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Reference-dependent preferences and the risk–return trade-off[☆]

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ABSTRACT

This paper studies the cross-sectional risk–return trade-off in the stock market. A fundamental principle in finance is the positive relation between risk and expected return. However, recent empirical evidence suggests the opposite. Using several intuitive risk measures, we show that the negative risk–return relation is much more pronounced among firms in which investors face prior losses, but the risk–return relation is positive among firms in which investors face prior gains. We consider a number of possible explanations for this new empirical finding and conclude that reference-dependent preference is the most promising explanation.

1. Introduction

This paper studies a basic tenet in finance: the cross-sectional risk–return trade-off in the stock market. Traditional asset pricing theory [e.g., the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965)] implies a positive relation between risk and expected returns. However, recent empirical studies find that low-risk firms tend to earn higher average returns when risk is measured by CAPM beta or stock return volatility. As forcefully argued by Baker, Bradley, and Wurgler (2011), this empirical evidence runs counter to the fundamental principle in finance that risk is compensated with higher expected return.

We first show a new empirical fact, namely, that the risk–return relation is positive among stocks with high capital gains overhang (CGO) and negative among stocks

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with low CGO. The reason we study the risk–return trade-off among firms with different levels of CGO is motivated by a specific argument that we will delineate in more detail in Section 3.1, and we delay further discussion until then. The basic idea is that investors could have different risk attitudes depending on whether their investments are in gains or losses relative to a reference point. Thus, by separating firms with capital gain investors from those with capital loss investors, we can investigate the risk–return trade-off within each group.

We use the method in Grinblatt and Han (2005) to calculate a proxy for capital gains of individual stocks, that is, stock-level CGO, which is essentially the normalized difference between the current stock price and the reference price.[1] We then sort all stocks into portfolios based on lagged CGO and various measures of risk. Using total volatility and CAPM beta to measure risk, we find that high-risk firms earn higher returns among firms with high CGO, and this risk–return association is significantly weaker and even negative among firms with low CGO. For example, among firms with prior capital losses, the returns of high-volatility firms are 106 basis points (bps) lower per month than those of low-volatility firms. In sharp contrast, among firms with prior capital gains, the returns of high-volatility firms are 60 bps higher per month than those of low-volatility firms.

To further explore the robustness of our empirical evidence, in addition to CAPM beta and return volatility, we use several alternative intuitive measures of risk: idiosyncratic return volatility, cash flow volatility, firm age, and analyst forecast dispersion. Individual investors, for example, could view firms' idiosyncratic volatility as risk because they fail to diversify it mentally due to mental accounting (MA). Previous studies use these alternative measures of risk as proxies for information uncertainty, parameter uncertainty, information quality, or divergence of belief under various circumstances. In this paper, we label these variables *alternative measures of risk*. Investors might simply view parameter uncertainty as a form of risk. As a result, these alternative measures of risk are correlated with the perceived risk measure in the minds of investors. Indeed, we find that CGO is an important determinant in each of these risk–return relations as well. Among low-CGO stocks, these relations are negative, whereas among high-CGO stocks, these relations typically become positive.

We then consider several possible explanations for our empirical finding that the risk–return relation is positive among high-CGO stocks and negative among low-CGO stocks. The first possible explanation is reference-dependent preference (RDP), which motivated our double-sorting exercise in the first place. RDP suggests that investors' risk-taking behavior in the loss region can be different from that in the gain region. For example, prospect theory (PT), which describes individuals' risk attitudes in experimental settings very well, posits that when facing prior loss relative to a reference point, individuals tend to be risk seeking rather than risk averse. As a result, if arbitrage forces are limited, there could be a negative risk–return relation among these stocks. In contrast, among stocks in which investors face capital gains, the traditional positive risk–return relation should emerge, since investors of these stocks are risk averse. Thus, RDP can potentially explain our new empirical finding and account for the weak (and sometimes negative) overall risk–return relation.

However, we acknowledge that the above static argument might not be valid in a dynamic setting (see, e.g., Barberis and Xiong, 2009). Thus, before fully embracing the argument, it would be helpful to develop a formal model in a dynamic setting, which is beyond the scope of our study. The main purpose of this paper is to show that the risk–return trade-off depends strongly on whether stocks are trading at a gain or at a loss and to suggest that RDP plays a role in this. Our results point to the usefulness of constructing such a dynamic model in future research.

The second possible explanation for our finding is underreaction to news. The logic is as follows: High-CGO firms typically have high past returns, meaning that high-CGO firms are likely to have experienced good news in the recent past. If information travels slowly across investors, which causes investor underreaction, then high-CGO firms would be typically underpriced. Meanwhile, if information travels even more slowly for high-risk firms due to higher information uncertainty, then among firms with recent good news, high-risk firms are likely to have higher future returns than low-risk firms because of the more severe current undervaluation. Thus, a positive risk–return relation among high-CGO firms is observed. In contrast, low-CGO firms probably have experienced negative news and therefore have been overpriced due to underreaction. This overpricing effect is stronger when risk is high, since the underreaction effect is larger. Thus, a negative risk–return relation exists among low-CGO firms. Under this explanation, the key driving factor is past news, and the observed opposing risk–return relations at different levels of CGO is simply due to the positive correlation between CGO and past news.

The final possible explanation we examine is mispricing due to the disposition effect. One could argue that CGO itself is a proxy for mispricing, as in Grinblatt and Han (2005). Because of the disposition effect (i.e., investors' tendency to sell securities whose prices have increased since purchase rather than those that have dropped), high-CGO stocks experience higher selling pressure and thus are underpriced, while low-CGO stocks are relatively overpriced. Meanwhile, compared with low-risk stocks, high-risk stocks are more subject to mispricing because they tend to have higher arbitrage costs. Taken together, within the high-CGO group, high-risk stocks would be even more underpriced than low-risk stocks, but the opposite holds for the low-CGO group. Similar to the underreaction to news explanation, this disposition effect-induced mispricing effect could potentially explain the negative risk–return relation among low-CGO firms and the positive risk–return relation among high-CGO firms. Notice that the RDP explanation is different from this disposition effect-induced mispricing explanation, because it does not require CGO to

[1] We also show that our results remain similar if CGO is calculated based on mutual fund holdings as in Frazzini (2006).

be a proxy for mispricing. It requires only that investors' risk attitude depends on a reference point.

To examine these three possible explanations, we perform a series of Fama and MacBeth (1973) regressions. First, we show that the interaction between CGO and risk positively predicts future returns, confirming that CGO plays a significant role in the risk–return trade-off, consistent with the RDP explanation. Second, to ensure that this positive interaction is not purely due to the correlation between CGO and past news as implied by the underreaction-to-news explanation, we add the interaction of past returns (a proxy for past news) and risk proxies to the regressions to control for the potential underreaction effect. We find that the interaction between CGO and risk remains significant. In addition, after controlling for the role of CGO, the interaction between past returns and risk proxies is no longer significant or even has a negative sign for three of the six risk proxies. Third, we add the interaction between mispricing and risk proxies to the regressions. Using several proxies for mispricing, we find that the effect of CGO on the risk–return trade-off remains significant. This implies that our results are not purely driven by the mispricing role of CGO due to the disposition effect. Instead, it suggests that the risk-taking and risk-averse behavior in the loss and gain regions, respectively, could drive our key results. Finally, we control for all channels simultaneously in the regressions and find that the interactions between CGO and risk proxies are consistently significant for all risk proxies.

In further robustness tests, we show that this CGO effect survives different subperiods, as well as the exclusion of Nasdaq stocks, small stocks, and illiquid stocks, and that it is also stronger among firms with more individual investors, who are more likely to have RDP. To further alleviate the effect from small stocks, we use weighted least square analysis in the Fama-MacBeth regressions. The CGO effect remains

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Lastly, a vast literature studies the relation between our alternative measures of risk (especially idiosyncratic return volatility and analyst forecast dispersion) and expected returns. Different theories have different implications for this relation, and the empirical evidence is mixed.[4] Existing studies typically focus on the unconditional relation between these alternative measures of risk and returns. By contrast, our study focuses on the risk–return trade-off *conditional* on different levels of CGO. By exploring the heterogeneity of this relation across different types of firms, our study emphasizes the non-monotonicity of this relation.

The rest of the paper is organized as follows. Section 2 defines the key variables used in our tests and presents a new empirical finding. Section 3 discusses several possible explanations for this new empirical finding, paying special attention to RDP since it motivates our key conditional variable, CGO. Additional robustness tests are covered in Section 4. Section 5 concludes.

2. Heterogeneity in the risk–return relation: a new empirical fact

In this section, we present a new empirical finding regarding the role of CGO on the risk–return trade-off. To proceed, we first define the key variables used in our tests. We then report summary statistics, the double-sorting portfolio, and the Fama-MacBeth regression analysis.

2.1. Definition of key variables

Our data are from several sources. Stock returns and accounting data are obtained from the Center for Research in Security Prices (CRSP) and Compustat Merged Database. Analyst forecast data are taken from the Institutional Brokers' Estimate System (I/B/E/S), and mutual fund holdings data are from the Thomson-Reuters Mutual Fund Holdings database (formerly CDA/Spectrum).[5] Our sample includes all common stocks traded on the NYSE, Amex, and Nasdaq from CRSP, with stock prices at least \$5 and non-negative book equity at the portfolio formation date from January 1962 to December 2014.

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:

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

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 260, the number of weeks in the previous 5 years; and k is a constant that makes the weights on past prices sum to one. Weekly turnover is calculated as weekly trading volume divided by the number of shares outstanding. To address the issue of double counting of volume for Nasdaq stocks, we follow Anderson and Dyl (2005). They propose a rule of thumb to scale down the volume of Nasdaq stocks by 50% before 1997 and 38% after 1997 to make it roughly comparable to the volume on the NYSE. Furthermore, to be included in the sample, a stock must have at least 100 weeks of non-missing data in the previous 5 years. 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:

$$CGO_t = \frac{P_{t-1} - RP_t}{P_{t-1}}. \tag{2}$$

To avoid market microstructure effects, the market price is lagged by 1 week. Finally, to obtain CGO at a monthly frequency, we use the last-week CGO within each month. Because we use 5-year daily data with a minimum requirement of 100-week non-missing values to construct CGO, our main sample period ranges from January 1964 to December 2014. Last, the reference point might not be the purchase price. Instead, the reference point could be the expected future price (see, e.g., Koszegi and Rabin, 2006; 2007) or a moving average of past prices. However, it is likely that the relation between purchase and expected or past prices is monotonic. Thus, using average purchase price as the reference point should not pose a big problem for our portfolio-sorting analysis.

To measure risk, we use the traditional CAPM beta (β) and return volatility (RETVOL) as our main proxies. We use a 5-year rolling window as in Fama and French (1992) to estimate the market beta for individual firms. Following the approach in Baker, Bradley, and Wurgler (2011), firm total volatility is calculated as the standard deviation of the previous 5-year monthly returns. Our results are robust to different measures of total volatility. For example, we can use daily data from the previous month as in French, Schwert, and Stambaugh (1987), or we can use monthly returns from the previous year to estimate volatility as in Baker and Wurgler (2006). The results based on different volatility measures are available upon request.

As argued before, investors also could use some alternative measures of risk as the proxy for true risk. We choose four alternative risk measure proxies. The first variable is idiosyncratic stock return volatility (IVOL). Following Ang, Hodrick, Xing, and Zhang (2006), we measure IVOL by the standard deviation of the residual values from the time-series model:

$$R_{i,t} = b_0 + b_1 R_{M,t} + b_2 SMB_t + b_3 HML_t + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,\,t}$ is stock i's daily excess return on date t, and $R_{M,\,t}$, SMB_t, and HML_t are the market factor, size factor, and value factor on date t, respectively.[6] We estimate Eq. (3) for

[4] Ang, Hodrick, Xing, and Zhang (2006, 2009), for example, find a negative relation between idiosyncratic volatility and expected returns, whereas Bali and Cakici (2008); Huang, Liu, Rhee, and Zhang (2010); Lehmann (1990); Malkiel and Xu (2002); Tinic and West (1986), and Spiegel and Wang (2010) show a positive or insignificant relation. Boehme, Danielsen, Kumar, and Sorescu (2009) find that this relation depends on short-sale constraints. In addition, Diether, Malloy, and Scherbina (2002) and Goetzmann and Massa (2005) show a negative relation between analyst dispersion and stock returns, whereas Qu, Starks, and Yan (2004) and Banerjee (2011) find the opposite.

[5] The mutual fund data include quarterly fund holdings from January 1980 to June 2014. The statutory requirement for reporting holdings is semiannual. However, about 60% of the funds file quarterly reports.

[6] We thank Ken French for providing and updated series for these factors.

each stock each month in the data set using the daily return from the previous month. In addition, we repeat our analysis using alternative measures of idiosyncratic volatility with weekly or monthly data. The results are robust and available upon request.

The other three variables are firm age (AGE), analyst forecast dispersion (DISP), and cash flow volatility (CFVOL). AGE is the number of years since the firm's first appearance in CRSP until the portfolio formation date; DISP is the standard deviation of analyst forecasts on 1-year earnings (obtained from I/B/E/S) at the portfolio formation date scaled by the prior year-end stock price to mitigate heteroskedasticity; and CFVOL is the standard deviation of cash flow over the previous 5 years.[7]

These alternative measures of risk can be viewed, and have been used, as proxies for information uncertainty in Zhang (2006), idiosyncratic parameter uncertainty or information risk in Johnson (2004), divergence of opinion in Diether, Malloy, and Scherbina (2002), parameter uncertainty over the firm's profitability in Korteweg and Polson (2009); Pastor and Veronesi (2003), and He, Li, Wei, and Yu (2014), and information quality in Veronesi (2000) and Armstrong, Banerjee, and Corona (2013). The existing theories suggest that, unconditionally, parameter/information risk can be unpriced (see, e.g., Brown, 1979), positively priced (see, e.g., Merton, 1987), or negatively priced (see, e.g., Miller, 1977). Here, we simply view these variables as proxies for investors' risk measures and examine how the conditional risk–return trade-off changes across firms with different levels of CGO.[8]

2.2. Summary statistics and one-way sorts

Fig. 1 plots the time series of the 10th, 50th, and 90th percentiles of the cross section of the CGO of all individual stocks. Consistent with Grinblatt and Han (2005), there is a fair amount of time-series variation in CGO. More important, there is wide cross-sectional dispersion in CGO, which is necessary for our analysis of the heterogeneity of the risk–return trade-off across firms with different levels of CGO.

Table 1 reports summary statistics for the portfolio excess returns sorted by lagged CGO. To facilitate a comparison with previous studies on momentum (see, e.g., Grinblatt and Han, 2005), we report equally weighted portfolio returns based on lagged CGO. However, we report value-weighted returns for the rest of our analysis. Delisting bias in the stock return is adjusted according to Shumway (1997). On average, high-CGO firms earn significantly higher subsequent returns, although these firms earn significantly lower returns during January. This pattern is the same as the findings in Table 2 of

[7] Following Zhang (2006), cash flows are calculated as follows: CF = (earnings before extraordinary items − total accruals)/average total assets in the past 2 years; total accruals = change in current assets − change in cash − change in current liabilities − depreciation expense + change in short-term debt.

[8] In untabulated analyses, we consider other proxies for uncertainty such as firm size and analyst coverage. The results, omitted for brevity and available upon request, are largely in line with those based on the proxies we use in the main text.

Table 1
Summary statistics.

Panel A reports the time-series averages of the monthly equally weighted excess returns for five portfolios sorted by capital gains overhang (CGO), the difference in the excess returns between the high- and low-CGO portfolios, the standard deviation of excess returns ($\sigma(RET)$), the intercepts of the Fama-French three-factor regression, and the corresponding t-statistics. The last four columns report the excess portfolio returns separately during January (JAN) and non-January (FEB-DEC) months. At the beginning of each month, we sort NYSE, Amex, and Nasdaq common stocks with stock prices of at least \$5 and non-negative book value of equity into five groups based on the quintile of the ranked values of weekly CGO as of the last week of the previous month. CGO at week t is computed as one less the ratio of the beginning of the week t reference price to the end of week $t-1$ price, where the week t reference price is the average cost basis calculated as $RP_t = \frac{1}{k}\sum_{n=1}^{T}\left(V_{t-n}\prod_{\tau=1}^{n-1}(1-V_{t-n-\tau})\right)P_{t-n}$, where V_t is week t's turnover in the stock, T is the number of weeks in the previous 5 years, and k is a constant that makes the weights on past prices sum to one. Turnover (TURNOVER)is calculated as trading volume divided by number of shares outstanding. The portfolio is rebalanced each month. Panel B reports the time-series averages of portfolio characteristics. LOGME is the log of size, BM is the book value of equity divided by market value at the end of last fiscal year, ILLIQ is the illiquidity measure from Amihud (2002) calculated as the average ratio of the daily absolute return to the daily dollar trading volume in the past year, MOM is the cumulative return from the end of month $t-12$ to the end of month $t-1$, β is the coefficient of the monthly capital asset pricing model (CAPM) regression in the past 5 years with a minimum of 2 years of data, and MARKET% is the portion of total market capitalization. %(IO) is the fraction of outstanding shares held by institutional investors. #(IO) is the number of institutional investors holding a firm's shares. Monthly excess returns are in percentages and illiquidity is in units of 10^{-6}. The sample period is from January 1964 to December 2014, except for %(IO) and #(IO), which are from January 1980 to December 2014. The t-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses.

Panel A: Five CGO portfolio returns

Portfolio	RET	tσ

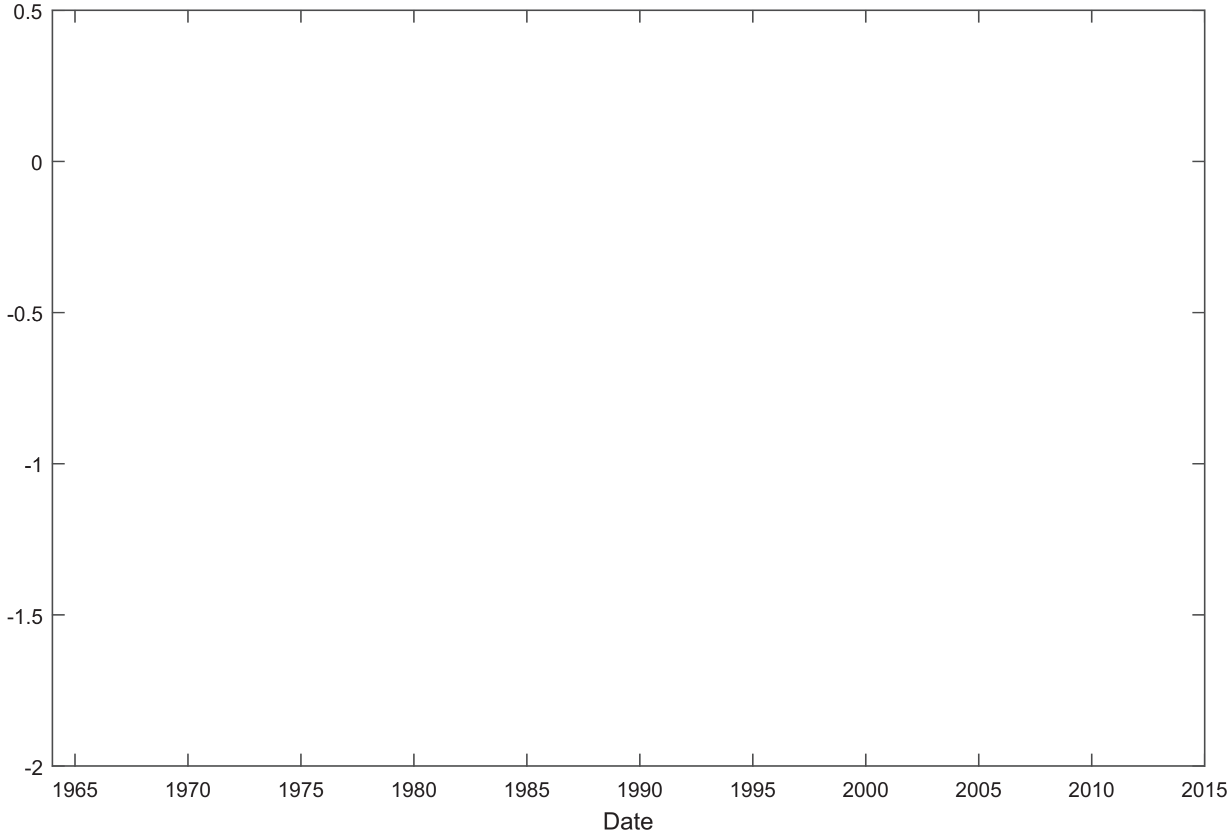
0.5
0
-0.5
-1
-1.5
-2
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
Date

Table 2
Single-sorted portfolios by risk proxies.

This table reports the time-series averages of the monthly value-weighted excess returns for portfolios sorted by our risk proxies, the difference in the excess returns between the high and low portfolios, the intercepts of the capital asset pricing model (CAPM) regression $[R_{i,t} - R_{ft} = \alpha + b_{i,M}(R_{M,t} - R_{ft}) + \varepsilon_{i,t}]$, the intercepts of the Fama-French three-factor regression $[R_{i,t} - R_{ft} = \alpha + b_{i,M}(R_{M,t} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}]$, and the t-statistics of the differences. We consider six proxies: β is the coefficient of the monthly CAPM regression $[R_{i,t} - R_{ft} = \alpha + \beta_{i,M}(R_{M,t} - R_{ft}) + \varepsilon_{i,t}]$ in the past 5 years with a minimum of 2 years of data. Stock volatility (RETVOL) is the standard deviation of monthly returns over the past 5 years with a minimum of 2 years of data. Idiosyncratic volatility (IVOL) is the standard deviation of the residuals from the Fama-French three-factor model using daily excess returns in the past month. Cash flow volatility (CFVOL) is the standard deviation of cash flow from operations in the past 5 years. Age (AGE) is the number of years since the firm was first covered by the Center for Research in Security Prices (CRSP). Analyst forecast dispersion (DISPER) is the standard deviation of analyst forecasts of 1-year earnings from the Institutional Brokers' Estimate System (I/B/E/S) scaled by the prior year-end stock price to mitigate heteroskedasticity. Risk proxies are defined as in Table 1. At the beginning of each month, we sort NYSE, Amex, and Nasdaq ordinary stocks with stock prices of at least $5 and non-negative book value of equity into five groups based on the quintile of the ranked values of each proxy. The sample period is from January 1964 to December 2014, except for DISPER, which is from January 1976 to December 2014. The excess returns are in percentages. The t-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses.

	Proxy					
Portfolio	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
P1	0.491	0.483	0.507	0.514	0.478	0.627
P2	0.503	0.536	0.539	0.542	0.558	0.629
P3	0.515	0.534	0.561	0.627	0.527	0.634
P4	0.520	0.566	0.551	0.498	0.549	0.662
P5	0.471	0.465	0.046	0.467	0.559	0.533
P5 - P1	−0.021	−0.018	−0.461	−0.047	0.081	−0.094
t-stat	(−0.08)	(−0.06)	(−1.75)	(−0.28)	(0.48)	(−0.42)
CAPM-α	−0.471	−0.475	−0.818	−0.285	−0.108	−0.267
t-stat	(−2.06)	(−1.86)	(−3.44)	(−1.96)	(−0.69)	(−1.19)
FF3-α	−0.301	−0.332	−0.765	−0.158	0.017	−0.651
t-stat	(−1.80)	(−1.83)	(−4.63)	(−1.47)	(0.15)	(−3.65)

to forces identified by previous studies such as leverage constraints, sentiment-induced mispricing, or index benchmarking. We discuss this in more detail in Subsection 3.4.

More interesting, among the group of firms with the lowest CGO, high-risk firms earn significantly lower returns. For instance, Table 3 shows that, among the lowest CGO group, the returns of high-beta firms are 64 bps lower per month than those of low-beta firms. Thus, the security market line is completely inverted among low-CGO firms. More dramatically, among the lowest CGO group, the returns of high-volatility firms are 106 bps lower per month than those of low-volatility firms, whereas among the highest CGO group, the returns of high-volatility firms are 60 bps higher per month than those of low-volatility firms. Similar results hold for other risk measures. That is, the risk–return relation is positive among high-CGO firms

Table 3
Double-sorted portfolio returns.
At the beginning of each month, we divide all NYSE, Amex, and Nasdaq common stocks with non-negative book equity and stock prices of at least \$5 into five groups based on lagged capital gains overhang (CGO); then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. CGO and risk proxies are defined as in Tables 1 and 2. The portfolio is then held for 1 month, and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1964 to December 2014, except for DISPER, which is from January 1976 to December 2014. The *t*-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses.

Portfolio	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy = β				Proxy = RETVOL			
P1	0.596	0.494	0.545		0.679	0.480	0.584	
P3	0.504	0.537	0.781		0.429	0.531	0.810	
P5	−0.046	0.378	0.885		−0.383	0.417	1.184	
P5 - P1	−0.642	−0.116	0.340	0.983	−1.062	−0.063	0.601	1.663
t-stat	(−2.31)	(−0.49)	(1.52)	(3.92)	(−2.84)	(−0.21)	(2.19)	(4.52)
FF3-α	−0.930	−0.429	0.172	1.103	−1.253	−0.408	0.334	1.587
t-stat	(−4.28)	(−2.59)	(0.97)	(4.24)	(−4.41)	(−1.76)	(1.43)	(4.20)
	Proxy = IVOL				Proxy = CFVOL			
P1	0.875	0.477	0.669		0.742	0.598	0.699	
P3	0.233	0.492	0.797		0.485	0.412	0.843	
P5	−1.050	0.072	0.989		0.274	0.306	0.936	
P5 - P1	−1.924	−0.405	0.320	2.244	−0.469	−0.292	0.237	0.706
t-stat	(−6.00)	(−1.62)	(1.58)	(7.97)	(−2.00)	(−1.48)	(1.25)	(2.68)
FF3-α	−2.093	−0.678	0.132	2.225	−0.515	−0.345	0.143	0.658
t-stat	(−8.48)	(−3.59)	(0.73)	(8.10)	(−2.47)	(−2.01)	(0.84)	(2.41)
	Proxy = 1/AGE				Proxy = DISPER			
P1	0.461	0.478	0.565		0.601	0.543	0.930	
P3	0.199	0.466	0.913		0.458	0.707	0.829	
P5	−0.005	0.526	1.096		−0.347	0.762	1.026	
P5 - P1	−0.466	0.048	0.531	0.997	−0.948	0.219	0.095	1.043
t-stat	(−2.01)	(0.32)	(3.40)	(4.05)	(−2.66)	(0.90)	(0.41)	(3.12)
FF3-α	−0.473	−0.046	0.430	0.903	−1.490	−0.234	−0.284	1.207
t-stat	(−2.42)	(−0.33)	(2.93)	(3.43)	(−4.54)	(−1.07)	(−1.30)	(3.21)

116 bps per month for CAPM beta [versus 98 bps using the Grinblatt and Han (2005) CGO measure], 153 bps per month for stock total volatility (versus 166 bps), 206 bps per month for idiosyncratic volatility (versus 224 bps), 60 bps per month for cash-flow volatility (versus 71 bps), 115 bps per month for firm age (versus 100 bps), and 101 bps per month for analyst forecast dispersion (versus 104 pbs). In addition, the *t*-statistics for all of these quantities are significant.

In sum, our results from both turnover-based CGO and holding-based CGO suggest that the risk–return relation is positive among high-CGO firms and negative among low-CGO firms. In other words, cross-sectional heterogeneity exists in the risk–return trade-off across firms with different levels of CGO.

2.4. Fama-MacBeth regressions

Although the double-sorting approach is simple and intuitive, it cannot explicitly control for other variables that could influence returns. Since CGO is correlated with other stock characteristics, in particular, past returns and shares turnover, concern could arise that the results in Tables 3 and 4 are driven by effects other than the capital gains or losses that investors face. To address this important concern, we perform a series of Fama and MacBeth (1973) cross-sectional regressions, which allow us to conveniently control for additional variables. We estimate 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):

$$\begin{aligned} R = \alpha &+ \beta_1 \times CGO + \beta_2 \times PROXY \\ &+ \beta_3 \times PROXY \times CGO + \beta_4 \times LOGBM \\ &+ \beta_5 \times LOGME + \beta_6 \times MOM(-1,0) \\ &+ \beta_7 \times MOM(-12,-1) \\ &+ \beta_8 \times MOM(-36,-12) + \beta_9 \times TURNOVER + \epsilon, \quad (6) \end{aligned}$$

where R is monthly stock return in month $t+1$, CGO is as defined in Grinblatt and Han (2005) at the end of month t, $PROXY$ is one of our six risk proxies at the end of month t, $LOGBM$ is the natural log of the book-to-market ratio at the end of month t, $LOGME$ is the natural log of market equity at the end of month t, $MOM(-1,0)$ is the stock return in month t, $MOM(-12,-1)$ is the stock return from the end of month $t-12$ to the end of month $t-1$, $MOM(-36,-12)$ is the stock return from the end of month $t-36$ to the end of month $t-12$, and $TURNOVER$ is stock turnover in month t.

Columns (1) and (2) in Table 5 report the results. The benchmark regression in Column (1) shows that the coefficient on CGO is significant and positive, confirming the Fama-MacBeth regression results of Grinblatt and Han (2005). In Column (2), we add the list of traditional return predictors, such as firm size, book-to-market, past returns,

Table 4
Double-sorted portfolio returns using the Frazzini (2006) capital gains overhang (CGO).
At the beginning of each month, we divide all NYSE, Amex, and Nasdaq common stocks with non-negative book equity and stock prices of at least \$5 into five groups based on lagged CGO following (Frazzini, 2006); then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. Risk proxies are defined as in Tables 1 and 2. The portfolio is then held for 1 month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1980 to October 2014. The *t*-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses.

Portfolio	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy = β				Proxy = RETVOL			
P1	1.013	0.765	0.538		1.068	0.828	0.675	
P3	0.978	0.738	0.921		0.602	0.615	1.204	
P5	0.391	0.473	1.076		−0.113	0.385	1.026	
P5–P1	−0.622	−0.292	0.538	1.160	−1.181	−0.443	0.351	1.532
t-stat	(−1.36)	(−0.83)	(1.35)	(2.70)	(−2.50)	(−1.08)	(0.95)	(3.24)
FF3-α	−1.067	−0.632	0.228	1.296	−1.568	−0.721	0.169	1.737
t-stat	(−3.00)	(−2.61)	(0.66)	(2.77)	(−4.17)	(−2.62)	(0.54)	(3.41)
	Proxy = IVOL				Proxy = CFVOL			
P1	1.070	0.875	0.839		1.067	0.868	0.681	
P3	0.530	0.588	1.025		1.043	0.689	1.130	
P5	−0.768	0.299	1.060		0.652	0.476	0.865	
P5–P1	−1.838	−0.575	0.221	2.059	−0.415	−0.393	0.184	0.599
t-stat	(−4.71)	(−1.97)	(0.77)	(4.96)	(−1.82)	(−1.85)	(0.73)	(2.02)
FF3-α	−2.180	−0.777	0.197	2.378	−0.639	−0.459	0.075	0.714
t-stat	(−7.63)	(−3.60)	(0.73)	(5.87)	(−2.55)	(−2.41)	(0.33)	(2.21)
	Proxy = 1/AGE				Proxy = DISPER			
P1	0.905	0.754	0.686		0.988	0.617	0.901	
P3	0.649	0.756	1.210		0.678	0.643	0.997	
P5	0.201	0.451	1.132		0.087	0.617	1.010	
P5–P1	−0.704	−0.304	0.446	1.150	−0.901	0.000	0.109	1.011
t-stat	(−2.07)	(−1.33)	(2.24)	(3.26)	(−1.93)	(0.00)	(0.50)	(2.11)
FF3-α	−0.797	−0.385	0.344	1.141	−1.675	−0.493	−0.107	1.568
t-stat	(−2.62)	(−1.90)	(1.87)	(2.94)	(−4.63)	(−2.34)	(−0.42)	(3.39)

and shares turnover, as well as the interaction term between CGO and risk proxies. The results confirm the previous double-sorting analysis that the interaction term is always significant and positive for all risk measures, even after controlling for size, book-to-market, past returns, and share turnover.[10]

In sum, the results from both portfolio sorts and Fama-MacBeth regressions highlight the importance of CGO in the risk–return trade-off.

3. Inspecting the mechanisms

In this section, we investigate several possible explanations for the risk–return trade-off pattern presented in Section 2. We consider the role of RDP, underreaction to news, and the disposition effect-induced mispricing.

3.1. The role of RDP

The first explanation we investigate is RDP. We argue that, in a static sense, that RDP can generate the empirical pattern shown in Section 2, and could be responsible for the heterogeneity in the risk–return trade-off.

Most asset pricing models assume expected utility and thus imply a positive risk–return relation. A key assumption of these models is that decision makers have a utility function that is globally concave and, hence, investors are uniformly risk averse. This assumption has been the basic premise of most research in finance and economics. However, many researchers, including Friedman and Savage (1948); Markowitz (1952), and Kahneman and Tversky (1979), have questioned the assumption of global risk aversion on both theoretical and empirical grounds.

The PT of Kahneman and Tversky (1979) has attracted considerable attention in the finance literature and has been applied to explain many asset pricing phenomena.[11] A critical element in this theory is the reference point. The theory predicts that most individuals have an S-shaped value function that is concave in the gain domain and convex in the loss domain, both measured relative to the reference point (i.e., diminishing sensitivity). Thus, most individuals exhibit a mixture of risk-seeking and risk-averting behaviors, depending on whether the outcome is below or

[10] The *t*-statistics are based on Newey and West (1987) with lag = 12 to account for possible autocorrelation and heteroskedasticity. Because there are no overlapping observations in dependent variables, using lag = 0 (i.e., White, 1980 *t*-statistics) is also reasonable. The results based on lag = 0, omitted for brevity, are typically stronger.

[11] PT has been used to account for several phenomena in finance including, but not limited to, the disposition effect (see, e.g., Barberis and Xiong, 2012; Odean, 1998; Shefrin and Statman, 1985), the equity premium puzzle (see, e.g., Barberis and Huang, 2001; Benartzi and Thaler, 1995), and momentum (see, e.g., Grinblatt and Han, 2005). For a recent survey on the application of PT in economics, see Barberis (2013).

Table 5
Fama-MacBeth regressions.

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2015), and other variables are defined as in Tables 1 and 2. The coefficients are reported in percentages. The sample period is from January 1964 to December 2014, except for DISPER, which is from January 1976 to December 2014. Independent variables are winsorized at 1% and 99%. The *t*-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses. We

Table 5 (*continued*)

Variable	PROXY=1/AGE				PROXY=DISPER			
	(2)	(3)	(4)	(5)	(2)	(3)	(4)	(5)
PROXY× MOM(-12,-1)		2.288		1.697		23.131		16.244
		(2.59)		(1.87)		(2.74)		(2.02)
PROXY× SCORE			−0.081	−0.075			−0.734	−0.677
			(−4.20)	(−3.92)			(−3.50)	(−3.35)
LOGBM	0.115	0.116	0.134	0.135	0.076	0.077	0.096	0.096
	(1.68)	(1.69)	(1.96)	(1.97)	(0.81)	(0.81)	(1.03)	(1.04)
LOGME	−0.082	−0.084	−0.079	−0.081	−0.099	−0.099	−0.116	−0.115
	(−2.33)	(−2.39)	(−2.28)	(−2.32)	(−2.47)	(−2.47)	(−2.93)	(−2.93)
MOM(-1,0)	−5.316	−5.329	−5.404	−5.414	−4.280	−4.314	−4.409	−4.432
	(−11.18)	(−11.21)	(−11.17)	(−11.19)	(−8.30)	(−8.34)	(−8.34)	(−8.37)
MOM(-12,-1)	0.390	0.152	0.272	0.089	0.384	0.219	0.274	0.167
	(2.32)	(0.75)	(1.60)	(0.44)	(1.90)	(1.14)	(1.35)	(0.87)
MOM(-36,-12)	−0.180	−0.180	−0.143	−0.143	−0.115	−0.111	−0.078	−0.073
	(−3.28)	(−3.27)	(−2.60)	(−2.59)	(−1.86)	(−1.82)	(−1.33)	(−1.29)
SCORE			−0.011	−0.011			−0.012	−0.012
			(−4.76)	(−4.97)			(−4.08)	(−4.11)
TURNOVER	−1.901	−1.924	−1.023	−1.039	−1.554	−1.433	−1.104	−1.025
	(−1.17)	(−1.20)	(−0.64)	(−0.65)	(−1.55)	(−1.43)	(−1.08)	(−1.01)

above the reference point, respectively.[12] The MA of Thaler (1980, 1985) provides a theoretical foundation for the way in which decision makers set the reference point for each asset they own. The main idea underlying MA is that decision makers tend to mentally frame different assets as belonging to separate accounts and then apply RDP to each account while ignoring possible interactions among these assets.

To better understand how RDP and MA undermine the traditional positive risk–return relation, consider a concrete example with PT/MA in Fig. 2. Assume that in the last period, investors purchased one share of stocks A and B, each at a price of \$20, and the price is now \$15 for each. Thus, investors of stocks A and B are facing capital losses and are risk seeking. PT/MA investors focus on stocks A and B and separate them from the rest of their investments. One period later, the price of stock A can be either \$20 or \$10 with equal probability, and the price of stock B can be either \$18 or \$12 with equal probability. Thus, stocks A and B have an identical expected payoff, but stock A has higher volatility than stock B. As a result, stock A is more appealing to PT/MA investors because of the convexity illustrated in Fig. 2. Therefore, the demand for stock A by PT/MA investors is larger than the demand for stock B. In equilibrium, if the demand by rational investors is not perfectly elastic, the price of stock A could be higher than that of stock B, leading to a lower expected return for stock A. Thus, there is a negative risk–return relation in this scenario.

Now consider stocks C and D, shown in Fig. 3. Assume that investors purchased one share of stocks C and D, each at a price

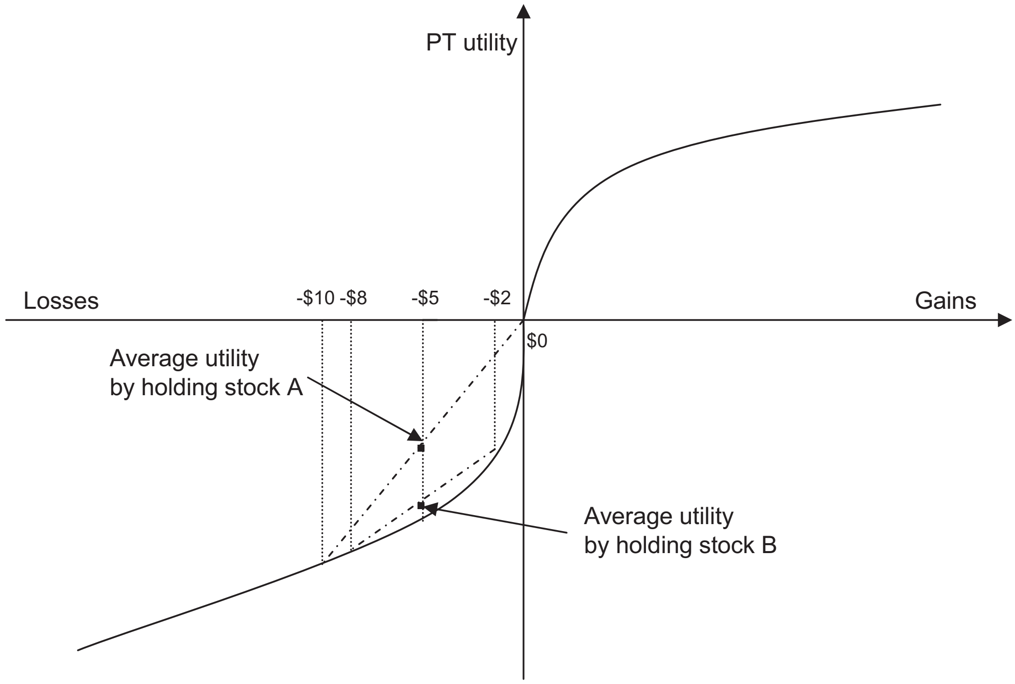

Fig. 2. Prospect theory (PT) and the risk–return trade-off utility: capital losses. Assume that investors purchased one share of stocks A and B, each at a price of $20, and the price is now $15 for each. One period later, the price of stock A can be either $20 or $10 with equal probability, and the price of stock B can be either $18 or $12 with equal probability. The figure shows the utility gain and loss of holding stocks A and B.

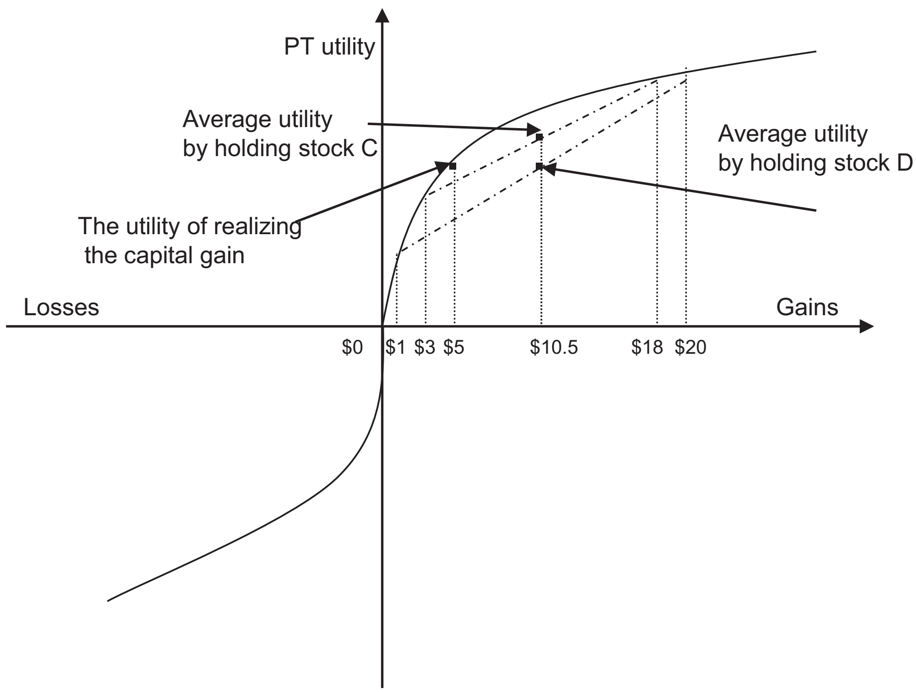

Fig. 3. Prospect theory (PT) and the risk–return trade-off utility: capital gains. Assume that investors purchased one share of stocks C and D, each at a price of $20, and the price is now $25 for each. Thus, investors are facing capital gains and are risk averse. One period later, stock C has a price of $38 or $23 with equal probability, and stock D has a price of $40 or $21 with equal probability. The figure shows the utility gain and loss of holding stocks C and D..

diminishing sensitivity in the loss region and, thus, the net effect could be an increased risk aversion after losses.

Overall, although RDP can potentially account for the heterogeneity of the risk–return trade-off based on our static argument, we acknowledge that our static argument might not survive in a dynamic setting and that developing a formal dynamic model would be helpful. However, this is beyond the scope of our study. Our focus is on showing that the risk–return trade-off depends strongly on whether stocks are trading at a gain or at a loss and that RDP may play a role in this. With this caveat in mind, our static argument implies that the risk–return relation should be weaker or even negative among stocks in which investors have experienced losses and thus are risk seeking and that the positive risk–return relation should emerge among stocks in which investors have experienced gains and thus are risk averse. That is, the risk–return trade-off should depend on individual stocks' CGO because CGO captures whether investors are below or above their reference point, namely, the purchase price.

In sum, RDP implies that the risk–return relation should be negative among firms with low and negative CGO, but positive among firms with high and positive CGO. This is consistent with the empirical pattern shown in Section 2.[14] However, it is too early to claim that the RDP explanation unequivocally explains our results. It is possible that other forces are driving this empirical pattern, and CGO is simply correlated with these underlying variables. We discuss two alternative explanations next, and show that even after controlling for these potential mechanisms, the effect of CGO on the risk–return trade-off remains significant.

3.2. The underreaction-to-news explanation

In this subsection, we examine the underreaction-to-news explanation. Zhang (2006) argues that information may travel slowly, 8

3.3. The disposition effect-induced mispricing explanation

The last potential explanation we consider is the disposition effect-induced mispricing effect. CGO, as first proposed by Grinblatt and Han (2005), could be a proxy for mispricing itself, caused by the disposition effect (i.e., investors' tendency to sell securities whose prices have increased since purchase rather than those that have dropped in value). Compared with low-CGO stocks, high-CGO stocks tend to experience higher selling pressure due to the disposition effect, which leads to underpricing and high future returns. In other words, there is a heterogeneity of degree of mispricing across firms with different levels of CGO: High-CGO stocks are relatively more underpriced than low-CGO stocks. Meanwhile, compared with low-risk stocks, high-risk stocks are more subject to mispricing, because they tend to have higher arbitrage costs. For example, Pontiff (2006) argues that idiosyncratic risk is the single largest cost faced by arbitrageurs. Since idiosyncratic return volatility is one of our risk proxies and our other five risk proxies are also correlated with idiosyncratic risk, the high-risk stocks in our tests are likely to have higher arbitrage costs. Taken together, among the high-CGO group, high-risk stocks tend to be even more underpriced than low-risk stocks, suggesting a positive risk–return relation. In contrast, among the low-CGO group, high-risk stocks tend to be even more overpriced than low-risk stocks, suggesting a negative risk–return relation. This conjecture is then consistent with the new empirical pattern shown in Section 2. Notice that this channel does not rely on investors' risk-seeking preference when facing prior losses. It requires only that the risk proxies are related to limits to arbitrage and CGO itself is associated with mispricing.

To alleviate the concern that CGO proxies only for mispricing rather than risk preference, we control directly for the mispricing effect. However, mispricing is not directly observable, and the best we can do is to construct an imperfect proxy for it. An obvious resource for this purpose is the evidence on return anomalies, which are differences in average returns that challenge risk-based models. Following Stambaugh, Yu, and Yuan (2015), we measure the mispricing by aggregating 11 key characteristics that are well-known predictors of future stock returns. Each month, for each anomaly, we assign a rank to each stock that reflects the sorting on that given anomaly variable, where the highest rank is assigned to the value of the anomaly variable associated with the lowest

Table 6
Fama-MacBeth regressions controlling for the V-shaped disposition effect.
Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. V-shaped net selling propensity (VNSP) is a measure of the V-shaped disposition effect calculated based on An (2016), and other variables are defined as in Tables 1 and 2. The coefficients are reported in percentages. The sample period is from January 1964 to December 2014, except for DISPER, which is from January 1976 to December 2014. Independent variables are winsorized at 1% and 99%. The *t*-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses. We use NYSE, Amex, and Nasdaq common stocks with a price of at least $5 and non-negative book equity. The intercept of the regression is not reported.

Variable	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.645	−0.821	−1.214	0.710	0.841	0.650
	(2.38)	(−2.22)	(−4.63)	(2.73)	(4.41)	(2.51)
PROXY	0.091	−1.472	−28.833	−2.735	−1.510	−22.081
	(0.69)	(−0.71)	(−6.01)	(−3.90)	(−3.38)	(−3.40)
PROXY× CGO	0.539	16.882	96.692	6.049	4.255	45.935
	(2.87)	(6.27)	(9.91)	(2.96)	(3.92)	(2.68)
PROXY× MOM(-12,-1)	0.009	−4.267	−41.870	1.937	2.036	17.854
	(0.07)	(−2.65)	(−3.99)	(1.23)	(2.25)	(1.95)
PROXY× VNSP	0.556	15.324	127.201	13.539	7.413	110.905
	(1.26)	(2.41)	(5.43)	(2.64)	(3.04)	(3.23)
LOGBM	0.160	0.115	0.100	0.095	0.142	0.100
	(2.44)	(1.83)	(1.45)	(1.43)	(2.08)	(1.07)
LOGME	−0.080	−0.081	−0.102	−0.086	−0.080	−0.091
	(−2.26)	(−2.64)	(−2.95)	(−2.51)	(−2.30)	(−2.26)
MOM(-1,0)	−6.065	−6.094	−5.657	−5.677	−5.702	−4.690
	(−12.43)	(−12.58)	(−12.26)	(−11.58)	(−11.93)	(−9.43)
MOM(-12,-1)	0.189	0.668	1.149	0.023	−0.036	0.088
	(1.03)	(2.46)	(4.57)	(0.11)	(−0.18)	(0.47)
MOM(-36,-12)	−0.200	−0.222	−0.183	−0.226	−0.221	−0.121
	(−3.73)	(−4.07)	(−3.25)	(−3.82)	(−3.88)	(−1.93)
VNSP	1.015	0.008	−0.593	0.769	1.063	0.787
	(1.74)	(0.01)	(−1.19)	(1.87)	(2.28)	(1.56)
TURNOVER	−1.993	−1.478	−0.511	−1.178	−1.573	−0.860
	(−1.57)	(−1.25)	(−0.33)	(−0.66)	(−0.97)	(−0.85)

are more likely to sell a security when the magnitude of their gains or losses on this security increase, and their selling schedule, characterized by a V shape, has a steeper slope in the gain region than in the loss region. Motivated by this more precise description of investor behavior, An (2016) shows that stocks with large unrealized gains and losses tend to outperform stocks with modestly unrealized gains and losses. More important, the V-shaped Net Selling Propensity (VNSP), a more precise mispricing measure, subsumes the return predictive power of CGO. Therefore, we calculate VNSP as the difference between capital gain overhang and 17% of capital loss overhang, as in An (2016), and add VNSP and its interaction with our risk proxies to our previous regressions.[17] In particular, we 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):

$$\begin{aligned} R = \alpha &+ \beta_1 \times CGO + \beta_2 \times PROXY \\ &+ \beta_3 \times PROXY \times \; CGO + \beta_4 \times VNSP \\ &+ \beta_5 \times PROXY \times VNSP + \beta_6 \times MOM(-12,-1) \\ &+ \beta_7 \times PROXY \times MOM(-12,-1) \\ &+ \beta_8 \times LOGBM + \beta_9 \times LOGME + \beta_{10} \times MOM(-1,0) \\ &+ \beta_{11} \times MOM(-36,-12) + \beta_{12} \times TURNOVER + \epsilon, \end{aligned} \tag{9}$$

where *VNSP* is the VNSP in An (2016), and all other variables are defined as in Eq. (6). Table 6 reports the results. The interactions between CGO and risk proxies remain significant after controlling for this more precise mispricing measure (VNSP) derived from the V-shaped disposition effect.[18]

In sum, the Fama-MacBeth regression analysis in this subsection suggests that investors' RDP for risk may play a role in the risk–return relation.[19]

3.4. On the weak risk–return relation among high-CGO firms

The previous three explanations imply that the risk–return relation should be positive among high-CGO firms. This is especially true for the RDP, in which investors are risk averse in the gain region, leading to the standard

[17] The 17% in front of the loss overhang is to capture the asymmetry of the V-shaped selling propensity. See An (2016) for details of this measure.

[18] In Table A3 in the Internet Appendix, we also control for the interaction between another proxy of limits of arbitrage (i.e., illiquidity) and CGO in our Fama-MacBeth regressions. Again, we find that the coefficients on the interaction of CGO and risk proxies remain very similar.

[19] In addition, under a real-option framework, Johnson (2004) shows that the interaction term between leverage and idiosyncratic parameter risk negatively predicts future stock returns. Given that low-CGO stocks typically have high leverage, if our risk proxies reflect idiosyncratic parameter risk to some extent, the negative risk–return relation among low-CGO stocks could then be potentially driven by this real option effect from Johnson (2004). To alleviate this concern, in untabulated tests, we also control for this leverage effect in Fama-MacBeth regressions by including leverage and its interaction with risk proxies. The interactions between CGO and risk proxies continue to be consistently significant and positive. These results are available upon request.

Table 7
Double-sorted portfolio returns during periods of low investor sentiment.

We perform the double-sorting analysis following low levels of investor sentiment, as divided based on the median level of the index of Baker and Wurgler (2006). At the beginning of each low-sentiment month, we divide all NYSE, Amex, and Nasdaq common stocks with stock prices of at least $5 and non-negative book value of equity into five groups based on lagged capital gains overhang (CGO); then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. CGO and risk proxies are defined as in Tables 1 and 2. The portfolio is then held for 1 month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from July 1965 to January 2011, except for DISPER, which is from January 1976 to January 2011. The *t*-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses.

Portfolio	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy = β				Proxy = RETVOL			
P1	0.419	0.151	0.456		0.495	0.272	0.617	
P3	0.544	0.484	1.043		0.769	0.557	1.040	
P5	0.848	0.943	1.250		0.654	1.212	1.626	
P5–P1	0.429	0.792	0.794	0.365	0.159	0.939	1.009	0.850
t-stat	(0.82)	(2.17)	(2.21)	(1.03)	(0.34)	(2.23)	(2.99)	(1.89)
FF3-α	−0.159	0.195	0.387	0.547	−0.415	0.314	0.411	0.826
t-stat	(−0.44)	(0.63)	(1.35)	(1.68)	(−1.24)	(0.76)	(1.51)	(1.89)
		Proxy = IVOL			Proxy = CFVOL			
P1	0.836	0.310	0.743		0.513	0.414	0.707	
P3	0.875	0.611	0.997		0.756	0.464	1.124	
P5	−0.488	0.679	1.435		0.858	0.379	1.111	
P5–P1	−1.323	0.370	0.693	2.016	0.345	−0.036	0.405	0.059
t-stat	(−3.21)	(0.98)	(2.38)	(5.39)	(1.12)	(−0.11)	(2.14)	(0.19)
FF3-α	−1.811	−0.170	0.239	2.049	0.174	−0.216	0.186	0.013
t-stat	(−6.39)	(−0.67)	(0.97)	(5.64)	(0.68)	(−0.88)	(1.08)	(0.05)
		Proxy = 1/AGE			Proxy = DISPER			
P1	0.638	0.337	0.713		1.089	0.555	1.063	
P3	0.669	0.565	1.115		1.114	0.600	1.028	
P5	0.826	0.659	1.383		0.904	1.200	1.583	
P5–P1	0.189	0.321	0.670	0.482	−0.185	0.645	0.520	0.704
t-stat	(0.56)	(1.55)	(3.66)	(1.32)	(−0.52)	(2.04)	(1.40)	(2.07)
FF3-α	0.009	0.136	0.518	0.509	−0.825	0.004	0.024	0.849
t-stat	(0.03)	(0.78)	(3.06)	(1.37)	(−2.63)	(0.01)	(0.08)	(2.10)

positive risk–return trade-off. However, although the relation between risk and expected returns among high-CGO firms is positive, this positive relation is still not very significant (see Table 3). This subsection provides further discussion on this weak positive risk–return relation among stocks in their gain regions.

As discussed in the introduction, many studies have suggested possible mechanisms that are responsible for the low-risk anomaly. Barberis and Huang (2008) and Baker, Bradley, and Wurgler (2011), for example, suggest that individuals might have an irrational preference for high-volatility stocks, probably due to a preference for positive skewness. Because of limits to arbitrage, high-volatility firms tend to be overpriced. Also, high-beta firms could be more sensitive to investor disagreement and sentiment (see, e.g., Hong and Sraer, 2011; Shen and Yu, 2012). Short-sale impediment implies that these high-risk firms tend to be overpriced on average. All of these mechanisms are likely to work simultaneously in the data, which could lead to overpricing for high-risk stocks, even among firms with capital gains.

Together with the reference-dependent effect on the risk–return trade-off studied in this paper, it follows that there are two countervailing forces on the risk–return trade-off among high-CGO firms, but two reinforcing forces among low-CGO firms. Thus, the negative return spreads between high- and low-risk firms among low-CGO firms should be larger than the positive return spreads among high-CGO firms. The positive association between expected returns and various measures of risk among firms with capital gains could be weakened or completely inverted by the previously identified mechanisms that leads to the unconditional overpricing of high-risk stocks. Indeed, Table 3 shows that the positive relation between risk and return is generally weak among high-CGO firms and that the negative return spreads between high- and low-risk firms among low-CGO firms typically are much larger than the positive return spreads among high-CGO firms.

In addition, as discussed earlier, previous studies have identified several mechanisms that could lead to a stronger risk–return trade-off during some subperiods. Thus, combining our mechanism with those mechanisms could guide us in finding a strengthened positive risk–return relation during some subperiods. For example, we should expect a stronger risk–return relation during low-sentiment periods based on Shen and Yu (2012). Indeed, Table 7 repeats the previous double-sorting portfolio analysis in

Table 8
Robustness Fama-MacBeth regressions tests.

This table reports a series of robustness Fama-MacBeth regressions tests. Each month, we run a cross-sectional regression of returns on lagged variables in the form of Column (5) in Table 5, and calculate the time-series average of the regression coefficients. All variables are defined as in Tables 1 and 2. To save space, only the coefficients of the interaction term of CGO and PROXY are reported. For all these tests, we first apply several common filters including common stocks, stock price at least $5, and non-negative book equity. Starting with this sample, we further include only NYSE/Amex stocks in Panel A, the top 90% liquid stocks based on the Amihud (2002) illiquidity measure in Panel B, and the largest one thousand stocks in Panel C. We run a cross-sectional weighted least squares (WLS) regression in Panel D. In Panels A to D, the sample period is from January 1964 to December 2014, except for DISPER, which is from January 1976 to December 2014. In Panel E, we divide the sample into two equal subperiods: January 1964–June 1989 and July 1989–December 2014, for all risk proxies except for DISP, for which the two subperiods are January 1976–June 1995 and July 1995–December 2014. Independent variables are winsorized at 1% and 99%. The regression coefficients are reported in percentages. The *t*-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses. The intercept of the regression is not reported.

	PROXY					
Variable	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
Panel A: NYSE and Amex stocks						
PROXY× CGO	0.487	18.164	107.341	9.289	4.888	88.916
	(2.47)	(6.90)	(8.91)	(3.32)	(3.39)	(2.69)
Panel B: Top 90% liquid stock						
PROXY× CGO	0.376	13.465	86.861	5.200	4.455	65.979
	(2.15)	(4.56)	(7.17)	(2.21)	(3.12)	(2.65)
Panel C: Largest one thousand stocks						
PROXY× CGO	0.614	18.266	109.089	7.237	7.757	99.257
	(2.17)	(4.61)	(5.72)	(2.54)	(3.55)	(2.51)
Panel D: WLS regressions						
PROXY× CGO	0.582	10.441	66.567	5.197	5.337	80.636
	(2.00)	(3.09)	(4.79)	(1.40)	(2.07)	(3.33)
Panel E: Subperiod analysis						
		(I): January 1964–June 1989				January 1976–June 1995
PROXY× CGO	0.518	18.700	114.913	5.234	4.726	8.069
	(1.96)	(5.08)	(7.36)	(1.79)	(2.51)	(0.85)
		(II): July 1989–December 2014				July 1995–December 2014
PROXY× CGO	0.050	8.622	54.779	4.892	3.0	(7.36)

Table 9
Double-sorted portfolio by capital gains overhang (CGO) and residual risk proxies.
At the beginning of each month, we divide all firms into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged residual risk proxies orthogonal to idiosyncratic skewness. We run cross-sectional regressions of each of six risk proxies on the skewness of the residuals from the Fama-French three-factor model using daily excess returns over the past year, and these regression residuals are the residual risk proxy. CGO and risk proxies are defined as in Table 1. The portfolio is then held for 1 month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. All NYSE, Amex, and Nasdaq common stocks with a price of at least $5 and non-negative book equity are used in the double-sorting procedure. The sample period is from January 1964 to December 2014, except for DISPER, which is from January 1976 to December 2014. The *t*-statistics are calculated based on Newey and West (1987) adjusted standard errors and reported in parentheses.

Portfolio	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy = β				Proxy = RETVOL			
P1	0.573	0.493	0.518		0.640	0.560	0.602	
P3	0.527	0.551	0.749		0.393	0.537	0.804	
P5	−0.054	0.372	0.929		−0.364	0.350	1.155	
P5–P1	−0.627	−0.121	0.410	1.037	−1.004	−0.210	0.554	1.557
t-stat	(−1.90)	(−0.45)	(1.72)	(3.95)	(−2.77)	(−0.72)	(2.04)	(4.21)
FF3-α	−0.890	−0.433	0.244	1.133	−1.163	−0.518	0.289	1.452
t-stat	(−3.55)	(−2.16)	(1.28)	(4.18)	(−4.14)	(−2.44)	(1.22)	(3.71)
	Proxy = IVOL				Proxy = CFVOL			
P1	0.857	0.501	0.697		0.761	0.624	0.688	
P3	0.173	0.442	0.794		0.468	0.411	0.898	
P5	−1.035	0.087	1.050		0.332	0.280	0.876	
P5–P1	−1.892	−0.414	0.353	2.245	−0.429	−0.343	0.188	0.617
t-stat	(−6.22)	(−1.70)	(1.71)	(7.77)	(−1.83)	(−1.62)	(1.35)	(2.81)
FF3-α	−2.047	−0.661	0.192	2.239	−0.459	−0.388	0.096	0.555
t-stat	(−8.59)	(−3.53)	(0.98)	(7.64)	(−2.15)	(−2.60)	(0.79)	(2.45)
	Proxy = 1/AGE				Proxy = DISPER			
P1	0.429	0.539	0.625		0.474	0.524	0.986	
P3	0.188	0.413	0.941		0.528	0.569	0.720	
P5	−0.045	0.519	1.053		−0.297	0.736	1.071	
P5–P1	−0.474	−0.020	0.428	0.902	−0.771	0.212	0.084	0.855
t-stat	(−2.09)	(−0.13)	(2.65)	(3.64)	(−2.18)	(0.87)	(0.39)	(2.45)
FF3-α	−0.460	−0.077	0.349	0.809	−1.254	−0.210	−0.264	0.991
t-stat	(−2.32)	(−0.58)	(2.26)	(2.98)	(−3.72)	(−0.97)	(−1.32)	(2.42)

Third, to further ensure that our results are not driven by small stocks, we repeat both the Fama-MacBeth regression and the double-sorting analysis with the one thousand largest stocks by market capitalization. Panel C of Table 8 shows that the results remain largely unchanged. The double-sorting analysis, reported in Table A6 in the Internet Appendix, yields essentially the same conclusion as well. In fact, among the one thousand largest stocks, high-beta firms earn lower returns on average (not reported), but the security market line is upward sloping among high-CGO firms. Thus, our results are not driven by the inclusion of small cap stocks.

Fourth, one potential concern when using Fama-MacBeth regressions is that each stock is treated equally. Even though our results hold when we focus on the one thousand largest firms, a standard cross-sectional regression places the same weight on a very large firm as on a small firm. Thus, the results based on equal-weighted regressions could be disproportionately affected by small firms, which account for a relatively small portion of total market capitalization. Although the result based on equal-weighted regressions reflects the effect of a stronger among firms with more individual investors since RDP might be a better description of individuals' risk attitudes than institutional investors' risk attitudes.

Last, it is possible that our risk measures are related to skewness, and it is investors' preference for skewness that leads to lower average return for high-risk firms, since high-risk firms typically also have high skewness. Indeed, Barberis and Huang (2008) and Bali, Brown, Murray, and Tang (2014) provide theoretical and empirical support for this explanation. To see if preferences for skewness can completely explain our result, at each month, we run cross-sectional regressions of various risk measures on daily idiosyncratic skewness over the past year. We then use the residual risk measures to repeat our double-sorting exercise. The results, reported in Table 9, show that the pattern regarding the risk–return trade-off is still there when we use the residual risk measures. Thus, preferences for skewness do not appear to be a complete story for our results, and our evidence is at least partially consistent with the notion that investors are risk averse among high-CGO firms and risk seeking among low-CGO firms. Further, in untabulated analysis, we perform the Fama-MacBeth regression by controlling for the interaction between idiosyncratic skewness and CGO. Our main conclusion remains the same.

Overall, the risk–return trade-off pattern is robust to subperiods, as well as the exclusion of Nasdaq stocks, highly illiquid stocks, or stocks with small market capitalization.[20] Moreover, our results of investors' RDP for risk are not purely driven by investors' preference for skewness.

5. Conclusion

The risk–return trade-off is a fundamental theme in finance. However, there is weak empirical support for this basic principle. In this paper, we