Anchoring Heuristic and the Equity Premium Puzzle

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Abstract

What happens when the anchoring and adjustment heuristic of Tversky and Kahneman (1974) is incorporated in the standard consumption-based capital asset pricing model (CCAPM)? The surprising finding is that it not only resolves the high equity-premium and low risk-free rate puzzles with a low risk-aversion coefficient, but also provides a unified framework for understanding countercyclical equity-premium, excess volatility, size, value, and momentum effects, and abnormal returns and volatilities following stock-splits and reverse stock-splits. The anchoring approach makes the following prediction: equity in firms with less volatile earnings would outperform equity in firms with more volatile earnings.

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Anchoring Heuristic and the Equity Premium Puzzle

What happens when the anchoring and adjustment heuristic of Tversky and Kahneman is incorporated in the standard consumption-based asset pricing model (CCAPM)? The surprising finding is that it not only resolves the high equity-premium (Mehra and Prescott (1985)) and low risk-free rate (Weil (1989)) puzzles with a low risk-aversion coefficient, but also provides a unified framework for understanding countercyclical equity-premium, excess volatility, size, value, and momentum effects, and abnormal returns and volatilities following stock-splits and reverse stock-splits.

For explaining high average equity-premium, not requiring a high risk-aversion coefficient is important, because high risk-aversion makes the attitudes to large monetary gambles unreasonable (see the discussion in Barberis and Huang (2008)). It is precisely this difficulty of reconciling the high equity-premium with reasonable attitudes to large-scale monetary gambles that launched the equity-premium literature in the first place.[2]

This article develops the theoretical framework without asserting that the proposed framework completely explains all of the puzzles listed above. Such an assertion demands a comprehensive empirical examination of a large number of phenomena and a detailed comparison of the anchoring explanation with other explanations, a feat which no single article can achieve. The primary aim of this article is to demonstrate that the anchoring and adjustment heuristic must be considered as an alternative explanation. In this respect, the article makes a methodological contribution by showing how the anchoring and adjustment heuristic can be incorporated in the standard paradigm. The broad theme of this article is that we may be able to improve our understanding of the equity premium and other puzzles, by looking at how people make judgments in *experimental* settings. Specifically, this article argues that the *anchoring and adjustment heuristic,* a key idea that has emerged from over 40 years of extensive experimental investigation, may play an important role in asset pricing.

By focusing on developing the theoretical foundations, the article aims to pave the way for future empirical testing of the anchoring-adjusted CCAPM. The anchoring-adjusted CCAPM makes the following prediction: *Equity in firms with less volatile earnings would outperform equity in firms with more volatile earnings*. This prediction is strongly counter-intuitive as it seems to suggest that less risk is rewarded with more return, instead of high risk getting high return. Although directly

[2] Consult Mehra (2008) for a broad spectrum review of the literature on the equity premium puzzle.

testing this prediction is beyond the scope of this article, I discuss a large body of indirect evidence from the existing empirical literature that strongly supports this prediction.

The standard CCAPM, despite being intuitive and theoretically appealing, has largely been an empirical failure.[3] This article identifies a possible path to resurrecting CCAPM by incorporating the anchoring and adjustment heuristic in the standard paradigm. Hence, it builds the case that general equilibrium behavioral finance may save the CCAPM.

If m_{t+1} is the stochastic discount factor, then to generate a large equity premium, a mechanism is needed that increases its volatility *across states of nature*, $\sigma(m_{t+1})$. The average value of the discount factor *across states,* $E(m_{t+1})$ must also be high to account for the low risk-free rate, whereas $\sigma\big(E(m_{t+1})\big)$ must be low to be consistent with low interest rate variation *over time.* Furthermore, to generate a large equity premium (Sharpe ratio) in the long-run, we need the volatility of the discount factor, $\sigma(m)$, to increase linearly with horizon. The anchoring approach achieves all of this surprisingly easily. This is in sharp contrast with the habit-formation literature that typically requires careful reverse-engineering to keep $\sigma\big(E(m_{t+1})\big)$ low, and to keep $\sigma(m)$ increasing linearly with the horizon.[4] Furthermore, the anchoring approach also makes $\sigma(m)$ counter-cyclical.

Anchoring, as modeled here, is a rare bird among cognitive biases as it makes investors more cautious. An anchoring-prone investor underprices equities and invests more in the risk-free asset. For other biases such as optimism or overconfidence, one may think of institutional mechanisms that make investors more cautious (such as cooling-off periods) in an attempt to "*tie Ulysses to the mast to save him from the Sirens*". Not so for anchoring as modeled here, as the exact opposite of caution and prudence is required to mitigate anchoring. Hence, it is unlikely that the institutional mechanisms to mitigate anchoring will emerge.

Starting from Tversky and Kahneman (1974), over 40 years of research has demonstrated that while forming estimates, people tend to start from what they know and then make adjustments to their starting points. However, adjustments typically remain biased towards the starting value known as the anchor (see Furnham and Boo (2011) for a general review of the literature). Describing the anchoring heuristic, Epley and Gilovich write (2001), "*People may spontaneously anchor on information that readily comes to mind and adjust their response in a direction that seems appropriate, using what Tversky and Kahneman (1974) called the anchoring and adjustment heuristic. Although*

[3] See the discussion in Lettau and Ludvigson (2001) and references therein.
[4] See Cochrane (2008) for a detailed discussion of these points.

this heuristic is often helpful, the adjustments tend to be insufficient, leaving people's final estimates biased towards the initial anchor value." (Epley and Gilovich (2001) page. 1).

A few examples illustrate this heuristic quite well. When respondents were asked which year George Washington became the first US President, most would start from the year the US became a country (in 1776). They would reason that it might have taken a few years after that to elect the first president so they add a few years to 1776 to work it out, coming to an answer of 1778 or 1779. George Washington actually became president in 1789, implying that, starting from 1776, adjustments are typically insufficient. Similarly, what is the fair price of a 3-bedroom house in a given neighbourhood of Melbourne? If you know the price of a 4-bedroom house in the same neighbourhood but in a slightly better location, you would probably start from that price and adjust for differences between the two properties. Anchoring bias implies that such adjustments tend to be insufficient. The adjustments are insufficient because of the tendency to stop adjusting once a plausible value is reached (Epley and Gilovich (2006)).

Anchoring has been found to be a robust phenomenon in a wide variety of decision-making contexts. The situations tested are diverse and include price estimation (Amado et al (2007)), probability calculations (Chapman and Johnson (1999)), as well as factual knowledge (Blankenship et al (2008), Wegener et al (2001)). Overall, the anchoring bias is "exceptionally robust, pervasive and ubiquitous" (Furnham and Boo 2011, p. 41) regarding experimental variations.

Hirshleifer (2001) considers anchoring to be an *"important part of psychology based dynamic asset pricing theory in its infancy"* (p. 1535). Shiller (1999) argues that anchoring appears to be an important concept for financial markets. This argument has been supported quite strongly by recent empirical research on financial markets. Anchoring has been found to matter for credit spreads that banks charge to firms (Douglas et al (2015), it matters in determining the price of target firms in mergers and acquisitions (Baker et al (2012), and it also affects the earnings forecasts made by analysts in the stock markets (Cen et al (2013)). Furthermore, Siddiqi (2015) shows that anchoring provides a unified explanation for a number of key puzzles in options market. Siddiqi (2015a) extends the anchoring idea to CAPM. Given the importance of this bias in financial decision making, it is natural to see what happens when a canonical asset pricing model of the stature of CCAPM is adjusted for anchoring. This is the contribution of this article.

In the stock market, prominent blue-chips get a lion's share of analyst and media coverage. A study suggests that about 83% of full time stock analysts only focus on the blue-chips, which are only 4% of the firms.[5] Such companies are typically household names, are well-established, and well-researched with plenty of data available about them. In a typical research report written by a stock analyst, the firm being analyzed is almost always compared with the sector leader, which typically is a prominent blue-chip company. Popular MBA and CFA texts teach the same approach.[6] Industry analysis, which is almost a universal part of every research report written by stock analysts, naturally focuses on the major sectoral players (the prominent blue-chips).

Given the key role of prominent blue-chips in stock analysis and the ubiquitous human reliance on anchoring, plausibly, a typical investor may use the payoffs of prominent blue-chips as starting points, which are then adjusted to form judgments about other firms. Consider the following firms: Apple, Applied Materials, and Auto Desk. All three are large information technology firms included in the S&P 500 index. However, Apple is a household name that clearly stands out. Apple is the largest information technology firm in the world, and gets a lion's share of analysts and media coverage when compared with the other two firms. Given its prominence, a typical investor may start from Apple and then attempt to make appropriate adjustments to form judgments about the other two firms.

A key stylized fact noted in the anchoring literature is that higher the task complexity or cognitive load involved in a judgment task, larger is the error caused by anchoring (Kudryavtsev and Cohen (2010), Meub and Proeger (2014), references therein). From a given starting distribution, adjusting for volatility perhaps requires more effort than adjusting for expected payoffs. In principle, the only adjustment required for expected payoff is "size adjustment"; however, in order to estimate volatility, many other differences such as the differential response to external shocks must also be accounted for. Plausibly, due to the higher cognitive load involved, the anchoring bias is larger in volatility estimation. For simplicity, I assume that expected payoffs are correctly estimated and the anchoring bias is displayed in volatility estimation only. Alternatively, without changing results, one could assume that the anchoring bias is present in both expected payoff and volatility estimation with the bias being larger in volatility estimation. This focus on volatility instead of expected payoffs is typical of the Bayesian learning literature (see Weitzman (2007) and references therein). This is in sharp contrast with

[5] http://punchinvest.com/wp-content/uploads/2011/11/The-Blind-Spot-Impact-of-Analyst-Coverage1.pdf
[6] One example is the popular textbook on financial management of Petty and Titman (2012).

other asset pricing literature that allows for errors in expected payoffs while assuming that volatilities are correctly estimated (partly because of convenience).

Another key stylized fact from the anchoring literature is that greater the distance between the starting point and the correct value, larger is the error due to anchoring (Epley and Gilovich (2006) (2001) and references therein). When estimating the population of New York (correct value: 8.5 million approx.), people make larger errors if the initial anchor is 1 million, when compared with 5 million. When considering payoff volatilities, one simple way of capturing this is to use the following formulation: $\sigma_A(X_{Target}) = (1-m)\sigma(X_{BlueChip}) + m\sigma(X_{Target})$ with $0 \leq m \leq 1$.

In the above formulation, if $m = 1$, there is no anchoring bias and the anchoring influenced value, $\sigma_A(X_{Target})$, is equal to the correct value, $\sigma(X_{Target})$. If $m = 0$, the anchoring bias is maximal and the anchoring influenced value is equal to the starting value. Consistent with the anchoring literature, for a given positive m, greater the distance between the starting value, $\sigma(X_{BlueChip})$, and the correct value, $\sigma(X_{Target})$, larger is the error due to the anchoring bias.

To sum up, the notion that the payoff distributions of prominent blue-chips may be starting points for forming judgments about the payoff distributions of other firms can be made precise by using the following stylized facts: Stylized fact #1) Error due to anchoring is larger if the cognitive load involved in the judgment task is higher => focus on payoff volatilities instead of expected payoffs. Stylized fact #2) Error due to anchoring is larger if the distance between the starting value and the correct value is larger. A simple formulation capturing this is: $\sigma_A(X_{Target}) = (1-m)\sigma(X_{BlueChip}) + m\sigma(X_{Target})$.

This paper is organized as follows. Section 1 illustrates the implications of incorporating anchoring in asset pricing through a simple numerical example.

1. Anchoring Heuristic in Asset Prices: A Numerical Example

To fix ideas, consider a simple case of two risky assets (L and S) and one risk-free asset (F). There is one time-period marked by two points in time, t and $t + 1$. There are two states of nature at $t + 1$ called the Green and Blue states. The chance of each is 50%. The current time is t. One risky asset (L) belongs to a well-established (prominent blue-chip) firm with large payoffs. The second risky asset belongs to a newer firm (S) with much smaller payoffs. The payoffs from L, S and F are shown in Table 1.

L is a well-established asset and investors know the true distribution which is 200 in the Green state and 100 in the Blue state, implying a mean of 150 and a standard deviation of 50. Investors do not know the correct distribution of payoffs associated with S. However, they know that the Green state payoff is larger than the Blue state payoff for S as well. Assume that they use the payoff distribution of L as a starting point to which a series of cognitive operations are applied to generate a plausible distribution for S. The idea is that S and L are similar (in the same sector). Investors understand L better than S, so they start from what they know and then attempt to make appropriate adjustments.

Assume that starting from the expected payoff of L (150), the expected payoff of S is correctly estimated as 15. However, the anchoring bias is displayed in volatility judgment, and starting from the standard deviation of L (50), the standard deviation of S is overestimated to be 15 instead of the correct value of 10. It follows that the anchoring bias leads investors to believe that S pays 30 in the Green state and 0 in the Blue state, whereas the true state-wise payoffs are 25 and 5 respectively.

To fully appreciate the implications of this bias, we need to compare the outcomes under omniscience (when all payoffs are correctly known) with outcomes under anchoring (when the standard deviation of S is overestimated due to anchoring). In a typical application of CCAPM, omniscience is assumed. This article is aimed at replacing the assumption of omniscience with anchoring. This is the only change and the rest of the framework is left unchanged.

In section 1.1, in the context of the example in Table 1, I examine the case of omniscience. Continuing with the same example, in section 1.2, I look at the implications of the anchoring bias.

Table 1 Payoffs from well-established, relatively new, and risk-free assets			
Asset Type	**Price**	**Green State**	**Blue State**
L	P_L	200	100
S	P_S	25 (Omniscience) 30 (Anchoring)	5 (Omniscience) 0 (Anchoring)
F	P_F	110	110
Investors use the payoff distribution of L as a starting point for forming judgments about the payoff distribution of S. Anchoring bias implies that they fail to adjust fully and the volatility judgment remains biased towards the starting value. In this example, starting from the payoff standard deviation of L, which is 50, instead of correctly estimating the standard deviation of S to be 10, the standard deviation is overestimated to be 15.			

1.1. CCAPM with Omniscience

Given the payoffs of L, F, and S (assuming omniscience) in Table 1, what are the equilibrium prices of these assets? This question is answered next.

Suppose there exists a representative agent with a time-separable utility function who maximizes the following:

$$max_{n_L,n_s,n_F} U(c_t) + \beta E_t[c_{t+1}]$$

where n_L, n_s, and n_F are the number of shares of L, S, and F respectively. The current and next period consumption are c_t and c_{t+1} respectively, and β is the time discount factor.

The agent maximizes expected utility of consumption subject to the following constraints:

$$c_t = e_t - n_L P_L - n_s P_s - n_F P_F$$

$$\tilde{c}_{t+1} = e_{t+1} + n_L \tilde{X}_L + n_s \tilde{X}_s + n_F X_F$$

where $\tilde{X}_L, \tilde{X}_s$ *and* X_F are payoffs of L, S, and F respectively and are given in Table 1. The agent receives endowments e_t and e_{t+1} at t and $t+1$ respectively. P_L, P_s, and P_F denote prices.

The first order conditions of the maximization problem are:

$$P_L = E_t[SDF_i \cdot X_{Li}]$$

$$P_s = E_t[SDF_i \cdot X_{si}]$$

$$P_F = E_t[SDF_i] \cdot X_F$$

where $SDF_i = \frac{\beta U'(c_{t+1i})}{U'(c_t)}$ evaluated at optimal allocation, and i is the state indicator.

Assume that the representative agent must hold one unit of each asset to clear the market. Assume that utility function is $ln(c)$, $\beta = 1$, and $e_t = e_{t+1} = 500$. Solving the model with these parameter values, the results are shown in Table 2. The second column in Table 2 shows the results under "Omniscience". The SDF is $\{0.44326, 0.517637\}$. That is, $E[SDF] = 0.480449$, and $\sigma(SDF) = 0.037189$. The Sharpe ratio of the large asset is equal to the Sharpe ratio of the small asset at 0.077404. The present value of the Sharpe ratio is 0.037189. In other words, the present value of the Sharpe ratio is equal to the standard deviation of the stochastic discount factor. That is, the following is true:

$$\frac{E_t[R_{it+1}] - R_F}{R_F \cdot \sigma_t(R_{it+1})} = \sigma_t(SDF) \tag{1.1}$$

(1.1) is the capital market line (Sharpe (1964)) equivalent of Hansen-Jagannathan bound (Hansen and Jagannathan (1991)), which corresponds to the mean-variance frontier. In our example, with omniscience, both the L.H.S and the R.H.S in (1.1) are equal to 0.037189.

The equity premium puzzle is a puzzle because empirically L.H.S in (1.1) has been found to be much larger than the R.H.S in (1.1). With historical US data, the equity premium is 6%, the risk free rate is 1%, and the standard deviation of returns is 18%. This implies a present value of equity Sharpe ratio equal to 0.33. The standard deviation of SDF estimated from consumption data with power utility (reasonable risk-aversion of less than 2) is around 0.02. Hence, the L.H.S and the R.H.S are different by more than an order of magnitude. This is the equity premium puzzle in a nutshell.

1.2 CCAPM with Anchoring

Continue with the same example; however, replace the assumption of omniscience with the assumption that the agent uses the payoff distribution of the well-established asset as a starting point to which a series of cognitive operations are applied. Recall that we have assumed that the expected payoff is correctly estimated to be 15; however, there is anchoring bias in the standard deviation, as it is estimated to be 15, whereas the correct value is 10. It follows that the payoffs are estimated to be 30 and 0 in the Green and Blue states respectively, whereas, the corresponding correct values are 25 and 5.

Table 2 A Comparison of Anchoring with Omniscience		
	Omniscience	**Anchoring**
P_L	70.20785	70.16025
P_S	6.83484	6.61245
P_F	52.849335	52.930625
$SDF - Green\ State$	0.44326	0.44083
$SDF - Blue\ State$	0.517637	0.521545
$E(SDF)$	0.480449	0.481188
$\sigma(SDF)$	0.037189	0.040358
Ex-ante $u'(c_{t+1}) - Green\ State$	1/835	1/840
Ex-ante $u'(c_{t+1}) - Blue\ State$	1/815	1/810
$SharpeRatio(Present\ Value)\ L$	0.037189	0.040358
$Sharpe\ Ratio(Present\ Value)S$	0.037189	0.060536

Keeping everything else the same as in section 1.1, the prices of the three assets can be calculated and are shown in column three of Table 2. As can be seen, the equity prices are lower, and the risk-free asset price is higher with anchoring. The SDF is $\{0.44083, 0.521545\}$. That is, $E[SDF] = 0.481188$, and $\sigma(SDF) = 0.040358$.

Note that the distribution of SDF has changed: both the mean and standard deviation have gone up. The increase in $E(SDF)$ has lowered the risk-free rate, whereas the increase in $\sigma(SDF)$ has increased equity returns.

Changes in ex-ante marginal utility of consumption, $u'(c_{t+1}) - Green\ State$, and $u'(c_{t+1}) - Blue\ State,$ are the key drivers of changes in the distribution of SDF. Starting from the standard deviation of 50, estimating the standard deviation as 15 whereas the correct value is 10 implies that the anchoring-prone investor goes 87.5% of the way. In other words, the anchoring error is $(1 - 0.875)(50 - 10) = 5$. So, one can write the ex-ante marginal utility as:

$$u'(c_{t+1}) - Green\ State = \frac{1}{840} = \frac{1}{835 + 5} = \frac{1}{835 + (1 - 0.875)(50 - 10)}$$
$$= \frac{1}{Correct\ Value + (1 - m)(\sigma_L - \sigma_S)}$$

Similarly,

$$u'(c_{t+1}) - Blue\ State = \frac{1}{810} = \frac{1}{815-5} = \frac{1}{815-(1-0.875)(50-10)}$$
$$= \frac{1}{Correct\ Value - (1-m)(\sigma_L - \sigma_S)}$$

where σ_L and σ_S are the correct payoff standard deviations of the prominent blue-chip and the newer asset respectively, and m is the fraction of the distance the anchoring-prone investor goes while estimating the payoff volatility of the newer asset. If $m = 1$, the marginal utilities converge to their correct values.

With anchoring, the ex-ante marginal utility in the good state is lower than the correct value, whereas the ex-ante marginal utility in the bad state is higher than the correct value. This increases the marginal-utility-weighted expected payoff from the risk-free asset, while lowering the marginal-utility-weighted expected payoffs from the risky assets.

Anchoring distorts ex-ante marginal utilities though the term $(1-m)(\sigma_L - \sigma_S)$. The same term lowers the "good state" marginal utility while increasing the "bad state" marginal utility. So, even if the magnitude of this term fluctuates a lot *over time*, $E(u'(c_{t+1}))$ and $E(SDF)$ may remain stable *over time* due to simultaneous increasing and decreasing effects on marginal utilities *across states*. Hence, anchoring keeps $\sigma(E(SDF))$ naturally lower. Furthermore, as the payoff standard deviations increase with horizon, the anchoring distortion also increases with horizon. Hence, there is no difficulty in keeping $\sigma(SDF)$ increasing with horizon. Hence, the two difficulties that commonly afflict habit-persistence models, which are 1) how to keep $\sigma(E(SDF))$ low, and 2) how to keep $\sigma(SDF)$ high at longer horizons, do not arise in the anchoring framework.

The anchoring bias is also, quite plausibly, higher in "bad economic times" such as recessions because payoff volatilities are higher. In our example, σ_L is 50 and σ_S is 10. Let's say, in bad economic times, σ_L goes up by 10% to 55. Let's say σ_S goes up by 30% to 13 as smaller firms are plausibly affected more in bad times. The anchoring bias goes up to 5.25 from 5 (the anchoring bias is higher as long as σ_S goes up by less than 50%). This pushes up $\sigma(u'(c_{t+1}))$ and consequently $\sigma(SDF)$. Hence, counter-cyclical variations are plausible in $\sigma(SDF)$.

The empirical Sharpe ratio of the prominent asset is now different from the empirical Sharpe ratio of the newer asset. The empirical Sharpe ratio of the prominent asset is 0.083871.

The present value is 0.040358. Hence, (1.1) still holds for the large asset. The empirical Sharpe ratio of the newer asset is 0.125806 with a present value of 0.060536, which is larger than the standard deviation of the SDF (0.040358). Hence, (1.1) does not hold for the newer asset. It is easy to verify that the following holds for the newer asset instead:

$$\frac{E_t[R_{st+1}] - R_F}{R_F \cdot \left\{\sigma_t(R_{st+1}) + \frac{(1-m)(\sigma_L - \sigma_S)}{P_s}\right\}} = \sigma_t(SDF) \tag{1.2}$$

If $m = 1$, there is no anchoring bias, and (1.2) converges to (1.1). If $0 \leq m < 1$, then there is anchoring bias, and (1.2) and (1.1) are different.

With anchoring, as this example illustrates, Hansen-Jagannathan bound changes. The present value of the Sharpe ratio is no longer the lower bound for the standard deviation of the stochastic discount factor for anchoring influenced assets. Equity returns rise. The rise is substantially greater for anchoring-prone assets. The risk-free rate falls due to an increase in perceived aggregate risk. This looks promising regarding the equity premium puzzle. To directly address whether anchoring explains the equity premium puzzle, I consider the general case in section 2. I find that anchoring not only provides a plausible explanation for the equity premium puzzle, but also provides a unified explanation for a large number of other asset pricing puzzles.

1.3 Learning

Firms go through several classifications over their life-cycle, probably starting out as micro-caps with some eventually ending-up as blue-chips, if they survive and continue growing. The identifies of firms within each category keep on changing but the percentage of firms in a given category is approximately constant overtime. 50 years ago, roughly 4% of the firms were classified as blue-chips, and today the same percentage of firms are in the blue-chip category. [7]

Investors may learn the true distribution of S eventually, but the time it takes to do that, may mean a classification change for S, with S itself becoming L and some other newer firm taking its place. To take a more concrete example, S could be Cisco system's stock in 1990, and L could be IBM's stock at that time. In 1990, Cisco was just a new firm with only 6 years of experience. Now Cisco is considered a prominent blue-chip (like IBM) with other firms in the

[7] http://www.investopedia.com/articles/analyst/010502.asp

same spot where Cisco was in 1990 (even among blue-chips, some are more prominent than others. Apple, Applied Materials, and Autodesk are all blue-chip companies; however, Apple is much more prominent and substantially bigger). So, the role of the anchoring heuristic is unlikely to diminish with learning as there are always prominent blue-chips as well as lesser known firms in the market. Anchoring would not matter in the unlikely scenario in which the true payoff distribution of every firm in the market is accurately known. It is more likely that many such distributions are not merely unknown but perhaps are unknowable, a situation known as Knightian uncertainty. Plausibly, relying on the anchoring heuristic is a reasonable way to form judgments in such situations.

2. Anchoring Heuristic and Asset Prices

I consider a simple one-period situation with only two points in time, now and the future. (Mathematically, the first-order conditions from a multi-period version must decompose anyway into an overlapping sequence of first-order conditions from the two-points-in-time model. However, such details are not needed for the main message of this article, so I avoid creating unnecessary clutter of notation which could be distracting.). For the purpose of incorporating the anchoring heuristic into an otherwise standard CCAPM, I use a stark model in which everything except the most basic structure has been set aside.

Suppose there is one time-period marked by two points in time: t, and $t+1$. I assume the existence of a representative agent who is a risk-averse expected utility maximizer, and who is anchoring-prone. The representative agent maximizes:

$$U(c_t) + \beta E_t[c_{t+1}]$$

subject to:

$$c_t = e_t - \textstyle\sum_{i=1}^{N} n_i P_i$$

$$\tilde{c}_{t+1} = e_{t+1} + \sum_{i=1}^{N} n_i \tilde{X}_i$$

The total number of asset types is N. The other symbols have the same meanings as in the last section.

For each asset type, the following must be true in equilibrium:

$$P_i = E_t[SDF_h \cdot X_h] \tag{2.1}$$

where $SDF_h = \frac{\beta U'(c_{t+1h})}{U'(c_t)}$ evaluated at the optimal allocation, and h is the state index. In general, SDF_h with anchoring is different from SDF_h with omniscience, as illustrated in the last section.

For ease of reference, I label well-established stocks (prominent blue-chips) that supply the starting payoff distributions as the "leader" stocks. Other stocks are labeled as "normal" stocks.

Well-established stocks have larger payoff variances (standard deviations) than their respective follower stocks. This is due to their larger payoff sizes. Typically, prominent blue-chips have the largest asset bases in the industry, and consequently have the largest incomes. However, the leader stocks may have lower return variances (standard deviations) than their respective follower stocks. This is due to the larger prices of leader stocks. As an illustration of this feature, suppose the possible payoffs of the leader firm stock, in the next period, are 300, 350, and 400 with equal chance of each. The variance of these payoffs can be calculated easily and is equal to 1666.667. In a risk-neutral world, with zero risk-free interest rate, the price must be 350, so corresponding (gross) returns are: 0.857, 1, 1.143. So, the return variance is 0.010. Assume that the next period payoffs of the normal firm are 0, 35, and 70. The variance of these payoffs is 816.667. The risk neural price (with zero risk-free rate) is 35 leading to possible returns of 0, 1, and 2. The corresponding return variance is 0.66. As can be seen in this example, the payoff variance of the normal firm stock is smaller than the payoff variance of the leader firm stock, whereas the return variance of the normal firm is much larger.

In sections 2.1, 2.2, and 2.3, the following three cases are described:

1) One leader stock and one normal stock

2) One leader stock and many normal stocks

3) Many leader and many normal stocks

2.1 One Leader and One Normal Stock

This is the simplest case as there are only three assets in the market: two risky assets, and one risk free asset. Using L for the leader stock, S for the normal stock and F for the risk-free asset, their respective prices in equilibrium (from (2.1)) must be:

$$P_L = \frac{E[X_L]}{R_F} + \rho_L \cdot \sigma(SDF) \cdot \sigma(X_L) \tag{2.2}$$

$$P_s = \frac{E[X_s]}{R_F} + \rho_s \cdot \sigma(SDF) \cdot \sigma^A(X_s) \tag{2.3}$$

$$P_F = E[SDF] \cdot X_F \tag{2.4}$$

where ρ_i is the correlation coefficient of asset i with the SDF. The superscript A indicates that the standard deviation of the normal stock payoffs is anchoring influenced. In particular, the following simple form is assumed to be consistent with the key stylized fact discussed in the introduction:

$$\sigma^A(X_s) = (1-m)\sigma(X_L) + m\sigma(X_s) \tag{2.5}$$

where m is the fraction of distance the representative agent goes while starting from the standard deviation of the leader firm's payoffs. Note that if $m = 1$, there is no anchoring bias.

Substituting (2.5) in (2.3) and re-arranging leads to:

$$E[R_s] = R_F - \rho_s \cdot \sigma(SDF) \cdot \sigma(R_s) \cdot R_F - \rho_s \cdot \sigma(SDF) \cdot R_F \cdot (1-m) \cdot \frac{\big(\sigma(X_L) - \sigma(X_s)\big)}{P_s} \tag{2.6}$$

$$=> \frac{E[R_s] - R_F}{R_F \cdot \left\{\sigma(R_s) + \frac{(1-m)\big(\sigma(X_L) - \sigma(X_s)\big)}{P_s}\right\}} = -\rho_s \cdot \sigma(SDF) \tag{2.7}$$

As equities generally have higher expected returns than the risk-free rate, one can safely assume that $-1 \le \rho_s < 0$ (one exception: gold stocks). In the rest of the article, from this point onwards, for simplicity and ease of exposition, I assume that all stock payoff correlations with the SDF are negative. It follows that,

$$\frac{E[R_s] - R_F}{R_F \cdot \left\{\sigma(R_s) + \frac{(1-m)\big(\sigma(X_L) - \sigma(X_s)\big)}{P_s}\right\}} = |\rho_s| \cdot \sigma(SDF) \tag{2.8}$$

So,

$$\frac{E[R_s] - R_F}{R_F \cdot \left\{\sigma(R_s) + \frac{(1-m)\big(\sigma(X_L) - \sigma(X_s)\big)}{P_s}\right\}} \leq \sigma(SDF) \tag{2.9}$$

Hence, the Hansen-Jagannathan bound is no longer valid for the normal stock, and is replaced by (2.9). It is straightforward to check that the Hansen-Jagannathan bound remains valid for the leader stock and is given by:

$$\frac{E[R_L] - R_F}{R_F \cdot \{\sigma(R_L)\}} \leq \sigma(SDF) \tag{2.10}$$

It is easy to see that the aggregate market portfolio satisfies:

$$\frac{E[R_M] - R_F}{R_F \cdot \left\{\sigma(R_M) + \frac{|\rho_s|}{|\rho_M|}\frac{(1-m)\big(\sigma(X_L) - \sigma(X_s)\big) \cdot n'_s}{P_M}\right\}} = |\rho_M| \cdot \sigma(SDF) \tag{2.11}$$

where R_M is the return on the market portfolio, ρ_M is the correlation of the market portfolio's return with the SDF, and n'_s is the number of shares of the normal stock outstanding. It follows that:

$$\frac{E[R_M] - R_F}{R_F \cdot \left\{\sigma(R_M) + \frac{|\rho_s|}{|\rho_M|}\frac{(1-m)\big(\sigma(X_L) - \sigma(X_s)\big) \cdot n'_s}{P_M}\right\}} \leq \sigma(SDF) \tag{2.12}$$

2.1 One Leader and Many Normal Stocks

It is easy to extend the anchoring approach to a situation in which there is one well-established stock and a large number of normal stocks. Suppose there are k types of normal stocks. By closely following the same steps as in the previous section, we obtain the following lower bound with the aggregate market portfolio:

$$\frac{E[R_M] - R_F}{R_F \cdot \left\{\sigma(R_M) + \sum_{i=1}^{k} \frac{|\rho_{si}|}{|\rho_M|} \frac{(1-m)\big(\sigma(X_L) - \sigma(X_{si})\big) \cdot n'_{si}}{P_M}\right\}} \leq \sigma(SDF) \tag{2.13}$$

2.2. Many Leader and Many Normal Stocks

It is natural to expect that every sector has its own leader firm whose stock is used as a starting point to form judgments about other firms in the same sector. I assume that there are Q sectors and every sector has one leader firm. I assume that the number of normal firms in every sector is k. That is, the total number of normal firms in the market is $Q \times k$. As the total number of leader firms is Q. The total number of all firms (both leader and normal) in the market is $Q + (Q \times k)$.

Following a similar set of steps as in the previous two sections, we obtain the following lower bound with the aggregate market portfolio:

$$\frac{E[R_M] - R_F}{R_F \cdot \left\{\sigma(R_M) + \sum_{q=1}^{Q} \sum_{i=1}^{k} \frac{|\rho_{sqi}|}{|\rho_M|} \frac{(1-m)\left(\sigma\left(X_{Lq}\right) - \sigma\left(X_{sqi}\right)\right) \cdot n'_{sqi}}{P_M}\right\}} \leq \sigma(SDF) \tag{2.14}$$

The expected return on the market portfolio is given by:

$$E[R_M] = R_F + |\rho_M| \cdot \sigma(SDF) \cdot \sigma(R_M) \cdot R_F + \sigma(SDF) \cdot R_F \cdot \sum_{q=1}^{Q} \sum_{i=1}^{k} |\rho_{sqi}| \frac{(1-m)\left(\sigma\left(X_{Lq}\right) - \sigma\left(X_{sqi}\right)\right) \cdot n'_{sqi}}{P_M} \tag{2.15}$$

The price of the market portfolio is given by:

$$P_M = \frac{E[X_M]}{R_F} - |\rho_M| \cdot \sigma(SDF) \cdot \sigma(X_M) - \sigma(SDF) \cdot \sum_{q=1}^{Q} \sum_{i=1}^{k} |\rho_{sqi}| (1-m) \left(\sigma(X_{Lq}) - \sigma(X_{sqi})\right) \cdot n'_{sqi} \tag{2.16}$$

where n'_{sqi} is the number of shares outstanding of the normal stock i belonging to sector q.

3. Anchoring and Asset Pricing Puzzles

The standard consumption-based asset pricing model is a general equilibrium model that assumes a representative agent who is omniscient (accurately knows the payoff distribution of every asset in the market). The empirical record of this model is quite poor and a large number of phenomena exist that are inconsistent with its predictions. The difficulty in reconciling the high average equity-premium with low risk-aversion coefficient (Mehra and Prescott (1985)) is generally considered as the first exhibit against the standard CCAPM. There are other key puzzles as well such as the low risk-free rate, counter-cyclical equity premiums, excess volatility, size, value, and momentum effects, and the anomalous stock returns and volatility after stock-splits and reverse stock-splits.

In this section, I show that replacing the assumption of an omniscient representative agent with the assumption that the representative agent is anchoring-prone provides a plausible unified explanation for these puzzles.

3.1 The Equity Premium Puzzle

If there is no anchoring bias, then the following must be true:

$$\frac{E[R_M] - R_F}{R_F \cdot \{\sigma(R_M)\}} \leq \sigma(SDF) \tag{3.1}$$

The equity premium puzzle, first identified in Mehra and Prescott (1985), can be easily seen with the above formulation. The historical average return on US equity market is 6 to 7%, the average risk free rate is 1%, and the historical average standard deviation of returns is 18%. With these values, the L.H.S in (3.1) is equal to 0.33. The R.H.S estimated from consumption data is around 0.02 (power utility and risk-aversion less than 2). Hence, there is a very wide gap between the L.H.S and the R.H.S. This is the equity premium puzzle in a nutshell.

Considering a single stock, the corresponding bound with anchoring is given in (2.9):

$$\frac{E[R_s] - R_F}{R_F \cdot \left\{\sigma(R_s) + \frac{(1-m)\big(\sigma(X_L) - \sigma(X_s)\big)}{P_s}\right\}} \leq \sigma(SDF)$$

The Sharpe-ratio can be quite large when compared with $\sigma(SDF)$ with the additional term in the denominator ensuring that L.H.S remains smaller than R.H.S in the above inequality. Even, if we consider assets with the highest Sharpe-ratios, the above inequality is quite easily satisfied. To take an example, assume that $E[R_s]$ is 1.1, R_F is 1, and $\sigma(R_s)$ is 0.20. This gives a Sharpe-ratio of 0.5. Continue to conservatively assume that $\sigma(SDF)$ is correctly estimated from consumption data to be 0.02 (ex-ante $\sigma(SDF)$ is higher with anchoring so assuming 0.02 is being conservative from the anchoring perspective). With these number, we need the anchoring term in the denominator to be only as large as 4.8. As prominent blue-chips have payoff volatilities many times larger than the payoff volatilities of penny stocks, the anchoring term may cross 4.8 quite easily.

The resolution of the equity premium puzzle is even easier to see at the aggregate level. With anchoring, the corresponding lower bound at the aggregate level is given in (2.14). That is, there is an additional term in the denominator. The additional term is $\sum_{q=1}^{Q}\sum_{i=1}^{k}\frac{|\rho_{sqi}|}{|\rho_M|}\frac{(1-m)\big(\sigma(X_{Lq})-\sigma(X_{sqi})\big)\cdot n'_{sqi}}{P_M}$. Anchoring provides a plausible explanation for the equity premium puzzle if for reasonable values for this term, the R.H.S and the L.H.S in (2.14) are equal to each other. As before, I create a higher obstacle for anchoring by assuming that $\sigma(SDF)$ is correctly estimated from consumption data to be 0.02 even though with anchoring the ex-ante $\sigma(SDF)$ must be higher.

With the above historical values, if the anchoring term is 2.79, then the L.H.S and the R.H.S in (2.14) are equal to each other. In order to make it harder for the anchoring explanation to be successful, while choosing values below, I always err on the side of choosing values that make this term smaller.

There are about 5000 listed firms in the US equity market. Assuming that 5% of these are prominent blue-chips or well-established, we get 4750 as the number of firms that are influenced by anchoring. Prominent blue-chips are much smaller in number (less than 1%) and are not more than few dozens. By assuming that 5% of the firms in the market are prominent blue-chips, we are probably hugely overestimating their actual number (which is roughly 50). This means that the number of anchoring-prone firms is underestimated. Hence, my estimate of the number of anchoring- prone stocks is on the conservative side.

I set the anchoring parameter at $m = 0.98$. That is, the anchoring bias is kept quite small at only 2%. Continuing to make things difficult for the anchoring explanation, I underestimate typical $\sigma(X_{Lq}) - \sigma(X_{sqi})$ by assuming that a typical leader firm has a payoff standard deviation only 2 times larger than a typical normal firm. I assume that a typical normal firm has only 1000 shares outstanding, and the value of market portfolio is overestimated to be worth 30000 times the typical standard deviation of a normal stock. Even with such large values chosen to create harder obstacles for the anchoring explanation, the anchoring term is equal to 2.85 if typical $\frac{|\rho_{sqi}|}{|\rho_M|}$ is 0.45.

Hence, the equity premium puzzle is surprisingly easy to explain with anchoring.

3.2 The Low Risk Free Rate Puzzle

Weil (1989) is the first to point out that in a standard consumption-based asset pricing model, assuming a high risk-aversion coefficient makes the risk-free rate unreasonably high for reasonable values of the time discount factor. With anchoring, we do not need to invoke high risk aversion to explain the equity premium puzzle, so this problem is avoided. In fact, the risk-free rate tends to be quite low naturally with anchoring as the perceived aggregate risk is high, which pushes up the price of the risk-free asset lowering the risk-free return. This has also been illustrated with the example in section 1.

With the risk-free rate denoted by R_F, and the stochastic discount factor given by m, the following is true: $R_F = \frac{1}{E[m_{t+1}]}$. The anchoring bias increases $E[m_{t+1}]$. Hence, the risk-free rate is naturally lower with anchoring, and there is no need to separate the intertemporal elasticity of consumption and risk-aversion in order to explain the low risk-free rates.

The anchoring bias simultaneously decreases m in the good state and increases m in the bad state (see the example in section 1 for a clear illustration of this point). So, fluctuations in m over time may not show up in $E[m]$ as they may get cancelled across states, with $E[m]$ not fluctuating much over time. Hence, the anchoring bias keeps $\sigma(E[m])$ naturally low. Hence, the low volatility of the risk-free rate is also easy to explain with anchoring.

3.3 The Countercyclical Equity Premium

With anchoring, the price of the market portfolio is given in (2.16):

$$P_M = \frac{E[X_M]}{R_F} - |\rho_M| \cdot \sigma(SDF) \cdot \sigma(X_M) - \sigma(SDF) \cdot \sum_{q=1}^{Q} \sum_{i=1}^{k} |\rho_{sqi}| (1-m) \left(\sigma(X_{Lq}) - \sigma(X_{sqi})\right) \cdot n'_{sqi}$$

$$=> P_M = \frac{E[X_M]}{R_F} - |\rho_M| \cdot \sigma(SDF) \left\{ \sigma(X_M) + \sum_{q=1}^{Q} \sum_{i=1}^{k} \left|\frac{\rho_{sqi}}{\rho_M}\right| (1-m) \left(\sigma(X_{Lq}) - \sigma(X_{sqi})\right) \cdot n'_{sqi} \right\}$$

That is, there is an additional term due to anchoring given by:

$$\sum_{q=1}^{Q} \sum_{i=1}^{k} \left|\frac{\rho_{sqi}}{\rho_M}\right| (1-m) \left(\sigma(X_{Lq}) - \sigma(X_{sqi})\right) \cdot n'_{sqi}$$

Plausibly, the above term is countercyclical as payoff volatilities are larger in recessions. The term remains countercyclical even if the percentage increase in $\sigma(X_{sqi})$ is substantially larger than the percentage increase in $\sigma(X_{Lq})$ because, typically, we expect, $\sigma(X_{Lq}) \gg \sigma(X_{sqi})$. Plausibly, $\sigma(SDF)$ is countercyclical as well as the example in section 1 illustrates. This means that the market price is lower in recessions and higher in expansions leading to a countercyclical equity premium.

In general, with anchoring, one expects the following to hold:

Low prices, relative to fundamentals, precede high returns. High prices precede low returns.

3.4 High Stock Price Volatility

Shiller (1981) and LeRoy and Porter (1981) show that market prices are much more volatile than what can be justified by fundamentals. This feature is also easily seen with anchoring. With anchoring, the price of a normal firm stock is given by:

$$P_s = \frac{E[X_s]}{R_F} - |\rho_s| \cdot \sigma(SDF) \cdot \sigma(X_s) - |\rho_s| \cdot \sigma(SDF) \cdot (1-m) \cdot \big(\sigma(X_L) - \sigma(X_s)\big) \tag{3.2}$$

It follows that,

$$Var(P_s) = Cov\left(P_s, \frac{E[X_s]}{R_F}\right) - Cov\big(P_s, |\rho_s| \cdot \sigma(SDF) \cdot \sigma(X_s)\big) - (1-m) \cdot Cov\Big(P_s, |\rho_s| \cdot \sigma(SDF) \cdot \big(\sigma(X_L) - \sigma(X_s)\big)\Big)$$

Realizing that covariances in the second and third term in the above equation must be negative, we can write:

$$Var(P_s) = Cov\left(P_s, \frac{E[X_s]}{R_F}\right) + \big|Cov\big(P_s, |\rho_s| \cdot \sigma(SDF) \cdot \sigma(X_s)\big)\big| + (1-m)\Big|Cov\Big(P_s, |\rho_s| \cdot \sigma(SDF) \cdot \big(\sigma(X_L) - \sigma(X_s)\big)\Big)\Big|$$

If there is no anchoring bias, that is, $m = 1$, we are back to the standard formulation:

$$Var(P_s) = Cov\left(P_s, \frac{E[X_s]}{R_F}\right) + \big|Cov\big(P_s, |\rho_s| \cdot \sigma(SDF) \cdot \sigma(X_s)\big)\big|$$

Stock prices seem excessively volatile because the fluctuations in fundamentals, $E[X_s]$ and $\sigma(X_s)$ do not seem to be enough to justify the fluctuations in P_s. Anchoring bias adds a third term to the picture, which is given by $(1-m)\Big|Cov\Big(P_s, |\rho_s| \cdot \sigma(SDF) \cdot \big(\sigma(X_L) - \sigma(X_s)\big)\Big)\Big|$. Hence, news unrelated to fundamentals of a given stock, that is, idiosyncratic news only related to the leader stock in the sector also influences the stock price. Given the attention paid to prominent blue-chips, this additional term may dominate the other two firms.

3.5 Size, Value, and Momentum Effects

Expected return on a normal firm stock with anchoring is given by:

$$E[R_S] = R_F + |\rho_S| \cdot \sigma(SDF) \cdot R_F \left\{\sigma(R_S) + \frac{(1-m)\big(\sigma(X_L) - \sigma(X_S)\big)}{P_S}\right\} \tag{3.3}$$

Keeping all else the same, smaller size payoffs (of small-cap firm stocks) mean lower price and lower $\sigma(X_S)$. That is, the additional term due to anchoring $\frac{(1-m)\big(\sigma(X_L)-\sigma(X_S)\big)}{P_S}$ rises with smaller size. Hence, anchoring is consistent with the size premium: small-cap stocks tend to outperform large-cap stocks.

Value stocks tend to have smaller return volatility when compared with growth stocks. Fama-French (FF) value and growth indices (monthly returns data from July 1963 to April 2002) show the following standard deviations: FF small value: 19.20%, FF small growth: 24.60%, FF large value: 15.39%, and FF large growth: 16.65%. That is, among both small-cap and large-cap stocks, value stocks have less volatile returns than growth stocks. By definition, value stocks have higher book-to-market value when compared with growth stocks. That is, they have lower market prices. It follows that the value stocks have lower payoff volatilities as well when compared with growth stocks. Having lower payoff volatility and lower market price implies a higher value for the anchoring term in (3.3), which means higher returns. Hence, value premium arises in the anchoring framework.

According to (3.3), in a given cross-section of stocks, keeping everything else the same, low "m" stocks do better than high "m" stocks. But, how can we identify low vs high "m" stocks? Plausibly, we can identify them by looking at their recent performances. Stocks that have received unusually good news recently are "winning stocks", and stocks that have received unusually bad news recently are "losing stocks". Winning stocks are likely to get more strongly anchored to the leader stock as their recent success makes them more like the leader. For losing stocks, their recent bad spell makes them less like the leader. That is, "m" falls for winning stocks and rises for losing stocks. So, winning stocks continue to outperform losing stocks till the effect of differential news on "m" dissipates, and "m" returns to its normal level. This could be the basis for the momentum effect.

3.6 Stock-Splits and Reverse Stock-Splits

Stock-splits and reverse stock-splits appear to be merely accounting changes. A stock-split increases the number of shares proportionally. In a 2-for-1 split, a person holding one share now holds two shares. In a 3-for-1 split, a person holding one share ends up with three shares and so on. A reverse stock-split is the exact opposite of a stock-split. Stock-splits and reverse stock-splits appear to be merely changes in denomination, that is, they seem to be accounting changes only with no real impact on returns. With consumption-based asset pricing without anchoring, the impact of a stock-split on the equilibrium price of stock i can be seen in the following equation:

$$P_i = \frac{E[X_i]}{R_F} - |\rho_i| \cdot \sigma(SDF) \cdot \sigma(X_i) \tag{3.4}$$

A 2-for-1 split divides the standard deviation as well as the mean of payoffs by 2, so the price gets divided by 2 also. As both the price and the expected payoff are divided by 2, there is no change in expected return. As both the standard deviation of payoffs and the price are divided by 2, there is no change in the standard deviation of returns either. Hence, a stock-split and a reverse stock-split should not change the expected return or the standard deviation of returns, according to the standard CCAPM.

The situation is considerable different with anchoring adjusted CCAPM. The equilibrium price of a 'normal' stock is now given by the following equation:

$$P_i = \frac{E[X_i]}{R_F} - |\rho_i| \cdot \sigma(SDF) \cdot \sigma(X_i) - |\rho_i| \cdot \sigma(SDF) \cdot (1 - m) \cdot \left(\sigma(X_L) - \sigma(X_i)\right) \tag{3.5}$$

Due to the presence of an additional term in (3.5) when compared with (3.4), dividing the expected payoff and the standard deviation of $i's$ payoff by 2 lowers the price beyond division by 2. As price gets divided by more than 2, and the expected payoff and the standard deviation of payoff get divided by 2, both the expected return and the standard deviation of returns should rise after a split. The opposite conclusion holds for a reverse stock-split. The expected return as well as the standard deviation of returns should fall after a reverse stock-split.

Empirical evidence strongly supports the above predictions. Using data from 1975 to 1990, Ikenberry et al (1996) shows that stock-splits are associated with 8% positive abnormal returns after one year, and 16% abnormal returns over three years. Ikenberry et al (2003) uses data from 1990 to 1997 and confirms the earlier findings. Ohlson and Penman (1985) are the first to show that return volatility increases by about 30% following a stock split. Kim et al (2008) examine the long-run performance of 1600 firms with reverse stock-splits and reports negative abnormal returns. Koski (2007) shows a decrease in return volatility of 25% subsequent to a reverse stock-split.

4. Empirical Evidence

For an anchoring influenced stock, the expected return is given by:

$$E[R_S] = R_F + |\rho_S| \cdot \sigma(SDF) \cdot R_F \left\{ \sigma(R_S) + \frac{(1-m)\big(\sigma(X_L) - \sigma(X_S)\big)}{P_S} \right\}$$

A key prediction of the anchoring approach can be directly seen from the above equation. Keeping all else the same, equity with less volatile payoffs should earn higher returns than equity with more volatile payoffs. That is, having a low value of $\sigma(X_S)$ is beneficial. This prediction can be tested by using financial statement information to infer $\sigma(X_S)$.

There is strong (indirect) evidence for the above prediction. A significant body of empirical work has uncovered, what is known as, the low volatility anomaly. Stocks with highly volatile returns tend to have low average returns irrespective of whether volatility is measured as the variance of daily returns or as the variance of the residuals from the FF three-factor model (see Baker and Haugen (2012), Wurgler et al (2010), and Ang et al (2006) among others). Note, that even though the payoff or earnings volatility is not directly used, it is likely that stock return volatility and payoff volatility are closely related. In general, research in accounting, starting from Beaver et al (1970) confirms the positive association between payoff or earnings volatility from financial statements and stock return volatility as observed in financial markets.

Another set of indirect evidence comes from what is known as the accruals anomaly. Sloan (1996) is the first paper to find that low returns are associated with high accruals. Accruals arise because accounting decisions cause book earnings to differ from cash earnings. The finding is that equity in firms that have a large accrual component of earnings performs worse than the equity in firms that have a lower accrual component. One expects that firms with large accrual component of earnings have less persistent or more volatile earnings when compared with firms with smaller accrual component of earnings. Sloan (1996) explicitly tests for this and finds strong support. Hence, to the extent, high accruals are a proxy for high earnings volatility, the anchoring prediction is supported.

Given a large body of empirical evidence on both the low volatility and the accruals anomaly, it would be very surprising, if one does not find confirmatory evidence by directly using the earnings or payoff volatility.

4. Conclusions

The standard consumption-based asset pricing model is a general equilibrium model which assumes an omniscient representative agent who is able to form correct expectations regarding the future payoff distributions of all available assets. I drop the assumption of omniscience and assume that investors use the payoff distributions of prominent blue-chips as starting points which are then adjusted to form the required judgments. Anchoring bias implies that such adjustments typically fall short. I propose only one change in the standard model: The replacement of an omniscient representative agent with an anchoring-prone representative agent. I show that this change is sufficient to provide a plausible unified explanation for key asset pricing puzzles including the equity premium puzzle. The anchoring model makes the following prediction: *Equity in firms with less volatile earnings would outperform equity in firms with more volatile earnings.* Indirect empirical evidence strongly supports this prediction.

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