Literature Review on Cross-Sectional Empirical Asset Pricing

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Abstract

Finding the determinants of variation among expected stock return in cross-sections have been the focal aim of empirical asset pricing. We review the development and empirical findings of the Capital Asset Pricing Model and parsimonious multifactor models, the rise of anomalies and underlying economic mechanisms, and recent efforts to discipline and extract the stochastic discount factor from the high-dimensional Factor Zoo with machine learning techniques and big data.

1 Capital Asset Pricing Model and Multifactor Models

Pricing of risky assets is the core of modern finance. Since the propose of "Mean-Variance" analysis by Markowits (1952) and later the development of Capital Asset Pricing Model (CAPM) established by Sharpe (1964),Lintner (1965),Treynor (2012) and Mossin (1966), the examination and extension of the CAPM model becomes the major fighting filed for researchers. Hers we briefly summarize the induction and implication of the CAMP model and its empirical test methodology, i.e., Fama-MacBeth two-pass regressions.

In 1950s, "maximize discount expected returns" is an influential idea when it comes to investment but Markovwitz rejects it and proposes a new rule-of-thumb, "maximize discount expected utility", in other words, tradeoff mean and variance of the return when one makes investment portfolio choices, named as "Mean-Variance" analysis. The argument is simple, that the evidence of diversified asset holding contradicts to the "maximize discount expected

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returns" rule, which indicates to hold the single asset with maximum expected return. "Mean-Variance" analysis proposes a rule to discipline the choice set of assets, that one prefers the asset with lower volatility among assets with the same expected return, and prefers the asset with higher expected return among assets with the same volatility. Sharpe (1964),Lintner (1965),Treynor (2012) and Mossin (1966) simultaneously discover the same way to describe the choice set and then derives the CAPM model from it as follows: investors optimally choose risky assets on the mean-variance efficient frontier, where any asset is a linear combination of any other two assets, suppose the market portfolio is on the frontier and risk-free rate is independent with the market portfolio, then any asset i on the frontier satisfies,

$$\mathbb{E}[R_i] = r_f + \beta_i(\mathbb{E}[R_M] - r_f) \tag{1}$$

where R_i denotes for the return of the asset i, R_M denotes for the return of the market portfolio and $\beta_i = \frac{\mathrm{Cov}[R_i, R_M]}{\mathrm{Var}[R_M]}$ is the regression slope coefficient of R_i on R_M, named as "market beta". CAPM argues (1) holds for any asset in any time. In other words, for a panel data with multiply assets prices through a long time, every single point should satisfy (1), which makes the direct test of CAPM impossible since there is only one realization for R_i and R_M at one time. Therefore, one subtle assumption is made implicitly when test the model, β_i is constant over a long (short) horizon. As prices ranges over assets, in others words, cross-sections, and over time-series, one can examine the CAPM model in both dimensions but we often do the cross-sectional test following Fama and MacBeth (1973), which makes full use of the total information of the panel data. Fama and MacBeth (1973) suggests the following two-pass cross-sectional regression test on the multifactor models which produces standard errors in a very simple way. Suppose the balanced panel data contains N assets, K factors, and T time period, and $R^e_{i,t}$ denotes for the return of asset i at time t excess risk free rate, and $f_{k,t}$ denotes for the realization of factor k at time t. The multifactor factor model to be estimated is $\mathbb{E}[R^e_i] = \sum_{k=1}^{K} \beta_{i,k}\lambda_k$. In the first pass, we run the time-series regression to estimate betas, $\beta_{i,k}$ across assets for all factors as

$$R^e_{i,t} = a_i + \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + \varepsilon_{i,t}, t = 1, \cdots, T \tag{2}$$

and then run a cross-sectional regression

$$R^e_{i,t} = \sum_{k=1}^{K} \beta_{i,k}\lambda_{k,t} + \alpha_{i,t}, i = 1, \cdots, N \tag{3}$$

at each period to obtain T estimates $\lambda_{k,t}$ for λ_k. Here α stands for mispricing component of the assets relative to the multifactor model and our null hypothesis is that α jointly equals to zero across assets, i.e., $H_0 : \alpha_1 = \cdots = \alpha_N = 0$. We estimate λ_k and α_i as the average of cross-sectional estimates,

$$\hat{\lambda}_k = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{k,t}, \hat{\alpha}_i = \frac{1}{T}\sum_{t=1}^{T}\hat{\alpha}_{i,t} \tag{4}$$

and the corresponding standard errors as

$$\sigma^2(\hat{\lambda}_k) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\lambda}_{k,t} - \hat{\lambda}_k)^2, \sigma^2(\hat{\alpha}_i) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\alpha}_{k,t} - \hat{\alpha}_k)^2. \tag{5}$$

The tes statistics of H_0 is of quartic form: $\hat{\boldsymbol{\alpha}}' \operatorname{cov}(\hat{\boldsymbol{\alpha}})\hat{\boldsymbol{\alpha}} \sim \chi^2_{N-1}$ where $\hat{\boldsymbol{\alpha}}_t = [\hat{\alpha}_{1,t}, \cdots, \hat{\alpha}_{N,t}]$, $\hat{\boldsymbol{\alpha}} = \frac{1}{T}\sum_{t=1}^{T}\hat{\boldsymbol{\alpha}}_t$ and $\operatorname{cov}(\hat{\boldsymbol{\alpha}}) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\boldsymbol{\alpha}}_t - \hat{\boldsymbol{\alpha}})(\hat{\boldsymbol{\alpha}}_t - \hat{\boldsymbol{\alpha}})'$.

Empirical evidence using data until 1970s supports the CAPM model, e.g., Fama and MacBeth (1973). But in 1990s, Fama and French (1992) argues the beta is gone with the evidence that for each size decile, the capital market line is flat ! Hereafter, researchers attempt to save the CAPM model by introducing the conditional CAPM model which incorporates time-varying properties of beta, e.g., Jagannathan and Wang (1996),Brennan and Subrahmanyam (1996) and Avramov and Chordia (2006). The empirical performance of the conditional CAPM is not as good as expected, e.g., the conditional CAPM incorporates size, book-to-market and past returns fails to explain the momentum effect in Avramov and Chordia (2006) and the effort for saving the CAPM by introducing conditional information is largely discouraged by Lewellen and Nagel (2006) which shows the limitations of the conditional CAPM in explaining BM effect and momentum.

As a natural extension of CAPM, multifactor models take the place of CAPM to describe asset prices. The poinner work is done by Eugene F. Fama and Kenneth R. French in a series of papers, e.g., Fama and French (1992, 1993, 1996). Before diving into the multifactor model space, we briefly introduce the theoretical basis of the multifactor models, Intertemporal CAPM (ICAPM) model from Merton (1973), Arbitrage Pricing Theory (APT) theory from Ross (1976), and Consumption-based CAPM (CCAPM) model from Lucas (1978) and Breeden (1979).

In the ICAPM model, investors maximizing the expected utility of lifetime consumption and permitted to trade continuously, are subject to the uncertain changes in future investment opportunities. In equilibrium, they are compensated in terms of expected return for bearing market risk, and for bearing the risk of unfavorable aggregate shifts in the investment opportunity set, so there are multiply factors to determine the expected return of assets.

In the APT theory, returns on a particular subset of assets under consideration are subjectively perceived by investors as determined as being generated by the following model: $R_i = \mathbb{E}[R_i] + \sum_{k=1}^{K} \beta_{ik}\delta_k + \varepsilon_i$ where $\mathbb{E}[\delta_i] = \mathbb{E}[\varepsilon_i] = 0$ and ε_i are mutually uncorrelated in cross-sections. The no-arbitrage condition (zero-investment generates zero profit) implies the expected return must satisfies $\mathbb{E}[R_i] = \rho + \sum_{k=1}^{K} \gamma_k\beta_{ik}$ where ρ is the zero-beta rate and γ_k can be viewed as risk premium. Note that factors are subjectively perceived in the APT theory.

In the CCAPM model, investors maximize expected utility of lifetime consumption where consumption is generated by productive units which can be traded. In equilibrium, since all investors are homogenous, the demand and supply of the productive units are zero and the price is decided to satisfies this condition. The return of these units equals to the marginal rate of substitution of current for future consumption, which can involve risk aversion, time impatience and subjective probability.

These theories indicate the same generalized asset pricing equation (see Cochrane (2009) for textbook explanation or Harrison and Kreps (1979)and Kreps (1981) for tedious proof)

$$\mathbb{E}[MR_i] = 1 \tag{6}$$

where M stands for the stochastic discount factor (SDF) or pricing kernel. If the SDF has a linear structure on factors, i.e., $M = a + b'f$, then one can find γ and λ to make expected return satisfies the following beta-representation,

$$\mathbb{E}[R_i] = \gamma + \lambda'\beta_i \tag{7}$$

where β_i are the multiple regression coefficients of R_i on f with a constant. That is the one we do empirical test on. Since factors and corresponding risk premium are both unobservable, to examine (7), it is conventional to construct factors with tradable assets by construction of zero-investment portfolio for tradable factors or mimicking portfolio for non-tradable factors.

Fama and French (1993) establishes the first and most influential multifactor model, Fama-French three factor model, hereafter FF3, which constitutes of three factors, MKT, SMB and HML, formally written as

$$\mathbb{E}[R^e] = \beta_{MKT}MKT + \beta_{SMB}SMB + \beta_{HML}HML \tag{8}$$

where R^e denote for asset returns net risk free rate, the MKT factor equals to the return of market portfolio net risk free rate, the SMB factor equals to the return of the small stock portfolio minus the return of big stock portfolio and the HML factor equals to the return of high book-to-market stock portfolio minus the return of low book-to-market portfolio and the last two factors are designed to be independent with each other by bivariate sorting. Fama and French (1996) shows the FF3 model is able to explain anomalies related to firm characteristics effects like size, earnings/price, cash flow/price, book-to-market, past sales growth which can not be rationalized in the CAPM model. The term "able to explain" means for the asset universe, the data generating process

$$\mathbb{E}[R_i] = a + \gamma + \lambda' \beta_i \tag{9}$$

where a denotes for mispricing. If the null hypothesis $H_0 : a = 0$ is compatible to the data, in other words, H_0 can not be rejected, we agree that (7) can explain the data. If the null hypothesis is rejected, we document this as an anomaly. The estimation and inference for this examination is implemented by the Fama-MacBeth two-pass regression. The benchmark models usually cover CAPM, FF3 and FF4 (which adds the momentum factor on the basis of FF3).

When the factor explanation of FF3 gets widely accepted, Daniel and Titman (1997) proposes the characteristics-based explanation for the cross-sectional variation of stock returns, i.e., expected returns are a function of the observable, slowing varying firm attribute θ, $\mathbb{E}[R_{i,t}] = a + b'\theta_{i,t-1}$. This triggers the long-lasting debate on who are true determinants of stocks returns, characteristics or factors. The corresponding empirical test methodology of whether characteristics provides incremental information to the factors on the variations of cross-sectional stock returns are developed by Brennan et al. (1998) and Avramov and Chordia (2006) whose idea is to explain the return with factors first and the test whether characteristics can explain the risk-adjusted return.

2 Anomalies

Beta Anomaly

The main implication of the classic Capital Asset Pricing Model (CAPM) is the expected return of an asset equals to its market beta times the market risk premium where beta gauges the extent to which the asset is exposed to systematic risk of the market (Lintner, 1965; Sharpe, 1964). However, introducing financial constrains of investors into the CAPM model generates the beta anomaly, assets with high (low) market beta experience low (high) expected returns first proposed by Black (1972).

Frazzini and Pedersen (2014) proposes a beating-against-beta (BAB) anomaly based on an OLG model with funding constrains, e.g., leverage constrains and margin requirements, in which investors are not permitted to borrow capitals to add leverage and have to increase holding of high-beta assets, which induces low expected returns of these assets in both cross-sections and time-series. The BAB anomaly is constructed by the self-financing zero-beta portfolio that longs the low beta portfolio and shorts the high-beta portfolio,

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r^f) \tag{10}$$

where long and short portfolios are beta-rank weighted and beta is calculated with daily data and implemented shrinkage following Vasicek (1973) to eliminate the influence of outliers. The BAB portfolio weighting scheme is not conventional like $(r_{t+1}^L - r_{t+1}^H)$ as zero-cost portfolio with exposure to the systematic risk. As Liu et al. (2018) indicates, the BAB portfolio is a beta anomaly in addition with a net long portfolio,

$$r_{t+1}^{BAB} = (\alpha_{t+1}^L - \alpha_{t+1}^H) + [(\frac{1}{\beta_{t+1}^L} - 1)\alpha_{t+1}^L + (1 - \frac{1}{\beta_t^H})\alpha_{t+1}^H] \tag{11}$$

where $\alpha_{t+1}^L = r_{t+1}^L, \alpha_{t+1}^H = r_{t+1}^H$ and $\alpha_{t+1}^L < 1 < \alpha_{t+1}^H$. The BAB anomaly is robust across varying categories of assets, stocks over U.S. (monthly 70 basis points, bps) and international markets (monthly 64bps), treasury bonds (monthly 17bps), credit over U.S. (monthly 16bps) and etc.

From the risk factor perspective, Bali et al. (2017) argues that investors' preference for lottery-link stocks (captured by the average of the 5 highest daily returns of the given stock in a given month) is an important driver of the beta anomaly. Not only is the MAX-neutral BAB anomaly is not significant, but also the FMAX factor (constructed by long-short portfolio sorting on MAX cross-sectionally) explains the alpha of BAB anomaly.

From the mispricing perspective, Liu et al. (2018) combines the positive relation between idiosyncratic volatility (IVOL) and beta and the robust negative performance of IVOL anomaly to explain the beta anomaly in the same vein as the mispricing explanation of IVOL anomaly proposed by Stambaugh et al. (2015). As expected, the beta anomaly exists only in overpriced stocks and in time periods when the beta-IVOL correlation and the likelihood of overpricing are simultaneously high.

Extending Vasicek (1973) by introducing conditional beta estimates as prior information and applying bayesian updating procedure, Cosemans et al. (2016) proposes a hybrid beta and shows that this measure of beta generates a significantly positive market risk premium as predicted by CAPM, which is an implicit explanation of the beta anomaly, i.e., the beta used in previous studies is not a precise measure of market beta.

Boloorforoosh et al (2020) explains that beta risk, which means low-beta stocks's beta positively comoves with market variance and the SDF in a conditional CAPM model which allows for stochastic beta exposure. Schneider et al. (2020) proposes negative market premium is driven by investors's demand of compensation for coskewness risk. The two papers both absorb the beating-against-beta anomaly.

IVOL Anomaly

From the start of examining the pricing of aggregate marker volatility in the cross-sectional stock returns, Ang et al. (2006) first proposes the idiosyncratic volatility (IVOL) anomaly that stocks with high idiosyncratic volatility relative to the Fama and French (1993) model have abysmally low average returns. The risk premium of innovations in aggregate volatility is statistically significant and approximate -1% per annum but the long-short portfolio sorting on idiosyncratic volatility receives -1.06% return per month, which remains significant and robust to control firm characteristics, momentum and exposure to aggregate volatility risk.

Bali and Cakici (2008) challenges the robustness of the IVOL anomaly by changing the data frequency to estimate IVOL, weighting scheme, breakpoints and stock universes and examining the existence and significance of IVOL anomaly. Different from firm characteristics like size and boot-to-market, IVOL is not consistent over time for an asset. Starting from this point, Fu (2009) doubts the measure of expected IVOL of Ang et al. (2006), i.e., lagged IVOL and proposes to estimate it with the EGARCH model, finding a positive relation between expected IVOL and expected return. However, Guo et al. (2014) indicates the conclusion of Fu (2009) is driven by look-ahead-bias with strong parametric and empirical evidences (estimate the parameters of EGARCH and predict expected IVOL with data until time t instead of $t-1$). In other words, although the precise measure of expected IVOL point is charming, the empirical challenges still are not well established. The robust and persistent performance of the IVOL anomaly attracts ranges of attentions of researchers, and many explanations are proposed. Hou and Loh (2016) establishes a simple methodology to evaluate the explanation power of these potential explanations on the IVOL anomaly, finding these explanations can only explain less than 10% of the puzzle and all explanations can explain $29-54\%$ of the puzzle together. An interesting point of Hou and Loh (2016) is that instead of raw of Fama and French (1993) model adjusted excess return, they use DGTW-adjusted return as the independent variable.

From the mispricing perspective, Stambaugh et al. (2015) combines the arbitrage asymmetry and arbitrage risk (proxy using IVOL) to explain the IVOL anomaly. The arbitrage asymmetry, buying is easier than shorting for many equity investors, is similar to the funding constrains of Frazzini and Pedersen (2014) in the sense that investors make suboptimal decisions because of financial constrains, generating abnormal return for a subset of assets. IVOL represents arbitrage risk that deters arbitrage, resulting slow reduction of mispricing. Among overpriced (underpriced) stocks, stocks with high IVOL should be most overpriced (underpriced). With arbitrage asymmetry, arbitrage should eliminate more underpricing than overpricing, generating the IVOL anomaly. In this case, the IVOL anomaly is attributed to the overpriced stocks. An empirical challenge of the mispricing explanation is to construct a proxy of mispricing for each stocks. Stambaugh et al. (2015) crashes this obstacle by compositing the 11 robust anomalies surviving the three factors of Fama and French (1993), in which stocks with long signal (highest equal-weighted rank of anomalies in cross-sections) are underpriced and short signal (lowest equal-weighted rank of anomalies in cross-sections) signal are overpriced. In the time-series perspective, Stambaugh et al. (2015) measures the mispricing based on the market-wide investor sentiment constructed by Baker and shows that the IVOL anomaly exists only in the high sentiment time period, consistent with the arbitrage asymmetry explanation.

Exploiting the rich option data, Bégin et al. (2020) shows idiosyncratic risk premium of equities arises from jump risk and tail risk plays a crucial role of its pricing.

Liquidity

Liquidity is the immediacy that you buy or sell assets at low cost and without price impacts, which derived from many market frictions, e.g., asymmetric information, risk aversion and participation costs (Vayanos and Wang, 2009). There are three mainstream measures of liquidity of assets, return or price reversals and price reaction to trading volumes, bid-ask spreads, theoretically proposed by Roll (1984) and Grossman and Miller (1988), Kyle (1985) and Grossman and Miller (1988) respectively. Pricing ability of liquidity is empirically tested in cross-sections and time-series background in Amihud and Mendelson (1986); Brennan and Subrahmanyam (1996); Amihud (2002); Pástor and Stambaugh (2003) etc.

The move from individual measure of liquidity to marketwide liquidity is quiet common and intuitive, constructed in Amihud (2002) and Pástor and Stambaugh (2003), summation over assets in the markets cross-sectionally. Various empirical evidence of pricing ability of liquidity characteristics and factors inspire theoretical model to reconcile these results. Implementing transaction costs as the sources of illiquidity Acharya and Pedersen (2005) proposes a simple model to describe various channels through which liquidity risk affects asset prices. The condition excess net return of security i is

$$\mathbb{E}_t[r^i_{t+1} - c^i_{t+1}] = r^f + \lambda_t \frac{\mathrm{cov}(r^i_{t+1} - c^i_{t+1}, r^M_{t+1} - c^M_{t+1})}{\mathrm{var}_t(r^M_{t+1} - c^M_{t+1})} \tag{12}$$

which is a straight extension of CAPM in the sense that when c^i_{t+1} and c^M_{t+1} are both zero, (12) degenerate to the classic CAPM model where λ_t equals to market premium. The unconditional factor loading, i.e., unconditional expectation of the coefficient of λ_t contains four ingredients, including three channels through which liquidity affects asset returns, covariance between asset returns and market returns (market beta), covariance between asset liquidity costs and market liquidity costs, negative covariance between assets returns and market liquidity costs and negative covariance between assets transaction costs and market returns. The liquidity and liquidity are highly correlated, so single liquidity effects investigated in previous studies should be interpreted as an estimate of overall effects of liquidity and liquidity risks.

Skewness, Kurtosis and Max

The classic mean-variance analysis ignores high order moments characteristics of return distribution which may affect the preference of investors. The Skewness, Kurtosis and MAX anomalies depicts this intuition that investors prefer positive skewness to negative skewness, lower kurtosis to higher kurtosis, larger maximum to smaller maximum of returns. Through adding quartic and cubic terms of market return to the pricing kernel, Harvey and Siddique (2000) and Dittmar (2002) show that skewness and kurtosis are both priced in asset pricing models respectively. Bali et al. (2011) advocates the pricing ability of extreme positive returns in the cross-sectional pricing of stocks on the basis of two existing evidence, investors prefer lottery-like payoffs and many investors are poorly diversified.

Fundamental Values

In the dividend discount model, a stocks's price equals to the present value of expected dividends during the remaining life. In other words, firms that experiences greater growth in future cash flows should earn higher returns as else things equal. Empirical patterns violating this rule-of-thumb are anomalies. Sloan (1996) shows that firms with relatively high levels of accruals experience negative future abnormal stock returns since investors acts "fixate" on earnings, failing to distinguish fully between the different properties of the accrual and cash flows components of earning. Consistent with the rationale that financing the acquisition of productive assets by selling unproductive assets should generate abnormal positive returns, Novy-Marx (2013) proposes to use the gross profit scaled by book assets as the proxy for future profitability and find significant gross profitability premium not detected by previous studies. The reason to use gross profits is that items below the gross profits in the statements reflects not the true economic profitability, thus contaminate the measure of profitability. Through decomposing the book-to-market (BM) ratio into tangible information and intangible information, Daniel and Titman (2006) disputes the traditional review of the BM effect that high expected returns of stocks of "distressed" firms with poor past performance and shows that future returns are strongly negatively related to the component of news about future performance, i.e., the intangible information. They proposes the "composite share issuance" variable, $\iota(t-\tau,t) = \log(ME_t/ME_{t-\tau}) - r(t-\tau,t)$ (where r denotes for the stock return and ME denotes for market equity), to capture components of intangible information that are not taken into account by accounting-based variables; the rationale is the increase (decrease) of share issuance reflects the arrival (dismiss) of profitable investment opportunities or market undervaluation (overvaluation). Asset growth, measured as $ASSETG_t = (Asset_{t-1} - Asset_{t-2})/Asset_{t-2}$ where $Asset$ is the total asset (Compustat data item 6), is a strongly negatively related to the cross-section of stock returns (Cooper et al., 2008). The asset growth premium (negative) supports that growth is not fairly priced in the cross-section os stock returns, consistent with previous findings that corporate events associated with asset expansion (contraction), tend to be followed by abnormal negative (positive) returns. Hence, potential distortions of pricing or capitalization of asset investment are present and economically meaningful.

Momentum

Momentum is one of the most persistent and robust market anomalies across international markets and different assets. Jegadeesh and Titman (1993) first documents that strategies that buy stocks that performs well in the past and sell stocks that performs poor in the past generate significant positive returns over 3- to 12-month holding periods. The trading strategy that selects stocks on the basis of returns over past J months and hold them for K months, referred to as J-month/K-month strategy, is constructed as follows: at the beginning of each month t, the stock universe is ranked in ascending order on the basis of their returns over past J months. Ten decile portfolios are formed based on these rankings where stocks are equal-weighted. The top decile is called the winner decile and the bottom decile is called the loser decile. In each month t, the strategy buys the winner decile and sells the loser decile, holding the position for K months. Moreover, the trading strategy clears out the position initiated in month $t-K$, which weights $1/K$ over the whole position. The momentum effect defers a popular view that stock prices overreact to information which implies contrarian strategies, buying past losers and selling past winners, should generate abnormal returns. Jegadeesh and Titman (1993) shows that the momentum effect is driven by delayed price reactions to firm-specific information, instead of systematic risk or common factors.

A lot of work is dedicated to analyze characteristics and sources of the momentum effect.

Daniel and Moskowitz (2016) documents the downside risk of momentum that the momentum effect can experience infrequent and persistent crashes especially in market panic periods, when market declines, when market experiences highly volatility or rebounds. An interesting finding of Daniel and Moskowitz (2016) is that the Winner-Minus-Loser (WML) portfolio behaves as if it is effectively short a call option on the market in bear markets, i.e., it loses a lot when market rebounds from the trough. Moreover, the momentum premium is correlated with the strategy's time-varying exposure to volatility risk. Han et al. (2016) proposes a simple stop-loss strategy to mitigate the momentum downside risk, which clears out stocks once a certin loss level is triggered due to unkown changes of states. Dividing sorting variable of the momentum strategy, the past returns, into twelve to seven months return and six to two months returns prior to the portfolio formation, Novy-Marx (2013) shows that momentum is primarily driven by the intermediate, not recent past performance of the assets, contradicting to the coventional view of momentum, risking stocks tend to keep rising while falling stocks tend to keep falling. Lou (2012) proposes a flow-induced institutional trading explanation for the momentum effect, that mutual funds, by investing capital flows in their existing holdings that can concentrated in past winner stocks, drive up the subsequent returns of past winner stocks. This explanation is consistent with the high price momentum effect in China documented by Du et al. (2022). Hoberg et al. (2022) shows information diffusion explains the large momentum profits and momentum reversals in low competition market using a new measure of buy-side competition measure.

Not only momentum exists across assets and international regions, factors display strong cross-sectional momentum, indicating factors maybe at the root of momentum (Arnott et al., 2023). Return difference between past winners and losers during the formation period negatively predicts momentum profits (Huang, 2022).

Under the sports betting market setting, Moskowitz (2021) finds strong evidence of momentum, consistent with the delayed overreaction hypothesis and inconsistent withe underreaction and ration pricing.High turnover stocks exhibit short-term momentum, which is as profitable as conventional price momentum, consistent with investors underappreciating the information conveyed by prices (Medhat and Schmeling, 2022).

Cross-Stock Momentum

Firms are linked to each other through many types of relationships, e.g., related cash flows, common ownership. Related cash flows or economic links over firms generate return predictability in the cross-sectional stocks (Cohen and Frazzini, 2008) in the presence of limited attention. Shocks to one firms spread to economically linked firms through these channels in real quantities and stock prices. If investors ignore publicly available links due to limited attention, stock prices of related firms will generate a predictable lag in reacting to new information about linked firms. Two preliminaries are in need here, (1) information thought to be overlooked by investors should be available to the investing public before prices evolve, and (2) the information needs to be salient information that investors should be reasonably expected to gather. That is, investors are able to observe news about economic linked firms (partner firms) but it takes a long time to process these information and reflect them in stock prices of the focal firm due to limited attention or market segmentation. Cohen and Frazzini (2008) discovers the "customer momentum" through customer-supplier links between firms and the trading strategy exploiting the customer momentum yields abnormal returns of 1.55% per month, remaining unexplained by traditional risk factors including momentum. Menzly and Ozbas (2010) provides evidence on the gradual diffusion of information hypothesis with market segmentation resulting from investor specialization as underlying driven forces for the cross-section momentum, e.g., "customer momentum". Specifically, the extent to which stock prices are cross-sectional predictable is negatively related to the level of information in the market, proxy using the level of analyst coverage and institutional ownership; institutional investors make informed cross-market trading exploiting the cross-market content of informative signals. Lee et al. (2019) finds the technology momentum which is more pronounced for focal firms that have a more intense and specific technology, receive lower investor attention and more difficult to arbitrage, consistent with limited attention and limits to arbitrage. Yan (2023) proposes a data-driven cross-stock linkages which generates a monthly alpha of 1.62% and high factor momentum is due to the high cross-stock links. Huang et al (2020) shows information from lead firms that arrives continuously receives underreaction of investors while is absorbed into price quick when it comes in discrete amounts which implies information discreteness can reduce investor inattention.

From the common ownership link, Anton and Polk (2014) proposes that the shared ownership forecasts cross-sectional variation in return correlation with causal evidence from the 2003 mutual fund trading scandal. The common ownership is measured as the total value of stock held by common funds of the two stocks, scaled by the total market capitalization of the two stocks, i.e., a peer-to-peer measure. Stock prices are more subject to nonfundamental comovement when pressure from net mutual fund trading is high and when stocks have low float, i.e., the number of shares a firm has issued for public trading, and thus less liquid.

Besides aforementioned anomalies, researchers propose quantities of anomalies or stock return predictors in recent years, which largely enhance our understanding of stock prices, including lower bound of expected stock return induced from prices of options (Kadan and Tang, 2020), competition links between firms (Eisdorfer et al., 2022; Corhay et al., 2020), cyclical consumption (Atanasov et al., 2020), visual salience of stocks (Bose et al., 2022; Cakici and Zaremba, 2022), option disagreement (Golez and Goyenko, 2022), investor explanation management of firms (Johnson et al., 2020), fire sale risk (Aragon and Kim, 2023), changes of financial reports (Cohen et al., 2020), multivariate crash risk (Chabi-Yo et al., 2022), music sentiment (Edmans et al., 2022), narrative factors (Bybee et al., 2023), distance to consumers in a production network (Gofman et al., 2020), price trends (Jiang et al., 2023), resiliency as a measure of liquidity (Hua et al., 2020), systematic default (Bao et al., 2023), collateralizability (Ai et al., 2020), jump leverage risk (Bollerslev et al., 2022), etc. Instead of construct stock return predictors from firm fundamental values or trading data as we do one decade ago, these newly proposed predictors either stem from related capital market, e.g., lower bound of expected stock return induced from prices of options, and aggregate risk or expectation, e.g., cyclical consumption, or are constructed with machine learning technique as a finer measure of interested concepts, e.g., visual salience of stocks and price trends.

3 Factor Zoo, Machine Learning and Big Data

In the his presidential address in the theme "Discount Rates", Cochrane (2011) proposes four agendas for the empirical asset pricing in cross-sections, first, what characteristics really provide independent information about average returns ? Which are subsumed by others ? Second, does each new anomaly variable also correspond to a new factor formed on those same anomalies ? Third, how many of these new factors are really important ? Can we again account for N independent dimensions of expected returns with $K < N$ factor exposures ? Fourth, why do prices move ? In a nutshell, empirical asset pricing researchers are challenged by how to organize hundreds of factors (factor zoo) discovered in the past several decades effectively. The biggest obstacle is the high dimensionality nature of the factor zoo.

Lewellen (2014) investigates the cross-sectional properties of expected stock returns focusing on how much of cross-sectional variation in expected returns can be predicted and how reliable estimates of expected returns from Fama-MacBeth regression are with 15 stock characteristics. This paper inspires much proceeding work with novel angels of asset pricing, e.g., model comparison and forecasting short-(long-)horizon returns. Green et al. (2017) takes the challenge to identify the firm characteristics what provide independent information about U.S. monthly stock returns over 94 characteristics in the Fama-MacBeth regression framework. After controlling multicollinearlity, effects of microcaps and data-snooping concerns, Green et al. (2017) find only 12 characteristics robustly provide independent information for non-microcap stocks and there is a stunning fall of this number after 2003, which it potentially caused by the reduction of trading frictions and costs and subsequent rise of arbitrage against these anomalies.

Conventional methods like Fama-MacBeth regression and portfolio sorting are limited in the low dimensionality and can not reduce the dimensionality of the factor zoo effectively. Through combining two strands of literature on the treatment of the "unobserved factors", one specifying them as portfolios sorted on firm characteristics and another treating them as latent factors and use factor analytic techniques, Kelly et al. (2019) proposes a new technique named as instrumental principle component analysis (IPCA) to extract principle components as factors through returns with firm characteristics as instruments. Through the loading of firm characteristics on the IPCA factors, we can decide which factor matters. About the 30% of characteristics significantly contribute to the model by identifying IPCA factors and generating no alphas. Kozak et al. (2020) constructs a robust stochastic discount factor (SDF) which summarizes the joint explanation power of these predictors by implementing the shrinkage bayesian estimation on linear factors models to investigate the performance of characteristics-sparse factor models with a large set of cross-sectional return predictors, finding that a characteristics-sparse model can not adequately price the cross-section of stocks. The justification of for the shrinkage prior $\mu \sim N(0, \frac{\kappa^2}{\tau}\Sigma^{\eta})$ is that it encompasses priors that have appeared in empirical asset pricing, which is a novel response to Harvey (2017)'s proposed agenda to incorporate prior information into the test.

In contrast to the identification of factors which provide independent information of expected stock returns by Green et al. (2017), Feng et al. (2020) proposes a novel method, double-selection LASSO (Least Absolute Shrinkage and Selection Operator) with two-pass regression, to evaluate whether a new factor provide 'incremental' explanation power for asset pricing, relative to hundreds of factors identified before. The central obstacle is to select effective factors from the Factor Zoo as the baseline factors model with sparsity for a new factor since conventional tests for new factor are valid in low dimensionality only. Feng et al. (2020) overcomes this problem by introduce the double-selection LASSO in the decision of the baseline factor model. This procedure can be applied as a conservative check of new factors to discipline the proliferation of Factor Zoo. The shrinkage estimation is also applicable to maximize the sharpe-rato (approaching mean-variance efficiency) under a large number of underlying assets and time periods. Pursing the same goal as Feng et al. (2020), Freyberger et al. (2020) proposes the Adaptive group LASSO method to select characteristics nonparameterically and compatible with nonlinear function forms of the SDF.

DeMiguel et al. (2020) investigates the impact of transaction costs on the number of characteristics joint significant of the optimal portfolio, i.e., the dimension of the cross-section of stock returns. This is counterintuitive since the conventional view is transaction costs should drag significant anomalies into insignificant region. The rationale of the increase of dimension of the cross-section of stocks is that jointly trading multi-factors benefits from trading diversity, e.g., when one signal suggests to buy one asset while another signal suggests to sell the same asset, their trading signal cancels out so no transaction cost incurs. Gu et al. (2020) conducts a comprehensive comparative analysis of machine learning methods on measuring asset risk premiums. To detect the importance of variables, they leave it out while holding remaining variables unchanged, then calculate the reduction of panel predictive R^2 and the sum of squared partial derivatives of the model relative to the model with all variables as the measure of variable importance. Firm characteristics that matter most includes variations on momentum, liquidity and volatility.

With the development of machine learning techniques in asset pricing, researchers compete fiercely with each other to choose factor models as the response to Cochrane (2011)' agenda of true factor models. Tian (2021) data mines hundreds of randomly selected three-factor models and find some of them outperform widely accepted three factors models. Bryzgalova et al. (2023) analyzes 2.25 quadrillion linear multifactor models generated hundreds of factors under the bayesian framework. Fama and French (2020) indicates time-series models exhibits better performance in terms of explanation of average stocks returns when consist of cross-section factors only, than use time-series factors. Different from Kelly et al. (2019), Lettau et al. (2020) advances the principle component analysis (PCA) by introducing a penalty on the pricing error in expected returns, which select five factors as important factors. Factor model specification related issue are largely addressed by Manresa et al. (2023); Avramov et al. (2023).

After incorporating the impact of transaction costs, Detzel et al. (2023) compares influential multifactor models including Hou et al. (2015) q-factor mode, Barillas and Shanken (2018) six-factor model and Fama-French five(six)-factor models (Fama and French, 2015, 2018), and finds Fama-French five-factors models exhibit the highest squared sharpe ratio.

4 Conclusion

In this paper, we review the development of empirical assets pricing in cross-sections, which experiences two dramatic transform of research focus: the first period, from Markowits (1952) to Fama and French (1992), the Capital Asset Pricing Model is well-developed, extensively examined and widely accepted across researchers; the second period, from Fama and French (1993) to Cochrane (2011), plenties of anomalies are discovered on the basis of CAPM or FF3, FF4, among which momentum receives extensive attention, examination and explanation. Researchers attempt to rationalize these anomalies through introducing market frictions or behavior bias, and then propose parsimonious multifactor model to absorb these anomalies and explain the variation of expected stock return in cross-sections; the third period, to discipline the proliferation of Factor Zoo as the response to Cochrane (2011), under the assistance of machine learning techniques, researchers examine which factor provides incremental information about expected stock returns and which combination of factors can really address the variation of expected stock returns on the high dimensionality background.

From recent publication in top finance journals, the competition to find anomalies and 'true' factor models is still going on, but we are not satisfied to generate a significant alpha relative to benchmark factor models or dismiss alpha with factor models, instead, we pursue the underlying economic mechanism, e.g., the formation of investor expectations.

References

Acharya, V. V. and L. H. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77*(2), 375–410.

Ai, H., J. E. Li, K. Li, and C. Schlag (2020). The collateralizability premium. *Review of Financial Studies 33*(12), 5821 – 5855.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Amihud, Y. and H. Mendelson (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics 17*(2), 223–249.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *The Journal of Finance 61*(1), 259–299.

Anton, M. and C. Polk (2014). Connected stocks. *The Journal of Finance 69*(3), 1099–1127.

Aragon, G. O. and M. S. Kim (2023). Fire sale risk and expected stock returns. *Journal of Financial Economics 149*(3), 578–609.

Arnott, R. D., V. Kalesnik, and J. T. Linnainmaa (2023, 01). Factor Momentum. *The Review of Financial Studies 36*(8), 3034–3070.

Atanasov, V., S. V. Møller, and R. Priestley (2020). Consumption fluctuations and expected returns. *Journal of Finance 75*(3), 1677–1713.

Avramov, D., S. Cheng, L. Metzker, and S. Voigt (2023). Integrating factor models. *Journal of Finance 78*(3), 1593–1646.

Avramov, D. and T. Chordia (2006). Asset pricing models and financial market anomalies. *The Review of Financial Studies 19*(3), 1001–1040.

Bali, T. G., S. J. Brown, S. Murray, and Y. Tang (2017). A lottery-demand-based explanation of the beta anomaly. *Journal of Financial and Quantitative Analysis 52*(6), 2369–2397.

Bali, T. G. and N. Cakici (2008). Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial and Quantitative Analysis 43*(1), 29–58.

Bali, T. G., N. Cakici, and R. F. Whitelaw (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics 99*(2), 427–446.

Bao, J., K. Hou, and S. Zhang (2023). Systematic default and return predictability in the stock and bond markets. *Journal of Financial Economics 149*(3), 349–377.

Barillas, F. and J. Shanken (2018). Comparing asset pricing models. *The Journal of Finance 73*(2), 715–754.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of Business 45*(3), 444–55.

Bollerslev, T., A. Patton, and R. Quaedvlieg (2022). Realized semibetas: Disentangling "good" and "bad" downside risks. *Journal of Financial Economics 144*(1), 227–246.

Bose, D., H. Cordes, S. Nolte, J. C. Schneider, and C. F. Camerer (2022). Decision weights for experimental asset prices based on visual salience. *Review of Financial Studies 35*(11), 5094–5126.

Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics 7*(3), 265–296.

Brennan, M. J., T. Chordia, and A. Subrahmanyam (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics 49*(3), 345–373.

Brennan, M. J. and A. Subrahmanyam (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics 41*(3), 441–464.

Bryzgalova, S., J. Huang, and C. Julliard (2023). Bayesian solutions for the factor zoo: We just ran two quadrillion models. *Journal of Finance 78*(1), 487–557.

Bybee, L., B. Kelly, and Y. Su (2023). Narrative Asset Pricing: Interpretable Systematic Risk Factors from News Text. *The Review of Financial Studies 36*(12), 4759–4787.

Bégin, J.-F., C. Dorion, and G. Gauthier (2020). Idiosyncratic jump risk matters: Evidence from equity returns and options. *Review of Financial Studies 33*(1), 155–211.

Cakici, N. and A. Zaremba (2022). Salience theory and the cross-section of stock returns: International and further evidence. *Journal of Financial Economics 146*(2), 689–725.

Chabi-Yo, F., M. Huggenberger, and F. Weigert (2022). Multivariate crash risk. *Journal of Financial Economics 145*(1), 129–153.

Cochrane, J. (2009). *Asset pricing: Revised edition*. Princeton university press.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of finance 66*(4), 1047–1108.

Cohen, L. and A. Frazzini (2008). Economic links and predictable returns. *The Journal of Finance 63*(4), 1977–2011.

Cohen, L., C. Malloy, and Q. Nguyen (2020). Lazy prices. *Journal of Finance 75*(3), 1371–1415.

Cooper, M. J., H. Gulen, and M. J. Schill (2008). Asset growth and the cross-section of stock returns. *the Journal of Finance 63*(4), 1609–1651.

Corhay, A., H. Kung, L. Schmid, and S. Van Nieuwerburgh (2020). Competition, markups, and predictable returns. *Review of Financial Studies 33*(12), 5906–5939.

Cosemans, M., R. Frehen, P. C. Schotman, and R. Bauer (2016). Estimating security betas using prior information based on firm fundamentals. *The Review of Financial Studies 29*(4), 1072–1112.

Daniel, K. and T. J. Moskowitz (2016). Momentum crashes. *Journal of Financial economics 122*(2), 221–247.

Daniel, K. and S. Titman (1997). Evidence on the characteristics of cross sectional variation in stock returns. *the Journal of Finance 52*(1), 1–33.

Daniel, K. and S. Titman (2006). Market reactions to tangible and intangible information. *The Journal of Finance 61*(4), 1605–1643.

DeMiguel, V., A. Martin-Utrera, F. J. Nogales, and R. Uppal (2020). A transaction-cost perspective on the multitude of firm characteristics. *The Review of Financial Studies 33*(5), 2180–2222.

Detzel, A., R. Novy-marx, and M. Velikov (2023). Model comparison with transaction costs. *Journal of Finance 78*(3), 1743–1775.

Dittmar, R. F. (2002). Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *The Journal of Finance 57*(1), 369–403.

Du, J., D. Huang, Y.-J. Liu, Y. Shi, A. Subrahmanyam, and H. Zhang (2022). Retail investors and momentum. *Available at SSRN 4163257*.

Edmans, A., A. Fernandez-Perez, A. Garel, and I. Indriawan (2022). Music sentiment and stock returns around the world. *Journal of Financial Economics 145*(2, Part A), 234–254.

Eisdorfer, A., K. Froot, G. Ozik, and R. Sadka (2022). Competition links and stock returns. *Review of Financial Studies 35*(9), 4300–4340.

Fama, E. F. and K. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Fama, E. F. and K. French (2020). Comparing cross-section and time-series factor models. *Review of Financial Studies 33*(5), 1891–1926.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *the Journal of Finance 47*(2), 427–465.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. F. and K. R. French (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance 51*(1), 55–84.

Fama, E. F. and K. R. French (2018). Choosing factors. *Journal of Financial Economics 128*(2), 234–252.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81*(3), 607–636.

Feng, G., S. Giglio, and D. Xiu (2020). Taming the factor zoo: A test of new factors. *The Journal of Finance 75*(3), 1327–1370.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Freyberger, J., A. Neuhierl, and M. Weber (2020). Dissecting characteristics nonparametrically. *The Review of Financial Studies 33*(5), 2326–2377.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics 91*(1), 24–37.

Gofman, M., G. Segal, Y. Wu, and S. Van Nieuwerburgh (2020). Production networks and stock returns: The role of vertical creative destruction. *Review of Financial Studies 33*(12), 5856–5905.

Golez, B. and R. Goyenko (2022). Disagreement in the equity options market and stock returns. *Review of Financial Studies 35*(3), 1443–1479.

Green, J., J. R. Hand, and X. F. Zhang (2017). The characteristics that provide independent information about average us monthly stock returns. *The Review of Financial Studies 30*(12), 4389–4436.

Grossman, S. J. and M. H. Miller (1988). Liquidity and market structure. *the Journal of Finance 43*(3), 617–633.

Gu, S., B. Kelly, and D. Xiu (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies 33*(5), 2223–2273.

Guo, H., H. Kassa, and M. F. Ferguson (2014). On the relation between egarch idiosyncratic volatility and expected stock returns. *Journal of Financial and Quantitative Analysis 49*(1), 271–296.

Han, Y., G. Zhou, and Y. Zhu (2016). Taming momentum crashes: A simple stop-loss strategy. *Available at SSRN 2407199*.

Harrison, J. M. and D. M. Kreps (1979). Martingales and arbitrage in multiperiod securities markets. *Journal of Economic theory 20*(3), 381–408.

Harvey, C. (2017). Presidential address: The scientific outlook in financial economics. *Journal of Finance 72*(4), 1399–1440.

Harvey, C. R. and A. Siddique (2000). Conditional skewness in asset pricing tests. *The Journal of Finance 55*(3), 1263–1295.

Hoberg, G., N. Kumar, and N. Prabhala (2022). Buy-side competition and momentum profits. *Review of Financial Studies 35*(1), 254–298.

Hou, K. and R. K. Loh (2016). Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics 121*(1), 167–194.

Hou, K., C. Xue, and L. Zhang (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies 28*(3), 650–705.

Hua, J., L. Peng, R. A. Schwartz, and N. S. Alan (2020). Resiliency and stock returns. *Review of Financial Studies 33*(2), 747–782.

Huang, S. (2022). The momentum gap and return predictability. *Review of Financial Studies 35*(7), 3303–3336.

Jagannathan, R. and Z. Wang (1996). The conditional capm and the cross-section of expected returns. *The Journal of Finance 51*(1), 3–53.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance 48*(1), 65–91.

Jiang, J., B. Kelly, and D. Xiu (2023). (Re-)Imag(in)ing Price Trends. *Journal of Finance 78*(6), 3193–3249.

Johnson, T. L., J. Kim, E. C. So, and L. Cohen (2020). Expectations management and stock returns. *Review of Financial Studies 33*(10), 4580–4626.

Kadan, O. and X. Tang (2020). A bound on expected stock returns. *Review of Financial Studies 33*(4), 1565–1617.

Kelly, B. T., S. Pruitt, and Y. Su (2019). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics 134*(3), 501–524.

Kozak, S., S. Nagel, and S. Santosh (2020). Shrinking the cross-section. *Journal of Financial Economics 135*(2), 271–292.

Kreps, D. M. (1981). Arbitrage and equilibrium in economies with infinitely many commodities. *Journal of Mathematical Economics 8*(1), 15–35.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society 53*(6), 1315–1335.

Lee, C. M., S. T. Sun, R. Wang, and R. Zhang (2019). Technological links and predictable returns. *Journal of Financial Economics 132*(3), 76–96.

Lettau, M., M. Pelger, and S. Van Nieuwerburgh (2020). Factors that fit the time series and cross-section of stock returns. *Review of Financial Studies 33*(5), 2274–2325.

Lewellen, J. (2014). The cross section of expected stock returns. *Forthcoming in Critical Finance Review, Tuck School of Business Working Paper 4*(1), 1–44.

Lewellen, J. and S. Nagel (2006). The conditional capm does not explain asset-pricing anomalies. *Journal of Financial Economics 82*(2), 289–314.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance 20*(4), 587–615.

Liu, J., R. F. Stambaugh, and Y. Yuan (2018). Absolving beta of volatility's effects. *Journal of Financial Economics 128*(1), 1–15.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies 25*(12), 3457–3489.

Lucas, R. (1978). Asset prices in an exchange economy. *Econometrica 46*(6), 1429–45.

Manresa, E., F. Peñaranda, and E. Sentana (2023). Empirical evaluation of overspecified asset pricing models. *Journal of Financial Economics 147*(2), 338–351.

Markowits, H. M. (1952). Portfolio selection. *The Journal of Finance 7*(1), 71–91.

Medhat, M. and M. Schmeling (2022). Short-term momentum. *Review of Financial Studies 35*(3), 1480–1526.

Menzly, L. and O. Ozbas (2010). Market segmentation and cross-predictability of returns. *The Journal of Finance 65*(4), 1555–1580.

Merton, R. (1973). An intertemporal capital asset pricing model. *Econometrica 41*(5), 867–87.

Moskowitz, T. J. (2021). Asset pricing and sports betting. *Journal of Finance 76*(6), 3153–3209.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica 34*(4), 768–783.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics 108*(1), 1–28.

Pástor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political economy 111*(3), 642–685.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance 39*(4), 1127–1139.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory 13*(3), 341–360.

Schneider, P., C. Wagner, and J. Zechner (2020). Low-Risk Anomalies? *Journal of Finance 75*(5), 2673–2718.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance 19*(3), 425–442.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review 71*(3), 289–315.

Stambaugh, R. F., J. Yu, and Y. Yuan (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance 70*(5), 1903–1948.

Tian, M. (2021). Firm characteristics and empirical factor models: A model mining experiment. *Review of Financial Studies 34*(12), 6087–6125.

Treynor, J. L. (2012). *Toward a theory of market value of risky assets.*

Vasicek, O. A. (1973). A note on using cross-sectional information in bayesian estimation of security betas. *The Journal of Finance 28*(5), 1233–1239.

Vayanos, D. and J. Wang (2009, August). Liquidity and asset prices: A unified framework. Working Paper 15215, National Bureau of Economic Research.