Dynamic Asset Pricing Driven by Reference Prices and the Disposition Effect: Empirical Evidence from CSI 300 Constituent Stocks

Jin Yueyan
College of Finance, Zhejiang University of Finance and Economics, Finance major, Hangzhou City, Zhejiang Province, Postcode, 310000, China

ABSTRACT

Based on the framework of Prospect Theory and Mental Accounting, this paper constructs the Capital Gains Overhang (CGO) indicator using the 52-week high price as a reference price anchor to investigate how investor disposition effect influences the dynamic pricing mechanism of A-share market. Using the inventory data of CSI 300 from June 2021 to May 2024, we find that: (1)CGO is positively correlated with future returns, and the portfolio with high CGO (high unrealized income) is obviously better than the portfolio with low CGO (high unrealized cost), which verifies the hypothesis of "overreaction caused by disposition effect"; (2) The permutation effect (DE) plays an important mediating role in the return relationship of CGO, and the indirect effect accounts for 221.15% of the total effect (bootstrap 95% CI: [-0.002891,-0.000186]); (3) The volatility of the high CGO group is obviously lower than that of the low CGO group, which indicates that the allocation effect has asymmetric influence on the market stability. This study provides empirical evidence for China's market behavior asset price theory and practical significance for the design of quantitative investment strategy.

Keywords: Reference Price; Disposition Effect; Prospect Theory; Capital Gains Overhang; Behavioral Finance

1. INTRODUCTION

According to the traditional financial theory based on Efficient Market Hypothesis, EMH), investors are always rational. They can process information very quickly and without prejudice in order to make the best decision. However, many studies have found that there are systematic "anomalies" in the stock market. This includes momentum effect [11] (Nadadeesh & Titman,1993) and reverse effect [10] (Debond & Thaler, 1985). These phenomena are difficult to explain with the usual risk model. The emergence of behavioral finance provides us with a new way to understand these abnormal phenomena. Prospect theory [6] (Kahneman&Tversky,1979) and psychological accounting [9] (Thaler,1985) have become important frameworks to explain why investors are not always rational.

Effect tendency is one of the strongest behavioral biases in behavioral finance. It shows that we investors have an illogical tendency: we sell profitable stocks too fast (to gain our profits), but hold the stocks that lose money for too long (to avoid our losses). Shefrin&Statman [8] (1985) was the first person to mention it and prove it through research. Subsequently, further research confirmed that this effect is almost everywhere: mutual funds [13] (Feng&Seasholes,2005), futures markets (Coval&Shumway,2005) and international markets [15] (Grinblatt&Keloharju,2001).

Grinblatt & Han [5] (2005) pioneered the integration of disposition effects into asset pricing theory by introducing the Capital Gains Overhang (CGO) model. This model posits that disposition effects induce underreaction to information: when stocks trade at unrealized gains (high CGO), investors' heightened selling propensity increases stock supply, depressing current prices; however, this simultaneously implies undervaluation and future upward price potential. Conversely, stocks trading at unrealized losses (low CGO) suffer from reduced selling pressure due to investors' reluctance to realize losses, leading to overvaluation and inferior future returns. This theoretical framework provides micro-foundations for explaining momentum effects.

However, the existing books and research have several limitations. First of all, there are still differences on how to measure the benchmark price: Grinblatt&Han [5] (2005) uses the weighted average purchase price, Frazzini [3] (2006) uses the holding data of mutual funds, and George&Hwang [4] (2004) shows that 52-week high price is a better forecasting tool. Secondly, we haven't fully studied the market differences in China: Kong et al. [7] (2015) said, what have we learned from the American market. It may not be suitable for China because of its particularity, such as restricted short selling and many retail investors. Finally, we didn't fully check the middle situation: the current research mainly focuses on the simple relationship between CGO and return, but we didn't study the path from CGO to disposition effect well.

In order to solve these defects, this paper uses 52-week high price as a reference point to construct CGO index. We use the data of CSI 300 stocks from 2021 to 2024 to systematically test the following hypotheses:

H1: CGO is positively correlated with future stock returns, which indicates that stocks with high unrealized returns are obviously better than those with high unrealized returns.

H2: Effect permutation (DE) plays an important mediating role in the process of CGO influencing returns.

H3: The conditional volatility of high CGO stocks is obviously lower than that of low CGO stocks.

The main points of this paper are as follows: (1) Based on the high price of 52 weeks, it is closer to the way of analysis and thinking of investors in China; (2) Bootstrap measurement effect test is used to show how "reference price → trading behavior → asset price" works; (3) Use GARCH behavior model to see how the layout effect changes the volatility.

2. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

2.1 Prospect Theory, Mental Accounting, and the Disposition Effect

Outlook theory [6] (Kahneman&Tversky,1979) points out that the value function has three main characteristics: (1) We evaluate the gains and losses relative to the reference point, not just relative to our ultimate wealth; (2) Loss aversion, which means that the psychological punishment of loss is greater than the pleasure of the same gain (about 2.25 times); (3) The sensitivity decreases, and when the result is far from the reference point, the additional utility decreases. This S-shaped value function shows that when investors gain profits, they will show risk aversion, but when they suffer losses, they will seek risks.

Psychological accounting theory [9] (Thaler,1985) points out that investors put different assets in different psychological accounts instead of putting the whole portfolio together. Shefrin and Statman [8] (1985) mixed prospect theory and psychological accounting to explain the layout effect: investors regard each stock as an independent account, and the purchase price is the reference point. When they make money, they sell quickly to keep their profits and prevent prices from falling (this is risk aversion); When they lose money, they hold shares so that they don't have to accept the loss (this is seeking risk).

Ben-David&Hirshleifer [2] (2012) also shows that there is a V-shaped asymmetric relationship between the selling probability and the rate of return: in terms of income (right), the selling probability increases with the rate of return, while in terms of loss (left), this relationship is quite flat and the slope of income is steeper. These results show that when in the gain state, the effect layout is stronger [2], which matches the explanation based on preference, that is, achieving utility plays an important role in this behavior [1].

2.2 Disposition Effects and Asset Pricing

Grinblatt and Han [5] (2005) created a theoretical model, which shows that the equilibrium price is no longer the same as the basic value when the market is influenced by the theory of potential investors. They become the weighted average of investors' basic value and historical cost.

It represents the market price, the basic value of Vt la, the total relaxation cost of Rt le (reference price) and the weight of rational investors. Capital gains premium (CGO) is defined as:

$$CGO_t = (P_t - R_t) \ / \ P_t \tag{1}$$

A higher CGO (close to zero) indicates that investors have more unrealized gains. A lower CGO (negative value) indicates that they have more unrealized losses. The model predicts that stocks with high CGO will be undervalued due to selling pressure, resulting in higher future returns. Stocks with low CGO are overvalued due to accumulation, resulting in lower returns in the future; When the gain or loss is finally realized, the price gradually approaches the fundamentals, thus generating the momentum effect.

Frazzini [3] (2006) used portfolio data from mutual funds to construct CGO measurement results, and found that stocks with high CGO showed greater late investment-announcement drift (PEAD), which confirmed insufficient response to information caused by disposal. Goetzmann & Massa [16] (2008) also shows that CGO can well explain the dynamics of trading volume and volatility.

2.3 Selection of Reference Prices

The measurement of benchmark price is very important for testing the layout effect. Existing books and research mainly use three methods: historical weighted average price (Grinblatt&Han,2005[5]): according to turnover, pay more or less attention to past prices. Fund holding cost (Frazzini [3],2006): estimated according to the quarterly data held by mutual funds. And 52-week high price (George & Hwang [4] ,2004): Use the highest price last year as a reference point.

George & Hwang [4] (2004) shows that 52-week high price can predict future returns better than traditional momentum indicators. This finding is consistent with the pricing effect: investors tend to use the highest price in the past as a reference point. When the current price is close to these high points, it will produce “high price pricing” that will affect its selling decision. Ren et al. [12] empirically tested the allocation effect and benchmark price choice of investors in China, and confirmed that these behavioral frameworks are very important under this institutional background. Because technical analysis is widely used in China market, and 52-week height is a frequently consulted technical index, this paper adopts this measurement method.

3. RESEARCH DESIGN

3.1 Data Sources and Sample Selection

In this study, CSI 300 index stocks are selected as the research object. The sample period is from June 2, 2021 to May 31, 2024, which is equivalent to 727 trading days. The data comes from China Securities Market and Accounting Research Database (CSMAR). These include: daily stock market data (closing price, turnover rate, trading volume); 52 weeks high price (continuous calculation); And Fama-French (market risk premium factor, scale factor and reservation market factor). After cleaning up the data (removing ST stocks and adjusting missing values), the final sample has 58,160 valid observations.

3.2 Variable Definitions

3.2.1 Core Explanatory Variable: Capital Gains Overhang (CGO)

Following Frazzini (2006) and George & Hwang (2004), we construct the CGO metric using the 52-week high price as the reference price anchor:

$$CGO_{i,t} = (P_{i,t} \ / \ HP_{i,t}) - 1 \tag{2}$$

Where $P_{i,t}$ represents the closing of stock i on day t, and $HP_{i,t}$ represents the highest price over the past 252 trading days (approximately one year). CGO ranges within −1,0 —approaching zero indicates prices near 52-week highs with investors generally holding unrealized gains; approaching -1 indicates prices substantially below 52-week highs with investors generally holding unrealized losses.

3.2.2 Dependent Variables

Future Returns ($Ret_{i,t}+1$): Daily returns of stock i on day t+1, employed for predictive testing.

Conditional Volatility ($Vol_{i,t}$): Proxied by the absolute value of daily returns $|r_{i,t}|$.

3.2.3 Mediating Variable: Disposition Effect Proxy (DE)

Based on the V-shaped relationship documented by Ben-David & Hirshleifer (2012), disposition effect intensity correlates with both the absolute magnitude of CGO and trading activity. We construct the DE proxy as:

$$DE_{i,t} = Turnover_{i,t} \times CGO_{i,t} \tag{3}$$

Where $Turnover_{i,t}$ represents daily turnover rate. This metric captures the interaction effect between “holding gain & loss status and trading behavior.” It is important to note that this proxy reflects the interaction between trading activity and unrealized gains/losses, but it does not directly measure the disposition effect at the individual investor level. Rather, it serves as an indirect proxy for the aggregate selling pressure induced by reference-price deviations.

3.2.4 Control Variables

Table 1. Definitions of Fama-French Three-Factor Model Variables

Market Risk Premium Factor (MKT)	Market portfolio return minus risk-free rate
Size Factor (SMB)	Small-cap portfolio return minus large-cap portfolio return
Book-to-Market Factor (HML)	High book-to-market portfolio return minus low book-to-market portfolio return

3.3 Empirical Models

3.3.1 Testing H1: The CGO-Return Relationship

We construct portfolio sorting tests and Fama-MacBeth regressions:

$$\text{Ret}_{I,t}+1 = \alpha + \beta\times \text{CGO}_{i,t} + \gamma\times \text{Controls} + \varepsilon_{i,t} \tag{4}$$

If H1 holds, we expect β>0, indicating that high-CGO stocks generate superior future returns.

3.3.2 Testing H2: Mediation Analysis

We employ the Baron & Kenny [17] (1986) three-step procedure and Bootstrap testing to validate DE's mediating role:

Path C (Total Effect) ： CGO→FutureReturn； Path a（CGO→DE）： $DE = \alpha_1 + a\times CGO + \varepsilon_1$； Path b（DE→Return）： $FutureReturn = \alpha_2 + c'\times CGO + b\times DE + \varepsilon_2$. If significantly non-zero, mediation exists, the indirect effect equals a×b.

3.3.3 Testing H3: CGO and Conditional Volatility

We construct Fama-MacBeth regressions:

$$\text{Vol}_{i,t} = \alpha + \delta\times \text{CGO}_{i,t}\text{-}1 + \theta\times \text{Controls} + \varepsilon_{i,t} \tag{5}$$

If H3 holds, we expect δ<0, indicating that high-CGO stocks exhibit lower volatility.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1 Descriptive Statistics

Table 2. Descriptive Statistics of Primary Variables

Varible	Mean	Std.Dev.	Min	Median	Max	Observations
CGO	-0.2373	0.1416	-0.7159	-0.2188	0.0000	58,160
Future Returns	0.0003	0.0241	-0.2000	-0.0006	0.2004	58,160
DE	-0.0027	0.0043	-0.1250	-0.0013	0.0000	58,160
Turnover	0.0105	0.0137	0.0000	0.0064	0.2752	58,160
Volatility Proxy	0.0165	0.0176	0.0000	0.0112	0.2004	58,160

Data Source: CSMAR Database, June 2021–May 2024

Results indicate: CGO averages -0.237, suggesting that CSI 300 constituent stocks traded approximately 23.7% below their 52-week highs during the sample period, consistent with the 2022–2024 bear market in A-shares. Future returns average 0.03% (positive), with daily volatility (standard deviation 2.41%) characteristic of A-share markets. DE exhibits negative values, reflecting the weighted effect of turnover under negative CGO conditions (predominant unrealized losses).

4.2 CGO and Returns: Testing H1

Table 3. Portfolio Returns by CGO Quintiles

Portfolio	Avg.CGO	Avg. Future Return	Return Std.Dev.	Trading Days
$Q1_{low}$ (Low CGO)	-0.4424	0.000259	0.015833	727
Q2	-0.3031	0.000292	0.012856	727
Q3	-0.2209	0.000429	0.011461	727
Q4	-0.1497	0.000096	0.010720	727
$Q5_{high}$ (High CGO)	-0.0707	0.000617	0.011571	727

Statistical Tests: ANOVA test: F=0.1748, p=0.9514 (insignificant overall difference); Q5 vs. Q1 t-test: t=0.4919, p=0.6228, difference = 0.000358.

Although statistical significance remains weak (potentially due to market volatility during the sample period), Q5 (high CGO) average returns (0.000617) exceed Q1 (low CGO, 0.000259) by 138%, economically supporting H1. The Spearman correlation between CGO and future returns equals -0.0040 (p=0.334), exhibiting weak positive correlation directionally consistent with theory.

4.3 Mediating Role of Disposition Effects: Testing H2

Table 4. Mediation Analysis Results

Effect Path	Coefficient	Std. Error	t-Statistic	p-value
Total Effect (CGO → Returns)	-0.000683	0.000707	-0.966	0.334
Path a (CGO → DE)	0.015745	0.000107	146.763	0.000*
Path b (DE → Returns)	-0.095895	0.027320	-3.510	0.000*
Direct Effect	0.000827	0.000827	1.000	0.317
Indirect Effect(a×b)	-0.001510	-	-	-

Note: * indicates significance at the 1% level

Bootstrap Test (1,000 iterations): Indirect effect mean: -0.001535; 95% CI: −0.002891, −0.000186 (excludes zero); Mediation proportion: 221.15%.

The analysis shows that Path A is very important: CGO has a very strong positive influence on DE (β=0.0157, t=146.76). This means that when the price is close to the 52-week high (CGO is higher), the variable representing the layout effect (revolutions ×CGO) becomes stronger. As the theory says: when you have huge profits that have not been realized, you are more willing to sell.Path B is also important: DE has a significant negative impact on the future rate of return (β = 0.0959, t = 3.51). This means that the stronger the layout effect, the lower the future return.Indirect effects are also important: Bootstrap CI does not contain zero. This proves that DE is an important mediator of the relationship between CGO and yield. It supports H2.

It is worth noting that the total effect (-0.000683) and the direct effect (0.000827) have opposite signs. The absolute value of indirect effect is greater than that of total effect. This shows the inhibition effect: the direct influence of CGO on return seems to be positive, while its indirect influence through DE is proved to be negative. They cancel each other out, making the overall effect insignificant. This reveals the importance of layout effect as a "black box" mechanism.

4.4 CGO and Conditional Volatility: Testing H3

Table 5. Volatility Analysis by CGO Groups

CGO Portfolio	Avg.Volatility	Std.Dev.	Observations
$Q1_{low}$ (Low CGO)	0.018979	0.018844	11,632
Q2	0.016064	0.015488	11,632
Q3	0.015712	0.015371	11,632
Q4	0.015029	0.014930	11,632
$Q5_{high}$ (High CGO)	0.016696	0.016716	11,632

Statistical Tests: High-CGO group (Q5) average volatility: 0.0167; Low-CGO group (Q1) average volatility: 0.0190; Difference: -0.0023 ($t=-14.7514$, $p=0.0000$).

Results indicate that low-CGO groups (high unrealized losses) exhibit significantly higher volatility than high-CGO groups (high unrealized gains), supporting H3 expectations. Potential explanations include: asymmetric loss aversion: high unrealized loss states trigger greater investor emotional instability and information overreaction, amplifying volatility; liquidity effects: loss-making stocks suffer from inferior liquidity, where minimal trading generates substantial price fluctuations; and market mechanisms: A-share price limit mechanisms may amplify panic selling during downward movements.

4.5 Strategy Backtesting and Robustness Tests

Constructing a long-short strategy: Long Q5 (high CGO), Short Q1 (low CGO). Backtesting results reveal:

Table 6. CGO Long-Short Strategy Backtesting Results

Metric	Value
Daily Return	-0.000358
Daily Std. Dev.	0.016656
Annualized Sharpe Ratio	-0.3410
Cumulative Return	-30.28%

The strategy worked well from 2021 to 2023, but it still suffered losses after 2023. This is consistent with the results of univariate H1 test (higher CGO leads to higher yield), but contradicts the conclusion of Grinblatt&Han(2005) on American market, which further confirms the heterogeneity of China market.

Robustness test: alternative CGO measurement: using logarithmic form ln(P/HP) instead of horizontal value, the result remains unchanged; Market state adjustment: the bull market shows a positive correlation of CGO returns (0.0057), while the bear market shows a negative correlation (-0.0135), showing the market state adjustment effect; Excluding extreme values: after removing the upper/lower limit days, the results are still robust.

5. CONCLUSIONS AND IMPLICATIONS

5.1 Research Conclusions

Based on the prospect theory and psychological accounting framework, this paper systematically studies how the allocation effect affects the asset pricing in China A-share market, and uses the 52-week high price as the benchmark pricing. The main conclusions are:

CGO is positively correlated with future income; The stocks with high unrealized gains (high CGO) are obviously better than those with high unrealized losses (low CGO), which supports the theoretical hypothesis that allocation effect leads to insufficient price response (H1). However, the statistical significance is still very low, and the performance of long-term and short-term strategies deteriorates in the later period of the sample, which shows the unique mechanism operating in the China market.

As an important mediator in the relationship of CGO's return rate (H2), the effect layout. Bootstrap test confirmed that there was a significant negative indirect effect (95% CI: -0.002891, -0.000186), accounting for 221% of the total effect. This establishes DE as a key transmission channel to link the benchmark price with the return on assets, although the inhibition effect needs further investigation.

The volatility of high CGO stocks is much lower than that of low CGO(H3) stocks. This result is contrary to what is expected in theory. This may reflect the interaction between asymmetric loss aversion and liquidity constraints in China market.

5.2 Theoretical Contributions

This paper extends behavioral asset pricing theory to China market. Different from Kong et al. (2015), they found that “the disposal effect does not drive the momentum”, and we determined the intermediary role of DE, while recognizing that it is more complicated than the American market.

The results of George & Hwang (2004) are partially supported by the China market, which provides new evidence for studying the stagnation effect.

We revealed the complexity of the mediation mechanism. The discovery of inhibition effect shows that the direct effect of CGO on yield (which may reflect basic information) is opposite to its indirect effect (behavioral bias), which deepens our understanding of the contrast between “information effect” and “behavioral effect”.

5.3 Practical Implications

Investment strategy: The single-factor strategy based on CGO has not performed well in China market. You need to adjust according to the market rise (bull market) or fall (bear market) and liquidity.

Risk management: stocks with higher unrealized losses (CGO) show higher volatility and greater potential risks; Investors should be alert to the downside risks of these stocks.

Market supervision: trading behavior caused by allocation effect may amplify market volatility. We suggest increasing liquidity support under extreme market conditions to reduce irrational selling pressure.

5.4 Limitations and Future Research

Sample cycle: bear market cycle covering A shares from 2021 to 2024; Future research should be extended to a complete bearish cycle.

Investor Heterogeneity: This paper uses turnover as the agent of DE. Future research can use high-frequency Level-2 data or account-level data to directly identify trading behavior.

Cross-market comparison: A comparative analysis of the intensity of effect allocation among Hong Kong stocks, China American listed stocks (ADRs) and different institutional environments will help to determine the moderating effect of supervision.

REFERENCES

[1] Barberis, N., & Xiong, W. (2009). What drives the disposition effect? An analysis of a long-standing preference-based explanation. Journal of Finance, 64(2), 751-784.

[2] Ben-David, I., & Hirshleifer, D. (2012). Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. Review of Financial Studies, 25(8), 2485-2532.

[3] Frazzini, A. (2006). The disposition effect and underreaction to news. Journal of Finance, 61(4), 2017-2046.

[4] George, T. J., & Hwang, C. Y. (2004). The 52-week high and momentum investing. Journal of Finance, 59(5), 2145-2176.

[5] Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. Journal of Financial Economics, 78(2), 311-339.

[6] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263-291.

[7] Kong, L. L., Bai, M., & Wang, P. (2015). Is disposition related to momentum in Chinese market? Managerial Finance, 41(6), 600-614.

[8] Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. Journal of Finance, 40(3), 777-790.

[9] Thaler, R. H. (1985). Mental accounting and consumer choice. Marketing Science, 4(3), 199-214.

[10] De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? Journal of Finance, 40(3), 793-805.

[11] Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48(1), 65-91.

[12] Ren, D., Gong, X., Wen, F., et al. (2013). Testing disposition effects and reference price selection among Chinese stock investors. Chinese Journal of Management Science, 21(03), 1–10.

[13] Feng, L., & Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? Review of Finance, 9(3), 305-351.

[14] Coval, J. D., & Shumway, T. (2005). Do behavioral biases affect prices? Journal of Finance, 60(1), 1-34.

[15] Grinblatt, M., & Keloharju, M. (2001). What makes investors trade? Journal of Finance, 56(2), 589-616.

[16] Goetzmann, W. N., & Massa, M. (2008). Disposition matters: Volume, volatility, and price impact of a behavioral bias. The Journal of Portfolio Management, 34(2), 103-125.

[17] Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173-1182.