Minimize tracking error or volatility - Most sophisticated, highest cost

Trade-off: Simplicity vs customization vs cost

Rebalancing & Transaction Costs

Factor portfolios require regular rebalancing: - Momentum: Monthly (highest turnover ~100-200% annually) - Value: Quarterly or annually (lower turnover ~20-40%) - Quality: Semi-annual (lowest turnover ~15-25%)

Transaction costs matter: - Bid-ask spreads: 0.05-0.15% per trade - Market impact: 0.10-0.30% for institutional sizes - Annual cost: 0.50-1.50% for high-turnover strategies

Reality check: Costs can eliminate factor premia for small investors

Factor Crowding & Capacity

What happens when factors become popular: - More capital chasing same stocks - Valuations bid up - Returns compress

Evidence of crowding: - Value premium disappeared 2010-2020 - Quality premium compressed 2016-2020 - Low-volatility strategies struggled 2017-2021

Capacity estimates: - US equity factors: $1-2 trillion before severe crowding - Current smart beta AUM: $2.5 trillion globally - **We may be at capacity limits**

When Do Factors Fail?

Growth dominance (2017-2020): - Tech stocks (FAANG) dominated - Growth crushed value (-40% relative) - Size factor negative

Momentum crashes: - Sudden reversals in crisis periods - 2009: -75% drawdown in one quarter - Risk management essential

Factor correlations break down: - Factors typically low correlation - Crisis periods: all factors move together - Diversification benefit disappears when needed most

Key lesson: Factors are not risk-free arbitrages

Part III: Implementation & Evaluation

Factor Exposure Analysis

Goal: Understand what drives portfolio returns

Method: Regress portfolio returns on factor returns

$$R_{portfolio,t} - R_{f,t} = \alpha + \beta_{MKT}(R_{MKT,t} - R_{f,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_t$$

Interpretation: - **(alpha)**: Return not explained by factors (skill) - **coefficients**: Factor exposures - **R^2**: % of returns explained by factors

Practitioner use: Understand what you're actually betting on

Performance Attribution Example

Portfolio A: - 12% annual return - **_**MKT = 1.2, **_**HML = 0.5 (value tilt), **_**SMB = 0.3 (small-cap tilt)

Attribution (assume market = 8%, HML = 3%, SMB = 2%): - Market contribution: $1.2 \times 8\% = 9.6\%$ - Value contribution: $0.5 \times 3\% = 1.5\%$ - Size contribution: $0.3 \times 2\% = 0.6\%$ - **Alpha (skill)**: 12% - 9.6% - 1.5% - 0.6% = **0.3%**

Conclusion: Most return from factor exposures, not skill

Implementation: Factor Data Sources

Kenneth French Data Library: - Free factor returns (daily, monthly) - US and international factors - Standard for academic research - https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Bloomberg Terminal: - Factor indices (MXUS000V = Value, MXUS000M = Momentum) - Custom factor construction - Professional quality

AQR Capital: - Alternative factor definitions - International factors - https://www.aqr.com/Insights/Datasets

Factor Regression in Python

```
import pandas as pd
import statsmodels.api as sm

# Load portfolio returns and factor data
portfolio_returns = pd.read_csv('portfolio_returns.csv',
                                index_col='date', parse_dates=True)
factors = pd.read_csv('fama_french_factors.csv',
                      index_col='date', parse_dates=True)

# Merge data
data = portfolio_returns.join(factors, how='inner')

# Calculate excess returns
data['excess_return'] = data['portfolio_return'] - data['RF']

# Define factor model
X = data[['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA']]
```

Interpreting Factor Loadings

$> \mathbf{0}$: Positive exposure (you profit when factor performs well) - _HML $=$ 0.5 $\rightarrow$ tilted toward value stocks - _SMB $=$ 0.3 $\rightarrow$ tilted toward small caps

$< \mathbf{0}$: Negative exposure (you profit when factor performs poorly) - _HML $=$ -0.5 $\rightarrow$ tilted toward growth stocks - _UMD $=$ -0.3 $\rightarrow$ contrarian (bet against momentum)

$\mathbf{0}$: Neutral exposure - _HML $=$ 0.05 $\rightarrow$ essentially market-cap weighted

Practical use: Verify your portfolio matches your intentions

The Alpha Puzzle

What is alpha? - Return not explained by factor exposures - Theoretically, should be zero in efficient markets - Positive alpha = skill; negative alpha = poor execution

Reality: - Most active managers have negative alpha (after fees) - Positive alpha rare and unstable over time - "Alpha is a beggar : you can't reliably find it" : Larry Swedroe

Evidence (Fama and French 2010): - 97% of mutual fund alpha explained by chance, not skill - Only 3% showed statistically significant positive alpha

Implication: Focus on factor exposures, not chasing alpha

Factor Investing Costs

Explicit costs: - ETF expense ratios: 0.15-0.50% - Robo-advisor fees: 0.25-0.50% - Transaction costs: 0.10-0.30% per rebalance

Implicit costs: - Tracking error vs benchmark - Tax inefficiency (high turnover strategies) - Opportunity cost (simpler strategy might work)

Total cost estimate: 0.50-1.50% annually

Break-even: Factor premia must exceed 0.50-1.50% to add value

Monitoring Factor Performance

Track rolling factor returns: - Are factors delivering expected premia? - Has correlation structure changed?

Monitor portfolio exposures: - Do current holdings match target exposures? - Have betas drifted due to price changes?

Risk metrics: - Tracking error vs benchmark - Drawdown analysis (factor crashes) - Sharpe ratio vs market portfolio

Rebalance trigger: When exposures drift $>$20% from target

Regulatory & Client Considerations

Disclosure requirements: - Factor tilts must be disclosed to clients - Cannot claim "passive" if making active factor bets - Fee justification (why pay more than index?)

Suitability: - Factor strategies may underperform for years - Clients need patience and understanding - Risk tolerance matters (momentum = volatile)

Tax implications: - High-turnover factors generate short-term gains - Tax-loss harvesting less effective - Consider tax-advantaged accounts

Practical Recommendations

For retail investors: 1. Use low-cost factor ETFs (Vanguard, iShares core products) 2. Diversify across multiple factors (don't bet on one) 3. Rebalance annually (minimize costs) 4. Be patient (factors work over 5-10 year horizons)

For robo-advisors: 1. Offer factors as options, not defaults 2. Educate clients on factor risks 3. Monitor costs vs benefits continuously 4. Prepare for underperformance periods

For FIN306 students: 1. Understand factors theoretically first 2. Use free data (French library) for practice 3. Focus on attribution analysis (Lab 10) 4. Recognise limitations and costs

Current Debates in Factor Investing

1. Is value dead? - Underperformed 2007-2020 - Structural change (intangibles, tech dominance)? - Or just long cycle?

2. ESG as a factor? - Evidence weak and inconsistent - Risk-based or taste-based? - Regulatory pressure vs performance

3. Machine learning factors? - Can ML discover new factors? - Overfitting risk - See Gabaix et al. (2025) (embeddings approach)

4. Factor decay acceleration? - Are published factors arbitraged away faster? - Does transparency reduce premia?

Synthesis: Factors in FinTech Context

Factor investing connects to FinTech themes:

- **Democratisation** (Week 4-5): ETFs make factors accessible
- **Robo-advisors** (Week 6): Systematic factor implementation
- **Algorithmic strategies**: Removes emotion, enables discipline
- **Data science**: Factor construction is ML feature engineering
- **Platform economics**: Factor ETFs benefit from scale

Big picture: Factor investing is systematic, rules-based investment : perfect match for FinTech automation

For deeper theory: See Chapter 04: Robo-Advisors for portfolio optimization foundations

Key Takeaways

1. **Factors are systematic tilts** away from market-cap weighting that historically generated excess returns
2. **Not all factors are equal** : value weakened, momentum/quality stronger, but all face crowding
3. **Smart beta democratised factor investing** : ETFs make implementation accessible
4. **Costs matter** : transaction costs and fees can eliminate factor premia
5. **Attribution analysis essential** : understand what drives portfolio returns (factors vs skill)
6. **Patience required** : factors can underperform for years; discipline essential
7. **FinTech enables systematic implementation** : robo-advisors and ETFs automate factor strategies

Connection to FIN306 Assessments

Coursework 2 (Reflective Analysis): - Factor performance during your chosen period - Attribution analysis of strategies - Cost-benefit evaluation of factor tilts - Comparison to robo-advisor approaches

Key questions to explore: - Did factors add value in your time period? - How much alpha vs factor exposure? - Would smart beta have been worth the cost? - What would you recommend to clients?

Resources: Lab 10 provides factor regression code and French data access

Further Reading

Academic foundations: - Fama and French (1992) : Original three-factor model - Fama and French (2015) : Five-factor model - Harvey and Liu (2016) : Factor replication crisis

Practitioner perspectives: - Asness, Moskowitz, and Pedersen (2013) : Value premium defence (AQR) - Arnott et al. (2021) : Value obituary debate - Israelsen (2017) : Smart beta practical guide

FinTech applications: - Reher and Sokolinski (2024) : Robo-advisor factor strategies - Gabaix et al. (2025) : ML approach to factors

Free data: Kenneth French Data Library, AQR datasets

Next Week: Sequence Learning & Time Series

Preview: - Time series models for financial prediction - Recurrent neural networks (RNNs, LSTMs) - Transformers for financial sequence data - Temporal dependencies in markets

Connection: Factor strategies assume stable relationships; next week explores time-varying patterns

Questions?

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Resources: - Chapter 04: Robo-Advisors - Lab 10: Factor Attribution Analysis (coming next session) - Kenneth French Data Library

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