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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 similar.

In terms of related literature, Barberis and Huang (2001); 2008) and Barberis, Huang, and Santos (2001) theoretically explore the role of RDP (in particular, PT) in asset prices in equilibrium settings. These studies suggest that RDP can play a role in explaining asset pricing dynamics and cross-sectional stock returns.[2] Empirically, Grinblatt and Han (2005) find that past stock returns can predict future returns because past returns can proxy for unrealized capital gains. Frazzini (2006) shows that prospect theory/mental accounting (PT/MA) induces underreaction to news, leading to return predictability. [3] More recently, Barberis and Xiong (2009, 2012) and Ingersoll and Jin (2013) study realization utility with a reference-dependent feature. These theoretical models, in particular, (Ingersoll and Jin, 2013), imply a flatter capital market line and lower expected returns for high-volatility stocks relative to those predicted by equilibrium models such as the CAPM, because high-volatility stocks provide more opportunities for investors to earn realization utility benefits. In our study, we empirically investigate heterogeneity in the risk–return trade-off across firms with different levels of capital gains, as implied by RDP.

Many studies suggest possible mechanisms that are responsible for the failure of the risk–return trade-off implied by the CAPM. These include leverage constraints (see, e.g., Asness, Frazzini, and Pedersen, 2012; Black, 1972; Frazzini and Pedersen, 2014), benchmarked institutional investors (see, e.g., Baker, Bradley, and Wurgler, 2011; Brennan, 1993), money illusion (see, e.g., Cohen, Polk, and Vuolteenaho, 2005), disagreement (see, e.g., Hong and Sraer, 2011), and market-wide sentiment-induced mispricing (see, e.g., Shen and Yu, 2012). We propose that the reference-dependent feature in preferences is another potential mechanism responsible for the failure of the CAPM. All mechanisms could work simultaneously. We complement previous studies by showing that the negative risk–return relation is more pronounced among firms with capital losses, whereas the standard positive, albeit weak, risk–return relation holds among firms with capital gains. Moreover, most existing studies focus on the time-series variation of the risk–return trade-off. For example, Cohen, Polk, and Vuolteenaho (2005); Frazzini and Pedersen (2014); Hong and Sraer (2011), and Shen and Yu (2012) show that the slope of the security market line changes with inflation, the TED spread [the difference between London Interbank Offered Loan (LIBOR) and T-bill rates], aggregate disagreement, and investor sentiment, respectively. We complement these existing studies by focusing on cross-sectional, rather than time-series, heterogeneity in the risk–return trade-off.

In addition, Bali, Cakici, and Whitelaw (2011); Barberis and Huang (2008), and Bali, Brown, Murray, and Tang (2014) argue that the preference for skewness can potentially explain why firms with low volatility and low beta tend to earn higher returns. The idea is that high-risk firms also tend to have higher skewness. Because of the preference for skewness, these high-risk firms are overpriced and earn lower subsequent abnormal returns. This preference for skewness, along with our RDP for risk, implies that, in the gain domain, risk seeking due to skewness preferences (i.e., probability weighting) may be counteracted by risk aversion stemming from diminishing sensitivity, while in the loss domain, risk seeking due to skewness preference is amplified by risk seeking from diminishing sensitivity. This prediction is consistent with our new empirical finding on the heterogeneity in the risk–return trade-off.

To make sure our result is not completely driven by the preference for skewness, we repeat the double sorts by using residual risk measures, defined as cross-sectional residuals of risk proxies on idiosyncratic skewness. Using these residual risk measures, we find a similar pattern in the heterogeneity of the risk–return trade-off across firms with different levels of CGO.

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[2] In a two-period setting with cumulative PT preferences but without MA, Barberis and Huang (2008) show that the CAPM still holds under several assumptions such as the same reference point for all agents. When there is a violation of these assumptions (e.g., MA), the CAPM typically fails.

[3] Several other studies also apply the reference-dependent feature in decision making to understand financial phenomena. See Baker, Pan, and Wurgler (2012) on mergers and acquisitions, George and Hwang (2004) and Li and Yu (2012) on the predictive power of 52-week high prices, and Dougal, Engelberg, Parsons, and Van Wesep (2015) on credit spread.

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	$\sigma(RET)$	FF3-α	JAN	FEB-DEC
P1	0.394	0.067	−0.527	5.444	−0.066
t-stat	(1.45)		(−5.79)	(3.86)	(−0.24)
P2	0.567	0.055	−0.249	3.581	0.293
t-stat	(2.47)		(−3.66)	(3.25)	(1.27)
P3	0.707	0.050	−0.032	2.345	0.558
t-stat	(3.46)		(−0.62)	(2.68)	(2.68)
P4	0.847	0.049	0.173	1.766	0.764
t-stat	(4.03)		(3.08)	(2.28)	(3.59)
P5	1.211	0.053	0.615	1.337	1.200
t-stat	(5.37)		(7.71)	(2.19)	(5.37)
P5 - P1	0.817	0.044	1.142	−4.107	1.265
t-stat	(5.23)		(7.69)	(−3.86)	(8.24)

Panel B: Five CGO portfolio characteristics

Portfolio	CGO	LOGME	BM	ILLIQ	MOM
P1	−0.469	5.000	0.885	1.302	−0.119
P2	−0.108	5.389	0.868	0.642	0.050
P3	0.028	5.652	0.861	0.489	0.169
P4	0.137	5.725	0.862	0.493	0.306
P5	0.293	5.352	0.908	0.685	0.578
P5 - P1	0.762	0.352	0.023	−0.617	0.698
t-stat	(14.96)	(2.09)	(0.59)	(−2.58)	(19.10)

Portfolio	β	MARKET%	TURNOVER	%(IO)	#(IO)
P1	1.269	0.087	0.070	0.381	63.749
P2	1.133	0.178	0.076	0.456	107.828
P3	1.068	0.235	0.073	0.473	126.698
P4	1.066	0.266	0.067	0.466	123.767
P5	1.061	0.234	0.052	0.387	80.436
P5 - P1	−0.208	0.147	−0.019	0.005	16.688
t-stat	(−3.46)	(5.90)	(−2.11)	(0.27)	(2.17)

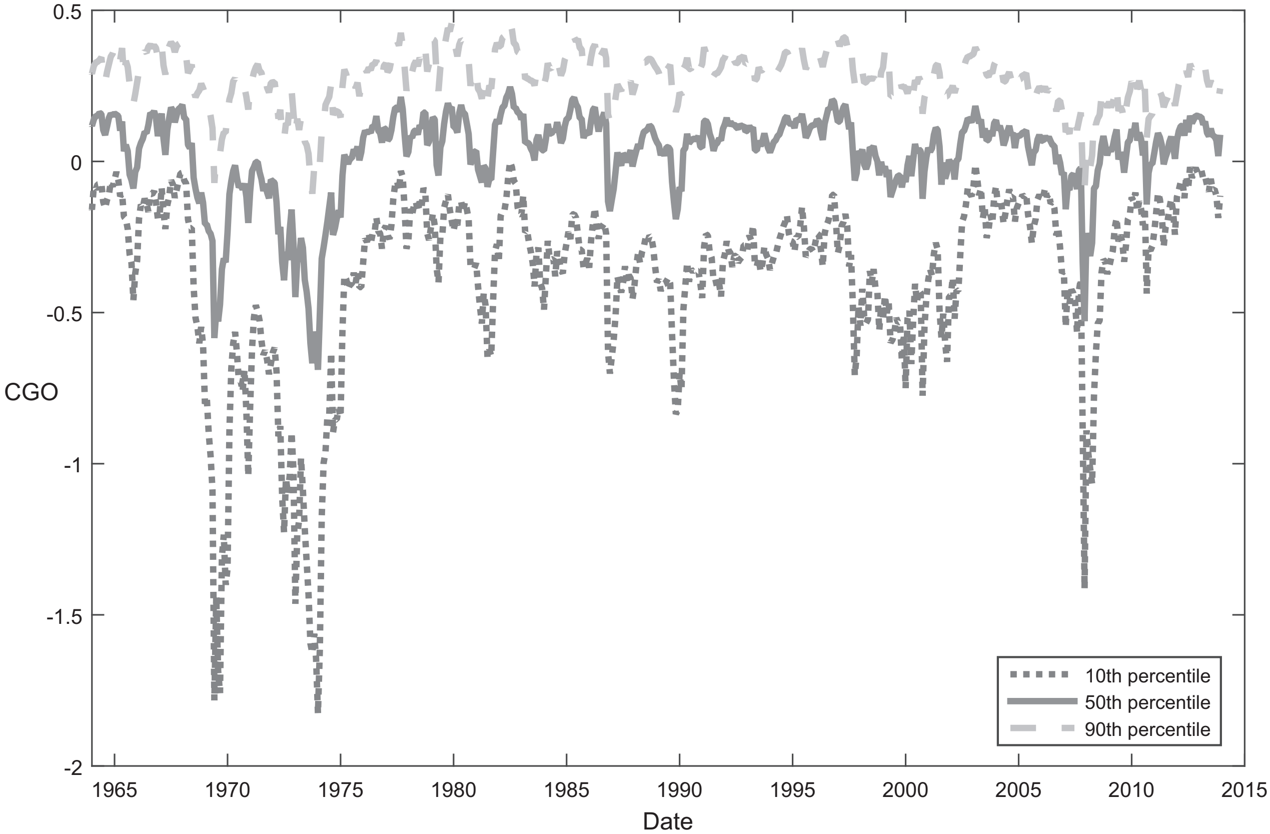

Fig. 1. Time series of cross-sectional percentiles of the capital gains overhang (CGO). This figure plots the time series of the empirical 10th, 50th, and 90th percentiles of the cross-sectional distribution of the capital gains overhang. The CGO is calculated at a weekly frequency from January 1964 to December 2014. We use all common stocks from NYSE, Amex, and Nasdaq with stock prices of at least $5 and non-negative book value of equity.

Grinblatt and Han (2005), consistent with the disposition effect and a December tax-loss selling effect.

Table 1 also reports other firm characteristics across CGO quintiles. Low-CGO firms tend to be smaller, be less liquid, and have higher CAPM beta. As expected, a strong monotonic relation exists between CGO and lagged returns. In addition, the bottom quintile has 8.7% of the total market value, and the top quintile has 23.4% of total market capitalization. Thus, although low-CGO firms tend to be smaller, they still account for a significant portion of total market capitalization. The percentage of institutional holdings is similar for high-CGO firms and low-CGO firms, and the number of institutional holders is slightly lower for low-CGO firms than for high-CGO firms.

Table 2 reports summary statistics for single-sorted, value-weighted portfolio excess returns based on various risk proxies. In general, high-risk firms do not earn significantly higher subsequent returns. Instead, firms with high total volatility earn lower returns on average, confirming the findings in Baker, Bradley, and Wurgler (2011). Firms with high idiosyncratic volatility and high analyst forecast dispersion also earn lower subsequent returns. These results are in line with the findings in Diether, Malloy, and Scherbina (2002) and Ang, Hodrick, Xing, and Zhang (2006), consistent with the notion in Miller (1977) that stock prices reflect optimistic opinions. Finally, the security market line is almost completely flat in our sample, consistent with Fama and French (1992) but in contradiction to the traditional CAPM. Moreover, if we use equal-weighted returns as in many earlier studies on the risk–return relation, alphas are all significant and negative, as shown in Table A1 in the Internet Appendix, consistent with Frazzini and Pedersen (2014). We focus on value-weighted returns because the results are less subject to the influence of small firms. In general, our results are stronger if equal-weighted returns are used.

2.3. Double sorts

We now turn to the key empirical finding of this paper. At the beginning of each month, we divide all firms in our sample into five groups based on lagged CGO, and within each of the CGO groups, we further divide firms into five portfolios based on various lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated.

Table 3 presents the main results. For all risk proxies, among the group with highest CGO, high-risk firms tend to earn higher subsequent returns. However, these results are not all statistically significant. This pattern could be due

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 and negative among low-CGO firms.

Finally, the differences between the high-minus-low spreads among the highest and lowest CGO groups are also significant. For example, for the idiosyncratic return volatility measure, the high-minus-low spread is 224 bps per month ($t = 7.97$) higher among the highest CGO group than the lowest CGO group. For all other risk measures, this difference is also significant both statistically and economically. The difference between the high-minus-low spread among high-CGO firms and low-CGO firms is 98 bps per month for CAPM beta ($t = 3.92$), 166 bps per month for total volatility ($t = 4.52$), 71 bps per month for cash flow volatility ($t = 2.68$), 100 bps per month for firm age ($t = 4.05$), and 104 bps per month for analyst forecast dispersion ($t = 3.12$). Even though our focus is on raw excess returns, we also report results adjusted by the Fama-French three-factor benchmark. In particular, the difference-in-differences remain similar and significant after adjusting for the Fama-French three-factor benchmark.

It is worth noting that although the unconditional relation between expected returns and various measures of risk is weak across risk proxies (see Table 2), the heterogeneity of this relation is strong and consistent across all risk proxies. The risk–return relation changes significantly across firms with different levels of CGO.

In addition to this turnover-based measure of CGO, we adopt an alternative measure using mutual fund holding data as in Frazzini (2006). In particular, the time series of net purchases by mutual fund managers and their cost basis in a stock are used to compute a weighted average reference price. At each month t, the reference price for each individual stock is defined as:

$$RP_t = \phi^{-1} \sum_{n=0}^{t} V_{t,t-n} P_{t-n}, \tag{4}$$

where $V_{t,t-n}$ is the number of shares purchased at date $t-n$ that are still held by the original purchasers at date t, P_t is the stock price at the end of month t, and ϕ is a normalizing constant such that $\phi = \sum_{n=0}^{t} V_{t,t-n}$. The stock price at the report date is used as a proxy for the trading price.[9] The CGO at month t is then defined as the normalized difference between current price and reference price:

$$CGO_t = \frac{P_t - RP_t}{P_t}. \tag{5}$$

The advantage of this approach is to identify exactly the fraction of shares purchased at a previous date that is still held by the original buyers at the current date. However, the resulting sample period is shorter, starting from 1980. Also, this approach assumes that mutual fund managers are a representative sample of the cross section of shareholders.

Table 4 reports the double-sorting results. Our key pattern largely remains. For example, the risk–return relation is negative among the lowest CGO firms for all risk proxies, although it is positive among the highest CGO firms. Moreover, the difference between the high-minus-low spread among high-CGO firms and that among low-CGO firms is

[9] Following Frazzini (2006), when trading, fund managers are assumed to use the "first in, first out" method to associate a quantity of shares in their portfolio with the corresponding reference price. Fund holdings are adjusted for stock splits and assumed to be public information with 1-month lag from the file date. The quarterly holdings data are merged with CRSP and filtered to eliminate potential errors in data. For details, see Frazzini (2006).

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):

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

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 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		PROXY=β				PROXY=RETVOL			
	(1)	(2)	(3)	(4)	(5)	(2)	(3)	(4)	(5)
CGO	1.184	0.712	0.779	0.550	0.644	−0.352	−0.817	−0.267	−0.697
	(7.48)	(2.94)	(2.95)	(2.28)	(2.83)	(−1.17)	(−2.40)	(−0.87)	(−2.01)
PROXY		0.189	0.180	0.328	0.338	0.792	1.463	8.677	9.787
		(1.91)	(1.81)	(2.05)	(2.40)	(0.52)	(0.90)	(4.19)	(4.66)
PROXY× CGO		0.434	0.365	0.386	0.314	12.857	16.028	10.882	13.546
		(2.90)	(2.16)	(2.40)	(2.04)	(6.17)	(6.57)	(4.81)	(5.56)
PROXY× MOM(-12,-1)			−0.014		0.014		−3.790		−3.520
			(−0.14)		(0.12)		(−2.46)		(−2.03)
PROXY× SCORE				−0.002	−0.002			−0.132	−0.142
				(−0.67)	(−1.05)			(−3.30)	(−3.58)
LOGBM	0.122	0.143	0.141	0.160	0.158	0.110	0.106	0.129	0.125
	(1.70)	(2.19)	(2.16)	(2.47)	(3.30)	(1.76)	(1.71)	(2.08)	(2.03)
LOGME	−0.085	−0.081	−0.081	−0.088	−0.091	−0.076	−0.073	−0.067	−0.065
	(−2.28)	(−2.28)	(−2.27)	(−2.52)	(−3.29)	(−2.42)	(−2.38)	(−2.17)	(−2.10)
MOM(-1,0)	−5.275	−5.712	−5.711	−5.798	−5.227	−5.664	−5.663	−5.774	−5.766
	(−11.12)	(−11.70)	(−11.71)	(−11.59)	(−17.71)	(−11.75)	(−11.71)	(−11.82)	(−11.78)
MOM(-12,-1)	0.395	0.411	0.449	0.291	0.256	0.322	0.862	0.166	0.695
	(2.32)	(2.67)	(2.57)	(1.84)	(1.55)	(1.94)	(3.29)	(1.01)	(2.44)
MOM(-36,-12)	−0.177	−0.161	−0.154	−0.123	−0.100	−0.181	−0.176	−0.149	−0.143
	(−3.21)	(−3.17)	(−3.01)	(−2.46)	(−2.63)	(−3.38)	(−3.34)	(−2.80)	(−2.73)
SCORE				−0.018	−0.017			−0.001	0.000
				(−5.14)	(−6.23)			(−0.28)	(0.06)
TURNOVER	−1.915	−2.721	−2.696	−1.911	−1.728	−2.487	−2.492	−1.934	−1.944
	(−1.18)	(−2.08)	(−2.07)	(−1.50)	(−1.44)	(−2.07)	(−2.08)	(−1.64)	(−1.65)
Variable		PROXY=IVOL				PROXY=CFVOL			
CGO		−0.548	−1.252	−0.447	−1.217	0.609	0.658	0.518	0.558
		(−2.31)	(−4.99)	(−1.86)	(−4.78)	(2.90)	(2.75)	(2.42)	(2.34)
PROXY		−15.587	−10.359	27.954	41.405	−0.905	−0.985	2.413	2.193
		(−4.79)	(−2.95)	(3.12)	(5.27)	(−1.58)	(−1.51)	(1.92)	(1.66)
PROXY× CGO		63.241	94.022	52.197	84.398	7.107	5.814	6.315	5.063
		(8.61)	(9.69)	(6.40)	(8.54)	(4.76)	(2.99)	(3.91)	(2.58)
PROXY× MOM(-12,-1)			−36.570		−42.643		3.184		3.190
			(−3.61)		(−4.38)		(1.97)		(1.96)
PROXY× SCORE				−0.802	−0.949			−0.060	−0.056
				(−4.83)	(−6.28)			(−2.49)	(−2.25)
LOGBM		0.083	0.080	0.082	0.078	0.069	0.071	0.077	0.077
		(1.19)	(1.16)	(1.17)	(1.12)	(1.05)	(1.08)	(1.17)	(1.18)
LOGME		−0.105	−0.099	−0.103	−0.096	−0.093	−0.091	−0.093	−0.092
		(−2.91)	(−2.83)	(−2.89)	(−2.77)	(−2.68)	(−2.65)	(−2.72)	(−2.70)
MOM(-1,0)		−5.016	−5.050	−5.164	−5.193	−5.305	−5.322	−5.380	−5.399
		(−10.86)	(−10.86)	(−10.90)	(−10.91)	(−10.55)	(−10.55)	(−10.61)	(−10.62)
MOM(-12,-1)		0.513	1.324	0.367	1.334	0.295	0.139	0.194	0.046
		(3.12)	(5.33)	(2.22)	(5.31)	(1.67)	(0.65)	(1.11)	(0.22)
MOM(-36,-12)		−0.139	−0.135	−0.109	−0.101	−0.189	−0.187	−0.170	−0.167
		(−2.53)	(−2.47)	(−2.01)	(−1.87)	(−3.26)	(−3.27)	(−2.93)	(−2.93)
SCORE				0.000	0.003			−0.011	−0.011
				(0.03)	(1.01)			(−4.15)	(−4.14)
TURNOVER		−1.205	−1.287	−0.361	−0.453	−1.504	−1.489	−0.379	−0.347
		(−0.78)	(−0.83)	(−0.24)	(−0.30)	(−0.83)	(−0.82)	(−0.22)	(−0.20)
Variable		PROXY=1/AGE				PROXY=DISPER			
CGO		0.528	0.744	0.463	0.618	0.544	0.691	0.447	0.536
		(2.91)	(3.67)	(2.62)	(3.12)	(2.33)	(2.93)	(1.99)	(2.34)
PROXY		−0.316	−0.628	4.375	3.868	−5.413	−5.473	37.511	35.004
		(−1.05)	(−1.99)	(4.32)	(3.70)	(−1.15)	(−0.98)	(3.25)	(3.09)
PROXY× CGO		6.822	4.670	5.413	3.843	67.483	49.109	58.754	47.356
		(6.16)	(4.05)	(4.55)	(3.42)	(4.35)	(2.54)	(3.66)	(2.47)

(*continued on next page*)

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 of $20, and the price is now $25 for each. Thus, investors are facing capital gains and, hence, 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, implying an equal expected value for stocks C and D. However, stock D has higher volatility than stock C and, hence, stock C is more appealing because of the concavity illustrated in Fig. 3. Thus, the price of stock C is higher than stock D, leading to a lower average subsequent return for stock C. As a result, the traditional positive risk–return relation emerges in this scenario.[13]

A related concept, the break–even effect coined by Thaler and Johnson (1990), could also imply that, following losses, gambles that offer a chance to break even appear especially attractive and, thus, investors could be risk seeking after losses. As discussed in the introduction, it is possible that realization utility with a reference-dependent feature might also generate different risk attitudes across loss and gain regions (see, e.g., Barberis and Xiong, 2012; Ingersoll and Jin, 2013). In sum, the reference-dependent feature in preferences could potentially produce different risk attitudes across loss and gain regions.

On the other hand, in an intriguing paper, Barberis and Xiong (2009) cast doubt on the conventional static argument based on PT. They show that if the reference point is the purchase price, PT does not necessarily predict increased risk seeking after losses. Intuitively, expected investment losses are typically smaller than expected investment gains, meaning that an investor is usually closer to the reference point after a loss than after a gain. Therefore, the kink induced by loss aversion can imply greater risk aversion after losses than after gains. This additional risk-aversion effect induced by loss aversion after losses could potentially dominate the risk-seeking effect because of

12 PT has several other important features such as loss aversion and probability weighting, which are studied extensively by Barberis and Huang (2001); 2008); Benartzi and Thaler (1995), and Barberis, Mukherjee, and Wang (2016), among others.

13 The static argument resembles the reasoning that S-shaped preferences can lead to the disposition effect, as argued in Grinblatt and Han (2005); Odean (1998); Shefrin and Statman (1985), and Frazzini (2006). In dynamic settings, Barberis and Xiong (2009, 2012) and Ingersoll and Jin (2013) raise doubts about whether pure PT can produce the disposition effect and, hence, emphasize the importance of the realization utility in addition to the RDP, in which investors enjoy realizing profits.

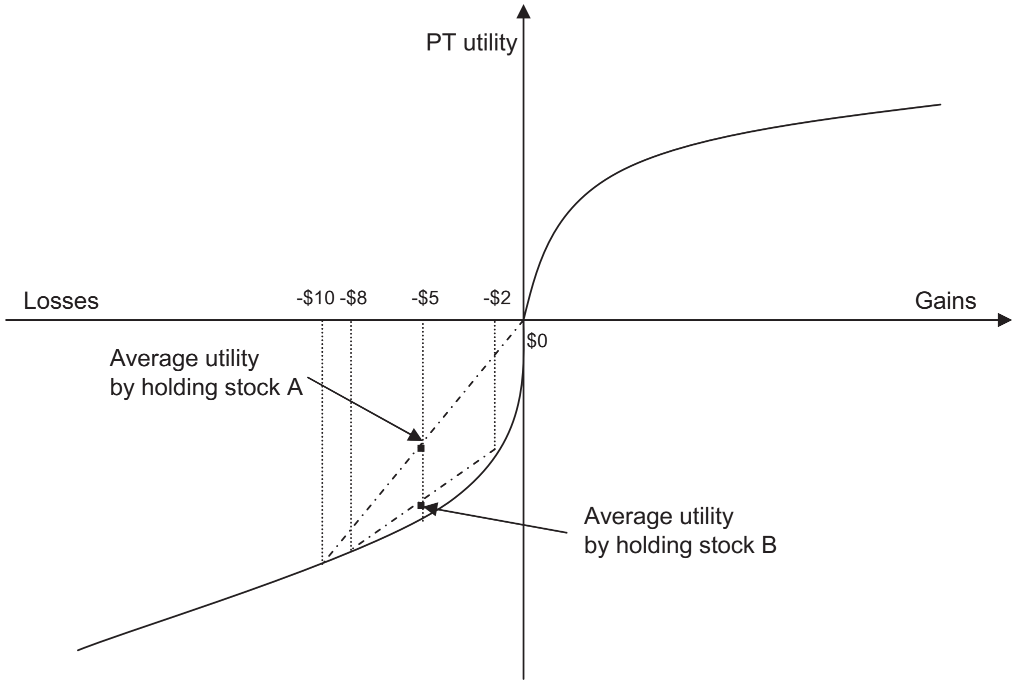

Fig. 2. Prospect theory (PT) and the risk–return trade-off utility: capital losses. Assume that investors purchased one share of stocks A and B, each at a price of $20, and the price is now $15 for each. One period later, the price of stock A can be either $20 or $10 with equal probability, and the price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

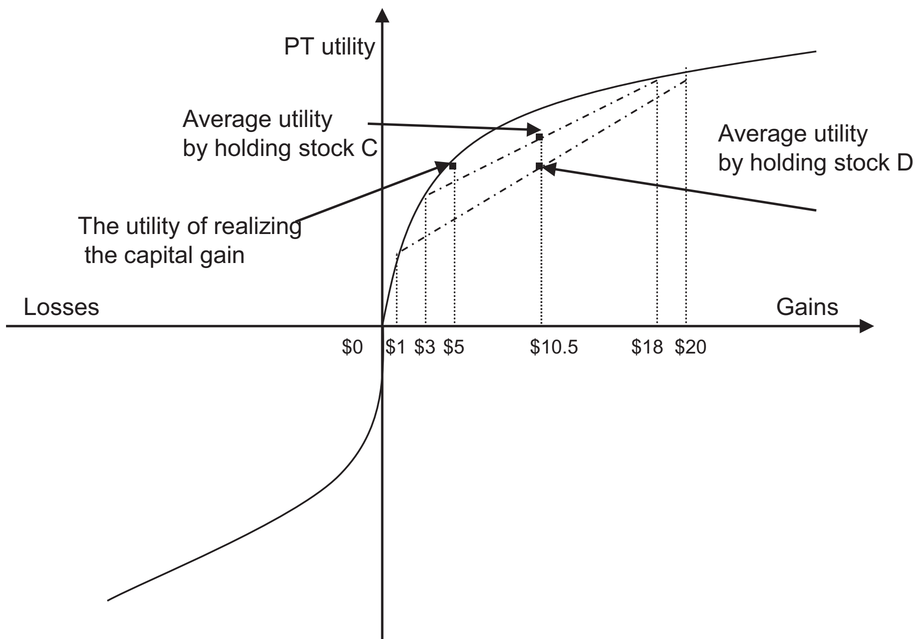

Fig. 3. Prospect theory (PT) and the risk–return trade-off utility: capital gains. Assume that investors purchased one share of stocks C and D, each at a price of $20, and the price is now $25 for each. Thus, investors are facing capital gains and are risk averse. One period later, stock C has a price 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, which can lead to underreaction to news. Furthermore, the greater the information uncertainty is, the more severe the underreaction is. Using past realized returns as a proxy for news, Zhang (2006) shows that greater information uncertainty could induce underpricing and generate relatively higher expected returns following good news and induce overpricing and generate relatively lower expected returns following bad news.

Because CGO is positively correlated with past returns, suggesting that low-CGO firms are likely to have experienced bad news and high-CGO firms are likely to have experienced good news in the recent past, the underreaction effect then implies that low-CGO stocks are on average overpriced and high-CGO stocks are on average underpriced. Meanwhile, compared with low-risk stocks, high-risk stocks are likely to be subject to a stronger underreaction effect according to Zhang (2006), because they have greater information uncertainty. Taken together, among low-CGO firms, which are typically overpriced due to underreaction, high-risk firms are even more overpriced and have lower expected returns than low-risk firms, since the underreaction effect is larger for these high-risk firms. That is, a negative relation exists between risk and return among low-CGO firms. In contrast, among high-CGO firms, which are typically underpriced due to underreaction, high-risk firms are even more underpriced and have higher expected returns than low-risk firms, since the underreaction effect is again larger for high-risk firms. That is, a positive relation exists between risk and return among high-CGO firms. This is consistent with the empirical pattern shown in Section 2.

We now perform Fama-MacBeth regressions by controlling for the interaction between past news and risk proxies. If the dependence of the risk–return relation on CGO is purely driven by the fact that CGO is correlated with past news and information travels more slowly among high-risk firms, then the interactions between CGO and risk proxies should become insignificant after controlling for the interactions between past news and risk proxies. Following Zhang (2006), we use past realized return as the proxy for news. Thus, we add the interaction between past returns and risk proxies into our previous regression Eq. (6) and 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):

$$\begin{aligned} R = {} & \alpha + \beta_1 \times CGO + \beta_2 \times PROXY + \beta_3 \times PROXY \times CGO \\ & + \beta_4 \times MOM(-12, -1) \\ & + \beta_5 \times PROXY \times MOM(-12, -1) + \beta_6 \times LOGBM \\ & + \beta_7 \times LOGME \\ & + \beta_8 \times MOM(-1, 0) + \beta_9 \times MOM(-36, -12) \\ & + \beta_{10} \times TURNOVER + \epsilon, \end{aligned} \tag{7}$$

where all variables are defined the same as in Eq. (6). Column (3) in Table 5 reports the results. The interactions of CGO and risk proxies remain significant even after controlling for the interaction between past return and risk proxies. Indeed, the t-statistic for the interaction between CGO and risk proxies is 2.16 for CAPM beta, 6.57 for total return volatility, 9.69 for idiosyncratic return volatility, 2.99 for cash flow volatility, 4.05 for firm age, and 2.54 for analyst forecast dispersion.

Interestingly, after controlling for the interaction of CGO and risk proxies, the interaction between past return and risk proxies is no longer significant and is sometimes even negative. This indicates that the underreaction to information effect identified by Zhang (2006) might be partly driven by the effect of RDP on the risk–return trade-off.[15]

[14] One could argue that the return spread between high- and low-risk firms should be positively related to the aggregate level of CGO. However, this time-series variation in the risk–return trade-off is not a very robust prediction of RDP, because of other potential countervailing effects. Countercyclical risk aversion, for example, predicts the opposite, as high-aggregate CGO tends to coincide with economic booms. However, our prediction for the cross-sectional heterogeneity of the risk–return trade-off is much less subject to these potential aggregate time-series effects. Thus, our current study focuses on the cross-sectional heterogeneity of this risk–return trade-off.

[15] In Table A2 in the Internet Appendix, we also control for the interaction between a proxy for the speed of information diffusion and CGO in our Fama-MacBeth regressions. Following Hou and Moskowitz (2005), we use price delay as the proxy for the speed of information diffusion. We find that the coefficients on the interaction of CGO and risk proxies remain very similar. In general, the interaction between CGO and risk

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 average abnormal returns, as reported in previous literature. Therefore, the higher the rank, the greater the relative degree of overpricing according to the given anomaly variable. A stock's composite mispricing score is then the arithmetic average of its ranking percentile for each of the 11 anomalies. Based on this approach, a firm with the highest score would be most overpriced and one with the lowest score would be most underpriced.

proxies is more significant than the interaction between CGO and price delay.

It is important to note that we only need this score to reflect relative mispricing. At any given time, for example, a stock with the lowest score, although identified as the most underpriced, could actually be overpriced, but such stocks would then be the least overpriced within the cross section. Arguably, this composite mispricing score is a more precise and broad measure of relative mispricing than CGO. Thus, controlling for this composite mispricing score helps alleviate the concern that our key finding is driven by the mispricing effect. If the dependence of the risk–return relation on CGO is purely driven by the fact that CGO is a mispricing measure and the mispricing effect is more pronounced among high-risk firms, then the coefficients on the interactions between CGO and risk proxies should become insignificant or be substantially reduced after controlling for the interactions between the composite mispricing score and risk proxies.

We add this mispricing score and its interaction with risk proxies into the regression Eq. (6) 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):

$$\begin{aligned} R = \alpha &+ \beta_1 \times CGO + \beta_2 \times PROXY \\ &+ \beta_3 \times PROXY \times \ CGO + \beta_4 \times SCORE \\ &+ \beta_5 \times PROXY \times SCORE + \beta_6 \times LOGBM \\ &+ \beta_7 \times \ LOGME + \beta_8 \times MOM(-1, 0) \\ &+ \beta_9 \times MOM(-12, -1) + \beta_{10} \times MOM(-36, -12) \\ &+ \beta_{11} \times TURNOVER + \epsilon, \end{aligned} \tag{8}$$

where *SCORE* is the mispricing score as defined in Stambaugh, Yu, and Yuan (2015) and all other variables are defined as in Eq. (6).

Indeed, Column (4) in Table 5 shows that the interaction term between the mispricing score and risk measures is significant and negative for five of six proxies, consistent with the notion that the mispricing effect is stronger among high-risk firms. However, controlling for the mispricing effect and its interaction with our risk proxies does not change our conclusions. The interaction between CGO and risk proxies remains statistically significant.[16] In addition, the coefficients on the interactions between CGO and risk proxies in Columns (2) and (4) have similar magnitude. In Column (5) of Table 5, we control for the previous two effects simultaneously (i.e., the underreaction-to-news effect and the disposition effect-induced mispricing effect). Our main conclusion remains unaltered.

Lastly, we acknowledge that our proxy for mispricing is far from perfect. Thus, as a robustness check, we use an alternative, and probably more precise (as compared with CGO), proxy for the disposition effect-induced mispricing. This alternative mispricing measure is derived from the V-shaped disposition effect as in An (2016). The V-shaped disposition effect is a refined version of the disposition effect: (Ben-David and Hirshleifer, 2012) find that investors

[16] Alternatively, one could measure the mispricing score based on more traditional anomalies as in Cao and Han (2011). The results remain similar if this alternative mispricing score is used instead. These results, omitted for brevity, are available upon request.

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	3.000	86.565
	(0.23)	(2.96)	(6.04)	(1.85)	(2.48)	(2.48)

the low-sentiment subperiods based on the sentiment index of Baker and Wurgler (2006). As shown, there is typically a significant positive return spread between high- and low-risk firms among high-CGO firms during low-sentiment periods. As argued in Shen and Yu (2012), market participants tend to be more rational during low- versus high-sentiment periods because of short-selling impediments. Thus, the role of the reference point should be weaker during low-sentiment periods. Indeed, the overall difference-in-differences results are not as significant as before. Another reason for the less significant difference-in-differences results is the smaller number of observations in Table 7.

4. Additional robustness checks

This section reports a series of additional tests. We first assess the robustness of our results about the heterogeneity of the risk–return trade-off under different empirical specifications. In particular, we perform both the Fama-MacBeth regression analysis in the form of Column (5) in Table 5 and double sorts as in Table 3. To save space, only the coefficients of the interaction term of CGO and PROXY from the Fama-MacBeth regressions are reported in Table 8. All the double-sorting results are reported in the Internet Appendix.

First, we want to make sure that the risk–return trade-off pattern is not due to the inclusion of Nasdaq stocks. In Panel A of Table 8, we exclude the Nasdaq firms. The results indicate that the risk–return trade-off pattern remains among the NYSE and Amex stocks. The economic magnitude also remains largely unchanged. In addition, the double-sorting results without Nasdaq stocks, reported in Table A4 in the Internet Appendix, are similar to those in Table 3 obtained with Nasdaq stocks.

Second, previous studies (see, e.g., Bali, Cakici, Yan, and Zhang, 2005) show that some asset pricing phenomena disappear once illiquid stocks are excluded from the sample. Thus, to ensure that our results are not driven by stocks with extremely low liquidity, we focus on the subset of stocks classified as the top 90% liquid stocks according to the Amihud (2002) liquidity measure. Specifically, we measure illiquidity by the average ratio of the daily absolute return to the daily dollar trading volume in the past year. The results in Panel B of Table 8 show that the risk–return trade-off pattern and the economic magnitude again remain virtually identical. The double-sorting analysis, reported in Table A5 in the Internet Appendix, also shows similar patterns. Thus, our results are not driven by highly illiquid stocks.

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 typical firm, it might not measure the effect of an average dollar. To alleviate this size effect, we perform the value-weighted Fama-MacBeth regressions, in which each return is weighted by the firm's market capitalization at the end of the previous month. Panel D of Table 8 shows that the interaction between CGO and risk proxies is still significant for all six proxies.

Fifth, Panel E of Table 8 reports the results of a standard subperiod analysis. The whole sample is divided equally into two subperiods. Because of a smaller number of observations, the statistical significance for the interaction of CGO and risk measures is slightly lower. However, the general pattern in the risk–return trade-off still emerges in both subperiods; that is, the risk–return relation is more positive among high-CGO firms than among low-CGO firms. The double-sorting analysis, reported in Table A7 in the Internet Appendix, also shows similar patterns.

Sixth, we separate the total sample into two subsamples based on the median of institutional holdings. We find that the effect of CGO on the risk–return trade-off is generally stronger among firms with lower institutional holdings. These results are reported in Tables A8 and A9 in the Internet Appendix and are consistent with the limits-to-arbitrage effect (see, e.g., Nagel, 2005). Moreover, this evidence is consistent with the notion that the effect of reference point on the risk–return trade-off should be 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 document a new empirical fact about the heterogeneity of the risk–return trade-off across firms with different levels of CGO. Among firms in which investors face capital gains, there is a positive, albeit not strong, risk–return relation. By sharp contrast, among firms in which investors face capital losses, there is a robust and significant inverted risk–return relation. We examine a number of possible explanations for our new empirical finding. Our results suggest that the most promising explanation may be the one based on RDP (e.g., PT). That is, the presence of reference-dependent investors undermines the traditional positive risk–return relation implied by standard preferences. However, before fully embracing this conclusion, it would be helpful to have a formal model. As Barberis and Xiong (2009) show, the intuition derived from a static setting does not necessarily carry through to a fully dynamic model. Thus, our results point to the usefulness of constructing such a dynamic model in future research.

In addition, investigating the role of RDP in other asset pricing phenomena would be interesting. For example, asset return skewness has gained a substantial amount of attention in the recent literature (see, e.g., Barberis and Huang, 2008; Boyer, Mitton, and Vorkink, 2010; Zhang, 2005). Similar to risk appetite, individuals' demand for positively skewed stocks may be higher when they are facing losses. Indeed, using a comprehensive list of proxies for firm-level skewness, An, Wang, Wang, and Yu (2016) find consistent evidence that skewness-related anomalies are more pronounced among stocks in which investors face losses.

[20] In addition, several robustness checks are performed in our untabulated analysis. For example, stocks with a price lower than $5 (penny stocks) are more subject to microstructure effects. Thus, we exclude those firms from our sample. However, our results are robust to the inclusion of penny stocks. Because our idiosyncratic volatility measure is computed based on daily returns, it also could be subject to microstructure effects. When we replace our daily return-based idiosyncratic volatility measure with monthly return-based measures, the results remain quantitatively unchanged. We also control for additional variables such as interaction between turnover and risk proxies, past 5-year returns, and so on. The results all remain similar and are available upon request.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

An, L., 2016. Asset pricing when traders sell extreme winners and losers. Review of Financial Studies 29, 823–861.

An, L., Wang, H., Wang, J., Yu, J., 2016. Lottery-related anomalies: the role of reference-dependent preferences. Unpublished working paper. Tsinghua University, University of Delaware, Chinese University of Hong Kong (Shenzhen), and University of Minnesota.

Anderson, A., Dyl, E., 2005. Market structure and trading volume. Journal of Financial Research 28, 115–131.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: international and further US evidence. Journal of Financial Economics 91, 1–23.

Armstrong, C., Banerjee, S., Corona, C., 2013. Factor-loading uncertainty and expected returns. Review of Financial Studies 26, 158–207.

Asness, C., Frazzini, A., Pedersen, L., 2012. Leverage aversion and risk parity. Financial Analysts Journal 68, 47–59.

Baker, M., Bradley, B., Wurgler, J., 2011. Benchmarks as limits to arbitrage: understanding the low-volatility anomaly. Financial Analysts Journal 67, 40–54.

Baker, M., Pan, X., Wurgler, J., 2012. The effect of reference point prices on mergers and acquisitions. Journal of Financial Economics 106, 49–71.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645–1680.

Bali, T., Brown, B., Murray, S., Tang, Y., 2014. Betting against beta or demand for lottery. Unpublished working paper. Georgetown University.

Bali, T., Cakici, N., 2008. Idiosyncratic volatility and the cross section of expected returns. Journal of Financial and Quantitative Analysis 43, 29–58.

Bali, T., Cakici, N., Whitelaw, R., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427–446.

Bali, T., Cakici, N., Yan, X., Zhang, Z., 2005. Does idiosyncratic risk really matter? Journal of Finance 60, 905–929.

Banerjee, S., 2011. Learning from prices and the dispersion in beliefs. Review of Financial Studies 24, 3025–3068.

Barberis, N., 2013. Thirty years of prospect theory in economics: a review and assessment. Journal of Economic Perspectives 27, 173–196.

Barberis, N., Huang, M., 2001. Mental accounting, loss aversion, and individual stock returns. Journal of Finance 56, 1247–1292.

Barberis, N., Huang, M., 2008. Stocks as lotteries: the implications of probability weighting for security prices. American Economic Review 98, 2066–2100.

Barberis, N., Huang, M., Santos, T., 2001. Prospect theory and asset prices. Quarterly Journal of Economics 116, 1–53.

Barberis, N., Mukherjee, A., Wang, B., 2016. Prospect theory and stock returns: an empirical test. Yale University, Hong Kong University of Science and Technology and Fordham University. Unpublished working paper

Barberis, N., Xiong, W., 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. Journal of Finance 64, 751–784.

Barberis, N., Xiong, W., 2012. Realization utility. Journal of Financial Economics 104, 251–271.
Ben-David, I., Hirshleifer, D., 2012. Are investors really reluctant to realized their losses? Trading responses to past returns and the disposition effect. Review of Financial Studies 25, 2485–2532.
Benartzi, S., Thaler, R., 1995. Myopic loss aversion and the equity premium puzzle quarterly. Journal of Economics 110, 73–92.
Black, F., 1972. Capital market equilibrium with restricted borrowing. Journal of Business 45, 444–455.
Boehme, R., Danielsen, B., Kumar, P., Sorescu, S., 2009. Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets miller (1977). Journal of Financial Markets 12, 438–468.
Boyer, B., Mitton, T., Vorkink, K., 2010. Expected idiosyncratic skewness. Review of Financial Studies 23, 169–202.
Brennan, M., 1993. Agency and asset pricing. Unpublished working paper. University of California, Los Angeles.
Brown, S., 1979. The effect of estimation risk on capital market equilibrium. Journal of Financial and Quantitative Analysis 14, 215–220.
Cao, J., Han, B., 2011. Idiosyncratic risk, costly arbitrage, and the cross-section of stock returns. Unpublished working paper. Chinese University of Hong Kong and University of Texas, Austin.
Cohen, R., Polk, C., Vuolteenaho, T., 2005. Money illusion in the stock market: the Modigliani-Cohn hypothesis. Quarterly Journal of Economics 120, 639–668.
Diether, K., Malloy, C., Scherbina, A., 2002. Differences of opinion and the cross-section of stock returns. Journal of Finance 57, 2113–2141.
Dougal, C., Engelberg, J., Parsons, C., Van Wesep, E., 2015. Anchoring on credit spreads. Journal of Finance 70, 1039–1080.
Fama, E., French, K., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.
Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.
Frazzini, A., 2006. The disposition effect and underreaction to news. Journal of Finance 61, 2017–2046.
Frazzini, A., Pedersen, L., 2014. Betting against beta. Journal of Financial Economics 111, 1–25.
French, K., Schwert, W., Stambaugh, R., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.
Friedman, M., Savage, L., 1948. The utility analysis of choices involving risk. Journal of Political Economy 56, 279–304.
George, T., Hwang, C., 2004. The 52-week high and momentum investing. Journal of Finance 59, 2145–2176.
Goetzmann, W., Massa, M., 2005. Dispersion of opinion and stock returns. Journal of Financial Markets 8, 324–349.
Grinblatt, M., Han, B., 2005. Prospect theory, mental accounting, and momentum. Journal of Financial Economics 78, 311–339.
He, Z., Li, S., Wei, B., Yu, J., 2014. Uncertainty, risk, and incentives: theory and evidence. Management Science 60, 206–226.
Hong, H., Sraer, D., 2011. Speculative betas. Unpublished working paper. Princeton University.
Hou, K., Moskowitz, T., 2005. Market frictions, price delay, and the cross-section of expected returns. Review of Financial Studies 18 (3), 981–1020.
Huang, W., Liu, Q., Rhee, S., Zhang, L., 2010. Return reversals, idiosyncratic risk, and expected returns. Review of Financial Studies 23, 147–168.
Ingersoll, J., Jin, L., 2013. Realization utility with reference-dependent preferences. Review of Financial Studies 26, 723–767.
Johnson, T., 2004. Forecast dispersion and the cross section of expected returns. Journal of Finance 59, 1957–1978.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–291.
Korteweg, A., Polson, N., 2009. Corporate credit spreads under parameter uncertainty. Unpublished working paper. Stanford University and University of Chicago.
Koszegi, B., Rabin, M., 2006. A model of reference-dependent preferences. Quarterly Journal of Economics 121, 1133–1165.
Koszegi, B., Rabin, M., 2007. Reference-dependent risk attitudes. American Economic Review 97, 1047–1073.
Lehmann, B., 1990. Residual risk revisited. Journal of Econometrics 45, 71–97.
Li, J., Yu, J., 2012. Investor attention, psychological anchors, and stock return predictability. Journal of Financial Economics 104, 401–419.
Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Review of Economics and Statistics 47, 13–37.
Malkiel, B.G., Xu, Y., 2002. Idiosyncratic risk and security returns. Unpublished working paper. University of Texas, Dallas.
Markowitz, H., 1952. Portfolio Selection. John Wiley and Sons, New York, NY.
Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–510.
Miller, E., 1977. Risk, uncertainty, and divergence of opinion. Journal of Finance 32, 1151–1168.
Nagel, S., 2005. Short sales, institutional investors, and the cross-section of stock returns. Journal of Financial Economics 78, 277–309.
Newey, W., West, K., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance 53, 1775–1798.
Pastor, L., Veronesi, P., 2003. Stock valuation and learning about profitability. Journal of Finance 58, 1749–1790.
Pontiff, J., 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics 42, 35–52.
Qu, S., Starks, L., Yan, H., 2004. Risk, dispersion of analyst forecasts and stock returns. Unpublished working paper. University of Texas, Austin.
Sharpe, W., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. Journal of Finance 19, 425–442.
Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and ride losers too long: theory and evidence. Journal of Finance 40, 777–791.
Shen, J., Yu, J., 2012. Investor sentiment and economic forces. Unpublished working paper. University of Minnesota.
Shumway, T., 1997. The delisting bias in CRSP data. Journal of Finance 52, 327–340.
Spiegel, M., Wang, X., 2010. Cross-sectional variation in stock returns: liquidity and idiosyncratic risk. Unpublished working paper. Yale University.
Stambaugh, R., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70, 1903–1948.
Thaler, R., 1980. Toward a positive theory of consumer choice. Journal of Economic Behavior and Organization 1, 39–60.
Thaler, R., 1985. Mental accounting and consumer choice. Marketing Science 4, 199–214.
Thaler, R., Johnson, E., 1990. Gambling with the house money and trying to break even: the effects of prior outcomes on risky choice. Marketing Science 36, 613–660.
Tinic, S., West, R., 1986. Risk, return, and equilibrium: a revisit. Journal of Political Economy 94, 126–147.
Veronesi, P., 2000. How does information quality affect stock returns. Journal of Finance 55, 807–837.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48, 817–838.
Zhang, F., 2006. Information uncertainty and stock returns. Journal of Finance 61, 105–137.
Zhang, Y., 2005. Individual skewness and the cross-section of average returns. Unpublished working paper. Yale University.