Big Data Asset Pricing

Lecture 6: Asset Pricing with Frictions

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Overview of the Course: Big Data Asset Pricing

Lectures

- Quickly getting to the research frontier
  1. A primer on asset pricing
  2. A primer on empirical asset pricing
  3. Working with big asset pricing data (videos)
- Twenty-first-century topics
  4. The factor zoo and replication
  5. Machine learning in asset pricing
  6. **Asset pricing with frictions**

Exercises

1. Beta-dollar neutral portfolios
2. Construct value factors
3. Factor replication analysis
4. High-dimensional return prediction
5. Research proposal

Overview of this Lecture

- Fundamentals of asset pricing with frictions
- Transaction costs and market liquidity risk
- Funding liquidity risk
- Frictions meet machine learning:
    - ML about optimal portfolios with transaction costs

Fundamentals of Asset Pricing with Frictions

Recall: Fundamentals of Asset Pricing

Question: What determines prices and expected returns?

Answer (asset pricing without frictions):

State prices, m (and how m is determined)

Asset Pricing with Frictions

Question: What determines prices and expected returns?

Answer from asset pricing with frictions:

- m **may not exist**
  - "No-arbitrage condition" can break for "paper profits"
  - We can still look at implications of
    - A. no arbitrage *net of frictions*
    - B. agent optimality
    - C. equilibrium

Asset Pricing with Frictions: Approaches I

- **Frictional finance**: Focus on the frictions. Asset prices depend on overall frictions and asset-specific frictions, e.g.,
  - **Transaction costs and market liquidity risk**: Amihud and Mendelson (1986), Acharya and Pedersen (2005)
  - **Funding liqudity and margin requirements:** Gârleanu and Pedersen (2011)
  - **Over-the-counter markets:** Duffie et al. (2005), Lagos et al. (2011), overview: Weill (2020)

  When asset prices depend not only on covariances, but also on other characteristics (e.g., each asset's t-cost or haircut), then pricing not summarized by m

Asset Pricing with Frictions: Approaches II

- **Behavioral finance**:
  - Frictions generate limits of arbitrage
  - Limits of arbitrage means that correlated investor mistakes affect prices (Shleifer and Vishny (1997))
  - Focus on psychologically-motivated mistakes (Barberis and Thaler (2003), Hirshleifer (2015))

- **State price deflators, again**
  - If we have a set of assets without arbitrage (e.g., because of enough noise), then we can still look for m and empirically analyze (without theory foundation) whether it depends on
    - frictions (liquidity risk, e.g., Pástor and Stambaugh (2003))
    - behavioral effects (sentiment, e.g., Baker and Wurgler (2006))

Asset Pricing with Frictions: Approaches III

- **Network effects in asset pricing:**
  - Empirics: Bailey et al. (2018), Kuchler et al. (2020), survey: Kuchler and Stroebel (2020)
  - Theory: Pedersen (2022)
- **Demand-based asset pricing:**
  - Theory and evidence for derivatives Gârleanu et al. (2009), bonds Greenwood and Vayanos (2014), and the overall market Gabaix and Koijen (2021)
  - Demand systems: Koijen and Yogo (2019) and teaching material: `https://financialmarketinsights.com/`
- **Expectations data in asset pricing**: overview prepared for the Handbook of Economic Expectations: Adam and Nagel (2022)

Transaction Costs and Market Liquidity Risk

Market Liquidity Risk: Overlapping Generations Model

- Based on Acharya and Pedersen (2005)
- Each agent of generation t:
  - trades in periods t and $t+1$,
  - consumes at time $t+1$
  - has constant absolute risk aversion
- Security $i \in \{1, \dots, I\}$:
  - pays dividend D_t^i, ex-dividend share price of P_t^i, shares S^i
  - illiquidity cost of C_t^i
  - D_t^i and C_t^i are AR(1) processes
  - Relative illiquidity cost

$$c_t^i = \frac{C_t^i}{P_{t-1}^i}$$

  - Market return

$$r_t^{Mkt} = \frac{\sum_i S^i (D_t^i + P_t^i)}{\sum_i S^i P_{t-1}^i}$$

  - Relative market illiquidity,

$$c_t^{Mkt} = \frac{\sum_i S^i C_t^i}{\sum_i S^i P_{t-1}^i}$$

Liquidity-Adjusted CAPM

Result

In the unique linear equilibrium, the CAPM holds for net returns

$$E_t(r^i_{t+1} - c^i_{t+1}) = \lambda_t \frac{Cov_t(r^i_{t+1} - c^i_{t+1}, r^{Mkt}_{t+1} - c^{Mkt}_{t+1})}{\mathrm{Var}_t(r^{Mkt}_{t+1} - c^{Mkt}_{t+1})}$$

where $\lambda_t = E_t(r^{Mkt}_{t+1} - c^i_{t+1})$, *that is,*

$$\begin{aligned}
E_t(r^i_{t+1}) = \quad & E_t(c^i_{t+1}) && \textit{liquidity level} \\
& +\lambda_t \frac{Cov_t(r^i_{t+1}, r^{Mkt}_{t+1})}{\mathrm{Var}_t(r^{Mkt}_{t+1} - c^{Mkt}_{t+1})} && \textit{standard beta, } \beta^{i1} \\
& +\lambda_t \frac{Cov_t(c^i_{t+1}, c^{Mkt}_{t+1})}{\mathrm{Var}_t(r^{Mkt}_{t+1} - c^{Mkt}_{t+1})} && \textit{commonality in liquidity, } \beta^{i2} \\
& -\lambda_t \frac{Cov_t(r^i_{t+1}, c^{Mkt}_{t+1})}{\mathrm{Var}_t(r^{Mkt}_{t+1} - c^{Mkt}_{t+1})} && \textit{return beta to Mkt liquidity, } \beta^{i3} \\
& -\lambda_t \frac{Cov_t(c^i_{t+1}, r^{Mkt}_{t+1})}{\mathrm{Var}_t(r^{Mkt}_{t+1} - c^{Mkt}_{t+1})} && \textit{liquidity beta to Mkt return, } \beta^{i4}
\end{aligned}$$

- Simplying assumption: OLG $\rightarrow$ people must trade each time period
- Dynamic portfolio choice (not OLG)
  - with constant transaction costs, risk-neutrality and eq. returns: Amihud and Mendelson (1986), long-term investors overweight illiquid assets
  - predictability in partial equilibrium: later in this lecture

Empirical Evidence on Market Liquidity Risk

- Acharya and Pedersen (2005):
  - Use Amihud measure of liquidity and US stock returns
  - "illiquid securities also have high liquidity risk" based on the 3 liquidity betas (correctly signed), β^{i2}, $-\beta^{i3}$, $-\beta^{i4}$
  - Consistent with "flight to liquidity" in down markets or illiquid markets
  - "While this collinearity is itself interesting, it also complicates the task of distinguishing statistically the relative return impacts of liquidity, liquidity risk, and market risk"
  - Under the model restrictions, the difference in expected return from the least liquid portfolio to the most liquid is 3.5% due to liquidity level, $E(c)$, and 1.1% due to liquidity risk, $\beta^{i2} - \beta^{i3} - \beta^{i4}$
    - This magnitude further complicates inference
- Replication studies:
  - Holden and Nam (2019) and Kazumori et al. (2019)
    - Replication code from former paper: http://www.excelmodeling.com/Holden_and_Nam_LCAPM_Replication_and_Extension_Code_2018_11_05.zip
    - Differences with each other and original study
    - Evidence broadly consistent with liquidity risk being price, but reject exact function form of LCAPM
  - Acharya and Pedersen (2019) discuss broader implications

Empirical Evidence on Market Liquidity Risk, continued

- Pástor and Stambaugh (2003):
  - Compute their own measure of liquidity L
  - Regress stock returns on L and sort stocks on their liquidity beta
  - Find that stocks with more liquidity risk have higher expected returns
  - Consistent with pricing of β^{i3} in Acharya and Pedersen (2005)
  - No issue with multi-collinearity since no control for $E(c)$, β^{i2}, β^{i4}
- Replication studies:
  - Li et al. (2019) and Pontiff and Singla (2019)
    - Evidence consistent with liquidity risk being priced, also out of sample, but some challenges to robustness wrt. methods
    - Pástor and Stambaugh (2019) discuss evidence
- Amihud (2002):
  - Expected market illiquidity positively predicts stock returns
  - Unexpected illiquidity shocks negatively related to contemporaneous returns
  - Consistent with implications of Acharya and Pedersen (2005)
- Replication studies:
  - Drienko et al. (2019) and Harris and Amato (2019)
    - Consistent with original study, also out-of-sample, though weaker
    - Amihud (2019) discusses

Empirical Evidence on Market Liquidity Risk, continued

- Illiquid-Minus-Liquid (IML)
  - Introduced in Amihud et al. (2015), evidence positive average return around the world
  - Amihud and Noh (2021) find that beta to IML is priced, similar to $-\beta^{i3}$
- Security Exchange Commission (SEC)'s tick-size experiment
  - exogenous shock to liquidity, Albuquerque, Yao, and Song (2017)
- Market liquidity risk in other markets
  - corporate bond markets: Bao, Pan, and Wang (2011), Lin, Wang, and Wu (2011), Acharya, Amihud and Bharath (2013)
  - government bond markets: Beber, Brandt, and Kavajecz (2008))
  - private equity: Franzoni, Nowak, and Phalippou (2012)
  - foreign exchange markets: Mancini, Ranaldo, and Wrampelmeyer (2013)
  - derivatives markets: Bongaerts, de Jong, and Driessen (2011)

Funding Liquidity Risk

Understanding Funding Constraints

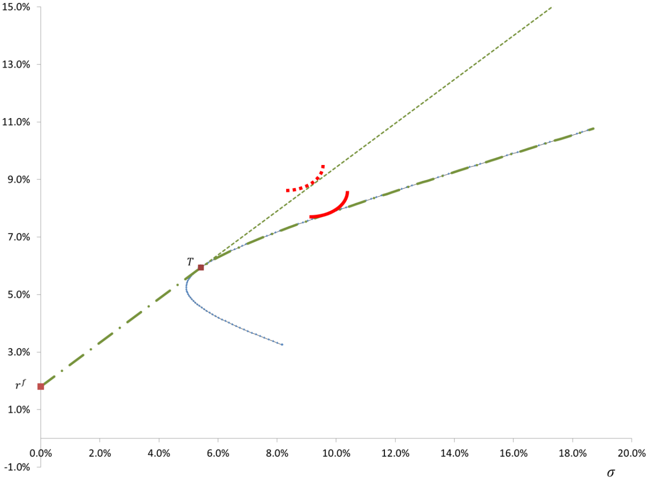
Recall: portfolio weights can be measured as

- fractions of wealth, w_t, invested in each asset, x_t^i
- money (say, dollars) invested in each asset, $x_t^{\$,i}$
- shares invested in each asset, $\bar{x}_t^i$
- Connection: $x_t^i w_t = x_t^{\$,i} = \bar{x}_t^i p_t^i$

Different types of funding constraints:

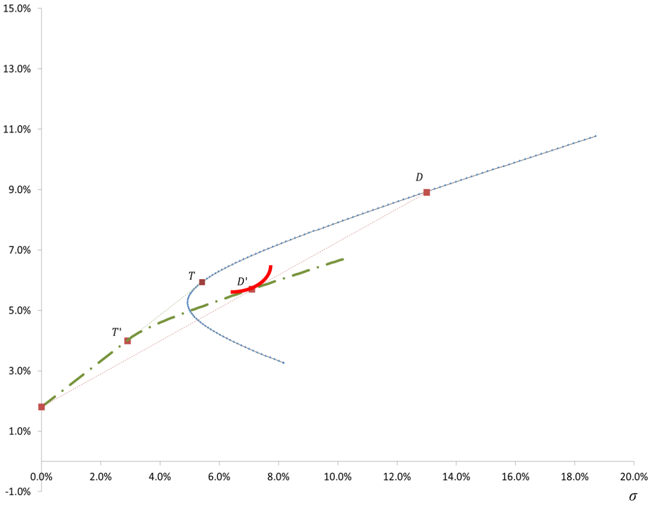
1. **No net leverage**: $\sum_i x^{\$,i} \leq w$, i.e., $\sum_i x^i \leq 1$
2. **Must hold fraction cash** $1 - \frac{1}{m}$ with $m > 1$: $m \sum_i x^i \leq 1$
3. **Common margin req.** of $m \leq 1$, shorting frees up cash: $m \sum_i x^i \leq 1$
4. **Margin req.** of m^i for asset i: $\sum_i m^i |x^i| \leq 1$
5. **Margin req.** of m^{i+} for longs and m^{i-} for shorts:
   $\sum_{i:x^i>0} m^{i+} x^i + \sum_{i:x^i<0} m^{i-} |x^i| \leq 1$

No Net Leverage



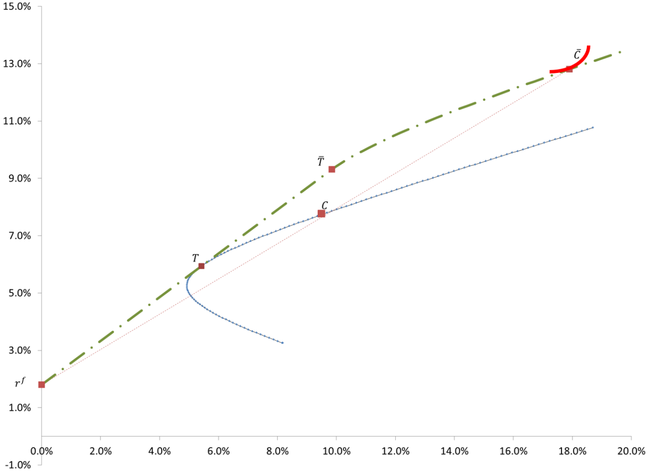
Source: Frazzini and Pedersen (2014)

Must Hold Cash



Source: Frazzini and Pedersen (2014)

Common Margin Requirement



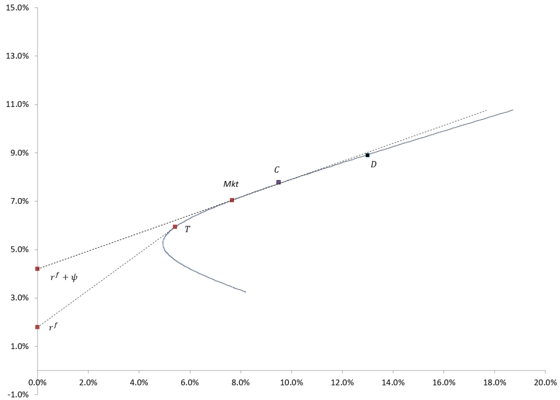
Source: Frazzini and Pedersen (2014)

Implications of Simple Constraints

- All investors choose portfolios, which consist of
  - a portfolio of risky assets on the hyperbola
  - a cash position, long or short (i.e., cash or borrowing)
- Combinations of portfolios on hyperbola remain on the hyperbola
  - All these portfolios are spanned by any two of them

→ Mkt is on the hyperbola, to the right of the tangency portfolio

→ CAPM holds with fictitious interest rate, $r^f + \psi$



Betting Against Beta

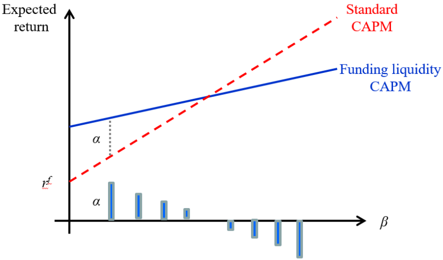
Result

When each investor has mean-variance utility subject to no net leverage, must hold cash, or common margin requirements (can differ across investors), equilibrium expected excess returns are

$$E_t(r^i_{t+1}) = \psi_t + \lambda_t \beta^i_t$$

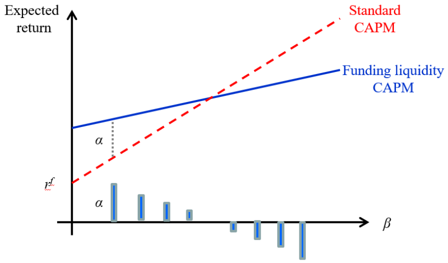
where $\beta^i_t = \frac{Cov_t(r^i_{t+1}, r^{Mkt}_{t+1})}{\mathrm{Var}_t(r^{Mkt}_{t+1})}$, $\lambda_t = E_t(r^{Mkt}_{t+1} - \psi_t)$, *and* $\psi_t \geq 0$ *is investors' average Lagrange multiplier measuring the tightness of the funding constraints.*

- *In other words, the security market line is too flat relative to the CAPM*
- *A security's alpha wrt. market is,* $\alpha^i_t = \psi_t(1 - \beta^i_t)$ *, which decreases with* β^i_t



Betting Against Beta, continued

- Finance papers often illustrate an economic effect via a portfolio return
- Typically, portfolio is long high-alpha and short low-alpha
- If we go long \$1 in high-alpha (=low-beta) assets, short \$1 in low-alpha (high-beta) assets
  - What is the alpha?
  - What is the expected return?
- Investors cannot "eat" alpha — how do you make money on this effect?
  - In general, or
  - if you must simultaneously be market neutral (to visualize alpha)?



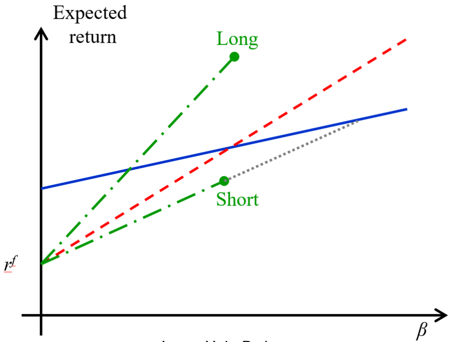
Betting Against Beta, continued

- Sort stocks into low-beta portfolio L and high-beta portfolio H
- BAB excess return defined as, $r_{t+1}^{BAB} = \frac{1}{\beta_t^L} r_{t+1}^L - \frac{1}{\beta_t^H} r_{t+1}^H$

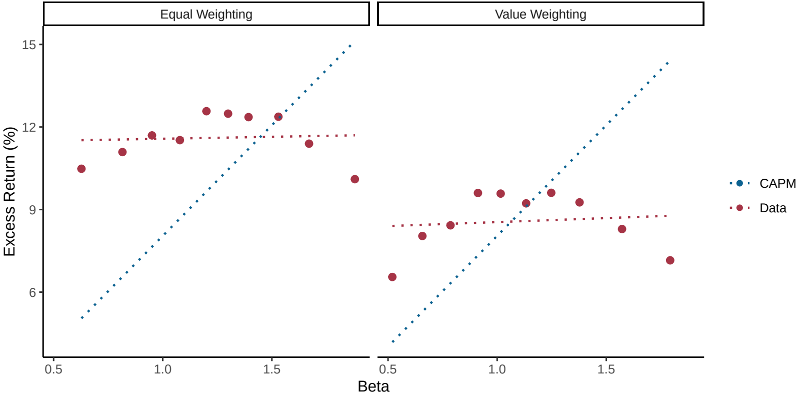
Result

When investors have mean-variance utility subject to no net leverage, must hold cash, or common margin requirements, the expected excess return of BAB is

$$E_t(r_{t+1}^{BAB}) = \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H} \psi_t \geq 0$$

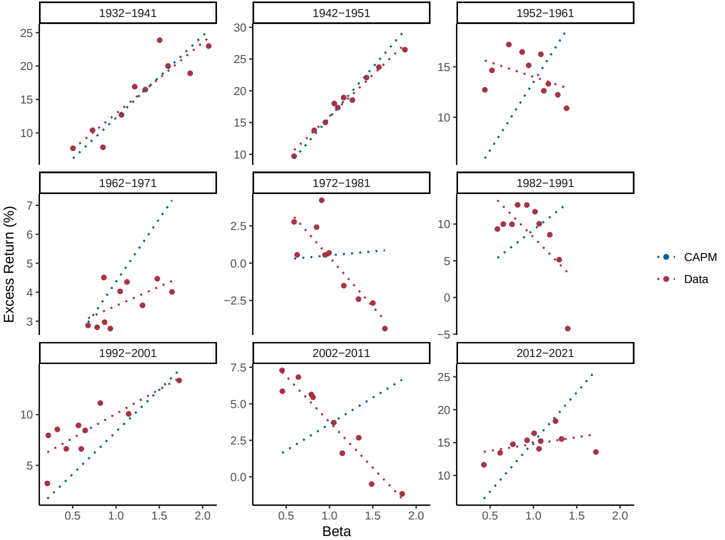


Security Market Line is Too Flat: Evidence



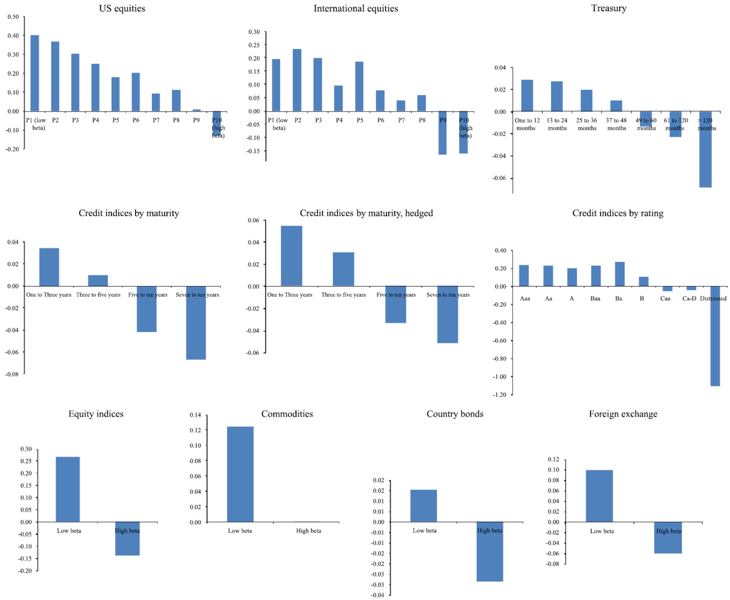
Data: U.S. equity portfolios, 1931-2020

Security Market Line is Too Flat: Evidence by Decade

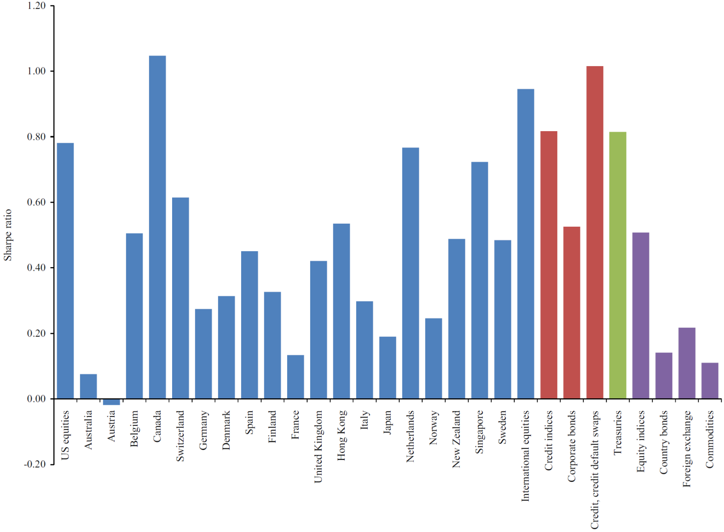


Data: U.S. equity portfolios vw. **Note**: Last 5 decades are out-of-sample wrt. Black et al. (1972) and last decade is out-of-sample wrt. Frazzini and Pedersen (2014)

High Beta is Low Alpha: Test Across Global Asset Classes

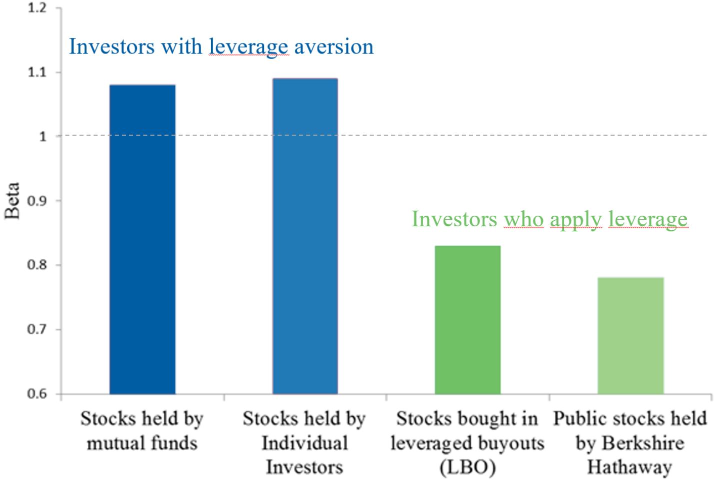


Betting Against Beta: Test Across Global Asset Classes



How does magnitude of SR compare to those of the Fama-French factors?

Testing the Portfolio Predictions



Margin CAPM

Result

When investors have mean-variance utility subject to security-specific margin requirements, m_t^i, equilibrium expected excess returns are

$$E_t(r_{t+1}^i) = \psi_t m_t^i + \lambda_t \beta_t^i$$

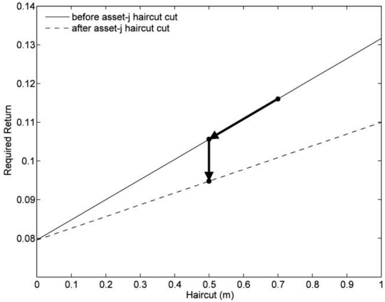
where $\beta_t^i = \frac{Cov_t(r_{t+1}^i, r_{t+1}^{Mkt})}{\mathrm{Var}_t(r_{t+1}^{Mkt})}$, λ_t *is a risk premium, and* $\psi_t \geq 0$ *funding tightness.*

- *Each security's margin req. matters, especially during crises when* ψ_t *is large*

- Ashcraft et al. (2010) derive this result in discrete time
- Gârleanu and Pedersen (2011) derive similar result in continuous time

Margin CAPM: Monetary Policy

- The idea of TALF and other central bank lending facilities
  - Trying to unfreeze credit market
  - Lower margin requirement (=lower haircut) can have two effects
    1. Move the security down the haircut-return curve
    2. Shift the whole curve down by lowering ψ_t (equilibrium effect)
  - Haircut-return curve: Now the x-axis is margin requirements

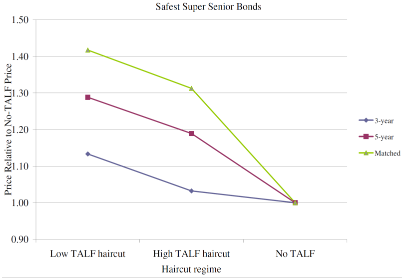


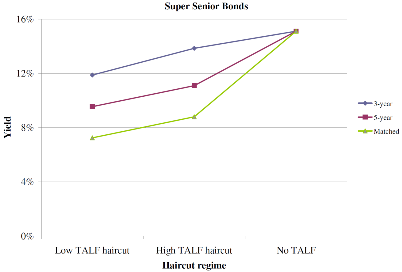
  - Fed cares mostly about new issues (new funding), but
    - Fed can only lower margin of new issues by limited amount
    - Funding existing securities can also help with 2. effect

Margin CAPM: Evidence

Ashcraft et al. (2010) show implications of margin-CAPM

- Effects on production and consumption
  - funding constraint→business cycles (Margin Constraint Accelerator)
- Implications for monetary policy that changes r^f or m^i
- Evidence from Fed's TALF program
  - Survey of market participants during the global financial crisis
  - Left figure: average survey bid price of super senior CMBS A4 bonds
  - Right figure: the corresponding annual yields – both by haircut group
  - These bonds were considered very safe, but difficult to borrow against
    - idea is that the effect is driven by margin-CAPM
    - must acknowledge risk and risk-shifting as alternatives

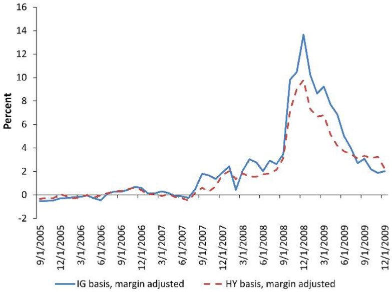


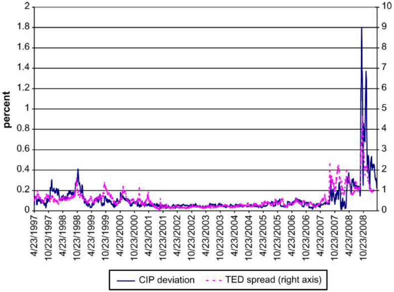


Margin-CAPM and Deviations from the Law of One Price

Gârleanu and Pedersen (2011): Margin-CAPM with

- Endogenous interest rate
- Linking ψ_t to collateralized/uncollateralized interest-rate spread
- Deviations from the Law of One Price
  - Securities with identical cash flows and different margins
    →endogenously different betas (funding liquidity risk)
    →different $E(r)$ due to different m's and β's
- Evidence related to
  - CDS-bond basis
  - Covered interest-rate parity (CIP)





Machine Learning and the Implementable Efficient Frontier

Based on Jensen et al. (2022)

Are Standard ML-Based Portfolios Implementable?

- ML models are great at predicting stock returns
  - For example, Gu et al. (2020)
- But most ML papers ignore trading costs, implying unrealistic
  - performance (Li et al., 2020; Chen and Velikov, 2021; Detzel et al., 2021)
  - profits from illiquid stocks (Avramov et al., 2023)
  - key characteristics, e.g. short-term reversal (Chen et al., 2023)
- Questions:
  - Can investors benefit from ML after t-costs?
  - Which signals have greatest economic feature importance?
  - Lessons for asset pricing?

T-Cost-Aware ML

How can we make ML aware of t-costs?

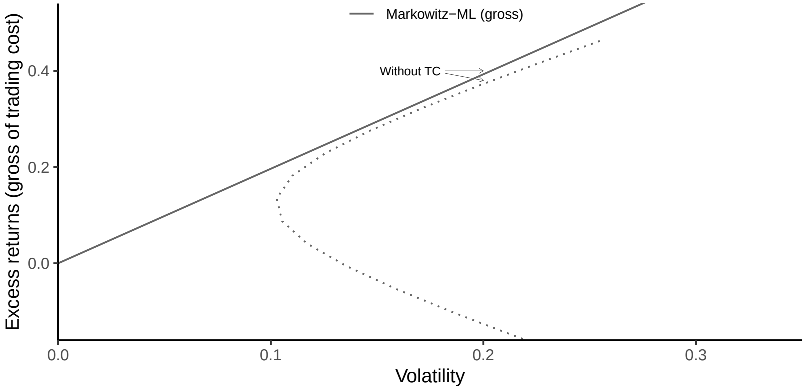
Base ML on insights from portfolio theory

- No t-costs: Markowitz (1952)
- T-costs and iid returns: Constantinides (1986), Davis and Norman (1990)
- T-costs and factor predictability:
  - Gârleanu and Pedersen (2013), Collin-Dufresne et al. (2020)
  - Stationary framework with general predictability $\rightarrow$ useful for ML Jensen et al. (2022)

The Implementable Efficient Frontier

- The "Implementable efficient frontier" (IEF)
  - After-cost, out-of-sample version of standard efficient frontier
- Standard ML implementations leads to a poor IEF
- New theory-guided ML leads to
  - a powerful IEF
  - different – more economic – feature importance:
    - quality and value: large impact on the IEF
    - short-term reversal: limited impact for a large investor

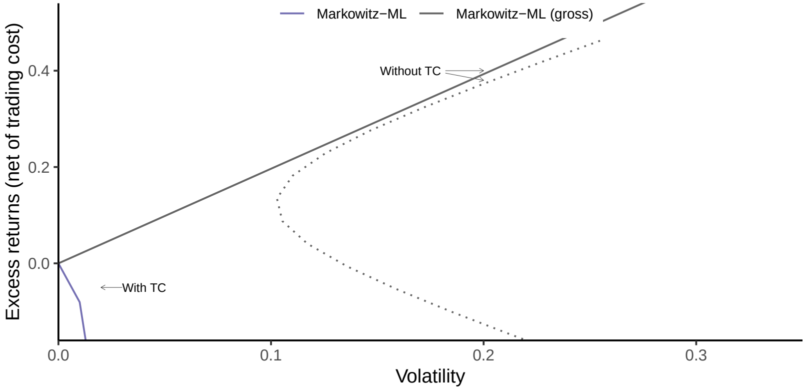
Almost the Standard Efficient Frontier – but OOS



Everything is out-of-sample: 1981-2020

Dotted line: Mean-variance frontier of risky assets, $\sum_i \pi_i = 1$, without t-costs

The Implementable Efficient Frontier



Risk and expected return net of t-costs with a wealth of $10B by 2020

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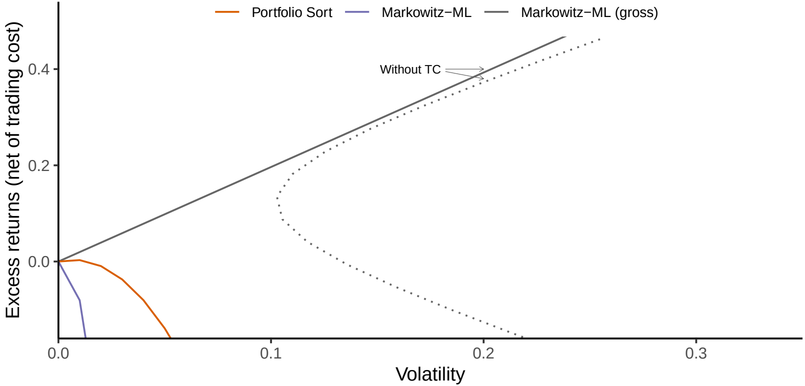

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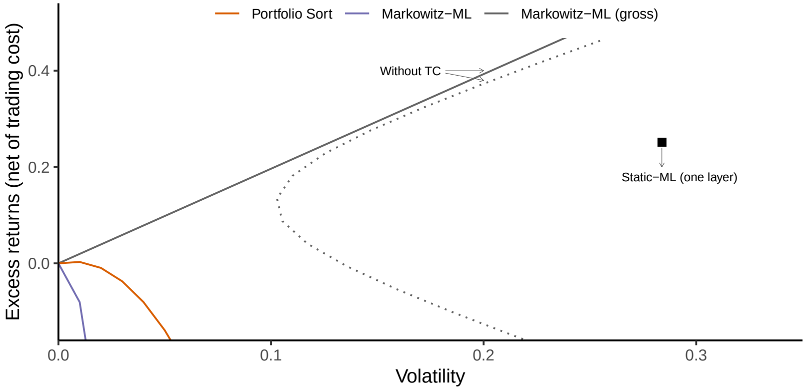

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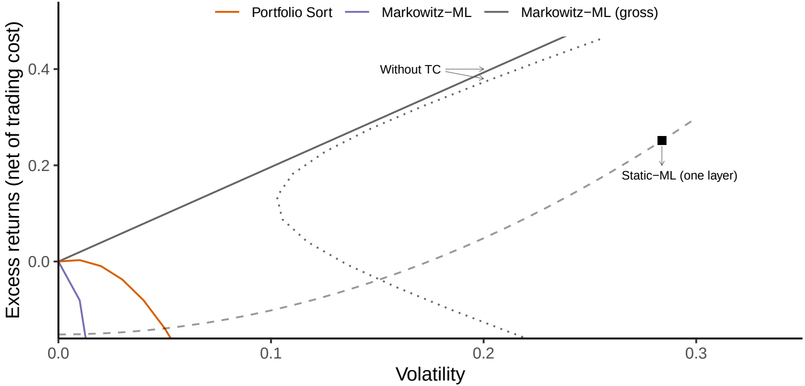
Markers: Relative risk aversion (left to right): 100 ⊠, 20 +, 10 □, 5 △, 1 ○

The Implementable Efficient Frontier



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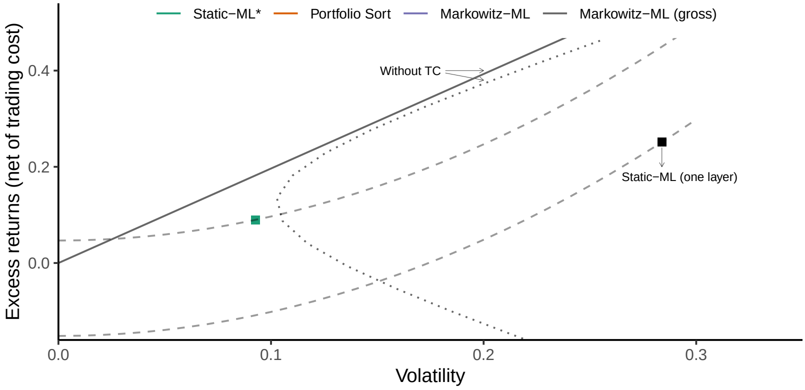

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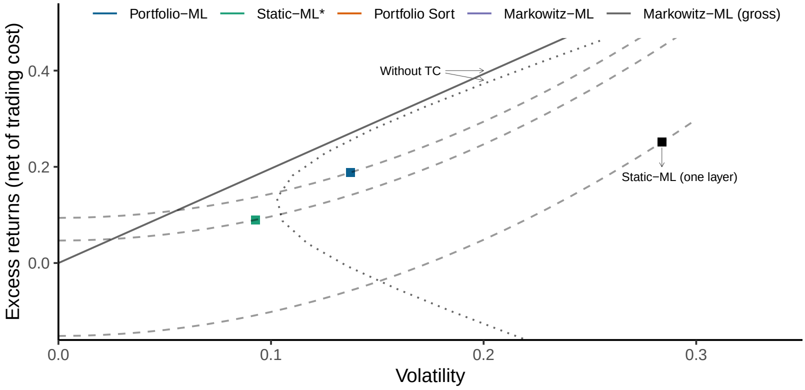
Markers: Relative risk aversion (left to right): 100 $\boxtimes$, 20 $+$, 10 $\square$, 5 $\triangle$, 1 $\circ$

The Implementable Efficient Frontier



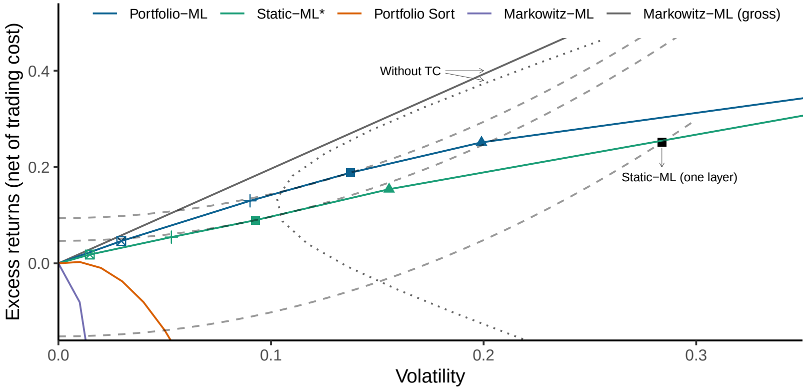
Risk and expected return net of t-costs with a wealth of $10B by 2020

Everything is out-of-sample: 1981-2020

Dotted line: Mean-variance frontier of risky assets, $\sum_i \pi_i = 1$, without t-costs

Markers: Relative risk aversion (left to right): 100 ⊠, 20 +, 10 □, 5 △, 1 ○

The Implementable Efficient Frontier



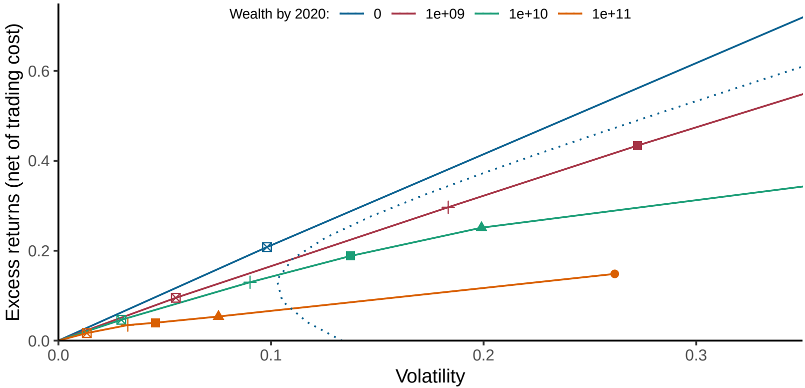
Risk and expected return net of t-costs with a wealth of $10B by 2020

Everything is out-of-sample: 1981-2020

Dotted line: Mean-variance frontier of risky assets, $\sum_i \pi_i = 1$, without t-costs

Markers: Relative risk aversion (left to right): 100 ⊠, 20 +, 10 □, 5 △, 1 ○

The Implementable Efficient Frontier: By AUM/Wealth



Risk and expected return net of t-costs using Portfolio-ML

Everything is out-of-sample: 1981-2020

Dotted line: Mean-variance frontier of risky assets, $\sum_i \pi_i = 1$, without t-costs

Markers: Relative risk aversion (left to right): 100 ⊠, 20 +, 10 □, 5 △, 1 ∘

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