Risk and Return Trade-off in Chinese Market

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Abstract

We replicate Wang, Yan, and Yu (2016)'s CGO-dependent risk–return framework in the Chinese A-share market using CSI 500 stocks from 2014 to 2023. Our objective is to test whether capital gains overhang (CGO) conditions the risk–return tradeoff in an emerging market with high retail participation and unique trading constraints. We construct a turnover-based CGO measure following Wang et al. (2016) and employ six risk proxies: CAPM beta, return volatility (RETVOL), idiosyncratic volatility (IVOL), cash-flow volatility (CFVOL), age, and analyst forecast dispersion. Using single sorts, CGO double sorts, and Fama–MacBeth regressions, which additionally controls Underreaction to News and Disposition Effect. We confirm a robust low-risk anomaly: high-volatility portfolios consistently earn lower returns. However, we find no statistically significant interaction between CGO and risk across all specifications. Our results suggest that the CGO-dependent risk-return relation documented in the U.S. does not generalize to the CSI 500 during this period, likely due to market-specific features. From a factor investing perspective, low-risk signals appear more reliable than CGO conditioning in the Chinese large–mid cap universe over 2014–2023.

1. Introduction

Existing studies (Wang et al., 2016) show that capital gains overhang (CGO) strongly conditions the risk–return relation in the U.S.: high-CGO firms exhibit a positive risk–return tradeoff, while low-CGO firms show an inverted pattern. Given significant differences between the U.S. and China's A-share markets, it is unclear whether this behavioral mechanism holds in China.

This project replicates Wang et al. (2016) using the CSI 500 universe to assess whether CGO shapes the risk–return tradeoff in an emerging market characterized by high retail participation and unique regulations.

We find a robust low-risk anomaly, indicating lower-risk stocks earn higher returns, but no consistent evidence that CGO meaningfully alters the risk-return relationship. This suggests that CGO-based pricing dynamics may not generalize across market contexts, highlighting the importance of case-by-case behavioral factors analysis in asset pricing.

The remainder of this report is structured as follows. Section 3 details our methodology, including data construction, CGO and risk proxy definitions, and empirical strategies (sorting and Fama–MacBeth regressions). Section 4 presents our key findings.

2. Literature review

The risk–return relationship is a cornerstone of finance. In 1964, Capital Asset Pricing Model (CAPM) proposed a positive relation between an asset's risk and its expected return (Sharpe, p.425). Yet early empirical studies—by Black (1972, p.445), Black, Jensen, and Scholes (1972, p.44), and Haugen and Heins (1975, p.782)—found little evidence of such a relationship. Fama and French (1992, p.449) later showed that the return–risk slope flattens after controlling for firm size. Post-2000 research further corroborates this: Blitz and van Vliet (2007, p.112) documented superior risk-adjusted returns for low-volatility stocks; Frazzini and Pedersen (2014, p.20) observed similar patterns across equities, Treasuries, corporate bonds, and futures; Blitz, Pang, and van Vliet (2013, p.44) reported flat or negative risk–return relations across markets; and Baker, Bradley, and Wurgler (2011, p.40) challenged the convention of high risk compensated by high return.

The reason for CAPM failure may not be that risks cannot be priced, but a key assumption has been violated. CAPM assumes investors uniformly prefer high returns and low risk (Sharpe, 1964, p.428). Yet behavioral evidence showed risk preferences are state-dependent. Prospect Theory (Kahneman & Tversky, 1979, p.279) posited a reference-dependent utility function: concave (risk-averse) in gains, convex (risk-seeking) in losses, with losses weighted more heavily, as shown in Figure 1. Thaler's (1985, p.200) mental accounting further explains how investors deviate from rational choice. Odean's (1998, p.1795-1797) disposition effect—holding losers and selling winners—aligned with this state-dependent risk preference. Barberis, Huang, and Santos (2001, p.18-19) argued that this phenomenon may be due to losses after prior losses are especially painful, and

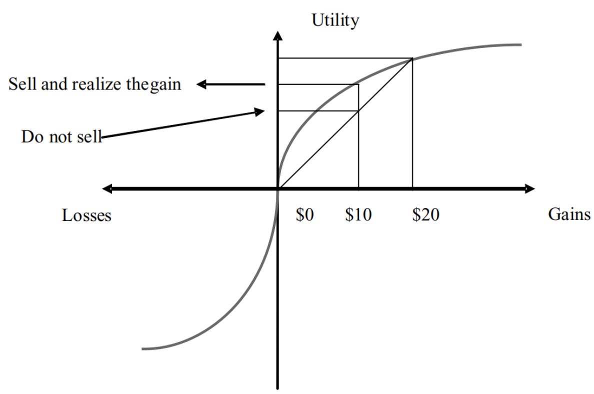

Figure 1. Utility Curve

gains that enable people with prior losses to break even are very attractive.

The variation of investor's risk preference directly undermines CAPM's risk-return prediction. Wang, Yan, and Yu (2016, p.1) showed the risk–return relation is positive for stocks with high capital gains overhang (CGO) and negative for low-CGO stocks. They proposed three mechanisms: (1) reference-dependent preference (RDP)—investor's risk-seeking in losses leads to overpricing of high-risk stocks and lower future return (p.9); (2) underreaction to news—high-CGO firms underreact to good news, leading to underpricing and higher future returns, while low-CGO firms underreact to bad news, causing overpricing and lower returns, with risk amplifying these effects (p.13); and (3) disposition-driven mispricing—selling pressure and limited arbitrage cause high-CGO (low-CGO) stocks to be underpriced (overpriced), especially among high-risk stocks (p.14). Empirically, RDP emerges as the most plausible explanation (p.15).

Building on this framework, we replicate Wang et al. (2016) in the Chinese stock market to examine whether the similar CGO dependent risk-return relation also exists in this emerging market.

3. Methodology

3.1. Data Preprocessing

In general, our datasets are from several sources, including those fetched from CSMAR and others provided by the instructor. They comprise market trading data, fundamentals, and market forecast data. Our data is converted to monthly frequency, ranging from 2014-01 to 2023-12, with underlying assets being CSI500 stocks for each period. Blacklisted stocks and untradable stocks are excluded when calculating indicators and portfolio returns. Missing values were skipped when calculating CGO and forward filled when constructing risk proxies to maintain the continuity of look-back windows and data samples. All features were winsorized at 1% and 99% and zscore normalized cross-sectionally for outlier mitigation and to ensure comparability across variables.

3.1.1. Risk Proxies

There are 6 risk factors used in total, respectively CAPM beta, Idiosyncratic Volatility (IVOL), Return Volatility (RETVOL), Reciprocal Firm Existence Age (1/Age), Analyst Forecast Dispersion (DISP), Cash Flow Volatility (CFVOL), in monthly frequency.

The data for the first 4 proxies are all A-share market data given by instructor. The CAPM beta and IVOL use FF5 factors excess return in monthly frequencies. The dependent variable excess stock return is calculated by monthly return minus monthly risk-free rate, which is resampled from daily frequency to monthly frequency by calculating mean value. Since the result we want is in monthly frequencies, time-series rolling regression is carried out with the regression window of 5 months for each beta and regression residuals. We then estimate idiosyncratic volatility by the time-series rolling standard deviation of residuals from Fama-French 3 factor regressions with the rolling window of 5 months. The return volatility is estimated by the rolling standard deviation of return, with the rolling window of 5 months. The existence ages of stocks are the time from their IPO month to the month of data point, which eliminate the first month and is calculated in month.

The data for the last 2 risk proxies are from CSMAR database. The analyst forecast of earnings per share data is used, which is originally in daily frequency, representing the date the forecast is reported (not release date). The forecast data is grouped into months and calculated the standard deviation within each month. Finally, the close price of the end of the month for each stock is taken as the denominator to scalarize the standard deviation. The result would be forward filled since some stocks at sometimes would lack of analyst forecast, and the latest forecast can be viewed meaningfully as the most current forecast. The cash flow volatility is calculated by

$$\frac{\text{earnings before extraordinary items} - \text{total accruals}}{\text{average total assets in the past 2 periods}},$$

where total accruals is change in current assets - change in cash - change in current liabilities - depreciation expense + change in short-term debt. The standard deviation of the cash flow is calculated with 5 months rolling window. The original data is in quarter frequency. Therefore, quarterly cash flow volatility is calculated first, then resampled and forward filled into monthly data, estimating the monthly cash flow volatility. Also note that the original data before operations contain missing data that should not be missing, which only affects one of the proxies and the effect is not extreme, so we take it as noise.

3.1.2. Reference Prices & CGO

The data period starts earlier to ensure sufficient historical coverage, while the backtest spans January 2014 to January 2023. The stock universe is based on the CSI500 Index, comprising all stocks that were part of the index at any point during the backtest. A unified "date-asset" index is established to align data consistently.

Daily closing prices, turnover, and volume are loaded and standardized. Data is cleaned to address suspensions, delistings, and untradable constraints. A shares outstanding proxy is derived to support weekly calculations.

Daily data is resampled to weekly frequency. To measure CGO, we first use the turnover-based measure from Grinblatt and Han (2005) to calculate the reference price. At each week t , the reference price for each stock is defined as:

$$RP_t = \sum_{n=1}^{T} \left(V_{t-n} \prod_{\tau=1}^{n-1} (1 - V_{t-n+\tau}) \right) P_{t-n}.$$

where P_t is the stock price at the end of week t; V_t is week t's turnover in the stock; T is 130, the number of weeks; and k is a constant that makes the weights on past prices sum to one. Given A-shares' high turnover, this window is shorter than standard practices and fits the market's characteristics. Weekly turnover is calculated as weekly trading volume divided by the number of shares outstanding. As argued by Grinblatt and Han (2005), the weight on P_{t-n} reflects the probability that the share purchased at week $t-n$ has not been traded since.

The CGO at week t is defined as:

$$CGO_t = \frac{P_{t-1} - RP_t}{P_{t-1}}.$$

Weekly CGO is then computed using this reference price and the prior week's price, avoiding look-ahead bias and market microstructure effect.
Monthly CGO adopts the final week's data of the month, while monthly turnover aggregates weekly values. The panel is aligned to CSI500 constituents, resulting in 2014–2023 dataset with 500 stocks per month.

3.2. Methods

3.2.1. Single Sort

For six different risk proxies and CGO, we conduct single sort to construct 5 portfolios. We rebalance it each month based on the CSI500 component stocks, where Q1 stands for lowest risk or CGO group and Q5 stands for largest risk or CGO group. All the portfolio are equal-weighted and t statistic are calculated based on Newey-West (1987) adjusted standard errors and reported in parentheses.

3.2.2. Double Sort

To test how CGO affects risk-return relation, we performed double sorts. At the end of each month, we divide all firms in our sample into five groups based on this month's CGO, and within each of the CGO groups, we further divide firms into five portfolios based on various risk proxies. The portfolio is then held for one month and equal-weighted returns are calculated. All records containing missing values were dropped to ensure consistent ranking and grouping within each time period for this section.

3.2.3. Simple Fama-MacBeth Regressions

The Fama-MacBeth regression is a two-step method used to test cross-sectional return predictors. First, monthly cross-sectional regressions of returns on lagged firm characteristics are run. Second, the time-series averages of these monthly coefficients are calculated, with statistical significance assessed using Newey-West standard errors.

This approach is ideal for our study as it controls for multiple firm-specific variables and market-wide shocks through time-series averaging. Crucially, it allows us to reliably test the interaction effect between capital gains overhang (CGO) and risk, which is central to our hypothesis, while isolating it from other confounding factors.

In our Fama-MacBeth regressions, we control for several well-established cross-sectional return predictors to isolate the unique explanatory power of the CGO-risk interaction. We include firm size (LOGME) and the book-to-market ratio (LOGBM) to account for the size and value premia. Momentum effects are controlled using short-term reversal (MOM(-1,0)), intermediate-term momentum (MOM(-12,-1)), and long-term reversal (MOM(-36,-12)). Additionally, we include share turnover (TURNOVER) to account for liquidity or trading activity effects. The inclusion of these variables ensures that the estimated coefficient on our key variable of interest, the interaction between CGO and risk, represents its net effect on expected returns after conditioning on other powerful determinants of stock returns.

$$\begin{aligned} R = &\alpha + \beta_1 \times CGO + \beta_2 \times PROXY \\ &+ \beta_3 \times PROXY \times CGO \\ &+ \beta_4 \times LOGBM + \beta_5 \times LOGME \\ &+ \beta_6 \times MOM(-1,0) + \beta_7 \times MOM(-12,-1) \\ &+ \beta_8 \times MOM(-36,-12) + \beta_9 \times TURNOVER + \epsilon \end{aligned}$$

3.2.4. Regression Controlling for News

Furthermore, we are using the Fama-MacBeth regression to test 2 behavior finance phenomena, Underreaction to News and Dispositional Effect.

The underreaction-to-news explanation posits that information diffuses slowly across investors, leading to delayed stock price adjustments. When news arrives, investors underreact, resulting in temporary mispricing: stocks with good news become underpriced, while those with bad news become overpriced. This effect is stronger for firms with higher information uncertainty, which is estimated by risk proxies since we consider information is usually uncertain.

In theory (Wang, et al, 2016), underreaction to news is hypothesized to be correlated with the factor return of CGO. However, this hypothesis is tested unsignificant. In the project, we intend to explore the effect of underreaction to news to the predictability of CGO factor by adding an interaction term of risk proxies and momentum, which captures the information of high risk and underreaction.

$$\begin{aligned}R =&\alpha + \beta_1 \times CGO + \beta_2 \times PROXY \\ &+ \beta_3 \times PROXY \times CGO + \beta_4 \times MOM(-12,-1) \\ &+ \beta_5 \times PROXY \times MOM(-12,-1) \\ &+ \beta_6 \times LOGBM + \beta_7 \times LOGME \\ &+ \beta_8 \times MOM(-1,0) \\ &+ \beta_9 \times MOM(-36,-12) \\ &+ \beta_{10} \times TURNOVER + \epsilon\end{aligned}$$

3.2.5. Regression Controlling for Disposition Effects

We want to test whether CGO is actually disposition effect-induced mispricing effect rather than change of risk preference.

Disposition effect means that investors exhibit a tendency to realize paper gains quickly while holding onto paper losses. Thus, when capital gains overhang (CGO) is high, selling pressure from gains leads to underpricing and predicts higher subsequent returns. Within this high-CGO group, high-risk stocks face stronger limits to arbitrage, so their mispricing is corrected less aggressively and their next-period returns are exceptionally high, whereas low-risk stocks invite more arbitrage capital, tempering the mispricing and delivering lower subsequent returns. Conversely, when CGO is low, investors cling to losses, creating overpriced stocks that earn lower future returns. Among these low-CGO firms, high-risk stocks again encounter tighter arbitrage constraints, so the overpricing persists and future returns stay depressed, while low-risk stocks are easier to arbitrage, so their prices revert more and generate higher subsequent returns.

We add this mispricing score and its interaction with risk proxies into the regression Eq. (1) and run the monthly Fama-MacBeth cross-sectional regressions of stock returns on lagged variables in the following form (both the time subscript and the firm subscript are omitted for brevity):

$$\begin{aligned}R = \alpha &+ \beta_1 \times \text{CGO} + \beta_2 \times \text{PROXY} \\ &+ \beta_3 \times \text{PROXY} \times \text{CGO} + \beta_4 \times \text{SCORE} \\ &+ \beta_5 \times \text{PROXY} \times \text{SCORE} + \beta_6 \times \text{LOGBM} \\ &+ \beta_7 \times \text{LOGME} + \beta_8 \times \text{MOM}(-1,0) \\ &+ \beta_9 \times \text{MOM}(-12,-1) + \beta_{10} \times \text{MOM}(-36,-12) \\ &+ \beta_{11} \times \text{TURNOVER} + \epsilon,\end{aligned} \tag{1}$$

where SCORE is the mispricing score as defined in Stambaugh, Yu, and Yuan (2015). We use one fundamental indicator LOGBM and one market indicator Momentum(-11,-2) to construct the score due to lack of raw data.

This cross-sectional Fama–MacBeth regression framework lets us diagnose whether the CGO channel is simply capturing mispricing. If after adding these mispricing terms, the CGO × PROXY coefficient loses statistical significance or shrinks markedly while the SCORE × PROXY coefficient is significant with the expected sign (positive for underpricing, negative for overpricing), the evidence points to a disposition-effect story. The heterogeneity in the risk–return relation is accounted for by mispricing captured by the mispricing score, not by CGO itself. Conversely, if CGO × PROXY stays significant and roughly unchanged even after controlling for MISPRICING × PROXY, then mispricing cannot be the sole driver that CGO must be proxying for additional mechanisms beyond what the explicit mispricing measure explains.

4. Empirical results

4.1. Single Sort

Table 1 summarizes the single-sort evidence. Each month we sort all eligible stocks into quintiles and report the average equal-weighted excess return in percent with Newey–West t-statistics correction for standard error. Consistent with the low-risk anomaly, portfolios sorted on total volatility or idiosyncratic volatility exhibit a strong monotonic decline in returns. The high-volatility quintile (Q5) underperforms the low-volatility quintile (Q1) by 1.08% per month for RETVOL (t = –3.15) and by 1.22% per month for IVOL (t = –3.96). The spread for cash-flow volatility is negative but insignificant, while the age-sorted spread is virtually zero. Interestingly, analyst-dispersion-sorted portfolios display the opposite pattern. Q5 outperforms Q1 by 58 bps (t = 2.95). Finally, the CGO quintiles show little variation in mean returns; the Q5 minus Q1 spread is a modest 14 bps and statistically indistinguishable from zero.

Table 1. Proxy Metrics Table

Portfolio	β_{MKT}	RETVOL	IVOL	CFVOL	AGE	DISP	CGO
	0.75%	1.26%	1.33%	0.77%	0.72%	0.30%	0.64%
Q1	(1.19)	(2.13)	(2.10)	(1.16)	(1.14)	(0.46)	(0.99)
	0.91%	0.84%	0.88%	0.87%	0.76%	0.67%	0.56%
Q2	(1.40)	(1.26)	(1.38)	(1.41)	(1.15)	(1.07)	(0.85)
	0.74%	0.68%	0.80%	0.62%	0.76%	0.59%	0.86%
Q3	(1.13)	(1.05)	(1.19)	(1.01)	(1.25)	(0.92)	(1.26)
	0.70%	0.53%	0.47%	0.82%	0.65%	0.87%	0.68%
Q4	(1.03)	(0.77)	(0.73)	(1.21)	(0.96)	(1.31)	(1.03)
	0.47%	0.18%	0.11%	0.48%	0.59%	0.88%	0.78%
Q5	(0.76)	(0.26)	(0.17)	(0.70)	(0.87)	(1.42)	(1.18)
	-0.28%	-1.08%	-1.22%	-0.29%	-0.12%	0.58%	0.14%
Q5–Q1	(-1.05)	(-3.15)	(-3.96)	(-1.23)	(-0.51)	(2.95)	(0.31)

4.2. Double Sort

Table 2 presents the main results for double sort. Monthly excess returns are reported in percentages and t-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses.

Among the lowest CGO group (CGO1), high-risk firms tend to earn lower returns than low-risk firms for most proxies — for example, the high-minus-low spread is –0.45% for IVOL (t = –1.06) and –0.68% for CFVOL (t = –1.74). However, these differences are only marginally significant and do not hold uniformly across all risk measures (e.g., the spread for β is –0.03% with t = –0.10).

More importantly, among the highest CGO group (CGO5), we also identified similar evidence of a negative risk–return relation. In fact, for IVOL and CFVOL, high-risk firms underperform low-risk firms (spreads of –1.08% and –0.76%, respectively), with t-statistics of –2.48 and –1.52. However, for other proxies, the high-minus-low spreads are statistically insignificant.

In sum, our results suggest that the CGO-conditioned risk–return relationship documented in the U.S. does not replicate in the CSI 500 universe. The low-risk anomaly appears robust, but this pattern is not meaningfully reshaped by CGO, regardless of the risk proxy used.

4.3. Simple Fama-MacBeth Regressions

Table 3 is the result of original Fama-MacBeth regression. The insignificant interaction terms between CGO and all risk proxies in our project contrast with the findings of Wang et al (2016) in US market. This may stem from structural differences in the Chinese market, where investor behavior may be more influenced by policy signals or market trends than by individual reference points. The shorter sample period (2014-2023) may also fail to capture a stable long-term behavioral effect. These results suggest the reference-dependent preference mechanism may be weaker or operate differently in the A-share market context. We also notice that the significance level of TURNOVER factor is high, which goes the other way of results according to Wang et al (2017). This probably implies some factors contributing to the differece between results.

4.4. Regression Controlling for News

Table 4 is the result of Fama-MacBeth regression with an interaction term of proxy and momentum(-12, -1) that capture the underreaction to news.
The result is overall similar to the original regression. The uniformly insignificant interaction terms between past returns (MOM) and risk proxies indicate no supporting evidence for the underreaction channel in our sample. This could be due to faster information diffusion or even overreaction among A-share investors, unlike the gradual diffusion assumed in the original theory. The generally weak momentum effect (MOM itself is insignificant) further undermines the foundation for this interaction. Therefore, the news underreaction mechanism documented in US markets does not appear to be a primary driver of the risk-return trade-off in this CSI500 sample.

4.5. Regression Controlling for Disposition Effects

Table 5 reports the Fama–MacBeth regressions that include both the CGO interaction and the mispricing score interaction. Across all six risk proxies the coefficient on PROXY × CGO is economically tiny and statistically insignificant. The point estimates range from –0.075% (IVOL) to +0.067% (DISP), with absolute t-statistics uniformly below 1.0, indicating that CGO does not generate any incremental risk–return heterogeneity once the mispricing score is controlled for. The standalone CGO effect is likewise muted, and the mispricing score itself carries a negative sign but is also insignificant. Although the PROXY × SCORE terms are positive for every proxy, which is consistent with the idea that mispricing might interact with perceived risk, none of them reach conventional significance levels. Overall, this specification finds no evidence that CGO contributes to the cross-sectional pricing of risk in excess of what is captured by the mispricing score, nor does it yield direct support for the mispricing interaction itself.

4.6. Limitations

Our empirical results should be interpreted with several important limitations in mind. First, the CSI 500 sample covers only 2014–2023, a relatively short horizon that limits statistical power and may reflect sample-specific features due to index revisions and structural shifts in the A-share market, limiting generalizability. Second, China's A-share market's unique trading rules may disrupt the CGO mechanism. The ±10% price limit hinders rapid price adjustments, prolonging mispricing and weakening CGO's reference price correction effect. Finally, our simplified mispricing control (SCORE) and lack of transaction cost modeling mean that the absence of significant CGO effects should be interpreted as the evidence in this setting, not definitive proof of CGO irrelevance in China.

4.7. Challenges

During the empirical analysis, we encountered two main data challenges. First, when constructing CGO, missing values within the lookback window would traditionally result in a missing CGO value. To preserve sample integrity, we skipped missing observations and computed CGO using only available data within the window. Second, analyst forecast dispersion (DISP) exhibited extensive missing values due to limited analyst coverage for many CSI 500 stocks. Rather than forward-filling data and calculating dispersion, we calculated DISP only when sufficient forecasts were available and then forward-filled the resulting dispersion series to maintain temporal continuity without distorting its statistical properties.

5. Discussions and Conclusions

This project replicates the CGO-conditioned risk–return framework of Wang, Yan, and Yu (2016) in the Chinese A-share market using CSI 500 stocks from 2014–2023. We confirm a pronounced low-risk anomaly in portfolio sorts, but we do not find robust evidence that CGO reshapes the risk–return relation through double sorts or through regression interactions. Across multiple Fama–MacBeth specifications (Appendix Tables 3–5), the CGO × risk interaction is consistently insignificant, and CGO itself has weak predictive power, suggesting that theory proved in the U.S. market does not generalize to this Chinese large-mid capital universe over our sample period.

Several factors could contribute to this non-replication, including differences in market microstructure and trading constraints, a potentially different investor reference point in a high-turnover environment, and measurement noise introduced by indicator constructions, which could come from the quantitative finance environment established in recent decays. From a practical factor-investing perspective, our results suggest that low-risk signals (especially volatility-based measures) appear more reliable than CGO conditioning in CSI 500 during 2014–2023, and that CGO-based conditional risk strategies should be treated cautiously unless supported by further robustness checks on longer samples, alternative reference-point constructions, and richer mispricing measures.

6. Appendix

Table 2. Double-sorted portfolio returns

Portfolio	**CGO1**	**CGO3**	**CGO5**	**CGO1**	**CGO3**	**CGO5**
	Proxy = β			**Proxy = RETVOL**		
P1	0.73%	0.94%	0.46%	0.68%	1.05%	0.80%
P3	0.67%	0.94%	0.32%	0.83%	0.76%	0.83%
P5	0.70%	0.63%	0.89%	0.31%	0.60%	0.65%
P5 - P1	−0.03%	−0.31%	0.43%	−0.37%	−0.45%	−0.15%
t-stat	(−0.10)	(−1.14)	(1.15)	(−1.03)	(−1.33)	(−0.35)
	Proxy = IVOL			**Proxy = CFVOL**		
P1	1.03%	1.57%	1.26%	1.14%	1.53%	1.26%
P3	0.39%	0.70%	0.93%	0.51%	0.69%	0.57%
P5	0.59%	0.23%	0.18%	0.46%	0.27%	0.50%
P5 - P1	−0.45%	−1.33%	−1.08%	−0.68%	−1.26%	−0.76%
t-stat	(−1.06)	(−3.61)	(−2.48)	(−1.74)	(−3.23)	(−1.52)
	Proxy = $1/$**AGE**			**Proxy = DISPER**		
P1	0.70%	0.98%	0.64%	0.56%	0.56%	0.51%
P3	0.72%	1.04%	1.20%	0.70%	0.82%	0.83%
P5	0.60%	0.66%	0.53%	0.84%	0.90%	0.98%
P5 - P1	−0.10%	−0.32%	−0.10%	0.27%	0.34%	0.47%
t-stat	(−0.34)	(−0.74)	(−0.26)	(1.35)	(1.28)	(0.90)

Table 3. Fama-MacBeth Regression Results with CGO and Risk Proxies (First Specification)

Variable	PROXY					
	CAPM β	IVOL	RETVOL	1/AGE	DISP	CFVOL
CGO	0.000741 (0.741)	0.000300 (0.266)	0.000431 (0.429)	0.000780 (0.731)	0.000449 (0.424)	0.000645 (0.610)
PROXY	-0.000244 (-0.278)	-0.001209 (-1.712)	-0.000906 (-1.106)	0.000126 (0.191)	0.001238 (2.027)**	0.000080 (0.158)
CGO $\times$ PROXY	-0.000165 (-0.336)	-0.001000 (-1.307)	-0.000744 (-1.060)	-0.000223 (-0.393)	0.000743 (0.951)	-0.000330 (-0.668)
LOGBM	0.000724 (0.470)	0.000124 (0.077)	0.000383 (0.248)	0.000653 (0.415)	0.000651 (0.409)	0.000769 (0.482)
LOGME	-0.002645 (-2.503)***	-0.002338 (-2.110)**	-0.002540 (-2.355)**	-0.002582 (-2.433)**	-0.002407 (-2.254)**	-0.002581 (-2.366)**
MOM(-1, 0)	-0.000156 (-0.115)	0.000193 (0.141)	-0.000054 (-0.038)	-0.000077 (-0.058)	0.000029 (0.022)	0.000043 (0.033)
MOM(-12, -1)	0.002219 (1.391)	0.002224 (1.426)	0.002151 (1.368)	0.001966 (1.319)	0.001880 (1.241)	0.001995 (1.354)
MOM(-36, -12)	-0.001399 (-1.638)	-0.001527 (-1.669)*	-0.001211 (-1.420)	-0.001534 (-1.745)*	-0.001424 (-1.597)	-0.001479 (-1.776)**
TURNOVER	-0.004758 (-4.132)***	-0.004685 (-4.026)***	-0.004502 (-3.935)***	-0.004765 (-4.321)***	-0.004388 (-3.923)***	-0.004613 (-4.007)***

Table 4. Fama-MacBeth Regression Results with CGO, Risk Proxies, and Underreaction to News Interaction

Variable	PROXY					
	CAPM β	IVOL	RETVOL	1/AGE	DISP	CFVOL
CGO	0.000732	0.000189	0.000359	0.000871	0.000447	0.000663
	(0.733)	(0.166)	(0.820)	(0.422)	(0.629)	(0.012)
PROXY	-0.000122	-0.001078	-0.000845	0.000189	0.001572	-0.000005
	(-0.143)	(-1.488)	(-1.055)	(0.290)	(2.015)**	(-0.008)
CGO × PROXY	-0.000108	-0.000876	-0.000746	0.000238	0.000214	-0.000176
	(-0.190)	(-1.135)	(-1.052)	(0.356)	(0.250)	(-0.318)
PROXY × MOM(-12, -1)	0.000152	-0.000012	0.000298	-0.001169	0.001288	-0.000690
	(0.324)	(-0.019)	(0.452)	(-1.620)	(1.280)	(-1.168)
LOGBM	0.000743	0.000101	0.000373	0.000640	0.000692	0.000687
	(0.480)	(0.063)	(0.240)	(0.407)	(0.432)	(0.426)
LOGME	-0.002612	-0.002286	-0.002543	-0.002515	-0.002399	-0.002612
	(-2.478)**	(-2.093)**	(-2.368)**	(-2.389)**	(-2.231)**	(-2.366)**
MOM(-1, 0)	-0.000154	0.000138	-0.000089	-0.000097	0.000096	0.000029
	(-0.112)	(0.099)	(-0.061)	(-0.073)	(0.072)	(0.022)
MOM(-12, -1)	0.002235	0.002367	0.002352	0.001706	0.001848	0.002002
	(1.370)	(1.359)	(1.345)	(1.169)	(1.188)	(1.368)
MOM(-36, -12)	-0.001466	-0.001554	-0.001169	-0.001609	-0.001440	-0.001459
	(-1.715)*	(-1.676)*	(-1.342)	(-1.842)*	(-1.604)	(-1.717)*
TURNOVER	-0.004652	-0.004676	-0.004555	-0.004706	-0.004475	-0.004611
	(-4.004)***	(-4.016)***	(-3.858)***	(-4.148)***	(-3.987)***	(-4.000)***

Table 5. Panel regressions with CGO interaction

Variable	PROXY = β_{MKT}	PROXY = RETVOL	PROXY = IVOL	PROXY = CFVOL	PROXY = AGE	PROXY = DISP
Constant	0.674%	0.679%	0.685%	0.671%	0.666%	0.674%
	(0.98)	(0.99)	(1.00)	(0.98)	(0.97)	(1.00)
CGO	0.030%	0.003%	−0.019%	0.021%	0.045%	0.006%
	(0.28)	(0.03)	(−0.16)	(0.19)	(0.41)	(0.06)
PROXY	−0.010%	−0.086%	−0.122%	−0.013%	−0.073%	0.138%
	(−0.11)	(−1.00)	(−1.63)	(−0.24)	(−0.64)	(1.66)
PROXY×CGO	0.004%	−0.056%	−0.075%	−0.040%	0.047%	0.067%
	(0.08)	(−0.79)	(−0.98)	(−0.79)	(0.49)	(0.81)
SCORE	−0.160%	−0.120%	−0.094%	−0.106%	−0.116%	−0.162%
	(−0.98)	(−0.74)	(−0.53)	(−0.64)	(−0.70)	(−0.97)
PROXY×SCORE	0.041%	0.072%	0.103%	0.080%	0.034%	−0.061%
	(0.93)	(1.46)	(1.90)	(1.54)	(0.42)	(−1.12)
LOGBM	−0.092%	−0.090%	−0.109%	−0.039%	−0.069%	−0.081%
	(−0.43)	(−0.44)	(−0.50)	(−0.18)	(−0.32)	(−0.38)
LOGME	−0.282%	−0.267%	−0.243%	−0.275%	−0.274%	−0.269%
	(−2.68)	(−2.47)	(−2.15)	(−2.50)	(−2.57)	(−2.51)
MOM$(-1, 0)$	0.009%	0.009%	0.029%	0.018%	0.014%	0.025%
	(0.07)	(0.07)	(0.21)	(0.14)	(0.10)	(0.19)
MOM$(-12, -1)$	0.124%	0.160%	0.189%	0.146%	0.133%	0.113%
	(0.72)	(0.88)	(1.03)	(0.88)	(0.82)	(0.66)
MOM$(-36, -12)$	−0.142%	−0.138%	−0.185%	−0.153%	−0.153%	−0.131%
	(−1.56)	(−1.61)	(−2.00)	(−1.84)	(−1.77)	(−1.51)
TURNOVER	−0.455%	−0.441%	−0.457%	−0.440%	−0.462%	−0.416%
	(−3.77)	(−3.70)	(−3.76)	(−3.60)	(−3.83)	(−3.50)

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