Realization Utility:
Explaining Volatility and Skewness Preferences

Min Kyeong Kwon* and Tong Suk Kim†

March 16, 2014

ABSTRACT

Using the realization utility model with a jump process, we find three implications for the stock market. First, a positive relation between volatility and investment return does not exist among impatient investors. Second, investors exhibit a positive skewness preference in all but conditions of severe negative skewness, with slightly stronger preference among impatient investors. Third, investors trade more frequently when they are impatient, stock return volatility is high, and skewness is low. Empirical observations support the implications. We also find that investor impatience is closely related to investor sentiment.

Keywords: Realization Utility, Volatility Preference, Skewness Preference, Turnover Rate, Impatience, Sentiment
JEL classification: G10, G11, G12
EFM classification: 310, 320, 330, 350

* Corresponding Author; Ph.D. candidate, School of Management Engineering, Korea Advanced Institute of Science and Technology; S387, 85 Hoegiro Dongdamoon-gu Seoul 130-722 South Korea; tel: +82-2-958-3689; email: terrapin@business.kaist.ac.kr.
† Professor, School of Management Engineering, Korea Advanced Institute of Science and Technology; S386, 85 Hoegiro Dongdamoon-gu Seoul 130-722 South Korea; tel: +82-2-958-3018; email: tskim@business.kaist.ac.kr.

The concept of realization utility was first proposed by Shefrin and Statman (1985). The idea is that investors have utility when they realize gains or losses from selling stocks. While a traditional utility function is based on a change in wealth and the value function of prospect theory is based on paper gains and losses, a realization utility function is based on realized gains and losses. Barberis and Xiong (2012) specify the concept and construct a mathematical framework. Their realization utility model enables us to understand empirical asset pricing issues that traditional asset pricing models cannot explain, such as the poor performance of volatile stocks (see Ang, Hodrick, Xing and Zhang (2006)). In addition, the model has implications for investor trading behavior such as the disposition effect (see Odean (1998)). Ingersoll and Jin (2013) later generalize the model and make it more realistic.

The realization utility model of Barberis and Xiong (2012) and Ingersoll and Jin (2013) assumes the stock process follows geometric Brownian motion. The model can effectively address the effects of stock return volatility on both asset pricing and investor trading behavior. However, it cannot explain the effect of skewness. For this reason, we adopt a jump process in addition to geometric Brownian motion to model stock price movements.

We obtain numerical solutions and run simulations to examine the effects of stock return volatility and skewness, designed to ensure that the effects do not interfere with each other. For example, when we look at the effect of volatility, we control for skewness by setting it to be constant. Similarly, when we look at the effect of skewness, we control for volatility by setting it to be constant.

Our model has three salient implications for the stock market. First, a positive relation between volatility and investment return does not exist among impatient investors. Second, investors exhibit a positive skewness preference in all but conditions of severe negative skewness, with stronger preference among impatient investors. Finally, investors trade more frequently when they are impatient, stock return volatility is high, and skewness is low. While the implications related to skewness are completely new, some of the implications related to volatility were already introduced in previous works on the realization utility model by Barberis and Xiong (2012) and Ingersoll and Jin (2013). We state them again since we test them empirically in a unique way.

Our empirical analysis constructs a new measure, the moment-adjusted turnover rate (MATURN). This measure is motivated by the model's implication that impatient investors trade more frequently. Specifically, we form five portfolios in order of turnover rate while controlling for stock return moments. The highest-*MATURN* portfolio is a proxy for stocks that impatient investors are most likely to trade for any reason except related to stock return moments. On the other hand, the lowest-*MATURN* portfolio is a proxy for stocks that impatient investors are least likely to trade. Furthermore, proceeding from an investor's perspectives, we adopt past volatility as a proxy for ex ante volatility and the MAX5 measure of Bali, Cakici and Whitelaw (2011) as a proxy for ex ante skewness.

We find supportive empirical evidence for the model's implications. First, investigating how ex ante volatility affects asset pricing, within each *MATURN* portfolio, we form five portfolios sorted by past volatility while controlling for *MAX5*. There is a positive relation between past volatility and investment returns within the lowest-*MATURN* portfolio. The difference between the monthly returns of highest- and lowest-past volatility portfolios reaches 1.57% and is statistically significant. On the other hand, there is no such positive relation within the highest-*MATURN* portfolio. The difference is -0.01% and not statistically significant. The spread between the two return differentials is -1.57%, which is economically and statistically significant. This finding is consistent with the model's first implication, that a positive relation between volatility and investment return does not exist among impatient investors.

Second, investigating how ex ante skewness affects asset pricing, we form 20 portfolios by *MAX5* while controlling for past volatility. We find overall positive skewness preference like Bali et al. (2011). The difference between the monthly returns of the highest- and lowest-*MAX5* portfolios is -1.38% and statistically significant. However, the pattern is not uniform across *MAX5* portfolios. The difference between the lowest- and middle-*MAX5* portfolio returns is much smaller than that between the middle- and highest-*MAX5* portfolio returns. About 89% of the total difference comes from the second part. Moreover, *MAX5* portfolios ranking lower than fourth do not exhibit any positive skewness preference. This finding supports the second implication of the model, that investors exhibit a positive skewness preference in all but conditions of severe negative skewness.

In another test of the effects of skewness, within each *MATURN* portfolio, we form five portfolios sorted by *MAX5* while controlling for past volatility. All the *MATURN* portfolios exhibit a positive skewness preference. However, the strengths are different. The spread of long–short returns from buying the higest-*MAX5* portfolio and selling the lowest-*MAX5* portfolio between the highest- and lowest-*MATURN* portfolios is -0.26% and statistically marginally significant, although its significance weakens after we adjust for the well-known factor models. In further analysis, when we restrict the sample to only NASDAQ firms, to which the realization utility model is more applicable, the result is clearer. The long–short returns decrease monotonically in *MATURN*. The spread of long–short returns between the highest- and lowest-*MATURN* portfolios is -1.06% and statistically significant even after we adjust for the factor models. This result is consistent with the model's another part of second implication, that positive skewness preference is stronger among impatient investors.

Third, investigating how stock return volatility and skewness affect the contemporaneous turnover rate, we construct a skewness-adjusted volatility measure and a volatility-adjusted skewness measure. The result shows that, when the other moment is controlled for, the contemporaneous turnover rate increases with volatility and decreases with skewness. Another test, using Fama–MacBeth (1973) cross-sectional regression also confirms the result. It supports the third implication of the model, that investors trade more frequently when stock return volatility is high and skewness is low.

Baker and Wurgler (2006, 2007) describe investor sentiment as a shift in the propensity to speculate. Investor impatience is also related to the propensity to speculate because, according to our model, impatient investors like positive volatility and positive skewness (and possibly extremely negative skewness), which are features of speculative stocks. While the investor sentiment of Baker and Wurgler (2006, 2007) exhibits time-series variations, the investor impatience in our analysis exhibits cross-sectional variations. Investigating how cross-sectional variations of investor impatience is related to time-series variations of investor sentiment, we conduct several empirical tests using the sentiment indexes of Baker and Wurgler (2007). The result shows that investor sentiment affects all investors' preferences for speculative stocks by the same amount, regardless of their cross-sectional level of impatience. However, the speed of reaction to a time-series variation in sentiment level is different: While impatient investors react quickly, patient investors react slowly. In addition, the cross-sectional dispersion of the preference for speculative stocks is high when sentiment is rising and low when sentiment is dropping.

This paper contributes to the finance literature in three ways. First, it shows how stock return volatility and skewness affect asset pricing and investor trading behavior within a single framework. Second, it explains why some investors prefer highly skewed stock returns. To our knowledge, only two theoretical models in the finance literature have described it, Brunnermeier, Gollier and Parker (2007) and Barberis and Huang (2008). Third, this paper provides supporting empirical observations for the realization utility model, which are overall economically and statistically very significant.

This paper is organized as follow. Section I reviews the literature. Section II describes the realization utility model with a jump process. The numerical solution and simulation results are presented in Section III. Section IV discusses the empirical analysis, proposing a new measure to proxy for investor impatience. We present empirical evidence of volatility and skewness effects on asset pricing and investor trading behavior in Section V and the relation between investor impatience and investor sentiment in Section VI. Section VII concludes the paper. The Appendix presents a mathematical description of the model.

I. Review of the Literature

The concept of realization utility was first proposed by Shefrin and Statman (1985). The idea is that investors have utility when they realize gains or losses from selling stocks. While a traditional utility function is based on change in wealth and the value function of prospect theory is based on paper gains and losses, a realization utility function is based on realized gains and losses. Barberis and Xiong (2012) specify the concept and develop a realization utility model that provides possible explanations for certain controversial issues in finance. However, the model seems unrealistic because it predicts that investors never sell stocks voluntarily. Ingersoll and Jin (2013) solve the problem by suggesting a more generalized form of the realization utility function.

A realization utility model assumes that the investor is not rational. This investor resembles more closely to an individual investor than an institutional investor. However, despite the model's restricted coverage of investor type, if there are enough realization utility investors and arbitrage restrictions in the market, the model can still have implications on asset pricing. In this sense, Han and Kumar (2013) use a realization utility model to address the behavior of retail investors. They find that stocks whose trading is dominated by risk-seeking realization utility investors tend to earn significantly negative alphas.

The realization utility model by Barberis and Xiong (2012) and Ingersoll and Jin (2013) enables us to understand controversial issues that the traditional asset pricing model cannot explain, such as the poor performance of highly volatile stocks and the disposition effect. The poor performance of highly volatile stocks was first reported by Ang et al. (2006). The traditional finance literature claims the existence of a positive risk–return relation. Stock return volatility is an important source of risk, so a highly volatile stock should earn high expected returns. However, Ang et al. (2006) find a negative relation between volatility and return in the U.S. stock market. This finding is clearly anomalous in the context of the traditional asset pricing model and is sometimes called the volatility puzzle.

The disposition effect is the investors' tendency of holding losing stocks too long and selling winning stocks too soon (Odean (1998)). Because past winner stocks are likely to outperform past loser stocks, according to Jegadeesh and Titman (1993), why the disposition effect appears has been a challenging question for researchers.

On the other hand, the literature states that investors are likely to prefer highly skewed investment returns. Theoretical work by Brunnermeier and Parker (2005) and Brunnermeier et al. (2007) suggests an optimal expectation model. In this model, investors are optimistic in states associated with the most skewed Arrow–Debreu securities. As a result, they overinvest in the securities and their expected returns are relatively low. Barberis and Huang (2008) use Tversky and Kahneman's (1992) cumulative prospect theory. According to their model, the fact that investors overweight small probabilities leads to negative excess returns on positively skewed securities. Mitton and Vorkink (2007) claim that if some investors are skewness-seeking, then idiosyncratic skewness and expected returns will have a negative relation. Empirically, Boyer, Mitton and Vorkink (2010) construct an expected skewness measure and find it to be negatively correlated with expected returns. Bali et al. (2011) find that the high MAX5 measure as a proxy for lottery-like assets predicts negative excess returns. Conrad, Dittmar and Ghysels (2013) estimate ex ante risk-neutral skewness from option prices and argue that stocks with greater skewness have lower subsequent returns.

Share turnover is a representative measure of how often investors trade stocks. It is closely related to the stock's characteristics. For example, Lo and Wang (2000) state that turnover rate is higher when a stock has high idiosyncratic volatility. Chordia, Huh, and Subrahmanyam (2007) analyze the relation between stock characteristics and future turnover rates in the cross-section. At the same time, share turnover is also related to the characteristics of the investors holding the stock.

Grinblatt and Keloharju (2009) claim that investors who get more speeding tickets tend to trade stocks more frequently. Dorn and Sengmueller (2009) report that investors who enjoy investing or gambling also trade stocks more frequently.

II. **Model**

The previous realization utility model assumes the stock price process follows geometric Brownian motion. While it addresses the effects of stock return volatility on both asset pricing and investor trading behavior, it does not consider the effect of stock return skewness. For this reason, we add a jump process to geometric Brownian motion for stock price movement. Our intuition is as follows. Assume two different stocks, A and B. Investors believe that the price of stock A will surge if a certain event takes place. Since investors price this possibility, the stock's price should be higher than that of otherwise similar stocks. If the possibility is realized, investors will earn a very high return. If not, they will earn a relatively low return because the profit and dividend levels will not justify the high price. Therefore, the stock returns exhibit positive skewness. On the other hand, investors believe that the price of stock B will plunge if a certain event occurs. The stock price should be lower than that of otherwise similar stocks. If the possibility is realized, investors will earn a very low return. Otherwise, they will earn a relatively high return because the price is low relative to the stock's profit and dividend levels. The stock returns exhibit negative skewness. We investigate which type of stock investors prefer and are more likely to trade.

We adopt Ingersoll and Jin's (2013) entire setting with the exception of the stock price process. They assume that realization utility is defined at the level of the gain or loss from an individual asset. Ingersoll and Jin's modified Tversky–Kahneman utility function is a function of the size of the gain or loss G and the reference level R:

$$U(G,R) = \begin{cases} \frac{R^\beta\left[\left(1+\frac{G}{R}\right)^{\alpha_G}-1\right]}{\alpha_G}, \; G \geq 0 \\ -\frac{\lambda R^\beta\left[1-\left(1+\frac{G}{R}\right)^{\alpha_L}\right]}{\alpha_L}, \; -R \leq G < 0 \end{cases} \quad \text{where } \alpha_G, \alpha_L \neq \beta \tag{1}$$

We assume that stock prices follow

$$\frac{dS}{S} = \mu dt + \sigma dZ + jdq \tag{2}$$

where μ and σ are the first and second moments of stock returns, respectively; Z is standard Brownian motion; j is the height of a jump; and dq is a Poisson counter of intensity f.

A jump is driven by fundamentally or sentimentally important events, which are likely to make investors reevaluate the stock's value. Therefore, we assume that when a jump happens, investors change their reference price to after-jump price and exploit utility from the difference between the old and new reference prices. That is, investors have utility without selling stocks only for the moment of jumps.[1]

The solution of this model is similar to Ingersoll and Jin's one. The details are shown in the Appendix.

III. **Results**

For the stock price process and transaction cost parameters, we set the initial values $\mu = 0.09, \sigma = 0.50, k_s = 0.01$ and $k_p = 0.01$. Then we set the parametric values of the modified TK utility function: $\lambda = 1.5, \alpha_G = 0.5$, and $\alpha_L = 4.0$. Although arbitrary, the choices are reasonable. If α_L is too high, the maximum loss of the utility function will be unrealistically small. If α_L is too low, investors will never voluntarily realize losses, which is also unrealistic. We choose a small value for

[1] Alternatively, we can assume that investors sell their shares at after-jump price immediately after a jump. If investors think the jump will eventually change the stock's future skewness, they are likely to sell the stock because it no longer fits their skewness preference. In this case, the results show a very similar pattern to those presented later in this paper.

α_L within the range in which investors realize losses voluntarily. The results are qualitatively similar for higher α_L values as well.[2]

We investigate the effect of stock return volatility while controlling for skewness (see Figure 1). The parameter σ varies while both f and j are fixed at zero. The upper left and right graphs show the standard second and third moments of stock returns, respectively.[3] Volatility is increasing in σ, while skewness remains constant. The bottom left graph shows the equivalent mean lines along which an investor has the same amount of utility. The parameter δ is the investor's subjective discount rate. For example, when $\delta = 0.05$, a stock with $\mu = 0.077$ and $\sigma = 0.200$ yields the same utility to the investor as a stock with $\mu = 0.090$ and $\sigma = 0.500$ does. A high equivalent mean implies that investors do not like the stock and therefore require high expected returns. The preference patterns are totally different, depending on δ. Investors with $\delta = 0.05$ do not like volatility and therefore require greater expected returns for high volatility. This is because their utility function exhibits loss aversion. This result is consistent with the traditional asset pricing model's prediction of a positive risk–return relation. On the other hand, investors with $\delta = 0.10$ like volatility and so allow relatively low expected returns for high volatility. This is because their discount rate is so high that they prefer quick realizations of positive utility and high-volatility stocks are more likely to yield such opportunities than low-volatility stocks. This shows a negative relation between volatility and expected return, which contradicts the traditional asset pricing model. This result is exactly the same as that of Ingersoll and Jin (2013, Figure 4) .

We also investigate the effect of stock return skewness while controlling for volatility (see Figure 2). While f is fixed at one, j varies from -0.4 to 0.4. At the same time, σ is adjusted for

---

2 We conduct several tests using higher values of α_L, up to 10. These show patterns consistent with this paper's results.

3 The standard second and third moments of stock returns following the equation (2) are $\sigma^2 + fj^2$ and $\frac{fj^3}{(\sigma^2+fj^2)^{\frac{2}{3}}}$, respectively.

each j, following the equation $\sigma = \sqrt{0.5^2 - f \cdot j^2}$ so that the standard second moment of stock returns is fixed at 0.5. The upper graphs show skewness increases with j, while volatility remains constant. The bottom left graph shows the equivalent mean lines. It reveals that investors exhibit a skewness preference in all but the severely negative skewness domain. The graphs of equivalent mean peak between $j = -0.28$ and -0.25, depending on δ. To the right of the peaks, investors exhibit a positive skewness preference. The intensity of positive skewness preference is stronger among investors with a high discount rate, even though the difference is not as large as in the bottom left graph of Figure 1. To the left of the peaks, investors prefer more negatively skewed stocks, because these stocks offer a very high rate of return (more than 30% in this case) as long as no jumps occur.[4] However, sudden price drops of more than 25% are not usual. Furthermore, considering that the skewness that affects asset pricing is ex ante skewness, not ex post skewness, normal stocks do not exhibit such extremely negative ex ante skewness.[5] Therefore, a positive skewness preference is likely overall.

Finally, we estimate the turnover rates from 300,000 simulation runs. The results are presented in the bottom right graphs of Figures 1 and 2. Figure 1 shows that investors trade more frequently when volatility is high and Figure 2 shows that investors trade more frequently when skewness is low. Both Figures 1 and 2 show that investors with a high discount rate have higher turnover rates.

The implications of the realization utility model with a jump process can be summarized as follows. First, a positive relation between volatility and investment return does not exist among investors with high discount rate. Second, investors exhibit a positive skewness preference in all but the severely negative skewness domain, with stronger preferences among investors with a high

[4] The first moment of stock returns following the equation (2) is $\mu + f \cdot j$. When $\delta = 0.05$, $f = 1$, and $j = -0.27$, the expected return is about 0.11. Therefore, μ is about 38%. This return is the amount investors earn in the case of no jump.

[5] The special case of financially distressed stocks, which are exposed to default risk, is exceptional. Negative skewness preference in the area left of the peaks can explain the overvaluation of financially distressed stocks (see Campbell, Hilscher and Szilagyi (2008)).

discount rate. Finally, investors trade more frequently when stock return volatility is high, skewness is low, and their discount rate is high.

IV. Measure Construction

The subjective discount rate represents the investor impatience level. The word *impatience* primarily means intolerance of or irritability with anything that impedes or delays. Equivalently, investors with a high discount rate require higher future utility in return for holding off today's consumption. The second meaning of *impatience* is a restless desire for change and excitement.[6] According to the model, investors with a high discount rate prefer high volatility and high skewness (and possibly extremely negative skewness). Therefore, it is reasonable to call investors with a high discount rate impatient investors.

The implications of the realization utility model with a jump process in Section III can be restated as follows, with the word *impatience*. First, a positive relation between volatility and investment return does not exist among impatient investors. Second, investors exhibit a positive skewness preference in all but conditions of severe negative skewness, with stronger preference among impatient investors. Third, investors trade more frequently when they are impatient, stock return volatility is high, and skewness is low.

We construct a new measure that can proxy for cross-sectional investor impatience levels. It is motivated by the model's implication that impatient investors trade more frequently. The turnover rate, that is, the trading volume divided by the number of outstanding shares, is the representative measure for estimating stock-level trading frequency. According to the model, it is affected by the moments of stock returns, as well as investor impatience levels. To isolate the effects of only investor impatience levels, we control for the first, second, and third moments of stock returns and estimate MATURN. If

[6] The two meanings of "impatience" are from Collins English Dictionary by HarperCollins Publishers 1991, 1994, 1998, 2000, 2003.

factors other than stock return moments attract impatient investors and these factors persist for at least several months, MATURN is a good proxy for investor impatience. To be specific, first, we form 10 portfolios in the order of the past 12 months' daily stock return volatility and assign percentile rankings ranging continuously from zero to one in the order of the past 12 months' daily average stock turnover rate within each decile portfolio. Second, we form 10 portfolios in the order of the past 12 months' stock return skewness, and assign new percentile rankings in the order of those obtained from the first step within each decile portfolio. Finally, we form 10 portfolios in the order of the past 12 months' cumulative stock returns and create five groups in the order of the percentile ranking obtained from the second step within each decile portfolio. Now each stock has a *MATURN* value ranging from one to five according to the last quintile portfolio to which it belonged. The value of *MATURN* for stocks in the lowest-ranking group is one and *that* in the highest-ranking group is five. The lowest-*MATURN* stocks proxy for those stocks that impatient investors are least likely to trade and the highest-*MATURN* stocks proxy for those stocks that impatient investors are most likely to trade. Because the NASDAQ has a different trading system from that of the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX),[7] we run the steps separately for NYSE and AMEX stocks and for NASDAQ stocks.

From the perspective of investors, we adopt the past 12 months' daily stock return volatility as a proxy for ex ante volatility. Because volatility is strongly autocorrelated and past volatility is easy to observe, investors are likely to perceive past volatility as a predictor of future volatility. On the other hand, past skewness is not likely to be perceived as a good predictor of future skewness, since skewness does not have such strong autocorrelation. The finance literature describes several measures that predict future skewness. For example, Boyer et al. (2010) suggest an expected skewness measure, which is constructed through cross-sectional regression. However, the measure is not suitable for our

[7] While NYSE and AMEX are primarily auction markets, NASDAQ is a dealer market where trades with dealers are included in the reported trading volume. Therefore, the reported trading volume of NASDAQ stocks is overestimated relative to NYSE and AMEX stocks (see Atkins and Dyl (1997)).

analysis because it uses past volatility as one of the most important components in the regression and we should isolate the effect of skewness from the effect of volatility. The ex ante risk-neutral skewness measure of Conrad et al. (2013) is estimated from option prices. It is also not suitable for our analysis, since the fact that it requires option prices significantly reduces the number of sample stocks. On the other hand, the MAX5 measure of Bali et al. (2011) has many advantages. It is defined as the average of the five highest daily stock returns during the month. It is a salient and easily observable measure for investors. It is also likely that investors naively think of high-MAX5 stocks as lottery-like stocks. Although MAX5 is correlated to past volatility, it still has impressive power to predict future cross-sectional stock returns after past volatility is controlled for, as Bali et al. (2011) show. For these reasons, we choose the MAX5 measure as a proxy for ex ante skewness.

V. **Empirical Evidence of Volatility and Skewness Effects**

A. Data

The data is from the Center for Research in Security Prices and covers common stocks in the NYSE, AMEX, and NASDAQ. It includes daily stock returns, volumes, and the numbers of outstanding shares. In addition, we obtain equity book values from COMPUSTAT to construct a book-to-market measure. The Fama–French three factors (excess market returns, SMB, and HML) and the momentum factor are obtained from *Fama–French Portfolios and Factors* by Wharton Research Data Services. The main sample period is from July 1962 to December 2012, for comparability with the cross-sectional analysis literature.

B. Basic Statistics and Correlations

Panel A in Table I shows basic statistics of the variables for NYSE and AMEX stocks. The variable *Turnover* is the past 12 months' daily average stock turnover rate; *MATURN* is the moment-adjusted turnover rate measure as defined in the Section IV; *Ret* is the past 12 months' cumulative stock return; *Vol* and *Skew* are the past 12 months' standard second and third moments of daily stock returns, respectively; *MAX5* is the average of the five highest daily stock returns during the month, as for Bali et al. (2011); *Amihud* is the past 12 months' Amihud (2002) measure; *ME* and *PRC* are the natural logarithms of the market value and stock price, respectively. All measures are estimated at the end of each month. Since most of the measures use the past 12 months' data, autocorrelation is estimated for an interval of one year.

Recall that if factors besides moments of stock returns attract impatient investors and these persist for at least the next several months, MATURN might be a good proxy for cross-sectional investor impatience levels. The autocorrelation of *MATURN*, 0.72, is strong enough to satisfy the persistency condition. The variable *Vol* has very strong autocorrelation, 0.80, whereas *Skew* does not have. The strong autocorrelation of *Vol* implies that investors are highly likely to perceive past volatility as a predictor of future volatility.

Panel B of Table I is a correlation table. As mentioned earlier, while *Turnover* is correlated with the moments of stock returns, *MATURN* is hardly correlated. Figure 3 shows the variations of *Ret*, *Vol*, *Skew*, *MAX5*, and *Turnover* in quintile portfolios sorted by *Turnover* and *MATURN*, respectively. The variations of *Ret*, *Vol*, *Skew*, and *MAX5* are much more stable across *MATURN* portfolios than across *Turnover* portfolios, whereas the variations of *Turnover* are large enough in both portfolios. It is clear that the *MATURN* variable's construction method effectively controls for stock return moments while maintaining sufficient variability in *Turnover*. Furthermore, *MATURN* is positively correlated with market value of equity and stock price. In our untabulated result, firms with high *MATURN* tend to have low book-to-market values and high Piotroski (2000)'s F-score as well.

Another notable feature of the correlation table is the high correlation of *Vol* and *MAX5* (0.73). To isolate the volatility and skewness effects from each other, we adopt a double-sorting method. For a *MAX5*-adjusted *Vol* measure, we first sort stocks into 10 groups by *MAX5* and then sort them by *Vol* within each decile portfolio into as many groups as needed. The *Vol*-adjusted *MAX5* measure is constructed similarly, but the first sorting measure is *Vol* and the second sorting measure is *MAX5*. These two after-adjustment measures are used to investigate the volatility and skewness effects in the following sections.

C. How Does Ex Ante Volatility Affect Asset Pricing?

To investigate the model's first implication, that a positive relation between volatility and investment return does not exist among impatient investors, we construct 5×5 portfolios subsequently sorted by *MATURN* and *Vol* at the end of each month. Stock performance is estimated for the next month with equal weights. The result is reported in Panel A of Table II. We find different patterns across *MATURN* portfolios. The lowest-*MATURN* portfolios exhibit a positive relation between volatility and investment returns. Returns are monotonically increasing in *Vol*. The return difference between the highest- and lowest- *Vol* portfolios is 1.02%, which is economically and statistically significant. After we adjust the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model, the alphas are still significant, although weaker than the difference in raw returns. Because highly volatile stocks tend to be small and have high book-to-market values, some portion of the return difference can be attributed to a risk premium in the sense of the risk factor models. On the other hand, the highest-*MATURN* portfolios exhibit a negative relation between volatility and investment returns. The returns are decreasing in *Vol*. The return difference between the highest- and lowest-*Vol* portfolios is -1.23%, which is economically and statistically significant. The three- and four-factor adjusted alphas are even more significant than the difference in raw returns, which means that high-volatility stocks are popular even though they are riskier in the sense of the factor models. The 5–1 spread, the difference in differences between the highest- and lowest-*MATURN* portfolios, is -2.25% and economically and statistically very significant.

Panel B of Table II shows the volatility effect after controlling for *MAX5*. All return differences between highest- and lowest-*Vol* portfolios are higher than those that are not controlled for. It might be due to the elimination of the skewness effect. Because high ex ante skewness is closely related to high ex ante volatility (see Boyer et al. (2010)), a positive skewness preference makes high-volatility stocks overvalued. Controlling for *MAX5* reduces the overvaluation. In Panel B, the positive relation between volatility and investment returns within the lowest-*MATURN* portfolios becomes stronger. The negative relation within the highest-*MATURN* portfolios becomes very weak; however, it is still far from a positive relation.[8] The 5–1 spread is -1.57% and statistically significant. In conclusion, the results indicate that a positive relation between volatility and investment return does not exist among impatient investors.

D. How Does Ex Ante Skewness Affect Asset Pricing?

First, to investigate the model's second implication that investors exhibit a positive skewness preference in all but conditions of severe negative skewness, we construct 20 portfolios ordered by the *Vol*-adjusted *MAX5* measure (see Table III). The 20–1 spread shows the long–short portfolio return from buying the highest-*MAX5* portfolio and selling the lowest-*MAX5* portfolio: It is -1.38% and significantly different from zero, implying a positive skewness preference overall, as Bali et al. (2011) point out. The last two columns *Less10* and *Less10 t-stat* exhibit the differences in returns between each portfolio and the 10th portfolio and their *t*-statistics. For example, the *Less10* value of the lowest *MAX5* portfolio is $1.54\% - 1.39\% = 0.16\%$. The 20-1 spread, -1.38%, can be decomposed by the *Less10* value of the lowest portfolio, 0.16%, and that of the highest portfolio, -1.23%. About 89% of

[8] When we estimate the three-, six-, and twelve-month stock return performances allowing overlapping, as Jegadeesh and Titman (1993) do, the long–short strategy returns from buying highest-*Vol* portfolios and selling the lowest-*Vol* portfolios *in* the highest-*MATURN* portfolios are more negative than that of the one-month performance. For example, in case of the six-month performance estimation, it is -0.42% and marginally significant (*t*-value -1.72). Factor model-adjusted alphas are much more significant, at -0.72% (-3.29), -0.74% (-4.06), and -0.38% (-2.17) relative to the capital asset pricing model (CAPM), the Fama–French three factor model, and Carhart's four-factor model, respectively.

the long–short return is due to the second part, which means that a positive skewness preference is not proportional to the *MAX5* ranking. Figure 4 shows *Less10* and *Less10 t-stat* in graphical form. In terms of *t*-statistics, there is a maximum point around the fourth lowest *MAX5* portfolio. The domain left of the maximum does not exhibit a positive skewness preference. Overall, Figure 4 looks similar to the bottom left graph in Figure 2. These findings support the model's second implication, that investors exhibit a positive skewness preference in all but conditions of severe negative skewness.

Second, to investigate the other part of the model's second implication, that a positive skewness preference is stronger among impatient investors, we construct 5×5 portfolios subsequently sorted by *MATURN* and *MAX5*. Table IV shows the results. Because *MAX5* is correlated to *Vol*, Panel A's results using *MAX5* without controls is similar to the results in Panel A of Table II. However, Panel B's results using the *Vol*-adjusted *MAX5* measure shows a different pattern: All *MATURN* portfolios exhibit a positive skewness preference. The return differences between the highest- and lowest-*MAX5* portfolios are ranging from -1.21% to -0.95%, which are economically and statistically significant. The positive skewness preference among the highest-*MATURN* portfolios is stronger than that of the lowest-*MATURN* portfolios. Therefore, the 5-1 spread is -0.26% and marginally significant, although it is not statistically significant after the factor models are adjusted.

According to Kumar (2009, Table III), individual investors prefer NASDAQ stocks. His regression result shows that individual investors tend to invest more in NASDAQ stocks and less in S&P500 stocks, while institutional investors do the opposite. Because a realization utility investor resembles more closely to an individual investor than an institutional investor, we further investigate only NASDAQ firms in Panel C of Table III. Due to the lack of trading volume data of NASDAQ firms before November 1982, our analysis covers the period from October 1983 to December 2012. We find that all *MATURN* portfolios exhibit a positive skewness preference. In addition, the return differences between the highest- and lowest-*MAX5* portfolios are ranging from -1.80% to -0.74%, which are monotonically decreasing in *MATURN*. The 5-1 spread is -1.06% and statistically significant even after the factor models are adjusted. These results are consistent with the notion that positive skewness preference is stronger among impatient investors.

E. Fama–MacBeth Cross-Sectional Regression of Investment Returns

We run Fama–MacBeth (1973) cross-sectional regressions to reconfirm the model's first and second implications. The regression specification is

$$\mathrm{r}_{\mathrm{i,t+1}} = \alpha_t + \beta_{1,t}Vol_{i,t} + \beta_{2,t}MATURN^0_{i,t} \cdot Vol_{i,t} + \beta_{3,t}MAX5_{i,t} + \beta_{4,t}MATURN^0_{i,t} \cdot MAX5_{i,t} + \gamma_t X_{i,t} + u_{i,t+1} \quad (3)$$

where $\mathrm{r}_{\mathrm{i,t+1}}$ is the one-month investment return and $X_{i,t}$ is a set of well-known control variables that predict stock returns, including the natural logarithm of the value of market equity, the natural logarithm of the cumulative stock return of months $\mathrm{t} - 11$ to $\mathrm{t} - 1$, and the book-to-market ratio. The variable $MATURN^0$ has a value of $MATURN - 1$ ranging from zero to four. For example, stocks in the lowest-*MATURN* portfolio have a value of zero, while stocks in the highest-*MATURN* portfolio have a value of four.

Following the first implication, if a positive volatility–return relation exists except in the case of impatient investors, then $\beta_1 > 0$ and $\beta_2 < 0$. Following the second implication, if a positive skewness preference exists and its intensity is higher among impatient investors, then $\beta_3 < 0$ and $\beta_4 < 0$. The results are shown in Panel A of Table V. All coefficient estimates are standardized and *t*-statistics are Newey–West (1987) adjusted, using 12 lags. The signs of the coefficients of the control variables are consistent with the literature. The first equation shows $\beta_1 > 0$, consistent with "volatility puzzle". However, it is not statistically significant and even inverted when *MAX5* is considered in the second equation. On the other hand, the sixth equation, which we consider the main equation, confirms the first and second implications. The parameter β_1 is significantly positive and β_2, β_3, and β_4 are negative even though the absolute significance level of β_4 is not very high.

Compared to the second equation, a positive relation between volatility and investment returns is much clearer when interaction terms with $MATURN^0$ are considered: The parameter β_1 increases by 72.5 percent. Another interesting result is that the sixth equation shows that the coefficient estimate of the interaction of $MATURN^0$ with the logarithm of market equity is significantly positive. This finding implies that impatient investors prefer small stocks, compared to other investors. As a result, the size effect appears weaker among impatient investors. Equations 7 to 10 show that the idiosyncratic volatility measure obtained from the four-factor model has a similar effect to that of the simple volatility measure.

We also run the regressions for the period during which trading volume data of NASDAQ firms are available (see Panel B). The results reconfirm that a positive skewness preference is stronger among impatient investors especially in NASDAQ firms. Again, it is due to the fact that realization utility investors are likely to invest more in NASDAQ firms.

In Panel C, we report the regression results with longer estimation periods for investment returns. The results are qualitatively similar to the sixth equation result of Panel A, although the volatility and skewness effects become weaker as time passes.

F. How Do Volatility and Skewness Affect Contemporaneous Turnover Rate?

To investigate the model's third implication, that investors trade more frequently when stock return volatility is high and skewness is low, we first construct the *Skew*-adjusted *Vol* measure and the *Vol*-adjusted *Skew* measure in the same way as the *MAX5*-adjusted *Vol* and the *Vol*-adjusted *MAX5* measures are constructed. We form 10 portfolios sorted by the *Skew*-adjusted *Vol* measure and estimate *Turnover* for each portfolio. Next we form 10 portfolios sorted by the *Vol*-adjusted *Skew* measure and estimate *Turnover* for each portfolio. Due to the fact that the NASDAQ's trading system is different from that of the NYSE and AMEX, we restrict the sample to NYSE and AMEX firms.

The results are shown in Figure 5. After we control for the other moment, *Turnover* is increasing in volatility and decreasing in skewness, consistent with the implication.

We also conduct another test: the Fama–Macbeth cross-sectional regression of *Turnover*. The regression specification is

$$Turnover_{\mathrm{i,t}} = \alpha_t + \beta_{1,t} Vol_{i,t} + \beta_{2,t} Skew_{i,t} + \beta_{3,t} Ret_{i,t} + \gamma_t X_{i,t-12} + u_{i,t} \tag{4}$$

where $X_{i,t}$ is a set of control variables that can predict turnover rate, including the past 12 months' Amihud (2002) measure, the natural logarithm of the value of market equity, the book-to-market ratio, the natural logarithms of the number of months since listing, financial leverage defined as book debt divided by total assets, the natural logarithms of one plus the number of analysts following, and forecast dispersion defined as standard deviation of earnings per share.

The results are shown in Table VI. Panel A is for NYSE and AMEX firms and Panel B is for NASDAQ firms. All coefficient estimates are standardized and the *t*-statistics are Newey–West (1987) adjusted, using 12 lags. Equations 1 and 2 imply that *Turnover* is increasing in volatility and decreasing in skewness. The negative relation between *Skew* and *Turnover* becomes stronger when we control for *Vol* in equations 3 and 4 especially in NASDAQ firms. In conclusion, empirical observations support the prediction that investors trade more frequently when stock return volatility is high and skewness is low.

VI. **Investor Impatience and Investor Sentiment**

Investor sentiment is closely related to investor impatience. Baker and Wurgler (2006, 2007) describe investor sentiment as a shift in the propensity to speculate. That is, when sentiment is high, investors are more likely to buy speculative stocks. Similarly, according to the realization utility model in Section II and III, impatient investors are more likely to buy stocks that are expected to have high volatility and high skewness (and possibly extremely negative skewness), in other words, speculative stocks. Moreover, turnover rate is critical to both investor sentiment and investor impatience. For example, Baker and Stein (2004) state that turnover rate can serve as a sentiment index. Baker and Wurgler (2006, 2007) construct investor sentiment indexes that include the NYSE's aggregate turnover rate as one of their components. In our model, turnover rate is sensitive to investor impatience. We use stock-level turnover rates to construct MATURN as a proxy for cross-sectional investor impatience levels. Therefore, there should be a close connection between investor sentiment and investor impatience.

Investor sentiment changes over time. Baker and Wurgler (2007) construct two monthly investor sentiment time-series indexes: one for the absolute sentiment level and the other for relative sentiment changes.[9] On the other hand, MATURN focuses only on cross-sectional variations in investor impatience. The close tie between investor sentiment and investor impatience can help understand the time-series characteristics of investor impatience.

We divide the entire period into two separate ones according to whether the investor sentiment level in the portfolio formation month was above its time-series median or not. Then, for each period, we conduct subsequent double-sorting experiments with *MATURN* and *Vol*, as in Panel A of Table II.[10] For simplicity, only long–short performance from buying the highest-*Vol* portfolio and selling the lowest-*Vol* portfolio within each *MATURN* portfolio is presented in Table VII. When we compare the two periods, we find the level of long–short returns to be much lower when the sentiment index was above the median than when below it. Low long–short returns mean that investors are more likely to buy speculative stocks during periods of high sentiment. This result is consistent with Baker and Wurgler (2007). To be specific, three or four long–short returns are negative, depending on the

[9] We use orthogonal versions of the sentiment indexes, which are available on Wurgler's website, at http://people.stern.nyu.edu/jwurgler. These cover the period from July 1962 to December 2010.

[10] There is no need to control for the *MAX5* measure, because speculative stocks feature high *Vol* and high *MAX5* and the two measures are highly correlated (see Table II). Therefore, as a proxy for speculative stocks, we use the *Vol* measure itself instead of the *MAX5*-adjusted *Vol*.

adjusting model, when investor sentiment was high. On the other hand, almost all long–short returns except for the highest-*MATURN* portfolio are positive when sentiment was low.

As in Panel A of Table II, the long–short returns are monotonically decreasing in *MATURN*. The two 5-1 spreads, differences in differences between the highest- and lowest- *MATURN* long–short strategy returns, are significantly negative. It is hard to say that any 5-1 spread is greater than the other. For example, in the case of raw returns, the above-median 5-1 spread, at -2.56%, is lower than the below-median one, at -2.05%. However, in case of four-factor–adjusted returns, the above-median 5-1 spread, at -1.93%, is higher than the below-median one, at -1.96%. This finding means that there are always sufficient cross-sectional variations in investor impatience, and their amounts do not change much with regard to the investor sentiment.

Next, we run time-series regressions of the long–short returns on the investor sentiment level and change indexes. The purpose of the regression is to investigate how quickly investors respond to investor sentiment levels. The regression equation is

$$r_{t+1}^{long} - r_{t+1}^{short} = \alpha + d_1 SENT_t^{level} + d_2 SENT_t^{change} + \gamma X_t + u_{t+1} \quad (5)$$

where $SENT_t^{level}$ and $SENT_t^{change}$ are the sentiment level index and the sentiment change index, respectively, of Baker and Wurgler (2007), where $SENT_t^{change}$ represents a change in investor sentiment between time *t*-1 and *t* and $\mathrm{X_t}$ represents the controlling factors from the CAPM, the Fama–French three-factor model, and the Carhart's four-factor model.

The results are shown in Table VIII. The table only shows the results for d_1 and d_2 for simplicity. All coefficient estimates are standardized. We focus on the last two columns, the four-factor model results. The d_1 values are all negative across *MATURN* portfolios and have little variation. The d_1 value of the 5–1 spread is not statistically different from zero, at -0.12, with a *t*-statistic of -0.50. That is, sentiment level affects the preference for speculative stocks of all investors by almost the same amount, regardless of their cross-sectional level of impatience. When the sentiment level is high, the preference of all investors becomes stronger; when sentiment level is low, the preference of all investor becomes weaker.

We find an interesting result for d_2. The values are all significantly positive, except for the highest-*MATURN* portfolio, and they are monotonically decreasing with *MATURN*. Because sentiment change represents the relative difference between previous and current sentiments, the significantly positive d_2 value of the lowest-*MATURN* portfolio (1.15, with a *t*-statistic of 4.69) means that the preference of patient investors depends on not only current sentiment but also previous sentiment.[11] For example, patient investors are relatively reluctant to buy speculative stocks when the previous sentiment level was low compared to when it was high. Because the signs of d_1 and d_2 are opposite, the effect of $d_1SENT_t^{level}$ is countered by the effect of $d_2SENT_t^{change}$ in the case of patient investors; that is, their reaction is somewhat slow. On the other hand, the d_2 values of the highest-*MATURN* portfolio are 0.38, with a *t*-statistic of 1.40, and not statistically significant. It is only one-third of the d_2 value of the lowest-*MATURN* portfolio. Impatient investors do not care much about the previous sentiment level; only current sentiment level matters to them. The d_2 value of the 5-1 spread is significantly negative, at -0.77, with a *t*-statistic of -3.24, showing that the difference is highly significant. In conclusion, patient investors react slowly to time-series variations in investor sentiment, while impatient investors react quickly.

The fact that patient investors react slowly to time-series variations in investor sentiment while impatient investors react quickly can be explained in two ways. First, it might be due to the difference in investment time horizons. While investor reactions to a change in $d_1SENT_t^{level}$ are related to the first differential of the sentiment level, investor reactions to a change in $d_2SENT_t^{change}$ are related to the second differential. It is obvious that the second differential reveals a relatively long-term trend

[11] A long–short return at time *t*+1 is a result of investor preference for speculative stocks at time *t*. Therefore, the current sentiment level (at time *t*) affects investor preference (at time *t*) through $d_1SENT_t^{level}$, and the previous relative sentiment level (at time *t*-1) affects investor preference (at time *t*) through $d_2SENT_t^{change}$.

for sentiment level. Because patient investors are defined as investors with a low discount rate, they consider long-term performance important. Therefore, they adjust their preferences to long-term trends of sentiment. On the other hand, because impatient investors consider short-term performance important, they chase short-term trends of sentiment. Therefore, different investor' investment time horizons might be one explanation. The second explanation can simply be the difference in turnover rates: Patient investors do not trade much, so that they cannot follow recent trends in sentiment. On the other hand, impatient investors are fleet-footed traders and they quickly grab stocks that are in fashion. This can lead to the difference in reaction speed between impatient and patient investors.

The significantly negative d_2 value of the 5-1 spread also implies that the cross-sectional dispersion of the preference for speculative stocks changes over time. When sentiment is rising, the negative 5-1 spread becomes more negative, that is, the cross-sectional dispersion of preferences is high. When sentiment is dropping, the negative 5-1 spread becomes less negative, that is, the dispersion is low. This can be a good explanation for the asymmetry of aggregate market volatility. When sentiment is rising, investors exhibit various trading behaviors depending on their level of impatience making the cross-sectional dispersion of their preferences high. The aggregation of various trading behaviors makes the market stable, resulting in a low-volatility market. However, when sentiment is dropping, investors exhibit limited trading behaviors making the cross-sectional dispersion of their preferences low. As investor trading behaviors resemble each other, the aggregate market movement is amplified, which leads to a high-volatility market. Therefore, rising sentiment can lead to low market volatility and diminishing sentiment can lead to high market volatility.

In conclusion, this section provides empirical evidence of a close connection between investor impatience and investor sentiment. Specifically, investor sentiment level affects the preference for speculative stocks of all investors by the same amount, regardless of their cross-sectional level of impatience. However, the reaction speed to time-series variations in sentiment levels is different: While impatient investors react quickly, patient investors react slowly. In addition, the cross-sectional dispersion of the preference for speculative stocks is high when sentiment is rising and low when sentiment is dropping.

VII. Conclusions

We theoretically and empirically examine how stock return volatility and skewness affect asset pricing and investor trading behavior. We propose a theoretical extension of the realization utility model in which the stock price is modeled by geometric Brownian motion with a jump process. This model has three implications for the stock market. First, a positive relation between volatility and investment return does not exist among impatient investors. Second, investors exhibit a positive skewness preference in all but conditions of severe negative skewness, with stronger preference among impatient investors. Third, investors trade more frequently when they are impatient, stock return volatility is high, and skewness is low.

Empirically, we define the moment-adjusted turnover measure as a proxy for cross-sectional investor impatience levels. Empirical observations using this measure are consistent with the model's implications. In addition, we find that investor sentiment levels affect the preference for speculative stocks of all investors by the same amount, regardless of their cross-sectional level of impatience. However, while impatient investors react quickly to time-series variations in investor sentiment, patient investors react slowly. In addition, the cross-sectional dispersion of the preference for speculative stocks is high when sentiment is rising and low when sentiment is dropping.

This paper contributes to the finance literature in three ways. First, it shows how stock return volatility and skewness affect asset pricing and investor trading behavior within a single framework. Second, it explains why some investors prefer highly skewed stock returns. To our knowledge, only two theoretical models in the finance literature have described it, Brunnermeier et al. (2007) and

Barberis and Huang (2008). Third, this paper provides supporting empirical observations for the realization utility model, which are overall economically and statistically very significant.

Appendix

An investor's subjective discount rate is δ and the purchase and sale transaction cost parameters are k_p and k_s, respectively. Assume that, in the case of no jumps, the reference level $R_t = k_1 X_t$ and the realized gains $G_t = k_2 X_t - R_t$ where $k_1 = (1-k_s)/(1+k_p)$, $k_2 = 1-k_s$ and X is the investment amount, as for Ingersoll and Jin (2013). On the other hand, if a jump happens, assume that $R_t = X_t$ and $G_t = X_t - R_t$, because investors do not sell stocks and therefore do not pay transaction costs.

The indirect utility is

$$V(X_t, R_t) = \text{MAX}_{\tilde{\tau}}\, E_t[\textstyle\sum_{k=1}^{N(\tilde{\tau})} e^{-\delta \widetilde{t_k}} U\big(\tilde{X}_{t+\widetilde{t_k}} - \tilde{R}_{t+\widetilde{t_k}},\ \tilde{R}_{t+\widetilde{t_k}}\big) + e^{-\delta\tilde{\tau}} U\big(k_2 \tilde{X}_{t+\tilde{\tau}} - \tilde{R}_{t+\tilde{\tau}},\ \tilde{R}_{t+\tilde{\tau}}\big) +$$

$$e^{-\delta\tilde{\tau}} V(k_1 \tilde{X}_{t+\tilde{\tau}}, k_1 \tilde{X}_{t+\tilde{\tau}})] \qquad \text{(A1)}$$

where $\tilde{\tau}$ is the time until the next sale, $\widetilde{t_k}$ is the time until the *k*-th jump, and $N(\tilde{\tau})$ is the number of jumps before $\tilde{\tau}$.

For simplicity, let $U(G,R) = R^{\beta} u(k_2 x)$ if an investor sell stocks in the case of no jump and $U(G,R) = R^{\beta} u(x)$ if a jump happens where $x = X/R$ and

$$\text{u}(x) = \begin{cases} \dfrac{[x^{\alpha_G - 1}]}{\alpha_G},\ x \geq 1 \\ -\dfrac{\lambda[1 - x^{\alpha_L}]}{\alpha_L},\ 0 \leq x < 1 \end{cases} \qquad \text{(A2)}$$

Then $V(X,R)$ can be simplified to $R^{\beta} v(x)$.

There are two cases. For a sale,

$$v(x) = u(k_2 x) + k_1^{\beta} x^{\beta} v(1) \qquad \text{(A3a)}$$

Between sales, $E\big[d\{e^{\delta t} V(X,R)\}\big] = 0$. When a jump happens between sales,

$$dV = R^{\beta}\big[u\{(1+j)x\} + (1+j)^{\beta} x^{\beta} v(1)\big] - V(X,R) + V_X(X,R)dX +$$

$$\frac{1}{2} V_{XX}(X,R)(dX)^2 \qquad \text{(A3b)}$$

If there is no jump between sales,

$$dV = V_X(X,R)dX + \frac{1}{2}V_{XX}(X,R)(dX)^2 \tag{A3c}$$

Therefore,

$$\frac{1}{2}\sigma^2 x^2 v'' + \mu x v' - (\delta + f)v + fu\big((1+j)x\big) + f(1+j)^\beta x^\beta v(1) \ = 0 \tag{A4}$$

Between sales, there are two distinct intervals. First, when $0 \le x < \frac{1}{1+j}$, then equation (A4) would be

$$\frac{1}{2}\sigma^2 x^2 v'' + \mu x v' - (\delta + f)v + \frac{f\lambda}{\alpha_L}\big((1+j)\big)^{\alpha_L} x^{\alpha_L} + f(1+j)^\beta v(1) x^\beta - \frac{f\lambda}{\alpha_L} = 0 \tag{A5}$$

Let $v(x) = A_1 x^{\gamma_1} + A_2 x^{\gamma_2} + A_3 x^{\alpha_L} + A_4 x^\beta + A_5$

$$\text{where } \gamma_1, \gamma_2 = \frac{-\left(\mu - \frac{1}{2}\sigma^2\right) \pm \sqrt{\left(\mu - \frac{1}{2}\sigma^2\right)^2 + 2\sigma^2(\delta + f)}}{\sigma^2} \tag{A6a}$$

$$A_3 = \frac{-\frac{f\lambda}{\alpha_L}\big((1+j)\big)^{\alpha_L}}{\frac{1}{2}\sigma^2 \alpha_L(\alpha_L - 1) + \mu\alpha_L - \delta - f} \tag{A6b}$$

$$A_4 = \frac{-f(1+j)^\beta (v(1) - A_4)}{\frac{1}{2}\sigma^2 \beta(\beta - 1) + \mu\beta - \delta - f + f(1+j)^\beta}\,(v(1) - A_4) \tag{A6c}$$

and

$$A_5 = \frac{-f\lambda}{\alpha_L(\delta + f)} \tag{A6d}$$

Second, when $x \ge \frac{1}{1+j}$, equation (A4) would be

$$\frac{1}{2}\sigma^2 x^2 v'' + \mu x v' - (\delta + f)v + \frac{f}{\alpha_G}\big((1+j)x\big)^{\alpha_G} + f(1+j)^\beta v(1) x^\beta - \frac{f}{\alpha_L} = 0 \tag{A7}$$

Let $v(x) = B_1 x^{\gamma_1} + B_2 x^{\gamma_2} + B_3 x^{\alpha_G} + B_4 x^\beta + B_5$, where

$$B_3 = \frac{-\frac{f}{\alpha_G}\big((1+j)\big)^{\alpha_G}}{\frac{1}{2}\sigma^2 \alpha_G(\alpha_G - 1) + \mu\alpha_G - \delta - f} \tag{A8a}$$

$$B_4 = A_4 \tag{A8b}$$

and

$$B_5 = \frac{-f}{\alpha_G(\delta+f)} \tag{A8c}$$

When $\frac{1}{1+j} < 1$, $v(1) = B_1 + B_2 + B_3 + B_4 + B_5$. If $\theta_1 < \frac{1}{1+j} < \theta_2$ and $\theta_1 < 1 < \frac{1}{k_2} < \theta_2$, then the first two smoothing conditions for $x = \frac{1}{1+j}$ are as follows.

$$A_1x^{\gamma_1} + A_2x^{\gamma_2} + A_3x^{\alpha_L} + A_4x^{\beta} + A_5 = B_1x^{\gamma_1} + B_2x^{\gamma_2} + B_3x^{\alpha_G} + B_4x^{\beta} + B_5 \tag{A9a}$$

$$\gamma_1A_1x^{\gamma_1} + \gamma_2A_2x^{\gamma_2} + \alpha_LA_3x^{\alpha_L} + \beta A_4x^{\beta} = \gamma_1B_1x^{\gamma_1} + \gamma_2B_2x^{\gamma_2} + \alpha_GB_3x^{\alpha_G} + \beta B_4x^{\beta} \tag{A9b}$$

The other four smoothing conditions are as follows (six conditions in total).

$$A_1\theta_1^{\gamma_1} + A_2\theta_1^{\gamma_2} + A_3\theta_1^{\alpha_L} + A_4\theta_1^{\beta} + A_5 = -[1-(k_2\theta_1)^{\alpha_L}] + k_1^{\beta}\theta_1^{\beta}v(1) \tag{A9c}$$

$$\gamma_1A_1\theta_1^{\gamma_1} + \gamma_2A_2\theta_1^{\gamma_2} + \alpha_LA_3\theta_1^{\alpha_L} + \beta A_4\theta_1^{\beta} = \lambda k_2^{\alpha_L}\theta_1^{\alpha_L} + \beta k_1^{\beta}v(1)\theta_1^{\beta} \tag{A9d}$$

$$B_1\theta_2^{\gamma_1} + B_2\theta_2^{\gamma_2} + B_3\theta_2^{\alpha_G} + B_4\theta_2^{\beta} + B_5 = [(k_2\theta_2)^{\alpha_G} - 1]\frac{1}{\alpha_G} + k_1^{\beta}\theta_2^{\beta}v(1) \tag{A9e}$$

$$\gamma_1B_1\theta_2^{\gamma_1} + \gamma_2B_2\theta_2^{\gamma_2} + \alpha_GB_3\theta_2^{\alpha_G} + \beta B_4\theta_2^{\beta} = k_2^{\alpha_G}\theta_2^{\alpha_G} + \beta k_1^{\beta}v(1)\theta_2^{\beta} \tag{A9f}$$

If $\frac{1}{1+j} < \theta_1 < 1 < \frac{1}{k_2} < \theta_2$, the smoothing conditions are as follows (four conditions in total).

$$B_1\theta_1^{\gamma_1} + B_2\theta_1^{\gamma_2} + B_3\theta_1^{\alpha_G} + B_4\theta_1^{\beta} + B_5 = -[1-(k_2\theta_1)^{\alpha_L}] + k_1^{\beta}\theta_1^{\beta}v(1) \tag{A10a}$$

$$\gamma_1B_1\theta_1^{\gamma_1} + \gamma_2B_2\theta_1^{\gamma_2} + \alpha_GB_3\theta_1^{\alpha_G} + \beta B_4\theta_1^{\beta} = \lambda k_2^{\alpha_L}\theta_1^{\alpha_L} + \beta k_1^{\beta}v(1)\theta_1^{\beta} \tag{A10b}$$

$$B_1\theta_2^{\gamma_1} + B_2\theta_2^{\gamma_2} + B_3\theta_2^{\alpha_G} + B_4\theta_2^{\beta} + B_5 = [(k_2\theta_2)^{\alpha_G} - 1]\frac{1}{\alpha_G} + k_1^{\beta}\theta_2^{\beta}v(1) \tag{A10c}$$

$$\gamma_1B_1\theta_2^{\gamma_1} + \gamma_2B_2\theta_2^{\gamma_2} + \alpha_GB_3\theta_2^{\alpha_G} + \beta B_4\theta_2^{\beta} = k_2^{\alpha_G}\theta_2^{\alpha_G} + \beta k_1^{\beta}v(1)\theta_2^{\beta} \tag{A10d}$$

When $\frac{1}{1+j} \geq 1$, $v(1) = A_1 + A_2 + A_3 + A_4 + A_5$. If $\theta_1 < \frac{1}{1+j} < \theta_2$ and $\theta_1 < 1 < \frac{1}{k_2} < \theta_2$, then the first two smoothing conditions for $x = \frac{1}{1+j}$ are as follows.

$$A_1x^{\gamma_1} + A_2x^{\gamma_2} + A_3x^{\alpha_L} + A_4x^{\beta} + A_5 = B_1x^{\gamma_1} + B_2x^{\gamma_2} + B_3x^{\alpha_G} + B_4x^{\beta} + B_5 \tag{A11a}$$

$$\gamma_1A_1x^{\gamma_1} + \gamma_2A_2x^{\gamma_2} + \alpha_LA_3x^{\alpha_L} + \beta A_4x^{\beta} = \gamma_1B_1x^{\gamma_1} + \gamma_2B_2x^{\gamma_2} + \alpha_GB_3x^{\alpha_G} + \beta B_4x^{\beta} \tag{A11b}$$

The other four smoothing conditions are as follows (six conditions in total).

$$A_1\theta_1^{\gamma_1} + A_2\theta_1^{\gamma_2} + A_3\theta_1^{\alpha_L} + A_4\theta_1^{\beta} + A_5 = -[1-(k_2\theta_1)^{\alpha_L}] + k_1^{\beta}\theta_1^{\beta}v(1) \quad \text{(A11c)}$$

$$\gamma_1 A_1\theta_1^{\gamma_1} + \gamma_2 A_2\theta_1^{\gamma_2} + \alpha_L A_3\theta_1^{\alpha_L} + \beta A_4\theta_1^{\beta} = \lambda k_2^{\alpha_L}\theta_1^{\alpha_L} + \beta k_1^{\beta}v(1)\theta_1^{\beta} \quad \text{(A11d)}$$

$$B_1\theta_2^{\gamma_1} + B_2\theta_2^{\gamma_2} + B_3\theta_2^{\alpha_G} + B_4\theta_2^{\beta} + B_5 = [(k_2\theta_2)^{\alpha_G} - 1]\frac{1}{\alpha_G} + k_1^{\beta}\theta_2^{\beta}v(1) \quad \text{(A11e)}$$

$$\gamma_1 B_1\theta_2^{\gamma_1} + \gamma_2 B_2\theta_2^{\gamma_2} + \alpha_G B_3\theta_2^{\alpha_G} + \beta B_4\theta_2^{\beta} = k_2^{\alpha_G}\theta_2^{\alpha_G} + \beta k_1^{\beta}v(1)\theta_2^{\beta} \quad \text{(A11f)}$$

If $\theta_1 < 1 < \frac{1}{k_2} < \theta_2 < \frac{1}{(1+j)k_2}$, the smoothing conditions are as follows (four conditions in total).

$$A_1\theta_1^{\gamma_1} + A_2\theta_1^{\gamma_2} + A_3\theta_1^{\alpha_L} + A_4\theta_1^{\beta} + A_5 = -[1-(k_2\theta_1)^{\alpha_L}] + k_1^{\beta}\theta_1^{\beta}v(1) \quad \text{(A12a)}$$

$$\gamma_1 A_1\theta_1^{\gamma_1} + \gamma_2 A_2\theta_1^{\gamma_2} + \alpha_L A_3\theta_1^{\alpha_L} + \beta A_4\theta_1^{\beta} = \lambda k_2^{\alpha_L}\theta_1^{\alpha_L} + \beta k_1^{\beta}v(1)\theta_1^{\beta} \quad \text{(A12b)}$$

$$A_1\theta_2^{\gamma_1} + A_2\theta_2^{\gamma_2} + A_3\theta_2^{\alpha_L} + A_4\theta_2^{\beta} + A_5 = [(k_2\theta_2)^{\alpha_G} - 1]\frac{1}{\alpha_G} + k_1^{\beta}\theta_2^{\beta}v(1) \quad \text{(A12c)}$$

$$\gamma_1 A_1\theta_2^{\gamma_1} + \gamma_2 A_2\theta_2^{\gamma_2} + \alpha_L A_3\theta_2^{\alpha_L} + \beta A_4\theta_2^{\beta} = k_2^{\alpha_G}\theta_2^{\alpha_G} + \beta k_1^{\beta}v(1)\theta_2^{\beta} \quad \text{(A12d)}$$

The set of four and six equations can be solved using numerical methods.

Table I. Basic Statistics and Correlations

This table shows the basic statistics and correlations of the variables for NYSE and AMEX stocks. The sample period is from July 1962 to December 2012. The variable *Turnover* is the past 12 months' daily average stock turnover rate; *MATURN* is the moment-adjusted turnover rate measure as defined in the Section IV; *Ret* is the past 12 months' cumulative stock return; *Vol* and *Skew* are the past 12 months' standard second and third moments of daily stock returns, respectively; *MAX5* is the average of the five highest daily stock returns during the month; *Amihud* is the past 12 months' Amihud (2002) measure; and *ME* and *PRC* are the natural logarithms of the value of market equity and stock price, respectively. All measures are estimated at the end of each month. Panel A shows basic statistics, including the mean, standard deviation, skewness, kurtosis, and autocorrelation. Autocorrelation is estimated with a one-year interval. Panel B shows the correlations of the variables.

	Turnover	***MATURN***	***Ret***	***Vol***	***Skew***	***MAX5***	***Amihud***	***ME***	***PRC***
Panel A: Basic Statistics									
Mean	0.33	3.00	14.99	2.81	0.50	3.46	0.00	5.15	2.71
Std	0.32	1.41	49.90	1.67	1.09	2.80	0.00	1.96	1.05
Skew	4.98	-0.00	3.34	2.95	2.32	4.11	5.31	0.09	-0.68
Kurt	80.94	-1.29	40.50	23.75	22.22	44.93	54.27	-0.33	1.28
AR	0.69	0.72	0.03	0.80	0.11	0.48	0.86	0.98	0.92
Panel B: Correlation									
Turnover	1	0.63	0.13	0.20	-0.02	0.13	-0.25	0.12	0.10
MATURN		1	0.02	0.00	-0.03	-0.01	-0.37	0.29	0.24
Ret			1	-0.05	0.18	-0.02	-0.06	0.15	0.29
Vol				1	0.28	0.73	0.34	-0.55	-0.72
Skew					1	0.18	0.15	-0.23	-0.16
MAX5						1	0.26	-0.40	-0.54
Amihud							1	-0.56	-0.42
ME								1	0.78
PRC									1

Table II. MATURN and Volatility Preference

This table shows the one-month equal-weighted investment returns of 5×5 portfolios subsequently sorted by *MATURN* and *Vol*. The portfolios are constructed at the end of each month. The variable *MATURN* is the moment-adjusted turnover rate measure as defined in the Section IV, *Vol* is the past 12 months' standard second moment of daily stock returns, and *MAX5* is the average of the five highest daily stock returns during the month. The column labeled *Diff* shows the raw return differences between the highest- and lowest-*Vol* portfolios and the columns labeled *CAPM*, *FF3*, and *FF4* reveal the factor-model–adjusted ones. Panel A and B cover NYSE, AMEX, and NASDAQ firms from July 1962 to December 2012. Panel C cover only NASDAQ firms from October 1983 to December 2012. Panel A uses the raw *Vol* measure, whereas Panel B and C use the *MAX5*-adjusted *Vol* measure, which is obtained from the 10×5 subsequent double-sorting method with *MAX5* and *Vol*.

	***Vol*1**	***Vol* 2**	***Vol*3**	***Vol*4**	***Vol*5**	**Diff**	**CAPM**	**FF3**	**FF4**
Panel A: Main Sample with a Raw *Vol* Measure									
Estimate									
***MATURN*1**	1.15	1.29	1.45	1.55	2.16	1.02	0.75	0.49	0.71
***MATURN*2**	1.13	1.34	1.48	1.43	1.89	0.76	0.42	0.26	0.57
***MATURN*3**	1.11	1.26	1.38	1.27	1.66	0.55	0.16	0.00	0.37
***MATURN*4**	1.11	1.29	1.30	1.08	0.85	-0.26	-0.70	-0.80	-0.42
***MATURN*5**	1.15	1.16	1.00	0.61	-0.08	-1.23	-1.71	-1.72	-1.24
5-1						-2.25	-2.46	-2.21	-1.95
***t*-Statistic**									
***MATURN*1**	8.71	7.50	6.92	5.88	5.99	3.44	2.67	2.07	2.97
***MATURN*2**	8.05	7.10	6.31	4.77	4.79	2.28	1.36	1.03	2.31
***MATURN*3**	7.54	6.21	5.56	4.04	3.92	1.53	0.48	0.00	1.44
***MATURN*4**	7.15	6.18	4.92	3.29	1.97	-0.73	-2.19	-3.22	-1.73
***MATURN*5**	6.98	5.30	3.64	1.74	-0.17	-3.26	-5.12	-6.41	-4.80
5-1						-8.99	-10.28	-9.65	-8.52
Panel B: Main Sample with a *MAX5*-Adjusted *Vol* Measure									
Estimate									
***MATURN*1**	0.90	1.11	1.43	1.68	2.47	1.57	1.42	1.18	1.37
***MATURN*2**	0.94	1.13	1.38	1.60	2.22	1.28	1.08	0.94	1.16
***MATURN*3**	0.90	1.05	1.19	1.43	2.10	1.20	0.96	0.82	1.11
***MATURN*4**	0.90	0.94	0.99	1.18	1.61	0.71	0.43	0.38	0.61
***MATURN*5**	0.83	0.75	0.71	0.73	0.82	-0.01	-0.32	-0.33	-0.03
5-1						-1.57	-1.74	-1.51	-1.40
***t*-Statistic**									
***MATURN*1**	5.74	5.75	6.67	6.90	8.14	7.71	7.21	6.83	7.91
***MATURN*2**	5.48	5.41	5.83	5.92	6.72	5.80	5.16	5.26	6.53
***MATURN*3**	5.04	4.80	4.71	5.05	5.97	5.08	4.36	4.40	6.07
***MATURN*4**	4.75	4.13	3.84	3.95	4.39	2.94	1.95	2.17	3.50
***MATURN*5**	4.20	3.09	2.58	2.33	2.13	-0.02	-1.40	-1.68	-0.16
5-1						-7.91	-9.18	-8.36	-7.63

	***Vol*1**	***Vol*2**	***Vol*3**	***Vol*4**	***Vol*5**	**Diff**	**CAPM**	**FF3**	**FF4**
Panel C: Only NASDAQ Firms with a *MAX5*-Adjusted *Vol* Measure									
Estimate									
***MATURN*1**	0.87	0.99	1.17	1.64	2.25	1.38	1.19	1.19	1.37
***MATURN*2**	0.93	1.00	1.31	1.47	2.22	1.29	1.02	1.13	1.40
***MATURN*3**	0.91	0.91	1.06	1.25	1.93	1.02	0.71	0.82	1.19
***MATURN*4**	0.90	0.82	0.78	0.79	1.34	0.44	0.07	0.30	0.64
***MATURN*5**	0.64	0.60	0.32	0.25	0.45	-0.19	-0.63	-0.36	0.09
5-1						-1.58	-1.81	-1.55	-1.28
***t*-Statistic**									
***MATURN*1**	4.75	4.32	4.58	5.15	6.17	5.15	4.60	4.67	5.41
***MATURN*2**	4.32	3.72	4.05	3.93	4.79	3.89	3.24	3.78	4.82
***MATURN*3**	3.66	2.99	3.02	3.07	3.72	2.77	2.04	2.50	3.77
***MATURN*4**	3.43	2.64	2.10	1.81	2.38	1.08	0.18	0.89	2.00
***MATURN*5**	2.35	1.67	0.77	0.53	0.73	-0.42	-1.49	-0.96	0.26
5-1						-4.39	-5.21	-4.94	-4.15

Table III. Skewness Preference

This table shows the one-month investment returns of 20 portfolios sorted by *Vol*-adjusted *MAX5*. The portfolios are constructed at the end of each month. The sample period is from July 1962 to December 2012. The variable *Vol* is the past 12 months' standard second moment of daily stock returns and *MAX5* is the average of the five highest daily stock returns during the month. *Vol*-adjusted *MAX5* measure is obtained from 10×20 subsequent double-sorting method with *Vol* and *MAX5*. Investment returns are estimated with equal-weighting. The last two columns, *Less10* and *Less10 t*-stat, show the return differences between each portfolio and the 10th portfolio and their *t*-statistics.

Rank	**Ret**	**Std**	***t*-Stat**	**CAPM alpha**	**CAPM *t*-stat**	**FF3 alpha**	**FF3 *t*-stat**	**FF4 alpha**	**FF4 *t*-stat**	**Less10**	**Less10 *t*-stat**
1	1.54	5.30	7.18	0.70	4.77	0.41	3.85	0.58	5.6 2	0.16	1.5 4
2	1.71	5.90	7.14	0.78	5.33	0.49	4.79	0.69	7.17	0.32	4.03
3	1.68	5.94	6.96	0.73	5.23	0.45	5.08	0.63	7.49	0.29	4.36
4	1.69	5.99	6.94	0.72	5.41	0.47	5.51	0.62	7.63	0.30	4.95
5	1.58	6.19	6.3 1	0.59	4.43	0.33	4.02	0.52	6.74	0.20	3.41
6	1.60	6.17	6.36	0.60	4.56	0.34	4.38	0.51	7.09	0.21	3.65
7	1.56	6.21	6.17	0.56	4.19	0.30	3.71	0.48	6.49	0.17	2.95
8	1.34	6.15	5.34	0.34	2.64	0.09	1.15	0.25	3.42	-0.05	-0.93
9	1.42	6.24	5.61	0.41	3.23	0.17	2.28	0.33	4.49	0.03	0.61
10	1.39	6.17	5.53	0.39	2.99	0.14	1.80	0.31	4.29	0.00	
11	1.22	6.18	4.86	0.22	1.72	-0.02	-0.32	0.14	2.01	-0.17	-2.78
12	1.23	6.37	4.76	0.22	1.62	-0.01	-0.17	0.18	2.45	-0.15	-2.73
13	1.15	6.37	4.46	0.15	1.05	-0.10	-1.16	0.07	0.89	-0.23	-3.66
14	1.06	6.32	4.14	0.06	0.42	-0.19	-2.51	-0.03	-0.47	-0.32	-5.30
15	0.90	6.25	3.56	-0.10	-0.75	-0.34	-4.57	-0.17	-2.51	-0.48	-7.95
16	0.84	6.31	3.30	-0.16	-1.16	-0.39	-4.92	-0.22	-2.96	-0.54	-7.82
17	0.75	6.32	2.93	-0.25	-1.77	-0.49	-5.89	-0.36	-4.43	-0.64	-9.09
18	0.64	6.27	2.51	-0.35	-2.44	-0.60	-7.26	-0.46	-5.76	-0.75	-10.09
19	0.42	6.36	1.64	-0.56	-3.75	-0.80	-8.86	-0.66	-7.43	-0.96	-12.25
20	0.16	6.23	0.64	-0.80	-5.10	-1.03	-9.78	-0.91	-8.62	-1.23	-12.30
20-1	-1.38	3.09	-11.00	-1.49	-12.46	-1.44	-12.07	-1.48	-12.23		

Table IV. MATURN and Positive Skewness Preference

This table shows the one-month equal-weighted investment returns of 5×5 portfolios subsequently sorted by *MATURN* and *MAX5*. The portfolios are constructed at the end of each month. The variable *MATURN* is the moment-adjusted turnover rate measure as defined in the Section IV, *Vol* is the past 12 months' standard second moment of daily stock returns, and *MAX5* is the average of the five highest daily stock returns during the month. The column labeled *Diff* shows the raw return differences between the highest- and lowest-*MAX5* portfolios and the columns labeled *CAPM*, *FF3*, and *FF4* reveal the factor-model–adjusted ones. Panel A and B cover NYSE, AMEX, and NASDAQ firms from July 1962 to December 2012. Panel C cover only NASDAQ firms from October 1983 to December 2012. Panel A uses the raw *MAX5* measure, whereas, Panel B and C use the *Vol*-adjusted *MAX5* measure, which is obtained from 10×5 subsequent double-sorting method with *Vol* and *MAX5*.

	***MAX*1**	***MAX*2**	***MAX*3**	***MAX*4**	***MAX*5**	**Diff**	**CAPM**	**FF3**	**FF4**
Panel A: Main Sample with a Raw *MAX5* Measure									
Estimate									
***MATURN*1**	1.29	1.59	1.69	1.69	1.37	0.08	-0.16	-0.31	-0.16
***MATURN*2**	1.32	1.55	1.59	1.60	1.21	-0.11	-0.40	-0.49	-0.29
***MATURN*3**	1.29	1.49	1.47	1.40	1.03	-0.26	-0.58	-0.66	-0.44
***MATURN*4**	1.30	1.42	1.33	1.17	0.40	-0.90	-1.26	-1.32	-1.05
***MATURN*5**	1.24	1.27	1.10	0.72	-0.47	-1.72	-2.12	-2.11	-1.73
5-1						-1.80	-1.96	-1.80	-1.56
***t*-Statistic**									
***MATURN*1**	8.35	8.84	8.02	6.73	4.12	0.35	-0.74	-1.63	-0.84
***MATURN*2**	7.98	7.89	6.92	5.64	3.33	-0.42	-1.62	-2.41	-1.39
***MATURN*3**	7.51	7.19	5.91	4.71	2.66	-0.89	-2.20	-3.08	-2.04
***MATURN*4**	7.34	6.50	5.16	3.72	1.01	-3.12	-4.84	-6.49	-5.22
***MATURN*5**	6.85	5.51	3.98	2.11	-1.14	-5.48	-7.72	-9.38	-7.91
5-1						-8.39	-9.48	-8.97	-7.80
Panel B: Main Sample with a *Vol*-Adjusted *MAX5* Measure									
Estimate									
***MATURN*1**	1.76	1.90	1.80	1.35	0.81	-0.95	-1.03	-1.00	-1.07
***MATURN*2**	1.77	1.83	1.56	1.32	0.78	-0.99	-1.05	-1.02	-1.08
***MATURN*3**	1.85	1.57	1.49	1.14	0.64	-1.21	-1.24	-1.21	-1.31
***MATURN*4**	1.65	1.48	1.19	0.84	0.46	-1.19	-1.20	-1.19	-1.23
***MATURN*5**	1.38	0.98	0.82	0.50	0.17	-1.21	-1.22	-1.22	-1.24
5-1						-0.26	-0.20	-0.22	-0.18
***t*-Statistic**									
***MATURN*1**	8.52	8.60	8.13	5.91	3.53	-8.80	-9.72	-9.37	-9.89
***MATURN*2**	7.70	7.64	6.50	5.43	3.14	-9.08	-9.81	-9.47	-9.84
***MATURN*3**	7.37	6.21	5.85	4.49	2.45	-10.85	-11.13	-10.73	-11.50
***MATURN*4**	6.34	5.54	4.44	3.17	1.76	-12.06	-12.04	-11.75	-11.95
***MATURN*5**	5.02	3.45	2.94	1.78	0.61	-10.82	-10.87	-10.61	-10.61
5-1						-1.82	-1.40	-1.55	-1.22

	***MAX*1**	***MAX*2**	***MAX*3**	***MAX*4**	***MAX*5**	**Diff**	**CAPM**	**FF3**	**FF4**
Panel C: Only NASDAQ Firms with a *Vol*-Adjusted *MAX5* Measure									
Estimate									
***MATURN*1**	1.51	1.79	1.65	1.25	0.77	-0.74	-0.84	-0.76	-0.81
***MATURN*2**	1.73	1.73	1.51	1.45	0.54	-1.19	-1.26	-1.16	-1.22
***MATURN*3**	1.82	1.39	1.38	0.99	0.48	-1.35	-1.40	-1.30	-1.38
***MATURN*4**	1.43	1.49	0.94	0.68	0.08	-1.35	-1.38	-1.38	-1.41
***MATURN*5**	1.37	0.91	0.33	0.09	-0.43	-1.80	-1.82	-1.83	-1.85
5-1						-1.06	-0.99	-1.07	-1.04
***t*-Statistic**									
***MATURN*1**	6.00	6.77	6.14	4.33	2.58	-3.80	-4.33	-3.99	-4.17
***MATURN*2**	5.31	5.48	4.65	4.26	1.56	-5.75	-6.11	-5.72	-5.97
***MATURN*3**	5.12	3.94	3.82	2.83	1.22	-6.33	-6.57	-6.36	-6.68
***MATURN*4**	3.86	3.87	2.45	1.80	0.21	-7.83	-8.00	-7.99	-8.10
***MATURN*5**	3.23	2.13	0.80	0.21	-1.04	-9.11	-9.14	-9.09	-8.99
5-1						-3.90	-3.62	-3.95	-3.76

Table V. Fama–MacBeth Cross-Sectional Regression of Investment Returns

This table shows the Fama–MacBeth (1973) cross-sectional regression results. The variables are constructed at the end of each month. The regression specification is

$$\mathrm{r}_{\mathrm{i,t+1}} = \alpha_t + \beta_{1,t} Vol_{i,t} + \beta_{2,t} MATURN^0_{i,t} \cdot Vol_{i,t} + \beta_{3,t} MAX5_{i,t} + \beta_{4,t} MATURN^0_{i,t} \cdot MAX5_{i,t} + \gamma_t X_{i,t} + u_{i,t+1}$$

where $\mathrm{r}_{\mathrm{i,t+1}}$ is the one-month investment stock return and $X_{i,t}$ is a set of well-known control variables that predict stock return. The variable $MATURN^0$ is the moment-adjusted turnover rate measure ranging from zero to four; *Vol* is the past 12 months' standard second moment of daily stock returns; *Ivol* is the past 12 months' standard idiosyncratic second moment of daily stock returns obtained from the four-factor model; *MAX5* is the average of the five highest daily stock returns during the month; *ME* is the natural logarithms of the value of market equity; *MOM* is the natural logarithm of the cumulative stock return from months $t-12$ to $t-2$; and *BM* is the book-to-market ratio. All coefficient estimates are standardized and the *t*-statistics, in parentheses, are Newey–West (1987) adjusted using 12 lags.

	Vol	***MATURN⁰ · Vol***	***Ivol***	***MATURN⁰ · Ivol***	***MAX5***	***MATURN⁰ · MAX5***	***ME***	***MATURN⁰ · ME***	***MOM***	***BM***	**Adjrsq**
Panel A: Main Period (1962. 7‑2012. 12)											
1	-0.19						-0.38		0.25	0.13	0.046
	(-1.48)						(-6.31)		(2.65)	(1.96)	
2	0.40				-0.84		-0.35		0.15	0.14	0.050
	(2.93)				(-9.10)		(-5.69)		(1.46)	(2.12)	
3	-0.00	-0.27					-0.31		0.26	0.10	0.051
	(-0.02)	(-4.93)					(-5.27)		(2.81)	(1.70)	
4					-0.45	-0.32	-0.41		0.18	0.13	0.047
					(-4.18)	(-5.07)	(-5.15)		(1.60)	(2.16)	
5	0.59	-0.21			-0.80	-0.14	-0.29		0.16	0.12	0.057
	(4.12)	(-2.20)			(-6.75)	(-1.46)	(-4.62)		(1.48)	(2.08)	
6	0.69	-0.39			-0.81	-0.14	-0.46	0.29	0.17	0.10	0.058
	(4.40)	(-3.31)			(-6.59)	(-1.45)	(-6.55)	(7.03)	(1.64)	(1.68)	
7			-0.21				-0.39		0.26	0.13	0.044
			(-1.59)				(-6.63)		(2.67)	(2.07)	
8			0.40		-0.82		-0.34		0.16	0.14	0.048
			(2.97)		(-8.74)		(-5.63)		(1.51)	(2.21)	
9			-0.01	-0.28			-0.33		0.27	0.11	0.050
			(-0.12)	(-4.91)			(-5.59)		(2.82)	(1.78)	
10			0.69	-0.38	-0.79	-0.13	-0.45	0.29	0.17	0.11	0.057
			(4.33)	(-3.57)	(-6.29)	(-1.40)	(-6.56)	(7.51)	(1.67)	(1.76)	

	Vol	*MATURN*^{0} · *Vol*	*Ivol*	*MATURN*^{0} · *Ivol*	*MAX5*	*MATURN*^{0} · *MAX5*	*ME*	*MATURN*^{0} · *ME*	*MOM*	*BM*	Adjrsq
Panel B: Period Including NASDAQ Firms (1983.11-2012. 12)											
All	0.38	-0.30			-0.35	-0.42	-0.45	0.40	0.08	0.14	0.038
	(2.86)	(-3.30)			(-3.45)	(-4.14)	(-4.80)	(8.01)	(0.49)	(2.21)	
NYSE+ AMEX	0.47	-0.50			-0.43	-0.07	-0.23	0.32	0.10	0.07	0.049
	(3.53)	(-4.31)			(-4.00)	(-0.64)	(-2.86)	(6.33)	(0.55)	(1.63)	
NASDAQ	0.36	-0.32			-0.36	-0.56	-0.77	0.67	0.14	0.17	0.038
	(2.55)	(-3.11)			(-2.93)	(-4.38)	(-6.08)	(7.55)	(0.99)	(2.10)	
Panel C: Other Performance Estimation Periods											
Three months	1.05	-1.19			-1.00	-0.22	-1.02	0.66	0.61	0.39	0.070
	(2.26)	(-4.06)			(-7.31)	(-1.23)	(-5.21)	(6.37)	(2.14)	(2.36)	
Six months	1.43	-2.20			-1.00	-0.24	-1.78	1.06	0.93	0.97	0.070
	(1.55)	(-4.19)			(-5.61)	(-1.03)	(-4.36)	(5.07)	(1.67)	(3.25)	
Nine months	1.84	-3.08			-0.92	-0.38	-2.52	1.41	0.92	1.51	0.069
	(1.37)	(-3.96)			(-3.89)	(-1.36)	(-3.96)	(4.30)	(1.26)	(3.63)	
Twelve months	2.32	-3.93			-0.97	-0.38	-3.31	1.77	0.68	1.99	0.067
	(1.32)	(-3.95)			(-2.99)	(-1.09)	(-3.81)	(4.13)	(0.80)	(3.59)	

Table VI. Fama–MacBeth Cross-Sectional Regression of Contemporaneous Turnover Rates

This table shows the Fama–MacBeth (1973) cross-sectional regression results for NYSE and AMEX firms. The variables are constructed at the end of each month. The regression specification is

$$Turnover_{i,t} = \alpha_t + \beta_{1,t}Vol_{i,t} + \beta_{2,t}Skew_{i,t} + \beta_{3,t}Ret_{i,t} + \gamma_t X_{i,t-12} + u_{i,t}$$

where $X_{i,t}$ is a set of control variables that can predict turnover rate. The variable *Turnover* is the past 12 months' daily average stock turnover rate; *Vol* and *Skew* are the past 12 months' standard second and third moments of daily stock returns, respectively; *Ret* is the past 12 months' cumulative stock return; *Amihud* is the past 12 months' Amihud (2002) measure; *ME* is the natural logarithms of the value of market equity; *BM* is the book-to-market ratio; *Age* is the natural logarithms of the number of months since listing; *Lever* is book debt divided by total assets; *Anal* is the natural logarithms of one plus the number of analysts following; and *Disp* is forecast dispersion defined as standard deviation of earnings per share. All coefficient estimates are standardized and the *t*-statistics are Newey–West (1987) adjusted using 12 lags.

	Vol	*Skew*	*Ret*	*Amihud*	*ME*	*BM*	*Age*	*Lever*	*Anal*	*Disp*	**Adjrsq**
Panel A: NYSE and AMEX (1984. 1-2012. 12)											
1	0.155			-0.070	-0.042	-0.003	0.003	0.011	0.116	0.046	0.255
	(7.29)			(-12.32)	(-5.14)	(-0.72)	(0.88)	(2.55)	(5.92)	(2.56)	
2		-0.009		-0.084	-0.114	-0.009	-0.016	0.016	0.145	0.140	0.161
		(-3.14)		(-11.77)	(-9.62)	(-1.75)	(-4.29)	(3.35)	(6.20)	(5.54)	
3	0.157	-0.018		-0.070	-0.043	-0.003	0.004	0.012	0.116	0.047	0.257
	(7.31)	(-2.92)		(-12.26)	(-5.30)	(-0.70)	(0.96)	(2.64)	(5.94)	(2.63)	
4	0.159	-0.021	0.011	-0.069	-0.043	-0.003	0.005	0.012	0.115	0.046	0.262
	(7.42)	(-3.29)	(3.16)	(-12.27)	(-5.36)	(-0.65)	(1.14)	(2.71)	(5.92)	(2.58)	
Panel B: NASDAQ (1985. 1-2012. 12)											
1	0.231			-0.158	0.084	-0.049	-0.048	-0.008	0.245	0.052	0.316
	(8.31)			(-7.84)	(5.31)	(-6.28)	(-4.30)	(-1.07)	(12.57)	(1.76)	
2		-0.001		-0.210	-0.006	-0.083	-0.092	-0.011	0.277	0.164	0.260
		(-0.10)		(-5.20)	(-0.39)	(-6.89)	(-6.82)	(-1.30)	(12.93)	(3.43)	
3	0.237	-0.027		-0.158	0.082	-0.048	-0.047	-0.008	0.245	0.052	0.317
	(8.57)	(-5.92)		(-7.81)	(5.18)	(-6.25)	(-4.21)	(-1.04)	(12.59)	(1.79)	
4	0.240	-0.031	0.014	-0.158	0.083	-0.046	-0.045	-0.007	0.243	0.050	0.321
	(8.78)	(-6.26)	(1.53)	(-7.83)	(5.29)	(-6.14)	(-4.16)	(-0.95)	(12.50)	(1.73)	

Table VII. MATURN and Speculative Stock Performance with Regard to Investor Sentiment

This table shows the one-month investment returns of 5×5 portfolios subsequently sorted by *MATURN* and *Vol*. The portfolios are constructed at the end of each month. The sample period is from July 1962 to December 2010. It is divided into two separate periods according to whether the Baker–Wurgler (2007) sentiment level index in the portfolio formation month was above its time-series median or not. The variable *MATURN* is the moment-adjusted turnover rate measure as defined in the Section IV and *Vol* is the past 12 months' standard second moment of daily stock returns. Only long–short returns are shown here, for simplicity.

	Estimate				*t*-Statistic			
	Raw	**CAPM**	**FF3**	**FF4**	**Raw**	**CAPM**	**FF3**	**FF4**
Long–Short Strategy Returns When the Sentiment Level Index Was above the Median								
***MATURN*1**	0.18	0.04	0.14	0.39	0.42	0.09	0.38	1.06
***MATURN*2**	-0.28	-0.46	-0.22	0.10	-0.52	-0.95	-0.55	0.25
***MATURN*3**	-0.70	-0.91	-0.57	-0.12	-1.20	-1.71	-1.36	-0.29
***MATURN*4**	-1.50	-1.75	-1.30	-0.89	-2.56	-3.37	-3.41	-2.38
***MATURN*5**	-2.38	-2.65	-2.10	-1.54	-3.84	-4.86	-5.25	-4.05
5-1	-2.56	-2.68	-2.24	-1.93	-6.51	-7.22	-6.83	-5.93
Long–Short Strategy Returns When the Sentiment Level Index Was below the Median								
***MATURN*1**	2.05	1.71	1.00	1.19	4.43	3.84	2.87	3.38
***MATURN*2**	2.05	1.64	0.94	1.28	4.20	3.57	2.71	3.73
***MATURN*3**	1.94	1.47	0.70	1.03	3.73	3.04	1.96	2.89
***MATURN*4**	1.22	0.71	-0.04	0.33	2.39	1.52	-0.11	1.02
***MATURN*5**	0.00	-0.56	-1.22	-0.77	0.00	-1.15	-3.07	-2.01
5-1	-2.05	-2.27	-2.21	-1.96	-5.51	-6.23	-6.03	-5.32

Table VIII. Preference for Speculative Stocks with Regard to Investor Sentiment

This table shows the result for the time-series regression of long–short returns, from buying the highest-*Vol* portfolio and selling the lowest-*Vol* portfolio within each *MATURN* portfolio, on investor sentiment level and change indexes. The variables are constructed at the end of each month. The sample period is from July 1962 to December 2010. The regression equation is

$$r_{t+1}^{long} - r_{t+1}^{short} = \alpha + d_1 SENT_t^{level} + d_2 SENT_t^{change} + \gamma X_t + u_{t+1}$$

where $SENT_t^{level}$ and $SENT_t^{change}$ are the sentiment level index and sentiment change index, respectively, of Baker and Wurgler (2007); X_t is the set of controlling factors from the CAPM, Fama–French three-factor model, and the Carhart's four-factor model. *MATURN* is the moment-adjusted turnover rate measure as defined in the Section IV and *Vol* is the past 12 months' standard second moment of daily stock returns. All coefficient estimates are standardized. The table only shows the results for d_1 and d_2 for simplicity.

	No Control		**CAPM**		**FF3**		**FF4**	
	d_1	d_2	d_1	d_2	d_1	d_2	d_1	d_2
Regression Coefficients of the Sentiment Indexes on Long–Short Strategy Returns								
***MATURN*1**	-1.10	0.99	-0.93	0.99	-0.62	1.11	-0.61	1.15
	(-3.44)	(3.11)	(-3.09)	(3.31)	(-2.48)	(4.47)	(-2.46)	(4.69)
***MATURN*2**	-1.21	0.73	-1.00	0.73	-0.59	0.93	-0.56	0.98
	(-3.33)	(2.00)	(-2.96)	(2.16)	(-2.19)	(3.50)	(-2.18)	(3.82)
***MATURN*3**	-1.36	0.68	-1.12	0.67	-0.66	0.90	-0.64	0.97
	(-3.45)	(1.71)	(-3.08)	(1.86)	(-2.33)	(3.20)	(-2.33)	(3.57)
***MATURN*4**	-1.54	0.33	-1.27	0.33	-0.80	0.58	-0.77	0.65
	(-3.93)	(0.85)	(-3.62)	(0.95)	(-3.01)	(2.21)	(-3.05)	(2.57)
***MATURN*5**	-1.53	0.03	-1.23	0.03	-0.76	0.30	-0.73	0.38
	(-3.68)	(0.07)	(-3.34)	(0.08)	(-2.60)	(1.02)	(-2.65)	(1.40)
5-1	-0.43	-0.96	-0.30	-0.96	-0.14	-0.82	-0.12	-0.77
	(-1.57)	(-3.55)	(-1.15)	(-3.73)	(-0.56)	(-3.35)	(-0.50)	(-3.24)

Figure 1: Effect of Stock Return Volatility, Controlling for Skewness

For the stock price process and transaction cost parameters, we set initial values $\mu = 0.09, k_s = 0.01$, and $k_p = 0.01$. Then we set the parametric values of the modified TK utility function: $\lambda = 1.5, \alpha_G = 0.5$, and $\alpha_L = 4.0$. The parameter σ varies from 0.2 to 0.7, while both f and j are fixed at zero. The upper left and right graphs show the standard second and third moments of stock returns, respectively. The bottom left graph shows the equivalent mean lines along which an investor has the same amount of utility. The bottom right graph shows the turnover rates estimated from 300,000 simulation runs.

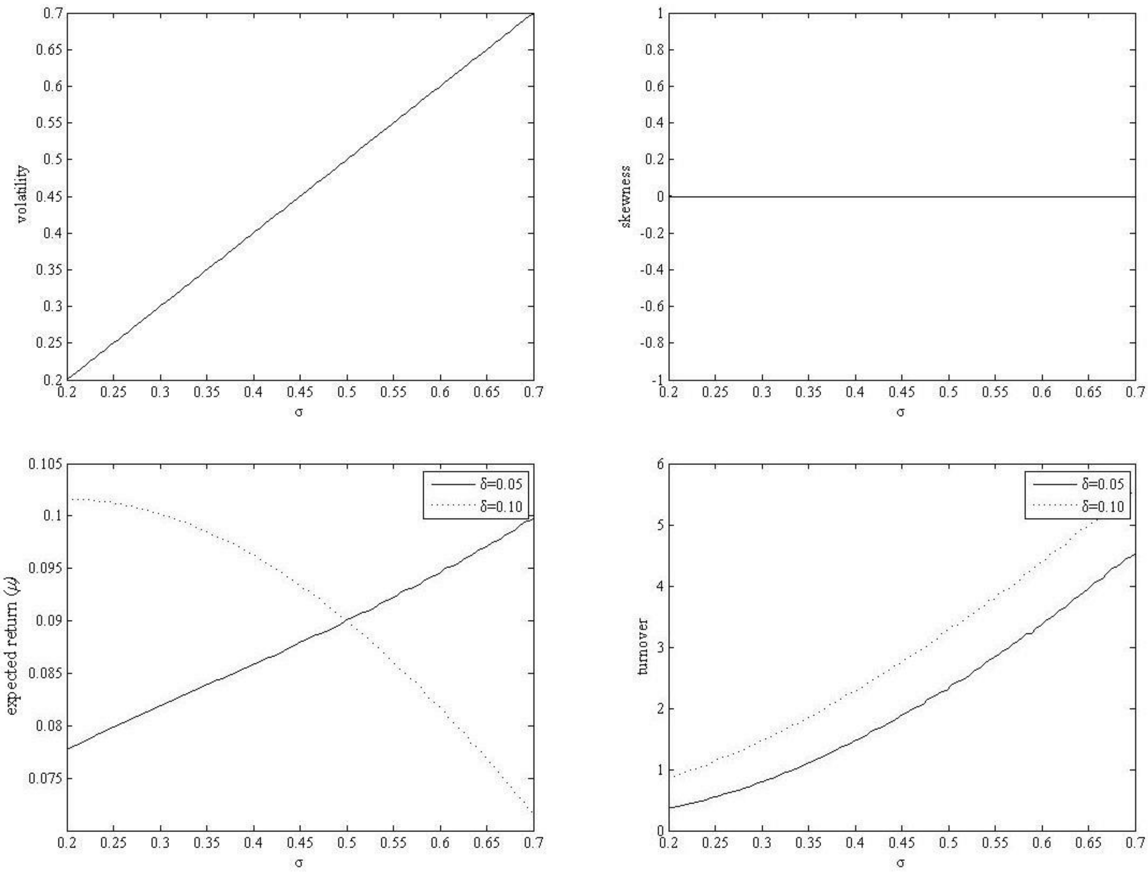


Figure 2: Effect of Skewness of Stock Returns, Controlling for Volatility

For the stock price process and transaction cost parameters, we set the initial values $\mu = 0.09, k_s = 0.01$, and $k_p = 0.01$. Then we set the parametric values of the modified TK utility function: $\lambda = 1.5, \alpha_G = 0.5$, and $\alpha_L = 4.0$. While f is fixed at one, j varies from -0.4 to 0.4. At the same time, σ is adjusted for each j following the equation $\sigma = \sqrt{0.5^2 - f \cdot j^2}$, so that the standard second moment of stock returns is fixed at 0.5. The upper left and right graphs show the standard second and third moments of stock returns, respectively. The bottom left graph shows the equivalent mean lines along which an investor has the same amount of utility. The bottom right graph shows the turnover rates estimated from 300,000 simulation runs.

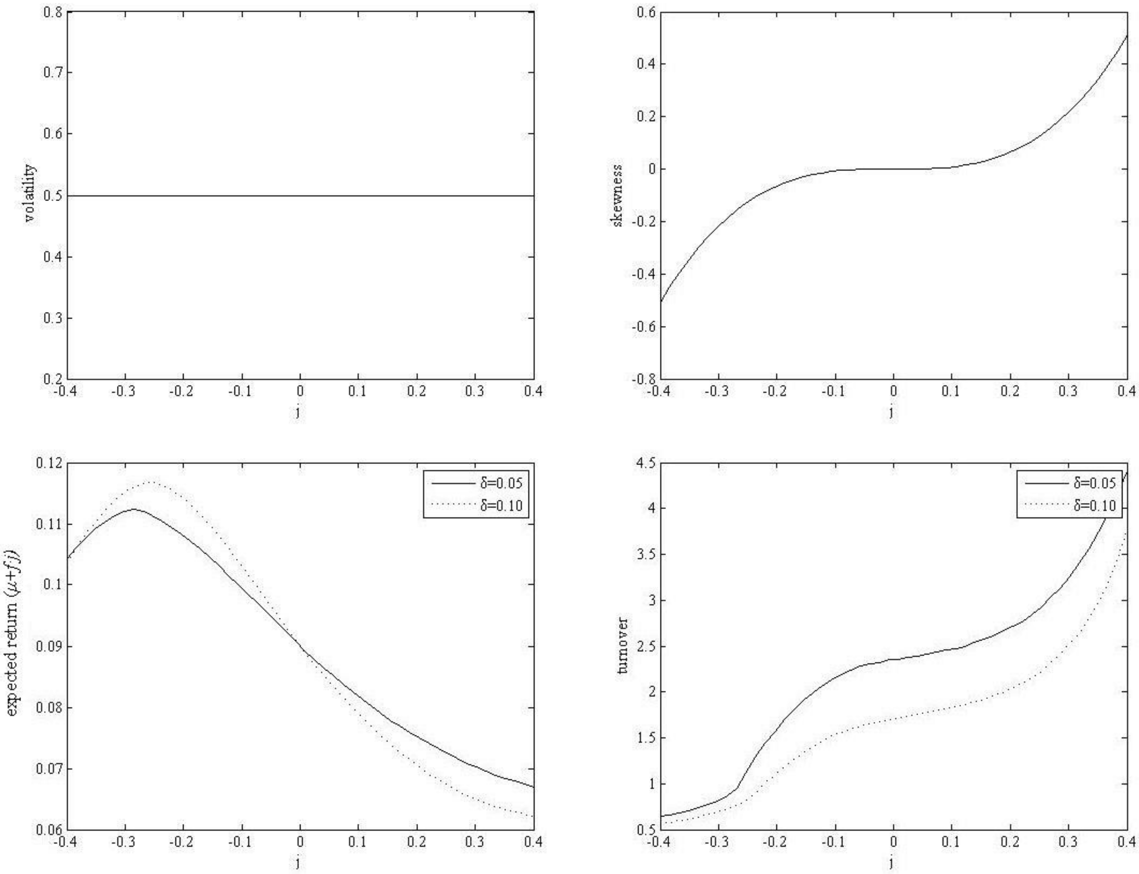
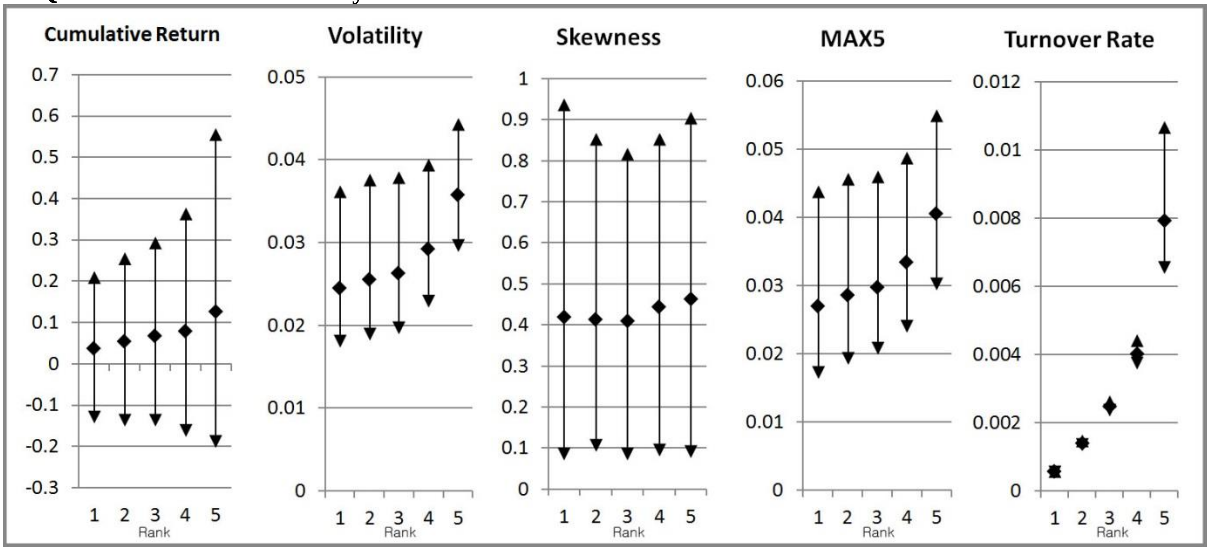


Figure 3: Variations of Characteristics in the Portfolios Sorted by *Turnover* and *MATURN*

This graph shows the variations of *Ret*, *Vol*, *Skew*, *MAX5*, and *Turnover* of for the quintile portfolios sorted by *Turnover* and *MATURN*, respectively. The portfolios are constructed at the end of each month. The sample period is from July 1962 to December 2012. The variable *Turnover* is the past 12 months' daily average stock turnover rate; *MATURN* is the moment-adjusted turnover rate measure as defined in the Section IV; *Vol* and *Skew* are the past 12 months' standard second and third moments of daily stock returns, respectively; and *MAX5* is the average of the five highest daily stock returns during the month. The upward and downward arrows denote the 25th and 75th percentiles, respectively. The points between them denote their medians.

A: Quintile Portfolios Sorted by *Turnover*



B: Quintile Portfolios Sorted by *MATURN*

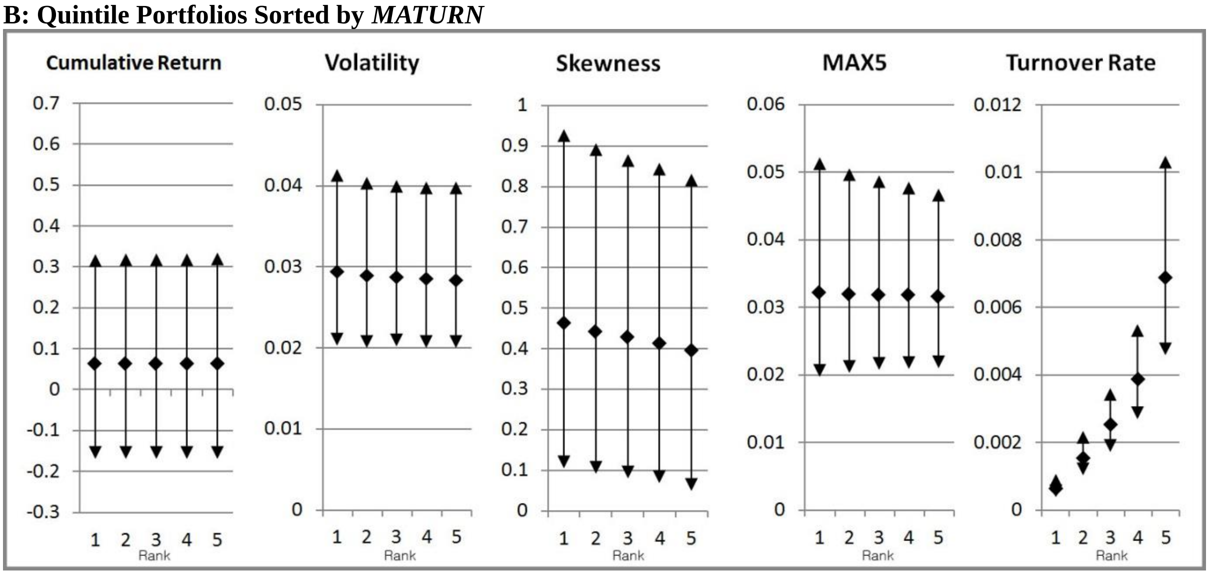


Figure 4: Skewness Preference

This figure shows the value of *Less10* and *Less10 t-stat* from Table III in graphical form. Those line and bars denote *Less10* and *Less10 t-stat*, respectively. The horizontal axis denotes the *Vol*-adjusted *MAX5* ranking. The left vertical axis denotes *Less10* and the right axis denotes *Less10 t-stat*.

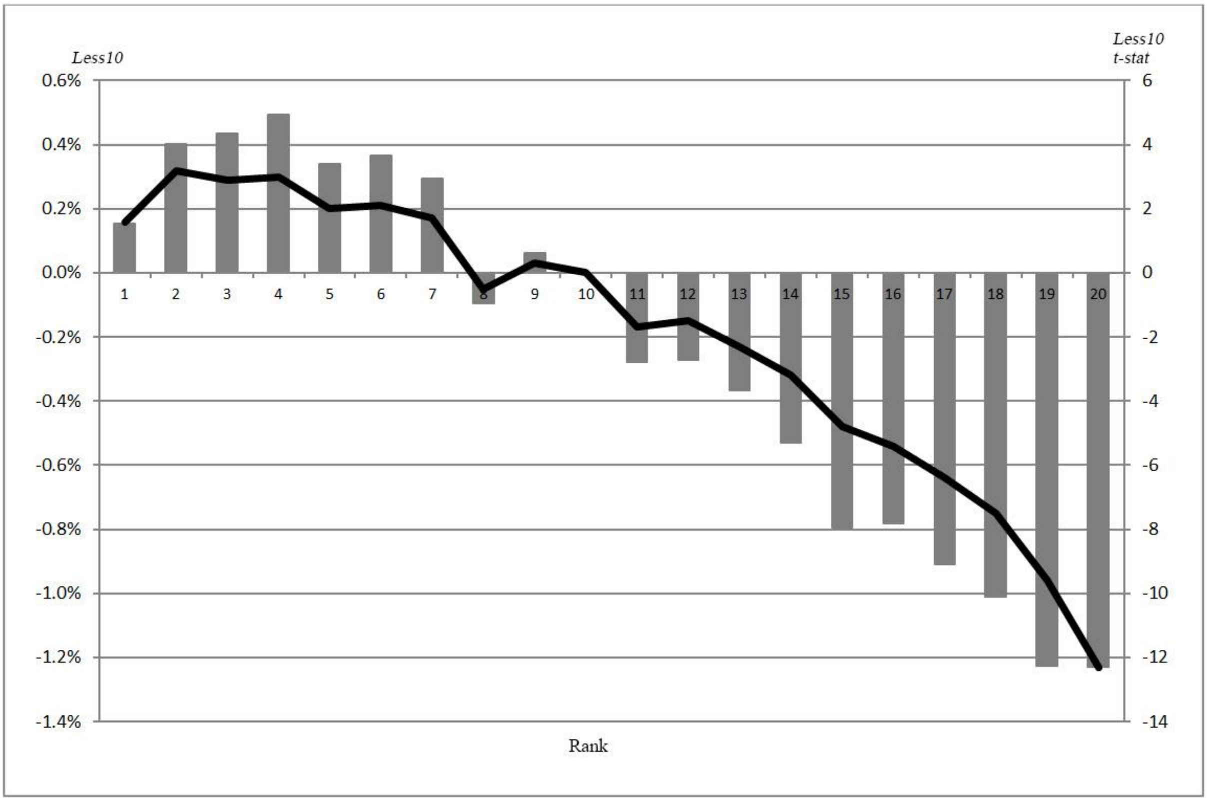
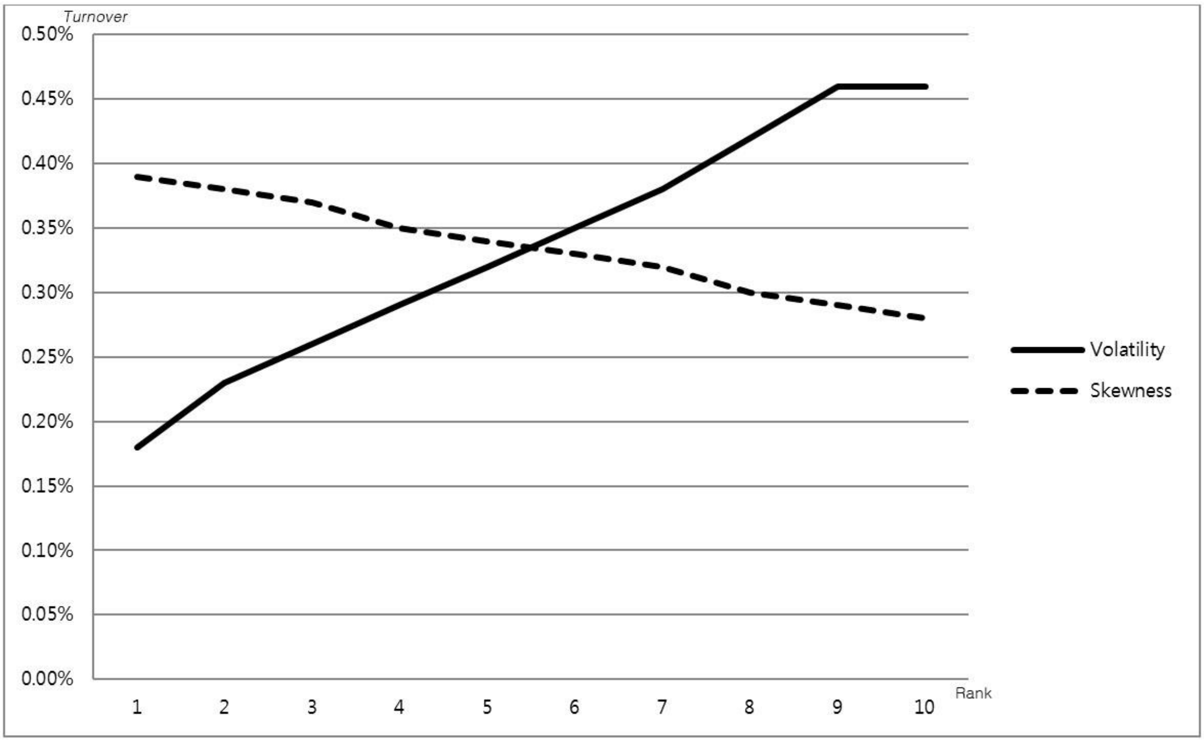


Figure 5: Volatility and Skewness Effects on Contemporaneous Turnover Rates

This graph shows the amount of *Turnover* for each decile portfolio by *Skew*-adjusted *Vol* and *Vol*-adjusted *Skew*. The sample is restricted to NYSE and AMEX firms. The portfolios are constructed at the end of each month. The sample period is from July 1962 to December 2012. The variable *Turnover* is the past 12 months' daily average stock turnover rate and *Vol* and *Skew* are the past 12 months' standard second and third moments of daily stock returns, respectively. The *Skew*-adjusted *Vol* measure is obtained from 10×10 subsequent double-sorting method with *Skew* and *Vol; Vol*-adjusted *Skew* is obtained from 10×10 subsequent double-sorting method with *Vol* and *Skew*. The solid line denotes *Turnover* of *Skew*-adjusted *Vol* portfolios and the dashed line denotes that of *Vol*-adjusted *Skew* portfolios. The horizontal axis represents the ranks of the decile portfolios; the vertical axis represents *Turnover*.



References

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

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Atkins, Allen B., and Edward A. Dyl, 1997, Market structure and reported trading volume: Nasdaq versus the nyse, *Journal of Financial Research* 20, 291–304.

Baker, Malcolm, and Jeremy C. Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271–299.

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

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–152.

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.

Barberis, Nicholas, and Wei Xiong, 2012, Realization utility, *Journal of Financial Economics* 104, 251–271.

Boyer, Brian, Todd Mitton, and Keith Vorkink, 2010, Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169–202.

Brunnermeier, Markus K., Christian Gollier, and Jonathan A. Parker, 2007, Optimal beliefs, asset prices, and the preference for skewed returns, *American Economic Review* 97, 159–165.

Brunnermeier, Markus K., and Jonathan A. Parker, 2005, Optimal expectations, *American Economic Review* 95, 1092–1118.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chordia, Tarun, Sahn-Wook Huh, and Avanidhar Subramanyam, 2007, The cross-section of expected trading activity, *Review of Financial Studies* 20, 709–740.

Conrad, Jennifer, Robert F. Dittmar, and Eric Ghysels, 2013, Ex ante skewness and expected stock returns, *Journal of Finance* 68, 85–124.

Dorn, Daniel, and Paul Sengmueller, 2009, Trading as entertainment? *Management Science* 55, 591–603.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Grinblatt, Mark, and Matti Keloharju, 2009, Sensation seeking, overconfidence, and trading activity, *Journal of Finance* 64, 549–578.

Han, Bing, and Alok Kumar, 2013, Speculative retail trading and asset prices, *Journal of Financial and Quantitative Analysis* 48, 1–53.

Ingersoll, Jonathan E., and Lawrence J. Jin, 2013, Realization utility with reference-dependent preferences, *Review of Financial Studies* 26, 723–767.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Kumar, Alok, 2009, Who gambles in the stock market? *Journal of Finance* 64, 1889–1933.

Lo, Andrew W., and Jiang Wang, 2000, Trading volume: Definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 13, 257–300.

Mitton, Todd, and Keith Vorkink, 2007, Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20, 1255–1288.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Odean, Terrance, 1998, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775–1798.

Piotroski, Joseph D, 2000, Value investing: The use of historical financial statement information to separate winners from losers, *Journal of Accounting Research* 1–41.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777–790.

Tversky, Amos, and Daniel Kahneman, 1992, Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297–323.