Asset Pricing Anomalies

Asset pricing anomalies are empirical deviations from the equilibrium prices predicted by a given asset pricing model.

The existence of an anomaly means that either the asset pricing model is incorrect or the assumption of market efficiency is flawed.

- Does the anomaly represent a common risk across assets that explains their relative prices over time?
- Or, is it a friction that drives a wedge between the fundamental value and market price of an asset?

The former case identifies a missing risk factor in the asset pricing model. The latter is a friction unrelated to risk.
Asset risk premia are the expected excess returns to holding an asset.

- Asset pricing models predict an asset’s expected excess returns through the systematic relationship between excess returns and the model’s risk factor, or an asset’s loading on the risk factor.

- Thus, empirically testing the validity of a factor evaluates this relationship between factor loadings and the cross-section of excess returns. If we reject the null hypothesis that the factor risk premium cannot be distinguished from 0, then the risk factor is “priced.”
Two-Stage Fama MacBeth Framework

1\textsuperscript{st} Stage. Time series estimates of betas. Individual asset return relationships to risk factor.

2\textsuperscript{nd} Stage. Cross sectional estimate of risk premium, regressing average returns on betas.

CAPM as an example: \( E(R_i) = \alpha + \beta_i \lambda \)

Test: \( H_0^{\lambda = 0} \)

Are relative expected excess returns explained by factor loadings?

Notes:

1\textsuperscript{st} stage test assets are often grouped into portfolios.

Motivation: Increasing number of assets in each portfolio diversifies idiosyncratic risk.

- Since betas are estimated with error, it makes sense that idiosyncratic error should be increasingly diversified away as more and more betas are grouped into each portfolio.

However, there is a potentially offsetting effect of the cross-sectional information loss in the beta distribution when portfolios are used to achieve more precise (but fewer) beta estimates.

Our contribution is to evaluate this trade-off (Ang, Liu and Schwarz, 2020).

- Simulation results show that the minimum mean square error of the lambda estimates is achieved with either a large number of portfolios (at least 250) or with individual assets (no portfolios).

- Data features that increase the likelihood of mis-assigning assets into portfolios shift the balance toward using individual test assets.
A large and sustained relative price deviation in cash-flow matched U.S. Treasury securities is attributable to a liquidity feedback loop. The interaction of Treasury market quantities and prices shows that the dynamics are driven by the liquidity risk pricing of investors with heterogeneous security preferences and by intermediaries facing inventory risk. The results are also new in giving direct empirical evidence for Amihud and Mendelson’s (1986) prediction that investors with longer expected holding horizons will select less-liquid assets in equilibrium (distinct from the widely-documented relationship between bid-ask spreads and expected returns). This clientele effect empirically bridges work on demand-driven frictions with the evolving intermediary asset pricing theory, showing unique evidence of the role of intermediary heterogeneity in liquidity risk pricing.
Clientele Effect: Investors’ Holding Horizon Drives Security Selection

Short-horizon/highly levered investors buy rich securities when they’re most expensive.

Increases trading frequency of rich/liquid securities.
Liquidity Provider Impounds Carry Risk in Bid-Ask Spread

Market Maker rationally charges lower bid-ask spread for more frequently traded securities.
This figure plots the share of the trough-to-peak yield spread change that is attributable to the K-spread (y axis) versus the country CDS spread (x axis), for each country separately, on average over maturities. The plotted values are based on coefficient estimates from a regression of sovereign bond yield spreads onto the K-spread and the country sovereign CDS spreads. Panel A shows the trough-to-peak yield spread change from January 2007 to January 2009. The coefficient estimates are from Panel B in Table 3. Panel B shows the trough-to-peak yield spread change from January 2010 to January 2012. Greece data are available only through the Financial Crisis subsample period. The coefficient estimates are from shown in Panel C of Table 3.
Some investors may exploit the price effect of others’ demand to buy on the month end date.

But, not enough to erase the effect.


This figure plots the annualized Sharpe ratios from holding a 2-, 5-, and 10-year zero-coupon Treasury security on the t-to-last trading days of each month. Sharpe ratios are computed as the average of excess returns in equations (1) and (2), divided by the standard deviation of these excess returns, and then multiplied by the square root of 12. The sample period is from 1990 to 2018.
Insurer type relates to Barclays Agg Index securities added/dropped.

Life insurers are most benchmark-constrained group.
➢ disproportionately buy index additions on last day of month.

Consistent with Musto, Nini, Schwarz (2018), showing that insurers in aggregate tend to buy high and sell low.

But, effect is not sustained, contrasting with Musto, Nini, Schwarz's (2018) liquidity-risk feedback loop that explains the large Treasury anomaly over the financial crisis.
Fundamental Value

In a standard asset pricing model, a shock (e.g. index changes) must convey new information on fundamentals in order to generate a price effect.

- However, in U.S. Treasury indices, the constituent changes are already known by the rebalancing date since they are mechanically associated with security issuance and duration.
- Moreover, Treasury securities do not differ in fundamentals.