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, whereas recent empirical evidence suggests the opposite. We apply reference-dependent preferences to shed light on this violation. Reference-dependent preferences (e.g., prospect theory) typically posit that when facing prior losses, individuals tend to be risk seeking rather than risk averse. Consequently, among stocks where average investors face prior losses, there could be a negative risk-return relation. By contrast, among stocks where average investors face capital gains and are risk averse, the traditional positive relation should emerge. Using several intuitive risk measures, we provide consistent support for our hypotheses.

JEL Classification: G02, G12, G14

Keywords: prospect theory, risk-return trade-off, beta, risk, uncertainty, capital gains overhang

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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. In this study, we apply reference-dependent preferences (e.g., prospect theory) and mental accounting (MA) to understand this anomalously weak and sometimes negative risk-return association.

One fundamental assumption for the positive risk-return trade-off is that investors are risk averse, and thus investors demand compensation for bearing risk. However, reference-dependent preferences suggest that investor 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 the arbitrage forces are limited, there could be a negative risk-return trade-off among these stocks. By contrast, among the stocks where investors face capital gains, the traditional positive risk-return trade-off should emerge, since investors of these stocks are risk averse.

To better understand how reference-dependent preferences and MA undermine the traditional positive risk-return trade-off, let's consider a concrete example with PT/MA in Figure 1. 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, average 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 as well. 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 due to the convexity illustrated in Figure 1, and 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 stock B, leading to a lower expected return for stock A. Thus, there is a negative risk-return association in this scenario.

Now consider stocks C and D, shown in Figure 2. 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 as well, 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 due to the concavity illustrated in Figure 2. 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 trade-off emerges in this scenario.[1] Indeed, using the same brokerage data set as in Barber and Odean (2000), we show in Table A1 in the Appendix that individual investors' propensity to sell a winner is higher when volatility of the underlying winner stock is higher, and the propensity to sell a loser is lower when volatility of the underlying loser stock is higher, consistent with our reasoning in Figures 1 and 2.

To formally test our hypotheses, we first utilize the method in Grinblatt and Han (2005) to calculate the capital gains overhang (CGO) for individual stocks, which is essentially the normalized difference between the current stock price and the reference price. We then sort all individual stocks into portfolios based on lagged CGO and various measures of risk. The central prediction is that high-risk firms should have higher returns among firms with large CGO, and this risk-return association should be weaker and even negative among firms with negative CGO. Our empirical evidence shows strong support for these predictions. In particular, among firms with prior capital losses, the returns of firms with high return volatility are 115 basis points (bps) lower per month than those of firms with low return volatility. By sharp contrast, among firms with prior capital gains, the returns of firms with high return volatility are 45 bps higher per month than those of firms with low return volatility. Similar results hold when risk is measured by CAPM beta. Although prior evidence on the negative risk-return association posits a challenge for traditional asset

[1] The above static argument resembles the reasoning that S-shaped preferences can lead to the disposition effect, as argued in Shefrin and Statman (1985), Odean (1998), Grinblatt and Han (2005), and Frazzini (2006). In dynamic settings, Barberis and Xiong (2009, 2012) and Ingersoll and Jin (2013) raise doubts about whether pure prospect theory can produce the disposition effect, and hence emphasize the importance of the realization utility in addition to the reference-dependent preferences, where investors enjoy realizing profits. On the other hand, Li and Yang (2013) show that with reasonable parameterizations, PT can still produce the disposition effect in a general equilibrium setting. In addition, Meng (2014) argues that with the reference point being expected future wealth, PT can induce the disposition effect, even in a dynamic setting.

pricing models, our evidence suggests that reference-dependent preferences and MA could potentially account for the empirical failure of classical theory.

To further explore the role of reference-dependent preferences in asset prices, in addition to CAPM beta and return volatility, we use several alternative intuitive measures of risk: cash flow volatility, firm age, idiosyncratic return volatility, and analyst forecast dispersion. Individual investors, for example, could view firm idiosyncratic volatility as risk because they fail to diversify it mentally due to MA. Previous studies have used these alternative measures of risk as proxies for information uncertainty, parameter uncertainty, information quality, or divergence of belief under various circumstances. To fix the terminology 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 are correlated with the true risk measure in the minds of investors. Thus, reference-dependent preferences have the same implications regarding the relation between expected returns and these alternative risk measures. Indeed, we find that CGO is an important determinant in each of these risk-return relations. Among low-CGO stocks, these relations are negative, whereas among high-CGO stocks, these relations typically become positive, supporting the role of reference-dependent preferences in asset prices.

Although the above empirical evidence on the risk-return trade-off is consistent with our hypotheses, an alternative explanation for our findings is underreaction to news. Take idiosyncratic volatility as an example. Firms with high CGO are likely to have experienced good news in the recent past. If information travels slowly across investors and information travels even slower when idiosyncratic volatility is high, then among firms with recent good news, high idiosyncratic volatility is likely to predict higher future returns due to the current undervaluation. Thus, a positive relation between idiosyncratic volatility and return among firms with high CGO is observed. On the other hand, firms with low CGO have probably experienced negative news and therefore have been overpriced due to underreaction. This overpricing effect is stronger when idiosyncratic volatility is high, since the underreaction effect is larger. Thus, there is a negative relation between idiosyncratic volatility and return among firms with low CGO.

To control for the potential effect from underreaction and several other possible mechanisms, we perform a series of Fama-MacBeth regressions. First, we show that our results still hold even if we control for the interaction of past returns (proxy for past news) and risk proxies. In fact, after controlling for the role of CGO, the interaction between past returns and risk proxies is no longer significant. Second, we control for a battery of additional variables such as shares turnover, leverage, a composite mispricing proxy, and a mispricing measure derived from the V-shaped disposition effect. The effect of CGO on the risk-return trade-off remains significant. In particular, we show that the mispricing role of CGO due to the disposition effect does not drive our results. Rather, it is the risk-taking/risk-averse behavior in the loss/gain regions that drives our key results. Moreover, this effect is robust to different subperiods, as well as the exclusion of NASDAQ stocks, penny stocks, and illiquid stocks. Lastly, the effect is stronger among firms with more individual investors, who are more likely to have reference-dependent preferences.

In terms of related literature, Barberis and Huang (2001), Barberis, Huang, and Santos (2001), and Barberis and Huang (2008) theoretically explore the role of reference-dependent preferences (in particular, prospect theory) in asset prices in equilibrium settings. These studies suggest that reference-dependent preferences can play an important 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 PT/MA induces underreaction to news, leading to return predictability. More recently, Barberis and Xiong (2009, 2012), and Ingersoll and Jin (2013) study realization utility with reference-dependent preferences. 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), since high volatility stocks provide more opportunities for investors to earn realization utility benefits. Moreover, the effect of realization utility on the risk-return relation should be stronger among firms with capital losses than among firms with capital gains. For stocks with capital gains, volatility does not provide more opportunities to earn realization utility benefits, due to diminishing sensitivity in the preference. In our study, we empirically investigate the heterogeneity in the risk-return trade-off across firms with different levels of capital gains, as implied by both reference-dependent preferences and realization utility.

Many studies have suggested possible mechanisms responsible for the failure of the risk-return trade-off implied by the CAPM. These include leverage constraints (Black (1972), Asness, Frazzini, and Pedersen (2012), and Frazzini and Pedersen (2011)), benchmarked institutional investors (Brennan (1993), Baker, Bradley, and Wurgler (2011)), money illusion

[2]In a two-period setting with cumulative prospect theory preferences but without mental accounting, 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., mental accounting), the CAPM typically fails.

(Cohen, Polk, and Vuolteenaho (2005)), disagreement (Hong and Sraer (2011)), and market wide sentiment-induced mispricing (Shen and Yu (2012)). We propose that the reference-dependent feature in preferences is another potential mechanism for the failure of CAPM. All mechanisms could work simultaneously. We complement previous studies by showing that the negative risk-return relation exists only among firms with capital losses, whereas the standard positive 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 (2011), Hong and Sraer (2011), and Shen and Yu (2012) document that the slope of the security market line changes with inflation, the TED spread (the difference between LIBOR and T-Bill rates), aggregate disagreement, and investor sentiment, respectively. We complement these existing studies by focusing on the cross-sectional, rather than the time-series, heterogeneity in the risk-return trade-off.

A huge literature also 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 relationship, and the empirical evidence is mixed as well.[3] Existing studies typically focus on the unconditional relation between these alternative risk measures 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 nonmonotonicity of this relation.

The rest of the paper is organized as follows. Section 2 discusses theoretical background and hypotheses. Section 3 describes the definition of risk proxies and presents the main empirical findings. Additional robustness tests are covered in Section 4. Section 5 concludes.

[3] Ang, Hodrick, Xing, and Zhang (2006, 2009), for example, find a negative relation between idiosyncratic volatility and expected returns, whereas Tinic and West (1986), Lehmann (1990), Malkiel and Xu (2002), Huang, Liu, Rhee, and Zhang (2010), and Spiegel and Wang (2010) document a positive 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) document a negative relation between analyst dispersion and stock returns, whereas Qu, Starks, and Yan (2004) and Banerjee (2011) finds the opposite.

2 Theoretical Background and Hypotheses

Most asset pricing 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 a 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. Building on the reference-dependent preference model by Kahneman and Tversky (1979), many subsequent studies have demonstrated that reference-dependent utility can better capture human behavior in decision making (see, e.g., Koszegi and Rabin (2006, 2007)).

In particular, the prospect theory of Kahneman and Tversky (1979) has attracted a lot of attention in finance literature and has been applied to account for many asset pricing phenomena.[4] 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 behavior, depending on whether the outcome is below or above the reference point, respectively.[5] The mental accounting of Thaler (1980, 1985) provides a theoretical foundation for the way in which decision makers set reference points for each asset they own. The main idea underlying mental accounting is that decision makers tend to mentally frame different assets as belonging to separate accounts, and then apply reference-dependent preferences to each account by ignoring possible interaction among these assets.

Specifically, under the assumption of reference point being the lagged status quo, diminishing sensitivity predicts the willingness to take unfavorable risks to regain the previous status quo. Gomes (2005) shows that if the reference point is the purchase price, an investor whose investment is in losses will be risk-seeking in waiting for a price to recover before selling. That is, the status-quo bias implies more risk lovingness following losses (see,

[4]Specifically, prospect theory has been used to account for a number of phenomena in finance including, but not limited to, the disposition effect (Shefrin and Statman (1985), Odean (1998), and Barberis and Xiong (2012)), the equity premium puzzle (Benartzi and Thaler (1995) and Barberis, Huang, and Santos (2001)), and momentum (Grinblatt and Han (2005)).

[5]Prospect theory has several other important features such as loss aversion and probability weighting, which have been studied extensively by Benartzi and Thaler (1995), Barberis, Huang, and Santos (2001), Barberis and Huang (2008), and Barberis, Mukherjee, and Wang (2013), among others.

also Koszegi and Rabin (2006, 2007)). A related concept, the breaking-even effect coined by Thaler and Johnson (1990), also implies that following losses, gambles that offer a chance to break even appear especially attractive, and thus investors could be risk-seeking after losses.

On the other hand, Barberis and Xiong (2009) show that if the reference point is the lagged state quo, PT does not necessarily predict an increased risk lovingness after losses. Intuitively, to induce an investor to take on risky investments, investment losses are typically smaller than investment gains. Therefore, an investor is typically closer to the reference point after a loss than after a gain. Thus, 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 due to diminishing sensitivity in the loss region, and thus the net effect could be an increased risk aversion after losses. However, empirical studies by Odean (1998) and Genesove and Mayer (2001) suggest that individuals do take more incremental risk after losses. In addition, theoretical study by Meng (2014) shows that if expected future wealth operates as a reference point, there is still an increased risk lovingness after losses. In this case, the reference point is usually higher than the lagged status quo since investors typically anticipate a positive return for their investments. The increased reference point makes an investor closer to the reference point after the gain than after the loss. Thus, after a gain, an investor is likely to be more risk averse due to the kink generated by loss aversion. After a loss, especially a larger loss, an investor is farther away from the reference point, and the diminishing sensitivity predicts the usual risk-loving. Thus, following losses, especially large losses, diminishing sensitivity can still lead to excessive risk-taking behavior.

In sum, a natural implication from reference-dependent preferences and mental accounting is that the risk-return trade-off should be weaker or even negative among stocks where investors have experienced losses, especially large losses, and thus are risk seeking, and that the positive risk-return relation should emerge among stocks where investors have experienced gains and thus are risk averse. That is, the risk-return trade-off should crucially depend on individual stocks' CGO. Thus, we arrive at the following hypotheses:

Hypothesis 1: A negative association between expected returns and risk exists among firms with small and negative CGO.

Hypothesis 2: A positive association between expected returns and risk exists among firms with large and positive CGO.

We use CAPM beta and stock return volatility as our main measures of risk. However, the alternative measures of risk mentioned in the introduction may also appear to be intuitive to investors. These measures include firm age, cash flow volatility, analysis forecast dispersion, and idiosyncratic stock volatility. These measures have been used as proxies for parameter uncertainty or information uncertainty in previous studies. Investors, however, may simply treat parameter uncertainty or information uncertainty as a measure of risk when making decisions under uncertainty. Thus, these alternative measures of risk are positively associated with the true risk measure in the minds of investors. As a result, the above two hypotheses should also apply to the relation between alternative measures of risk and expected returns.

Finally, as discussed in the introduction, many studies have suggested possible mechanisms that are responsible for the low-risk anomaly. 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. Due to limits to arbitrage, high-volatility firms tend to be overpriced. It is also possible that high-beta firms are more sensitive to investor disagreement and sentiment (see Hong and Sraer (2011) and 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. Thus, the positive association between expected returns and various measures of risk among firms with a positive CGO might be weakened or completely inverted due to the overpricing of high-risk stocks. That is, Hypothesis 2 might not hold well in the data. However, a more robust prediction of our argument is the following:

Hypothesis 3: The return spread between high- and low-risk stocks among firms with capital gains should be larger than that among firms with capital losses.

One might be attempted to 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 reference-dependent preferences, due to other potential countervailing effects. Countercyclical risk aversion, for example, would predict the opposite, since 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.

3 Empirical Results

To test our hypotheses, we first define the key variables used in our tests. We then report summary statistics, the double-sorting analysis, and the Fama-MacBeth regression analysis. Finally, we provide a battery of robustness checks.

3.1 Definition of Key Variables

Our sample includes all ordinary nonfinancial stocks traded in NYSE, AMEX, and NASDAQ from CRSP, with stock prices at least \$5 and nonnegative book equity from January 1962 to December 2011.

To measure CGO, we first use the turnover-based measure from Grinblatt and Han (2005) to calculate the reference price. In particular, at each week t, the reference price for each individual stock is defined as

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

where V_t is week t's turnover in the stock and T is 260, the number of weeks in the previous five years. 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 rough rule of thumb to scale down the volume of NASDAQ stocks by 38% after 1997 and by 50% before 1997 to make it roughly comparable with the volume on NYSE. Further, to be included in the sample, a stock must have at least 200 weeks of nonmissing data in the previous five years. The term in parentheses is a weight that sums up to one. 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 capital gains overhang (CGO) at week t is defined as

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

To avoid market microstructure effects, the market price is lagged by one week. Finally, to obtain CGO at a monthly frequency, we simply use the last week CGO within each month. Since we use five-year daily data to construct CGO, the CGO variable ranges from January 1966 to December 2011, which is our main sample period. Lastly, it is possible that the reference point is not the purchase price. Instead, the reference price might be the expected future price (see, Koszegi and Rabin (2006, 2007) and Meng (2014)). However, it is likely that the relation between purchase and expected 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 and return volatility as our main proxies. Specifically, we use a five-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 five-year of 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 in the previous year to estimate volatility as in Baker and Wurgler (2006). The results based on different measures of volatility are available upon request.

As argued before, investors could also use some alternative measures of risk as the proxy for true risk. Thus, reference-dependent preferences can also be applied to understand the relation between these alternative measures of risk and expected returns. 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 following time-series model:

$$R_{i,d,t} = b_0 + b_1 R_{M,d,t} + b_2 SMB_{M,d,t} + b_3 HML_{M,d,t} + \varepsilon_{i,d,t},$$

where $R_{i,d,t}$ is stock i's daily excess return in month t day d, and $R_{M,d,t}$, $SMB_{M,d,t}$, and $HML_{M,d,t}$ are the market factor, the size factor, and the value factor in month t day d, respectively. We estimate the above equation for each stock each month in the data set using the daily return in the previous month. In addition, we can measure 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). Firm age is measured as the number of years since the firm's first appearance in CRSP until the portfolio formation date; DISP is measured as the standard deviation of analyst forecasts on one-year earnings (obtained from I/B/E/S) at the portfolio formation date scaled by the prior year-end stock price to mitigate heteroscedasticity; and CFVOL is measured as the standard deviation of cash flow over the previous five years ending at the portfolio formation date.[6]

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 Pastor and Veronesi (2003), Korteweg and Polson (2009), and He, Li, Wei and Yu (2013), and information quality in Veronesi (2000) and Armstrong, Banerjee, and Corona (2013). The existing theories suggest that, unconditionally, parameter/information risk can be unpriced (Brown (1979)), positively priced (Merton (1987)), or negatively priced (Miller (1977)). Here, we simply view these variables as proxies for investors' measures of risk and examine how the conditional risk-return trade-off changes across firms with different levels of CGO.[7]

Although we use all six variables as proxies for firm risk for individual investors, they are not equally precise proxies. Some of the variables are more precise than others. For example, stock total volatility is probably a better proxy for risk than analyst forecast dispersion. It seems more natural for individuals to use past stock return volatility as a measure of firm risk than to use analyst forecast dispersion when making decisions. In addition, although analyst forecast dispersion could be a proxy for firm uncertainty, it may also be a proxy for divergence of opinion or information asymmetry. Thus, analyst forecast dispersion may not be as clean as stock volatility as a proxy for individual investors' measure of risk. As a result, the effect of reference-dependent preferences on the risk-return trader-off might be stronger using volatility as a proxy than using analyst forecast dispersion as a proxy.

3.2 Summary Statistics and One-Way Sorts

Figure 3 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 a 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.

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

[7] In untabulated analysis, we have considered 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 reports the summary statistics for the portfolio returns sorted by lagged CGO. To facilitate a comparison with previous studies on momentum (e.g., Grinblatt and Han (2005)), we focus on the sample period from January 1966 to December 2011, and 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, firms with high CGO earn significantly higher subsequent returns. However, high-CGO firms earn significantly lower returns during January. Consistent with the findings in Table 2 of Grinblatt and Han (2005), this pattern supports the view of price underreaction to information induced by reference-dependent preferences, and a December tax-loss selling effect.

Table 1 also reports other firm characteristics across CGO quintiles. Firms with low CGO tend to be smaller in size, higher in book-to-market, less liquid, and have higher leverage and higher CAPM beta. As expected, there is a strong monotonic relation between CGO and lagged returns. In addition, the bottom quintile has 9.7% of the total market value, and the top quintile has 24.7% of total market capitalization. Thus, although firms with low CGO tend to be smaller, they still account for a significant portion of the 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 lower for low-CGO firms than for high-CGO firms. With less institutional holders among low-CGO firms, it is more likely that the reference-dependent effect is at play. Thus, it is more likely to find risk seeking behavior among low-CGO firms, leading to a potential negative risk-return relation among these firms.

Table 2 reports the summary statistics for single-sorted value-weighted portfolio returns based on various risk proxies. In general, high-risk firms do not earn significantly higher subsequent returns. Instead, firms with high total volatility tend to 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 et al. (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, which is consistent with Fama and French (1992) but contradicts the traditional CAPM.

As mentioned earlier, existing theories suggest that parameter/information risk can either be unpriced, positively priced, or negatively priced. The empirical evidence on the unconditional relation between expected returns and the proxies for risk is indeed weak. For all proxies, return spreads are negative and insignificant. In the next section, we explore how the *conditional* risk-return trade-off changes across firms with different levels of CGO.

3.3 Double Sorts

We now turn to the key results of this paper. At the beginning of each month, we first divide all firms in our sample into five groups based on lagged CGO, and within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted returns are calculated. Table 3 presents the main results. It is evident that for all risk proxies except for analyst forecast dispersion, among the group with large CGO, the high-risk firms indeed tend to earn higher returns, consistent with Hypothesis 2. However, these results are not statistically significant. This could be due to the forces identified by previous studies such as leverage constraints, sentiment-induced mispricing, or index benchmarking.

Several theories proposed in the literature can generate a capital market line with a slope less steep than that implied by the traditional CAPM. However, these existing theories still typically imply a positive slope, i.e., a positive risk-return trade-off. For example, both leverage constraints and index benchmarking typically imply a positive, albeit weaker, risk-return trade-off. Our argument, which relies on the reference-dependent preferences and mental accounting, can produce a negative risk-return trade-off among one particular type of firm. It is almost certain that in reality, all the forces are at play. Given the empirical evidence on the negative risk-return trade-off, we view our proposed mechanism as complementary to the economic forces proposed by previous studies. In addition, our focus is on the cross-sectional, rather than the time-series, variation in the risk-return trade-off.

More interestingly, among the group of firms with the lowest CGO, high-risk firms earn significantly lower returns, consistent with Hypothesis 1. For instance, Table 3 shows that among the group with the lowest CGO, the returns of high-beta firms are 72 bps lower per month than those of low-beta firms. Thus, the security market line is completely inverted among firms with low CGO. More dramatically, among the group with the lowest CGO, the returns of firms with high total return volatility are 115 bps lower per month than those of firms with low total return volatility, whereas among the group with the highest CGO, the returns of firms with high total return volatility are 45 bps higher per month than those of firms with low total return volatility. Similar results also hold for other risk measures. That is, the risk-return relation is positive among high-CGO firms (except for analyst forecast dispersion proxy), and negative among low-CGO firms.

Finally, the differences between the high-minus-low spreads among the highest and the lowest CGO group are always highly significant, confirming Hypothesis 3. For example, for the idiosyncratic return volatility measure, the high-minus-low spread is 221 bps per month (t-statistic = 6.14) higher among the highest CGO group than the lowest CGO group. For all other risk measures, this difference is also highly significant both statistically and economically. The difference between the high-minus-low spread among high-CGO firms and among low-CGO firms is 102 bps per month for firm age (t-statistic = 4.13), 79 bps per month for cash flow volatility (t-statistic = 3.10), 54 bps per month for analyst forecast dispersion (t-statistic = 2.07), 160 bps per month for stock total volatility (t-statistic = 4.80), and 101 bps per month for CAPM beta (t-statistic = 3.24). Even though our focus is on the raw excess returns, we also report the 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 remarkably strong and consistent across all the risk proxies, lending strong support to our hypotheses. In particular, the risk-return relation changes significantly across firms with different levels of CGO, consistent with Hypothesis 3.

Our findings also shed light on the debate regarding the relation between idiosyncratic volatility and expected returns. Merton (1987), for example, argues that idiosyncratic volatility may be compensated when each investor knows only about a subset of available securities. On the other hand, if idiosyncratic volatility is a proxy for divergence of opinion, then together with short-sale impediments, Miller (1977) implies that firms with high idiosyncratic volatility tend to be overpriced and these firms should earn lower subsequent returns. We notice that the theory of Merton (1987) assumes global risk aversion. When investors are risk seeking, firms with high idiosyncratic risk should earn a lower return. Indeed, we find that firms with high idiosyncratic volatility earn much lower returns among firms with low CGO, but the opposite holds among firms with high CGO. This may partially explain the existing mixed evidence on the relation between idiosyncratic volatility and expected returns. Hence, our study complements the previous literature by exploring the heterogeneity of this relation across different types of firms, rather than the unconditional relation.

To summarize, we find that among firms with low CGO, high-risk firms indeed earn lower subsequent returns, whereas among firms with high CGO, high-risk firms earn higher returns. However, the negative return spreads between high- and low-risk firms among firms with low CGO typically are much larger in magnitude than the positive return spreads among firms with high CGO. This asymmetry might be due to an unconditional overpricing effect of high-risk firms. Indeed, previous studies (e.g., Baker, Bradley, and Wurgler (2011) and Shen and Yu (2012)) have identified several mechanisms that could lead to an unconditional overpricing for high-risk firms. 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, asymmetric return spreads between high- and low-risk firms among firms with low and high CGO emerge.

The results in Table 3 also indicate that the positive relation between risk and expected returns among the high-CGO firms is still not very significant. Previous studies have identified several mechanisms that could lead to a stronger risk-return trade-off during some subperiod of time. Combining our mechanism with the previously identified forces could guide us in finding a strengthened positive risk-return trade-off among a subset of firms. For example, we should expect a stronger risk return trade-off during low-sentiment periods based on Shen and Yu (2012). Indeed, Table 4 repeats the previous double-sorting portfolio analysis in 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. However, due to a smaller number of observations, the overall difference-in-difference results are not as significant as before.

3.4 Fama-MacBeth Regressions

The simple double-sorting approach in the previous section provides support to our hypotheses. However, the different risk-return trade-off behavior across firms with different CGO could be driven by forces other than those we propose. Double sorting cannot explicitly control for other variables that might influence returns, and sorting on three or more variables is impractical. Thus, to investigate other possible mechanisms, we perform a series of Fama and MacBeth (1973) cross-sectional regressions, which allows us to conveniently control for additional variables.

Table 5 reports the results. In all the regressions, we control for a list of traditional return predictors, such as firm size, book-to-market, past returns, and shares turnover. The benchmark regression shows that the coefficient on GCO is significant and positive, confirming the Fama-MacBeth regression results of Grinblatt and Han (2005). Regression (1) includes the interaction term between CGO and risk proxies. The results confirm the double-sorting analysis in the previous section that the interaction term is always significant and positive for all the risk measures, even after controlling for size, book-to-market, past returns, and shares turnover.[8]

3.4.1 An Underreaction to News Story

Regression (1) shows that the interaction between CGO and risk proxies is always significant and positive after controlling for several traditional return-predictors. It is also possible, however, that some other forces could account for this empirical pattern. Zhang (2006), for example, argues that information may travel slowly, which can lead to underreaction to news. This underreaction effect might be stronger among firms with high risk (or information uncertainty in Zhang's (2006) terminology). Thus, among the firms with recent good news, high risk is likely to forecast high future returns due to the current undervaluation. Since high-CGO firms tend to have had good news in the past, a positive relation between risk and return among firms with high CGO is likely to be observed. On the other hand, firms with low CGO are likely to have experienced negative news and been overpriced due to underreaction. This overpricing effect is stronger when risk is larger, since the underreaction effect is larger. Thus, there is a negative relation between risk and return among firms with low CGO.

To make sure that our empirical results are not driven purely by this underreaction-to-news effect, we perform a Fama-MacBeth regression by controlling for the interaction between past news and CGO.[9] Following Zhang (2006), we use past realized return as the proxy for news. Regression (2) in Table 5 indicates that the interactions of CGO and risk proxies remain highly significant even after controlling for the interaction of past return and

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

[9]Moreover, Frazzini (2006) argues that the disposition effect induces underreaction to news, leading to return predictability. In particular, due to the disposition effect, the underreaction effect to good (bad) news is most severe among firms with capital gains (capital losses).

risk proxies. Indeed, the t-statistic for the interaction between CGO and risk proxies is 3.13 for CAPM beta, 6.74 for total return volatility, 9.51 for idiosyncratic return volatility, 4.36 for cash flow volatility, 2.15 for firm age, and 2.08 for analyst forecast dispersion.

Interestingly, after controlling for the interaction of CGO and risk proxies, the interaction between past return and risk proxies (i.e., proxies for information uncertainty in the language of Zhang (2006)) is no longer significant and sometimes carries a negative coefficient. This indicates that the effect of underreaction to information identified by Zhang (2006) might partly be driven by the effect of reference-dependent preferences in the risk-return trade-off.

3.4.2 A Real Options Story

Johnson (2004) argues that analyst forecast dispersion can be interpreted as a proxy for idiosyncratic parameter risk. For a levered firm, the negative relation between dispersion and expected return obtains because equity is a call option on the firm's underlying assets. More important, Johnson (2004) shows that the interaction between leverage and idiosyncratic parameter risk should negatively predict future returns due to convexity in the general options-pricing formula. Indeed, Johnson (2004) finds empirical evidence that the interaction term negatively predicts future returns. In addition, after controlling for the interaction of leverage and analyst dispersion (a proxy for idiosyncratic parameter risk), analyst forecast dispersion itself no longer forecasts stock returns.

Since CGO is negatively linked to firm leverage, as shown in Panel B of Table 1, it is possible that the significant role of CGO in the risk-return trade-off is at least partly driven by the leverage effect identified by Johnson (2004), when dispersion is used as a proxy for risk. Thus, to control for this leverage effect, we include leverage and its interaction with analyst forecast dispersion into the Fama-MacBeth regressions. Regression (3) confirms Johnson's (2004) finding that the interaction between analyst forecast dispersion and leverage carries a negative sign in the predictive regression. More important, regression (3) shows that the interaction between CGO and analyst forecast dispersion remains significant even after controlling for the leverage effect.

Furthermore, one could also view idiosyncratic return volatility, cash flow volatility, and firm age as potential proxies for idiosyncratic parameter risk in the sense of Johnson (2004). Indeed, these variables tend to be positively correlated with analyst dispersion used in Johnson (2004). Thus, we also control for the interaction between leverage and these risk proxies in the corresponding Fama-MacBeth regressions. Regression (3) in Table 5 shows that the interaction between CGO and all the risk proxies has a consistent significant positive sign, consistent with our Hypothesis 3. Table 5, however, indicates that the interaction between leverage and other proxies such as idiosyncratic risk does not carry a significant negative sign. In fact, many of those interactions have a positive sign, contrary to the prediction of Johnson (2004).[10] Thus, the leverage effect appears to be specific to analyst forecast dispersion and does not apply to other proxies for idiosyncratic parameter risk.

3.4.3 A Mispricing Story

Similar to the underreaction-to-news story, one might argue that CGO itself is a proxy for mispricing as in Grinblatt and Han (2005). Due to the disposition effect (i.e., the investors' tendency to sell securities whose prices have increased since purchase rather than those have dropped in value), firms with high CGO experience higher selling pressure and thus are underpriced. Since stocks with high risk tend to have higher arbitrage costs, the mispricing effect is stronger among high-risk firms. This could potentially explain the significant and positive interaction between CGO and risk proxies in the Fama-MacBeth regressions. Our proposed mechanism is different, since it does not require CGO as a proxy for mispricing. We only need the average investors to be risk aversion among high-CGO firms and risk-seeking among low-CGO firms. To alleviate this concern, we control directly for the mispricing effect by including a proxy for mispricing in the Fama-MacBeth regressions.

Following Stambaugh, Yu, and Yuan (2013), we measure the mispricing score by aggregating 11 key characteristics that are well-known predictors of future stock returns. A firm with a high mispricing score tends to be overvalued and thus has a low subsequent return. Indeed, regression (4) in Table 5 shows that the interaction term between the mispricing score and the risk measure is typically significant and negative, 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 of CGO and risk proxies remains statistically significant.[11]

[10] In a related study, Ang et al. (2009) also find that the coefficient on the interaction between leverage and idiosyncratic volatility carries a significant and positive sign in predicting future stock returns. Our findings are consistent with theirs. In addition, the leverage effect is sensitive to the definition of leverage. If we instead use the leverage measure in Fama and French (1992), the leverage effect is gone even for analyst forecast dispersion. On the other hand, the interaction of CGO and risk proxies is always significant and insensitive to the choice of the leverage measure.

[11] Alternatively, one could measure the mispricing score based on more traditional anomalies as in Cao and

Finally, in regression (5) of Table 5 , we control all the previous effects simultaneously (i.e., the underreaction-to-news effect, the leverage effect, and the mispricing hypothesis), and our main conclusion again remains unaltered. In sum, the Fama-MacBeth regression analysis in this section provides strong and consistent support to the role of reference-dependent preferences in the risk-return trade-off. This effect is not driven by underreaction to information, the leverage effect, or the mispricing effect.

4 Additional Robustness Checks

We now conduct a series of additional tests to assess the robustness of our results under different empirical specifications. We perform both Fama-MacBeth regression analysis and double sorting. To save space, only the Fama-MacBeth regression results are reported in the main text, and the results based on double sorting are relegated to the appendix.

First, we want to make sure that the pattern in the risk-return trade-off is not due to the inclusion of NASDAQ stocks. In Table 6, we repeat the Fama-MacBeth regression analysis in Table 5 but exclude the NASDAQ firms. The results indicate that the pattern in the risk-return trade-off remains among the NYSE/AMEX stocks. The economic magnitude also remains largely the same. In addition, the double-sorting results without NASDAQ stocks, reported in the appendix, are similar to those in Table 3 obtained with NASDAQ stocks.

Second, previous studies (e.g., Bali et al. (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 that can be classified as the top 90% liquid stock according to Amihud's (2002) liquidity measure. Specifically, illiquidity is the average ratio of the daily absolute return to the daily dollar trading volume in the past year. The results in Table 7 show that the pattern in the risk-return trade-off and the economic magnitude again remain virtually identical. Thus, our results are not driven by highly illiquid stocks. Notice that the results are usually weaker if analyst forecast dispersion is used as a proxy. This is consistent with the view that analyst forecast dispersion may not be as a good proxy for individual investors' measure of risk as other variables, such as stock return volatility.

Han (2010). The results remain similar if this alternative mispricing score is used instead. These results, omitted for brevity, are available upon request. More important, in robustness check Section 4, we also control for an alternative mispricing measure which is derived directly from the V-shape disposition effect as in An (2013).

Third, many strategies in practice focus only on the top $1,000$ largest firms by market capitalization. Thus, we repeat both the Fama-MacBeth regression and the double-sorting analysis with the top $1,000$ largest stocks. Table 8 indicates that the results again remain virtually the same. In fact, among the top $1,000$ largest stocks, high-beta firms earn lower returns on average (not reported), but the security market line is upward sloping among firms with large CGO. Thus, our results are not driven by the inclusion of small cap stocks. The double-sorting analysis, reported in the appendix, yields essentially the same conclusion.

Fourth, one potential concern about the use of the Fama-MacBeth regression is that each stock is treated equally. Even though our results hold when we focus on the top $1,000$ 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 equally-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 Table 9, where each return is weighted by the firm's market capitalization at the end of the previous month. Table 9 shows that the coefficients and t-statistics on the interaction between CGO and risk proxies are similar to those obtained in standard Fama-MacBeth regressions in Table 5. In particular, all the t-statistics are still larger than 1.96.

Fifth, Table 10 reports the results of a standard subperiod analysis. The whole sample is divided equally into two subperiods. Due to 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: the risk-return relation is more positive among firms with high CGO than among firms with low CGO. Moreover, the slope coefficients on the interaction of CGO and risk proxies do not change significantly across the two subperiods. In addition, we also separate the whole 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 the appendix as Tables A6 and A7 and are consistent with the limits-to-arbitrage effect (e.g., Nagel (2005)). Moreover, this evidence is also 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 the reference-dependent preference might be a better description of individuals' risk attitudes than institutional investors' risk attitude.

Lastly, we provide an alternatively approach to address the concern that our results might be driven by the mispricing hypothesis. Due to the disposition effect observed in the data, CGO might be a proxy for mispricing as in Grinblatt and Han (2005). In the previous section, we have controlled for a composite mispricing measure based on 11 anomalies, and our results remain significant. An alternative, and probably more direct, way to address this concern is to control for a mispricing measure which is derived directly from the more precisely documented V-shaped disposition effect as in An (2013). The V-shaped disposition effect is a newly-documented and more precise description of investor behavior. Ben-David and Hirshleifer (2012) show that investors' selling propensity is a V-shape function of past profits: the probability to sell a security increases when the magnitude of gains or losses on it increases, with the gain regime having a steeper slope than the loss regime. Our construction of this mispricing measure (VSP) is calculated as the difference between gain overhang and 20% of loss overhang, the same as in An (2013).[12] The main idea is that when the magnitude of losses or gains on a stock is high, the selling pressure is high. Hence, firms with both large unrealized gains and large unrealized losses (in absolute value) tend to be underpriced. Thus, VSP should be a more precise measure of mispricing derived from investors' V-shaped disposition effect. Indeed, An (2013) shows that after controlling for VSP, CGO loses its power in predicting future returns. Table 11 shows that our results remain significant after controlling for this more precise mispricing measure (VSP) derived from the V-shaped disposition effect. Specifically, interactions between CGO and risk proxies remain significant, whereas interactions between VSP and risk proxies are insignificant or have a wrong sign.

Overall, the pattern of the risk-return trade-off is very robust to subperiods, as well as the exclusion of highly illiquid stocks, NASDAQ stocks, or stocks with small market capitalization.[13]

[12]The 20% in front of the loss overhang is to capture the asymmetry of the V-shaped selling propensity. Please refer to An (2013) for details of this measure.

[13]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 have excluded those firms from our sample so far. However, our results are robust to the inclusion of penny stocks. Since our idiosyncratic volatility is computed based on daily returns, it might also 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.

5 Conclusion

The risk-return trade-off is a fundamental theme in finance. However, there is very weak empirical support for this basic principle. We argue that reference-dependent preferences play a prominent role in the cross-sectional risk-return relation. Among firms where investors face capital gains, there is a positive, albeit not strong, risk-return association. By sharp contrast, among firms where investors face capital losses, there is a robust and significant inverted risk-return relation. This pattern is consistent with the notion that the presence of reference-dependent investors destroys the traditional positive risk-return relation implied under standard preferences.

Investigating the role of reference-dependent preferences in other asset pricing phenomena would be interesting. For example, asset return skewness has gained a substantial amount of attention in recent literature (see, e.g., Zhang (2005), Barberis and Huang (2008), and Boyer, Mitton, and Vorkink (2010)). Similar to risk appetite, individuals' preference on skewness could depend on whether investors are in the loss or gain domain. Indeed, Table 12 provides suggestive evidence that among firms with large CGO, high-skewness firms tend to earn higher subsequent returns, whereas the opposite holds among firms with low CGO. The difference-in-difference is 60 bps per month with a t-statistic = 2.57. This evidence is consistent with the notion that in the loss domain, investors have a high appetite for positive skewed assets to break even. A similar role of CGO on the distress anomaly is also found in the data.[14] Exploring the role of reference-dependent preferences in the pricing of skewness or the distress anomaly seems worthwhile. We leave this topic for future research.

[14]Specifically, firms with higher distress risk, measured by Ohlson's (1980) O-score, tend to earn lower subsequent returns on average. However, among firms with high CGO, this relation distress-return is reversed. On the other hand, the negative relation is more pronounced among firms with low CGO. These results are available upon request.

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Figure 1: Prospect Theory and the Risk-Return Tradeoff 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 (loss) of holding stocks A and B.

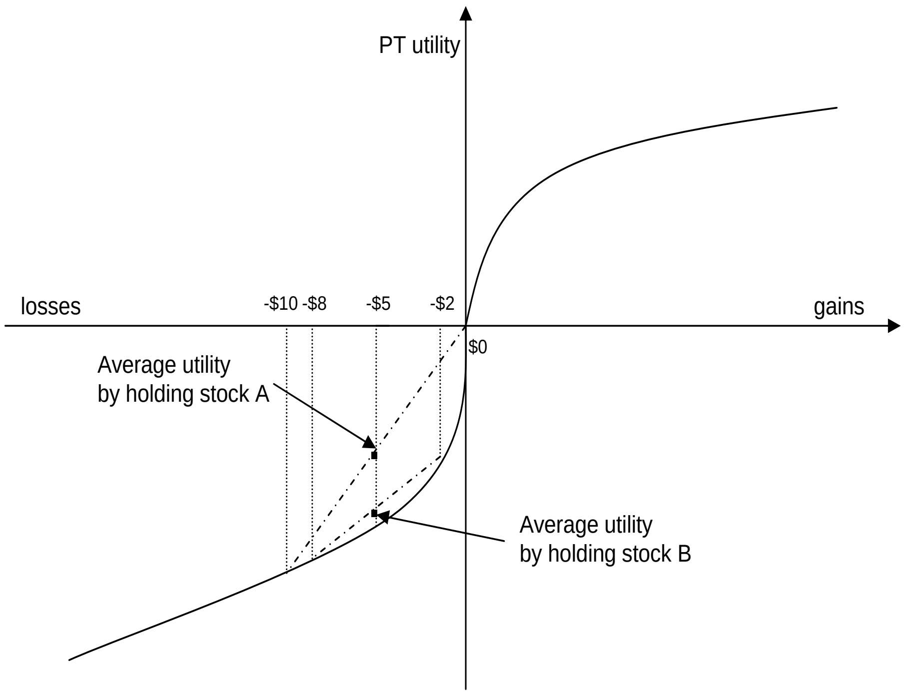

Figure 2: Prospect Theory and the Risk-Return Tradeoff Utility: Capital Gains

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 a \$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 (loss) of holding stocks C and D.

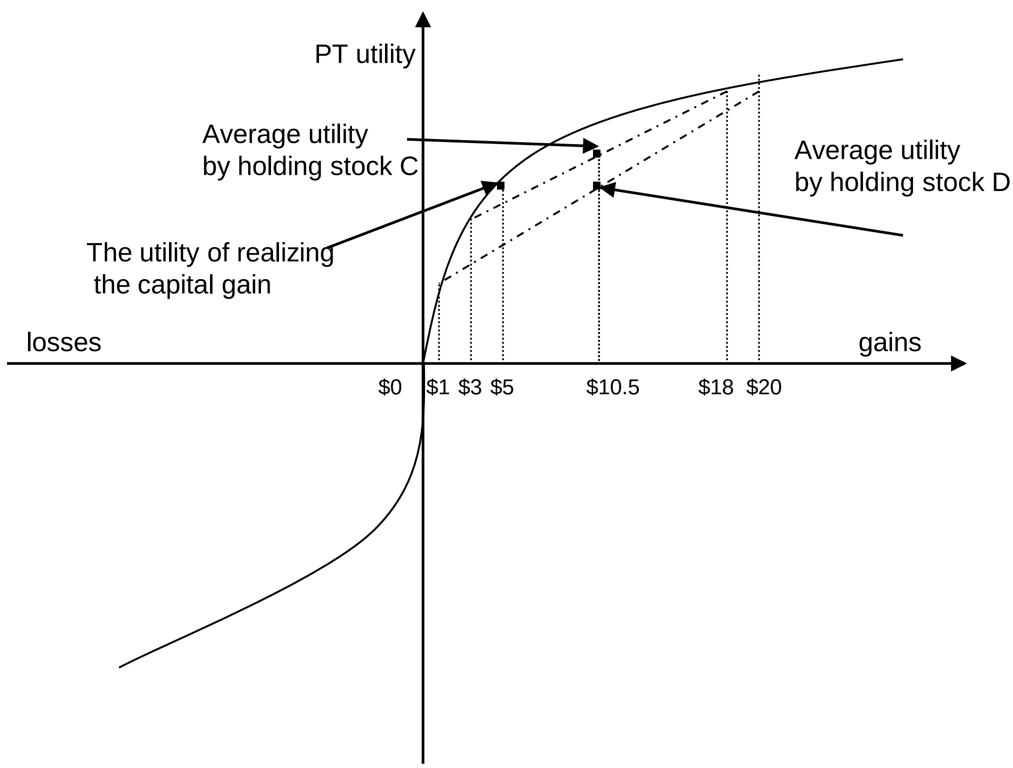

Figure 3: Time Series of Cross-Sectional Percentiles of the Capital Gains Overhang

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 1966 to December 2011. We use all common nonfinancial stocks from NYSE/AMEX/NASDAQ with stock prices of at least $5 and nonnegative book value of equity.

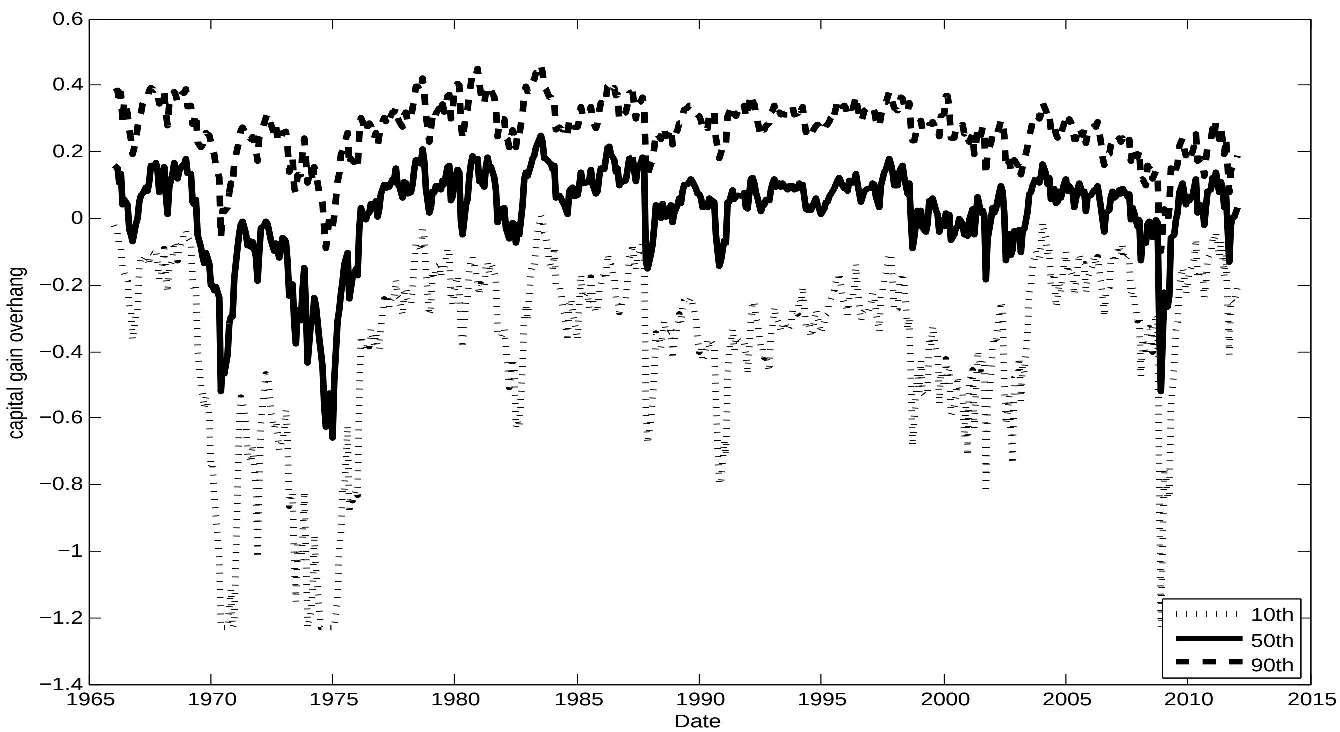

Table 1: Summary Statistics

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 portfolio, 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 and non-January months. At the beginning of every month, we sort NYSE, AMEX, and NASDAQ common nonfinancial stocks with stock prices od at least \$5 and nonnegative 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 $RP_t = \sum_{n=1}^{T}\left(V_{t-n}\prod_{\tau=1}^{n-1}(1-V_{t-n-\tau})\right)P_{t-n}$, and V_t is week t's turnover in the stock and T is the number of weeks in the previous five years. Turnover is calculated as trading volume divided by number of shares outstanding. The portfolio is rebalanced every 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 month $t-12$ to $t-1$, β is the coefficient of the monthly CAPM regression in the past five years with a minimum of two years of data, and MARKET% is the portion of total market capitalization. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. %(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 1966 to December 2011, except for %(IO) and #(IO), which are from January 1980 to December 2011 . The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12 in Panel A and lag = 36 in Panel B.

	Panel A: Five CGO Portfolio Returns								
	RET	t-stat	$\sigma(RET)$	FF3-α	t-stat	JAN	t-stat	FEB-DEC	t-stat
P1	0.490	1.74	6.726	-0.320	-2.99	5.272	3.74	0.065	0.23
P2	0.512	2.16	5.562	-0.174	-2.09	3.068	2.76	0.285	1.19
P3	0.619	2.90	5.073	0.006	0.10	1.812	2.04	0.513	2.39
P4	0.669	3.07	5.042	0.105	1.79	1.304	1.56	0.613	2.76
P5	1.098	4.49	5.472	0.604	6.84	0.950	1.42	1.111	4.58
P5-P1	0.608	3.53	4.368	0.924	5.62	-4.322	-3.89	1.047	6.23

	Panel B: Five CGO Portfolio Characteristics										
	CGO	LOGME	BM	ILLIQ	MOM	β	MARKET%	LEVERAGE	TURNOVER	%(IO)	#(IO)
P1	-0.406	4.840	0.952	1.090	-0.116	1.250	0.097	0.456	0.070	0.366	59.826
P2	-0.101	5.590	0.878	0.687	0.054	1.119	0.177	0.417	0.076	0.422	101.060
P3	0.025	5.893	0.843	0.551	0.177	1.054	0.223	0.395	0.074	0.427	115.806
P4	0.130	5.984	0.802	0.538	0.319	1.069	0.257	0.355	0.071	0.431	118.868
P5	0.282	5.735	0.751	0.743	0.627	1.088	0.247	0.290	0.057	0.372	84.334
P5-P1	0.688	0.896	-0.201	-0.347	0.743	-0.163	0.150	-0.166	-0.013	0.006	24.508
t-stat	17.78	5.44	-4.44	-2.30	21.99	-3.40	4.04	-9.63	-2.40	0.29	3.04

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 portfolio, 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 five years with a minimum of two years. Stock volatility (RETVOL) is the standard deviation of monthly returns over the past five years with a minimum of two years. 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 five years. Age is the number of years since the firm was first covered by CRSP. Analyst forecast dispersion (DISPER) is the standard deviation of analyst forecasts of one-year earnings from I/B/E/S scaled by the prior year-end stock price to mitigate heteroscedasticity. At the beginning of every month, we sort NYSE, AMEX, and NASDAQ ordinary nonfinancial stocks with stock prices of at least $5 and nonnegative book value of equity into five groups based on the quintile of the ranked values of each proxy. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The excess returns are in percentages. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

Proxy	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
P1	0.422	0.459	0.466	0.475	0.435	0.668
P2	0.466	0.488	0.528	0.524	0.427	0.447
P3	0.496	0.482	0.509	0.561	0.423	0.420
P4	0.443	0.495	0.552	0.418	0.490	0.369
P5	0.405	0.414	0.122	0.346	0.408	0.350
P5-P1	-0.017	-0.044	-0.345	-0.129	-0.027	-0.318
t-stat	-0.06	-0.16	-1.43	-0.76	-0.15	-1.51
FF3-α	-0.225	-0.294	-0.632	-0.132	-0.019	-0.722
t-stat	-1.08	-1.54	-3.69	-1.15	-0.15	-3.36

Table 3: Double-Sorted Portfolio Returns

At the beginning of each month, we divide all NYSE/AMEX/NASDAQ common nonfinancial stocks with nonnegative book equity and stock prices of at least $5 into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag =12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.702	0.490	0.489		0.790	0.417	0.450	
P3	0.606	0.531	0.660		0.458	0.450	0.674	
P5	-0.017	0.274	0.776		-0.356	0.364	0.904	
P5-P1	-0.719	-0.216	0.288	1.006	-1.146	-0.054	0.454	1.600
t-stat	-2.20	-0.70	1.03	3.24	-4.02	-0.18	1.57	4.80
FF3-α	-0.958	-0.412	0.154	1.112	-1.346	-0.317	0.229	1.575
t-stat	-3.74	-1.74	0.69	3.44	-5.59	-1.44	0.84	4.23
	Proxy=IVOL				Proxy=CFVOL			
P1	0.943	0.320	0.535		0.769	0.621	0.636	
P3	0.227	0.380	0.835		0.441	0.391	0.809	
P5	-0.848	0.042	0.950		0.267	0.178	0.919	
P5-P1	-1.791	-0.278	0.415	2.205	-0.502	-0.443	0.283	0.785
t-stat	-5.10	-1.04	1.59	6.14	-2.04	-1.90	1.91	3.10
FF3-α	-2.037	-0.480	0.206	2.243	-0.450	-0.439	0.249	0.699
t-stat	-6.79	-2.21	0.81	5.81	-1.79	-2.60	1.84	2.57
	Proxy=1/AGE				Proxy=DISPER			
P1	0.608	0.435	0.481		0.887	0.570	0.974	
P3	0.312	0.472	0.686		0.607	0.587	0.610	
P5	0.162	0.180	1.057		-0.044	0.253	0.584	
P5-P1	-0.448	-0.283	0.584	1.015	-0.931	-0.317	-0.390	0.541
t-stat	-2.07	-1.51	2.95	4.13	-3.42	-1.62	-1.81	2.07
FF3-α	-0.470	-0.319	0.525	0.988	-1.457	-0.642	-0.810	0.646
t-stat	-2.26	-2.14	2.87	3.89	-6.46	-3.14	-4.14	2.42

Table 4: 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/NASDAQ common nonfinancial stocks with stock prices of at least $5 and nonnegative book value of equity into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.535	0.217	0.490		0.700	0.220	0.552	
P3	0.915	0.564	0.924		0.856	0.595	0.925	
P5	0.739	0.796	1.272		0.481	1.027	1.356	
P5-P1	0.204	0.579	0.782	0.578	-0.218	0.808	0.804	1.022
t-stat	0.46	1.46	2.26	1.49	-0.56	2.05	2.37	2.53
FF3-α	-0.337	0.066	0.389	0.726	-0.659	0.253	0.314	0.973
t-stat	-1.07	0.18	1.21	1.90	-2.50	0.70	0.95	2.48
	Proxy=IVOL				Proxy=CFVOL			
P1	0.957	0.224	0.685		0.641	0.526	0.731	
P3	0.569	0.454	0.974		0.801	0.517	1.119	
P5	-0.035	0.629	1.287		0.881	0.285	1.101	
P5-P1	-0.991	0.404	0.601	1.593	0.240	-0.241	0.370	0.130
t-stat	-2.35	1.01	1.96	3.88	0.77	-0.75	1.88	0.41
FF3-α	-1.441	0.020	0.160	1.601	0.217	-0.333	0.250	0.033
t-stat	-4.91	0.06	0.57	3.96	0.72	-1.21	1.26	0.12
	Proxy=1/AGE				Proxy=DISPER			
P1	0.722	0.290	0.638		1.037	0.683	1.175	
P3	0.855	0.707	1.089		0.988	0.565	1.068	
P5	0.528	0.616	1.074		0.659	0.564	1.236	
P5-P1	-0.206	0.271	0.451	0.616	-0.378	-0.120	0.061	0.439
t-stat	-0.76	1.04	2.01	1.98	-0.76	-0.33	0.15	0.97
FF3-α	-0.275	0.101	0.280	0.521	-1.127	-0.577	-0.408	0.719
t-stat	-0.96	0.52	1.47	1.48	-3.18	-1.89	-1.03	1.47

Table 5: Fama-MacBeth Regressions

Every month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding, where the volume is the reported value from CRSP for NYSE/AMEX stocks, and 62% of CRSP reported value after 1997 and 50% of that before 1997 for NASDAQ stocks. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The excess returns are in percentages. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12. We only use common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least $5 and nonnegative book equity. The intercept of the regression is not reported.

		PROXY=β					PROXY=RETVOL				
		(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
CGO	1.251	0.504	0.593	0.698	0.298	0.658	-0.662	-1.218	-0.740	-0.627	-1.045
	(6.87)	(2.00)	(2.28)	(2.83)	(1.22)	(2.47)	(-1.88)	(-3.14)	(-2.02)	(-1.75)	(-2.67)
PROXY×CGO		0.697	0.540	0.643	0.580	0.490	16.014	20.047	17.663	14.506	18.128
		(4.07)	(3.13)	(3.84)	(3.39)	(2.72)	(5.77)	(6.74)	(5.59)	(5.08)	(5.66)
PROXY×MOM(-12,-1)			0.019			0.000		-3.608			-3.513
			(0.14)			(0.00)		(-2.32)			(-2.24)
PROXY×LEVERAGE				-0.127		-0.279			10.715		6.914
				-(0.51)		-(1.11)			(2.87)		(1.89)
PROXY×SCORE					-0.005	-0.002				-0.165	-0.122
					(-2.02)	(-0.59)				(-4.18)	(-3.24)
LEVERAGE				0.408		1.080			-0.933		-0.048
				(1.51)		(3.60)			-(2.59)		-(0.12)
LOGBM	0.007	0.000	-0.010	-0.010	-0.004	-0.006	0.000	-0.010	-0.002	-0.004	-0.009
	(0.20)	(0.00)	(-0.38)	(-0.34)	(-0.14)	(-0.19)	(-0.01)	(-0.34)	(-0.08)	(-0.13)	(-0.35)
LOGME	-0.072	-0.070	-0.078	-0.064	-0.097	-0.074	-0.082	-0.076	-0.073	-0.080	-0.061
	(-1.80)	(-1.78)	(-1.99)	(-1.68)	(-2.50)	(-1.98)	(-2.20)	(-2.09)	(-2.10)	(-2.15)	(-1.79)
MOM(-1,0)	-5.220	-5.755	-5.619	-5.951	-5.603	-5.881	-5.633	-5.691	-5.853	-5.741	-5.847
	(-11.16)	(-11.86)	(-11.36)	(-12.50)	(-11.12)	(-12.21)	(-11.76)	(-11.98)	(-12.48)	(-11.89)	(-12.01)
MOM(-12,-1)	0.135	0.138	0.154	0.082	-0.023	-0.073	0.136	0.687	0.117	-0.097	0.453
	(0.85)	(0.95)	(0.68)	(0.54)	(-0.14)	(-0.32)	(0.87)	(2.42)	(0.75)	-(0.62)	(1.63)
MOM(-36,-13)	-0.193	-0.196	-0.224	-0.209	-0.135	-0.097	-0.181	-0.210	-0.184	-0.125	-0.098
	(-3.59)	(-3.86)	(-4.13)	(-4.10)	(-2.64)	(-2.06)	(-3.39)	(-3.76)	(-3.36)	(-2.34)	(-1.87)
PROXY		0.063	0.067	0.136	0.337	0.327	-1.742	-0.947	-5.224	7.009	4.176
		(0.54)	(0.58)	(0.94)	(2.04)	(1.72)	(-0.99)	(-0.53)	(-2.99)	(2.87)	(1.77)
SCORE					-0.020	-0.025				-0.004	-0.010
					(-6.09)	(-5.96)				(-1.01)	(-2.28)
TURNOVER	-2.704	-2.684	-2.792	-2.815	-1.358	-1.427	-2.043	-1.973	-1.963	-1.078	-1.389
	(-1.67)	(-2.13)	(-2.17)	(-2.30)	(-1.05)	(-1.18)	(-1.75)	(-1.75)	(-1.71)	(-0.94)	(-1.21)

	PROXY=IVOL					PROXY=CFVOL				
CGO	-0.746	-1.363	-0.857	-0.638	-1.504	0.600	0.466	0.657	0.460	0.467
	(-2.63)	(-4.77)	(-3.03)	(-2.21)	(-5.25)	(2.54)	(1.91)	(2.84)	(1.91)	(1.87)
PROXY×CGO	82.204	106.418	89.437	68.460	107.534	7.441	10.091	8.667	5.864	7.308
	(8.84)	(9.51)	(8.36)	(6.75)	(8.40)	(4.17)	(4.36)	(4.60)	(3.07)	(3.18)
PROXY×MOM(-12,-1)		-26.080			-34.713		-1.296			-1.503
		(-3.26)			(-4.24)		(-0.60)			(-0.63)
PROXY×LEVERAGE			45.256		41.444			2.732		1.482
			(3.20)		(2.85)			(1.14)		(0.62)
PROXY×SCORE				-0.936	-0.943				-0.113	-0.077
				(-5.35)	(-5.89)				(-3.90)	(-2.39)
LEVERAGE			-0.615		-0.122			0.165		0.659
			(-2.15)		(-0.37)			(0.67)		(2.44)
LOGBM	0.001	-0.009	-0.009	-0.003	-0.002	0.010	-0.012	-0.008	-0.004	-0.006
	(0.02)	(-0.31)	(-0.30)	(-0.10)	(-0.07)	(0.38)	(-0.44)	(-0.32)	(-0.15)	(-0.23)
LOGME	-0.090	-0.084	-0.080	-0.093	-0.076	-0.047	-0.044	-0.034	-0.060	-0.042
	(-2.34)	(-2.23)	(-2.14)	(-2.45)	(-2.08)	(-1.32)	(-1.27)	(-0.99)	(-1.66)	(-1.21)
MOM(-1,0)	-5.124	-5.128	-5.281	-5.267	-5.357	-5.338	-5.466	-5.588	-5.425	-5.505
	(-11.10)	(-11.22)	(-11.63)	(-11.23)	(-11.37)	(-10.48)	(-10.72)	(-11.17)	(-10.52)	(-10.86)
MOM(-12,-1)	0.234	0.851	0.221	0.016	0.844	0.109	0.195	0.070	-0.072	0.019
	(1.49)	(4.12)	(1.40)	(0.10)	(3.71)	(0.59)	(0.86)	(0.37)	-(0.40)	(0.08)
MOM(-36,-13)	-0.155	-0.175	-0.159	-0.100	-0.057	-0.174	-0.205	-0.192	-0.105	-0.079
	(-2.93)	(-3.18)	(-2.92)	(-1.91)	(-1.10)	(-2.75)	(-3.04)	(-2.75)	(-1.64)	(-1.17)
PROXY	-16.082	-12.511	-31.418	29.949	20.438	-1.444	-1.709	-1.762	3.950	1.953
	(-3.65)	(-2.79)	(-4.66)	(3.21)	(2.19)	(-2.17)	(-2.45)	(-1.68)	(2.84)	(1.21)
SCORE				-0.006	-0.006				-0.018	-0.021
				(-1.75)	(-1.47)				(-5.48)	(-5.68)
TURNOVER	-1.908	-1.879	-1.836	-0.577	-0.488	-2.610	-2.536	-2.778	-1.105	-1.125
	(-1.33)	(-1.35)	(-1.31)	(-0.42)	(-0.36)	(-1.59)	(-1.56)	(-1.70)	(-0.68)	(-0.72)

	PROXY=1/AGE					PROXY=DISPER				
CGO	-0.472	-0.784	-0.673	-0.711	-0.715	0.591	0.609	0.825	0.337	0.570
	(-0.86)	(-0.66)	(-0.82)	(-1.15)	(-0.74)	(2.31)	(2.37)	(3.54)	(1.19)	(2.05)
PROXY×CGO	19.945	20.650	22.128	19.215	18.430	35.351	19.677	31.832	16.800	34.502
	(4.53)	(2.15)	(3.39)	(3.77)	(2.31)	(2.23)	(2.08)	(2.35)	(2.02)	(2.05)
PROXY×MOM(-12,-1)		0.537			2.121		-2.249			-9.673
		(0.10)			(0.50)		(-0.23)			(-0.92)
PROXY×LEVERAGE			8.256		5.231			-38.896		-47.915
			(1.79)		(1.42)			(-4.82)		(-4.90)
PROXY×SCORE				-0.188	-0.133				-0.562	0.015
				(-3.82)	(-2.76)				(-2.66)	(0.24)
LEVERAGE			-0.537		0.352			0.582		1.027
			(-1.00)		(0.83)			(1.98)		(3.49)
LOGBM	0.006	-0.006	-0.006	-0.001	-0.001	0.020	0.040	0.046	0.049	0.039
	(0.18)	(-0.21)	(-0.19)	(-0.03)	(-0.04)	(0.66)	(1.50)	(1.70)	(1.63)	(1.35)
LOGME	-0.068	-0.067	-0.059	-0.074	-0.058	-0.111	-0.109	-0.103	-0.131	-0.128
	(-1.69)	(-1.70)	(-1.50)	(-1.87)	(-1.50)	(-2.53)	(-2.51)	(-2.39)	(-3.19)	(-3.13)
MOM(-1,0)	-5.328	-5.413	-5.500	-5.401	-5.460	-4.015	-4.034	-4.269	-3.604	-4.362
	(-11.39)	(-11.74)	(-12.13)	(-11.43)	(-11.81)	(-7.71)	(-7.95)	(-8.54)	(-8.65)	(-9.90)
MOM(-12,-1)	0.111	0.311	0.075	-0.081	-0.091	0.299	0.320	0.222	0.203	0.119
	(0.70)	(0.47)	(0.46)	-(0.51)	-(0.17)	(1.46)	(1.62)	(1.09)	(1.09)	(0.66)
MOM(-36,-13)	-0.199	-0.228	-0.209	-0.141	-0.101	-0.093	-0.110	-0.106	-0.041	-0.026
	(-3.77)	(-4.12)	(-3.87)	(-2.69)	(-1.98)	(-1.44)	(-1.64)	(-1.62)	(-0.66)	(-0.42)
PROXY	-0.625	-0.913	-3.399	8.917	5.678	-21.000	-18.900	1.097	9.247	1.206
	(-0.58)	(-0.75)	(-1.57)	(3.14)	(2.08)	(-5.64)	(-5.15)	(0.73)	(0.89)	(0.35)
SCORE				-0.012	-0.018				-0.017	-0.022
				(-2.27)	(-3.25)				(-6.03)	(-6.86)
TURNOVER	-2.710	-2.634	-2.575	-1.333	-1.007	-0.674	-0.459	-0.404	-0.182	0.238
	(-1.71)	(-1.70)	(-1.66)	(-0.87)	(-0.67)	(-0.49)	(-0.36)	(-0.32)	(-0.13)	(0.18)

Table 6: Fama-MacBeth Regressions of NYSE/AMEX Stocks

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use common nonfinancial stocks from NYSE/AMEX with a price of at least $5 and nonnegative book equity to perform the cross-sectional regression. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.498	-1.117	-1.392	0.155	-0.836	0.409
	(1.72)	(-2.63)	(-3.97)	(0.50)	(-0.86)	(1.40)
PROXY×CGO	0.526	18.547	107.567	10.568	20.048	27.641
	(2.79)	(5.65)	(7.26)	(3.51)	(2.47)	(1.02)
PROXY×MOM(-12,-1)	-0.005	-3.737	-35.472	-3.350	2.328	0.885
	(-0.03)	(-2.15)	(-4.10)	(-1.35)	(0.53)	(0.06)
PROXY×LEVERAGE	-0.253	5.974	40.818	2.005	5.621	-8.018
	(-0.92)	(1.50)	(2.51)	(0.78)	(1.42)	(-0.43)
PROXY×SCORE	-0.003	-0.095	-0.884	-0.109	-0.100	-0.637
	(-0.84)	(-2.07)	(-4.21)	(-3.04)	(-1.69)	(-3.32)
LEVERAGE	1.064	0.151	0.032	0.709	0.355	0.920
	(3.41)	(0.37)	(0.09)	(2.71)	(0.83)	(3.40)
LOGBM	-0.015	0.003	-0.015	-0.031	-0.012	0.040
	(-0.47)	(0.09)	(-0.49)	(-1.04)	(-0.40)	(1.25)
LOGME	-0.070	-0.062	-0.078	-0.042	-0.065	-0.125
	(-1.86)	(-1.81)	(-2.09)	(-1.22)	(-1.70)	(-2.93)
MOM(-1,0)	-5.559	-5.574	-5.056	-5.180	-5.126	-3.856
	(-10.30)	(-10.22)	(-9.34)	(-9.08)	(-9.76)	(-6.42)
MOM(-12,-1)	-0.144	0.404	0.778	0.098	-0.113	0.027
	(-0.65)	(1.32)	(3.34)	(0.38)	(-0.21)	(0.12)
MOM(-36,-13)	-0.078	-0.074	-0.029	-0.061	-0.075	0.004
	(-1.43)	(-1.24)	(-0.50)	(-0.80)	(-1.27)	(0.06)
PROXY	0.309	2.406	15.145	3.125	2.663	4.414
	(1.63)	(0.89)	(1.29)	(1.71)	(0.91)	(1.08)
SCORE	-0.021	-0.012	-0.006	-0.017	-0.017	-0.017
	(-4.71)	(-2.35)	(-1.27)	(-4.07)	(-2.99)	(-4.97)
TURNOVER	-1.537	-1.619	-0.522	-1.452	-1.113	0.031
	(-1.28)	(-1.42)	(-0.39)	(-0.94)	(-0.75)	(0.03)

Table 7: Fama-MacBeth Regressions of TOP 90% Liquid Stocks

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use the top 90% liquid common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity to perform the cross-sectional regression. Illiquidity is measured by Amihud's (2010) illiquidity measure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.406	-1.308	-1.787	0.260	-0.868	0.401
	(1.40)	(-3.29)	(-5.72)	(0.98)	(-0.79)	(1.50)
PROXY×CGO	0.637	19.497	118.425	9.233	19.652	22.244
	(3.25)	(6.09)	(9.90)	(3.70)	(2.23)	(2.03)
PROXY×MOM(-12,-1)	-0.063	-4.542	-38.579	-3.132	3.982	-9.154
	(-0.42)	(-2.55)	(-4.39)	(-1.01)	(1.14)	(-1.04)
PROXY×LEVERAGE	-0.351	5.864	39.834	1.984	3.228	24.870
	(-1.36)	(1.55)	(2.29)	(0.70)	(0.87)	(2.06)
PROXY×SCORE	-0.001	-0.119	-1.038	-0.068	-0.086	-0.436
	(-0.35)	(-3.15)	(-6.29)	(-1.88)	(-1.59)	(-1.71)
LEVERAGE	1.059	-0.019	-0.124	0.595	0.448	0.729
	(3.56)	-(0.05)	-(0.35)	(2.09)	(1.10)	(2.38)
LOGBM	0.003	-0.002	0.004	-0.006	0.012	0.015
	(0.09)	(-0.06)	(0.13)	(-0.19)	(0.36)	(0.46)
LOGME	-0.078	-0.069	-0.083	-0.060	-0.064	-0.129
	(-2.15)	(-1.99)	(-2.31)	(-1.69)	(-1.67)	(-3.10)
MOM(-1,0)	-5.648	-5.616	-5.128	-5.211	-5.217	-4.125
	(-11.50)	(-11.41)	(-10.78)	(-9.93)	(-10.89)	(-7.98)
MOM(-12,-1)	0.023	0.611	0.956	0.185	-0.274	0.075
	(0.10)	(2.18)	(3.81)	(0.69)	-(0.64)	(0.37)
MOM(-36,-13)	-0.085	-0.084	-0.037	-0.067	-0.084	-0.050
	(-1.81)	(-1.64)	(-0.73)	(-1.00)	(-1.67)	(-0.91)
PROXY	0.265	3.807	24.583	1.104	2.181	-11.677
	(1.32)	(1.51)	(2.36)	(0.59)	(0.55)	(-0.96)
SCORE	-0.025	-0.009	-0.004	-0.020	-0.022	-0.018
	(-5.56)	(-2.05)	(-0.92)	(-5.17)	(-4.17)	(-5.13)
TURNOVER	-1.732	-1.759	-0.932	-1.834	-1.536	-0.239
	(-1.44)	(-1.57)	(-0.72)	(-1.17)	(-1.06)	(-0.22)

Table 8: Fama-MacBeth Regressions of Largest 1,000 Stocks

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use the largest 1,000 common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least $5 and nonnegative book equity to perform the cross-sectional regression. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	-0.698	-1.708	-1.928	-0.011	-1.599	0.116
	(-1.84)	(-3.58)	(-5.20)	(-0.03)	(-1.44)	(0.40)
PROXY×CGO	1.176	21.360	122.400	9.163	23.925	89.621
	(4.55)	(5.41)	(7.44)	(2.78)	(2.57)	(2.08)
PROXY×MOM(-12,-1)	-0.145	-2.050	-36.491	-0.091	2.182	-8.395
	(-0.82)	(-0.92)	(-3.44)	(-0.04)	(0.44)	(-0.52)
PROXY×LEVERAGE	-0.216	4.764	40.191	1.255	2.072	9.939
	(-0.76)	(1.03)	(2.10)	(0.44)	(0.61)	(0.33)
PROXY×SCORE	-0.003	-0.047	-1.000	-0.038	-0.069	-0.379
	(-1.00)	(-1.21)	(-4.48)	(-0.93)	(-1.31)	(-1.49)
LEVERAGE	0.801	0.105	-0.135	0.582	0.499	0.751
	(2.50)	(0.25)	(-0.37)	(2.18)	(1.63)	(2.46)
LOGBM	0.005	0.010	0.014	-0.008	0.012	-0.003
	(0.19)	(0.36)	(0.48)	(-0.23)	(0.41)	(-0.09)
LOGME	-0.094	-0.085	-0.097	-0.072	-0.081	-0.129
	(-2.27)	(-2.07)	(-2.36)	(-1.83)	(-1.87)	(-2.84)
MOM(-1,0)	-5.226	-5.227	-4.706	-5.090	-4.691	-3.823
	(-9.32)	(-9.32)	(-8.52)	(-8.72)	(-8.67)	(-6.60)
MOM(-12,-1)	0.190	0.351	0.958	0.028	0.060	0.114
	(0.72)	(1.05)	(3.67)	(0.11)	(0.10)	(0.55)
MOM(-36,-13)	-0.036	-0.052	-0.007	-0.058	-0.050	-0.005
	(-0.69)	(-0.92)	(-0.13)	(-0.83)	(-0.91)	(-0.08)
PROXY	0.252	0.035	18.120	-0.298	2.193	-26.080
	(1.27)	(0.01)	(1.49)	(-0.15)	(0.78)	(-1.43)
SCORE	-0.018	-0.015	-0.002	-0.019	-0.017	-0.017
	(-4.06)	(-3.27)	(-0.44)	(-5.07)	(-3.06)	(-4.77)
TURNOVER	-1.228	-1.159	-0.329	-1.099	-0.991	0.331
	(-0.98)	(-1.03)	(-0.25)	(-0.70)	(-0.67)	(0.26)

Table 9: Fama-MacBeth WLS Regressions

Each month, we run a cross-sectional weighted least squares regression of returns on lagged variables with market equity of last month as the weighting. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use all the common nonfinancial stock from NYSE/AMES/NASDAQ with a price of at least $5 and nonnegative book value of equity. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag =12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	-0.934	-1.358	-1.680	-0.545	-1.021	-0.164
	(-1.73)	(-2.49)	(-3.27)	(-1.04)	(-1.13)	(-0.38)
PROXY×CGO	1.157	15.088	99.380	10.071	16.606	84.772
	(3.02)	(3.90)	(5.24)	(2.10)	(1.98)	(2.16)
PROXY×MOM(-12,-1)	0.189	-0.389	-25.730	-0.338	11.050	-30.558
	(0.72)	(-0.12)	(-1.84)	(-0.11)	(3.26)	(-1.40)
PROXY×LEVERAGE	-0.843	-5.473	30.062	4.060	-2.405	-59.258
	(-2.77)	(-1.05)	(1.22)	(0.91)	(-0.39)	(-3.61)
PROXY×SCORE	0.001	-0.054	-1.225	0.106	0.028	-0.030
	(0.16)	(-0.82)	(-3.79)	(2.02)	(0.28)	(-0.33)
LEVERAGE	1.260	0.877	-0.093	0.275	0.297	0.714
	(3.12)	(1.61)	(-0.18)	(0.68)	(0.40)	(2.24)
LOGBM	0.094	-0.037	0.082	0.072	0.097	0.118
	(1.83)	(-0.73)	(1.61)	(1.33)	(1.96)	(1.57)
LOGME	-0.099	-0.093	-0.114	-0.113	-0.092	-0.093
	(-2.50)	(-2.11)	(-2.88)	(-2.54)	(-2.19)	(-1.85)
MOM(-1,0)	-4.682	-4.587	-4.011	-3.955	-3.846	-2.968
	(-8.62)	(-8.07)	(-6.84)	(-6.59)	(-7.26)	(-4.72)
MOM(-12,-1)	0.227	0.477	0.994	0.472	-0.501	0.401
	(0.62)	(1.18)	(2.76)	(1.33)	(-1.55)	(1.47)
MOM(-36,-13)	0.055	0.020	0.078	0.052	0.003	-0.007
	(0.68)	(0.25)	(0.98)	(0.66)	(0.04)	(-0.10)
PROXY	0.200	4.228	23.832	-9.476	-3.143	5.247
	(0.72)	(1.04)	(1.48)	(-3.55)	(-0.54)	(0.85)
SCORE	-0.018	-0.010	0.004	-0.021	-0.025	-0.015
	(-2.97)	(-1.54)	(0.66)	(-5.23)	(-2.99)	(-3.91)
TURNOVER	-1.546	-2.563	-1.719	-2.568	-2.820	-0.823
	(-0.90)	(-1.75)	(-0.82)	(-1.01)	(-1.33)	(-0.54)

Table 10: Fama-MacBeth Regressions: Subperiod Analysis

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Newey-West robust t-statistics are reported in parentheses. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. All variables are winsorized at 1% and 99%. We perform the Fama-MacBeth regression analysis of two subperiods: 1966-1988, and 1989-2011 for all risk proxies except for DISP, for which the two subperiods are 1976-1993 and 1994-2011.

	Panel A: Subperiod: 1966-1988					1976-1993
	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.199	-1.545	-1.725	0.386	-2.527	0.497
	(0.48)	(-2.56)	(-4.96)	(0.94)	(-1.20)	(1.62)
PROXY×CGO	0.892	25.390	137.685	7.603	35.066	0.895
	(3.50)	(4.95)	(6.95)	(1.96)	(2.07)	(0.13)
PROXY×MOM(-12,-1)	0.167	-2.972	-43.944	-2.254	-2.304	-5.387
	(0.78)	(-1.05)	(-3.16)	(-0.46)	(-0.26)	(-0.61)
PROXY×LEVERAGE	-0.143	8.734	46.754	-0.144	5.632	26.525
	(-0.39)	(1.42)	(1.91)	-(0.04)	(1.31)	(1.42)
PROXY×SCORE	0.004	-0.032	-0.681	-0.092	-0.103	-0.414
	(0.72)	(-0.54)	(-2.58)	(-1.83)	(-1.24)	(-2.70)
LEVERAGE	1.226	0.217	0.074	1.225	0.565	1.184
	(2.41)	(0.33)	(0.13)	(3.14)	(1.29)	(3.11)
LOGBM	-0.047	0.026	-0.046	-0.027	-0.038	0.020
	(-0.89)	(0.66)	(-0.91)	(-0.57)	(-0.74)	(0.51)
LOGME	-0.117	-0.115	-0.129	-0.071	-0.109	-0.176
	(-1.85)	(-2.08)	(-2.04)	(-1.21)	(-1.71)	(-2.70)
MOM(-1,0)	-8.218	-8.247	-7.571	-7.258	-7.667	-5.542
	(-18.54)	(-17.59)	(-15.49)	(-12.14)	(-17.41)	(-7.28)
MOM(-12,-1)	-0.167	0.477	1.052	0.292	0.605	0.570
	(-0.46)	(1.24)	(3.39)	(0.85)	(0.55)	(2.59)
MOM(-36,-13)	-0.108	-0.122	-0.042	-0.063	-0.102	0.087
	(-1.47)	(-1.46)	(-0.54)	(-0.51)	(-1.29)	(0.98)
PROXY	0.017	-2.244	-1.677	1.922	2.017	-12.213
	(0.06)	(-0.70)	(-0.11)	(0.69)	(0.43)	(-0.90)
SCORE	-0.032	-0.024	-0.014	-0.025	-0.020	-0.020
	(-5.38)	(-3.77)	(-2.24)	(-4.93)	(-2.10)	(-5.29)
TURNOVER	-3.349	-3.378	-1.985	-3.799	-2.876	-1.184
	(-1.58)	(-1.74)	(-0.83)	(-1.33)	(-1.08)	(-0.58)

	Panel B: Subperiod: 1989-2011					1994-2011
	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.883	-0.544	-1.283	0.482	0.553	0.480
	(3.28)	(-1.13)	(-2.85)	(1.60)	(1.88)	(1.28)
PROXY×CGO	0.196	10.867	77.383	7.263	6.222	60.431
	(0.88)	(3.38)	(5.69)	(2.70)	(2.09)	(2.09)
PROXY×MOM(-12,-1)	-0.170	-4.055	-25.481	-1.032	2.582	-10.875
	(-1.36)	(-2.98)	(-3.08)	(-0.71)	(1.51)	(-0.53)
PROXY×LEVERAGE	-0.407	5.093	36.134	3.030	2.485	-12.611
	(-1.20)	(1.30)	(2.30)	(0.95)	(0.70)	(-0.60)
PROXY×SCORE	-0.007	-0.212	-1.204	-0.064	-0.197	-0.688
	(-2.00)	(-5.48)	(-7.49)	(-1.54)	(-4.53)	(-3.55)
LEVERAGE	0.917	-0.312	-0.319	0.162	0.434	0.303
	(2.86)	(-0.78)	(-1.13)	(0.48)	(1.10)	(0.63)
LOGBM	0.037	-0.043	0.042	0.012	0.041	0.054
	(1.28)	(-1.51)	(1.53)	(0.44)	(1.45)	(1.40)
LOGME	-0.031	-0.008	-0.024	-0.018	-0.002	-0.093
	(-0.81)	(-0.21)	(-0.72)	(-0.47)	(-0.06)	(-1.63)
MOM(-1,0)	-3.499	-3.446	-3.143	-3.481	-3.173	-3.172
	(-7.50)	(-8.05)	(-7.33)	(-8.20)	(-7.24)	(-5.82)
MOM(-12,-1)	0.041	0.429	0.636	-0.182	-0.351	-0.273
	(0.16)	(1.07)	(1.94)	-(0.55)	(-1.60)	(-0.91)
MOM(-36,-13)	-0.081	-0.075	-0.071	-0.092	-0.090	-0.147
	(-1.43)	(-1.19)	(-1.10)	(-1.35)	(-1.41)	(-2.05)
PROXY	0.624	10.596	42.552	1.925	11.102	6.239
	(2.57)	(3.74)	(4.85)	(1.05)	(6.30)	(1.60)
SCORE	-0.019	0.003	0.002	-0.018	-0.012	-0.016
	(-3.37)	(0.72)	(0.40)	(-3.38)	(-2.54)	(-2.72)
TURNOVER	0.426	0.601	1.008	1.125	0.850	1.681
	(0.44)	(0.57)	(0.85)	(0.81)	(0.66)	(1.29)

Table 11: Fama-MacBeth Regressions Controlling for the V-shaped Disposition Effect

Every month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding, where the volume is the reported value from CRSP for NYSE/AMEX stocks, and 62% of CRSP reported value after 1997 and 50% of that before 1997 for NASDAQ stocks. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. VSP is a measure of V-shaped disposition effect calculated based on An (2013). The coefficients are reported in percentages. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The excess returns are in percentages. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12. We only use common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity. The intercept of the regression is not reported.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.330	-1.510	-2.127	0.570	-1.561	0.547
	(0.79)	(-2.94)	(-5.16)	(1.99)	(-0.99)	(2.00)
PROXY×CGO	0.910	23.471	142.476	8.781	26.381	46.456
	(2.85)	(5.02)	(6.90)	(3.32)	(2.01)	(2.60)
PROXY×MOM(-12,-1)	0.063	-2.995	-22.809	-0.936	4.520	3.737
	(0.52)	(-2.00)	(-2.87)	(-0.39)	(1.92)	(0.30)
PROXY×LEVERAGE	0.296	8.267	35.506	1.024	10.006	-24.459
	(1.34)	(2.24)	(2.57)	(0.39)	(1.87)	-(2.44)
PROXY×VSP	-0.096	4.374	4.767	-1.961	2.426	-86.133
	(-0.16)	(0.58)	(0.15)	(-0.33)	(0.14)	(-3.10)
LEVERAGE	-0.002	-0.636	-0.366	0.259	-0.708	0.580
	-(0.01)	-(1.83)	-(1.42)	(1.08)	-(1.12)	(2.10)
LOGBM	-0.008	-0.007	-0.005	-0.012	-0.005	0.051
	(-0.31)	(-0.26)	(-0.21)	(-0.48)	(-0.18)	(1.94)
LOGME	-0.060	-0.075	-0.072	-0.026	-0.059	-0.094
	(-1.60)	(-2.14)	(-1.98)	(-0.80)	(-1.53)	(-2.21)
MOM(-1,0)	-6.238	-6.174	-5.636	-5.807	-5.131	-4.573
	(-13.11)	(-12.90)	(-12.21)	(-11.94)	(-12.57)	(-8.96)
MOM(-12,-1)	-0.145	0.333	0.513	0.056	-0.345	0.014
	-(0.72)	(1.23)	(2.43)	(0.22)	-(1.81)	(0.07)
MOM(-36,-13)	-0.271	-0.273	-0.248	-0.230	-0.261	-0.159
	(-4.69)	(-4.37)	(-4.07)	(-2.96)	(-4.39)	(-2.49)
PROXY	-0.076	-5.460	-29.130	-1.790	-5.937	2.216
	(-0.52)	(-2.25)	(-3.76)	(-1.20)	(-2.46)	(1.47)
VSP	1.749	1.430	2.194	1.321	2.191	2.327
	(2.17)	(1.61)	(3.05)	(2.26)	(1.10)	(4.21)
TURNOVER	-2.219	-1.212	-1.410	-2.573	-2.214	0.273
	(-1.76)	(-1.02)	(-0.96)	(-1.50)	(-1.37)	(0.20)

Table 12: Double-Sorted Portfolio Returns by CGO and Skewness

At the beginning of each month, we divide all common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity into five groups based on lagged CGO; within each of the CGO groups, firms are further divided into five portfolios based on lagged skewness. Monthly skewness is calculated using daily returns within the month. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1966 to December 2011. Excess returns are reported in percentages. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff
SKEW1	0.523	0.232	0.421	
SKEW3	0.511	0.354	0.589	
SKEW5	0.154	0.440	0.650	
SKEW5-SKEW1	-0.369	0.209	0.229	0.598
t-stat	-1.98	1.36	1.64	2.57
FF3-α	-0.346	0.201	0.192	0.539
t-stat	-1.78	1.30	1.29	2.11

Appendix: Tables for Additional Robustness Checks

Table A1: Individual Investors' Propensity to Sell Stocks

The table presents results from probit regressions in which the dependent variable is a dummy equal to 1 if a stock was sold, and 0 otherwise. The data set contains the daily holdings of 10,000 retail investors who are randomly selected from 78,000 households with brokerage accounts at a large discount broker from January 1991 to December 1996. Observations are at the investor-stock-day level. The same data set is used in Barber and Odean (2000, 2001, 2002) and more recently in Ben-David and Hirshleifer (2012). Ret^+ (Ret^-) is the return since purchase if the return since purchase is positive (negative), zero otherwise. Return since purchase is defined as the difference between current price and purchase price divided by purchase price (or weighted average price in case of multiple purchases). The current price is the selling price, price of buying additional shares, or end-of-day price each day. $I_{Ret>0}$ ($I_{Ret=0}$) is a dummy equal to 1 if the return since purchase is positive (zero), 0 otherwise. Log(buy price) is the log of purchase price in dollars. Vol is the total volatility calculated as the standard deviation of daily returns in the past year. Sqrt(time owned) is the square root of the number of days since purchase. Standard errors are clustered at the investor level. A positive coefficients on $Ret^+ \times vol$ implies that individual investors' propensity to sell a winner is higher when volatility of the underlying stock is higher. Since $Ret^- \leq 0$, a positive coefficients on $Ret^- \times vol$ also implies that the propensity to sell a loser is lower when volatility of the underlying stock is higher. The coefficients are multiplied by 100.

Variable	Coefficient	t-stat	Coefficient	t-stat
Intercept	-2.915	-229.51	-2.978	-110.85
$I_{Ret>0}$			0.199	20.13
$I_{Ret=0}$			-0.022	-1.38
$Ret^- \times vol$	9.048	10.89	13.718	17.97
$Ret^+ \times vol$	6.695	10.65	1.863	2.71
log(buy price)			0.067	11.11
vol	8.306	21.91	8.660	26.14
Ret^-	0.365	9.38	-0.554	-18.03
Ret^+	-0.309	-15.12	0.042	1.96
sqrt(time owned)			-0.023	-36.36

Table A2: Double-Sorted Portfolio Returns of NYSE/AMEX Stocks

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 risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only the common nonfinancial stocks in NYSE/AMEX with a price of at least \$5 and nonnegative book equity are used in the double-sorting procedure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.569	0.427	0.474		0.624	0.353	0.439	
P3	0.549	0.422	0.679		0.291	0.453	0.543	
P5	0.078	0.390	0.744		-0.129	0.595	0.931	
P5-P1	-0.491	-0.037	0.270	0.761	-0.753	0.242	0.492	1.245
t-stat	-1.71	-0.14	1.15	2.66	-2.40	0.82	2.14	4.19
FF3-α	-0.730	-0.263	0.103	0.832	-0.993	-0.061	0.211	1.204
t-stat	-2.82	-1.27	0.53	2.56	-3.96	-0.27	1.02	3.92
	Proxy=IVOL				Proxy=CFVOL			
P1	0.816	0.290	0.553		0.577	0.536	0.556	
P3	0.336	0.468	0.516		0.348	0.321	0.521	
P5	-0.317	0.307	0.772		0.247	0.441	0.785	
P5-P1	-1.134	0.017	0.219	1.353	-0.330	-0.094	0.229	0.559
t-stat	-4.33	0.07	1.06	5.49	-1.36	-0.46	1.40	2.00
FF3-α	-1.402	-0.177	-0.021	1.381	-0.394	-0.098	0.143	0.537
t-stat	-6.79	-0.86	-0.12	5.90	-1.48	-0.64	0.95	1.77
	Proxy=1/AGE				Proxy=DISPER			
P1	0.466	0.421	0.492		0.745	0.662	0.815	
P3	0.550	0.470	0.665		0.548	0.622	0.629	
P5	0.207	0.096	0.999		-0.065	0.213	0.498	
P5-P1	-0.259	-0.324	0.507	0.766	-0.810	-0.449	-0.317	0.493
t-stat	-1.09	-1.48	2.55	2.49	-2.83	-1.93	-1.20	1.91
FF3-α	-0.304	-0.382	0.476	0.780	-1.274	-0.758	-0.734	0.539
t-stat	-1.22	-1.99	2.34	2.36	-5.17	-2.97	-3.02	1.97

Table A3: Double-Sorted Portfolio Returns of Largest 1000 Stocks

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 risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only the 1,000 largest common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity are used in the double-sorting procedure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.589	0.414	0.456		0.633	0.382	0.483	
P3	0.365	0.349	0.640		0.511	0.229	0.761	
P5	0.052	0.342	0.702		-0.027	0.496	1.031	
P5-P1	-0.536	-0.071	0.246	0.782	-0.660	0.115	0.548	1.208
t-stat	-1.83	-0.24	0.89	3.03	-2.01	0.39	2.07	4.43
FF3-α	-0.752	-0.204	0.161	0.913	-0.867	-0.058	0.366	1.234
t-stat	-3.45	-0.93	0.79	3.46	-3.85	-0.28	1.64	4.66
	Proxy=IVOL				Proxy=CFVOL			
P1	0.863	0.271	0.559		0.583	0.645	0.536	
P3	0.419	0.401	0.724		0.554	0.334	0.607	
P5	-0.376	0.230	0.766		0.319	0.259	0.837	
P5-P1	-1.238	-0.041	0.207	1.445	-0.264	-0.385	0.301	0.565
t-stat	-3.71	-0.18	0.89	4.79	-1.11	-1.72	2.00	2.32
FF3-α	-1.431	-0.192	0.049	1.480	-0.260	-0.277	0.286	0.546
t-stat	-5.53	-1.06	0.22	5.25	-1.07	-1.54	1.86	2.03
	Proxy=1/AGE				Proxy=DISPER			
P1	0.436	0.411	0.532		0.835	0.589	0.993	
P3	0.406	0.383	0.748		0.482	0.580	0.523	
P5	0.288	0.182	1.190		-0.202	0.097	0.530	
P5-P1	-0.148	-0.228	0.658	0.807	-1.037	-0.492	-0.463	0.574
t-stat	-0.55	-1.13	3.39	2.78	-3.96	-2.06	-1.81	2.14
FF3-α	-0.097	-0.195	0.644	0.742	-1.442	-0.751	-0.869	0.574
t-stat	-0.42	-1.19	3.65	2.47	-5.85	-2.82	-3.60	2.07

Table A4: Double-Sorted Portfolio Returns of Top 90% Liquid Stocks

At the beginning of each month, we divide all firms in NYSE/AMEX/NASDAQ into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only the top 90% liquid (using Amihud's (2002) illiquidity measure) common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity are used in the double-sorting procedure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.645	0.431	0.458		0.644	0.359	0.455	
P3	0.411	0.493	0.637		0.324	0.328	0.740	
P5	-0.003	0.217	0.731		-0.190	0.367	1.029	
P5-P1	-0.648	-0.214	0.273	0.921	-0.834	0.008	0.574	1.408
t-stat	-2.19	-0.65	0.96	3.07	-2.94	0.03	1.84	4.08
FF3-α	-0.863	-0.350	0.193	1.056	-1.056	-0.206	0.395	1.451
t-stat	-3.54	-1.48	0.87	3.29	-4.60	-0.93	1.35	3.76
	Proxy=IVOL				Proxy=CFVOL			
P1	0.858	0.299	0.533		0.789	0.542	0.605	
P3	0.371	0.362	0.824		0.380	0.321	0.719	
P5	-0.727	-0.002	1.013		0.419	0.141	0.818	
P5-P1	-1.585	-0.301	0.480	2.065	-0.370	-0.402	0.213	0.583
t-stat	-5.25	-1.23	1.94	6.56	-1.43	-1.81	1.37	2.19
FF3-α	-1.812	-0.464	0.325	2.137	-0.403	-0.317	0.195	0.598
t-stat	-7.50	-2.22	1.37	6.59	-1.63	-1.98	1.31	2.13
	Proxy=1/AGE				Proxy=DISPER			
P1	0.432	0.462	0.519		0.779	0.601	0.978	
P3	0.357	0.409	0.571		0.429	0.457	0.554	
P5	0.202	0.114	1.100		-0.123	0.173	0.534	
P5-P1	-0.230	-0.348	0.581	0.811	-0.902	-0.428	-0.444	0.458
t-stat	-1.05	-1.70	2.94	2.88	-3.67	-1.85	-1.84	1.94
FF3-α	-0.236	-0.360	0.565	0.801	-1.313	-0.727	-0.860	0.454
t-stat	-1.09	-2.31	3.17	2.60	-5.61	-2.84	-3.90	1.73

Table A5: Double-Sorted Portfolio Returns: Subperiod Analysis

At the beginning of each month, we divide all common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12. We perform the double-sorting analysis for two subperiods, 1966-1988 and 1989-2011, for all risk proxies except for DISP, for which the two subperiods are 1976-1993 and 1994-2011.

	1966-1988				1989-2011			
	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
				Proxy=β				
P1	0.717	0.655	0.375		0.647	0.255	0.546	
P3	0.938	0.823	0.777		0.282	0.079	0.541	
P5	0.191	0.377	0.990		-0.282	0.294	0.567	
P5-P1	-0.527	-0.278	0.615	1.142	-0.929	0.039	0.020	0.950
t-stat	-0.96	-0.53	1.26	2.15	-3.08	0.11	0.08	3.76
FF3-α	-0.894	-0.651	0.312	1.206	-1.112	0.031	-0.013	1.100
t-stat	-2.04	-2.14	0.98	2.23	-4.66	0.09	-0.06	4.30
				Proxy=RETVOL				
P1	0.781	0.690	0.428		0.492	0.048	0.455	
P3	0.276	0.563	1.061		0.205	0.195	0.299	
P5	0.107	0.417	1.319		-0.498	0.398	0.835	
P5-P1	-0.674	-0.273	0.891	1.565	-0.991	0.350	0.380	1.370
t-stat	-1.86	-0.61	1.60	2.67	-2.56	0.91	1.24	3.57
FF3-α	-0.962	-0.692	0.561	1.523	-1.167	0.209	0.206	1.374
t-stat	-2.93	-2.64	1.24	2.45	-3.99	0.68	0.77	3.67
				Proxy=IVOL				
P1	1.073	0.606	0.654		0.666	-0.082	0.419	
P3	0.369	0.499	0.913		0.119	0.271	0.692	
P5	-0.929	-0.163	1.275		-0.614	0.071	0.642	
P5-P1	-2.002	-0.769	0.620	2.622	-1.281	0.153	0.222	1.503
t-stat	-3.55	-1.83	1.31	4.44	-4.38	0.50	0.86	4.86
FF3-α	-2.321	-1.044	0.417	2.739	-1.414	0.027	-0.105	1.309
t-stat	-4.81	-3.26	1.13	4.64	-5.45	0.09	-0.42	4.05

	1966-1988				1990-2011			
	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
				Proxy=CFVOL				
P1	0.699	0.727	0.673		0.607	0.336	0.523	
P3	0.528	0.247	1.067		0.123	0.388	0.392	
P5	0.281	0.138	0.905		0.117	0.319	0.626	
P5-P1	-0.418	-0.590	0.231	0.649	-0.490	-0.017	0.104	0.594
t-stat	-1.19	-1.77	1.01	1.91	-1.57	-0.05	0.60	1.59
FF3-α	-0.480	-0.678	0.107	0.587	-0.445	0.212	0.182	0.627
t-stat	-1.43	-3.12	0.60	1.60	-1.23	0.94	0.93	1.61
				Proxy=1/AGE				
P1	0.645	0.654	0.598		0.430	0.214	0.354	
P3	0.241	0.429	0.966		0.070	0.220	0.428	
P5	0.227	0.352	1.115		0.003	-0.246	1.138	
P5-P1	-0.419	-0.302	0.517	0.936	-0.427	-0.460	0.783	1.210
t-stat	-1.08	-1.06	1.62	2.15	-1.35	-1.31	2.32	2.66
FF3-α	-0.578	-0.459	0.446	1.024	-0.330	-0.339	0.782	1.112
t-stat	-1.67	-2.51	1.78	2.41	-1.11	-1.22	2.16	2.16
	Proxy=DISPER: 1976-1993				Proxy=DISPER: 1994-2011			
P1	0.988	0.523	0.882		0.653	0.596	1.049	
P3	0.388	0.439	0.384		0.464	0.559	0.755	
P5	-0.154	0.344	0.506		-0.001	0.201	0.570	
P5-P1	-1.142	-0.179	-0.376	0.766	-0.654	-0.395	-0.479	0.175
t-stat	-2.74	-0.54	-1.07	2.17	-2.11	-1.59	-1.53	0.58
FF3-α	-1.489	-0.444	-0.775	0.713	-1.376	-0.777	-0.933	0.444
t-stat	-3.88	-1.26	-2.29	1.85	-5.14	-3.41	-3.49	1.33

Table A6: Double-Sorted Portfolio Returns Based on Stocks with Bottom 50% Institution Holding Stocks

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 risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only stocks with the bottom 50% institutional holdings are used in the double-sorting procedure. Data on institutional holdings are obtained from Thomson Reuters. The sample period is from January 1980 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.722	0.772	0.365		0.819	0.735	0.376	
P3	0.726	0.762	0.724		0.522	0.395	1.340	
P5	0.047	0.585	0.912		-0.360	0.322	1.001	
P5-P1	-0.675	-0.187	0.548	1.223	-1.179	-0.413	0.624	1.804
t-stat	-1.58	-0.46	1.49	2.94	-2.98	-1.06	1.55	3.30
FF3-α	-1.119	-0.569	0.281	1.400	-1.492	-0.852	0.260	1.752
t-stat	-3.04	-2.13	0.94	3.08	-3.94	-2.81	0.67	2.87
	Proxy=IVOL				Proxy=CFVOL			
P1	1.035	0.700	0.453		1.025	0.835	0.520	
P3	0.647	0.421	1.279		0.646	0.513	1.223	
P5	-1.515	-0.107	0.884		-0.014	0.422	0.941	
P5-P1	-2.551	-0.807	0.431	2.982	-1.039	-0.413	0.422	1.460
t-stat	-5.16	-1.96	1.32	6.02	-2.59	-0.90	1.37	2.92
FF3-α	-2.854	-1.177	0.232	3.086	-1.175	-0.677	0.262	1.437
t-stat	-7.34	-3.56	0.72	6.33	-3.04	-2.12	0.82	2.74
	Proxy=1/AGE				Proxy=DISPER			
P1	0.478	0.792	0.374		0.964	0.765	0.896	
P3	0.378	0.484	0.843		0.517	0.768	0.327	
P5	0.203	0.429	1.131		-0.359	0.342	0.340	
P5-P1	-0.274	-0.363	0.757	1.032	-1.323	-0.423	-0.556	0.766
t-stat	-0.99	-1.27	2.87	2.87	-3.61	-1.79	-2.15	2.11
FF3-α	-0.455	-0.423	0.659	1.114	-1.932	-0.661	-0.887	1.045
t-stat	-1.60	-1.69	2.93	2.91	-5.39	-3.06	-3.51	2.51

Table A7: Double-Sorted Portfolio Returns Based on Stocks with Top 50% Institution Holding Stocks

At the beginning of each month, we divide all firms in NYSE/AMEX/NASDAQ into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only stocks with the top 50% institutional holdings are used in the double-sorting procedure. The sample period is from January 1980 to December 2011. Data on institutional holdings are obtained from Thomson Reuters. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.908	0.670	0.644		0.946	0.699	0.661	
P3	0.928	0.818	0.890		0.752	0.649	1.052	
P5	0.390	0.568	1.004		0.498	0.574	1.433	
P5-P1	-0.518	-0.101	0.359	0.877	-0.448	-0.125	0.772	1.220
t-stat	-1.26	-0.26	0.83	2.01	-1.40	-0.39	1.74	2.51
FF3-α	-0.773	-0.378	0.108	0.881	-0.619	-0.331	0.582	1.201
t-stat	-2.33	-1.21	0.30	1.94	-1.96	-1.27	1.51	2.23
	Proxy=IVOL				Proxy=CFVOL			
P1	1.073	0.615	0.946		1.039	0.756	0.686	
P3	1.031	0.677	0.821		0.478	0.475	1.084	
P5	-0.051	0.474	1.270		0.467	0.587	0.959	
P5-P1	-1.124	-0.141	0.324	1.448	-0.573	-0.170	0.273	0.846
t-stat	-3.34	-0.48	1.01	4.11	-1.93	-0.78	1.16	2.41
FF3-α	-1.330	-0.288	0.215	1.545	-0.571	-0.100	0.226	0.797
t-stat	-4.48	-1.03	0.82	4.50	-1.91	-0.50	1.14	2.07
	Proxy=1/AGE				Proxy=DISPER			
P1	0.814	0.650	0.611		0.956	0.935	1.053	
P3	0.627	0.948	0.932		0.799	0.424	0.608	
P5	0.534	0.372	1.464		-0.037	0.313	0.802	
P5-P1	-0.280	-0.278	0.853	1.133	-0.992	-0.622	-0.251	0.741
t-stat	-0.97	-1.22	3.09	3.17	-3.72	-3.12	-0.84	2.06
FF3-α	-0.199	-0.325	0.901	1.099	-1.342	-0.936	-0.644	0.697
t-stat	-0.70	-1.53	3.79	2.96	-5.48	-4.24	-2.50	1.93