Some selected asset pricing topics

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1 Conditional CAPM

The traditional static CAPM assume that beta is constant over time. This seems unrealistic because firms' risk changes over time.

$$E[R_i] = \gamma_0 + \gamma_1 \beta_i$$

$$\beta_i = Cov(R_i, R_m)/Var[R_m]$$

Fama and French [1992] empirically study this model and find that: (i) the estimated γ_1 is close to zero or too "flat" and (ii) the strong evidence of size premium againts the CAPM.Jagannathan and Wang [1996] relax two assumptions of the static CAPM: (i) allow beta and market premiums depend on the information set at any given point in time and vary over time and (ii) extending the proxy for the market return to include a measure of return on human capital R^{labor} (in addition to R^{vw}).

Conditional CAPM

$$E[R_{it}|I_{t-1}] = \gamma_{0t-1} + \gamma_{1t-1}\beta_{it-1}$$

$$\beta_{it-1} = Cov(R_{it}, R_m|I_{t-1})/Var(R_m|I_{t-1})$$

Take unconditional expectation of both sides of equation, we have:

$$E[R_{it}] = \gamma_0 + \gamma_1 \overline{\beta}_i + Cov(\gamma_{1t-1}, \beta_{it-1})$$

Intuitions:

- If the covariance between the conditional beta of asset i and the conditional market premium is zero, then the static CAPM is restored
- However, in general, the conditional market risk premium and conditional beta are correlated

Decompose the conditional beta β_{it-1} into three parts: $\beta_{it-1} = \overline{\beta}_i + \upsilon_i(\gamma_{1t-1} - \gamma_1) + \eta_{it-1}$

- The first part is $\overline{\beta}_i$, expected beta
- $\upsilon_i(\gamma_{1t-1} - \gamma_1)$: random variable that perfectly correlated with market risk premium. Here υ_i is *beta-prem sensitivity*, measured the sensitivity of conditional beta to the market risk premium

- η_{it-1}: on average zero and uncorrelated with market risk premium

Replace this decomposition into the unconditional expectation equation:

$$E[R_{it}] = \gamma_0 + \gamma_1 \overline{\beta}_i + Var(\gamma_{1t-1})\upsilon_i$$

Implications:

- First, cross-sectionally, the unconditional expected return on any asset *i* is a linear function of its expected beta and its beta-prem sensitivity
- The beta-prem sensitivity of an asset measures the instability of the asset's beta over the business cycle.
- Stocks with higher expected betas have higher unconditional expected returns. Likewise, stocks with betas that are prone to vary with the market risk premium and hence are less stable over the business cycle also have higher unconditional expected returns.
- Hence, the one-factor conditional CAPM leads to a ***two-factor model*** for unconditional expected returns.

Two-beta model Define two betas as follows:

1. Market beta: $\beta_i = Cov(R_{it}, R_{mt})/Var(R_{mt})$, measure average market risk
2. Premium beta: $\beta_i^{\gamma} = Cov(R_{it}, \gamma_{1t-1})/Var(\gamma_{1t-1})$, measure beta-instability risk

Then the two-beta model in Theorem 1:

Theorem. *If β_i^{γ} is not a linear function of β_i then there are some constants such that $E[R_{it}] = a_0 + a_1\beta_i + a_2\beta_i^{\gamma}$ holds for every asset i.*

Empirical tests: three-beta model

1. Authors use R_{t-1}^{prem}, the yield spread between BAA and AAA rated bonds, to proxy for γ_{1t-1}. Then prem-beta is: $\beta_i^{prem} = Cov(R_{it}, R_{t-1}^{prem})/Var(R_{t-1}^{prem})$. Accordingly, the model is: $E[R_{it}] = c_0 + c_m\beta_i + c_{prem}\beta_i^{prem}$
2. Authors use R_t^{labor}, growth rate in per capita labor income, to proxy for human capital returns. The market beta in this case includes two components: vw-beta and labor-beta or we can write $\beta_i = b_{vw}\beta_i^{vw} + b_{labor}\beta_i^{labor}$. Accordingly, the *Premium-Labor* (PL) imodel is: $E[R_{it}] = c_0 + c_m\beta_i + c_{prem}\beta_i^{prem} = c_0 + c_{vw}\beta_i^{vw} + c_{prem}\beta_i^{prem} + c_{labor}\beta_i^{labor}$.
3. In econometric tests, they use cross-section regression or GMM:

$$E[R_{it}] = c_0 + c_{size}log(ME_i) + c_{vw}\beta_i^{vw} + c_{prem}\beta_i^{prem} + c_{labor}\beta_i^{labor}$$

$$E[R_{it}(\delta_0 + \delta_{vw}R_t^{vw} + \delta_{prem}R_{t-1}^{prem} + \delta_{labor}R_t^{labor})] = 1$$

2 Labor mobility

Actually, firms do not own the labors but just rent them. Thus, labors could leave them to other industries. Which factors will affect the labor mobility? It is labor skills. For example, industry-specific skills such as medical doctors and general skills such as salesperson. If the skill is too industry-specific, the labor supply is less mobile (how a supermarket needs a medical doctor?).

An industry with high mobile labor supply suffers more risks when having industry-specific shocks:

- Less elastic wage: difficult to decrease wage too much when there is an industry-specific shock. Why? Employees will move to another industry.

- High elastic employment and high elastic cash flows: as a result, these firms see the drop in employment and profits (CF) when there is a bad thing.

Thus, high labor mobility (LM) stocks have higher expected returns relative to low LM stocks (a long-short portfolio of LM could earn 5%/year). LM also implies higher implied cost of capital and is positively related to market beta.

Model Production function with normalized capital to unity: $Y_t = A_t L \alpha_t$

L is industry-specific skills and A is total factor productivity (TFP).

Occupation j:

$$l_j = \left(\frac{\delta}{j}\right)^{1-\delta} \; where\, 0 < \delta < 1$$

Parameter δ represents the level of LM: low δ means low LM (segmented industry) and high δ means high LM (integrated industry).

Total operating profits: $\Pi_t = Y_t - L_t W_t^s = (1-\alpha) A_t L_t^{\alpha}$ where W^s is industry-specific wage.

An employee in occupation *j* is indifferent between stay and leave an industry if: $W_t^S l_j = W_t^G$ where W^G is general skill wage. This condition means that expected labor income is the same inside and outside the industry (where he use general skill to earn W_t^G).

At equilibrium, profits: $\Pi_t^* = (1-\alpha) A_t x_t^{\frac{\alpha\delta}{1-\alpha\delta}}$

Main expectations:

1. Labor-induced operating leverage (sensitivity of cash flow growth to shock of TFP growth): If general skills are sufficiently smooth then $\frac{\partial \Theta(\delta)}{\partial \delta} > 0$. Implications: firms with high LM suffer more loss in cash flow when there is TFP shocks.

2. The returns: $\frac{\partial E_t(R_t)}{\partial \delta} > 0$. High LM firms earn more stock returns.

3. Because δ is unobservable so they use inverse of ***inter-industry occupation concentration*** as proxy for LM. The concentration of industry *i*, occupation *j*, at time *t* is: $CONC_{j,t} = \left(\frac{emp_{i,j,t}}{\sum_i emp_{i,j,t}}\right)^2$. Then, aggregate from occupation-level to industry-level to get LM as inverse of this concentration measure.

Empirical results

- When there is a shock in TFP, firms tend to decrease wage, sack employess, and lose profits. However, high LM firms tend to suffer more losts and see more drop in employment. The reason is they could not decrease wage too much (less bargaining power with their employess) (see Table 4)

- Long high LM and short low LM firms could earn 5%/year by both Value-weighted and Equal-weighted. Panel regression supports this idea (positive between Mobility and Returns).

- Implied cost of capital: also positive relation with Mobility

- CAPM beta: high LM firms have higher beta in unconditional CAPM and conditional CAPM with equal-weighted returns

3 Liquidity risk

Acharya and Pedersen [2005] propose the effect of *liquidity risk* and *commonality* in liquidity and how they affect asset pricing. *Commonality* here includes the covariances of a stock i liquidity and return with the market M liquidity and return.

As a result, they propose a liquidity-adjusted CAPM: if the illiquidity cost is c^i for stock i then:

- $E(r^i)$ increasing with its expected liquidity and *net beta* (i.e., proportional to $cov(r^i - c^i; r^M - c^M)$
- The *net beta* could be decomposed into standard market beta ($cov(r^i; r^M)$) and three betas representing different form of illiquidity risk:
  - Commonality in liquidity with market liquidity, $cov(c^i; c^M)$
  - Return sensitivity to market liquidity, $cov(r^i; c^M)$
  - Liquidity sensitivity to market return, $cov(c^i; r^M)$

They use Amihud (2002) illiquidity measure to proxy for c^i and find that:

- Their model performs better than standard CAPM in term of R^2 and p-values in specification tests
- The model can fit the portfolios sorted on liquidity, liquidity variation, and size; but fails to explain B/M effect
- Illiquidity stocks (high average c^i) tend to have higher liquidity risk (higher commonality $cov(c^i; c^M)$, $cov(r^i; c^M)$, and $cov(c^i; r^M)$)
- Economic significance: 3 types of liquidity risk contribute 1.1% annually to risk premium between high expected illiquidity and low expected illiquidity stocks, which can be decomposed as follows:
  - Commonality in liquidity with market liquidity, $cov(c^i; c^M)$, is 0.08%. Investors require a *small* return premium for a security that is illiquid when the market is illiquid.
  - Return sensitivity to market liquidity, $cov(r^i; c^M)$, is 0.16%. This is model-implied premium for stocks with high returns when the market is illiquid.
  - Liquidity sensitivity to market return, $cov(c^i; r^M)$, is 0.82%. Investors are willing to pay a premium for a security that is liquid when the market return is low. This is *the most important source* of liquidity risk, but not yet found in litarature.
- The return premium due to level of liquidity is calibrated based on average turnover to be 3.5%. Thus, the combined effect of difference in liquidity risks and difference in level of liquidity is estimated to be $3.5 + 1.1 = 4.6\%$, which turns out to be relatively important.
- Since the liquidity is persistent, *liquidity predicts future returns* and *liquidity co-moves with contemporaneous returns*. This is because a positive shock to current illiquidity predicts high future illiquidity, which raises required returns and lowers the contemporaneous prices.

4 Post-Publication mispricing returns

McLean and Pontiff [2016] study how the mispricing anomalies perform after the publication from researchers. They find that out-of-sample returns decline by 26% (which is the upper bound of data mining) and the post-publication returns decline by 58%. Thus, the investors learn about $58\% - 26\% = 32\%$ from the published papers. It is surprising that informed-investors trade on the published strategies to reduce the mispricing returns.

In general, this paper considers 97 different predictors in literature and find that on average, a predictor could produce a 0.582%/month or nearly 7% annual return in-sample period. They study the regression:

$$R_{it} = \alpha_i + \beta_1 Post\,sample\,Dummy_{it} + \beta_2 Post\,publication\,Dummy_{it} + e_{it}$$

The β_1 estimates the statistial bias, while the β_2 estimates both the statistical bias and impact of publication. The authors propose 3 hypotheses: Statistical bias, Mispricing, and Rational Expectation with different predictions:

- If predictors' returns are entirely the result of in-sample Statistical bias (Data mining): the predictors do not exist at all but just a spurious regression. Thus, the predicted $\beta_1 = \beta_2 = -0.582$. Overall, there is no relation at all.

- If predictors' returns are entirely the result of mispricing and arbitrage correct all mispricing after the papers are published: then $\beta_1 = 0$ and $\beta_2 = -0.582$

- If entirely rational expectation, no statistical bias and investors do not learn: then $\beta_1 = \beta_2 = 0$

The results show that $\beta_1 = -0.15$ and $\beta_2 = -0.33$ and both significant. Thus, there are some statistical bias and investors also learn from published predictors and trade to reduce the predictors' returns. When they interact between two variables with the mean of predictors' returns and the t-statistics in the papers, all interactions are negative significant. It means that if the results are stronger in the papers, the predictors tend to have *larger degree of statistical bias* and investors will *reduce these predictors more* in post-publication periods.

Type of predictors They split the predictors into 4 types: market (price, volume, outstanding, returns), event (share issues, analyst recommendation, R&D increase), valuation (B/M), and fundamental (from financial statement such as debts, accruals).

- Market predictor type has higher returns in pre-public period, while the fundamental type has the lowest pre-public returns.

- Then they interact the $Post\,Publication$ with these type indicators and find that the *fundamental predictor* types' returns decrease more after the publication. In addition, the sum of $PostPublication \times Market + Market$ is not significant, supporting idea that the higher in-sample returns tend to decrease more in post-publication so their returns will not higher than those of other predictors anymore.

Cost of arbitrage and Decline of predictors' returns They interact the $PostPublication$ and measures of costly arbitrage such as: Firm Size, Bid-Ask spread, Trading Volume, Idiosyncratic Risk, Dividend Payers, and Arbitrage Cost index. The idea is that they test the sum of coefficients of Costly Arbitrage (CA) and the interaction ($CA * PostPublication$) and test whether it is zero. Stocks that are less costly to arbitrage should see a larger decline in predictors' returns in the post-publication.

Furthermore, for stocks in the predictors will observe a higher trading volume; less volatility due to less noise trading; and larger difference between the short side and long side (larger $\Delta SI = SI_{short} - SI_{long}$) because investors recognize that predictor portfolio stocks are mispriced, then they should short more in the sort side than in the long side.

Predictor return pre- and post-publication correlation

- ***Before publication***, the *in-sample predictors' returns are highly correlated* because of the *mispricing forces.*
- ***After publication***, the predictors' returns are *now traded by arbitragers* so they are *correlated more with other published predictors' returns*; but *less correlated with unpublished predictors.*

5 Innovative capacity investment and Stock returns

Kumar and Li [2016] consider the capital investment of R&D intensive firms and how this increase in capital investment affects firms' stock returns, investment, and profitability.

In literature, an increase in capital investment could affect stock returns:

- *Traditional real options view*: **negative relation**, because firms in technologically mature industries undertake capital investment to convert growth options into assets-in-place.
- In rich possibilities for innovation industries, firms undertake capital investment to develop innovative capacity and commercialize potential future innovations. So the relation will be **positive**.

To measure innovative capacity and capital invesment, they use the R&D expense and asset growth, respectively. Innovative capacity (IC) investment will be the asset growth (AG) of R&D-active firms. In addition, they use large firm size to proxy for firms with nonincreasing revenue return on IC investment.

Empirical results They run regression of cross-section stock returns on AG annually, but split between large and small + R&D active and non-active firms.

The empirical results show that *for large IC firms*, the effect of AG is insignificant over the first 5 years, but become significantly positive as the sixth year. They do not find this pattern for small IC firms. In addition, IC firms show significantly higher future investments and positively related to profitability for large IC firms.

The verify the findings, they check two alternative explanations: empire building and risk-shifting in idiosyncrati volatility (IVOL). The *empire-building* view predicts that investors undereact to empire building behaviors (such as capital investment) so there is negative relation between IC investment and stock returns. The levered firms tend to undertake projects with high IVOL because the loss will be concentraded to debtholders, so the *risk-shifting* view predicts a negative between IC investment and stock returns too. The results reject these two alternative hypotheses:

- For empire-building: they run $RET = AG + AG \times HRDS\&LDCF + Size + BM + Mom$ where $HRDS\&LDCF$ is dummy that equals one if firms R&D/Sale is not missing and Debt/CF is lower than sample median. They find that the interaction is positive rather than negative.
- For risk-shifting: They calculate IVOL for each group of IC investment of RD-active and RD-non-active firms and find that IVOL declines over time after increase in asset growth.

Theoretical Model At time t, firms are endowed with initial asset-in-place (AIP) and with stochastic initial earning Y_t^0. It could decide to make an IC investment X with success rate λ. Firms have productive capacity $K = K(X)$ which depends on IC investment. Fixed cost is $f_K K(X)$ and variable cost is normalized to zero.

The *incremental* earning from new IC investment is: $Y_t^n = P_t(X, \Gamma_t, K(X)) - f_k K(X)$

where Γ_t is random sale productivity; P_t is revenue function, and can be rewritten as $P_t = \Gamma_t X^a \sqrt{K(X)}$, where $0 < a < 1$ is marginal revenue product of IC investment.

The stochastic pricing kernel $m_{t+1} = m_t exp(-r - \frac{\sigma_v^2}{2} - v_{t+1})$ where r is risk-free rate, and v is shocks. The intrinsic systematic risk of new investment X is $\theta = cov(\epsilon, v)$.

Conditional on X, ***pre-exercise firm valuation*** is:

$$V_t = V_t^A - V_t^X + V_t^N$$

where V_t^A is value of initial asset-in-place, V_t^X is discounted fixed cost associated with IC investment, and V_t^N is value of potential innovation.

Post-exercise firm valuation is:

$$V_t = V_t^A + V_t^P - V_t^F$$

where V_t^A is value of initial asset-in-place, V_t^P is discounted value of new revenue part, and V_t^F is fixed operating cost of both X and K.

Then, they can write the expected return as a value-weighted average of component assets' expected returns. Specifically, in pre- and post-arrival/exercise regimes, we have:

$$E_t[R_{t+1}] = \begin{cases} \bar{\omega}_t^A e^{r+\theta} - \bar{\omega}_t^X e^r + \bar{\omega}_t^N \bar{R}^N & if\, t < T \\ (\hat{\omega}_t^A + \hat{\omega}_t^P) e^{r+\theta} - \hat{\omega}_t^F R^r & if\, t > T \end{cases}$$

where $\omega^j = \frac{V^j}{V_t}$ is weight of component asset j, so $\bar{\omega}^X$ and $\bar{\omega}^F$ reflect operating leverage; $e^{r+\theta}$ and e^r are risky asset return and risk-free return; $\bar{R}^N = e^{r+\theta} - (e^\theta - 1)(1-\lambda)$ is return on potential innovation, will be converted to revenue with risky asset return (but depend on success rate λ), so $e^r < \bar{R}^N < e^{r+\theta}$.

The impact of X on future expected returns is:

$$\frac{\partial E_t[R_{t+1}]}{\partial X} = \begin{cases} \frac{\partial \bar{\omega}_t^A}{\partial X}(e^{r+\theta} - e^r) + \frac{\partial \bar{\omega}_t^N}{\partial X}(\bar{R}^N - e^r) + \bar{\omega}_t^N \lambda'(X)(e^\theta - 1) & if\, t < T \\ \frac{\partial \hat{\omega}_t^F}{\partial X}(e^{r+\theta} - e^r) & if\, t > T \end{cases}$$

Intuitions:

- When t>T (after innovations are generated and exercised): $\frac{\partial \hat{\omega}_t^F}{\partial X} > 0$ and $\frac{\partial E_t[R_{t+1}]}{\partial X} > 0$ so IC investment is positively related to returns, as long as nonincreasing revenue returns (or $a < 1/2$)
- When t<T: ambiguous sign, so no predictions
- When there is an IC investment of large firms (i.e., nondecreasing marginal return on X), then profitability increase and investment increase too
- Factor loading:
  - Factor loading on HML increases as options converted (growth options become asset-in-place or innovations are generated and exercises)
  - Loading on SML should decrease because firms are bigger and bigger (AG increase)

6 Speculative Beta

6.1 The intuitions of the model

The speculative beta model in this paper stands in three main pillars:

1. In complete market

2. Aggregate disagreement in the market

3. Short sale constraint

The main idea of this paper is when there are short sale constraints, the market is left with only optimistic investors because persimistic investors withdraw from the market. As a result, the market price is overpriced because the price is from optimistic investors. This idea is originated from Miller (1977).

Hong and Srael (2016) expands this idea by finding that the high beta stocks are more sensitive to aggregate disagreement. In other words, beta amplifies the disagreement about the macroeconomy. Thus, the *high beta stocks tend to be more overpriced* when there is a short sale constraint and high aggregate disagreement, relative to the low beta stocks. Arbitragers cound not drive the price to intrinsic value due to limited shorting. The price in the market is equilibrium overpricing.

I do not present the whole model here due to its complication. A further reading to paper in detail is more appropriate. The following subsection provides brief summary and main findings of two predictions of the papers:

1. High aggregate disagreement leads to concave (inverted-U shaped) SML (SML is relation between stock returns and beta).

2. High aggregate disagreement leads to flatter SML.

6.2 Measurements

Using CRSP data from 1981 to 2014, Hong and Sraer [2016] propose the idea of speculative beta to explain the beta anomaly: high beta stocks have lower returns. They exlude the penny stocks (price < 5). Value-weighted market returns are from French website. Risk free is US Treasury bill rate.

The proxy for agreement (or investors' beliefs) is I/B/E/S's EPS long-term growth rate.

Post-ranking beta For each month, they use the Dimson (1979) beta by running the regression for each stock i using past 12-months of daily returns:

$$R_t^i - R_t^f = \alpha + \beta_0(R_t^M - R_t^f) + \sum_{j=1}^{5} \beta_j R_{t-j}^M$$

Then sum all six betas to get preranking beta: $\beta = \sum_{j=0}^{5} \beta_j$

Using this *pre-ranking beta* to sort data to 20 NYSE β portfolios. Then, compute daily portfolio equal- and value-weighted returns.

Post-ranking beta is estimated similarly but using portfolio returns of portfolio p:

$$R_t^p - R_t^f = \alpha + \beta_0(R_t^M - R_t^f) + \sum_{j=1}^{5} \beta_j R_{t-j}^M$$

Then sum six beta again to get the post-ranking beta at portfolio levels.

Aggregate disagreement Stock-level disagreement is dispersion in analyst forecast of EPS LTG. Then, aggregate this stock-level disagreement measure to portfolio-level using the preranking beta (to focus on aggregate factor z, rather than the idiosyncratic factor ϵ).

Other alternative measures of aggregate disagreement are:

- Analyst forecast dispersion of S&P 500 index annual EPS: fewer analysts forecast this quantity (about 20 analysts) compared to thousands of individual stock forecasts.
- Dispersion of macroforecasts from SPF (Survey of Professional Forecasters): use first principal component of cross-sectional standard deviation of forecasts on GPD, IP, corporate profit, and unemployment.

All time-series of aggregate measures are standardized to have mean zero and variance one.

Forward excess returns They calculate the forward excess returns for different horizons: 3, 6, 12, 18 months. This is the average of excess returns of each in 20 β-ranked portfolios for next 3, 6, 12, and 18 months horizons.

6.3 Fama-Macbeth two steps regression

Inverted-U shaped SML The first test is **high aggregate disagreement leads to a concave SML** (i.e., Prediction 1 of this paper).

In first step, in each month-by-month from 12/1981 to 12/2014:

$$r_{pt}^{(12)} = \kappa_t + \pi_t \beta_p + \phi_t (\beta_p)^2 + \epsilon_{pt}$$

They run this regression for each of 20 beta-sorted portfolios, where $r_{pt}^{(12)}$ is 12-month forward excess returns (they also check robustness for other horizons), β_p is postranking beta of portfolio. From these regressions, they have a time-series of coefficient estimates κ_t, π_t, and ϕ_t.

In second step, run time-series regressions for each of 20 portfolios:

$$\begin{aligned}
\phi_t &= c_1 + AggDisp_{t-1} + R_{mt}^{(12)} + HML_{mt}^{(12)} + SMB_{mt}^{(12)} + UMD_{mt}^{(12)} + X_{it-1} \\
\pi_t &= c_2 + AggDisp_{t-1} + R_{mt}^{(12)} + HML_{mt}^{(12)} + SMB_{mt}^{(12)} + UMD_{mt}^{(12)} + X_{it-1} \\
\kappa_t &= c_3 + AggDisp_{t-1} + R_{mt}^{(12)} + HML_{mt}^{(12)} + SMB_{mt}^{(12)} + UMD_{mt}^{(12)} + X_{it-1}
\end{aligned}$$

Every variable with superscript (12) means that this is the excess return from month t to $t + 11$ of the factor. All time-series regressions are adjusted using Newey-West standard errors with 11 lags.

Findings and intuitions:

- The coefficients of $AggDisp$ is positive for π mean that at first, higher beta is associated with higher returns
- The coefficients of $AggDisp$ is negative for ϕ mean that the SML curve (or beta-return relation) is inverted-U shaped or a concave SML line

Slope of SML The second test is **high aggregate disagreement is negatively associated with slope of SML**.

First step,

$$r_{pt}^{(12)} = \kappa_t + \pi_t \beta_p + \epsilon_{pt}$$

here π is slope of SML in month t (i.e., variable of interest). Then repeat the second step as above. They find that higher aggregate disagreement in month $t-1$ actually predicts a significantly flatter SML line in the following month. In other words, the coefficient of $AggDisp$ is significantly negative (see Internet Appendix Table II.AVI).

6.4 Heteroskedastic Idiosyncratic Variance

The Prediction 2 of this paper holds that the slope of SML is *more sensitive* to aggregate disagreement for stock with *high* B_i/σ_i^2 *ratio* relative to stocks with low B_i/σ_i^2 ratio. The stocks with high B_i/σ_i^2 ratio than sample median in month t are speculative stocks and vice versa.

1. First stage, rank stock each month based on their preranking ratio of B_i/σ_i^2. Stocks with B_i/σ_i^2 ratio higher than median are speculative stocks and vice versa. Now we have two groups of stocks.

2. Second, within each of two groups, *rerank stocks based on their estimated beta* in ascending order at the end of previous month and assign to 20 beta-sorted portfolios again using NYSE breakpoints. Then, compute full-sample beta of these 40 value-weighted portfolios using the same market model.

3. For each group and each month, estimate the following cross-sectional regression where p is one of 20-beta sorted portfolios, $s \in \{speculative; non\, speculative)$ and t is month:

$$r_{p,s,t}^{(12)} = \iota_{s,t} + \chi_{s,t}\beta_{p,s} + \varrho_{s,t}ln(\sigma_{p,s,t-1}) + \epsilon_{p,s,t}$$

where $\beta_{p,s}$ is 12-month excess return of portfolio, $\sigma_{p,s,t-1}$is median idiosyncratic volatility of stocks in portfolio (p, s). Because of high skewness, they take log of the idiosyncratic volatility.

Then, they have a time-series of estimates of $\iota_{s,t}$, $\chi_{s,t}$, and $\varrho_{s,t}$. Then they apply a time-series regressions as in above processes.

The findings in Figure 7 and Table 5

The coefficient of $\chi_{s,t}$ is *negative and significant in speculative stock* group and not significant in non-speculative stock group. Intuitively, a higher aggregate disagreement in month $t-1$ is associated with a flatter SML. This finding only holds for speculative stocks (high ratio β/σ^2).

1. For nonspeculative stocks, SML is not related (in a clear way) to the aggregate disagreement.

2. For speculative stocks, when aggregate disagreement is high, the SML exhibits an inverted-U shape, while there is no such pattern in low aggregate disagreement.

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