Table of Contents

Week 3: Review of Asset Pricing

Fama, Eugene F., and Kenneth R. French (1992). "The cross-section of expected stock returns." *The Journal of Finance*, 47(2), 427-465.

Objective

- Aims to identify pricing factors that best explain the cross-section of stock returns from the pool of pricing factors identified in prior literature at the time.
- E.g. market excess return, size, book to market, earnings to price ratio, negative/positive earnings dummy, market leverage, and book leverage.

Methodology

- Examines return spread across single & double sorted portfolios and FM regressions.
- In FM regressions, a pricing factor is said to help explain cross-section of stock returns when it has a significant factor/risk premia. This simple 2-step method accounts for cross correlation between stocks/portfolios returns within each time period.
    - 1) Time-series regressions are run for each portfolio/stock for each time period to estimate the factor loadings or betas on each potential pricing factor in the regression.
    - $R_{i,t} = \alpha_{i,t} + \beta_{i,F_1} F_{1,t} + \beta_{i,F_2} F_{2,t} + \ldots\ldots + \beta_{i,F_m} F_{m,t} + \epsilon_{i,t}$
    - 2) Using the estimated factor loadings, at each time period, a cross-sectional regression is conducted to estimate the factor premia for each factor. The risk premia for each factor across all time periods are then averaged.
    - $R_{i,T} = \gamma_{T,0} + \gamma_{T,1}\hat{\beta}_{i,F_1} + \gamma_{T,2}\hat{\beta}_{i,F_2} + \ldots\ldots + \gamma_{T,m}\hat{\beta}_{i,F_m} + \epsilon_{i,t}$
- Stocks are sorted into portfolios based on pricing factor deciles resulting in 10 portfolios based on one factor. The average monthly returns are then calculated for each portfolio. If the pricing factor can explain cross-sectional returns, we should observe a noticeable return spread across the 10 portfolios sorted on that factor.
- Portfolios may be double sorted i.e. sorted on two factors to identify whether there is a return spread for one factor while controlling for the other and vice versa. E.g. For the original 10 sorted portfolios, each portfolio is then sorted into 10 portfolios based on the second pricing factor, resulting in 100 double-sorted portfolios. This alleviates the concern that another factor is behind the results.

Findings

- Ln(ME) Size and ln(BE/ME) book-to-market factors together help explain the cross-section of expected stock returns, whereas the market beta is insignificant in FM regressions.
- The earnings to price ratio and earning dummy has insignificant explanatory power when including the ln(BE/ME) factor and ln(ME) size factor in FM regressions.
- Book leverage and market leverage has insignificant explanatory power when including the ln(BE/ME) book to market factor in FM regressions.
- Double-sorting portfolios based on size and predicted market betas indicates that variation in returns across beta portfolios is too small relative to the variation in market betas for each size portfolio expected under the CAPM. Whereas, large return variations across size deciles are observed for each market beta portfolio. Same results for B/M ratio.
- Large monthly return variation across book to market and size is observed for double-sorted portfolios based on size and book to market.

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

Objective
- Identifies five common risk factors in returns on stocks and bonds
- There are three stock market factors: *MKT, SIZE, Book-to market equity*
- Two bond market factors: related to *maturity and default risks*

Contributions: extends asset pricing tests in Fama & French 1992 in 3 ways
- **1) Expand set of asset returns to be explained**
- Only assets considered in F&F are common stocks; tests in paper include US corporate bonds and stocks; *Argue that if markets are integrated a single model should explain bond returns*
- **2) Expand set of variables used to explain returns;** size & BM variables in F&F are directed at stocks; Extend the list to term-structure variables likely to play a role in bond returns;
- Goal is to **examine** whether variables important in bond returns help explain stock returns vice versa; *Argue if markets integrated there is most likely an overlap between return processes for bonds and stocks*
- **3) Most important contribution:** approach to asset pricing models is unique. F&F 1992 use cross section regressions of Fama and MacBeth 1973; the cross section of stock returns is regressed on variables hypothesised to explain average returns; it would be difficult to add bonds to the cross section regressions; since explanatory variables like SIZE, BM equity have no obvious meaning for government and corporate bonds

Methodology
- Paper uses time series regression approach of Black, Jensen and Scholes 1972
- Monthly returns on stocks and bonds are regressed on the returns to a market portfolio of stocks and mimicking portfolios for size, (book to market equity) BE/ME and term structure risk factors in returns
- Time series regression slopes; are factor loadings that have a clear interpretation as risk factors for bonds as well as stocks; unlike size or BE/ME

Findings
- **A) Central theme**: if assets are priced rationally, variables relating to average returns e.g. size and BM/BE must be a proxy for sensitivity to common risk factors in returns. Time series regressions give direct evidence on this issue. In particular, slopes and R^2 show whether mimicking portfolios for risk factors related to size and BE/ME captures shared variation in stock and bond returns not explained by other factors.
- **B) Time series regressions:** use excess returns (monthly stock or bond returns minus one-month T-bill rate) as dependent variables; excess returns or returns on zero-investment portfolios as explanatory variables - estimated intercepts provide a return metric and a formal test of how well different combinations of the common factors capture the cross-section of average returns.

Overall
- For stocks: portfolios constructed to mimic risk factors related to size and BE/ME capture strong common variation in returns; regardless of other variables in time-series regressions
- Evidence that size and book to market equity proxy for sensitivity to common risk factors in stock returns; Observe for stock portfolios the intercepts from 3-factor regressions include excess market return and mimicking returns for size and BE/ME factors - that are close to 0. Hence market factors and proxies for risk factors (size & BE/ME) do hold explanatory power over the cross section of average stock returns.
- I.e., Common return factors related to size and BM/BE that help capture the cross-section of average stock returns in a way that is consistent with multi-factor asset pricing models. *(page 5 interpret.)*
- Fama and French 1992 show that size and BE/ME are related to systematic patterns in relative profitability and growth that could be the source of common risk factors in returns
- For Bonds: mimicking portfolios for two term-structure factors; term premium and default premium capture most of the variation in returns on our government and corporate bond portfolios. The term structure factors also explain average returns on bonds, but average premium i.e. excess bond returns are close to 0.

- So the hypothesis that all corporate and government bond portfolios have the same long term expected returns CANNOT be rejected
- Common variation: in stock returns are largely captured by three stock portfolio returns; in bond returns are explained by two bond-port returns. Results suggest there are at least 3 stock market factors and 2 term structure factors in returns.
- Stock returns have shared variation due to stock market factors; and are linked to bond returns through shared variation in the bond market factors
- Only the two term structure factors produce common variation in returns on government and corporate bonds (excluding for low grade corporate bonds).

Fama, Eugene F., and Kenneth R. French (2004). "The capital asset pricing model theory and evidence." *The Journal of Economic Perspectives*, 18(3), 25-46.

Objective/Methodology

- To provide a literature review on the background of the CAPM and why it is empirically redundant in explaining stock returns.

Findings

- The CAPM model is based on the Markowitz portfolio theory where investors are risk averse and therefore seek to maximise mean-variance expected returns for time period t. These mean-variance maximised portfolios lie on the return-risk efficient frontier. The CAPM or Sharpe-Lintner (SL) model builds on this and assumes investors can borrow or lend at a risk-free rate based on some zero-beta asset.
- The line that passes through the risk-free rate (intercept) and is tangent to the efficient frontier is the capital market line which represents the optimal combinations of the risk-free asset and tangency/market portfolio dependent on individual investor risk preferences. Therefore, returns on an asset should be explained solely by the risk-free asset and the sensitivity β to the market excess returns. $Ri = Rf + \beta(Rm - Rf)$
    - Assumptions of the CAPM are rather strict and do not hold in reality.
        - Unlimited borrowing and lending at identical rates.
        - Infinite short-selling allowed.
        - Investors have identical information and expectations on prices of assets at time t based on time t-1 information.
- Empirical testing of the CAPM
    - Testing the CAPM involves running time-series regressions and cross-sectional regressions to estimate beta and identify the intercept or alpha.
    - Difficulty in testing the CAPM
        - How do we estimate the market portfolio? The tangency/market portfolio also includes assets outside of stocks such as real estate, bonds etc. Do we include international assets? Human capital? Research suggests that including additional assets such as US real-estate makes little difference as the volatility of the portfolio is dominated by US stocks.
        - Beta estimates are rather imprecise due to noise and cross-correlation. Although mitigated by methods such as using portfolios, FM regressions etc.
    - Early tests suggest that CAPM could explain returns sufficiently well through positive betas and with a positive market risk premium (slope) although the market risk premium did not appear to equal the expected market return.
    - However, in the late 70s, research suggests the CAPM doesn't hold. Including additional factors such as earnings to price ratios, size, and book to market helps explain the cross-section of returns.

- The observed slope between returns and beta is too flat relative to what is expected under the CAPM, suggesting that returns on low-beta assets are too high/underpriced while returns on high-beta stocks are too low/overpriced. Betting against beta strategy involves believing CAPM is correct by shorting high-beta stocks and buying low-beta stocks.
- When including additional pricing factors into models based on the arbitrage pricing theory such as FF 3 factor model, Carhart 4 factor model and FF 5 factor model, market betas fail to explain variation in portfolio returns when portfolios are sorted on other price factors such as size or book to market.
- **There is a risk interpretation and mispricing interpretation of these results.** The mispricing interpretation is that CAPM is correct and is what the market uses to set prices. However, due to irrational behaviour such as over/underreaction which could possibly explain size and book-to-market results, this does not appear in reality. The risk interpretation suggests that the CAPM model is too simplistic and doesn't capture all undiversifiable risk or maximisation objectives and therefore a more complicated pricing model is required. An example of this would be the ICAPM model and APT models which allows for additional state variables.

Week 4: More on Asset Pricing and Anomalies

McLean, R. David, and Jeffrey Pontiff. (2016). "Does academic research destroy stock return predictability?" *The Journal of Finance*, 71(1), 5-32.

Objective

- Does academic research destroy stock return predictability?
- Can we measure the impacts of research publication on actions of market players?

Methodology

- 97 predictor variables, from past literature. These are used to form long-short portfolios based on the expected relationships, which are then used to test their validity.
    - They don't aim to replicate each study, as it is impossible due to CSRP changes over time. The authors seek to calculate a characteristics that captures the intent of the study
- The performance of the long-short portfolio is assessed over the sample period, out-of-sample-sample period, and post-publication period
    - The out-of-sample level of persistence speaks to data-mining in the original sample, whereas the post-publication decline speaks to market markers incorporating these aspects into their investment strategies – taking positions to correct the mispricing for example. The variable of interest is the difference moving from out-of-sample to post-publication.
- Periods segmented by end-of-sample (statistical bias) and publication dates (learn about predictor)
- $R_{it} = \alpha_i + \beta_1 PostSampleDummy_{i,t} + \beta_2 PostPublicationDummy_{i,t} + \varepsilon_{it}$
- Monthly return for predictor i in month t
- Various robustness tests to ensure validity.

Findings

- The findings between in-sample and out-of-sample indicate a statistical bias effect of 26%. The average predictors return declines 58% post-publication (both statistical biases and traders incorporating it). This implies a publication effect of 32% on average. This is statistically and economically significant.
- This paper finds that published research has an impact on the market, and that market players follow literature. Also shows that while a significant portion of price predictability may be due to statistical biases (data mining for example), a significant portion also is not.

Takeaways

- Academic research does matter, and holds an impact on the actions of arbitrage makers in the market
- This study may not be as feasible if it were to be replicated today, since the rise in working papers being easily available.

Berkman, Henk, Ben Jacobsen, and John B. Lee (2011). "Time-varying rare disaster risk and stock returns." *Journal of Financial Economics* 101(2), 313-332.

Objective

- How do crises affect stock returns and return volatility?

Methodology

- The International Crisis Behaviour (ICB) database details 447 major international political crises occurring from 1918-2006, with 66 crisis dimensions and control variables
- Multiple dummy variables are used to describe the nature of crises in each monthly time period
- Crisis severity index aggregates the 6 other variables + 1 and is highly correlated with the # of crises
- Crisis probabilities are calculated based on sample frequencies (983 crisis actors, 167 countries)
- **Relationship between number of crises and actual consumption disasters:** probit model
Depression = multi-year decline of consumption or GDP by 10% or more
$DepressionStart_{c,y} = \alpha + \beta_1 Start_{c,y} + \beta_2 During_{c,y} + \beta_3 End_{c,y} + \varepsilon_{c,y}$ where y = year and c = crisis actor
- **Relationship between number of crises and world stock returns:** linear regression
$r_t^{world} = \mu + \alpha_1 Crisis_t + \varepsilon_t$ where r = total return on world market and t = month
$$r_t^{world} = \mu + \alpha_1 Start_t + \alpha_2 During_t + \alpha_3 End_t + \varepsilon_t$$
- **Relationship between number of crises and world stock volatility:** GARCH(1,1) model
$$r_t^{world} = \mu + \alpha_1 Start_t + \alpha_2 During_t + \alpha_3 End_t + \varepsilon_t$$
where $\varepsilon_t \sim N(0, {\sigma_t}^2), {\sigma_t}^2 = \beta_0 + \beta_1 {\varepsilon_t}^2 + \beta_2 {\sigma_{t-1}}^2 + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \varepsilon_t$
- **Relationship between disaster risk and number of crises ongoing:** AR(1) model
$Start_t + During_t = \alpha + \beta[Start_{t-1} + During_{t-1}] + \varepsilon_t$where fitted = expected and residual = unexpected
$$r_t^{world} = \alpha + \beta_1 ExpectedDisasterRisk_t + \beta_2 UnexpectedDisasterRisk_t + \varepsilon_t$$
H1: expected stock market excess return is an increasing function of expected disaster risk
H2: unexpected disaster risk has a negative effect on contemporaneous stock market returns
- **Relationship between crisis sensitivity and future returns:** F-M regression
$r_{i,\tau} = \alpha_{i,t-1} + {\beta_{i,t-e}}^{MKTRF} MKTRF_\tau + {\beta_{i,t-e}}^{SMB} SMB_\tau + {\beta_{i,t-e}}^{HML} HML_\tau + {\beta_{i,t-e}}^{Crisis} Crisis_\tau + \eta_{i,\tau}$where r = excess return on industry portfolio, i = portfolio, τ= month, crisis = residual in crisis measure sorted into deciles and scaled to [0,1]
$$r_{i,t} = \gamma_t + \gamma_{MKTRF,t} {\beta_{i,t-1}}^{MKTRF} + \gamma_{SMB,t} {\beta_{i,t-1}}^{SMB} + \gamma_{HML,t} {\beta_{i,t-1}}^{HML} + \gamma_{Crisis,t} {\beta_{i,t-1}}^{Crisis} + \varepsilon_{i,t}$$

Findings

- An average month has 2.47 crises (0.413 starting, 0.413 ending, 1.645 in the middle)
- A crisis commencing in one month increases the likelihood of a crisis commencing the next, vice versa
- Real GDP decreases by an average of 24.9% to the minimum following the start of a war
- Years in which a country becomes an actor in an international political crisis have a 2.8% higher probability of being the start of a consumption disaster, -2.3% vice versa
- On average, a crisis reduces monthly stock returns by 0.12% (3.6% annual - average annual crises) and carries an average cost of 0.72%
- The increase in crisis probability at the start of a crisis has a significant negative impact on stock returns and positive impact on return volatility, while the decrease in crisis probability at the end of a crisis has a significant positive impact on stock returns and negative impact on return volatility
- More severe crises, with a higher probability of a dramatic negative impact on future consumption, have a stronger impact on stock returns
- There is some evidence that expected stock market excess return is an increasing function of expected disaster risk, and clear significant evidence that unexpected disaster risk has a negative contemporaneous impact on stock market returns
- Crisis risk is priced - industries that are more crisis risk sensitive yield a higher return on average

Week 5: Behavioural Finance

Malcolm Baker and Jeffrey Wurgler (2006). "Investor sentiment and the cross-section of stock returns," *The Journal of Finance*, 61(4), 1645-1680.

Objectives

- This paper highlights investor sentiment has a significant impact on the cross-section of stock returns.
- Mispricing is the result of an uninformed demand shock in the presence of binding arbitrage constraints, predictions made on a broad-base wave of sentiment has cross-sectional effects when sentiment-based demands or arbitrage constraints vary across stocks. These two distinct channels lead to quite similar predictions because stocks are likely to be most sensitive to speculative demand and are most likely the riskiest and most costly to arbitrage.
- Investor sentiment is therefore likely to affect newer, smaller, more volatile, unprofitable, non-dividend paying, distressed or with extreme growth potential, and firms with analogous characteristics.

Methodology

- Cross-sectional patterns of sentiment-driven mispricing would be difficult to identify directly, cross-sectional predictability patterns in stock markets depend on market proxies for beginning-of-period sentiment. They remain mindful of the joint hypothesis theory.
- Gather a set of proxies for investor sentiment to use as time-series conditioning variables. They consider a series of proxies based on prior variables to inform an index, constructed based on a first principal component.
- Orthogonalization of the investor sentiment proxy to several macro-economic factors separates the proxy from systematic risk. Sentiment indices align with historical accounts of bubbles & crashes.
- Tests how cross-section of subsequent stock returns varies with the beginning of period sentiment. Equally-weighted decile portfolios on several firm characteristics (Long-short portfolios with lagged sentiment prior to trading). Assume large firms less affected by sentiment so value weighting would obscure findings.

Findings

- Then patterns were investigated. When sentiment is low, small stocks earn high returns, but when high, there is no size effect.
- When sentiment is low, subsequent returns are higher on very young stocks/unprofitable/high return volatility/non-dividend payers compared to old/profitable/low return volatility/dividend paying stocks. These patterns reverse in high sentiment.
- The sort also suggests that sentiment affects extreme growth and distressed firms in similar ways. When sorted into deciles by sales growth, book-to-market, or external financing activity, growth and distress firms tend to lie at opposing extremes, with more stable firms in the middle deciles.
- When sentiment is low, returns are high at either end of the spectrum but low in the middle (not B/M). Consistent - extreme growth firms have subjective valuations and are costly to arbitrage.
- A regression (high-low portfolios in terms of sentiment sensitivity) is considered to control for co-movement using Fama-French factors.
    - Turn to tests assessing compensation for systematic risk. – tests cast doubt.
    - Test second directly, find no link between returns and patterns with betas.
    - When sentiment is low, older etc firms would require a risk premia which is counterintuitive. Other results imply there are other factors than systematic risk.

Takeaways

- Sentiment helps explain the time series of returns.
- This theory argues that competition among rational investors, who diversify to optimize the statistical properties of their portfolios, will lead to an equilibrium in which prices equal the rationally discounted value of expected cash flows, and in which the cross section of expected returns depends on the cross-

section of systematic risks. Even if some investors are irrational, the theory argues their demands are offset by arbitrageurs and thus have no significant impact on prices.

Da, Z., Engelberg, J., & Gao, P. (2014). "The sum of all FEARS investor sentiment and asset prices," *The Review of Financial Studies*, 28(1), 1-32.

Objective

- How can we measure investor sentiment? (market-based measures i.e. volume, IPO returns etc. (noisy), surveys (not live & subjective)...solution: internet search volume)
- Can internet search volume predict asset prices?

Methodology

- Volume of queries related to household concerns (e.g., "recession," "unemployment," and "bankruptcy") to construct a Financial and Economic Attitudes Revealed by Search (FEARS) index: $FEARS_t = \sum_{i=1}^{30} R^i(\Delta ASVI_t)$ where $\Delta ASVI_{jt} = ln(SVI_{jt}) - ln(SVI_{jt})$and SVI = Search volume Index from google.
- The researchers took the 30 search terms that are the most important for returns using backward rolling regression on market returns.
- They then measured the FEARS index ability to predict returns using: $return_{i,t+k} = \beta_0 + \beta_1 FEARS_t + \sum_m y_m Control_{i,t}^m + u_{i,i+k}$
- Then used two measures of stock market volatility to see the relationship between FEARS and volatility.
    - Realized volatility (RV) using an ARFIMA model: $(1-L)^d(adj\ rv - \beta_1 FEARS_t - \sum_m \beta_m Control_{i,t}^m) = (1-L)\varepsilon_t$
    - CBOE daily market volatility index (VIX) using an ARFIMA model: $(1-L)^d(adj\ vix - \beta_1 FEARS_t - \sum_m \beta_m Control_{i,t}^m) = (1-L)\varepsilon_t$
    - Then finally, tested FEARS and fund flows using: $flow_{i,t+k} = \beta_0 + \beta_1 FEARS_t + \sum_m y_m Control_{i,t}^m + u_{i,i+k}$

Findings

- A negative contemporaneous correlation between FEARS and stock market returns. Increases in FEARS correspond with low returns. FEARS also predicts short-term return reversals in the days following, consistent with sentiment induced temporary mispricing. The reversal is strongest among stocks with higher beta, higher volatility, greater downside risk consistent with the predictions in Baker and Wurgler (2006, 2007).
- A positive contemporaneous correlation between FEARS and safe assets (treasury bonds) i.e. a flight to safety and likewise this relationship reverses in the following days.
- A positive contemporaneous relationship between FEARS and Volatility (VIX or realized). This relationship is also temporary and reverses in the days following.
- They analyse mutual fund flows (90% is held by individual investors) as a proxy for noise traders. FEARS predicts significant outflow from equity funds one day after an increase in FEARS and an inflow to bond funds one day after a significant withdrawal from equity funds. This also indicates noise traders flight to safety.
- Taken together, the results are broadly consistent with theories of investor sentiment.

Ben-Rephael, A., Da, Z., & Israelsen, R. D. (2017). "It depends on where you search: institutional investor attention and underreaction to news," *The Review of Financial Studies*, 30(9), 3009-3047.

Objective

- Information needs to attract investor attention before it can be processed and incorporated into asset prices via trading.
- Limited investor attention is often associated with slow information diffusion and underreaction to news.
- We propose a novel measure of institutional investor attention using the news searching and news reading activity for specific stocks on Bloomberg terminals.

Methodology - *The paper has some really good graphs illustrating the VAR effect of AIA leading DADSVI

- We define abnormal institutional attention (hereafter, AIA) as a dummy variable that is equal to one when there is a spike in institutional investor attention during that day, and zero otherwise.
- Compared to other measures that are indirect or based on equilibrium outcomes, such as returns and trading volume, AIA directly reveals institutional investor attention.
- AIA directly identifies the news that attracts institutional attention.
- The likelihood of an institutional attention shock decreases monotonically from Monday to Friday.
- Finally, in the cross-section, larger and more volatile stocks with greater analyst coverage are more likely to experience institutional attention shocks.
- AIA and the Google search-based measure are positively and significantly correlated at the daily frequency, they explain less than 2% of each other's variation.
- Calculated Mean, Median and SD for each of the samples across 16 variables including AIA, DADSVI (retail attention), and Size
    - Average stocks in the full sample experience abnormal institutional and retail attention on 8.9% and 9.2% of trading days.
    - Average firm size is $6.2B, trading volume and intraday volatility is also higher during EA's.
- A vector autoregression (VAR) analysis reveals that AIA leads retail attention, confirming that institutional investors have greater resources and stronger incentives to quickly pay attention to news.
    - Attention constraints are more likely to be binding for retail investors. For example, we find that retail attention allocated to a given stock is significantly lower when other stocks are in the news on the same day.

Findings

- We find strong and consistent evidence that institutional attention facilitates information incorporation for both types of announcements.
    - Announcements accompanied with abnormal institutional attention experience larger returns (in absolute terms) during the announcement day and very little subsequent price drift.
    - Post-announcement drifts come almost exclusively from announcements with limited institutional investor attention.
- We find that retail attention does not facilitate the incorporation of information during earnings and recommendation change announcements.
- We also examine the profitability of calendar time portfolio strategies using earnings announcement and recommendation change events.
    - Our results confirm that a long-short portfolio of stocks with AIA equal to zero that is long on positive news events and short on negative news events earns around 63 to 95 basis points over a period of five to ten trading days.
    - A portfolio that captures the differences in drifts (i.e., low AIA minus high AIA) reveals a positive and statistically significant difference in drifts that is economically large.

Week 6: Currency Markets

Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A. (2012). “Currency momentum strategies,” *Journal of Financial Economics*, 106(3), 660–684.

Objective

- Investigate the prevalence of momentum in the foreign exchange market
- Assess the profitability and feasibility of momentum-based trading strategies in the foreign exchange market
- Test whether there are similarities with carry-trade trading strategy
- Compare to momentum in other assets to see if there are common root causes of the phenomenon

Methodology

- Monthly excess return calculated as RX = ft – St+1 = i^kt –it – log change spot rate
- $R_x = F_t - S_{t+1} = i^k t - it - log(\Delta S \quad)$?
- Portfolios are then constructed based on a formation period of 3,6,9, and 12 months and then held for 3,6,9 and 12 months
- Then to test whether these strategies could have been implemented in real time they sort the 144 possible strategies into 9 portfolios from best to worst based on lag returns for 1,3,6,9,12,60 and 120 months
- Test the relationship between MOM and CAR through correlation matrix and double sort portfolios
- Test for inverted “U” by for every monthly portfolio formed of 1,6 and 12 holding portfolios they are held for 60 months
- Double sort portfolios based on idiosyncratic risk, country risk and ER volatility and then do tests accounting for currencies that were not tradable or very difficult to

Findings

- Best formation and holding strategy of 1,1 delivers excess return 10%
- High low momentum trading strategy yields 8% return at a month lag so it was feasible to implement the strategy in sample.
- Momentum is not related to the carry trade strategy
- Not significantly related to any macro-economic variables or to the three standard FF risk factors
- Momentum returns are very time varied and thus a long investment horizon is needed to profit, impeding arbitrage by many big FX participants like HF’s, trading desks and asset managers
- Exhibits the inverted “U” shape seen in stock returns showing initial underreaction and high returns followed by overreaction and low returns
- Momentum returns are being driven by currencies with high country risk, idiosyncratic risk and exchange rate volatility
- Accounting for transaction costs and capital controls do not eliminate profits
- Momentum in the FX market demonstrates similar properties to momentum in both bonds and stocks; stocks with high credit risk are main drivers and bonds with non-investment grades are main drivers

Corte, Pasquale Della, Steven J. Riddiough, and Lucio Sarno (2016). "Currency premia and global imbalances" *The Review of Financial Studies*, 29(8), 2161-2193.

Objective

- Does the exposure to a country's external imbalances explain currency risk premia?

Rationale:

- A global imbalance risk factor that captures the spread in countries' external imbalances and their propensity to issue external liabilities in foreign currency explains the cross-sectional variation in currency excess returns
- Debtor countries offer a currency risk premium to compensate investors willing to finance negative external imbalances

Methodology

Sample of fifty five currencies and a subsample of fifteen developed countries for the period 1983 to 2014. Uses daily spot and one month forward exchange rates from the USD from Barclays and Reuters.

Hypothesis 1: Currency Excess returns are higher when the funding (investment) country is a net foreign creditor (debtor) and has a higher propensity to issue liabilities denominated in domestic (foreign) currency

- They test J1 by forming portfolios sorted on external imbalances, and the share of foreign liabilities in domestic currency to examine whether they provide predictive information for the cross section of currency excess returns.
- They show that this portfolio sort generates a sizable and stat significant spread in returns, confirming hypo 1, that currency excess returns are higher for net-debtor countries with higher propensity to issue liabilities in foreign currency.

Hypothesis 2: In the presence of a financial disruption (i.e., risk-bearing capacity is low and global risk aversion is high), net-debtor countries experience a currency depreciation, unlike net-creditor countries

- They test H2 by doing a battery of panel regressions, finding evidence in favour of said hypothesis.

Findings

- This paper sheds light on the macroeconomic forces driving currency risk premia - sorting currencies on net foreign asset positions and a country's propensity to issue external liabilities in domestic currency generates a large spread in returns
- A risk factor that captures exposure to global imbalances and the currency denomination of external liabilities explains the bulk of currency excess returns in a stranded asset pricing model
- When risk aversion spikes, net debt nations experience a sharp currency depreciation

Colacito, Riccardo, Steven J. Riddiough, and Lucio Sarno (2020). "Business cycles and currency returns," *Journal of Financial Economics*, 137(3), 659-678.

Objective

- Does a country's business cycle (macro-economic factor) explain excess currency returns?
- $R_x = F_t - S_{t+1} = i^k t - it - log(\Delta S \quad)$ - Based on the uncovered interest parity
- Where rx is excess return, ft is the forward price, St+1 is the spot price, ikt is the foreign currency interest rate, it is the home currency interest rate, and ΔS is the change in the log spot exchange rate.

Methodology

- Measure macroeconomic conditions using the output gap, defined as the difference between a country's actual and potential level of output, for a broad sample of 27 developed and emerging market economies.
- The output gap is defined as the logarithm of the difference between the actual (yt) and "potential" (y¯t) output: gapt = yt − y¯t. A country's potential output is not directly observable and must therefore be estimated using four techniques: (i) the linear projection method of Hamilton (2018), (ii) the Hodrick and Prescott (1980, 1997) filter, (iii) the Baxter and King (1999) filter, and (iv) the quadratic trend specification. This is done via time series GAPTS and cross sectional GAPCS. Note: Unlike the cross-sectional strategies described above, the GAPTS strategy is not dollar neutral because the number of currencies with output gaps above the US varies over time. The strategy is therefore exposed to any (macro) factor that impacts the evolution of the US dollar over time
- Next they rank the countries output gap relative to the US output gap and create 5 portfolios - Portfolio 5 corresponds to countries with the highest output gap relative to the US, whereas Portfolio 1 comprises countries with the lowest output gap relative to the US.
- We refer to the zero-cost dollar-neutral strategy that takes a long position in Portfolio 5 (P5) and a short position in Portfolio 1 (P1) as the GAPCS strategy. - tradeable investment portfolio that exploits the relative cross-sectional spread in business cycle conditions around the world.

Findings

- Business cycles (proxied by a country's output gap) are a key driver and powerful predictor of both currency excess returns and spot exchange rate fluctuations in the cross-section and this predictability can be understood from a risk-based perspective.
- Cross-sectional predictability arising from business cycles stems primarily from the spot exchange rate component rather than from interest rate differentials. That is, currencies of strong economies tend to appreciate and those of weak economies tend to depreciate over the subsequent month
- Both cross sectional and time series generate excess returns. However, time series performs worse than cross sectional during times of crisis.
- The findings can be used in real time as a trading strategy going long (short) currencies issued by countries with output gaps above (below) the US.

Week 7: Market Imperfections

Ljungqvist, A. and Qian, W. (2016). "How constraining are limits to arbitrage?" *The Review of Financial Studies*, *29*(8), 1975-2028.

Objective

- Do short selling firms earn abnormal returns net shorting costs after releasing short reports?
- How do short reports influence market prices?
- Do all short reports generate the same response?
- Which firms tend to be targeted by these short reports?
- Identify whether mispriced stocks with higher costs to arbitrage can be corrected.

Background

- Stocks that have high costs to arbitrage such as relatively high put prices, high shorting fees or low availability of shares available for shorting makes it difficult for arbitrageurs to correct mispricing. Attempting to short these stocks is risky due to being exposed to greater noise trader risk and higher possibility of margin calls as there are high shorting costs and inability to greatly influence share prices resulting in an unknown period of time for mispricing to correct itself.
- **Short report firms dedicated to providing new information** to the public in the form of short reports may be able to correct mispricing on stocks even with high costs to arbitrage by exposing this mispricing.
- This would theoretically be through increased selling by longs and/or increased shorting by other market participants after the short report is released.
- Hence arbitrageurs with small amounts of capital or limited ability to short can greatly influence prices in a short defined period of time.

Methodology

- Data consists of 31 arbitrageurs with 358 short reports for the sample period July 2006 to December 2011.
- Event studies are conducted based on the date the short report is released and looks at a variety of information such as trading volume, institutional ownership, volatility, SEC actions etc.
- 1-day abnormal returns, 60-day cumulative abnormal returns, and estimated trading profit are calculated using the 3 pricing models from the date a short report is released.
- Surveys of these arbitrageurs to identify the costs and process of generating new information.
- Analysis of short report content identifies whether it produces new information or repeats existing information and the basis/reasoning for why they believe the firm is mispriced.
- Credibility of a short report firm is dependent on the CAR of its past reports.

Findings

- 295 of 358 short reports tend to produce new information with their basis for mispricing including financial misreporting or red flag events. (Table 4). 63 of 358 short reports simply repeat existing information and are essentially sell recommendations.
- Short report firms tend to make 22% abnormal profit net shorting & information costs.
- On day 0, prices on average fall by 7.54% relative to the 4 factor model. Follow-on reports (after the first short report) fall on average 3.1%. These are statistically significant and suggest that these reports contain new and believable information. Also, significantly increased SEC filing views on the target firm for 4 days after a report is released.
- Information in these reports are generally correct after more confirmation/research by market participants. Over a 3-month period, prices continue to fall resulting in a price reduction of around 21.4% to 26.2% relative to day -1. This is supported by lawsuits, SEC investigations, auditor resignations in Table 7. 90% of firms targeted by short reports result in some sort of action being taken such as fraud being discovered, earnings restated etc.

- The average market value drop for target firms is around $119.7M over 3 months and $133M over a 1-year period.
- Volatility of the stock significantly increases by 236% on day 0 and remains elevated for a week. Trading activity increases by 339% and remains elevated for 23 trading days. This suggests that it takes time for investors to incorporate this information.
- Pricing correction is mainly due to increased selling by shareholders since shorting and put options volume are economically small due to constraints and expensive and that long trading volume increases by 524%.
- Institutional transactions are mostly sales with no increase in buying as aggregate sales from institutions increased by 123%. Shares available for shorting also decrease. This suggests retail investors are the ones who are purchasing these shares.
- Returns on short reports are higher from firms that were more credible in the past and provides new information to the market compared to those which have a less credible history and simply restates publicly known information.
- Overall, mispriced stocks with high costs to arbitrage can be corrected.

Jylhä, P. (2018). “Margin requirements and the security market line.” *The Journal of Finance*, *73*(3), 1281-1321.

Objective

- To identify whether leverage constraints are responsible for the observed flattening of the securities market line (SML)

Background

- Empirically, the SML has been flat compared to what is expected under the CAPM. Hence low-beta stocks earn higher than expected returns while high-beta stocks earn lower than expected returns.
- One theoretical explanation is leverage constraints. When investors want to achieve a higher beta portfolio one would borrow the risk-free asset and purchase the optimal/market portfolio. However, if there are binding leverage constraints, one would simply have to purchase higher-beta stocks, causing the prices of those high beta stocks to increase relative to low beta stocks, which in turn flattens the SML.
- Federal Reserve initial margin requirements have changed 22 times over the sample period.
- Pension, mutual funds, international investors etc may have different binding initial margin requirements. However, in sample, individual US investors provided the majority of capital.

Methodology

- Leverage constraints are proxied by U.S government mandated initial margin requirements instead of the commonly used TED spread which is simply the difference between the LIBOR and treasury rate. TED spread is a worse measure of leverage constraint as it rather measures the cost of leverage (or liquidity premium on treasuries) which may (does) not constrain leverage. TED spread is also endogenous since it is also influenced by investor portfolio choice i.e. demand for treasuries/risk-free assets.
- The below equation models the relationship between the expected return on a stock and the expected return on the market and beta. *Ψ* measures the shadow price of the margin constraint and *m* represents the initial margin requirement. When m is 0, expected return on a stock is equal to the beta of the stock * expected return on the market which is simply the original SML equation. When *m* exceeds 0, i.e. a margin requirement exists, we observe a higher intercept and a flatter SML line.

$$E\left(r_s^e\right) = \psi m + \beta_s \left[E\left(r_M^e\right) - \psi m\right]$$

- Determine whether initial margin requirement changes are exogenous by a linear and logit regression. If it is exogenous, the probability of an initial margin requirement change should not be correlated or predicted by lagged economic or market variables/conditions (and vice versa) that also influence investor preferences/portfolio choice/the SML. Examples include market volatility etc in table 2, table4
- Linear regression is conducted with estimated SML slope and intercept being regressed onto a lagged initial margin requirement variable. - table 6

$$intercept_t = a_1 + b_1\, margin_{t-1} + c_1\, r^e_{M,t} + d_1\, X_t + u_{1,t},$$

$$slope_t = a_2 + b_2\, margin_{t-1} + c_2\, r^e_{M,t} + d_2\, X_t + u_{2,t}.$$

Findings

- A change in the initial margin requirement is negatively correlated with a change in the amount of credit/leverage used in the market. It is also considered to be exogenous.
- SML slope is negatively correlated with margin requirements. (flatter slope as m increases)
- SML intercept is positively correlated with margin requirements.
- Fails to explain the negative sloping SML curve when initial margin requirements are between 75% and 100%. Should be positively sloped regardless of leverage constraints.
- R^2 value is below 2% indicating other factors also influence the SML.

Weller, B. M. (2018). Does Algorithmic Trading Reduce Information Acquisition? *The Review of Financial Studies*, *31*(6), 2184-2226.

Objective

- Does algorithmic trading discourage and reduce the incentive for information acquisition?
- If so, when does this occur?

Intuition

If algo trading discourage fundamental information search then earnings announcements come as more of a surprise resulting in a high price jump ratio & vice versa.

Methodology

- **Absolute Cumulative Abnormal Return (ACAR)**
  Shows how much information might be available to acquire
  $$CAR_{it}{}^{(k_1,k_2)=} = \sum_{t=k_1}^{k_2} (r_{it} - a_i - \sum_{m=1}^{M} \beta_{im} r_{mt}) = \sum_{t=k_1}^{k_2} \varepsilon_{it}$$
  Where i = stock, t = date, k = start and end dates around announcement date T, $\alpha$and β= estimate from an M-factor model and r = log return
- **Price jump ratio**
  Quantifies the share of information acquired and incorporated into prices pre-announcement
  Normalizes the CAR bya measure of total announcement-related variation
  $$jump_{it}{}^{(21,2)} = \frac{CAR_{it}{}^{(T-1,T+2)}}{CAR_{it}{}^{(T-21,T+2)}}$$
- **Algorithmic trading proxies**
  (1) Odd lot volume ratio (2) trade-to-order volume ratio (3) cancel-to-trade ratio (4) average trade size
  Higher of (1) and (3) indicate more algorithmic trading
- **Relationship between price jump ratio and algorithmic trading:** panel regression
  $jump_{it}{}^{(21,2)} = \alpha + \beta x_{it} + \gamma \times controls_{it} + \varepsilon_{it}$where x= AT proxies, i = stock, and t = date (repeated with a lag log price variable)
- **Relationship between price response ratio and algorithmic trading:** panel regression
  $$x_{it}{}^{(k)} = \zeta + \eta lprice_{it}{}^{(k)} + \theta \times controls_{it}{}^{(k)} + \delta_{it}$$
  $$responseratio_{it}{}^{(k,21)} = \alpha + \beta^{(k)} x_{it}{}^{(k)} + \gamma \times controls_{it}{}^{(k)} + \varepsilon_{it}$$

Findings

- Higher algorithmic trading is associated with a decrease in the fraction of earnings announcement price impact that occurs pre-announcement - it decreases information acquisition across all proxies of algorithmic trading
- Strong evidence against there being no information gap across the pre-announcement and post-announcement period

Week 8: Return Seasonalities

Wagner, M., Lee, J., Margaritis, D. (2020). “Mutual Fund Flows and Seasonalities in Stock Returns” R&R *Journal of Banking and Finance*.

Objective

- Can mutual fund flows explain the Sell in May effect and the January effect?

Methodology

- Flows are simply calculated by taking the difference in total net assets of funds after accounting for returns: $Flow_{it} = TNA_{it} - TNA_{i,t-1}(1 + r_{it})$
- To test for seasonalities in stock returns the researchers use a simple regression: $r_t = \mu + \beta_1 Season_t + \beta_2 Flow_t + y^i Control_t + \varepsilon_t$
- where rt is the return on the stock index for month t, μ is a constant and εt is the error term. Season is a seasonal dummy for either the Sell in May effect or January effect.
- Given that (1) fund flow can explain the seasonal pattern in stock returns and (2) fund flows are predictable, the researchers then decompose fund flows into expected and unexpected flows using a seasonal ARIMA model.
- They then try to analyse two competing hypotheses (price pressure and feedback trading hypothesis) for the co-movement of fund flow and market returns (reverse causality) using a VAR model.
- To test whether flow helps explaining the January regularity alongside other alternatives they first estimate abnormal returns and flow in January using: $r_t = \mu_t + \beta_{1r_{t-1}} + \beta_2 Jan_{1995} + \beta_3 Jan_{1996} + \ldots + \beta_{21} Jan_{2014} + \varepsilon_t$ and: $Flow_t = \mu_t + \beta_1 Flow_{t-1} + \beta_2 Jan_{1995} + \ldots + \beta_{21} Jan_{2014} + \varepsilon_t$
- They compare their flow method to the maximum potential tax-loss selling at the end of a year (PTS), which is another method used to analyse the Jan effect in the literature.
- They then run a regression where the dependent variable is the estimated January effect using equation (4) and where abnormal flow is estimated using equation (5) and PTS.

Findings

- The Sell in May effect is positive in years when fund flows during the winter months are higher than those during summer months.
- After controlling for mutual fund flows the Sell in May effect becomes insignificant.
- Excess fund flow in winter months explains about half of the variation in the Sell in May effect.
- Fund flows help to explain the January effect and better than other methods (PTS is insignificant in their regression whereas Flow is statistically significant)
- Both the January effect and the Sell in May effect are primarily driven by flows of retail funds and unanticipated flows.
- The unrestricted VAR model shows that flows contain information on returns and vice versa (two-way causality). Consistent with the price pressure (investors buying shares results in upward moves in share markets) and the positive feedback trading hypothesis (investors buy shares in response to good stock market performance).

Keloharju, M. , Linnainmaa, J.T. , Nyberg, P. (2021). “Are return seasonalities due to risk or mispricing?” *Journal of Financial Economics*, 139, 138–161.

Objective

- Risk-based explanation is that seasonality stems from seasonality in systematic risk or in investor demand.
- Mispricing-based explanation is that if seasonality is caused by mispricing then there must be seasonal reversals
- Assess whether there is evidence for a mispricing based explanation of seasonality in stock return by testing for the presence of both seasonality and seasonal reversals.

Methodology

- Plot the average coefficients from cross-sectional regressions of month t returns against month $t - k$ returns and show how different assumptions affect same month and other month predictive power
- Construct a model to produce simulated returns based on the assumption that stocks exhibit LT reversals, seasonalities and perfect seasonal reversals such that same month returns and other month returns sum to zero, and then run these returns through the same regression.
- Do monthly FM cross-sectional regressions adding the variables of same month and other month returns, they then do the same for daily returns adding same weekday and other weekday variables.
- Presence outside of US stocks: Lagged same month and other month returns using international stock returns, country level indices and commodities
- Relationship with sentiment: FM regressions using historically high and low mood months returns
- Testing Seasonality factor: Regress seasonality factor returns, and seasonal reversal factor returns on returns to the 4 Carhart factors to test if seasonality and seasonal reversal information is captured by these factors
- Construct optimal historical portfolios limiting the portfolios to exposures to different factors

Findings

- Significant evidence of a mispricing-based explanation for seasonality due to the presence of seasonal reversals
- Seasonality and seasonal reversals are present both daily and monthly, and exist outside of US stock returns, in international stock returns, country level indices and commodities.
- Seasonality and reversals appear in both high and low mood months and non-high or low-mood months
- Seasonality and seasonal reversals both capture information that is not captured by the four Carhart factors.
- When allowing exposure to the seasonal and seasonal reversals factors the Sharpe ratio of the optimal historical portfolios increases dramatically by an average of 0.6 and shows the importance of them.

Hirshleifer, D., Jiang, D., Meng, Y. (2020). “Mood betas and seasonalities in stock returns,” *Journal of Financial Economics*, 137 (1), 272–295.

Objective

- Introduces; Mood Beta defined as the asset’s return sensitivity to investor mood variation
- Hypothesizes that seasonalities are induced by seasonal variations in investor mood
- Mood is based on seasons rather than sentiment which is linked to a macro perspective on the economy; look at both the time-series and cross section (first study to do so)
- Proxies for Mood: **Positive mood state**; Friday, January, March due to upbeat time of week anticipating the weekend ; new year; recovery from SAD; **Negative mood state:** Monday, September, October; downbeat start of the week SAD (Seasonal affective disorder)
- **Assumption:** Mood varies predictably across seasons (Proxies motivated based on prior lit in behavioural finance)

Methodology

- Designed to test two key hypotheses:
- 1) Mood recurrence and reversal effects: In the cross-section, security’s historical returns are positively correlated with its future seasonal returns under a **congruent**-mood **(repeating)** period and negatively related to its future seasonal returns under a **non-congruent**-mood **(opposing)** period.
- 2) The mood beta effect: Mood beta; (measure of assets return sensitivity to mood) positively predicts the cross section of security returns during high mood periods and negatively predicts cross section of returns during low mood periods

Testing hypothesis 1) Such regressions help to assess whether certain stocks tend to repeatedly outperform other stocks during the congruent-mood months year after year

- $RET_{high(Low), t} = \eta_{k,t} + \gamma_{k,t}\, RET_{high(Low), t-k} + \varepsilon_t$

- Estimate FMB regressions of hypothesised high or low mood months across assets on their historical seasonal returns earned; during these prespecified congruent mood-months at three sets of annual lags
- **k = 1, 2–5,** and 6–10 (multiple year lags for k>1) and **$RET_{high(Low),t}$ is the current mood month** (high or low) asset return in year t, and [$RET_{high(Low), t-k}$] is the historical average congruent (high or low) mood month return in year t − k for the same asset.
- Example: annual lag k = 1; independent variable; average Jan/March return of asset of prior year when forecasting Jan/March returns of current year - same holds for Sept/Oct

Testing hypothesis 2) note: monthly regression is the same for weekly (swap out terms)
Mood beta is measured by an asset’s return sensitivity to the equal-weighted market excess returns during the past high and low mood periods

- 1st stage - compute mood betas with time-series regressions:
- $XRET_{i\ moodmonth} = \alpha + \beta_{iMoodmonth} * XRET_{A,moodmonth} + \varepsilon_t$: Mood beta estimated for each asset, using 10-year rolling window of monthly returns;includes 8 months in a year; 4 prespecified and 4 realised high and low mood months
- 2nd stage - Fama MacBeth regressions:
- $RET_{high(low),t} = \eta_{k,t} + \lambda_{k,t}\, \beta_{iMoodmonth,\ t-k} + \gamma_{k,t} RET_{high(Low),t-k} + \varepsilon_t$

Findings

- Seasonal variations in investor mood are in part responsible for both aggregate and cross-sectional return seasonalities
- Assets that outperform in **past periods** when investors are in ascending moods tend to
- Outperform in **future periods** when an ascending mood is expected
- Underperform in **future periods** when a descending mood is expected

- High mood beta stocks outperform during future ascending mood periods and underperform during future descending mood period

Week 9: Climate Risk

Bolton, Patrick and Marcin Kacperczyk (2020) “Do investors care about carbon risk?” NBER Working Paper 26968. http://www.nber.org/papers/w26968

Introduction: Carbon emissions are a potential considerable risk for investors.
Recent developments: Renewed policy and further engagement

- Paris COP 21 climate agreement commitment to limit global warming to well below 2 degrees of pre-industrial levels.
- Argue that even despite Trump there was still a significant level of momentum toward transitioning to a low carbon economy.
- Accountability is shifting from government organisations to non-governmental organisations.
- Institutional investors have followed suit with some types of institutional investors on a relative basis taking more notice. Mutual and insurance funds, while hedge funds are an outlier.

RQ/ Motivation:

- How do CO2 emissions affect stock returns?
    - Systematically explores whether investors demand a carbon risk premium by looking at how stock returns vary with CO2 emission across firms and industries.
    - Undertake cross-sectional analysis asking whether carbon emissions affect cross sectional US stock returns.

Motivations

- Asset pricing literature hasn’t incorporated corporate carbon emissions.
- Observation of renewed policy developments and increased engagement.
- Lack of consensus view among institutional investors regarding the explanations for this.

Hypothesis:

- H1: Carbon Risk Premium; Key determinant: Systematic factor
- H2: Market inefficiency, or carbon alpha
- H3: Divestment Hypothesis: Key determinant: Exclusion methodology

Methodology:

- **Data:** Construct a primary database from 2005-2017 by matching:
    - FactSet: Cross sectional returns, fundamentals & institutional ownership
    - Trucost data: Corporate carbon and other greenhouse gas emission
    - Broken down into three groups of emissions
        - Scope 1 emissions: direct from owned or controlled sources
        - Scope 2: emissions are indirect emissions from the generation of purchased energy.
        - Scope 3: value chain and broken into upstream and downstream
- Use Cross sectional regression model:

Results:

- Significance at total emissions level, year on year growth level, while it isn't a significant effect on an emissions intensity level on returns.
- Our main finding that stock returns are positively related to the level (and changes) of carbon emissions.
- Carbon alpha hypothesis is rejected.
- In contrast to prior literature: Investors only appear to divest at a scope 1 level. Difference between hedge funds and insurance, mutual and pension funds.
- Premium larger following Paris agreement at a total emissions level and also growth rate in total emissions level, however emissions intensity isn’t.

Conclusion:

- Firms with higher emissions generate higher returns (after controls)
- Carbon risk premium is statistically and economically significant across all scopes.
- When breaking down institutional owners, mutual funds, pension funds and insurance companies are underweight companies with high levels of emissions, however limited to scope 1.

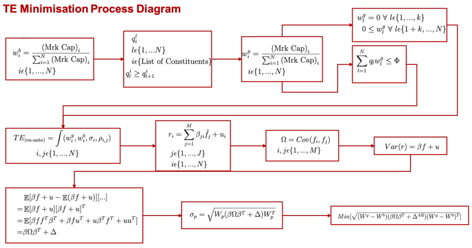
Andersson, Mats, Patrick Bolton, and Frederic Samama (2016) “Hedging climate risk,” *Financial Analysts Journal*, 72(3), 13-32.

Objective

- How to hedge climate risk?

Methodology

TE Minimisation Process Diagram



Findings

- Dynamic Investment Strategies enable long-term passive investors to hedge climate risk without sacrificing

- Pure-play indexes focusing on renewable technology, clean technology and/or environmental services
- Decarbonized indexes (‘Green Betas’ indexes) who's basic construction principle is to remove/underweight companies with relatively high carbon-intensities from standard benchmarks (S&P 500, NASDAQ 100)
- Decarbonized indexes will perform the same as the benchmark until CO2 emissions are priced meaningfully and consistently with limits introduced. After, they will outperform the benchmark

The basic idea is to construct a portfolio with fewer constituents but a similar aggregate risk exposure level to all priced risk factors as Koch and Bassen (2013) found evidence carbon risk is asymmetrically concentrated in a few firms. The only aggregate risk exposure difference is in respect to carbon risk

- Minimise TE: Eliminate high carbon footprint composite stocks, with the objective of meeting a target carbon foot reduction from the green index, reweight the remaining stocks in order to minimise tracking error with the benchmark index (Preferred)
- Maximise CFR: The dual formulation is to begin by imposing a constraint on maximum allowable tracking error with the benchmark index and then, subject to this constraint, exclude the reweight composite stocks in the benefit

A filtering rule that excludes the stocks of companies with the highest absolute emission levels will tend to be biased against the largest companies, which could result in a high TE for the decarbonized index. A filter based on a normalized measure would be better at selecting the least wasteful companies in terms of GHG

- Simple and effective climate risk– hedging strategy for passive long-term institutional investors and complement to climate change mitigation policies (GHG emission controls, Cap & Trade Carbon Credits vs Tax, Solar and wind subsidies). Index decarbonization can boost support for such policies from a large fraction of the investor community
- As more and more funds are allocated to decarbonized indexes, stronger market incentives will materialize, inducing the world’s largest corporations—the publicly traded companies—to invest in reducing GHG emissions
- The encouragement of climate risk hedging can have real effects on reducing GHG emissions even before climate change mitigation policies are introduced.
- The anticipation of the introduction of climate change mitigation policies will create immediate incentives to initiate a transition to renewable energy

A simple, costless policy in support of climate risk hedging that governments can adopt immediately is to mandate disclosure of the carbon footprint of their state-owned investment arms (public pension funds and sovereign wealth funds)

A more direct way to support investment in low carbon, low-TE indexes is to push public asset owners and their managers to make investments in above ground, diversifiable, non-energy companies

- Governments could thus play an important role as catalysts to accelerate the mainstream adoption of such investment policies

Engle, R., S. Giglio, H. Lee, B. Kelly, and J. Stroebel (2020) "Hedging climate change news," *Review of Financial Studies*, 33(3), 1184-1216.

Objective

Implement a procedure to dynamically hedge climate change news

- Use a mimicking portfolio approach to build climate change hedge portfolios
- The approach is reinforced by using third party ESG scores (MSCI and Sustainalytics) of firms to model their climate risk exposure; this yields industry balanced portfolios that perform well in hedging innovations in climate news both in and out of sample
- Main contribution: By hedging innovations in news about long-run climate change, period by period an investor can hedge long run exposure to climate risk

Methodology

- Construct 2 News indexes: WSJ Climate change news index & CH negative climate change news index
- WSJ: collect 19 climate change white papers from sources such as IPCC; contextual analysis to convert WSJ term into td-dif; term frequency inverse document frequency
- **WSJ index uses WSJ** news as it's a salient new source for investors about climate risks and has access to complete articles as early as 1980's which provides flexibility in choosing how build news index to measure
- **CH negative climate change news index** - specifically focuses on bad news regarding climate change

Construction of Hedge Portfolios - Variables: Rt, returns; CCt; climate risk shocks Bcc and B; risk exposures of the n assets to the climate news factor

- To construct portfolios that hedge climate change news: Author's observe which stocks rise which fall in value when (negative) news about climate change materializes.
- They construct portfolios that overweight stocks that perform well when negative news is announced,
- An investor will have a portfolio that will increase in value whenever negative news about climate change materializes.
- Consistently (period by period) update this portfolio based on new information about the relationship between climate news and stock returns, this leads to a portfolio that pays off as climate change materialises
- Key assumption: portfolios assumed to have constant risk exposure to climate news over time

Have monthly data from Sept 2009-Dec 2016: Main variables of interest: CC WSG, Negative news for time t

- Variables are the two proxies for innovation in climate change news
- Use Sustainalytics E-scores (700-800) firms & MSCI E-score (1700-1900 firms) as part of portfolio construction
- Summary stats: Are in terms of time series; examine number of firms for MSCI and Sustainalytics & mean scores over time - E scores are similar for both Data Sources; run a correlation analysis to determine whether they capture the same characteristics - found a 0.65 correlation indicates that both data sources capture the same exposure to climate change risk
- Key issue; discontinuous breaks and changes to models to calculate Escores - proprietary data they could not obtain - presents data integrity issues - address this through 2 methods: 1) Absolute scores: demanding monthly data i.e. removing the mean of data from observations; 2) Ranked scores; rank firms observations based on E scores; demean then rescale E scores between -0.5 and 0.5; may present issues with disregarding absolute values

Findings

- **In sample:** WSJ; E score portfolio performance has a significant positive relationship with periods of more innovation on negative climate news - indicating E score's have hedging abilities
- CH negative climate change news: similar results except the MSCI E scores are not significant
- The difference could be caused due to 2 sources news focus; WSJ on general climate change news vs. CH specifically focuses on negative climate news - this implies that MSCI E scores dont effectively hedge **negative new**
- **Out of sample: conduct two tests:** Results: WSJ and Negative news (table 3); hedge portfolios have better returns during periods of positive innovations in terms of climate change risk; column 1 shows correlation between exposure to the risk factor and respective performance - SUS based portfolio's have significantly higher correlation without exposure compared to the other portfolio's constructed - indicates SUS hedge portfolio outperforms in the case of WSJ news

- CH negative climate change news index; MSCI_A and MSCI_R correlation with returns have increased and performed significantly better out of sample; author's suggests that MSCI is better suited to capturing negative climate news
- Overall findings: E scores have hedging abilities in terms of forming portfolio's, Sustainalytics performs well to capture general climate news of WSJ
- MSCI is better suited to capturing negative climate news

Week 10: Market Structure and Stock Returns

Hou, K., and Robinson, D. (2006). "Industry concentration and average stock returns." *The Journal of Finance*, 61, 1927–1956.

Objective

- Does market structure affect firm returns?

Methodology

- **2 hypothesis** - firms in highly concentrated industries earn lower returns because they are better insulated from undiversifiable, aggregate demand shocks, and firms in more concentrated industries engage in less innovation
- **Herfindahl-Hirschman Index (HHI)** used to measure industry concentration
  $HHI = \sum_{i=1}^{I} \quad S_{ij}^{\ 2}$ where i = firm, j = industry, s = market share
- **Relationship between characteristics and concentration:** F-M regression
  $H(Sales)_{jt} = \alpha_t + \sum_{n=1}^{N} \quad \lambda_{nt} X_{jt} + \varepsilon_{jt}$ where n = industry characteristic, t = time period, j = stock, X = industry average characteristics, λ= coefficients
- **Relationship between stock returns and concentration:** concentration spread
  10 portfolios based on HHI quintiles - 5 at firm level 5 at industry level
  $spread = R_{Q5} - R_{Q1}$ where R = portfolio monthly return, Q5 = most concentrated
- **Relationship between stock returns and concentration:** F-M regression at firm and industry level

$$R_{it} = \alpha_t + \sum_{n=1}^{N} \quad \lambda_{nt} X_{it} + \varepsilon_{it}$$

- **Relationship between profitability surprise and concentration:**
  $E_t/A_t = \alpha_0 + \alpha_1 V_t/A_t + \alpha_2 DD_t + \alpha_3 D_t/B_t + \alpha_4 E_{t-1}/A_{t-1} + \varepsilon_t$ where E = earnings, A = assets, V = market value, D = non-dividend paying, D = dividends, B = book equity, fitted value = expected profitability, ε= unexpected profitability, analysed by quintile
- **Relationship between time and concentration premium:** F-M regression
  $\lambda_t^{\ H} = \alpha + \sum_{i=1}^{I} \quad \beta_i F_{it} + \sum_{j=1}^{J} \quad \gamma_j X_{jt} + \varepsilon_t$ where t = month, j = business cycle, F = factor-mimicking portfolio return, X = business cycle t-values, λ= concentration risk premia
- **Relationship between B/M and concentration:** F-M regression and quintile sorting

Findings:

- Concentration based on sales, assets and equity are highly correlated
- Most concentrated industries are smaller in size, are larger in average assets and sales, are more profitable, are expected to be more profitable and have less R&D
- The concentration spread is negative for raw and adjusted (controlled for size, B/M and momentum), indicating more concentrated industries earn lower returns
- Firms in concentrated industries earn lower stock returns than firms in more competitive industries and experience better than expected profitability, so profitability surprises cannot explain prior results
- Existing factors (**FF** - SMB, HML, momentum, **business cycle** - inflation, term spread, T-bill, GDP growth expected GDP growth) cannot fully explain the concentration premium observed, but the premium does appear to increase with HML, inflation rate, T-bill rate, GDP growth rate and expected GDP growth rate, and decrease with SMB, momentum and term spread.
- B/M ratio grows as industry concentration increases, and the spread in returns across B/M quintile portfolios is larger among the most concentrated industries.

Bustamante, M. C., and Donangelo, A. (2017). “Product market competition and industry returns.” The Review of Financial Studies, 30(12), 4216–4266.

Objective

- To explain why competitive industries have higher returns than concentrated industries.

Summary

- Develops a mathematical model that has three channels to explain the returns anomaly:

Operating leverage channel - competition affects firms’ exposure to systematic risk through its effect on profit margins. Intuitively, since firms in more competitive industries have lower profit margins to buffer adverse shocks, these firms have higher operating leverage and hence higher exposure to risk.

Entry threat channel - reduces the expected returns of incumbents due to the value destruction associated with the expected entry of new firms. Given that entry is more likely during expansions rather than contractions, the value destruction due to the entry threat renders the value of incumbents less procyclical and lowers their exposure to systematic risk. In isolation, this channel leads to lower expected returns in more competitive industries with lower barriers to entry

Risk feedback channel - The model shows that industries with higher exposure to systematic risk are less attractive to new entrants

While the operating leverage channel predicts a negative relation between expected returns and either concentration or markup, both the entry threat channel and the risk feedback channel predict the opposite.

Based on the three channels develop the following testable hypothesis:

Hypothesis 1 (unconditional implications for expected returns)
i. For industries with “sufficiently low” levels of operating leverage, expected returns are positively related to concentration and markup (entry threat channel dominates the operating leverage channel)
OL (competition increases risk) v ET channel (competition decreases risk)

ii. For most industries, the level of operating leverage is “sufficiently low” due to risk feedback (entry threat prevents operating leverage from getting to high)

Test - regression
dependent variable = returns. Independant variables = markup/concentration measure + controls
Find - positive relationship consistent with hypothesis 1

Hypothesis 2 (conditional implications for expected returns) The relation between expected returns and concentration or markup is relatively more positive in industries with relatively lower operating leverage
Confirm hypothesis 2

Hypothesis 3 (operating leverage and relative valuation ratios)
i.The average operating leverage is negatively related to concentration and markup
ii.The average earnings-to-price ratios are negatively related to concentration and markup (consistency test for the operating leverage and entry threat channels)

Findings

Results contradict Hou and Robinson article due to the use of census data for concentration and markup as opposed to compustat data. This is a result of the sample selection bias of companies that go public.

We find that competition affects expected asset returns through three distinct channels.

Priyank Gandhi and Hanno Lustig (2015). "Size anomalies in U.S. bank stock returns." *The Journal of Finance*, 70(2), 733-768.

Objective

- Large banks, i.e., banks with a larger balance sheet, more deposits and other liabilities, are less likely to be allowed to fail during financial crises.
  - The equilibrium stock returns investors demand for these bank stocks would be lower.
  - Not market capitalisation, but total book value – govn cares about this more when bailing out firms.
  - the government subsidizes large financial institutions to take on tail risk
- If a bank is deemed too big to fail, the expected return on its stock is lower in equilibrium than that of smaller banks because the government absorbs some of the large bank's tail risk.

Methodology

- Risk-adjusted regressions: Regressed excess returns against the FF3 factors in addition to two credit-risk factors after sorting commercial banks into deciles based on both market cap and book value: f_t=[market smb hml ltg crd]
  -Ltg = excess return on an index of 10-year bonds
  -Crd = excess return on an index on investment grade corporate bonds
- The Size Factor: The second principal component of normal risk-adjusted returns on size-sorted portfolios of bank stocks has loadings that depend monotonically on size.
  - Conduct time series analysis of excess returns against the risk factors and this new size factor – risk factors are FF3 + two credit risk factors

$$R^i_{t+1} - R^f_{t+1} = \alpha^i + \boldsymbol{\beta}^{i,\prime} \boldsymbol{f}_{t+1} + \beta^i_{PC,2} R[PC_2]_{t+1} + \varepsilon^i_{t+1}.$$

Findings

- Statistically significant negative alphas for the largest size portfolios in both book value and market cap for commercial banks
  - Investors price-in implicit guarantees in the financial sector
  - All else equal, a 100% increase in a bank's book value lowers its annual return by 2.23% per annum.
- The second principal component of the risk adjusted returns on size-sorted portfolios of commercial banks is a size factor that has exactly the right covariance with the portfolio returns to account for most of this pricing anomaly.
  - This size factor was constructed to be orthogonal to the FF3 factors + two credit risk factors.
- Government guarantees essentially grant stockholders of large banks a menu of path-dependent put options that can only be exercised after large declines in a broad index of stocks.
  - Kelly, Lustig, and Nieuwerburgh (2011) found that out-of-the-money put options on large banks were cheap during the crisis.
- We show that the financial disaster subsidy of the largest 10 banks increases immediately after bailout announcements – a direct link to bailouts.

Week 11: Bond Market Liquidity

Nils Friewald, Rainer Jankowitsch, and Marti G. Subrahmanyam, (2012). "Illiquidity or credit deterioration A study of liquidity in the US corporate bond market during financial crises," *Journal of Financial Economics*, 105, 18-36.

Objective

- Is liquidity an important price factor in the US corporate bond market?
- Is liquidity risk more pronounced during crisis periods?

Methodology

- They employ a wide range of liquidity measures from previous literature to quantify the liquidity effects in corporate bond yield spreads. Uses time-series and cross-sectional aspects of liquidity for the whole market as well as various important segments, using panel and Fama-McBeth regression respectively.
- Their dependent variable is the corporate bond yield spread, represented by the yield differential relative to that of a risk-free benchmark (treasury yield curve and the swap curve).
- They use a range of liquidity measures as their independent variables: bond characteristics (maturity, age etc), trading activity variables (trading volume, # of trades etc) and liquidity measurements (roll measure, amihud measure, price dispersion measure etc).
- They are interested in how the explanatory power of the independent variables differs in financial crises compared to normal market environments. Therefore, we define the following three sub periods: The GM/Ford crisis (March 2005–January 2006), the subprime crisis (July 2007– December 2008), , and the normal period in between (February 2006–June 2007) which are included as dummy variables.
- Additionally they are interested in how liquidity affects investment grade bonds or speculative bonds differently during crises using two dummy variables.
- **Panel regression:** $\Delta(Yield\ spread)_{it} = a_0 + a_1\Delta(Yield\ spread)_{i,t-1} + a_2\Delta(Trading\ activity\ variables)_{it} + a_3\Delta(Liquidity\ measures)_{it} + a_4\Delta(Rating\ dummies)_{it} + \varepsilon$
- **Fama McBeth regression:** $(Yield\ spread)_{it} = a_0 + a_1\Delta(Bond\ characteristics)_{it} + a_2\Delta(Trading\ activity\ variables)_{it} + a_3\Delta(Liquidity\ measures)_{it} + a_4\Delta(Rating\ dummies)_{it} + \varepsilon$

Findings

- The liquidity proxies in the specified regression models account for about 14% of the explained time-series variation of the yield spread changes.
- The effect of the liquidity measures is far stronger in both the GM/Ford crisis and the subprime crisis and in particular speculative grade bonds.
- All the liquidity proxies considered exhibit statistically as well as economically significant results
- Bonds with higher credit risk also are more exposed to liquidity risk.
- Liquidity is an important factor driving yield spread changes.

Bai, Jennie, Turan G. Bali, and Quan Wen (2019). "Common risk factors in the cross-section of corporate bond returns," *Journal of Financial Economics*, 131, 619–642.

Key points

- Downside risk is the strongest determinant of future bond returns.
- Introduces common risk factors based on the prevalent risk characteristics of corporate bonds – downside risk, credit risk, and liquidity risk-and find that these novel bond factors have economically and statistically risk premiums that cannot be explained by long established bond market factors.
- Newly proposed factors outperform all other models considered in the literature in explaining the returns of the industry and size/ maturity-sorted portfolios of corporate bonds.
- Difference between liquidity risk and liquidity level

Introduction:

- Stock returns have been the key focus of many academics, however less focus has been placed on bond cross sectional returns.
- The bond market and stock market have common factors, however there are many unique factors.
- Common:
    - Based on the same asset then they may share the same variation.
    - Company default risk will decrease if their equity price increases (i.e. the default loss of bonds changes with equity prices.
- Difference/ unique:
    - Credit risk: Credit risk refers to the possibility that a bond issuer fails to make a payment. Overall, it defines the borrower's ability to repay coupon and principal according to its original terms.
    - Downside risk: Bondholders are more sensitive to the downside risk. (Downside risk, when a security potential will result in loss of value when market conditions tend to be poor)
    - Liquidity risk: the OTC participants are mostly institutional investors, and bond trade through OTC, mostly prefer safety, and won't trade with a high frequency, therefore less liquidity. Note two types of liquidity – liquidity level and liquidity risk.
        - Bond market is much smaller however, with higher issuance
        - Increased importance of bonds within institutional portfolios

RQ/ Motivations:

- What are the common risk factors that explain corporate bond returns?
- Conducted via cross-sectional analysis
- Fama McBeth Methodology combining time series and cross sectional approach
- Asset pricing literature has predominantly been focused on the phenomena associated with stock market returns rather than bond returns.
- Enhance understanding of common risk factors.
- More accurate characterisation as there are different features to that of the stock market.

Methodology

Fama-Macbeth regression:

1. Run the time-series regression to the factor loading for each of the risk factor we use here
2. Run a cross-section analysis using the time "t" factoring loading to predict the time "t+1" return on bond, then we can get the factor prices, then we know whether the market prices these risks.

Findings

- Downside, credit & liquidity risk positively predict cross-sectional variation in future bond returns
- A four-factor model with the bond market plus new factors (DCF, CRF, LRF) outperforms all models considered in the literature in explaining the returns of the industry/size/maturity sorted portfolios
- All new factors are statistically and economically significant risk premiums.
- Large alpha is compensation