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Empirical Applications of Entropy-based Inference

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An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
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Abstract

Empirical Applications of Entropy-based Inference
By Yifeng Zhu

In the first chapter, I first propose two types of asymmetry measures which based on the tail distribution of the data instead of just the third moment-skewness for stock returns. With these new measures, greater tail asymmetries imply lower average returns in the cross section. In contrast, the relation between the skewness and the expected return is conditional. Then I discuss the relationship between asymmetries and several benchmark anomalies. Size and liquidity effects only appear among low upside asymmetry stocks, while momentum effect is getting stronger when upside asymmetry is increasing.

In the second chapter, we examine the potential effect of naturalization on the U.S. immigrants' earnings. We find the earning gap between naturalized citizens and non-citizens is positive over many years, with a tent shape across the wage distribution. We focus on a normalized metric entropy measure of the gap between distributions, and compare with conventional measures at the mean, median and other quantiles. In addition, we further examine the potential sources of the earning gap, the "wage structure" effect and the "composition" effect. Both of these sources contribute to the gap, but the composition effect, while diminishing somewhat after 2005, accounts for about 3/4 of the gap. The unconditional quantile regression and conditional quantile regressions confirm that naturalized citizens have generally higher wages, although the gap varies for different income groups.

In the last chapter, I propose linear and nonparametric models to predict crude oil price. Mainly, my forecast depends on three predictor variables, the change in crude oil inventories, its previous prices and product spread. By employing mean-squared prediction error (MSPE) and stochastic dominance (SD) tests, I find that the prediction result of our nonparametric models is significantly better than the random walk model, while the corresponding linear models' performance is better than the random walk model only for longer horizon forecasts (one to two years). And for the nonparametric model including all three predictors, I document MSPE reduction as high as 62.6% compared to the random walk model and the directional accuracy ratio as high as 77.5% at the two years horizon.

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Preface

The dissertation consists of three essays, which demonstrate the empirical applications of the entropy-based inference in asset pricing, labor economics, and time series forecasting .

Flexible Evaluative Functions (EFs) that account for different outcomes at different parts of the earnings distribution provide better support for functionals that go beyond the mean, median, and any single quantile, or merely reporting a set of quantiles. The classical literature on ideal measures of inequality provides the relevant backdrop and guidance. This literature identifies Entropy measure as “ideal” distribution functions.[1] As argued in Maasoumi and Wang (2015), the “gap” between two distribution is conveniently seen as the distance between the entropies (inequality measures) of the relevant distributions. When “metricness” is further required for distance functions (rather than mere divergence), a metric entropy member of the generalized entropy family emerges which is a normalization of the Bhattacharya-Matusita-Hellinger measure proposed by Granger, Maasoumi, and Racine (2004). Other entropy measures can be employed with qualitatively consistent results. But only a metric measure that satisfies the triangularity rule may support coherent statements about respective ”distances” amongst three or more distributions.

Besides the metric property, this relative entropy measure also possess several other properties: 1) it can be applied to discrete and continuous variables; 2) if the two distribution are equal, then entropy measure is 0, and lies between 0 and 1 as it is normalized; 3) it is invariant under continuous and strictly increasing transformation on the underlying variables; and 4) it is dimensionless, accommodating multivariable assessments. One dimension version is applied in my first two essays, and the two dimension version is used in the third essay.

The first essay answers an important question in empirical asset pricing, whether asymmetry can explain the stock expected returns. In finance theory, Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008), and Han and Hirshleifer (2015) point out that greater upside asymmetry should be associated with lower expected return.

[1] A brief review of the issues is given in Maasoumi and Wang (2015).

My two new asymmetry measures are based on the tail distribution of the data instead of the just third moment-skewness. The first asymmetry measure is based on the difference of probabilities of upside gains and downside risk of a stock. The second measure is based on entropy which is adapted from the Bhattacharya-Matusita-Hellinger distance measure, as implemented in Granger, Maasoumi, and Racine (2004). Mathematically, they can capture asymmetry induced by other moments. Statistically, through simulations, they can capture asymmetry more accurately than skewness. Economically, by using these two asymmetry measures, the relationship between upside asymmetry and the expected return is significantly negative in the cross section. Thus this empirical result supports the theoretical prediction in Barberis and Huang (2008), and Han and Hirshleifer (2015). However, the empirical result based on skewness is inconclusive in the stock level.

In the essay, I also examine the relation between asymmetry and return conditional on sentiment, VIX, aggregate stock market liquidity, and capital gains overhang, respectively. Skewness is only negatively significantly related to expected return during high sentiment, or during low aggregate stock market liquidity periods, or during high VIX periods, or for firms whose representative investors experienced capital losses. In contrast, the newly proposed upside asymmetry proxies are unconditionally negatively related with expected returns.

I further examine the relationship between asymmetries and several benchmark anomalies: size, momentum, and liquidity. The effect of these benchmark anomalies varies for different asymmetry levels. Size and liquidity effects only exist for low upside asymmetry stocks, while momentum effect only appears for high upside asymmetry stocks. Based on the findings, return asymmetry is a new source of mentioned benchmark anomalies, since anomalies' effects could be partially explained by return asymmetry.

In the first essay, entropy measure used to capture asymmetry information, as it can be treated as the "representative" difference between two distributions (the original one and the rotated one). While in second essay, entropy measure represents the general earning difference between two groups of people.

Specifically, we examine the potential effect of naturalization on the U.S. immigrants' earnings in the second essay. We find the earning gap between naturalized citizens and non-citizens is positive based on entropy and other conventional measures. The earning gap has a generally stable tent shape. Previous research on wage differentials is often based on certain distribution functions such as means and medians. Sumption and Flamm (2012) reports 50% to 70% gap for the median annual incomes during the period 1993-2010. However, the differences at some focal parts of the earnings distribution (mean, median or any percentile) may not be "representative" and may not aggregate well. In contrast, we report a normalized entropy measure of the entire distribution gap, and conventional measures at the mean, median and other quantile. In addition, naturalized citizen earnings (at least) second order stochastically dominate non-citizen earnings in many of the recent years. We construct two counterfactual distributions to further examine the potential sources of the earning gap, the "wage structure" effect and the "composition effect". Both of these sources contribute to the whole earning gap, but the composition effect, while diminishing somewhat after 2005, accounts for about 3/4 of the gap.

This work further examines the effect of changing the proportion of naturalization on the τth quantile of the unconditional distribution of log wages. This kind of analysis follows method-unconditional quantile regression that have been developed only recently, such as in Firpo, Fortin, and Lemieux (2009). The approach consists of running a regression of the Recentered Influence Function (RIF) of the unconditional quantile on desired explanatory variables. For each year from 1994 to 2012, we discover a tent shape for the citizenship effect, implying that this effect is different for different levels of income, and is highest between the median and the 75-th percentile . For comparison, we also implement the traditional conditional quantile regressions (see Koenker and Bassett Jr, 1978; Koenker, 2005).[2] The findings from different methods provide a robustness check, and generally agree that citizenship is generally associated with higher earnings, although the magnitudes are

[2]The conditional quantile regression coefficient can be interpreted as the marginal effect of citizenship ratio at the τth quantile of the conditional distribution of log wages. Our unconditional quantile approach, following Firpo, Fortin, and Lemieux (2009), provides the marginal effect on the unconditional τth quantile, averaged over conditioning sets.

varied for different income groups. Most of the previous studies on the earning gap between naturalized citizens and non-citizens place "citizenship" as an explanatory variable in a Mincer type earnings regression. These results focus on the coefficient of the citizenship variable in the conditional mean. By contrast, we are interested in possible heterogeneous effect of citizenship at different quantiles.

Entropy is also a measure of dependence, it is better in detecting dependence structure than traditional moment-based measures as it is a function of infinite moments of the underlying probability density function (PDF). The traditional loss functions like mean-squared prediction error (MSPE) can only capture the first and second moments. Thus I apply it to compare the predictability between models besides MSPE and directional accuracy ratio (DAR) in the third essay for crude oil price forecasting.

In the third essay, I propose linear and nonparametric models to predict one month, three months, six months, one year, eighteen months and two years ahead crude oil price. My forecasts mainly depend on three predictor variables: the change in crude oil inventories, previous prices and product spread. In general, for the sample period from 1995.1 to 2015.4, the model applying nonparametric estimation outperforms all other models in different horizon forecasting based on mean-squared prediction error (MSPE) and directional accuracy ratio. Except the linear 3 month ahead models, by employing the entropy method, I find that all models introduced in the essay have predictability. At the two years horizon, when applying the nonparametric model with all three predictors, MSPE reduction is as high as 62.5% compared to the random walk model. Directional accuracy ratio is 77.5%. It is among the best in the recent literature.[3] Furthermore, the results from Stochastic Dominance (SD) tests (Reference papers are Corradi and Swanson, 2013; Linton, Maasoumi, and Whang, 2005; and Donald and Hsu, 2014)suggest only employing nonparametric models instead of all others for different horizons forecasting.

In general, entropy method can capture information of the the whole distributions, thus

[3]For parametric models considered in the existing literature, (see, e.g., Alquist, Kilian, and Vigfusson, 2013; Baumeister and Kilian, 2015; Baumeister, Kilian, and Lee, 2014; Baumeister, Kilian, and Zhou, 2015; Baumeister and Kilian, 2014a,b).

it is more comprehensive than other quantiles measures of inequality.

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Chapter 1

Stock Return Asymmetry and Anomalies

Abstract

In this paper, we first propose two types of asymmetry measures which based on the tail distribution of the data instead of just the third moment-skewness for stock returns. With our new measures, greater tail asymmetries imply lower average returns in the cross section. In contrast, the relation between the skewness and the expected return is conditional on sentiment, VIX, aggregate stock market liquidity (ALIQ), and capital gains overhang (CGO). Then we discuss the relationship between asymmetries and several benchmark anomalies. Size and liquidity effects only appear among low upside asymmetry stocks, while momentum effect is getting stronger when upside asymmetry is increasing. These anomalies' effects could be partially explained by return asymmetry.

Keywords: Asymmetry, entropy, asset pricing, anomalies.

JEL Classification: G11, G17, G12

1.1 Introduction

Theoretically, Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008), and Han and Hirshleifer (2015) show that greater upside asymmetry is associated with lower expected return. Empirically, using skewness, the most popular measure of asymmetry, Harvey and Siddique (2000), Zhang (2005), Smith (2007), Boyer, Mitton, and Vorkink (2010), and Kumar (2009) find empirical evidence supporting the theory. However, Bali, Cakici, and Whitelaw (2011) recently find that the realized skewness is in fact not statistically significant in explaining the expected return in stock level.

In this paper, we propose two distribution-based measures of asymmetry. We argue that the inconclusive results based on skewness is likely due to its limited ability to measure asymmetry because it relies only on the third moment of the return distribution. In contrast, the new measures of asymmetry are based on entire tail distribution of the return that can capture the asymmetry in all the moments beyond the third. The first measure we propose is a simple difference between the upside probability and downside probability, which captures the degree of upside asymmetry based on probability difference. The second measure is a modified metric entropy measure proposed by Racine and Maasoumi (2007), assessing asymmetry based on integrated density difference. Statistically, we show via simulations that our distribution-based measures can capture asymmetry more accurately than the moment-based skewness measure.

Empirically, we examine the explanatory power of realized skewness and our new asymmetry measures in the cross-section of stock returns. We use two approaches. In the first approach, we study their performances in explaining the returns using Fama and MacBeth (1973) regressions. We find that, using data from January 1962 to December 2013, there is no apparent relation between the realized or expected skewness and the cross-sectional average returns. Our result is consistent with Bali, Cakici, and Whitelaw (2011). Since skewness is based on the third moment only, the inability of the skewness in explaining the returns may not necessarily mean asymmetry does not matter. It may simply indicate that the skewness measure is not sufficient in measuring asymmetry. Indeed, based on our new measures, we find that tail asymmetry does matter in explaining the cross-sectional variation of stock returns. The greater upside tail asymmetry, the lower the average returns. In the second approach, we sort stocks into decile portfolios of high and low asymmetry with respect to skewness or to our new asymmetry measures, respectively. We find again that while high skewness portfolios do not necessarily imply low returns, high upside asymmetries based on the new measures do associate with low returns.

Our empirical findings support the theoretical predictions of Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008), and Han and Hirshleifer (2015). Intuitively, our measures reflect investor's preference of upside asymmetry, or aversion to the downside asymmetry. Moreover, they also reflect the degree of short sale constraints on stocks. The more difficult the short sell, the more the distribution of the stock return is likely to lean towards the upper tail. This is also related to strategic timing of information by firm managers [Acharya, DeMarzo, and Kremer (2011)]. Both reasons indicate that the greater the upper tail asymmetry, the lower the expected return due to the likely overpricing of the stock [see Acharya, DeMarzo, and Kremer (2011); and Jones and Lamont (2002)].

In this paper, we also examine the correlation between asymmetry and return conditional on sentiment, VIX, ALIQ, and CGO, respectively. We find that skewness is only negatively significant related to the stock expected return during high sentiment periods (when sentiment is above the 0.5 or 1 standard deviation of the sentiment time series), or during low aggregate stock market liquidity periods (when liquidity is below the mean of the liquidity time series), or during high VIX periods (when VIX is above the mean of the VIX time series) or for firms whose representative investors experienced capital losses. The results are robust to alternative skewness measures: the total skewness, the idiosyncratic skewness and their expected counterparts. In contrast, using our measures, the expected returns are unconditionally negative for lottery-type stocks. The results are consistent with the theory that preference for upside asymmetry can be induced from the over-weighting of very low probability events [Tversky and Kahneman (1992); Polkovnichenko (2005); Barberis and Huang (2008)]. For sentiment, Baker and Wurgler (2006) point out firms which are difficult to arbitrage should be more overvalued during high sentiment periods. High skewness firms can still face high arbitrage risk, which are difficult to arbitrage, then the evaluation of them are largely impacted by sentiment. However, high upside asymmetry stock does not necessary associate with arbitrage risk, it should be less influenced by sentiment. Our conditional result on sentiment is consistent with Baker and Wurgler (2006)'s theory. Stambaugh, Yu, and Yuan (2012, 2015) consider impediments to short selling as the major obstacle to eliminating sentiment-driven mispricing. To the extent such mispricing exists, overpricing should then be more prevalent than underpricing, and overpricing should be more prevalent when market-wide sentiment is high. For ALIQ, as pointed out by Pastor, Stambaugh, and Taylor (2014), it is also a proxy for mispricing besides the investor sentiment in the stock market. The empirical evidence that the negative relationship between skewness and expected returns is only observed during the low liquidity periods is consistent with Pastor, Stambaugh, and Taylor (2014)'s suggestion, firms are more mispriced during the low liquidity periods. For CGO, Wang, Yan, and Yu (2014) find that among stocks where average investors face prior losses, there could be a negative risk-return relation. And recently, An et al. (2015) document that the skewness preference only holds for capital loss stocks. As we mentioned before, high skewness stocks can still associate with high arbitrage risk, thus its negative relationship with expected return exist among stocks with capital loss which consistent with by Wang, Yan, and Yu (2014)'s argument. But high upside asymmetry stock does not necessary associate with high risk, thus its relationship with expected return is less affect by CGO level.

At last, we examine the relationship between asymmetry and several benchmark anomalies, size, momentum, and illiquidity. There could be two reasons that these benchmark anomalies exist. First, efficient market hypothesis is wrong; second, we haven't consider about upside asymmetry. We find that these anomalies' effects could be partially explained by return asymmetry. Since mutual fund managers mainly use these anomalies as the investment style, they are crucial. We find that these anomalies' performances are conditional on asymmetry levels. For low upside asymmetry stocks, small or illiquidity firms are associated with high future returns, even after adjusted for Carhart-4 factors, but momentum effect is marginal, and even disappeared after adjusted for Carhart-4 factors. In contrast, for high upside asymmetry stocks, size and illiquidity effect disappear; while momentum effect is even more stronger.

The paper is organized as follows. Section 2 presents our new asymmetry measures. Section 3 provides simulations to gain insights on differences between skewness and our new asymmetry measures. Section 4 reports the empirical results for asymmetry proxies and their performance conditional on sentiment and CGO. Section 5 provides the relationships between size, momentum, or illiquidity and future return conditional on asymmetry level cross sectionally. And section 6 concludes.

1.2 Asymmetry Measures

Assume x is daily excess return which is standardized with mean 0 and variance 1. To assess tail asymmetry of the return distribution, we consider its excess tail probability (ETP), which defined as:

$$E_{\varphi 1} = \int_{1}^{+\infty} f(x)\,dx - \int_{-\infty}^{-1} f(x)\,dx = \int_{1}^{\infty} [f(x) - f(-x)]\,dx. \tag{1.1}$$

The above excess tail probability is evaluated at 1 standard deviation away from the mean (we use $E_{\varphi 1}$ to denote in the rest of the paper). The intuition is that, representative investors care less about small deviation away from the mean. But they value stocks that may have big upside potential and dislike stocks with big downside loss [Kelly and Jiang (2014); Barberis and Huang (2008); Kumar (2009); and Bali, Cakici, and Whitelaw (2011)]. The first term measures the cumulative chance of gain, while the second term measures the chance of loss. If $E_{\varphi 1}$ is positive, it implies that the probability of a large loss is less than the probability of a large gain. For an arbitrary concave utility, $E_{\varphi 1}$ is the first-order approximation, thus investors would expect a negative return for holding otherwise identical assets. In later section about the anomalies effect conditional on asymmetry level, we consider the measure with 2 standard deviation as the exceedance level to highlight the role of even larger gains and losses ($E_{\varphi 2}$),

$$E_{\varphi 2} = \int_{2}^{+\infty} f(x)\,dx - \int_{-\infty}^{-2} f(x)\,dx = \int_{2}^{\infty} [f(x) - f(-x)]\,dx. \tag{1.2}$$

Our second measure of distributional asymmetry is a entropy-based measure proposed by Racine and Maasoumi (2007) and Maasoumi and Racine (2008). While ETP (E_{φ}) measures equal-weighted asymmetry, entropy-based measure is more on the degree of asymmetry. Considering a (strictly) stationary series $\{Y_t\}_{t=1}^{T}$, let μ_y denote a measure of central tendency, say $\mu_y = E[Y_t]$, and let $f(y)$ denote the density function of the random variable Y_t. Then we use $\tilde{Y}_t = -Y_t + 2\mu_y$ to denote a rotation of Y_t about its mean, and let $f(\tilde{y})$ denote the density function of the random variable $\tilde{Y}_t$.

We say a series is symmetric about the mean (median, mode) if $f(y) \equiv f(\tilde{y})$ almost surely. Then the difference between $f(y)$ and $f(\tilde{y})$ could be treated as the asymmetry level. Entropy was first introduced by Shannon (1948), and later extended by Kullback and Leibler (1951). However, Shannon's entropy measure is not a metric, and thus it is not a proper measure of distance. In our paper, we use a metric entropy measure which is a normalization of the Bhattacharya-Matusita-Hellinger measure proposed by Granger, Maasoumi, and Racine (2004). The third equality is for our specific environment, since $f_2(y) = f(\tilde{y}) = f(-y + 2\mu_y)$, while $f_1(y) = f(y)$.

$$\begin{aligned} S_\rho &= \tfrac{1}{2}\int_{-\infty}^{\infty} (f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dy \\ &= \tfrac{1}{2}\int \Big[1 - \frac{f_2^{\frac{1}{2}}}{f_1^{\frac{1}{2}}}\Big]^2 dF_1(y) \\ &= \tfrac{1}{2}\int \Big[1 - \frac{f(-y + 2\mu_y)^{\frac{1}{2}}}{f(y)^{\frac{1}{2}}}\Big]^2 dF_(y). \end{aligned} \tag{1.3}$$

Compared with skewness, this entropy measure for asymmetry possesses several other desirable statistical properties: (1) it can be applied to both discrete and continuous variables [1]; (2) if $f_1 = f_2$, the original and rotated distributions are equal, then $S_\rho = 0$. Because of the normalization, the measure lies in between 0 and 1; (3) it is a metric, thus the larger number means large distance, and comparable; (4) it is invariant under continuous and strictly increasing transformation on the underlying variables. We could decompose the entropy measure into the linear combination of skewness, kurtosis or even higher moments. The detailed derivations of entropy decomposition are given in Appendix A.1.

Intuitively, we know asymmetry has two directions, downside or upside. However, the Bhattacharya-Matusita-Hellinger entropy is a distance measure, which cannot distinguish the downside asymmetry from the upside asymmetry. By adding the sign of $E_{\varphi 1}$, we could extend the distance measure to the asymmetry measure. Similar to $E_{\varphi 1}$, we define Signed S_ρ at 1 standard deviation which only captures the asymmetry information beyond the 1 standard deviation, expression is shown in Equation (1.4):

$$S_{\varphi 1} = \text{sign}(E_{\varphi 1}) \times \frac{1}{2}\left(\int_{-\infty}^{-1} (f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dy + \int_{1}^{\infty} (f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dy\right). \tag{1.4}$$

Estimating (1.4) requires the estimation of distribution densities. Given data, we can implement nonparametric method following Maasoumi and Racine (2008) and many others. In this paper, the "Parzen-Rosenblatt" kernel density estimator is defined as:

$$\hat{f}(y) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{Y_i - y}{h}\right), \tag{1.5}$$

where n is sample size of the data $\{Y_i\}$, h is a smoothing parameter or bandwidth and $k(\cdot)$ is a nonnegative bounded kernel function.

In order to select the optimal bandwidth for (1.5), we use the well-known Kullback-Leibler likelihood cross-validation method (see Li and Racine (2007) for details). This procedure minimizes the Kullback-Leibler divergence between the actual density and the estimated one.

[1]For the discrete variables, $S_\rho = \frac{1}{2}\sum(p_1^{\frac{1}{2}} - p_2^{\frac{1}{2}})^2$

$$\max_h \mathcal{L} = \sum_{i=1}^{n} \ln\left[\hat{f}_{-i}(Y_i)\right], \tag{1.6}$$

where $\hat{f}_{-i}(Y_i)$ is the leave-one-out kernel estimator of $f(Y_i)$ which is defined as follows:

$$\hat{f}_{-i}(Y_i) = \frac{1}{(n-1)h} \sum_{j=1 j\neq i}^{n} k\left(\frac{Y_i - Y_j}{h}\right). \tag{1.7}$$

Under the i.i.d. assumption or a weakly time dependent assumption, which are reasonable assumptions for stock returns, the estimated density converges to the actual density. Interested researchers could read Li and Racine (2007) for details. With the method above, we can estimate the densities in (1.1 and 1.4), and obtain the statistic $\hat{S}_\varphi$ by computing the integral numerically or using the summation.

1.3 Continuous Data Monte Carlo Simulation

In this section, we use the new asymmetry measures, S_φ and E_φ, to compare with the commonly used skewness ($SKEW$). Given i.i.d. data ($Y_i = \epsilon_i$), let the sample size $n = 500$, and consider a range of Data Generating Process's (DGP): $N(120, 240)$ (symmetric), $\chi^2(10)$ (asymmetric), $\chi^2(5)$ (asymmetric), $\chi^2(1)$ (asymmetric), $\chi^2(0.5)$ (asymmetric), and $\chi^2(0.05)$ (asymmetric). We conduct simulations for 1,000 times and report the average of $SKEW$, both integration version and summation version of S_φ, together with E_φ results in Panel A of Table 1.1. All χ^2 distributions have positive skewness, and we know skewness is increasing as the freedom parameter is decreasing which documented in the simulation. However, our S_φ or E_φ's performance is slightly different. The magnitudes of S_φ and E_φ are increasing first then decreases.

Now consider a more complex situation. The difference is defined as the difference of a two beta random variables: Beta(1,3.7)-Beta(1.3,2.3). As plotted in Figure 1.1, it has a longer left tail and negative asymmetry.[2] With the same $n = 500$ sample size and $M = 1000$

[2]The difference of a two beta distribution is a well-defined distribution whose density function is provided by Pham-Gia, Turkkan, and Eng (1993) and Gupta and Nadarajah (2004).

simulations as before, the skewness test is now unable to detect any asymmetry. Indeed, the fourth column of Table 1.1 shows that it has a value of 0.0004 with a t-statistic of 0.13. In contrast, both S_φ and E_φ have highly significant negative values, which correctly captures the asymmetric feature of Beta(1,3.7)-Beta(1.3,2.3).

[Insert Figure 1.1 about here]

Simulations given above are not enough as people may argue $SKEW$ is already an appropriate proxy of asymmetry, which is mainly accepted by the literature [see Conine Jr and Tamarkin (1981); Xu (2007); and Conrad, Dittmar, and Ghysels (2013)]. Panel B of Table 1.1 provides the paradigm that two same skewness (skewness=1) Beta distributions with different asymmetry levels which may due to the fifth moment or even higher odd moments. Let the sample size $n = 1,000$, Figure 1.2 plots the two asymmetric DGP(Beta(1,3.70) and Beta(2,12.42)). It is clear that Beta(1,3.70) has longer right tail, and higher upside asymmetry, which could be captured by S_φ either using summation or integration version. E_φ provides the similar result. To make our argument robust, after computing $SKEW$, S_φ, and E_φ, we regenerate another 999 samples, resulting in 1,000 $SKEW$, S_φ, and E_φ for Beta(1,3.70) and Beta(2,12.42). The mean values of these statistics are exhibited in Panel B of Table 1.1.

t tests of two sample with equal means confirm our conclusion. The equality of $SKEW$ cannot be rejected while the equality of mean is rejected for S_φ and E_φ. All our proposed asymmetry proxies suggest Beta(1,3.70) has higher upside asymmetry compared to Beta(2,12.42). which is consistent with our observation in Figure 1.2. This simulation example can explain why we recommend $S_{\varphi 1}$ ($S_{\varphi 1}$ utilizes the $E_{\varphi 1}$ for the direction which also focus more on the tail asymmetry, $S_{\varphi 2}$'s accuracy may hurt due to the sample size beyond 2 standard deviation) together with E_φ instead of $SKEW$ to denote asymmetry.

[Insert Table 1.1 about here]

[Insert Figure 1.2 about here]

1.4 Empirical Results

1.4.1 Data

We use stock return data from Center for Research in Securities Prices (CRSP), ranging from January 1962 to December 2013. The data include all common stocks (with share codes of 10 or 11) listed on NYSE, AMEX and NASDAQ. In order to address the issue of double-counted stock trading volume in NASDAQ, we make the adjustment based on the way proposed by Gao and Ritter (2010). We also restrict the sample to the stocks with beginning-of-month prices between \$1 and \$1,500 to eliminate stocks whose transaction cost is a huge part of their price and those that have very high prices.

In addition, We use the adjusted trading volume to calculate turnover ratio ($TURN$) and Amihud (2002) ratio ($ILLIQ$). Stock illiquidity ($ILLIQ$), is calculated as the absolute value of daily return divided by the daily the adjusted trading volume, averaged over one month. Then we normalize the Amihud ratio to adjust for inflation and truncated it at 30 to eliminate the effect of outliers following Acharya and Pedersen (2005) to obtain $ILLIQ$. The book value information comes from COMPUSTAT and is supplemented by the hand-collected book value data from Kenneth French's website. The book-to-market ratio (BM) is calculated then by the book value of equity (assumed to be available six months after the fiscal year end) divided by current market capitalization. It is truncated at 0.005 fractile and 0.995 fractile to eliminate the effect of extreme values. Following the literature, we take the natural log of the following variables: $SIZE$, $TURN$, and BM. Following Jegadeesh and Titman (1993), we use return over past six months to control for the effect of momentum (MOM).

Following Bali, Cakici, and Whitelaw (2011), volatility (VOL) and Maximum (MAX) of stock are defined as the standard deviation and maximum of daily returns of the previous month, while idiosyncratic volatility ($IVOL$) of stock is defined as the standard deviation of daily idiosyncratic returns of the previous month. Idiosyncratic S_φ (IS_φ), idiosyncratic E_φ (IE_φ) and idiosyncratic $SKEW$ ($ISKEW$) of stock are S_φ, E_φ and $SKEW$ calculated based lagged one year or three months daily residuals (daily returns regress on market return and market square return following Harvey and Siddique (2000) and Bali, Cakici, and Whitelaw (2011)), monthly updated.[3] We obtain Market Beta (β) by estimating CAPM model for each stock using daily observations every year.

Table 1.2 summarizes the correlation of volatility and the asymmetry measures. For comparison, the table reports the results for both the total measures (based on the raw returns) and the idiosyncratic measures (based on the market model residuals). It is interesting that the correlations are about the same in either case. $ISKEW$ has very small correlations with $IE_{\varphi 1}$ or $IS_{\varphi 1}$. But the latter two have a high correlation of over 67%. The volatility has around 8% correlation with the skewness, and much lower correlation with $IE_{\varphi 1}$ or $IS_{\varphi 1}$. The simple correlation analysis shows that he new measure capture information beyond volatility and skewness.

[Insert Table 1.2 about here]

Two sentiment proxies by Baker and Wurgler (2006), Baker and Wurgler (2007) and Huang et al. (2015) are applied in our paper. We use BW to denote the sentiment time series index suggest by Baker and Wurgler (2006) and Baker and Wurgler (2007), while $HJTZ$ represents the sentiment index proposed by Huang et al. (2015). Since the data provided by Jeffrey Wurgler's website only available until December 2010, we extend the data to December 2013 (from Guofu Zhou's website). In addition, $HJTZ$ is also obtained from Guofu Zhou's website.[4]. VIXM is monthly variance of daily value-weighted market return. Aggregate stock market liquidity (ALIQ) is provided by Pastor and Stambaugh (2003) (from Ľuboš Pástor's website). Following Grinblatt and Han (2005), we calculate the capital gain overhang (CGO) for representative investors for each month using weekly price and turnover ratio. The reference price is weighted average of past prices at which

[3]To calculate S_{φ} (IS_{φ}), E_{φ} (IE_{φ}), we exclude out stocks with less than 50 daily returns in the previous year. And for $E_{\varphi 2}$ ($IE_{\varphi 2}$) based on the previous three months daily returns, we exclude out stocks with less than 20 daily returns for the previous quarter. For $SKEW$ ($ISKEW$) measured over the previous year, we consider stocks with at least 30 daily returns exist, but for the proxy measured over the previous quarter, only stocks with less than 20 daily returns are excluded.

[4]BW is available at http://people.stern.nyu.edu/jwurgler/, the extended BW and $HJTZ$ are available at http://apps.olin.wustl.edu/faculty/zhou/

investor purchase stocks but never sell. As in Grinblatt and Han (2005), we use information for past 260 weeks (with at least 200 valid price and turnover observations) for each reference price, which reflects the unimportance of price information older than 5 years. The CGO at week t is the difference between price at week $t-1$ and reference price at week t (divided by the price at week $t-1$). In this way, the complicated microstructure effect can be avoided. Monthly CGO is the CGO of the last week in the month.

1.4.2 Stock Level Results

At first, we examine what types of stock are associated with asymmetries as measures by $ISKEW$, IE_φ and IS_φ. This question is of interest from an investment perspective as the answer helps investors to adjust their risk exposures on asymmetries.

Using idiosyncratic asymmetry measures as dependent variables, we run Fama-Macbeth regressions on common characteristics: $SIZE$, BM, MOM, $TURN$, $ILLIQ$ and the market beta (β),

$$IA_i = a_i + B_i X_{it} + \epsilon_{i,t}, \tag{1.8}$$

where IA_i is one of the five asymmetry measures of the i-th firm and X_i are firm characteristics. Following standard practice, idiosyncratic asymmetry measures are winsorized at 0.5 percentile and 99.5 percentile, and then the loadings are estimated by using the time-series averages of the cross-sectional regression slope coefficients. The Fama-MacBeth standard errors are adjusted using the Newey and West (1987) correction with three lags.

The results are shown in Table 1.3. Specifically, the dependent variables for the column (1) is $ISKEW$, column (2)-(3) is IS_φ at different points, and column (4)-(5) is IE_φ at 1SD and 2SD. Independent variables are the lagged month market capitalization ($SIZE$), the market beta (β), the lagged month book-to-market (BM) ratio, the cumulative pasted six months return (MOM), the measure of lagged month turnover ($TURN$), and the measure of illiquidity ($ILLIQ$). For the first characteristic-$SIZE$, since small firms are easy to face short sale constraints, it should be associated with high upside asymmetry, indicating negative relationship between size and $ISKEW$, IS_φ or IE_φ.

The only difference in characteristics between the asymmetry measurements is the $TURN$. High turnover stocks are associated with high upside asymmetry denoted by new proposed proxies, as high turnover ratio stocks are usually small growth companies. This result is consist with Kumar (2009) who finds that lottery type stocks have much higher turnover ratios. Since our asymmetry measures capture well the asymmetry of lottery type stocks, then it is not surprising that they are related to turn over positively and significantly. However, no clear relationship exists between turnover and idiosyncratic skewness, which is also consistent with Boyer, Mitton, and Vorkink (2010) and Bali, Cakici, and Whitelaw (2011)'s documents. For other characteristics, growth, winner in the past, illiquidity, risky stocks tend to associate with higher up asymmetry (The relationship between $ILLIQ$ and $S_{\varphi 2}$ is insignificant, but the sign is consistent with other asymmetry proxies). The corresponding characteristics table for total asymmetry proxies is shown in Table IA.1.

[Insert Table 1.3 about here]

Skewness is commonly used as the proxy for asymmetry in the literature. However, theoretical implications and empirical findings are mixed. In the Table IA.2, we confirm positive risk premium using the sample periods in Bali, Cakici, and Whitelaw (2011). However, if we extend the time period to the end of 2013, the positive significance of skewness will be eroded, which is presented in Panel B of Table IA.2. The reason is because for the period from 2005 to 2013, the risk premium of the realized skewness is actually negative, which provides the hint for us to think about whether skewness (measured over the preceding year's daily returns) is positively related with the current month's return. The result may depends on state variable which varies across time. In other words, the empirical correlation between skewness and return depends on the state of the economy which is different from what theoretical papers suggest such as Tversky and Kahneman (1992), Polkovnichenko (2005), and Barberis and Huang (2008), indicating skewness's effect is actually a conditional result instead of unconditional. In addition, if we utilize risk adjust return (RA, the excess return which adjusted for Fama-French three factors, see Brennan, Chordia, and Subrahmanyam, 1998) instead of the original excess return as the dependent variable, the positive significance of skewness will be further eroded, and the sign may even changed to negative in some specifications as shown in Table IA.2 Panel C. When using skewness as the measure is further illustrated by Figure 1.3 (a), which shows the $ISKEW$'s risk premium for the univariate regression applying the recursive scheme, the risk premium changes over time and can not be distinguished from zero at 10% level. Contrary to the idiosyncratic skewness, $IS_{\varphi1}$ and $IE_{\varphi1}$'s risk premium are always significant negative in Figure 1.3.

We present the time-series averages of the slope coefficients from the regressions of stock monthly adjusted-return (RA) or excess returns (R) on the lagged month market capitalization ($SIZE$), the market beta (β) (excluded when the dependent variable is RA), the lagged month book-to-market ratio (BM), momentum (MOM), turnover ($TURN$), illiquidity ($ILLIQ$), maximum daily return (MAX), volatility (VOL) or idiosyncratic volatility ($IVOL$), and the lagged month adjusted-return ($REVA$) or excess return (REV) besides realized idiosyncratic $S_{\varphi1}$ ($IS_{\varphi1}$), idiosyncratic $E_{\varphi1}$($IE_{\varphi1}$), and idiosyncratic skewness($ISKEW$). The goodness of applying idiosyncratic instead of total measurement is because that it can rule out the effect of market return. [5]

Standard Fama-MacBeth tests for average slopes determining whether explanatory variables, on average, have non-zero premiums or not. The full cross-sectional regression specification in panel A of Table 1.4 is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} IA_{i,t} + \lambda_{3,t} ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \tag{1.9}$$

where $IA_{i,t}$ is $IS_{\varphi1}$ or $IE_{\varphi1}$, $RA_{i,t+1}$ is the the realized adjusted-return on stock i in month $t+1$, or the adjusted-return in month t; $X_{i,t}$ is a set of control variables.

We use excess return as dependent variable in panel B of Table 1.4.

Table 1.4 reports the time-series average of the slope coefficients over the 624 months

[5] The idiosyncratic measures are the measures on the residuals obtained from regressions of returns on the market excess return and the squared market excess returns following the ideas and definitions in Bali, Cakici, and Whitelaw (2011) and Harvey and Siddique (2000).

from 1962 to 2013. Furthermore, we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973).[6] The coefficients in front of $IS_{\varphi 1}$ and $IE_{\varphi 1}$ are negative significant for all specifications (The results of using risk-adjusted return and excess return as the dependent variables are shown in Panel A and Panel B respectively). We obtain the 95% confidence interval by 399 bootstrap replications, [-1.3610, -3.4761] for the risk premium of $IE_{\varphi 1}$, and [-.9290, -.2071] for that of $IS_{\varphi 1}$, while [-.0237, .0181] is for $ISKEW$. The result confirms insignificant correlation between skewness and the expected cross section return, meanwhile indicates negative relationship between upside asymmetry (denoted by $IS_{\varphi 1}$ and $IE_{\varphi 1}$) and expected cross section return is consistent with Barberis and Huang (2008). From the table, we also observe that the significant relationship is unchanged even controlling skewness. This could be confirmed by the low correlation between $ISKEW$ and $IE_{\varphi 1}$ or $IS_{\varphi 1}$. The time series average of cross section correlation is -0.0611 for the full sample.[7]

The autocorrelations of $IS_{\varphi 1}$ and $IE_{\varphi 1}$ are 0.7259 and 0.8912, which is less than the autocorrelation of $ISKEW$, 0.9040 for our sample. And the average across months of the cross section stocks $IE_{\varphi 1}$ means is 0.0032, and its 95% CI is also positive, representing more stocks have positive asymmetry in daily returns distributions.

[Insert Table 1.4 about here]

[Insert Figure 1.3 about here]

Another concern for the skewness and return analysis is that investors care about expected future skewness instead of the realized skewness in a rational market as argued by Boyer, Mitton, and Vorkink (2010). Boyer, Mitton, and Vorkink (2010) use out-of-sample forecast to obtain expected idiosyncratic skewness ($E(ISKEW)$). By firstly estimating cross-sectional regressions of $ISKEW$ on lagged values of $ISKEW$ and other control vari-

[6] when adjusting for up to 24 lags, the result are qualitative the same. (Table IA.3)

[7] All asymmetry proxies are calculated based on the preceding year daily returns, the result is also robust for using the preceding six months daily returns (Table IA.4). We repeat the analysis in Table 1.4 including stock prices between $1 and $1,500 instead of stock prices between $5 and $1,500. The significance of $IS_{\varphi 1}$ or $IE_{\varphi 1}$ is even stronger.

ables, then use the regression parameters from the estimation, together with information available at each month, to forecast the expected skewness for each stock. Bali, Cakici, and Whitelaw (2011)'s method is slightly different. They just apply the fitted value from the month-by-month cross-sectional regressions. We try both methods (see Appendix A.2 for details), use $E(ISKEW)$ as the idiosyncratic skewness proxy, the result is shown in Table IA.5. From Table IA.5, the relationship between $E(ISKEW)$ (obtained from either method) and cross-sectional expected return is still unclear, the sign of its slope coefficient may change due to different specifications, which is similar with applying realized $ISKEW$.

1.4.3 Portfolio Level Results

Panel A of Table 1.5 reports the equal-weighted average monthly returns of decile portfolios that are formed by sorting the stocks based on the realized $ISKEW$. The results are reported for the sample period from Jan 1962 to December 2013. Portfolio 1 is the portfolio of stocks with the lowest $ISKEW$, while Portfolio 10 denotes the highest. The average raw return difference between the highest and lowest $ISKEW$ is insignificant. However, our new proposed asymmetry proxies shows economically and statistically significant difference between the highest and lowest decile portfolios excess return.

Panel B of Table 1.5 reports the equal-weighted average monthly returns of decile portfolios that are formed by sorting the stocks based on the realized $IS_{\varphi1}$. The average raw return difference between the highest and lowest idiosyncratic $IS_{\varphi1}$ is -0.19% per month with t-statistic of -3.42. And the average Carhart 4-factor alpha difference of highest and lowest idiosyncratic $S_{\varphi1}$ is -0.26% per month, indicating negative relation between upside tail asymmetry and expected return.

The equal-weighted average monthly returns result of decile portfolios that are formed by sorting the stocks based on the realized $IE_{\varphi1}$ is documented in Panel C of Table 1.5. The average raw return difference between the highest and lowest $IE_{\varphi1}$ is -0.18% per month with t-statistic of -2.57. And the average Carhart 4-factor alpha difference of highest and lowest $IE_{\varphi1}$ is -0.25% per month. The result is consistent with $S_{\varphi1}$. Thus, the single sort results also support the theory of Barberis and Huang (2008). Combined with Fama-MacBeth regression observations, the tail upside asymmetry denoted by $IS_{\varphi 1}$ and $IE_{\varphi 1}$ is priced.

[Insert Table 1.5 about here]

We also conduct the recursive scheme single sort by idiosyncratic asymmetry proxies. The beginning time is 1962, while the end time varied. The average raw return differences between the highest and lowest $ISKEW$, $IS_{\varphi 1}$ and $IE_{\varphi 1}$ decile portfolios are shown in Figure 1.4. The excess return difference of $ISKEW$ portfolios cannot distinguish from 0 as the 90% confidence interval contains 0 for most of time. Contrary to the idiosyncratic skewness, the $IS_{\varphi 1}$'s portfolio excess return difference is always significant negative, while $IE_{\varphi 1}$'s portfolio excess return difference is significant negative for most recent time (always after year 2001) (the region between upper bound and the lower bound covers 90% confidence interval).

[Insert Figure 1.4 about here]

1.4.4 Asymmetry Conditional on Sentiment

Baker and Wurgler (2006) point out firms which are difficult to arbitrage should be more overvalued during high sentiment period. Stambaugh, Yu, and Yuan (2012, 2015) consider impediments to short selling as the major obstacle to eliminating sentiment-driven mispricing. Overpricing should be more prevalent when market-wide sentiment is high.

For our paper, we find that the relationship between skewness and return is conditional on sentiment, while newly proposed asymmetry proxies are not. Firms with high skewness can still face high arbitrage risk, they are overpriced during the high sentiment period. However, high upside asymmetry stock does not necessary associate with arbitrage risk, it should be less influenced by sentiment. Our conditional result on sentiment is consistent with Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012, 2015)'s argument.

We show Fama MacBeth regression result by using the sentiment proxy (BW) introduced by Baker and Wurgler (2006, 2007) as the conditioning variable. The sample period is from July 1965 to December 2013. The idiosyncratic skewness is significantly negatively associated with the return when the sentiment is high (when the standardized sentiment index is large than (including) 0.5 or 1), as shown in column (1)-(4) of Panel A in Table 1.6. Even we utilize the last month's sentiment index as the condition, the result still holds.[8] This is because the time series sentiment index is highly persistent, autocorrelation is around 0.98. However, the relationship is unclear when sentiment is low, column (5)-(8) of Panel A in Table 1.6 document one of such examples for comparison.[9] In contrast, consider now the Fama-MacBeth regressions of the excess returns on IS_{φ} conditional on high and low sentiment periods. Panel B in Table 1.6 shows that IS_{φ} always have negatively risk premium, though it is more significant in high sentiment periods. The same pattern is observed on IE_{φ} in Panel C of Table 1.6. Overall, the results show that skewness is quite sensitive to sentiment, while IS_{φ} and IE_{φ} are much less so.[10]

[Insert Table 1.6 about here]

For robustness checks, we also use the cross section regression coefficients of idiosyncratic asymmetry proxies to regress on the standardized sentiment indexes from 1965.7 to 2013.12. If the slopes in front of sentiment indexes are significant, then sentiment can determine the idiosyncratic asymmetry performances. β_{ISKEW}, $\beta_{IE_{\varphi 1}}$ and $\beta_{IS_{\varphi 1}}$ denote the cross section coefficients obtained from univariate regressions of the adjusted-return (RA, the excess return which adjusted for Fama-French three factors (Brennan, Chordia, and Subrahmanyam, 1998)) on realized asymmetry proxies, $ISKEW$, $IE_{\varphi 1}$, and $IS_{\varphi 1}$ respectively.

$$RA_{i,t+1} = \lambda_{0,t} + \beta_{IA,t} \times IA_{i,t} + \epsilon_{i,t+1}, \tag{1.10}$$

where IA is $ISKEW$, $IE_{\varphi 1}$, or $IS_{\varphi 1}$. Then Table 1.7 reports the coefficients of following time series regressions.

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[8]The result holds for the sentiment index $HJTZ$ proposed by Huang et al. (2015).

[9]The total skewness sentiment conditional results are similar to the idiosyncratic skewness which presented in Table IA.6.

[10]Similar results are obtained if we use the excess returns (see Table IA.7).

$$\beta_{IA,t} = \alpha_0 + \alpha_1 \times SENT_t + \epsilon_{i,t}, \tag{1.11}$$

where $SENT_t$ is BW, LBW, $HJTZ$ or $LHJTZ$. LBW or $LHJTZ$ means the lagged one month or realized sentiment index BW or $HJTZ$.

From the table, idiosyncratic skewness is significantly related with sentiment, while our two new asymmetry proxies are not. Similar results for total asymmetry proxies documented in Table IA.8. High upside asymmetry stock doesn't necessary associate with arbitrage risk, thus are easy to arbitrage, it should be less influenced by sentiment which is consistent with Baker and Wurgler (2006)'s theory. However, skewness cannot fully capture upside asymmetry. Thus high skewness firms can still face high arbitrage risk, which are difficult to arbitrage, the evaluation of them are largely impacted by sentiment then.

[Insert Table 1.7 about here]

1.4.5 Asymmetry Conditional on VIX

Here we show results conditional on VIX in Table 1.8. Our results are similar to the results conditional on sentiment. The negative relationship between skewness and expected return only exist during highly volatile periods, while our true asymmetry measures are not subject to the problem and consistent with theoretical models such as Barberis and Huang (2008) and Han and Hirshleifer (2015) that high upside asymmetry means lower expected return. The results we shown are conditional on the previous month realized VIX-market volatility (VIXM). [11]

[Insert Table 1.8 about here]

[11] The findings are similar applying the previous month CBOE Volatility Index instead and they are available upon request.

1.4.6 Asymmetry Conditional on Aggregate Stock Market Liquidity

In this subsection, we examine how asymmetry measures vary during high and low aggregate stock market liquidity (ALIQ) periods. Pastor, Stambaugh, and Taylor (2014) point out that ALIQ is a proxy for potential mispricing, and mispricing is likely to be more prevalent when liquidity is low.

We run Fama-MacBeth regressions in two regimes. The high ALIQ periods are defined as those months when the Pastor and Stambaugh (2003) aggregate liquidity is above its mean. And the low ALIQ periods when the aggregate liquidity is below its mean. [12]

Table 1.9 shows that $IS_{\varphi 1}$ and $IE_{\varphi 1}$ always has negative loadings, although it is more significant in low ALIQ periods. In contrast, skewness is only negatively related with the expect returns during the low ALIQ periods. Overall, the results are similar to sentiment and VIX, showing that skewness is sensitive to ALIQ.

[Insert Table 1.9 about here]

1.4.7 Asymmetry Conditional on Capital Gains Overhang

We adopt the definition of the capital gains overhang (CGO) following Grinblatt and Han (2005). CGO is the normalized difference between the current stock price and the reference price, and the reference price is cost, or the weighted average of past stock prices. Here the weight is based on the past turnover. Then A larger CGO generally implies larger capital gains. An et al. (2015) find that the skewness preference existence depends on the CGO level, it only holds for stocks with capital loss. And Wang, Yan, and Yu (2014) document that the negative risk-return relation among capital loss stocks. However it doesn't mean the relationship between upside asymmetry and expected return is conditional on CGO. High skewness stocks can still associate with high arbitrage risk, while upside asymmetry stocks may not. CGO data is available from January 1962 to December 2013.

We confirm An et al. (2015)'s finding that only for investors with loss, skewness pref-

[12] The result we shown is conditional on the previous month ALIQ.

erence shows up significantly. But for the new asymmetry proxies we proposed, there are no such evidences. The demand for upside asymmetry always strong for different levels of CGO, although the magnitudes varied. Our finding is consistent with Wang, Yan, and Yu (2014)'s argument.

The conclusion exhibited through Fama-MacBeth regressions (Table 1.10) and double-sorting (Table 1.11). Table 1.10 shows the Fama-MacBeth regression results when we add the interaction term of CGO and asymmetry proxies. The interaction term of CGO and $ISKEW$ is significant for any specification, while the interaction term of CGO and $IS_{\varphi 1}$ or $IE_{\varphi 1}$ is not. For each panel, the dependent variable for column(1)-(4) is the risk adjusted return, and we utilize the excess returns as the dependent variable for regressions in column(5)-(7). The positive coefficients of the interaction term between $ISKEW$ and CGO indicate that the negative correlation between skewness and return may be reversed if CGO is high. Investors like positive skewed stocks only when they experienced a capital loss. But using our new asymmetry measures, we can see in Panel B that the preference of positive asymmetric stocks is invariant with respect to CGO.

The full cross-sectional regression specification in Table 1.10 is

$$\begin{aligned} RA_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} CGO_{i,t} + \lambda_{2,t} IA_{i,t} \\ &+ \lambda_{3,t} CGO_{i,t} \times IA_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \end{aligned} \tag{1.12}$$

here IA denotes $ISKEW$, $IE_{\varphi 1}$, or $IS_{\varphi 1}$, and $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for column(5)-(7).

[Insert Table 1.10 about here]

The similar results can be observed through double-sorting in Table 1.11. At the beginning of each month from 1962 to 2013, we first sort stocks by CGO into five quintile portfolios, and then within each CGO portfolio we sort stocks into portfolios by asymmetry proxies, the realized idiosyncratic skewness, and the measures we proposed $IS_{\varphi 1}$ or $IE_{\varphi 1}$. The monthly equal-valued excess returns or return differences are shown in Panel A, while the average Carhart four-factor alphas are displayed in Panel B. Columns P5-P1 denotes the return difference between portfolios with the highest asymmetry and the lowest asymmetry, we can call it asymmetry spreads. For $ISKEW$, the return difference or skewness spread is significantly negative only for the lowest CGO group. Thus the skewness preference holds only for stocks with capital loss. The skewness spread is increasing as CGO level increases, and it even changed to significant positive for the highest CGO group. In other words, for investors have most generous profits, they may even hate high skewness stocks. But the evidences are blurred for $IS_{\varphi 1}$ or $IE_{\varphi 1}$. The return difference between highest $IS_{\varphi 1}$ or $IE_{\varphi 1}$ and the lowest within each CGO portfolio always negative. And it is not monotonically increasing for $IS_{\varphi 1}$ or $IE_{\varphi 1}$. The Carhart four-factor alpha of $IS_{\varphi 1}$ or $IS_{\varphi 1}$ spread is still significant negative for the stocks with a previous gain (CGO5). Row Avg(C1-C5) reports the mean of return or return difference of five CGO portfolios. Then for the Avg(C1-C5), P5-P1 entry, it shows the result of asymmetry return difference after controlling for CGO. The effects of our asymmetry proxies are still preserved, with a equal-weighted average raw excess return difference between the high $IS_{\varphi 1}(IE_{\varphi 1})$ and low $IS_{\varphi 1}(IE_{\varphi 1})$ is significant different, -0.134%(-0.134%) per month.

[Insert Table 1.11 about here]

1.5 Benchmark Anomalies and Asymmetry

1.5.1 Short Term Asymmetry

To check the relationship between asymmetry and anomalies, we use asymmetry proxies for short term. In this section, $E_{\varphi 2}$ and $SKEW$ measured over the previous one quarter is applied. We call asymmetry proxies measured over three months or even one months short term asymmetry. Entropy-based measure $S_{\varphi 1}$ and $S_{\varphi 2}$ requires more than 5 points beyond 1 standard deviation or 2 standard deviation to estimate it, thus for one or three months, the estimation is not accurate. However, for E_{φ} estimation, we don't need to delete any points to estimate density, it is reasonable to use $E_{\varphi 2}$ and $SKEW$ to denote the short term asymmetry.

The summary statistics of short term asymmetry proxies provided by Table IA.9. Majority of stocks exhibit positive upside asymmetry as means or medians are all positive. Table IA.10 and Table IA.11 present summary statistics for the decile portfolio stocks. The tables report the average across the months in the sample of the median values with each month of various characteristics for short term asymmetry proxies portfolios and idiosyncratic asymmetry proxies portfolios respectively. $E_{\varphi 2}$ ($SKEW$ in Panel B), current month excess return (R), the lagged month market capitalization ($SIZE$), the market beta (β),the lagged month book-to-market (BM) ratio, the cumulative pasted six months return (MOM), the measure of lagged month turnover ($TURN$), the measure of illiquidity ($ILLIQ$) are reported. As expected, and consistent with previous findings, return decreases as asymmetry or idiosyncratic asymmetry increases. And the return difference between the high with low is higher for $E_{\varphi 2}$ ($IE_{\varphi 2}$) compared with $SKEW$ ($ISKEW$). From the Table IA.10 and Table IA.11, upside asymmetry or idiosyncratic asymmetry stock tend to be smaller market capitalization, risky, growth, past winner, higher turnover ratio, and illiquid firms.

Table IA.12 reports the characteristics of $E_{\varphi 2}$ ($IE_{\varphi 2}$) and $SKEW$ ($ISKEW$) by running a firm-level cross-sectional of asymmetry proxies on subsets of size ($SIZE$), book to market ratio (BM), momentum (MOM), turnover ($TURN$), liquidity measure ($ILLIQ$), and market beta (β). The finding is consistent with summary statistics of decile portfolio stocks in Table IA.10 and Table IA.11.

We also run a firm-level cross-sectional Fama MacBeth regression of the adjusted-return or excess return on realized $E_{\varphi 2}$ ($IE_{\varphi 2}$) and $SKEW$ ($ISKEW$) and other control variables defined in the Appendix to check how is $E_{\varphi 2}$ or $IE_{\varphi 2}$'s result compared with traditional asymmetry proxy $SKEW$ or $ISKEW$. The time-series averages of the regression slope coefficients and t test values based on adjusted the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973) are reported in Table IA.13 and Table IA.15. Although realized $SKEW$ is significant negatively related with the monthly return for univariate regressions, the significance disappear when adding $E_{\varphi 2}$ and even changed to positive significant after adding other control variables. By contrast, $E_{\varphi 2}$ is always significant negatively related with return for all specifications. The results are consistent with previous Fama MacBeth regression results in Table 1.4. Even we adjusted the Fama-MacBeth standard errors using Newey and West (1987) correction with 24 lags, the results (In Table IA.14) that significant negative risk premium of $E_{\varphi 2}$ still hold.

Table IA.16 and Table IA.17 reports the equal-weighted average monthly returns of portfolios that are formed by sorting the stocks based on the realized short term asymmetry ($E_{\varphi 2}$, $IE_{\varphi 2}$, $SKEW$ and $ISKEW$). The results are reported for the sample period from Jan 1962 to December 2013. Portfolio 1 is the portfolio of stocks with the lowest asymmetry, while Portfolio 5 denotes the highest. The average raw return differences between the highest and lowest are economically and statistically significant except $ISKEW$. Thus, both firm-level Fama MacBeth regression and equal-weighted single sorting sorts support that the greater tail asymmetries imply lower average returns in the cross section.

1.5.2 Benchmark Anomalies

In this paper, we mainly focus on benchmark anomalies, size, momentum, and liquidity. They are benchmark anomalies, and existence of these anomalies in the literature continue to challenge asset pricing theory. Size effect that smaller firms are associated with higher expected returns is first observed by Banz (1981), and it could be explained by higher risk for smaller firms. Later on, researchers find out that the liquidity risk is the main source for size effect [see Amihud and Mendelson (1986, 1989); Brennan, Chordia, and Subrahmanyam (1998, 2004); Chordia, Subrahmanyam, and Anshuman (2001); and Liu (2006)]. But other sources may also exist, for example, Zhang (2006) suggests that higher information uncertainty linked with smaller firms. And some researchers believe that small stocks contain some systematic risks, which are likely to have cash flow problems [see Chan and Chen (1991); Fama and French (1996); Berk, Green, and Naik (1999); Gomes, Kogan, and Zhang (2003); and Vassalou and Xing (2004)].

Momentum, is another popular and strong anomaly meaning that past stocks winners tend to provide higher expected return. Jegadeesh and Titman (1993) make a main contribution to the literature, they are the first to find out past winner, on average, outperform past losers over a horizon of 3 to 12 months. Following them, a lot of publications confirm momentum anomaly exist across countries and time periods [see Asness, Liew, and Stevens (1997); Rouwenhorst (1998); and Jegadeesh and Titman (2001)]. People try to explain the abnormal momentum returns from different aspects. For example, the efficient market hypothesis is wrong, and the real market is at least weak-form efficient [see Conrad and Kaul (1998); Berk, Green, and Naik (1999); Chordia and Shivakumar (2002); and Lewellen (2002)]. Behavioral explanations argue that the momentum arises due to inherent biases in the way that investors interpret information. And this explanation implies that market is inefficient [see Jegadeesh and Titman (1993, 2001, 2011); Barberis, Shleifer, and Vishny (1998); Daniel, Hirshleifer, and Subrahmanyam (1998); and Hong and Stein (1999)]. In addition, some papers focus on market friction explanations.[13]

For liquidity effect, several sources could generate the liquidity issues pointed out by Amihud, Mendelson, and Pedersen (2005): transaction costs, demand pressure, inventory risk, private information, and search friction.[14]

To examine size, momentum, and liquidity effect, we conduct a single-sort analysis. At the beginning of each month from 1962 to 2013, we sort stocks by $SIZE$, MOM, or $ILLIQ$ into five quintile portfolios. Table 1.12 reports the equal-weighted average excess returns, Fama French 3-factor alphas, and Carhart 4-factor alphas of quintile portfolios together with the return difference between the highest and lowest portfolios. Panel A of Table shows an pattern of deceasing returns across the quintiles, which implies that smaller size companies tend to associate with higher expected excess return. Moreover, the spread portfolio has

[13]They argue the at least part of the abnormal momentum returns is due to the transaction costs in the imperfect market [see Lesmond, Schill, and Zhou (2004); Korajczyk and Sadka (2004); Sadka (2006); and Ali and Trombley (2006)].

[14]the various liquidity measured used are often highly correlated with the size of tradable shares. Thus a pure size effect could be detected by examining the relation between the size of nontradable share and expected returns [see Cui and Wu (2007)].

a (negatively) large value of −0.298% per month that is statistically significant at the 5% level. However, this effect could be explained by size factor as its alphas are insignificant.

Panel B of Table 1.12 shows an pattern of increasing returns across the quintiles, suggesting past winner stocks tend to gain high for the next month. In addition, the spread portfolio has a large value of 0.829% per month that is statistically significant at the 1% level. And, its alphas are all significant.

Panel C of Table 1.12 exhibits the result for quintiles $ILLIQ$ portfolios and the spread. The excess return is increasing as illiquidity increases. However, although the excess return spread is economically significant (0.211%), it is statistically insignificant. And its alphas magnitudes are smaller, showing liquidity effect is not strong, but it maybe strong conditionally.

[Insert Table 1.12 about here]

1.5.3 Benchmark Anomalies and Short Term Asymmetry

In this subsection, we will discuss about how benchmark anomalies change conditional on different short term asymmetry levels. In general, benchmark anomalies' performances are dependent on stocks return asymmetry. Thus we contribute to the literature by finding another source for these anomalies.

Size and Short Term Asymmetry

We include the interaction term between $SIZE$ and asymmetry proxies ($SKEW$ and $E_{\varphi 2}$) for the Fama MacBeth regression analysis. The full cross-sectional regression specification in Table 1.13 Panel A is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} SIZE_{i,t} + \lambda_{2,t} ASYM_{i,t} + \lambda_{3,t} SIZE_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \tag{1.13}$$

here $ASYM$ denotes $SKEW$, or $E_{\varphi 2}$, and $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for Panel B.

From Table 1.13 Panel A, the interaction term between $SIZE$ and $E_{\varphi 2}$ or $SKEW$ is positively significant related with adjusted return, which is opposite to the negative relationship between $SIZE$ and return. The result is robust when adding other control variables in the fifth or ninth column. The opposite relationship means the $SIZE$ effect eroded for higher asymmetry stocks. As the average standard deviation for $E_{\varphi 2}$ and $SKEW$ are 0.0203 and 0.9116 respectively from Table IA.10, if asymmetry proxies increase for one standard deviation, the $SIZE$ loadings will increase $0.0203 \times 0.7995 \approx 0.0162$ for $E_{\varphi 2}$ and $0.9116 \times 0.0200 \approx 0.0182$ for $SKEW$ (focus on column (3) and (7) without other control variables). Thus the risk premium for $SIZE$ will changed to $-0.0691 + 0.0162 = -0.0367$ and $-0.0671 + 0.0182 = -0.0489$ based on column (3) and (7) for one standard deviation increase of $E_{\varphi 2}$ and $SKEW$ respectively. Fama MacBeth regression result shows that size effect is stronger for low upside asymmetry stocks. Similar result shown in Panel B when the dependent variable is the excess return. The result also hold for idiosyncratic asymmetry proxies (in Table IA.18).

We also conduct double sorting to confirm our finding. At the beginning of each month from 1962 to 2013, we first sort stocks by $E_{\varphi 2}$ or $SKEW$ into quintile portfolios, and then, within each $E_{\varphi 2}$ or $SKEW$ portfolio, we sort stocks into quintile portfolios by $SIZE$. Table 1.16 presents the results of the relation between future stock returns for each $SIZE$ portfolio after controlling for $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B). Inside the lowest $E_{\varphi 2}$ portfolio, the size effect is strong, and its Carhart 4-factor alpha is -0.300% per month, which is still statistically and economically significant at 1% level. However, for the highest $E_{\varphi 2}$ level stocks, the return spread between the highest and lowest $SIZE$ is -0.159%, and even changed to 0.069% for its Carhart 4-factor alpha. Both are insignificant, suggesting no size effect when stock upside asymmetry level is high. The seventh column of Table 1.16 shows the difference of 5-1 spread ($SIZE$ effect)between the highest and lowest $E_{\varphi 2}$, it is significant at 5% level, and even stronger for its Carhart 4-factor alpha, confirms that $SIZE$ effect is dependent on the $E_{\varphi 2}$ level. The double-sort result is consistent with Fama MacBeth regression result in Table 1.13. Similar result shown in Panel B when the upside asymmetry proxy is $SKEW$. Table IA.21 shows the double sorting result on idiosyncratic asymmetry and $SIZE$, confirming that the size effect is dependent on idiosyncratic asymmetry even the market effect is ruled out.

[Insert Table 1.13 about here]

[Insert Table 1.16 about here]

Momentum and Short Term Asymmetry

For the momentum effect performance conditional on stock upside asymmetry level, we include the interaction term between MOM and asymmetry proxies ($SKEW$ and $E_{\varphi 2}$) for the Fama MacBeth regression analysis first. The full cross-sectional regression specification in Table 1.14 Panel A is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} MOM_{i,t} + \lambda_{2,t} ASYM_{i,t} + \lambda_{3,t} MOM_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \tag{1.14}$$

here $ASYM$ denotes $SKEW$, or $E_{\varphi 2}$, and $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for Panel B.

Based on Table 1.14 Panel A, the interaction term between MOM and $E_{\varphi 2}$ or $SKEW$ is positively significant related with adjusted return, which will enhance the positive relationship between MOM and risk-adjusted return. Then the MOM effect will be even stronger for higher upside asymmetry stocks. As the average standard deviation for $E_{\varphi 2}$ and $SKEW$ are 0.0203 and 0.9116 respectively from Table IA.10, if asymmetry proxies increase for one standard deviation, the MOM loadings will increase $0.0203 \times 0.0663 \approx 0.0013$ for $E_{\varphi 2}$ and $0.9116 \times 0.0016 \approx 0.0015$ for $SKEW$ (focus on column (3) and (7) without other control variables). Thus the risk premium for MOM will changed to $0.0073 + 0.0013 = 0.0086$ and $0.0077 + 0.0015 = 0.0092$ based on column (3) and (7) for one standard deviation increase of $E_{\varphi 2}$ and $SKEW$ respectively. Fama MacBeth regression result shows that momentum effect is stronger for higher upside asymmetry stocks. The result is robust when the dependent variable is the excess return in Panel B and for idiosyncratic asymmetry proxies (in Table IA.19).

We also conduct double sorting to confirm our finding. At the beginning of each month from 1962 to 2013, we first sort stocks by $E_{\varphi 2}$ or $SKEW$ into five quintile portfolios, and then, within each $E_{\varphi 2}$ or $SKEW$ portfolio, we sort stocks into quintile portfolios by MOM. Table 1.17 presents the results of the relation between future stock returns for each MOM portfolio after controlling for $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B). Inside the lowest $E_{\varphi 2}$ portfolio, the spread difference in excess return is 0.529% per month, but its Carhart 4-factor alpha is only 0.031% per month, which is statistically and economically insignificant. In contrast, for the highest $E_{\varphi 2}$ level stocks, the excess return spread between the highest and lowest MOM is 1.212%, and still as high as 0.603% per month or 7.236% annually for its Carhart 4-factor alpha. The double-sort result suggests that the momentum effect is getting stronger when stock upside asymmetry level increases, which is consistent with Fama MacBeth regression result in Table 1.14. The seventh column of Table 1.17 shows the difference of 5-1 spread (MOM effect)between the highest and lowest $E_{\varphi 2}$. Its self and its Carhart 4-factor alpha are both significant at 1% level, confirming that MOM effect is dependent on the $E_{\varphi 2}$ level. Similar result shown in Panel B when the upside asymmetry proxy is $SKEW$. Table IA.22 shows the double sorting result for idiosyncratic asymmetry and MOM, confirming that the momentum effect is dependent on idiosyncratic asymmetry even the market effect is ruled out.

[Insert Table 1.14 about here]

[Insert Table 1.17 about here]

Liquidity and Short Term Asymmetry

For the liquidity effect performance conditional on stock upside asymmetry level, we include the interaction term between $ILLIQ$ and asymmetry proxies ($SKEW$ and $E_{\varphi 2}$) for the Fama MacBeth regression analysis first. The full cross-sectional regression specification in

Table 1.15 Panel A is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} ILLIQ_{i,t} + \lambda_{2,t} ASYM_{i,t} + \lambda_{3,t} ILLIQ_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \tag{1.15}$$

here $ASYM$ denotes $SKEW$, or $E_{\varphi 2}$, and $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for Panel B.

Based on Table 1.15 Panel A, the interaction term between $ILLIQ$ and $E_{\varphi 2}$ or $SKEW$ is negatively significant related with adjusted return, which is opposite to the positive relationship between $ILLIQ$ and risk-adjusted return. Then the $ILLIQ$ effect will be weaker for higher upside asymmetry stocks. As the average standard deviation for $E_{\varphi 2}$ and $SKEW$ are 0.0203 and 0.9116 respectively from Table IA.10, if asymmetry proxies increase for one standard deviation, the $ILLIQ$ loadings will decrease $0.0203 \times 0.3978 \approx 0.0081$ for $E_{\varphi 2}$ and $0.9116 \times 0.0088 \approx 0.0080$ for $SKEW$ (focus on column (3) and (7) without other control variables). Thus the risk premium for $ILLIQ$ will changed to $0.0151 - 0.0081 = 0.0070$ and $0.0143 - 0.0080 = 0.0063$ based on column (3) and (7) for one standard deviation increase of $E_{\varphi 2}$ and $SKEW$ respectively. Fama MacBeth regression result shows that illiquidity effect is weaker for higher upside asymmetry stocks. The result is robust when the dependent variable is the excess return in Panel B and for idiosyncratic asymmetry proxies (in Table IA.20).

Similar to previous two anomalies, we also conduct double sorting to confirm our finding. At the beginning of each month from 1962 to 2013, we first sort stocks by $E_{\varphi 2}$ or $SKEW$ into five quintile portfolios, and then, within each $E_{\varphi 2}$ or $SKEW$ portfolio, we sort stocks into quintile portfolios by $ILLIQ$. Table 1.18 presents the results of the relation between future stock returns for each $ILLIQ$ portfolio after controlling for $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B). Inside the lowest $E_{\varphi 2}$ portfolio, the spread difference in excess return is 0.446% per month, and its Carhart 4-factor alpha is 0.351% per month, both are statistically and economically significant. In contrast, for the highest $E_{\varphi 2}$ level stocks, the excess return spread between the highest and lowest $ILLIQ$ is 0.031%, and even changed to negative,

-0.108% per month for its Carhart 4-factor alpha, thus the liquidity effect disappeared when stock return upside asymmetry is high. The double-sort result suggests that the liquidity effect getting weaker when stock upside asymmetry level increases, which is consistent with Fama MacBeth regression result in Table 1.15. The seventh column of Table 1.18 shows the difference of 5-1 spread ($ILLIQ$ effect)between the highest and lowest $E_{\varphi 2}$, it is significant at 1% level, and its Carhart 4-factor alpha is also significant at 1% level, confirming that $ILLIQ$ effect is dependent on the $E_{\varphi 2}$ level. Similar result shown in Panel B when the upside asymmetry proxy is $SKEW$. Table IA.23 shows the double sorting result for idiosyncratic asymmetry and MOM, confirming that the liquidity effect is dependent on idiosyncratic asymmetry even the market effect is ruled out.

[Insert Table 1.15 about here]

[Insert Table 1.18 about here]

1.6 Conclusions

In this paper, we propose two distribution-based measures of stock return asymmetry. The first one is based on the probability difference of upside gains and downside risk of a stock, and the second is based on entropy which is improved from the Bhattacharya-Matusita-Hellinger distance measure in Racine and Maasoumi (2007). In contrast to the widely used skewness measure, our measures make use of the entire tail distribution beyond the third moment. As a result, they capture asymmetry more effectively as shown in our simulations.

Based on our new measures, we find that, in the cross section of stock returns, greater tail asymmetries imply lower average returns. This is statistically significant not only at firm-level Fama-MacBeth regressions, but also in the cross section of portfolios sorted based on the new asymmetry measures. Our empirical results are consistent with the predictions of theoretical models such as Barberis and Huang (2008), and Han and Hirshleifer (2015).

In this paper, we also examine the correlation between asymmetry and return conditional on sentiment and CGO, respectively. We find that skewness is only negatively significant related to the stock expected return during high sentiment period or for firms whose representative investors experienced capital losses. In contrast, using our measures, the expected returns are unconditionally negative for lottery-type stocks. The results are consistent with the theory that preference for upside asymmetry can be induced from the over-weighting of very low probability events.

At last, we find that three benchmark anomalies: size, momentum, liquidity could be partially explained by short-term asymmetry of stock returns. For high upside asymmetry stocks, size effect and liquidity effect disappear, and momentum effect enhanced. In contrast, the size and liquidity effect are strong (even for Carhart 4-factor alphas), while momentum effect disappears after controlling Carhart 4-factors.

Appendix

A.1 Bhattacharya-Matusita-Hellinger Entropy Decomposition

The expression for (2.2) decomposition is listed in (1.16).

$$S_\rho = \frac{1}{2}g(\mu) - g(\mu)^{\frac{1}{2}} + \frac{1}{2} + \beta_1 \cdot \sigma^2 + \beta_2 \cdot \gamma_1\sigma^3 + \beta_3 \cdot (\gamma_2 + 3)\sigma^4 + o(\sigma^4), \tag{1.16}$$

where $Ey = \mu$, $Var(y) = \sigma^2$, skewness is defined as $\gamma_1 = \frac{E(y-\mu)^3}{\sigma^3}$, kurtosis $\gamma_2 = \frac{E(y-\mu)^4}{\sigma^4} - 3$. The small o represents the higher order term. β_1, β_2, and β_3 defined as follows:

$$\beta_1 = \frac{g^{(2)}(\mu)}{4} + \frac{1}{8}g(\mu)^{-\frac{3}{2}}(g^{(1)}(\mu))^2 - \frac{1}{4}g(\mu)^{-\frac{1}{4}}g^{(2)}(\mu), \tag{1.17}$$

$$\beta_2 = \frac{g^{(3)}(\mu)}{12} - \frac{1}{16}g(\mu)^{-\frac{5}{2}}(g^{(1)}(\mu))^3 + \frac{1}{8}g(\mu)^{-\frac{3}{2}}g^{(1)}(\mu)g^{(2)}(\mu) - \frac{1}{12}g(\mu)^{-\frac{1}{2}}g^{(3)}(\mu), \tag{1.18}$$

$$\begin{aligned}\beta_3 &= \tfrac{g^{(4)}(\mu)}{48} + \tfrac{5}{128}g(\mu)^{-\frac{7}{2}}(g^{(1)}(\mu))^4 - \tfrac{3}{32}g(\mu)^{-\frac{5}{2}}(g^{(1)}(\mu))^2 g^{(2)}(\mu) + \tfrac{1}{32}g(\mu)^{-\frac{3}{2}}(g^{(2)}(\mu))^2 \\ &+ \tfrac{1}{24}g(\mu)^{-\frac{3}{2}}g^{(1)}(\mu)g^{(3)}(\mu) - \tfrac{1}{48}g(\mu)^{-\frac{1}{2}}g^{(4)}(\mu),\end{aligned} \tag{1.19}$$

here $g^{(n)}(y)$ means the nth order derivative of $g(y)$.

The detailed steps of obtaining this decomposition expression is explained as follows. From (2.2), we have the following expression,

$$\begin{aligned} S_\rho &= \tfrac{1}{2}\int \Big[1 - \frac{f(-y+2\mu_y)^{\frac{1}{2}}}{f(y)^{\frac{1}{2}}}\Big]^2 dF_(y) \\ &= \tfrac{1}{2}E_y\Big[1 - (\tfrac{f(-y+2\mu_y)}{f(y)})^{\frac{1}{2}}\Big]^2, \end{aligned} \tag{1.20}$$

Following Maasoumi and Theil (1979)'s notation, let $Ey = \mu_y = \mu$, $Var(y) = \sigma^2$, skewness $\gamma_1 = \frac{E(y-\mu)^3}{\sigma^3}$, kurtosis $\gamma_2 = \frac{E(y-\mu)^4}{\sigma^4} - 3$, and $g(y) = \frac{f(-y+2\mu)}{f(y)}$, then we have

$$\begin{aligned} S_\rho &= \tfrac{1}{2} E_y \Big[1 - g(y)^{\frac{1}{2}}\Big]^2 \\ &= \tfrac{1}{2} E_y \Big[g(y)\Big] - E_y \Big[g(y)^{\frac{1}{2}}\Big] + \tfrac{1}{2}. \end{aligned} \tag{1.21}$$

Utilize the Taylor expansion of $g(y)$ at the mean μ, we have

$$\begin{aligned} g(y) &= g(\mu) + g^{(1)}(\mu)(y-\mu) + \tfrac{g^{(2)}(\mu)}{2!}(y-\mu)^2 + \tfrac{g^{(3)}(\mu)}{3!}(y-\mu)^3 \\ &+ \tfrac{g^{(4)}(\mu)}{4!}(y-\mu)^4 + o((y-\mu)^4), \end{aligned} \tag{1.22}$$

then, take the expectation, we obtain

$$\begin{aligned} E\big[g(y)\big] &= g(\mu) + \tfrac{g^{(2)}(\mu)}{2!}\sigma^2 + \tfrac{g^{(3)}(\mu)}{3!}\gamma_1\sigma^3 \\ &+ \tfrac{g^{(4)}(\mu)}{4!}(\gamma_2+3)\sigma^4 + o(\sigma^4). \end{aligned} \tag{1.23}$$

Similarly, apply the Taylor expansion of $g(y)^{\frac{1}{2}}$ at the mean μ, we have

$$\begin{aligned} g(y)^{\frac{1}{2}} &= g(\mu)^{\frac{1}{2}} + (g(y)^{\frac{1}{2}})^{(1)}|_{y=\mu}(y-\mu) + \tfrac{(g(y)^{\frac{1}{2}})^{(2)}|_{y=\mu}}{2!}(y-\mu)^2 + \tfrac{(g(y)^{\frac{1}{2}})^{(3)}|_{y=\mu}}{3!}(y-\mu)^3 \\ &+ \tfrac{(g(y)^{\frac{1}{2}})^{(4)}|_{y=\mu}}{4!}(y-\mu)^4 + o((y-\mu)^4), \end{aligned} \tag{1.24}$$

then, take the expectation, we obtain

$$\begin{aligned} E\big[g(y)^{\frac{1}{2}}\big] &= g(\mu)^{\frac{1}{2}} + \tfrac{(g(y)^{\frac{1}{2}})^{(2)}|_{y=\mu}}{2!}\sigma^2 + \tfrac{(g(y)^{\frac{1}{2}})^{(3)}|_{y=\mu}}{3!}\gamma_1\sigma^3 \\ &+ \tfrac{(g(y)^{\frac{1}{2}})^{(4)}|_{y=\mu}}{4!}(\gamma_2+3)\sigma^4 + o(\sigma^4). \end{aligned} \tag{1.25}$$

Thus from expression of (1.21), we have the following decomposition for Bhattacharya-

Matusita-Hellinger entropy measure,

$$\begin{aligned}
S_\rho &= \tfrac{1}{2}g(\mu) - g(\mu)^{\frac{1}{2}} + \tfrac{1}{2} + \left[\tfrac{g^{(2)}(\mu)}{4} - \tfrac{(g(y)^{\frac{1}{2}})^{(2)}|_{y=\mu}}{2}\right]\sigma^2 \\
&+\left[\tfrac{g^{(3)}(\mu)}{12} - \tfrac{(g(y)^{\frac{1}{2}})^{(3)}|_{y=\mu}}{6}\right]\gamma_1\sigma^3 \\
&+\left[\tfrac{g^{(4)}(\mu)}{48} - \tfrac{(g(y)^{\frac{1}{2}})^{(4)}|_{y=\mu}}{24}\right](\gamma_2+3)\sigma^4 + o(\sigma^4) \\
&= \tfrac{1}{2}g(\mu) - g(\mu)^{\frac{1}{2}} + \tfrac{1}{2} \\
&+\left[\tfrac{g^{(2)}(\mu)}{4} + \tfrac{1}{8}g(\mu)^{-\frac{3}{2}}(g^{(1)}(\mu))^2 - \tfrac{1}{4}g(\mu)^{-\frac{1}{4}}g^{(2)}(\mu)\right]\sigma^2 \\
&+\left[\tfrac{g^{(3)}(\mu)}{12} - \tfrac{1}{16}g(\mu)^{-\frac{5}{2}}(g^{(1)}(\mu))^3 + \tfrac{1}{8}g(\mu)^{-\frac{3}{2}}g^{(1)}(\mu)g^{(2)}(\mu) - \tfrac{1}{12}g(\mu)^{-\frac{1}{2}}g^{(3)}(\mu)\right]\gamma_1\sigma^3 \\
&+\left[\tfrac{g^{(4)}(\mu)}{48} + \tfrac{5}{128}g(\mu)^{-\frac{7}{2}}(g^{(1)}(\mu))^4 - \tfrac{3}{32}g(\mu)^{-\frac{5}{2}}(g^{(1)}(\mu))^2g^{(2)}(\mu) + \tfrac{1}{32}g(\mu)^{-\frac{3}{2}}(g^{(2)}(\mu))^2\right. \\
&\left.+\tfrac{1}{24}g(\mu)^{-\frac{3}{2}}g^{(1)}(\mu)g^{(3)}(\mu) - \tfrac{1}{48}g(\mu)^{-\frac{1}{2}}g^{(4)}(\mu)\right](\gamma_2+3)\sigma^4 + o(\sigma^4) \\
&= \left[\tfrac{g^{(2)}(\mu)}{4} + \tfrac{1}{8}(g^{(1)}(\mu))^2 - \tfrac{1}{4}g^{(2)}(\mu)\right]\sigma^2 \\
&+\left[\tfrac{g^{(3)}(\mu)}{12} - \tfrac{1}{16}(g^{(1)}(\mu))^3 + \tfrac{1}{8}g^{(1)}(\mu)g^{(2)}(\mu) - \tfrac{1}{12}g^{(3)}(\mu)\right]\gamma_1\sigma^3 \\
&+\left[\tfrac{g^{(4)}(\mu)}{48} + \tfrac{5}{128}(g^{(1)}(\mu))^4 - \tfrac{3}{32}(g^{(1)}(\mu))^2g^{(2)}(\mu) + \tfrac{1}{32}(g^{(2)}(\mu))^2\right. \\
&\left.+\tfrac{1}{24}g^{(1)}(\mu)g^{(3)}(\mu) - \tfrac{1}{48}g^{(4)}(\mu)\right](\gamma_2+3)\sigma^4 + o(\sigma^4).
\end{aligned} \tag{1.26}$$

If the distribution is symmetric, then $g(y) = 1$, and $S_\rho = 0$. Additionally, if $f(y)$ is standardized, i.e. $E(y) = \mu = 0$, and $Var(y) = \sigma^2 = 1$. In this simplified case, $g(y)|_{y=0} = \frac{f(-y)}{f(y)}|_{y=0} = \frac{f(0)}{f(0)} = 1$, the decomposition (1.26) could be reduced to

$$\begin{aligned}
S_\rho &= \tfrac{1}{8}(g^{(1)}(0))^2 + \left[\tfrac{1}{8}g^{(1)}(0)g^{(2)}(0) - \tfrac{1}{16}(g^{(1)}(0))^3\right]\gamma_1 \\
&+\left[\tfrac{5}{128}(g^{(1)}(0))^4 - \tfrac{3}{32}(g^{(1)}(0))^2g^{(2)}(0) + \tfrac{1}{32}(g^{(2)}(0))^2\right. \\
&\left.+\tfrac{1}{24}g^{(1)}(0)g^{(3)}(0)\right](\gamma_2+3) + \ldots.
\end{aligned} \tag{1.27}$$

A.2 Variable Definitions

- 1SD ETP: 1SD excess tail probability or total 1SD excess tail probability (ETP1sd) of stock i in month t is defined as (1.1), x is the standardized current one year daily excess return. Thus letp1sd denotes the realized 1SD ETP of stock i in month t, that is the 1SD ETP of the lagged one year daily return.
- $S_{\varphi 1}$: $S_{\varphi 1}$ or total $S_{\varphi 1}$ of stock i in month t is defined as (1.4), y is the standardized current one year daily excess return. Thus $S_{\varphi 1}$ denotes the realized $S_{\varphi 1}$ of stock i in month t, that is the $S_{\varphi 1}$ of the lagged one year daily return.
- 2SD ETP: 2SD excess tail probability or total 2SD excess tail probability (ETP2sd) of stock i in month t is defined as (1.28), x is the standardized current one year daily excess return. Thus letp2sd denotes the realized 2SD ETP of stock i in month t, that is the 2SD ETP of the lagged one year daily return.

$$\text{2SD ETP} = \int_{-\infty}^{-2} f(x)\,dx - \int_{2}^{+\infty} f(x)\,dx = \int_{-\infty}^{-2} [f(x) - f(-x)]\,dx. \tag{1.28}$$

- $S_{\varphi 2}$: $S_{\varphi 2}$ or total $S_{\varphi 2}$ of stock i in month t is defined as (1.29), y is the standardized current one year daily excess return. Thus $S_{\varphi 2}$ denotes the realized $S_{\varphi 2}$ of stock i in month t, that is the $S_{\varphi 2}$ of the lagged one year daily return.

$$S_{\varphi 2} = -sign(etp1sd) \times \frac{1}{2}\left(\int_{-\infty}^{-2} (f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dy + \int_{2}^{\infty} (f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dy\right), \tag{1.29}$$

- BOOK-TO-MARKET (BM): Following Fama and French (1992, 1993), a firm's book-to-market ratio in month t is calculated using the market value of equity at the end of December of the last year and the book value of common equity plus balance-sheet deferred taxes for the firm's latest fiscal year ending in the prior calendar year. Our measure of book-to-market ratio, BM, is defined as the natural log of the book-to-market ratio.
- CAPITAL GAINS OVERHANG (CGO): Following Equation (9), page 319, and E-quation (11), page 320 in Grinblatt and Han (2005), The Capital gains overhang

(CGO) at week w is defined as:

$$CGO_w = \frac{P_{w-1} - RP_w}{P_{w-1}}, \tag{1.30}$$

where P_w is the stock price at the end of week w, and RP_w is the reference price for each individual stock which defined as follows.

$$RP_w = k^{-1} \sum_{n=1}^{W} (V_{w-n} \prod_{\tau=1}^{n-1} (1 - V_{w-n+\tau})) P_{w-n}, \tag{1.31}$$

where V_w is the turnover in week w, W is 260, the number of weeks in the previous five years, and k is the constant that makes the weights on past prices sum to one. Weekly turnover is calculated as the weekly trading volume divided by the number of shares outstanding. The weight on P_{w-n} reflects the probability that share purchased at week $w-n$ has not been traded since. The market price is lagged by one week, and the monthly CGO is just the last week CGO within each month. The CGO variable ranges from 1962 to 2013.

- EXPECTED IDIOSYNCRATIC SKEWNESS ($E(ISKEW)$): There are two methods in the literature, we apply both of them in our paper. Following Bali, Cakici, and Whitelaw (2011), $E(ISKEW)$ can be obtained as the fitted value from firm-level month-by-month cross-sectional regression of $ISKEW$ using daily returns over the subsequent year on subsets of $ISKEW$ calculated based on previous year daily return and ten control variables($SIZE$, BM, MOM, $TURN$, $ILLIQ$, β, MAX, $IVOL$, REV) that are defined here,

$$ISKEW_{i,t+13} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t} ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+13}, \tag{1.32}$$

here $ISKEW_{i,t+13}$ is the idiosyncratic skewness measured using daily returns over the subsequent year, and $ISKEW_{i,t}$ is calculated based on previous year daily returns. Second method following Boyer, Mitton, and Vorkink (2010) is different, we estimate cross-sectional regressions (Equation 1.33) first. Then, we can use the regression parameters from Equation 1.33 and available information of the current month to obtain $E(ISKEW)$.

$$ISKEW_{i,t} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t-12} + \lambda_{2,t}ISKEW_{i,t-12} + \Lambda_t X_{i,t-12} + \epsilon_{i,t}, \tag{1.33}$$

here $ISKEW_{i,t}$ and $ISKEW_{i,t-12}$ are calculated based on previous year daily returns and even one year before last year's daily returns respectively, $X_{i,t-12}$ is a vector containing firm characteristics available at month $t-12$ ($SIZE$, BM, MOM, $TURN$, $ILLIQ$, MAX, $IVOL$, REV).

$$E(ISKEW)_{i,t} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}ISKEW_{i,t} + \Lambda_t X_{i,t}, \tag{1.34}$$

here $ISKEW_{i,t}$ is calculated based on previous year daily returns , $X_{i,t}$ is a vector containing firm characteristics available at month t ($SIZE$, BM, MOM, $TURN$, $ILLIQ$, MAX, $IVOL$, REV).

- IDIOSYNCRATIC VOLATILITY: Following Bali, Cakici, and Whitelaw (2011), idiosyncratic volatility (idiovol) of stock i in month t is defined as the standard deviation of daily idiosyncratic returns within month t. First, we assume a single-factor return generating process:

$$R_{i,d} = \alpha_i + \beta_i \cdot R_{m,d} + \epsilon_{i,d}, d = 1, ..., D_t, \tag{1.35}$$

where $\epsilon_{i,d}$ is the idiosyncratic return on day d. Then idiosyncratic volatility of stock i in month t is defined as follows:

$$idiovol_{i,t} = \sqrt{var(\epsilon_{i,d})}, d = 1, ..., D_t., d = 1, ..., D_t. \tag{1.36}$$

- IDIOSYNCRATIC SKEWNESS, $S_{\varphi 1}(S_{\varphi 2})$, 1SD (2SD) ETP: Following Bali, Cakici, and Whitelaw (2011) and Harvey and Siddique (2000), when estimating idiosyncratic measurements other than volatility, we utilize the daily residuals $\epsilon_{i,d}$ in the following expression:

$$R_{i,d} = \alpha_i + \beta_i \cdot R_{m,d} + \gamma_i \cdot R_{m,d}^2 + \epsilon_{i,d}, \qquad (1.37)$$

where $R_{i,d}$ is the excess return of stock i on day d, $R_{m,d}$ is the market excess return on day d, and $\epsilon_{i,d}$ is the idiosyncratic return on day d.

Idiosyncratic skewness (idioskewness or idioskew) of stock i in month t is defined as the skewness of one year daily residuals $\epsilon_{i,d}$, thus lidioskew denotes the realized idiosyncratic skewness of stock i in month t which is the skewness of lagged one year daily residuals.

Idiosyncratic $S_{\varphi 1}(S_{\varphi 2})$ or idio$S_{\varphi 1}$(idio$S_{\varphi 2}$) of stock i in month t is defined as the $S_{\varphi 1}(S_{\varphi 2})$ of one year daily residuals $\epsilon_{i,d}$, thus lidio$S_{\varphi 1}$(lidio$S_{\varphi 2}$) denotes the realized idiosyncratic $S_{\varphi 1}(S_{\varphi 2})$ of stock i in month t, that is the $S_{\varphi 1}(S_{\varphi 2})$ of lagged one year daily residuals.

Idiosyncratic 1SD(2SD) ETP or idioETP1sd (idioETP2sd) of stock i in month t is defined as the 1SD(2SD) ETP of one year daily residuals $\epsilon_{i,d}$, thus lidioETP1sd(lidioETP2sd) denotes the realized idiosyncratic 1SD(2SD) ETP of stock i in month t, that is the 1SD(2SD) ETP of lagged one year daily residuals.

- ILLIQUIDITY ($ILLIQ$): Following Amihud (2002), the proxy for daily stock illiquidity is from normalizing $L_{i,d} = |R_{i,d}|/dv_{i,t}$. It is the ratio of absolute change of price $r_{i,d}$ to the dollar trading volume $dv_{i,d}$ for stock i at day d. The monthly $ILLIQ$ applied in the paper is the daily average of the illiquidity ratio for each stock. To get an accurate estimate of monthly Amihud ratio, we drop the months for stocks if the number of the monthly observations is less than 15. Following Acharya and Pedersen (2005), we also normalized the Amihud ratio to adjust for inflation and truncated it at 30 to eliminate the effect of outliers (the stocks with transaction cost larger than 30% of the price),

$$ILLIQ_{i,d} = \min(0.25 + 0.3L_{i,d} \times \frac{\text{capitalization of market portfolio}_{\text{d}-1}}{\text{capitalization of market portfolio}_{\text{July 1962}}}, 30). \tag{1.38}$$

- MARKET BETA: beta_capm

$$R_{i,d} = \alpha + \beta\_capm_{i,y} \cdot R_{m,d} + \epsilon_{i,d}, d = 1, ..., D_y, \tag{1.39}$$

where $R_{i,d}$ is the excess return of stock i on day d, $R_{m,d}$ is the market excess return on day d and D_y is the number of trading days in year y. beta_capm is yearly updated.

- MAXIMUM: max is the maximum daily return in a month following Bali, Cakici, and Whitelaw (2011):

$$max_{i,t} = max(R_{i,d}), d = 1, ..., D_t, \tag{1.40}$$

where $R_{i,d}$ is the excess return of stock i on day d and D_t is the number of trading days in month t.

- MOMENTUM (MOM): Following Jegadeesh and Titman (1993), the momentum effect of each stock in month t is measured by the cumulative return over the previous 6 months, with the previous one month skipped, i.e. the cumulative return from month $t-7$ to month $t-2$.

- SHORT-TERM REVERSAL: rev is following Jegadeesh (1990), Lehmann (1990) and Bali, Cakici, and Whitelaw (2011)'s definition. Reversal for each stock in month t is defined as the excess return on the stock over the previous month, i.e., the return in month $t-1$.

- SKEWNESS: skewness or total skewness of stock i for month t is computed using daily return within current year, the same with Bali, Cakici, and Whitelaw (2011):

$$skewness_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} (\frac{R_{i,d} - \mu_i}{\sigma_i})^3, \tag{1.41}$$

where D_t is the number of trading days in a year. $R_{i,d}$ is the excess return on stock

i on day d, μ_i is the mean of returns of stock i in the year, and σ_i is the standard deviation of returns of stock i in the year. lskewness denotes the realized skewness of stock i in month t which is the skewness of lagged one year daily returns.

- TURNOVER ($TURN$): $TURN$ is calculated monthly as the adjusted monthly trading volume divided by shares outstanding.
- VOLATILITY: volatility (vol) or total volatility of stock i in month t is defined as the standard deviation of daily returns within month t:

$$vol_{i,t} = \sqrt{var(R_{i,d})}, d = 1, ..., D_t. \tag{1.42}$$

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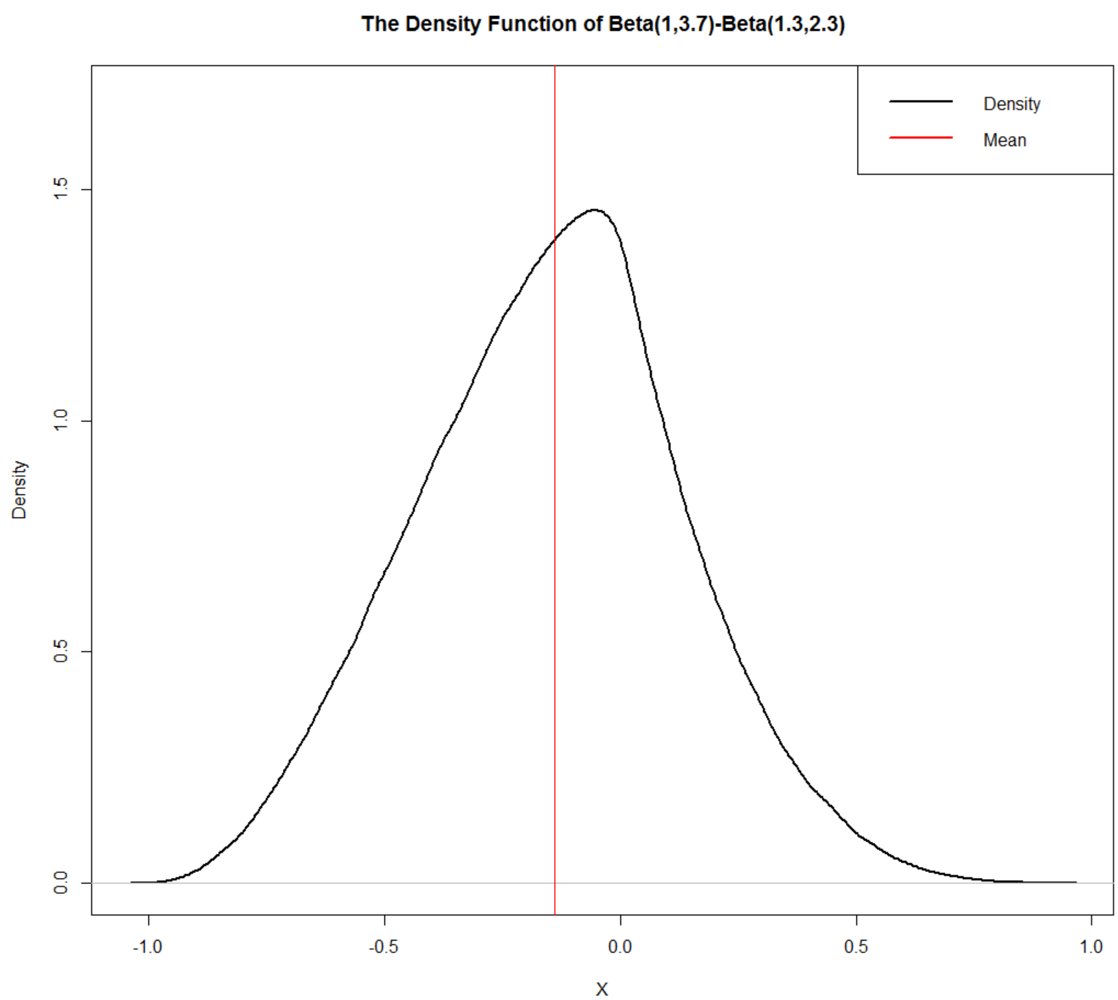


Figure 1.1: Asymmetric Distribution with skewness=0

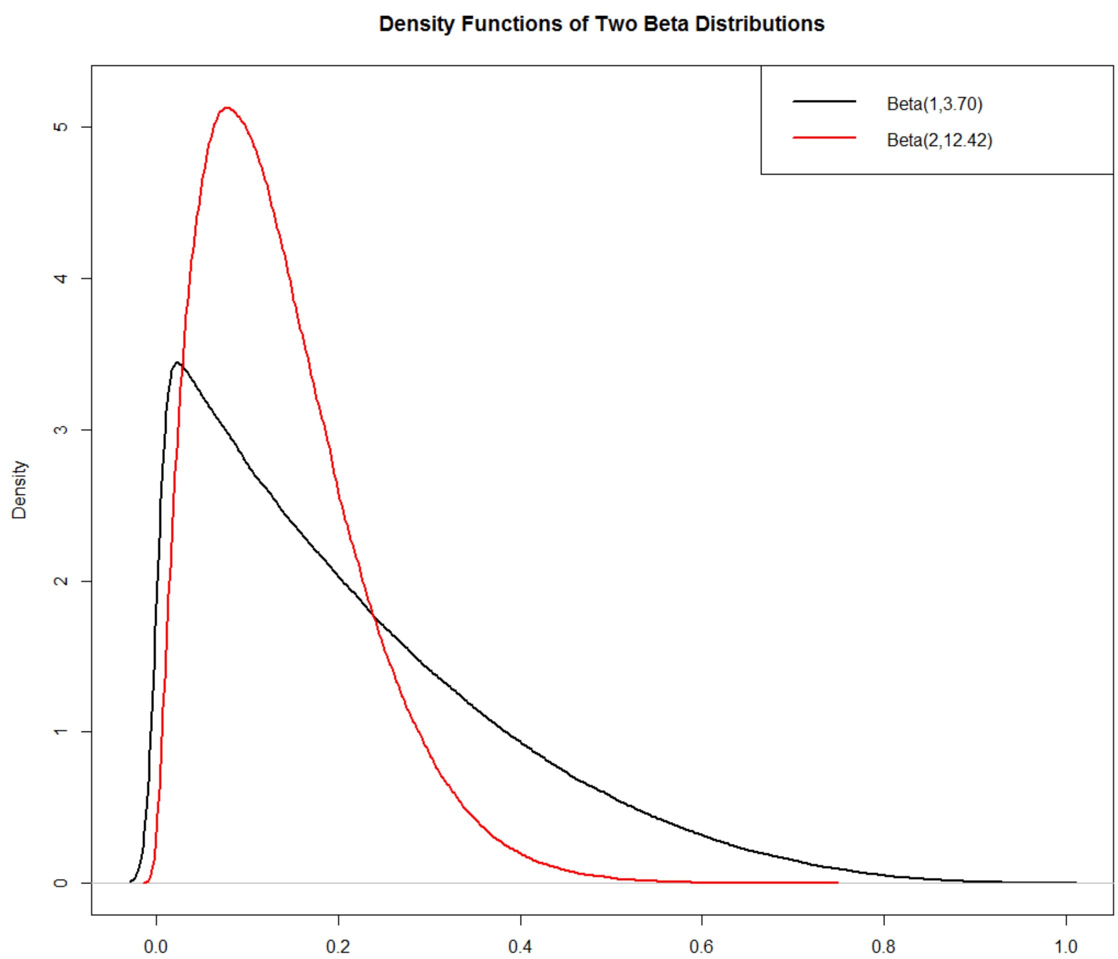
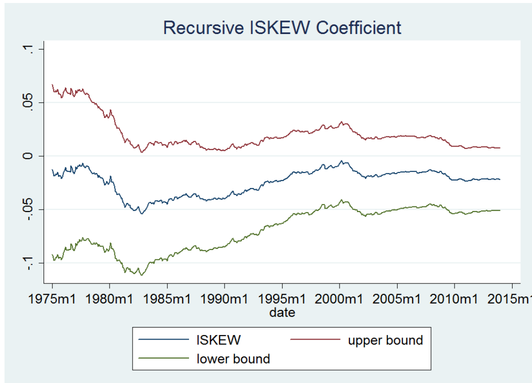
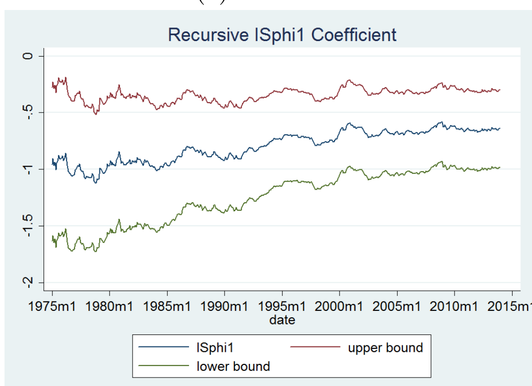


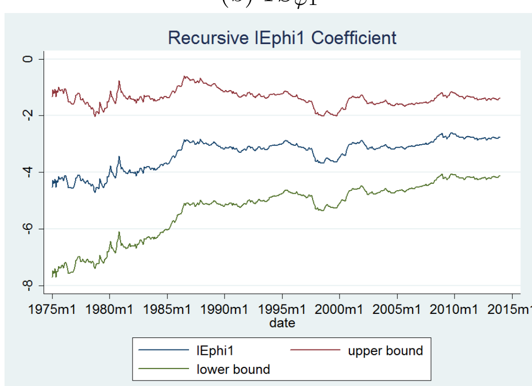
Figure 1.2: Different Asymmetry, skewness=1



(a) $ISKEW$

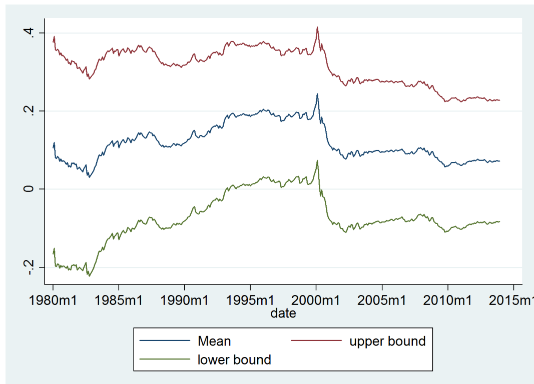


(b) $IS_{\varphi 1}$

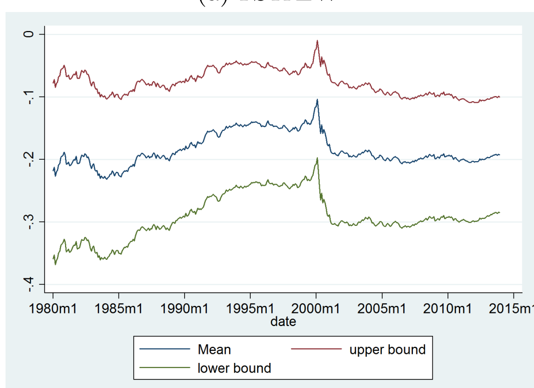


(c) $IE_{\varphi 1}$

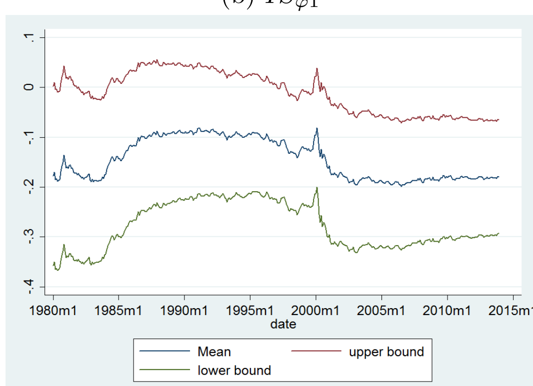
Figure 1.3: Recursive Gamma in the front of Idiosyncratic Asymmetry Proxies



(a) $ISKEW$



(b) $IS_{\varphi 1}$



(c) $IE_{\varphi 1}$

Figure 1.4: Recursive Idiosyncratic Asymmetry Portfolio10-1 Excess Return Difference(%)

Table 1.1: Simulation

Panel A provides the average values and associated t-statistics (in parentheses) of skewness($SKEW$), S_φs, S_φi, and E_φ from 6 DGPs 1,000 simulations. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. Panel B provides the average values of $SKEW$, S_φs, S_φi, and E_φ from 2 DGPs 1,000 simulations $SKEW$ means total skewness following the formula (1.41), S_φs denotes the summation version results of 1.4, or 1.29, and S_φi denotes the integration version results of 1.4, or 1.29.

Panel A: Asymmetry Level

	$N(120,240)$	$\chi^2(10)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(0.5)$	$\chi^2(0.05)$
$SKEW$	0.0038	0.8802***	1.2585***	2.7100***	3.7396***	9.5397***
	(1.05)	(170.56)	(183.30)	(173.64)	(157.05)	(126.22)
$S_{\varphi 1}$s	0.0004	0.0554***	0.2302***	0.1097***	0.1070***	0.0920***
	(0.44)	(11.95)	(55.85)	(60.62)	(55.84)	(36.41)
$S_{\varphi 1}$i	0.0008	0.0935***	0.3641***	0.1464***	0.1436***	0.1359***
	(0.57)	(12.51)	(56.22)	(61.69)	(56.85)	(35.37)
$S_{\varphi 2}$s	-0.0085	0.0192***	0.0663***	0.0863***	0.0858***	NA
	(-0.96)	(6.49)	(31.29)	(44.96)	(42.97)	NA
$S_{\varphi 2}$i	-0.0154	0.0286***	0.0958***	0.1240***	0.1222***	NA
	(-0.92)	(6.14)	(31.25)	(43.50)	(23.97)	NA
$E_{\varphi 1}$	0.0002	0.0035***	0.0164***	0.1216***	0.1018***	0.0344***
	(0.57)	(12.33)	(48.17)	(342.45)	(281.79)	(145.00)
$E_{\varphi 2}$	0.0001	0.0405***	0.0462***	0.0512***	0.0486***	0.0227***
	(0.49)	(255.66)	(301.54)	(238.72)	(219.14)	(121.69)

Panel B: Same Skewness, Different Asymmetry

	Beta(1,3.70)	Beta(2,12.42)	two-sample t-test	p value
$SKEW$	0.9959	0.9973	-0.3662	0.7142
$S_{\varphi 1}$s	0.3678	0.2026	29.7203	0
$S_{\varphi 1}$i	0.5710	0.3232	28.4207	0
$S_{\varphi 2}$s	0.0758	0.0684	2.7142	0.0067
$S_{\varphi 2}$i	0.1082	0.0947	3.5649	0.0003
$E_{\varphi 1}$	0.0231	0.0097	31.8812	0
$E_{\varphi 2}$	0.0496	0.0458	24.189	0

Table 1.2: Correlations of Asymmetry Measures and Volatility

Panel A provides the time series average of the n correlations of asymmetry measures and volatility for the period from January 1962 to December 2013. Panel B provides the same correlations for the idiosyncratic asymmetry measures.

Panel A: Total Measures				
	$SKEW$	$E_{\varphi 1}$	$S_{\varphi 1}$	VOL
$SKEW$	1.0000			
$E_{\varphi 1}$	-0.1233	1.0000		
$S_{\varphi 1}$	-0.0071	0.7051	1.0000	
VOL	0.0738	0.0312	0.0241	1.0000
Panel B: Idiosyncratic Measures				
	$ISKEW$	$IE_{\varphi 1}$	$IS_{\varphi 1}$	$IVOL$
$ISKEW$	1.0000			
$IE_{\varphi 1}$	-0.1649	1.0000		
$IS_{\varphi 1}$	-0.0342	0.6789	1.0000	
$IVOL$	0.0806	0.0610	0.0546	1.0000

Table 1.3: The Characteristics of $ISKEW$, IS_{φ}, and IE_{φ}

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of $ISKEW$, IS_{φ}, and IE_{φ} measured using daily returns over the lagged year on subsets of lagged predictor variables including size ($SIZE$), book to market ratio (BM), momentum (MOM), turnover ($TURN$), liquidity measure ($ILLIQ$), and market beta (β). In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Here idiosyncratic asymmetry measures are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$ISKEW$	$IS_{\varphi 1}$	$IS_{\varphi 2}$	$IE_{\varphi 1}$	$IE_{\varphi 2}$
$SIZE$	-0.0886***	-0.0011***	-0.0042***	-0.0003***	-0.0016***
	(-23.78)	(-9.64)	(-5.01)	(-7.56)	(-22.96)
BM	-0.0344***	-0.0019***	-0.0119***	-0.0006***	-0.0006***
	(-6.04)	(-11.73)	(-8.72)	(-11.46)	(-8.19)
MOM	0.0077***	0.0001***	0.0004***	0.0000***	0.0001***
	(23.85)	(13.73)	(12.49)	(6.43)	(27.68)
$TURN$	-0.0045	0.0028***	0.0166***	0.0012***	0.0004***
	(-0.82)	(18.22)	(13.33)	(21.33)	(6.08)
$ILLIQ$	0.0043***	0.0001***	0.0003	0.0000***	0.0000*
	(5.48)	(3.27)	(0.93)	(3.46)	(1.80)
β	0.0310**	0.0035***	0.0162***	0.0006***	0.0033***
	(2.53)	(9.78)	(6.93)	(6.10)	(22.26)
Constant	0.7820***	0.0059***	0.0129**	0.0019***	0.0144***
	(26.42)	(7.94)	(2.45)	(7.23)	(33.90)
OBS.	1,647,894	1,633,731	319,989	1,644,112	1,644,112
R^2	0.103	0.020	0.033	0.028	0.135

Table 1.4: Firm-Level Cross-Sectional Return Regressions

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return (RA, the excess return which adjusted for Fama-French three factors (Brennan, Chordia, and Subrahmanyam (1998)), the same definition for following tables' adjusted-return) in that month on subsets of lagged predictor variables including $IS_{\varphi 1}$, $IE_{\varphi 1}$ and $ISKEW$ measured over the preceding year and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Adjusted Return (RA) is the Dependent Variable											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
IS_{φ}	-0.6410***			-0.7295***	-0.7949***	-0.7838***	-0.6467***				
	(-3.04)			(-3.33)	(-4.05)	(-3.99)	(-3.20)				
IE_{φ}		-2.7588***						-3.2215***	-3.5363***	-3.5185***	-2.9227***
		(-3.15)						(-3.52)	(-4.90)	(-4.84)	(-3.96)
$ISKEW$			-0.0218	-0.0281	-0.0173	-0.0181	-0.0188	-0.0298	-0.0238	-0.0244	-0.0235
			(-1.15)	(-1.39)	(-1.00)	(-1.06)	(-1.06)	(-1.52)	(-1.42)	(-1.47)	(-1.36)
$SIZE$					-0.1324***	-0.1340***	-0.1230***		-0.1313***	-0.1330***	-0.1219***
					(-10.13)	(-10.21)	(-9.22)		(-10.01)	(-10.09)	(-9.11)
BM					0.0740*	0.0702*	0.0135		0.0731*	0.0693*	0.0126
					(1.95)	(1.85)	(0.35)		(1.93)	(1.83)	(0.33)
MOM					0.0093***	0.0092***	0.0084***		0.0093***	0.0091***	0.0084***
					(6.67)	(6.55)	(5.71)		(6.73)	(6.62)	(5.76)
$TURN$					0.1331***	0.1364***	0.1446***		0.1299***	0.1324***	0.1412***
					(4.16)	(4.13)	(4.31)		(4.09)	(4.05)	(4.24)
$ILLIQ$					0.0132***	0.0142***	0.0178***		0.0131***	0.0141***	0.0177***
					(2.67)	(2.96)	(3.62)		(2.67)	(2.93)	(3.61)
MAX					-0.0881***	-0.0820***	0.0183**		-0.0823***	-0.0766***	0.0226***
					(-8.46)	(-8.66)	(2.37)		(-7.96)	(-8.17)	(2.98)
VOL					-0.1049***				-0.1099***		
					(-2.86)				(-3.03)		
$IVOL$						-0.1325***	-0.3588***			-0.1355***	-0.3603***
						(-3.97)	(-12.10)			(-4.11)	(-12.36)
$REVA$							-0.0473***				-0.0475***
							(-13.02)				(-13.12)
Constant	0.0613*	0.0643**	0.0639*	0.0710**	1.2082***	1.2380***	1.1301***	0.0750**	1.1943***	1.2227***	1.1147***
	(1.87)	(1.97)	(1.81)	(1.98)	(10.36)	(10.56)	(9.32)	(2.10)	(10.27)	(10.48)	(9.26)
OBS.	1,511,723	1,519,800	1,522,828	1,511,723	1,471,738	1,471,738	1,452,787	1,519,800	1,475,918	1,475,918	1,456,833
R^2	0.001	0.001	0.002	0.003	0.031	0.031	0.037	0.003	0.031	0.031	0.036

Table 1.4 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables including $IS_{\varphi 1}$, $IE_{\varphi 1}$ and $ISKEW$ measured over the preceding year and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
IS_{φ}	-0.8584***			-0.9046***	-1.1043***	-1.1022***	-0.9415***				
	(-2.62)			(-2.78)	(-5.38)	(-5.35)	(-4.47)				
IE_{φ}		-3.4598***						-3.7902***	-4.6618***	-4.6899***	-4.0147***
		(-2.60)						(-2.66)	(-6.16)	(-6.16)	(-5.20)
$ISKEW$			0.0113	0.0085	-0.0232	-0.0189	-0.0145	0.0023	-0.0290*	-0.0247	-0.0191
			(0.39)	(0.27)	(-1.31)	(-1.08)	(-0.81)	(0.08)	(-1.66)	(-1.43)	(-1.08)
$SIZE$					-0.2168***	-0.2163***	-0.2062***		-0.2134***	-0.2128***	-0.2033***
					(-5.42)	(-5.48)	(-5.19)		(-5.34)	(-5.40)	(-5.12)
BM					0.2864***	0.2871***	0.2418***		0.2891***	0.2899***	0.2438***
					(5.35)	(5.36)	(4.46)		(5.40)	(5.41)	(4.50)
MOM					0.0101***	0.0100***	0.0093***		0.0101***	0.0100***	0.0093***
					(6.78)	(6.72)	(5.91)		(6.84)	(6.79)	(5.94)
$TURN$					-0.0235	-0.0359	-0.0082		-0.0275	-0.0407	-0.0114
					(-0.65)	(-1.00)	(-0.23)		(-0.77)	(-1.14)	(-0.32)
$ILLIQ$					0.0115**	0.0093*	0.0115**		0.0113**	0.0090*	0.0114**
					(2.05)	(1.75)	(2.14)		(2.02)	(1.70)	(2.13)
β					0.9224***	0.8780***	0.8015***		0.9134***	0.8660***	0.7913***
					(4.55)	(4.43)	(3.95)		(4.51)	(4.37)	(3.90)
MAX					-0.0442***	-0.0614***	0.0229***		-0.0363***	-0.0538***	0.0294***
					(-4.16)	(-5.97)	(2.99)		(-3.46)	(-5.29)	(3.85)
VOL					-0.3590***				-0.3618***		
					(-8.68)				(-8.86)		
$IVOL$						-0.2884***	-0.4705***			-0.2892***	-0.4714***
						(-8.01)	(-15.44)			(-8.12)	(-15.55)
REV							-0.0380***				-0.0383***
							(-10.12)				(-10.21)
Constant	0.6759***	0.6771***	0.6564***	0.6661***	2.1265***	2.0963***	2.0691***	0.6698***	2.0986***	2.0658***	2.0427***
	(2.88)	(2.90)	(2.84)	(2.90)	(7.16)	(7.21)	(7.00)	(2.92)	(7.08)	(7.12)	(6.92)
OBS.	1,860,476	1,884,898	1,905,096	1,860,476	1,593,622	1,593,622	1,593,622	1,884,898	1,599,204	1,599,204	1,599,204
R^2	0.001	0.002	0.003	0.004	0.088	0.088	0.093	0.005	0.088	0.088	0.093

Table 1.5: Equal-Weighted Average Monthly Returns of Decile Portfolios Based on $ISKEW$, $IS_{\varphi 1}$ and $IE_{\varphi 1}$

Decile portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the realized $ISKEW$. Portfolio 1 is the portfolio of stocks with the lowest $ISKEW$, while Portfolio 10 denotes the highest. And here the excess return and $ISKEW$ are winsorized at 0.5 percentile and 99.5 percentile.
10-1 spread denotes the average raw return difference between the highest and lowest $ISKEW$, FF3 alpha denotes the average Fama-French 3-factor alpha difference, and carhart4 alpha denotes the average Carhart 4-factor alpha difference, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: $ISKEW$

Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.477***	-0.216**	-0.033
	(2.26)	(-3.31)	(-0.57)
2	0.660***	-0.020	0.091*
	(3.35)	(-0.39)	(1.83)
3	0.659***	-0.033	0.059
	(3.32)	(-0.64)	(1.19)
4	0.687***	(-0.016)	0.033
	(3.39)	(-0.32)	(0.68)
5	0.751***	(0.044)	0.076
	(3.60)	(0.94)	(1.60)
6	0.782***	0.035	0.056
	(3.58)	(0.75)	(1.15)
7	0.723***	-0.018	-0.037
	(3.20)	(-0.37)	(-0.74)
8	0.735***	-0.030	-0.040
	(3.12)	(-0.58)	(-0.76)
9	0.659***	-0.094*	-0.109**
	(2.76)	(-1.80)	(-2.05)
10(highest)	0.550**	-0.168***	-0.198***
	(2.48)	(-2.97)	(-3.42)
10-1 spread	0.073	0.048	-0.165**
	(0.77)	(0.54)	(-2.03)

Table 1.5 (continued)

Decile portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the realized $IS_{\varphi 1}$. Portfolio 1 is the portfolio of stocks with the lowest $IS_{\varphi 1}$, while Portfolio 10 denotes the highest. And here the excess return and $IS_{\varphi 1}$ are winsorized at 0.5 percentile and 99.5 percentile.
10-1 spread denotes the average raw return difference between the highest and lowest $IS_{\varphi 1}$, FF3 alpha denotes the average Fama-French 3-factor alpha difference, and carhart4 alpha denotes the average Carhart 4-factor alpha difference, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: $IS_{\varphi 1}$			
Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.768***	0.026	0.051
	(3.51)	(0.49)	(0.95)
2	0.761***	0.019	0.079*
	(3.62)	(0.39)	(1.67)
3	0.702***	-0.014	0.057
	(3.44)	(-0.28)	(1.18)
4	0.714***	0.004	0.099**
	(3.59)	(0.08)	(2.04)
5	0.631***	-0.057	0.031
	(3.10)	(-1.25)	(0.70)
6	0.607***	-0.109**	-0.044
	(2.85)	(-2.49)	(-1.01)
7	0.632***	-0.078*	-0.031
	(2.94)	(-1.71)	(-0.67)
8	0.651***	-0.081*	-0.046
	(2.93)	(-1.82)	(-1.02)
9	0.631***	-0.097**	-0.103**
	(2.78)	(-2.18)	(-2.26)
10(highest)	0.575**	-0.162***	-0.213***
	(2.45)	(-3.09)	(-4.04)
10-1 spread	-0.193***	-0.188***	-0.264***
	(-3.42)	(-3.58)	(-5.11)

Table 1.5 (continued)

Decile portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the realized $IE_{\varphi 1}$. Portfolio 1 is the portfolio of stocks with the lowest $IE_{\varphi 1}$, while Portfolio 10 denotes the highest. And here the excess return and $IE_{\varphi 1}$ are winsorized at 0.5 percentile and 99.5 percentile.
10-1 spread denotes the average raw return difference between the highest and lowest $IE_{\varphi 1}$, FF3 alpha denotes the average Fama-French 3-factor alpha difference, and carhart4 alpha denotes the average Carhart 4-factor alpha difference, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel C: $IE_{\varphi 1}$			
Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.694***	-0.015	0.059
	(3.51)	(-0.29)	(1.11)
2	0.718***	-0.008	0.066
	(3.46)	(-0.16)	(1.39)
3	0.713***	-0.009	0.038
	(3.42)	(-0.19)	(0.82)
4	0.729***	0.006	0.069
	(3.47)	(0.13)	(1.58)
5	0.706***	-0.029	-0.026
	(3.29)	(-0.64)	(0.57)
6	0.701***	-0.030	0.002
	(3.24)	(-0.70)	(0.04)
7	0.623***	-0.096**	-0.064
	(2.87)	(-2.23)	(-1.48)
8	0.651***	-0.065	-0.047
	(2.97)	(-1.55)	(-1.11)
9	0.610***	-0.104**	-0.081*
	(2.73)	(-2.41)	(-1.84)
10(highest)	0.515**	-0.197***	-0.194***
	(2.28)	(-4.09)	(-3.92)
10-1 spread	-0.179**	-0.182***	-0.252***
	(-2.57)	(-3.11)	(-4.33)

Table 1.6: Cross-Section Regressions on Idiosyncratic Asymmetry During High and Low Sentiment Period

From July 1965 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables when the lagged month's standardized sentiment index (based on Baker and Wurgler (2006, 2007), extended by Huang et al. (2015) to December 2013)≥ 1 for Model 1 to Model 4 or the lagged month's standardized sentiment index ≤ -1 for Model 5 to Model 8. $ISKEW$ data is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: $ISKEW$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	-0.1951***	-0.1435***	-0.1491***	-0.1483***	-0.0229	0.0826*	0.1012**	0.0881*
	(-3.39)	(-2.74)	(-2.68)	(-2.66)	(-0.43)	(1.73)	(2.02)	(1.78)
$SIZE$		-0.1437***	-0.1521***	-0.1550***		-0.0775**	-0.0617*	-0.0697**
		(-3.23)	(-3.55)	(-3.65)		(-2.30)	(-1.81)	(-2.11)
BM		0.0988	0.1007	0.1031		0.2105*	0.2218*	0.2074*
		(1.05)	(1.01)	(1.06)		(1.76)	(1.83)	(1.71)
MOM		0.0118***	0.0120***	0.0121***		0.0034	0.0042	0.0043
		(2.82)	(3.02)	(2.96)		(0.79)	(1.00)	(1.02)
$TURN$		0.2496***	0.2512***	0.2420***		0.3203***	0.2637***	0.3128***
		(3.05)	(3.28)	(3.00)		(3.23)	(2.74)	(2.98)
$ILLIQ$		-0.0053	0.0025	0.0015		-0.0094	-0.0058	0.0004
		(-0.47)	(0.21)	(0.13)		(-1.00)	(-0.54)	(0.03)
MAX		-0.1516***	-0.1419***	-0.1376***		-0.1468***	-0.1847***	-0.1369***
		(-11.00)	(-5.18)	(-5.72)		(-10.43)	(-6.07)	(-4.35)
VOL			-0.0515				0.1522	
			(-0.46)				(1.31)	
$IVOL$				-0.0610				-0.0475
				(-0.62)				(-0.41)
Constant	0.2436**	1.6324***	1.7131***	1.7352***	0.0628	0.9176***	0.6624**	0.8637***
	(2.39)	(5.29)	(5.04)	(5.41)	(0.94)	(4.04)	(2.45)	(3.45)
OBS.	194,807	194,441	188,813	188,813	133,613	132,104	129,696	129,696
R^2	0.002	0.033	0.037	0.036	0.002	0.034	0.037	0.037

Table 1.6 (continued)

From July 1965 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables during high sentiment period when the lagged month's standardized sentiment index (based on Baker and Wurgler (2006, 2007), extended by Huang et al. (2015) to December 2013)≥ 1 for Model 1 to Model 4 or during low sentiment period when the lagged month's standardized sentiment index ≤ -1 for Model 5 to Model 8. IS_{φ} data is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: IS_{φ}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS_{φ}	-0.8445	-1.1749**	-1.2114**	-1.1954**	-0.6827	-0.6540	-0.7261	-0.6928
	(-1.42)	(-2.40)	(-2.40)	(-2.35)	(-0.98)	(-1.10)	(-1.19)	(-1.14)
$SIZE$		-0.1369***	-0.1420***	-0.1442***		-0.0876***	-0.0743**	-0.0823**
		(-3.06)	(-3.29)	(-3.38)		(-2.66)	(-2.27)	(-2.59)
BM		0.0988	0.1066	0.1066		0.2076*	0.2192*	0.2045*
		(1.04)	(1.07)	(1.10)		(1.73)	(1.80)	(1.68)
MOM		0.0109**	0.0112***	0.0112***		0.0039	0.0048	0.0048
		(2.61)	(2.82)	(2.75)		(0.91)	(1.15)	(1.15)
$TURN$		0.2801***	0.2671***	0.2636***		0.3189***	0.2654***	0.3135***
		(3.39)	(3.48)	(3.26)		(3.23)	(2.77)	(3.02)
$ILLIQ$		-0.0056	0.0003	-0.0002		-0.0084	-0.0045	0.0017
		(-0.49)	(0.03)	(-0.01)		(-0.92)	(-0.43)	(0.16)
MAX		-0.1675***	-0.1692***	-0.1626***		-0.1455***	-0.1806***	-0.1333***
		(-11.95)	(-6.50)	(-7.14)		(-10.66)	(-6.23)	(-4.38)
VOL			-0.0048				0.1418	
			(-0.04)				(1.24)	
$IVOL$				-0.0261				-0.0601
				(-0.27)				(-0.52)
Constant	0.1587	1.5932***	1.6307***	1.6583***	0.0578	0.9939***	0.7700***	0.9674***
	(1.63)	(5.14)	(4.87)	(5.23)	(0.94)	(4.40)	(2.91)	(3.92)
OBS.	192,966	192,650	187,782	187,782	133,096	131,654	129,348	129,348
R^2	0.001	0.033	0.036	0.036	0.002	0.034	0.037	0.037

Table 1.6 (continued)

From July 1965 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables during high sentiment period when the lagged month's standardized sentiment index (based on Baker and Wurgler (2006, 2007), extended by Huang et al. (2015) to December 2013)≥ 1 for Model 1 to Model 4 or during low sentiment period when the lagged month's standardized sentiment index ≤ -1 for Model 5 to Model 8. IE_φ data is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel C: IE_φ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IE_φ	-0.3841	-2.0696	-1.9359	-1.9896	-2.4736	-3.0146	-3.0818	-2.7374
	(-0.15)	(-1.04)	(-0.93)	(-0.96)	(-0.88)	(-1.28)	(-1.28)	(-1.13)
$SIZE$		-0.1311***	-0.1368***	-0.1389***		-0.0850**	-0.0709**	-0.0783**
		(-2.95)	(-3.18)	(-3.27)		(-2.57)	(-2.14)	(-2.45)
BM		0.1033	0.1097	0.1108		0.2092*	0.2201*	0.2054*
		(1.10)	(1.11)	(1.15)		(1.75)	(1.81)	(1.69)
MOM		0.0109**	0.0111***	0.0112***		0.0038	0.0048	0.0047
		(2.61)	(2.81)	(2.75)		(0.91)	(1.14)	(1.14)
$TURN$		0.2675***	0.2576***	0.2513***		0.3133***	0.2572***	0.3049***
		(3.28)	(3.39)	(3.14)		(3.19)	(2.70)	(2.95)
$ILLIQ$		-0.0055	0.0010	0.0002		-0.0088	-0.0047	0.0014
		(-0.49)	(0.08)	(0.02)		(-0.96)	(-0.45)	(0.13)
MAX		-0.1595***	-0.1572***	-0.1519***		-0.1420***	-0.1753***	-0.1290***
		(-11.76)	(-5.97)	(-6.64)		(-10.73)	(-6.12)	(-4.30)
VOL			-0.0213				0.1388	
			(-0.19)				(1.21)	
$IVOL$				-0.0355				-0.0594
				(-0.37)				(-0.52)
Constant	0.1509	1.5335***	1.5864***	1.6069***	0.0509	0.9623***	0.7285***	0.9222***
	(1.57)	(5.00)	(4.77)	(5.11)	(0.84)	(4.23)	(2.73)	(3.70)
OBS.	194,013	193,670	188,198	188,198	133,451	131,961	129,572	129,572
R^2	0.001	0.032	0.036	0.035	0.002	0.033	0.037	0.037

Table 1.7: Idiosyncratic Asymmetry Proxies Performance Conditional on the Sentiment

The table below presents the results (α_1) of time series regression analysis of the relation between the standardized sentiment indexes and slope coefficients of idiosyncratic asymmetry proxies from cross section regressions from July 1965 to December 2013. Two sentiment indexes: standardized sentiment index from Baker and Wurgler (2006, 2007) (BW, extended by Huang et al. (2015) to December 2013) and standardized sentiment index from Huang et al. (2015) ($HJTZ$), LBW or $LHJTZ$ means the corresponding lagged one month or realized sentiment index). β_{ISKEW}, $\beta_{IE_{\varphi 1}}$ and $\beta_{IS_{\varphi 1}}$ denote the cross section coefficients obtained from univariate regression of the adjusted-return on realized asymmetry proxies, $ISKEW$, $IE_{\varphi 1}$, and $IS_{\varphi 1}$ respectively. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

$$RA_{i,t+1} = \lambda_{0,t} + \beta_{IA,t} \times IA_{i,t} + \epsilon_{i,t+1},$$

where IA is $ISKEW$, $IE_{\varphi 1}$, or $IS_{\varphi 1}$. Then the table below reports the coefficients of following time series regressions.

$$\beta_{IA,t} = \alpha_0 + \alpha_1 \times SENT_t + \epsilon_{i,t},$$

where $SENT_t$ is BW, LBW, $HJTZ$ or $LHJTZ$.

	β_{ISKEW}	$\beta_{IE_{\varphi 1}}$	$\beta_{IS_{\varphi 1}}$
BW	-0.0536***	-0.4715	-0.1901
	(-2.93)	(-0.54)	(-0.88)
LBW	-0.0560***	-0.0906	-0.1287
	(-3.60)	(-0.10)	(-0.59)
$HJTZ$	-0.0699***	-0.0336	-0.2435
	(-3.82)	(-0.04)	(-1.12)
$LHJTZ$	-0.0752***	0.0186	-0.2928
	(-4.11)	(0.02)	(-1.35)

Table 1.8: Fama-MacBeth Regressions on Idiosyncratic Asymmetry in VIX Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $ISKEW$ and other stock characteristics variables (in the first column) for monthly data from January 1962 to December 2013 in high and low VIX periods. Columns (1)–(4) are those in high periods when the previous month VIX is above its mean, and Columns (5)–(8) are those in low periods when the previous month VIX is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: $ISKEW$

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	-0.1393***	-0.0874***	-0.0816**	-0.0794**	0.0637**	0.0369**	0.0060	0.0112
	(-2.63)	(-2.67)	(-2.36)	(-2.35)	(2.13)	(2.22)	(0.34)	(0.65)
$SIZE$		-0.2251***	-0.2593***	-0.2556***		-0.1527***	-0.1951***	-0.1956***
		(-2.97)	(-3.39)	(-3.42)		(-4.13)	(-5.23)	(-5.30)
BM		0.2850**	0.2826**	0.2824**		0.3082***	0.2975***	0.2988***
		(2.47)	(2.42)	(2.43)		(6.71)	(6.43)	(6.46)
MOM		0.0013	0.0018	0.0019		0.0122***	0.0128***	0.0127***
		(0.33)	(0.48)	(0.49)		(8.92)	(9.36)	(9.23)
$TURN$		0.1808**	0.1539*	0.1462*		-0.1350***	-0.1005***	-0.1159***
		(2.42)	(1.96)	(1.90)		(-4.26)	(-3.14)	(-3.58)
$ILLIQ$		-0.0400***	-0.0396***	-0.0392***		0.0075*	0.0290***	0.0258***
		(-3.80)	(-3.50)	(-3.60)		(1.67)	(5.85)	(5.24)
β		0.7968*	0.8791*	0.8675*		0.7522***	0.9237***	0.8628***
		(1.69)	(1.83)	(1.82)		(4.63)	(5.52)	(5.18)
MAX		-0.1105***	-0.0934***	-0.1020***		-0.1211***	-0.0152	-0.0362***
		(-10.00)	(-5.16)	(-5.43)		(-19.10)	(-1.47)	(-3.51)
VOL			-0.0974				-0.4593***	
			(-1.37)				(-11.77)	
$IVOL$				-0.0635				-0.3717***
				(-0.99)				(-10.01)
Constant	1.2943***	2.7956***	3.0738***	3.0339***	0.4346*	1.2860***	1.7434***	1.7126***
	(2.72)	(5.16)	(5.51)	(5.59)	(1.91)	(4.75)	(6.31)	(6.30)
R^2	0.003	0.109	0.112	0.112	0.003	0.076	0.079	0.079

Table 1.8 (continued)

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $IS_{\varphi 1}$ and other stock characteristics variables (in the first column) for monthly data from January 1962 to December 2013 in high and low VIX periods. Columns (1)–(4) are those in high periods when the previous month VIX is above its mean, and Columns (5)–(8) are those in low periods when the previous month VIX is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel B: $IS_{\varphi 1}$

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IS_{\varphi 1}$	-1.7662*	-1.7107***	-1.6969***	-1.6440***	-0.5427**	-0.9267***	-0.8219***	-0.8378***
	(-1.88)	(-3.67)	(-3.53)	(-3.40)	(-2.13)	(-4.60)	(-3.96)	(-4.03)
$SIZE$		-0.2310***	-0.2577***	-0.2555***		-0.1632***	-0.2013***	-0.2020***
		(-3.05)	(-3.39)	(-3.44)		(-4.34)	(-5.35)	(-5.42)
BM		0.2739**	0.2734**	0.2722**		0.3046***	0.2928***	0.2941***
		(2.37)	(2.34)	(2.34)		(6.61)	(6.33)	(6.35)
MOM		0.0008	0.0015	0.0015		0.0125***	0.0128***	0.0127***
		(0.20)	(0.40)	(0.40)		(9.16)	(9.48)	(9.37)
$TURN$		0.1993***	0.1733**	0.1689**		-0.1349***	-0.0930***	-0.1081***
		(2.63)	(2.21)	(2.20)		(-4.21)	(-2.88)	(-3.32)
$ILLIQ$		-0.0390***	-0.0386***	-0.0375***		0.0075*	0.0284***	0.0253***
		(-3.69)	(-3.38)	(-3.42)		(1.65)	(5.72)	(5.13)
β		0.8103*	0.8522*	0.8615*		0.7810***	0.9333***	0.8733***
		(1.71)	(1.77)	(1.80)		(4.74)	(5.56)	(5.22)
MAX		-0.1225***	-0.1110***	-0.1166***		-0.1273***	-0.0239**	-0.0441***
		(-10.59)	(-6.11)	(-6.16)		(-19.50)	(-2.35)	(-4.35)
VOL			-0.0703				-0.4511***	
			(-0.99)				(-11.71)	
$IVOL$				-0.0515				-0.3661***
				(-0.80)				(-9.94)
Constant	1.2563***	2.8375***	3.0502***	3.0285***	0.4740**	1.3724***	1.7903***	1.7637***
	(2.65)	(5.24)	(5.52)	(5.64)	(2.05)	(4.99)	(6.45)	(6.44)
R^2	0.002	0.109	0.112	0.112	0.001	0.076	0.079	0.079

Table 1.8 (continued)

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $IE_{\varphi 1}$ and other stock characteristics variables (in the first column) for monthly data from January 1962 to December 2013 in high and low VIX periods. Columns (1)–(4) are those in high periods when the previous month VIX is above its mean, and Columns (5)–(8) are those in low periods when the previous month VIX is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel C: $IE_{\varphi 1}$

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IE_{\varphi 1}$	-4.9582	-6.4421***	-6.4724***	-6.3326***	-2.9387***	-3.9268***	-3.3202***	-3.4426***
	(-1.35)	(-3.69)	(-3.61)	(-3.53)	(-2.60)	(-5.39)	(-4.49)	(-4.64)
$SIZE$		-0.2224***	-0.2526***	-0.2497***		-0.1588***	-0.1974***	-0.1981***
		(-2.94)	(-3.31)	(-3.35)		(-4.26)	(-5.26)	(-5.33)
BM		0.2833**	0.2825**	0.2814**		0.3060***	0.2945***	0.2957***
		(2.45)	(2.41)	(2.42)		(6.65)	(6.37)	(6.39)
MOM		0.0006	0.0013	0.0013		0.0125***	0.0128***	0.0127***
		(0.16)	(0.34)	(0.35)		(9.19)	(9.53)	(9.41)
$TURN$		0.1959***	0.1662**	0.1595**		-0.1355***	-0.0969***	-0.1122***
		(2.63)	(2.14)	(2.10)		(-4.27)	(-3.03)	(-3.47)
$ILLIQ$		-0.0394***	-0.0394***	-0.0386***		0.0072	0.0283***	0.0252***
		(-3.75)	(-3.48)	(-3.55)		(1.62)	(5.76)	(5.16)
β		0.7831*	0.8491*	0.8461*		0.7616***	0.9219***	0.8622***
		(1.66)	(1.77)	(1.77)		(4.65)	(5.51)	(5.16)
MAX		-0.1130***	-0.1013***	-0.1081***		-0.1205***	-0.0171*	-0.0373***
		(-10.11)	(-5.70)	(-5.78)		(-19.02)	(-1.69)	(-3.70)
VOL			-0.0737				-0.4525***	
			(-1.07)				(-11.81)	
$IVOL$				-0.0474				-0.3672***
				(-0.75)				(-10.02)
Constant	1.2530***	2.7706***	3.0079***	2.9765***	0.4769**	1.3346***	1.7577***	1.7306***
	(2.65)	(5.14)	(5.44)	(5.53)	(2.07)	(4.91)	(6.36)	(6.35)
R^2	0.002	0.108	0.111	0.111	0.001	0.075	0.078	0.078

Table 1.9: Fama-MacBeth Regressions on Idiosyncratic Asymmetry in ALIQ Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $ISKEW$ and other stock characteristics variables (in the first column) for monthly data from September 1962 to December 2013 in high and low ALIQ periods. Columns (1)–(4) are those in high periods when the previous month ALIQ is above its mean, and Columns (5)–(8) are those in low periods when the previous month ALIQ is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: $ISKEW$

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	0.0665*	0.0096	-0.0169	-0.0128	-0.0611	0.0050	-0.0112	-0.0047
	(1.96)	(0.51)	(-0.87)	(-0.66)	(-1.46)	(0.20)	(-0.42)	(-0.18)
$SIZE$		-0.1836***	-0.2273***	-0.2299***		-0.1575***	-0.1952***	-0.1891***
		(-4.43)	(-5.49)	(-5.63)		(-2.75)	(-3.35)	(-3.30)
BM		0.2575***	0.2499***	0.2498***		0.3549***	0.3436***	0.3469***
		(4.81)	(4.62)	(4.63)		(4.52)	(4.35)	(4.41)
MOM		0.0117***	0.0122***	0.0121***		0.0056**	0.0062**	0.0061**
		(7.64)	(7.95)	(7.87)		(2.07)	(2.35)	(2.33)
$TURN$		-0.1200***	-0.1045***	-0.1146***		0.0434	0.0677	0.0489
		(-3.13)	(-2.70)	(-2.97)		(0.84)	(1.28)	(0.92)
$ILLIQ$		0.0060	0.0261***	0.0242***		-0.0211***	-0.0102	-0.0137*
		(1.07)	(4.18)	(3.94)		(-3.15)	(-1.40)	(-1.90)
β		1.0036***	1.1819***	1.1400***		0.4818	0.6003*	0.5361*
		(5.17)	(5.96)	(5.73)		(1.56)	(1.90)	(1.71)
MAX		-0.1142***	-0.0207*	-0.0338***		-0.1252***	-0.0520***	-0.0786***
		(-16.06)	(-1.77)	(-2.97)		(-14.42)	(-3.64)	(-5.32)
VOL			-0.4104***				-0.3254***	
			(-9.18)				(-5.90)	
$IVOL$				-0.3571***				-0.2119***
				(-8.55)				(-4.06)
Constant	0.8773***	1.7004***	2.1553***	2.1439***	0.4499	1.7155***	2.0913***	2.0128***
	(3.80)	(5.87)	(7.39)	(7.47)	(1.18)	(3.96)	(4.68)	(4.60)
R^2	0.003	0.073	0.076	0.076	0.003	0.098	0.101	0.101

Table 1.9 (continued)

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $IS_{\varphi 1}$ and other stock characteristics variables (in the first column) for monthly data from September 1962 to December 2013 in high and low ALIQ periods. Columns (1)–(4) are those in high periods when the previous month ALIQ is above its mean, and Columns (5)–(8) are those in low periods when the previous month ALIQ is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel B: $IS_{\varphi 1}$

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IS_{\varphi 1}$	-0.5461	-1.1749***	-1.0838***	-1.0931***	-1.3455**	-1.1076***	-1.0322***	-1.0230***
	(-1.52)	(-4.90)	(-4.42)	(-4.45)	(-2.47)	(-3.47)	(-3.12)	(-3.07)
$SIZE$		-0.1937***	-0.2313***	-0.2342***		-0.1666***	-0.2002***	-0.1950***
		(-4.62)	(-5.55)	(-5.70)		(-2.88)	(-3.43)	(-3.39)
BM		0.2556***	0.2468***	0.2465***		0.3442***	0.3339***	0.3370***
		(4.76)	(4.55)	(4.55)		(4.38)	(4.23)	(4.29)
MOM		0.0118***	0.0121***	0.0120***		0.0057**	0.0063**	0.0062**
		(7.75)	(7.99)	(7.90)		(2.09)	(2.35)	(2.34)
$TURN$		-0.1160***	-0.0937**	-0.1031***		0.0489	0.0779	0.0603
		(-2.97)	(-2.40)	(-2.65)		(0.94)	(1.47)	(1.14)
$ILLIQ$		0.0065	0.0256***	0.0239***		-0.0212***	-0.0101	-0.0132*
		(1.14)	(4.09)	(3.88)		(-3.16)	(-1.38)	(-1.84)
β		1.0337***	1.1811***	1.1445***		0.5036	0.6054*	0.5489*
		(5.26)	(5.94)	(5.74)		(1.62)	(1.90)	(1.75)
MAX		-0.1218***	-0.0320***	-0.0438***		-0.1330***	-0.0625***	-0.0876***
		(-16.47)	(-2.76)	(-3.88)		(-14.90)	(-4.42)	(-5.96)
VOL			-0.3949***				-0.3160***	
			(-8.87)				(-5.80)	
$IVOL$				-0.3462***				-0.2094***
				(-8.30)				(-4.05)
Constant	0.9231***	1.7819***	2.1848***	2.1782***	0.4348	1.7848***	2.1214***	2.0536***
	(3.94)	(6.08)	(7.46)	(7.55)	(1.13)	(4.08)	(4.77)	(4.71)
R^2	0.001	0.073	0.076	0.076	0.002	0.098	0.101	0.101

Table 1.9 (continued)

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $IE_{\varphi 1}$ and other stock characteristics variables (in the first column) for monthly data from September 1962 to December 2013 in high and low ALIQ periods. Columns (1)–(4) are those in high periods when the previous month ALIQ is above its mean, and Columns (5)–(8) are those in low periods when the previous month ALIQ is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel C: $IE_{\varphi 1}$

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IE_{\varphi 1}$	-2.6684*	-4.7573***	-4.4286***	-4.5072***	-4.5150**	-4.4679***	-3.8375***	-3.9185***
	(-1.75)	(-5.44)	(-4.96)	(-5.06)	(-2.07)	(-3.76)	(-3.18)	(-3.23)
$SIZE$		-0.1892***	-0.2283***	-0.2311***		-0.1595***	-0.1941***	-0.1886***
		(-4.54)	(-5.49)	(-5.62)		(-2.78)	(-3.33)	(-3.29)
BM		0.2554***	0.2466***	0.2463***		0.3528***	0.3427***	0.3457***
		(4.76)	(4.55)	(4.55)		(4.49)	(4.34)	(4.39)
MOM		0.0117***	0.0120***	0.0120***		0.0056**	0.0062**	0.0062**
		(7.76)	(8.01)	(7.93)		(2.09)	(2.34)	(2.33)
$TURN$		-0.1172***	-0.0977**	-0.1075***		0.0473	0.0723	0.0537
		(-3.04)	(-2.53)	(-2.79)		(0.92)	(1.38)	(1.02)
$ILLIQ$		0.0058	0.0255***	0.0237***		-0.0210***	-0.0103	-0.0136*
		(1.04)	(4.10)	(3.88)		(-3.15)	(-1.42)	(-1.91)
β		1.0150***	1.1751***	1.1374***		0.4777	0.5914*	0.5286*
		(5.19)	(5.92)	(5.71)		(1.54)	(1.87)	(1.69)
MAX		-0.1152***	-0.0256**	-0.0377***		-0.1242***	-0.0532***	-0.0787***
		(-16.10)	(-2.23)	(-3.36)		(-14.33)	(-3.83)	(-5.41)
VOL			-0.3970***				-0.3183***	
			(-8.98)				(-5.93)	
$IVOL$				-0.3470***				-0.2083***
				(-8.37)				(-4.06)
Constant	0.9247***	1.7460***	2.1593***	2.1511***	0.4354	1.7260***	2.0728***	2.0010***
	(3.97)	(6.01)	(7.39)	(7.47)	(1.13)	(3.99)	(4.67)	(4.60)
R^2	0.001	0.073	0.076	0.076	0.002	0.098	0.101	0.100

Table 1.10: Cross-Section Regressions with Interaction Terms of Idiosyncratic Asymmetry Proxies and CGO

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return or the excess return in that month on subsets of $ISKEW$ which measured over the preceding year, CGO and the interaction terms of CGO and $ISKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). For column (1)-(4), the dependent variable is the adjusted-return, and excess return is the dependent variable for column (5)-(7). Here $ISKEW$ is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}CGO_{i,t} + \lambda_{2,t}ISKEW_{i,t} + \lambda_{3,t}CGO_{i,t} \times ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for column(5)-(7).

Panel A: Interaction Term of $ISKEW$ and CGO

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARS	RA	RA	RA	RA	R	R	R
CGO	0.3642***	0.3159***	0.3291***	0.2588***	0.5384***	0.5507***	0.4203***
	(3.79)	(3.12)	(3.27)	(3.56)	(4.35)	(4.49)	(5.80)
$ISKEW$			-0.0152	-0.0044		0.0172	0.0044
			(-0.81)	(-0.25)		(0.63)	(0.25)
$CGO \times ISKEW$		0.1676***	0.1413***	0.1479***	0.1686***	0.1253***	0.2003***
		(4.02)	(3.36)	(3.74)	(3.95)	(3.06)	(5.24)
$SIZE$				-0.1008***			-0.1989***
				(-8.02)			(-5.21)
BM				0.0450			0.2188***
				(1.21)			(4.14)
MOM				0.0064***			0.0056***
				(4.49)			(3.61)
$TURN$				0.1274***			-0.0099
				(3.79)			(-0.27)
$ILLIQ$				0.0227***			0.0153**
				(4.20)			(2.53)
β							0.7627***
							(3.78)
MAX				0.0221***			0.0237***
				(2.64)			(2.71)
$IVOL$				-0.3411***			-0.3895***
				(-11.45)			(-12.58)
$REVA$				-0.0506***			
				(-14.37)			
REV							-0.0457***
							(-12.64)
Constant	0.0399	0.0354	0.0437	0.9793***	0.7456***	0.7378***	1.9378***
	(1.14)	(1.02)	(1.19)	(7.99)	(3.52)	(3.55)	(6.73)
OBS.	1,270,066	1,270,052	1,270,052	1,230,285	1,356,999	1,356,999	1,262,604
R^2	0.007	0.009	0.010	0.041	0.014	0.016	0.099

Table 1.10 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return or the excess return in that month on subsets of $IS_{\varphi 1}$ which measured over the preceding year, CGO and the interaction terms of CGO and $IS_{\varphi 1}$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). For column (1)-(4), the dependent variable is the adjusted-return, and excess return is the dependent variable for column (5)-(7). Here $IS_{\varphi 1}$ is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} CGO_{i,t} + \lambda_{2,t} IS_{\varphi 1} + \lambda_{3,t} CGO_{i,t} \times IS_{\varphi 1} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for column(5)-(7).

Panel B: Interaction Term of $IS_{\varphi 1}$ and CGO

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARS	RA	RA	RA	RA	R	R	R
CGO	0.3642***	0.3602***	0.3590***	0.2983***	0.5846***	0.5851***	0.4838***
	(3.79)	(3.69)	(3.68)	(4.19)	(4.79)	(4.81)	(6.76)
$IS_{\varphi 1}$			-0.5389**	-0.5597**		-0.6785**	-0.7233***
			(-2.16)	(-2.39)		(-2.12)	(-3.00)
$CGO \times IS_{\varphi 1}$		0.8257	1.3261*	0.8455	0.9412	1.3068	1.4104*
		(1.10)	(1.68)	(1.09)	(1.21)	(1.63)	(1.79)
$ISKEW$				-0.0234			-0.0205
				(-1.31)			(-1.15)
$SIZE$				-0.1045***			-0.2042***
				(-8.28)			(-5.36)
BM				0.0442			0.2178***
				(1.19)			(4.12)
MOM				0.0066***			0.0057***
				(4.58)			(3.73)
$TURN$				0.1376***			0.0009
				(4.06)			(0.02)
$ILLIQ$				0.0224***			0.0149**
				(4.15)			(2.47)
β							0.7677***
							(3.81)
MAX				0.0177**			0.0186**
				(2.08)			(2.12)
$IVOL$				-0.3365***			-0.3836***
				(-11.14)			(-12.33)
$REVA$				-0.0504***			
				(-14.28)			
REV							-0.0455***
							(-12.58)
Constant	0.0399	0.0404	0.0447	1.0177***	0.7501***	0.7563***	1.9874***
	(1.14)	(1.15)	(1.28)	(8.20)	(3.54)	(3.58)	(6.91)
OBS.	1,270,066	1,265,583	1,265,583	1,227,616	1,351,289	1,351,289	1,259,662
R^2	0.007	0.008	0.009	0.042	0.013	0.015	0.099

Table 1.10 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return or the excess return in that month on subsets of $IE_{\varphi 1}$ which measured over the preceding year, CGO and the interaction terms of CGO and $IE_{\varphi 1}$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). For column (1)-(4), the dependent variable is the adjusted-return, and excess return is the dependent variable for column (5)-(7). Here $IE_{\varphi 1}$ is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}CGO_{i,t} + \lambda_{2,t}IE_{\varphi 1} + \lambda_{3,t}CGO_{i,t} \times IE_{\varphi 1} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for column(5)-(7).

Panel C: Interaction Term of $IE_{\varphi 1}$ and CGO	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARS	RA	RA	RA	RA	R	R	R
CGO	0.3642***	0.3610***	0.3608***	0.3060***	0.5833***	0.5821***	0.4848***
	(3.79)	(3.73)	(3.76)	(4.31)	(4.83)	(4.86)	(6.80)
$IE_{\varphi 1}$			-3.1221***	-3.0299***		-3.5006***	-3.4496***
			(-3.34)	(-3.67)		(-2.80)	(-4.14)
$CGO \times IE_{\varphi 1}$		2.1926	3.1843	1.9278	2.1762	2.7282	3.8479
		(0.87)	(1.24)	(0.78)	(0.80)	(1.02)	(1.45)
$ISKEW$				-0.0293*			-0.0257
				(-1.70)			(-1.48)
$SIZE$				-0.1027***			-0.2018***
				(-8.15)			(-5.28)
BM				0.0432			0.2169***
				(1.17)			(4.11)
MOM				0.0065***			0.0057***
				(4.61)			(3.72)
$TURN$				0.1340***			-0.0022
				(3.99)			(-0.06)
$ILLIQ$				0.0223***			0.0146**
				(4.14)			(2.44)
β							0.7606***
							(3.77)
MAX				0.0217***			0.0232***
				(2.59)			(2.65)
$IVOL$				-0.3345***			-0.3814***
				(-11.24)			(-12.30)
$REVA$				-0.0507***			
				(-14.40)			
REV							-0.0458***
							(-12.65)
Constant	0.0399	0.0401	0.0475	0.9943***	0.7496***	0.7601***	1.9631***
	(1.14)	(1.14)	(1.36)	(8.11)	(3.54)	(3.60)	(6.81)
OBS.	1,270,066	1,269,900	1,269,900	1,230,282	1,356,811	1,356,811	1,262,599
R^2	0.007	0.008	0.009	0.041	0.013	0.015	0.099

Table 1.11: Double-Sorted Portfolio Returns by CGO and Idiosyncratic Asymmetry Proxies

At the beginning of every month from January 1962 to December 2013, we first sort stocks by CGO into 5 portfolios and then within each CGO portfolio sort stocks into 5 portfolios by idiosyncratic asymmetry proxies-the realized $ISKEW$, $IS_{\varphi 1}$ and $IE_{\varphi 1}$. CGO1(P1) is the portfolio of stocks with the lowest CGO(asymmetry proxy), while CGO5(P5) denotes the highest. Here the excess return and idiosyncratic asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile.
In Panel A, the monthly equal-weighted excess returns are reported, and the average Carhart-4-factor alphas are shown in Panle B. P5-P1 spread denotes the average raw return(Carhart 4-factor alpha difference for Panel B) difference between the highest and lowest idiosyncratic asymmetry proxy within the same CGO quintile CGO portfolio or the Avg(C1-C5). Avg(C1-C5) report the return average of five quintile CGO portfolios, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Excess Return

	$ISKEW$			$IS_{\varphi 1}$			$IE_{\varphi 1}$		
Proxy	P1	P5	P5-P1	P1	P5	P5-P1	P1	P5	P5-P1
CGO1	0.751***	0.286	-0.465***	0.635**	0.404	-0.231***	0.644***	0.454*	-0.190**
t-stat	(2.93)	(1.09)	(-4.22)	(2.57)	(1.57)	(-2.75)	(2.70)	(1.76)	(2.10)
CGO2	0.572***	0.429*	-0.143	0.666***	0.456*	-0.210***	0.643***	0.440*	-0.202***
t-stat	(2.66)	(1.79)	(-1.48)	(2.98)	(1.94)	(-3.11)	(2.96)	(1.92)	(-2.81)
CGO3	0.522***	0.601***	0.078	0.737***	0.624***	-0.113*	0.683***	0.594***	-0.089
t-stat	(2.78)	(2.69)	(0.81)	(3.60)	(2.82)	(-1.67)	(3.51)	(2.78)	(-1.28)
CGO4	0.662***	0.771***	0.110	0.824***	0.775***	-0.049	0.816***	0.675***	-0.141**
t-stat	(3.62)	(3.66)	(1.22)	(4.19)	(3.65)	(-0.76)	(4.42)	(3.26)	(-2.00)
CGO5	0.937***	1.104***	0.167*	1.236***	1.169***	-0.067	1.212***	1.164***	-0.047
t-stat	(4.94)	(5.30)	(1.79)	(6.02)	(5.19)	(-0.91)	(6.23)	(5.42)	(-0.65)
Avg(C1-C5)	0.689***	0.638***	-0.051	0.820***	0.685***	-0.134***	0.799***	0.666***	-0.134***
t-stat	(3.50)	(2.90)	(-0.69)	(3.97)	(3.11)	(-3.32)	(4.06)	(3.10)	(-2.84)

Panel B: Carhart 4-factor Alpha

	$ISKEW$			$IS_{\varphi 1}$			$IE_{\varphi 1}$		
Proxy	P1	P5	P5-P1	P1	P5	P5-P1	P1	P5	P5-P1
CGO1	0.336***	-0.336***	-0.672***	0.099	-0.137	-0.236***	0.143*	-0.043	-0.185**
t-stat	(3.83)	(-3.41)	(-6.26)	(1.11)	(-1.58)	(-2.76)	(1.67)	(-0.50)	(-2.09)
CGO2	0.062	-0.300***	-0.363***	0.008	-0.230***	-0.237***	0.019	-0.188***	-0.208***
t-stat	(0.94)	(-4.05)	(-4.06)	(0.11)	(-3.33)	(-3.49)	(0.29)	(-2.81)	(-2.87)
CGO3	-0.034	-0.176***	-0.142*	0.039	-0.148**	-0.187***	0.015	-0.124**	-0.139**
t-stat	(-0.57)	(2.68)	(-1.71)	(0.63)	(-2.28)	(-2.80)	(0.24)	(-2.08)	(-2.10)
CGO4	0.000	-0.008	-0.009	0.035	-0.048	-0.082	0.098	-0.116*	-0.214***
t-stat	(0.01)	(-0.13)	(-0.11)	(0.57)	(-0.75)	(-1.28)	(1.61)	(-1.87)	(-3.26)
CGO5	0.166**	0.278***	0.111	0.379***	0.230***	-0.149**	0.392***	0.275***	-0.117
t-stat	(2.46)	(3.70)	(1.32)	(5.85)	(3.00)	(-2.07)	(5.78)	(3.61)	(-1.63)
Avg(C1-C5)	0.106***	-0.109**	-0.215***	0.112**	-0.067	-0.178***	0.133***	-0.039	-0.172***
t-stat	(2.33)	(-2.26)	(-3.57)	(2.46)	(-1.52)	(-5.04)	(2.98)	(-0.95)	(-4.33)

Table 1.12: Equal-Weighted Average Monthly Returns of Portfolios Based on Anomalies

Portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the anomalies ($SIZE$ and MOM). Portfolio 1 is the portfolio of stocks with the lowest $SIZE$ (MOM for Panel B), while Portfolio 5 denotes the highest. And here excess returns are winsorized at 0.5 percentile and 99.5 percentile.
5-1 spread denotes the average raw return difference between the highest and lowest $SIZE$ (MOM for Panel B), FF3 alpha denotes the average Fama-French 3-factor alpha difference, and carhart4 alpha denotes the average Carhart 4-factor alpha difference, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: $SIZE$

Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.821***	0.054	0.098
	(3.76)	(0.60)	(1.07)
2	0.722***	-0.113*	-0.054
	(3.04)	(-1.91)	(-0.91)
3	0.701***	-0.068	-0.007
	(3.01)	(-1.56)	(-0.16)
4	0.659***	-0.036	0.014
	(3.07)	(-0.82)	(0.32)
5(highest)	0.522**	-0.018	0.012
	(2.80)	(-0.53)	(0.35)
5-1 spread	-0.298**	-0.072	-0.087
	(-2.12)	(-0.73)	(-0.86)

Panel B: MOM

Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.200	-0.619***	-0.186***
	(0.76)	(-5.99)	(-2.74)
2	0.662***	-0.086	0.105*
	(3.18)	(-1.37)	(1.95)
3	0.752***	0.055	0.097*
	(3.95)	(1.11)	(1.93)
4	0.786***	0.108**	-0.000
	(4.02)	(2.11)	(-0.00)
5(highest)	1.030***	0.368***	0.054
	(4.35)	(4.59)	(0.95)
5-1 spread	0.829***	0.987***	0.240**
	(5.03)	(5.95)	(2.50)

Table 1.12 (continued)

Portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the anomalies ($ILLIQ$). Portfolio 1 is the portfolio of stocks with the lowest $ILLIQ$, while Portfolio 5 denotes the highest. And here excess returns are winsorized at 0.5 percentile and 99.5 percentile. 5-1 spread denotes the average raw return difference between the highest and lowest $ILLIQ$, FF3 alpha denotes the average Fama-French 3-factor alpha difference, and carhart4 alpha denotes the average Carhart 4-factor alpha difference, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel C: $ILLIQ$			
Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.580***	0.013	0.021
	(2.97)	(0.35)	(0.55)
2	0.678***	-0.023	0.024
	(3.02)	(-0.53)	(0.55)
3	0.705***	-0.071	-0.005
	(2.99)	(-1.60)	(-0.12)
4	0.729***	-0.102	-0.035
	(3.24)	(-1.63)	(-0.55)
5(highest)	0.736***	0.067	0.082
	(3.16)	(0.83)	(0.99)
5-1 spread	0.211	0.040	0.071
	(1.53)	(0.43)	(0.74)

Table 1.13: Cross-Section Regressions with Interaction Terms of Asymmetry Proxies and $SIZE$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of $E_{\varphi 2}$ or $SKEW$ which measured over the preceding three months, $SIZE$ and the interaction terms of $SIZE$ and $E_{\varphi 2}$ or $SKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} SIZE_{i,t} + \lambda_{2,t} ASYM_{i,t} + \lambda_{3,t} SIZE_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a set of control variables, and $ASYM_{i,t}$ denote $E_{\varphi 2}$ or $SKEW$.

Panel A: Adjusted Return (RA) is the Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SIZE$	-0.0578***	-0.0643***	-0.0691***	-0.0943***	-0.0578***	-0.0637***	-0.0671***	-0.0937***
	(-3.82)	(-4.17)	(-4.46)	(-7.37)	(-3.82)	(-4.18)	(-4.43)	(-7.26)
$E_{\varphi 2}$		-5.0955***	-8.6899***	-10.2488***				
		(-6.25)	(-4.76)	(-5.95)				
$SIZE \times E_{\varphi 2}$			0.7995**	0.9434***				
			(2.54)	(3.14)				
$SKEW$						-0.1039***	-0.1949***	-0.2416***
						(-5.68)	(-4.64)	(-6.26)
$SIZE \times SKEW$							0.0200***	0.0247***
							(2.72)	(3.59)
BM				0.1295***				0.1309***
				(3.45)				(3.51)
MOM				0.0100***				0.0101***
				(7.46)				(7.56)
$TURN$				-0.0468				-0.0487
				(-1.42)				(-1.47)
$ILLIQ$				-0.0075*				-0.0077*
				(-1.87)				(-1.92)
Constant	0.3673***	0.4425***	0.4657***	0.6609***	0.3673***	0.4259***	0.4424***	0.6481***
	(4.04)	(4.77)	(4.97)	(6.45)	(4.04)	(4.62)	(4.80)	(6.23)
OBS.	1,514,285	1,514,285	1,514,285	1,510,401	1,514,285	1,514,285	1,514,285	1,510,401
R^2	0.004	0.005	0.006	0.025	0.004	0.005	0.006	0.025

Table 1.13 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of $E_{\varphi 2}$ or $SKEW$ which measured over the preceding three months, $SIZE$ and the interaction terms of $SIZE$ and $E_{\varphi 2}$ or $SKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}SIZE_{i,t} + \lambda_{3,t}ASYM_{i,t} + \lambda_{4,t}SIZE_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $ASYM_{i,t}$ denote $E_{\varphi 2}$ or $SKEW$.

Panel B: Excess Return (R) is the Dependent Variable								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SIZE$	-0.0659**	-0.0704**	-0.0748**	-0.1372***	-0.0659**	-0.0703**	-0.0757**	-0.1369***
	(-2.04)	(-2.20)	(-2.35)	(-3.52)	(-2.04)	(-2.17)	(-2.32)	(-3.49)
$E_{\varphi 2}$		-4.2831***	-8.3655***	-9.6995***				
		(-3.72)	(-3.74)	(-5.42)				
$SIZE \times E_{\varphi 2}$			0.8675**	0.8591***				
			(2.31)	(2.70)				
$SKEW$						-0.0811***	-0.2089***	-0.2320***
						(-3.82)	(-4.30)	(-5.74)
$SIZE \times SKEW$							0.0279***	0.0269***
							(3.28)	(3.70)
BM				0.3580***				0.3579***
				(6.63)				(6.64)
MOM				0.0110***				0.0110***
				(7.50)				(7.51)
$TURN$				-0.2232***				-0.2230***
				(-5.89)				(-5.85)
$ILLIQ$				-0.0187***				-0.0188***
				(-4.12)				(-4.16)
β				0.6540***				0.6426***
				(3.38)				(3.32)
Constant	1.0024***	1.0599***	1.0817***	1.2912***	1.0024***	1.0462***	1.0736***	1.2802***
	(3.00)	(3.23)	(3.30)	(4.61)	(3.00)	(3.13)	(3.20)	(4.54)
OBS.	1,643,254	1,643,254	1,643,254	1,638,128	1,643,254	1,643,254	1,643,254	1,638,128
R^2	0.014	0.016	0.017	0.082	0.014	0.015	0.016	0.082

Table 1.14: Cross-Section Regressions with Interaction Terms of Asymmetry Proxies and MOM

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of $E_{\varphi 2}$ or $SKEW$ which measured over the preceding three months, MOM and the interaction terms of MOM and $E_{\varphi 2}$ or $SKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} MOM_{i,t} + \lambda_{2,t} ASYM_{i,t} + \lambda_{3,t} MOM_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $ASYM_{i,t}$ denote $E_{\varphi 2}$ or $SKEW$.

Panel A: Adjusted Return (RA) is the Dependent Variable								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOM	0.0079***	0.0082***	0.0073***	0.0093***	0.0079***	0.0083***	0.0077***	0.0098***
	(5.51)	(5.71)	(4.81)	(6.55)	(5.51)	(5.74)	(5.02)	(6.82)
$E_{\varphi 2}$		-5.3399***	-5.0901***	-5.5465***				
		(-7.01)	(-6.38)	(-7.39)				
$MOM \times E_{\varphi 2}$			0.0663**	0.0515**				
			(2.53)	(2.06)				
$SKEW$						-0.1074***	-0.0889***	-0.1081***
						(-6.24)	(-4.99)	(-6.48)
$MOM \times SKEW$							0.0016**	0.0011*
							(2.56)	(1.88)
$SIZE$				-0.0864***				-0.0867***
				(-6.77)				(-6.80)
BM				0.1282***				0.1311***
				(3.42)				(3.52)
$TURN$				-0.0474				-0.0517
				(-1.44)				(-1.58)
$ILLIQ$				-0.0078*				-0.0078*
				(-1.94)				(-1.94)
Constant	-0.0418	0.0011	-0.0019	0.6174***	-0.0418	-0.0121	-0.0234	0.6061***
	(-1.03)	(0.03)	(-0.05)	(5.99)	(-1.03)	(-0.29)	(-0.56)	(5.84)
Observations	1,510,401	1,510,401	1,510,401	1,510,401	1,510,401	1,510,401	1,510,401	1,510,401
R-squared	0.009	0.010	0.012	0.026	0.009	0.010	0.011	0.026

Table 1.14 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of $E_{\varphi 2}$ or $SKEW$ which measured over the preceding three months, MOM and the interaction terms of MOM and $E_{\varphi 2}$ or $SKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}MOM_{i,t} + \lambda_{3,t}ASYM_{i,t} + \lambda_{4,t}MOM_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $ASYM_{i,t}$ denote $E_{\varphi 2}$ or $SKEW$.

Panel B: Excess Return (R) is the Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOM	0.0091***	0.0093***	0.0085***	0.0104***	0.0091***	0.0093***	0.0089***	0.0105***
	(4.77)	(4.88)	(4.26)	(6.86)	(4.77)	(4.87)	(4.40)	(6.81)
$E_{\varphi 2}$		-4.1794***	-3.7250***	-5.1720***				
		(-3.59)	(-3.09)	(-6.50)				
$MOM \times E_{\varphi 2}$			0.0529*	0.0411				
			(1.78)	(1.64)				
$SKEW$						-0.0743***	-0.0481**	-0.0850***
						(-3.20)	(-2.00)	(-4.92)
$MOM \times SKEW$							0.0014**	0.0014***
							(2.05)	(2.61)
$SIZE$				-0.1311***				-0.1298***
				(-3.38)				(-3.34)
BM				0.3561***				0.3577***
				(6.59)				(6.63)
$TURN$				-0.2235***				-0.2257***
				(-5.92)				(-6.00)
$ILLIQ$				-0.0189***				-0.0188***
				(-4.17)				(-4.15)
β				0.6548***				0.6440***
				(3.39)				(3.33)
Constant	0.5510**	0.5805***	0.5782***	1.2565***	0.5510**	0.5679**	0.5558**	1.2371***
	(2.48)	(2.67)	(2.65)	(4.48)	(2.48)	(2.58)	(2.52)	(4.41)
OBS.	1,638,128	1,638,128	1,638,128	1,638,128	1,638,128	1,638,128	1,638,128	1,638,128
R^2	0.015	0.017	0.019	0.083	0.015	0.017	0.018	0.083

Table 1.15: Cross-Section Regressions with Interaction Terms of Asymmetry Proxies and $ILLIQ$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of $E_{\varphi 2}$ or $SKEW$ which measured over the preceding three months, $ILLIQ$ and the interaction terms of $ILLIQ$ and $E_{\varphi 2}$ or $SKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} ILLIQ_{i,t} + \lambda_{2,t} ASYM_{i,t} + \lambda_{3,t} ILLIQ_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $ASYM_{i,t}$ denote $E_{\varphi 2}$ or $SKEW$.

Panel A: Adjusted Return (RA) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ILLIQ$	0.0096*	0.0106**	0.0151***	-0.0041	0.0096*	0.0106**	0.0143***	-0.0048
	(1.91)	(2.08)	(2.69)	(-0.94)	(1.91)	(2.08)	(2.66)	(-1.15)
$E_{\varphi 2}$		-4.5294***	-2.2606**	-3.9919***				
		(-5.65)	(-2.34)	(-4.57)				
$ILLIQ \times E_{\varphi 2}$			-0.3978***	-0.3237***				
			(-4.83)	(-4.26)				
$SKEW$						-0.0900***	-0.0429**	-0.0839***
						(-5.01)	(-2.08)	(-4.48)
$ILLIQ \times SKEW$							-0.0088***	-0.0078***
							(-4.33)	(-3.91)
$SIZE$				-0.0859***				-0.0870***
				(-6.75)				(-6.80)
BM				0.1300***				0.1310***
				(3.46)				(3.50)
MOM				0.0100***				0.0101***
				(7.44)				(7.52)
$TURN$				-0.0475				-0.0482
				(-1.44)				(-1.46)
Constant	0.0484	0.0840*	0.0643	0.6039***	0.0484	0.0723*	0.0580	0.6003***
	(1.14)	(1.95)	(1.48)	(5.91)	(1.14)	(1.66)	(1.32)	(5.79)
OBS.	1,514,285	1,514,285	1,514,285	1,510,401	1,514,285	1,514,285	1,514,285	1,510,401
R^2	0.004	0.006	0.007	0.025	0.004	0.006	0.007	0.025

Table 1.15 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of $E_{\varphi 2}$ or $SKEW$ which measured over the preceding three months, $ILLIQ$ and the interaction terms of $ILLIQ$ and $E_{\varphi 2}$ or $SKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}ILLIQ_{i,t} + \lambda_{3,t}ASYM_{i,t} + \lambda_{4,t}ILLIQ_{i,t} \times ASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $ASYM_{i,t}$ denote $E_{\varphi 2}$ or $SKEW$.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ILLIQ$	0.0113	0.0120*	0.0170**	-0.0160***	0.0113	0.0119*	0.0167**	-0.0160***
	(1.62)	(1.72)	(2.25)	(-3.38)	(1.62)	(1.72)	(2.21)	(-3.47)
$E_{\varphi 2}$		-3.1800**	-0.9033	-3.8319***				
		(-2.54)	(-0.59)	(-3.95)				
$ILLIQ \times E_{\varphi 2}$			-0.4215***	-0.2819***				
			(-4.39)	(-3.52)				
$SKEW$						-0.0539**	-0.0003	-0.0613***
						(-2.29)	(-0.01)	(-3.18)
$ILLIQ \times SKEW$							-0.0102***	-0.0077***
							(-4.41)	(-3.82)
$SIZE$				-0.1309***				-0.1303***
				(-3.37)				(-3.35)
BM				0.3581***				0.3579***
				(6.63)				(6.63)
MOM				0.0110***				0.0110***
				(7.49)				(7.47)
$TURN$				-0.2233***				-0.2228***
				(-5.90)				(-5.85)
β				0.6516***				0.6419***
				(3.37)				(3.32)
Constant	0.6921***	0.7119***	0.6919***	1.2459***	0.6921***	0.7028***	0.6854***	1.2328***
	(2.94)	(3.10)	(3.03)	(4.46)	(2.94)	(3.02)	(2.95)	(4.40)
OBS.	1,643,254	1,643,254	1,643,254	1,638,128	1,643,254	1,643,254	1,643,254	1,638,128
R^2	0.009	0.012	0.013	0.082	0.009	0.011	0.012	0.082

Table 1.16: Equal-Weighted Bivariate Dependent Sort Portfolio Analysis-$SIZE$ and Asymmetry Proxies

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and each of $SIZE$ after controlling for $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B). At the beginning of every month from January 1962 to December 2013, we first sort stocks by $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) into 5 portfolios and then within each $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) portfolio, sort stocks into 5 portfolios by $SIZE$. The table reports the time-series means of the monthly equal-weighted excess returns formed on intersections of $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) and $SIZE$ portfolios. Factor sensitivities for each $SIZE$ High-Low portfolios are presented in the rows labeled β_{MKTRF}, β_{SMB}, β_{HML}, β_{UMD}. Diff denotes the 5-1 return spread difference between highest $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) portfolio and lowest portfolio. t-statistics testing the null hypothesis is equal to zero, are in parentheses. Here the excess return and asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile.

Panel A: Sort By $E_{\varphi 2}$ then $SIZE$

	$E_{\varphi 2}$ 1	$E_{\varphi 2}$ 2	$E_{\varphi 2}$ 3	$E_{\varphi 2}$ 4	$E_{\varphi 2}$ 5	Diff
$SIZE$ 1 (Low)	0.990***	0.893***	0.933***	0.767***	0.648***	NA
	(4.62)	(4.05)	(4.06)	(3.32)	(2.86)	NA
$SIZE$ 2	0.740***	0.816***	0.792***	0.694***	0.615**	NA
	(3.27)	(3.47)	(3.24)	(2.81)	(2.44)	NA
$SIZE$ 3	0.755***	0.731***	0.699***	0.591**	0.556**	NA
	(3.39)	(3.18)	(3.02)	(2.44)	(2.14)	NA
$SIZE$ 4	0.682***	0.673***	0.703***	0.626***	0.652***	NA
	(3.25)	(3.19)	(3.25)	(2.84)	(2.72)	NA
$SIZE$ 5 (High)	0.577***	0.505***	0.553***	0.454**	0.489**	NA
	(3.09)	(2.70)	(2.94)	(2.34)	(2.40)	NA
5-1 spread	-0.413***	-0.388***	-0.380**	-0.313**	-0.159	0.254**
	(-2.78)	(-2.60)	(-2.48)	(-2.08)	(-1.09)	(2.22)
Carhart4 α	-0.300***	-0.228**	-0.162	-0.029	0.069	0.3689***
	(-2.61)	(-2.03)	(-1.41)	(-0.26)	(0.57)	(3.16)
β_{MKTRF}	0.236***	0.211***	0.185***	0.178***	0.224***	NA
	(8.80)	(8.01)	(6.87)	(6.66)	(7.99)	NA
β_{SMB}	-0.837***	-0.869***	-0.912***	-0.873***	-0.726***	NA
	(-22.17)	(-23.47)	(-24.14)	(-23.22)	(-18.40)	NA
β_{HML}	-0.238***	-0.294***	-0.307***	-0.353***	-0.319***	NA
	(-5.74)	(-7.21)	(-7.38)	(-8.53)	(-7.36)	NA
β_{UMD}	0.091***	0.084***	0.041	-0.035	-0.055*	NA
	(3.43)	(3.23)	(1.54)	(-1.31)	(-1.96)	NA

Table 1.16 (continued)

Panel B: Sort By *SKEW* then *SIZE*	*SKEW* 1	*SKEW* 2	*SKEW* 3	*SKEW* 4	*SKEW* 5	Diff
SIZE 1 (Low)	0.878***	1.061***	0.912***	0.807***	0.568**	NA
	(4.09)	(4.85)	(3.97)	(3.49)	(2.49)	NA
SIZE 2	0.669***	0.833***	0.803***	0.735***	0.554**	NA
	(2.89)	(3.54)	(3.33)	(2.90)	(2.27)	NA
SIZE 3	0.743***	0.834***	0.760***	0.617**	0.620**	NA
	(3.29)	(3.70)	(3.21)	(2.47)	(2.49)	NA
SIZE 4	0.634***	0.699***	0.652***	0.592***	0.550**	NA
	(2.99)	(3.33)	(2.97)	(2.63)	(2.39)	NA
SIZE 5 (High)	0.526***	0.543***	0.524***	0.500**	0.523***	NA
	(2.80)	(2.89)	(2.74)	(2.55)	(2.67)	NA
5-1 spread	-0.353**	-0.518***	-0.388**	-0.307**	-0.045	0.308***
	(-2.37)	(-3.48)	(-2.47)	(-2.04)	(-0.32)	(2.72)
Carhart4 α	-0.236**	-0.348***	-0.157	-0.053	0.178	0.415***
	(-2.09)	(-3.22)	(-1.34)	(-0.44)	(1.49)	(3.65)
β_{MKTRF}	0.243***	0.221***	0.208***	0.186***	0.160***	NA
	(9.19)	(8.73)	(7.59)	(6.71)	(5.69)	NA
β_{SMB}	-0.864***	-0.884***	-0.925***	-0.838***	-0.665***	NA
	(-23.21)	(-24.83)	(-24.08)	(-21.54)	(-16.82)	NA
β_{HML}	-0.210***	-0.345***	-0.364***	-0.344***	-0.234***	NA
	(-5.13)	(-8.81)	(-8.61)	(-8.04)	(-5.40)	NA
β_{UMD}	0.076***	0.097***	0.044	-0.015	-0.073***	NA
	(2.87)	(3.85)	(1.61)	(-0.54)	(-2.60)	NA

Table 1.17: Equal-Weighted Bivariate Dependent Sort Portfolio Analysis-MOM and Asymmetry Proxies

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and each of MOM after controlling for $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B). At the beginning of every month from January 1962 to December 2013, we first sort stocks by $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) into 5 portfolios and then within each $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) portfolio, sort stocks into 5 portfolios by MOM. The table reports the time-series means of the monthly equal-weighted excess returns formed on intersections of $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) and MOM portfolios. Factor sensitivities for each MOM High-Low portfolios are presented in the rows labeled β_{MKTRF}, β_{SMB}, β_{HML}, β_{UMD}. Diff denotes the 5-1 return spread difference between highest $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) portfolio and lowest portfolio. t-statistics testing the null hypothesis is equal to zero, are in parentheses. Here the excess return and asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile.

Panel A: Sort By $E_{\varphi 2}$ then MOM

	$E_{\varphi 2}$ 1	$E_{\varphi 2}$ 2	$E_{\varphi 2}$ 3	$E_{\varphi 2}$ 4	$E_{\varphi 2}$ 5	Diff
MOM 1 (Low)	0.445*	0.333	0.300	0.009	-0.119	NA
	(1.72)	(1.27)	(1.12)	(0.03)	(-0.43)	NA
MOM 2	0.743***	0.718***	0.669***	0.611***	0.577**	NA
	(3.66)	(3.46)	(3.10)	(2.82)	(2.57)	NA
MOM 3	0.810***	0.806***	0.839***	0.696***	0.631***	NA
	(4.38)	(4.29)	(4.25)	(3.56)	(3.02)	NA
MOM 4	0.760***	0.782***	0.831***	0.820***	0.807***	NA
	(4.09)	(4.04)	(4.24)	(3.97)	(3.70)	NA
MOM 5 (High)	0.974***	0.988***	1.064***	0.997***	1.093***	NA
	(4.37)	(4.27)	(4.47)	(4.01)	(4.20)	NA
5-1 spread	0.529***	0.655***	0.765***	0.988***	1.212***	0.683***
	(3.35)	(3.98)	(4.33)	(5.38)	(6.55)	(5.37)
Carhart4 α	0.031	0.089	0.187*	0.380***	0.603***	0.572***
	(0.28)	(0.85)	(1.66)	(3.18)	(4.61)	(4.46)
β_{MKTRF}	-0.002	0.015	-0.020	-0.038	-0.019	NA
	(-0.09)	(0.60)	(-0.76)	(-1.35)	(-0.61)	NA
β_{SMB}	-0.133***	-0.111***	-0.007	0.039	0.114***	NA
	(-3.76)	(-3.21)	(-0.20)	(0.98)	(2.65)	NA
β_{HML}	0.086**	0.100***	0.017	0.049	0.053	NA
	(2.22)	(2.62)	(0.42)	(1.13)	(1.12)	NA
β_{UMD}	0.706***	0.755***	0.827***	0.849***	0.811***	NA
	(28.20)	(31.64)	(31.54)	(30.50)	(26.64)	NA

Table 1.17 (continued)

Panel B: Sort By *SKEW* then *MOM*	*SKEW* 1	*SKEW* 2	*SKEW* 3	*SKEW* 4	*SKEW* 5	Diff
MOM 1 (Low)	0.423	0.453*	0.323	0.072	-0.252	NA
	(1.59)	(1.75)	(1.19)	(0.26)	(-0.93)	NA
MOM 2	0.706***	0.762***	0.688***	0.649***	0.455**	NA
	(3.42)	(3.72)	(3.24)	(2.94)	(2.07)	NA
MOM 3	0.741***	0.848***	0.787***	0.722***	0.660***	NA
	(3.96)	(4.52)	(4.06)	(3.56)	(3.20)	NA
MOM 4	0.704***	0.848***	0.780***	0.765***	0.896***	NA
	(3.80)	(4.36)	(3.94)	(3.66)	(4.24)	NA
MOM 5 (High)	0.881***	1.056***	1.091***	1.040***	1.089***	NA
	(3.96)	(4.51)	(4.40)	(4.10)	(4.40)	NA
5-1 spread	0.457***	0.602***	0.768***	0.968***	1.341***	0.883***
	(2.82)	(3.53)	(4.20)	(5.28)	(7.69)	(6.94)
Carhart4 α	-0.068	0.007	0.121	0.316***	0.852***	0.920***
	(-0.64)	(0.07)	(1.04)	(2.65)	(6.61)	(7.19)
β_{MKTRF}	-0.007	0.030	-0.014	0.025	-0.089***	NA
	(-0.28)	(1.19)	(-0.53)	(0.91)	(-2.95)	NA
β_{SMB}	-0.179***	-0.075***	0.073*	0.013	0.106**	NA
	(-5.09)	(-2.15)	(1.90)	(0.33)	(2.49)	NA
β_{HML}	0.130***	0.051	0.071*	0.077*	0.010	NA
	(3.37)	(1.33)	(1.69)	(1.78)	(0.21)	NA
β_{UMD}	0.738***	0.822***	0.864***	0.862***	0.714***	NA
	(29.68)	(33.39)	(31.85)	(31.08)	(23.80)	NA

Table 1.18: Equal-Weighted Bivariate Dependent Sort Portfolio Analysis-$ILLIQ$ and Asymmetry Proxies

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and each of $ILLIQ$ after controlling for $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B). At the beginning of every month from January 1962 to December 2013, we first sort stocks by $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) into 5 portfolios and then within each $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) portfolio, sort stocks into 5 portfolios by $ILLIQ$. The table reports the time-series means of the monthly equal-weighted excess returns formed on intersections of $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) and $ILLIQ$ portfolios. Factor sensitivities for each $ILLIQ$ High-Low portfolios are presented in the rows labeled β_{MKTRF}, β_{SMB}, β_{HML}, β_{UMD}. Diff denotes the 5-1 return spread difference between highest $E_{\varphi 2}$ (Panel A, $SKEW$ for Panel B) portfolio and lowest portfolio. t-statistics testing the null hypothesis is equal to zero, are in parentheses. Here the excess return and asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile.

Panel A: Sort By $E_{\varphi 2}$ then $ILLIQ$

	$E_{\varphi 2}$ 1	$E_{\varphi 2}$ 2	$E_{\varphi 2}$ 3	$E_{\varphi 2}$ 4	$E_{\varphi 2}$ 5	Diff
$ILLIQ$ 1 (Low)	0.606***	0.582***	0.655***	0.526***	0.543***	NA
	(3.10)	(2.99)	(3.30)	(2.59)	(2.56)	NA
$ILLIQ$ 2	0.692***	0.666***	0.724***	0.650***	0.643**	NA
	(3.17)	(3.01)	(3.23)	(2.79)	(2.55)	NA
$ILLIQ$ 3	0.736***	0.743***	0.714***	0.582**	0.723***	NA
	(3.28)	(3.19)	(3.01)	(2.41)	(2.77)	NA
$ILLIQ$ 4	0.746***	0.812***	0.745***	0.668***	0.569**	NA
	(3.41)	(3.61)	(3.24)	(2.82)	(2.37)	NA
$ILLIQ$ 5 (High)	1.010***	0.860***	0.850***	0.647***	0.558**	NA
	(4.57)	(3.69)	(3.55)	(2.71)	(2.32)	NA
5-1 spread	0.446***	0.284*	0.333**	0.236	0.031	-0.379***
	(3.05)	(1.94)	(2.26)	(1.64)	(0.21)	(-3.39)
Carhart4 α	0.351***	0.141	0.152	0.051	-0.108	-0.371***
	(3.19)	(1.26)	(1.38)	(0.44)	(-0.86)	(-3.17)
β_{MKTRF}	-0.325***	-0.286***	-0.254***	-0.235***	-0.251***	NA
	(-12.36)	(-10.67)	(-9.81)	(-8.74)	(-8.49)	NA
β_{SMB}	0.856***	0.855***	0.890***	0.693***	0.583***	NA
	(20.76)	(20.14)	(22.12)	(17.81)	(13.91)	NA
β_{HML}	0.221***	0.172***	0.231***	0.331***	0.305***	NA
	(5.06)	(3.90)	(5.39)	(7.43)	(6.23)	NA
β_{UMD}	-0.063**	-0.071**	-0.033	-0.041	-0.062*	NA
	(-2.26)	(-2.54)	(-1.24)	(-1.44)	(-1.94)	NA

Table 1.18 (continued)

Panel B: Sort By *SKEW* then *ILLIQ*	*SKEW* 1	*SKEW* 2	*SKEW* 3	*SKEW* 4	*SKEW* 5	Diff
ILLIQ 1 (Low)	0.572***	0.611***	0.625***	0.556***	0.566***	NA
	(2.91)	(3.12)	(3.10)	(2.70)	(2.78)	NA
ILLIQ 2	0.628***	0.750***	0.687***	0.589***	0.611**	NA
	(2.84)	(3.39)	(2.99)	(2.48)	(2.55)	NA
ILLIQ 3	0.693***	0.822***	0.744***	0.689**	0.733***	NA
	(3.04)	(3.60)	(3.11)	(2.73)	(2.95)	NA
ILLIQ 4	0.700***	0.830***	0.766***	0.722***	0.503*	NA
	(3.15)	(3.69)	(3.36)	(2.99)	(2.11)	NA
ILLIQ 5 (High)	0.924***	1.038***	0.918***	0.713***	0.416*	NA
	(4.42)	(4.37)	(3.61)	(2.96)	(1.80)	NA
5-1 spread	0.334**	0.383**	0.437***	0.248*	-0.142	-0.389***
	(2.40)	(2.42)	(2.72)	(1.76)	(-1.13)	(-3.85)
Carhart4 α	0.235**	0.183	0.201*	0.091	-0.230**	-0.386***
	(2.28)	(1.62)	(1.68)	(0.75)	(-2.03)	(-3.75)
β_{MKTRF}	-0.317***	-0.313***	-0.297***	-0.235***	-0.171***	NA
	(-12.83)	(-11.53)	(-10.42)	(-8.73)	(-6.43)	NA
β_{SMB}	0.856***	0.905***	0.904***	0.691***	0.505***	NA
	(22.26)	(21.27)	(20.69)	(17.21)	(13.15)	NA
β_{HML}	0.216***	0.284***	0.244***	0.278***	0.253***	NA
	(5.30)	(6.55)	(5.26)	(5.96)	(5.67)	NA
β_{UMD}	-0.030	-0.084***	-0.066**	-0.067**	-0.068**	NA
	(-1.16)	(-3.00)	(-2.24)	(-2.25)	(-2.31)	NA

Table IA.1: The Characteristics of the S_φ, E_φ and $SKEW$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of $SKEW$, S_φ, and E_φ measured using daily returns over the lagged year on subsets of lagged predictor variables including size ($SIZE$), book to market ratio (BM), momentum (MOM), turnover ($TURN$), liquidity measure ($ILLIQ$), and market beta (β). In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Here asymmetry measures are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$SKEW$	$S_{\varphi 1}$	$S_{\varphi 2}$	$E_{\varphi 1}$	$E_{\varphi 2}$
$SIZE$	-0.0924***	-0.0017***	-0.0051***	-0.0004***	-0.0015***
	(-24.90)	(-15.08)	(-6.83)	(-8.63)	(-27.29)
BM	-0.0281***	-0.0006***	-0.0082***	-0.0004***	-0.0004***
	(-4.96)	(-2.91)	(-7.78)	(-6.27)	(-4.76)
MOM	0.0069***	0.0001***	0.0005***	0.0000***	0.0001***
	(25.27)	(15.81)	(15.24)	(10.25)	(27.30)
$TURN$	-0.0074	0.0017***	0.0144***	0.0009***	0.0003***
	(-1.40)	(10.35)	(14.30)	(13.72)	(5.19)
$ILLIQ$	0.0041***	-0.0000	-0.0005	-0.0000	0.0000**
	(5.51)	(-0.56)	(-1.25)	(-0.12)	(2.53)
β	-0.0078	0.0033***	0.0202***	0.0009***	0.0027***
	(-0.70)	(7.64)	(8.72)	(6.26)	(17.41)
Constant	0.8341***	0.0156***	0.0299**	0.0043***	0.0146***
	(29.47)	(17.92)	(6.04)	(13.40)	(35.43)
OBS.	1,617,900	1,633,761	380,052	1,644,114	1,644,114
R^2	0.102	0.018	0.032	0.024	0.111

Table IA.2: Firm-Level Cross-Sectional Return Regressions

Fama MacBeth Regression Replication of Bali, Cakici, and Whitelaw (2011) Table 13. Each month from July 1963 to December 2005 we run a firm-level cross-sectional regression of the excess return (R) in that month on subsets of $SKEW$ or $ISKEW$ measured over the preceding year and other lagged control variables defined in the Appendix. In each row,the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: with Max and Skewness: 1963-2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R	R	R	R	R	R	R	R
$SKEW$	0.0259	0.0455**	0.0445**	0.0091				
	(0.77)	(2.44)	(2.41)	(0.47)				
$SIZE$		-0.1614***	-0.1781***	-0.2342***		-0.1609***	-0.1775***	-0.2333***
		(-3.64)	(-3.88)	(-5.01)		(-3.62)	(-3.86)	(-4.97)
BM		0.2890***	0.2914***	0.2701***		0.2893***	0.2915***	0.2702***
		(4.57)	(4.64)	(4.30)		(4.58)	(4.65)	(4.30)
MOM		0.0102***	0.0103***	0.0105***		0.0102***	0.0103***	0.0105***
		(7.05)	(7.20)	(7.29)		(7.04)	(7.18)	(7.27)
REV		-0.0325***	-0.0313***	-0.0401***		-0.0326***	-0.0314***	-0.0402***
		(-7.60)	(-7.34)	(-9.64)		(-7.60)	(-7.34)	(-9.64)
$TURN$			-0.0533	-0.0179			-0.0533	-0.0175
			(-1.44)	(-0.47)			(-1.43)	(-0.46)
$ILLIQ$		0.0022	-0.0046	0.0145***		0.0023	-0.0045	0.0147***
		(0.39)	(-1.09)	(3.05)		(0.42)	(-1.07)	(3.08)
β		0.8453***	0.8878***	0.9964***		0.8441***	0.8866***	0.9980***
		(4.03)	(4.16)	(4.51)		(4.03)	(4.15)	(4.52)
MAX		-0.1056***	-0.1008***	0.0261***		-0.1052***	-0.1004***	0.0267***
		(-13.34)	(-14.25)	(3.04)		(-13.34)	(-14.23)	(3.13)
$IVOL$				-0.5103***				-0.5112***
				(-14.72)				(-14.76)
$ISKEW$					0.0321	0.0389**	0.0388**	0.0048
					(0.94)	(2.09)	(2.07)	(0.25)
Constant	0.6754***	1.5072***	1.5766***	2.1686***	0.6759***	1.5087***	1.5776***	2.1666***
	(2.69)	(4.53)	(4.75)	(6.31)	(2.69)	(4.52)	(4.74)	(6.27)
OBS.	1,583,260	1,353,097	1,353,097	1,308,928	1,583,207	1,353,091	1,353,091	1,308,927
R^2	0.003	0.089	0.091	0.094	0.003	0.089	0.091	0.094

Table IA.2 (continued)

Each month from January 1962 to December 2013 we run a firm-level cross-sectional regression of the excess return (R) in that month on subsets of $SKEW$ or $ISKEW$ measured over the preceding year and other lagged control variables defined in the Appendix. In each row,the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: with Max and Skewness: 1962-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R	R	R	R	R	R	R	R
$SKEW$	0.0052	0.0296*	0.0287*	-0.0037				
	(0.18)	(1.74)	(1.70)	(-0.21)				
$SIZE$		-0.1353***	-0.1509***	-0.2030***		-0.1348***	-0.1502***	-0.2020***
		(-3.61)	(-3.89)	(-5.14)		(-3.59)	(-3.87)	(-5.09)
BM		0.2677***	0.2690***	0.2483***		0.2673***	0.2684***	0.2478***
		(4.91)	(4.96)	(4.57)		(4.90)	(4.95)	(4.56)
MOM		0.0087***	0.0089***	0.0092***		0.0087***	0.0089***	0.0092***
		(5.47)	(5.68)	(5.86)		(5.50)	(5.70)	(5.89)
REV		-0.0306***	-0.0297***	-0.0383***		-0.0306***	-0.0298***	-0.0383***
		(-7.93)	(-7.78)	(-10.20)		(-7.93)	(-7.78)	(-10.20)
$TURN$			-0.0570	-0.0182			-0.0574*	-0.0183
			(-1.64)	(-0.51)			(-1.65)	(-0.51)
$ILLIQ$		-0.0004	-0.0073	0.0113**		-0.0002	-0.0072	0.0114**
		(-0.08)	(-1.55)	(2.10)		(-0.05)	(-1.53)	(2.12)
β		0.6504***	0.6912***	0.7845***		0.6527***	0.6938***	0.7901***
		(3.34)	(3.51)	(3.87)		(3.35)	(3.53)	(3.90)
MAX		-0.0935***	-0.0883***	0.0298***		-0.0933***	-0.0881***	0.0301***
		(-12.91)	(-13.44)	(3.86)		(-12.95)	(-13.47)	(3.92)
$IVOL$				-0.4742***				-0.4745***
				(-15.54)				(-15.56)
$ISKEW$					0.0113	0.0225	0.0220	-0.0089
					(0.39)	(1.35)	(1.32)	(-0.52)
Constant	0.6565***	1.4303***	1.5084***	2.0370***	0.6564***	1.4297***	1.5077***	2.0327***
	(2.84)	(5.03)	(5.32)	(6.96)	(2.84)	(5.02)	(5.30)	(6.91)
OBS.	1,905,173	1,647,899	1,647,899	1,600,732	1,905,096	1,647,893	1,647,893	1,600,731
R^2	0.003	0.087	0.089	0.092	0.003	0.087	0.089	0.092

Table IA.2 (continued)

Fama MacBeth Regression Replication of Bali, Cakici, and Whitelaw (2011) Table 13. Each month from January 1962 to December 2013 we run a firm-level cross-sectional regression of the adjusted-return (RA) in that month on subsets of $SKEW$ or $ISKEW$ measured over the preceding year and other lagged control variables defined in the Appendix. In each row,the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel C: with Max and Skewness Using RA as the Dependent Variable: 1962-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RA	RA	RA	RA	RA	RA	RA	RA
$SKEW$	-0.0283	-0.0001	0.0075	-0.0178				
	(-1.42)	(-0.01)	(0.45)	(-1.03)				
$SIZE$		-0.1023***	-0.0936***	-0.1251***		-0.1017***	-0.0929***	-0.1241***
		(-8.28)	(-7.14)	(-9.25)		(-8.21)	(-7.04)	(-9.11)
BM		0.0474	0.0520	0.0304		0.0466	0.0512	0.0294
		(1.22)	(1.35)	(0.78)		(1.20)	(1.33)	(0.75)
MOM		0.0082***	0.0082***	0.0085***		0.0082***	0.0081***	0.0085***
		(5.60)	(5.68)	(5.88)		(5.57)	(5.65)	(5.85)
REV		-0.0424***	-0.0418***	-0.0485***		-0.0424***	-0.0418***	-0.0486***
		(-11.86)	(-11.82)	(-13.78)		(-11.85)	(-11.80)	(-13.77)
$TURN$			0.0841***	0.1392***			0.0844***	0.1400***
			(2.69)	(4.17)			(2.69)	(4.19)
$ILLIQ$		-0.0023	0.0015	0.0177***		-0.0023	0.0016	0.0178***
		(-0.49)	(0.37)	(3.68)		(-0.48)	(0.39)	(3.70)
MAX		-0.0564***	-0.0640***	0.0334***		-0.0565***	-0.0641***	0.0332***
		(-8.46)	(-10.72)	(4.36)		(-8.51)	(-10.74)	(4.37)
$IVOL$				-0.3830***				-0.3829***
				(-13.31)				(-13.35)
$ISKEW$					-0.0218	0.0022	0.0085	-0.0151
					(-1.15)	(0.14)	(0.53)	(-0.90)
Constant	0.0641*	0.8507***	0.7713***	1.1457***	0.0639*	0.8478***	0.7692***	1.1411***
	(1.80)	(8.64)	(6.98)	(9.52)	(1.81)	(8.59)	(6.94)	(9.45)
OBS.	1,522,828	1,518,938	1,518,938	1,476,950	1,522,828	1,518,938	1,518,938	1,476,950
R^2	0.002	0.030	0.033	0.036	0.002	0.030	0.033	0.036

Table IA.3: Firm-Level Cross-Sectional Return Regressions with 24 Newey-West Lags

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables including $IS_{\varphi 1}$, $IE_{\varphi 1}$ and $ISKEW$ measured over the preceding year and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with 24 lags. Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Adjust Return is the Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
IS_{φ}	-0.6410***			-0.7295***	-0.7949***	-0.7838***	-0.6467***				
	(-3.06)			(-3.29)	(-4.32)	(-4.26)	(-3.21)				
IE_{φ}		-2.7588***						-3.2215***	-3.5363***	-3.5185***	-2.9227***
		(-2.86)						(-3.17)	(-4.69)	(-4.67)	(-3.54)
$ISKEW$			-0.0218	-0.0281	-0.0173	-0.0181	-0.0188	-0.0298	-0.0238	-0.0244	-0.0235
			(-0.93)	(-1.10)	(-0.78)	(-0.84)	(-0.82)	(-1.23)	(-1.14)	(-1.20)	(-1.08)
$SIZE$					-0.1324***	-0.1340***	-0.1230***		-0.1313***	-0.1330***	-0.1219***
					(-10.02)	(-9.91)	(-8.83)		(-9.85)	(-9.77)	(-8.69)
BM					0.0740*	0.0702	0.0135		0.0731*	0.0693	0.0126
					(1.69)	(1.61)	(0.30)		(1.66)	(1.58)	(0.28)
MOM					0.0093***	0.0092***	0.0084***		0.0093***	0.0091***	0.0084***
					(5.76)	(5.65)	(4.97)		(5.81)	(5.71)	(5.01)
$TURN$					0.1331***	0.1364***	0.1446***		0.1299***	0.1324***	0.1412***
					(3.36)	(3.33)	(3.37)		(3.28)	(3.24)	(3.31)
$ILLIQ$					0.0132**	0.0142**	0.0178***		0.0131**	0.0141**	0.0177***
					(2.36)	(2.51)	(3.19)		(2.35)	(2.49)	(3.19)
MAX					-0.0881***	-0.0820***	0.0183**		-0.0823***	-0.0766***	0.0226**
					(-6.28)	(-6.40)	(2.00)		(-5.86)	(-5.93)	(2.46)
VOL					-0.1049***				-0.1099***		
					(-2.80)				(-2.94)		
$IVOL$						-0.1325***	-0.3588***			-0.1355***	-0.3603***
						(-3.25)	(-9.17)			(-3.35)	(-9.25)
REV							-0.0473***				-0.0475***
							(-11.23)				(-11.32)
Constant	0.0613	0.0643	0.0639	0.0710	1.2082***	1.2380***	1.1301***	0.0750*	1.1943***	1.2227***	1.1147***
	(1.43)	(1.52)	(1.42)	(1.57)	(9.73)	(9.91)	(8.49)	(1.68)	(9.77)	(10.00)	(8.57)
OBS.	1,511,723	1,519,800	1,522,828	1,511,723	1,471,738	1,471,738	1,452,787	1,519,800	1,475,918	1,475,918	1,456,833
R^2	0.001	0.001	0.002	0.003	0.031	0.031	0.037	0.003	0.031	0.031	0.036

Table IA.3 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables including $IS_{\varphi1}$, $IE_{\varphi1}$ and $ISKEW$ measured over the preceding year and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with 24 lags as in Fama and MacBeth (1973). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: Excess Return is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
IS_φ	-0.8584**			-0.9046***	-1.1043***	-1.1022***	-0.9415***				
	(-2.46)			(-2.59)	(-4.94)	(-4.88)	(-3.94)				
IE_φ		-3.4598**						-3.7902**	-4.6618***	-4.6899***	-4.0147***
		(-2.49)						(-2.46)	(-5.49)	(-5.44)	(-4.41)
$ISKEW$			0.0113	0.0085	-0.0232	-0.0189	-0.0145	0.0023	-0.0290	-0.0247	-0.0191
			(0.32)	(0.22)	(-0.99)	(-0.82)	(-0.60)	(0.06)	(-1.27)	(-1.10)	(-0.82)
$SIZE$					-0.2168***	-0.2163***	-0.2062***		-0.2134***	-0.2128***	-0.2033***
					(-4.88)	(-4.90)	(-4.63)		(-4.80)	(-4.82)	(-4.56)
BM					0.2864***	0.2871***	0.2418***		0.2891***	0.2899***	0.2438***
					(4.91)	(4.93)	(4.07)		(4.92)	(4.94)	(4.08)
MOM					0.0101***	0.0100***	0.0093***		0.0101***	0.0100***	0.0093***
					(6.13)	(6.10)	(5.41)		(6.18)	(6.15)	(5.45)
$TURN$					-0.0235	-0.0359	-0.0082		-0.0275	-0.0407	-0.0114
					(-0.55)	(-0.82)	(-0.19)		(-0.64)	(-0.94)	(-0.27)
$ILLIQ$					0.0115*	0.0093	0.0115*		0.0113*	0.0090	0.0114*
					(1.70)	(1.44)	(1.73)		(1.67)	(1.40)	(1.72)
β					0.9224***	0.8780***	0.8015***		0.9134***	0.8660***	0.7913***
					(4.01)	(3.90)	(3.44)		(3.97)	(3.84)	(3.40)
MAX					-0.0442***	-0.0614***	0.0229**		-0.0363***	-0.0538***	0.0294***
					(-3.29)	(-4.32)	(2.39)		(-2.70)	(-3.76)	(3.02)
VOL					-0.3590***				-0.3618***		
					(-7.50)				(-7.59)		
$IVOL$						-0.2884***	-0.4705***			-0.2892***	-0.4714***
						(-6.63)	(-11.68)			(-6.68)	(-11.64)
REV							-0.0380***				-0.0383***
							(-8.56)				(-8.61)
Constant	0.6759***	0.6771***	0.6564***	0.6661***	2.1265***	2.0963***	2.0691***	0.6698***	2.0986***	2.0658***	2.0427***
	(3.22)	(3.22)	(3.23)	(3.30)	(7.19)	(7.24)	(6.99)	(3.32)	(7.13)	(7.16)	(6.93)
OBS.	1,860,476	1,884,898	1,905,096	1,860,476	1,593,622	1,593,622	1,593,622	1,884,898	1,599,204	1,599,204	1,599,204
R^2	0.001	0.002	0.003	0.004	0.088	0.088	0.093	0.005	0.088	0.088	0.093

Table IA.4: Firm-Level Cross-Sectional Return Regressions with $IS_{\varphi 1}$, $IE_{\varphi 1}$ and $ISKEW$ Based on 6 Months Daily Returns

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables including $IS_{\varphi 1}$, $IE_{\varphi 1}$ and $ISKEW$ measured over the preceding six months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Adjust Return is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
IS_{φ}	-0.2758*			-0.3790**	-0.5354***	-0.5296***	-0.3546**				
	(-1.84)			(-2.43)	(-3.66)	(-3.63)	(-2.41)				
IE_{φ}		-2.4163***						-3.0728***	-3.7962***	-3.7818***	-2.7711***
		(-4.01)						(-4.87)	(-6.86)	(-6.85)	(-4.91)
$ISKEW$			-0.0434**	-0.0493**	-0.0362**	-0.0371**	-0.0327*	-0.0543***	-0.0493***	-0.0499***	-0.0421**
			(-2.35)	(-2.56)	(-2.09)	(-2.15)	(-1.87)	(-2.83)	(-2.84)	(-2.90)	(-2.38)
$SIZE$					-0.1332***	-0.1353***	-0.1240***		-0.1323***	-0.1341***	-0.1227***
					(-10.16)	(-10.27)	(-9.24)		(-10.08)	(-10.17)	(-9.16)
BM					0.0756**	0.0720*	0.0151		0.0757**	0.0721*	0.0159
					(2.00)	(1.90)	(0.39)		(2.00)	(1.91)	(0.41)
MOM					0.0095***	0.0093***	0.0085***		0.0096***	0.0095***	0.0086***
					(6.75)	(6.63)	(5.79)		(6.87)	(6.75)	(5.86)
$TURN$					0.1306***	0.1335***	0.1411***		0.1271***	0.1292***	0.1373***
					(4.08)	(4.05)	(4.21)		(3.97)	(3.92)	(4.10)
$ILLIQ$					0.0134***	0.0144***	0.0180***		0.0131***	0.0141***	0.0177***
					(2.71)	(2.99)	(3.65)		(2.67)	(2.93)	(3.60)
MAX					-0.0846***	-0.0782***	0.0209***		-0.0781***	-0.0726***	0.0256***
					(-7.96)	(-8.08)	(2.62)		(-7.35)	(-7.53)	(3.28)
VOL					-0.1113***				-0.1152***		
					(-3.01)				(-3.14)		
$IVOL$						-0.1400***	-0.3637***			-0.1403***	-0.3638***
						(-4.16)	(-12.14)			(-4.21)	(-12.34)
$REVA$							-0.0472***				-0.0474***
							(-13.00)				(-13.04)
Constant	0.0580*	0.0608*	0.0690**	0.0725**	1.2105***	1.2445***	1.1343***	0.0773**	1.1959***	1.2251***	1.1173***
	(1.78)	(1.87)	(1.99)	(2.08)	(10.42)	(10.67)	(9.40)	(2.22)	(10.36)	(10.59)	(9.35)
OBS.	1,518,811	1,523,055	1,523,055	1,518,811	1,475,383	1,475,383	1,455,694	1,523,055	1,477,942	1,477,942	1,458,006
R^2	0.001	0.001	0.002	0.002	0.031	0.030	0.036	0.002	0.031	0.030	0.036

Table IA.4 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of of the excess return in that month on subsets of lagged predictor variables including $IS_{\varphi 1}$, $IE_{\varphi 1}$ and $ISKEW$ measured over the preceding six months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: Excess Return is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
IS_{φ}	-0.3936**			-0.4524**	-0.7011***	-0.6992***	-0.5323***				
	(-2.13)			(-2.33)	(-4.84)	(-4.84)	(-3.70)				
IE_{φ}		-2.2721***						-2.7584***	-4.0846***	-4.1038***	-3.1517***
		(-2.60)						(-2.87)	(-7.10)	(-7.12)	(-5.42)
$ISKEW$			-0.0121	-0.0190	-0.0538***	-0.0454***	-0.0398**	-0.0222	-0.0645***	-0.0561***	-0.0475***
			(-0.46)	(-0.68)	(-3.08)	(-2.60)	(-2.24)	(-0.80)	(-3.65)	(-3.19)	(-2.64)
$SIZE$					-0.2181***	-0.2177***	-0.2081***		-0.2151***	-0.2144***	-0.2051***
					(-5.46)	(-5.52)	(-5.25)		(-5.39)	(-5.44)	(-5.18)
BM					0.2914***	0.2920***	0.2467***		0.2928***	0.2936***	0.2476***
					(5.45)	(5.46)	(4.55)		(5.47)	(5.48)	(4.57)
MOM					0.0104***	0.0102***	0.0095***		0.0105***	0.0104***	0.0096***
					(6.87)	(6.79)	(5.99)		(6.99)	(6.92)	(6.06)
$TURN$					-0.0279	-0.0407	-0.0130		-0.0318	-0.0454	-0.0165
					(-0.78)	(-1.13)	(-0.36)		(-0.89)	(-1.27)	(-0.46)
$ILLIQ$					0.0116**	0.0094*	0.0117**		0.0113**	0.0090*	0.0114**
					(2.08)	(1.76)	(2.17)		(2.03)	(1.69)	(2.12)
β					0.9234***	0.8756***	0.8012***		0.9115***	0.8616***	0.7886***
					(4.56)	(4.41)	(3.95)		(4.51)	(4.35)	(3.90)
MAX					-0.0386***	-0.0568***	0.0268***		-0.0303***	-0.0488***	0.0339***
					(-3.58)	(-5.44)	(3.39)		(-2.83)	(-4.71)	(4.30)
VOL					-0.3687***				-0.3722***		
					(-8.83)				(-9.00)		
$IVOL$						-0.2959***	-0.4771***			-0.2966***	-0.4782***
						(-8.11)	(-15.32)			(-8.18)	(-15.42)
REV							-0.0378***				-0.0381***
							(-10.06)				(-10.13)
Constant	0.6706***	0.6725***	0.6654***	0.6705***	2.1346***	2.1042***	2.0790***	0.6738***	2.1102***	2.0754***	2.0531***
	(2.85)	(2.86)	(2.87)	(2.90)	(7.23)	(7.28)	(7.08)	(2.92)	(7.15)	(7.18)	(6.99)
OBS.	1,903,719	1,913,510	1,913,510	1,903,719	1,598,894	1,598,894	1,598,894	1,913,510	1,602,126	1,602,126	1,602,126
R^2	0.001	0.001	0.002	0.003	0.088	0.088	0.093	0.004	0.088	0.088	0.093

Table IA.5: Firm-Level Cross-Sectional Return Regressions Using $E(ISKEW)$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return or excess return in that month on subsets of expected idiosyncratic skewness $E(ISKEW)$ (following Bali, Cakici, and Whitelaw (2011)'s method) and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. For column (1)-(4), the dependent variable is the adjusted-return, and excess return is the dependent variable for column (5)-(8). Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}E(ISKEW)_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for column(5)-(8).

Panel A: $E(ISKEW)$ **Obtained Following Bali, Cakici, and Whitelaw (2011)'s Method**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARS	RA	RA	RA	RA	R	R	R	R
$E(ISKEW)$	0.2717**	2.6540***	3.3467***	2.0769***	0.2124	0.5358	1.8326*	-0.8119
	(2.11)	(5.60)	(5.89)	(3.00)	(0.90)	(1.10)	(1.91)	(-0.42)
$SIZE$		0.1158**	0.1732***	0.0806		-0.1191*	-0.0491	-0.2017
		(2.18)	(2.80)	(1.14)		(-1.96)	(-0.47)	(-1.49)
BM		-0.1472**	-0.2210***	-0.1905***		0.2571***	0.2137**	0.3439***
		(-2.56)	(-3.35)	(-2.71)		(4.04)	(2.28)	(2.88)
MOM		0.0108***	0.0114***	0.0094***		0.0114***	0.0147***	0.0060
		(6.94)	(6.86)	(5.07)		(7.53)	(6.05)	(0.97)
$TURN$		0.1649***	0.2161***	0.1902***		-0.1210**	0.0164	-0.1562
		(3.63)	(4.44)	(3.63)		(-2.19)	(0.19)	(-0.98)
$ILLIQ$		-0.0042	-0.0028	0.0034		0.0028	-0.0047	0.0088
		(-0.57)	(-0.34)	(0.39)		(0.36)	(-0.46)	(0.37)
β						0.7737***	0.5286*	0.9453
						(3.71)	(1.73)	(1.34)
MAX		-0.1441***	-0.1016***	-0.0024		-0.1309***	-0.0438**	0.0337*
		(-14.64)	(-7.84)	(-0.19)		(-14.63)	(-2.15)	(1.88)
$IVOL$			-0.2209***	-0.4184***			-0.4099***	-0.4183***
			(-4.56)	(-8.38)			(-7.63)	(-3.74)
$REVA$				-0.0450***				
				(-10.42)				
REV								-0.0489***
								(-5.01)
Constant	-0.0597	-1.2881***	-1.8138***	-0.9711	0.4984**	1.2034**	0.7410	2.1994**
	(-0.93)	(-2.75)	(-3.20)	(-1.47)	(2.51)	(2.50)	(1.02)	(2.15)
OBS.	1,449,368	1,449,368	1,449,368	1,430,267	1,568,832	1,568,832	1,568,832	1,568,832
R^2	0.006	0.033	0.036	0.041	0.018	0.088	0.090	0.093

Table IA.5 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return or excess return in that month on subsets of expected idiosyncratic skewness $E(ISKEW)$ (following Boyer, Mitton, and Vorkink (2010)'s method) and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and we adjust the Fama-MacBeth standard errors using the Newey and West (1987) correction with three lags as in Fama and MacBeth (1973). Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. For column (1)-(4), the dependent variable is the adjusted-return, and excess return is the dependent variable for column (5)-(8). Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}E(ISKEW)_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a set of control variables. $RA_{i,t+1}$ changed to $R_{i,t+1}$ for column(5)-(8).

Panel B: $E(ISKEW)$ **Obtained Following Boyer, Mitton, and Vorkink (2010)'s Method**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARS	*RA*	*RA*	*RA*	*RA*	*R*	*R*	*R*	*R*
$E(ISKEW)$	0.5258***	2.7844***	3.3816***	2.3697***	0.5214**	1.8268***	3.2037***	-8.9406
	(4.16)	(6.93)	(6.85)	(3.71)	(2.30)	(3.85)	(4.86)	(-0.84)
$SIZE$		0.1158***	0.1657***	0.0999		-0.0494	0.0393	-0.4649
		(2.76)	(3.17)	(1.52)		(-0.92)	(0.61)	(-0.71)
BM		-0.1696***	-0.2204***	-0.1918***		0.1611***	0.0548	0.2734
		(-3.17)	(-3.77)	(-3.11)		(2.67)	(0.80)	(1.48)
MOM		0.0109***	0.0118***	0.0100***		0.0113***	0.0137***	-0.0227
		(7.24)	(7.17)	(5.42)		(7.68)	(8.74)	(-0.67)
$TURN$		0.1428***	0.2032***	0.1803***		0.0240	0.1893***	-0.9142
		(3.37)	(4.39)	(3.59)		(0.48)	(2.81)	(-0.78)
$ILLIQ$		-0.0046	-0.0023	0.0070		-0.0037	-0.0054	0.1969*
		(-0.73)	(-0.34)	(0.94)		(-0.47)	(-0.62)	(1.76)
β						0.4136	0.1070	4.2046
						(1.55)	(0.35)	(1.16)
MAX		-0.1454***	-0.0889***	-0.0057		-0.1353***	-0.0582***	0.6144
		(-15.11)	(-7.99)	(-0.48)		(-14.93)	(-4.18)	(1.01)
$IVOL$			-0.2830***	-0.4308***			-0.4168***	-0.5888***
			(-6.22)	(-9.07)			(-8.34)	(-5.01)
$REVA$				-0.0387***				
				(-8.89)				
REV								-0.1377
								(-1.32)
Constant	-0.1043*	-1.1907***	-1.5108***	-0.9041	0.5399***	0.6789	0.2288	2.1027
	(-1.66)	(-3.02)	(-3.21)	(-1.54)	(2.65)	(1.53)	(0.43)	(0.43)
OBS.	1,476,950	1,476,950	1,476,950	1,457,629	1,600,731	1,600,731	1,600,731	1,600,731
R^2	0.006	0.034	0.036	0.041	0.018	0.087	0.089	0.092

Table IA.6: Cross-Section Regressions on Skewness During High and Low Sentiment Period

From July 1965 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables when the lagged month's standardized sentiment index (based on Baker and Wurgler (2006, 2007), extended by Huang et al. (2015) to December 2013)≥ 1 for Model 1 to Model 4 or the lagged month's standardized sentiment index ≤ -1 for Model 5 to Model 8. $SKEW$ data is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SKEW$	-0.2095***	-0.1377***	-0.1414***	-0.1356***	-0.0543	0.1034**	0.0986**	0.1003**
	(-3.79)	(-3.05)	(-2.96)	(-2.86)	(-1.03)	(2.20)	(2.06)	(2.12)
$SIZE$		-0.1533***	-0.1612***	-0.1590***		-0.1766***	-0.1851***	-0.1803***
		(-3.19)	(-3.37)	(-3.37)		(-4.59)	(-4.79)	(-4.81)
BM		0.1249	0.1236	0.1236		0.2906**	0.2833**	0.2842**
		(1.21)	(1.19)	(1.20)		(2.54)	(2.47)	(2.49)
MOM		0.0119***	0.0119***	0.0119***		0.0014	0.0019	0.0019
		(3.11)	(3.16)	(3.14)		(0.34)	(0.47)	(0.47)
$TURN$		0.1769**	0.1953**	0.1821**		-0.1382	-0.1117	-0.1271
		(2.30)	(2.56)	(2.41)		(-1.35)	(-1.14)	(-1.23)
$ILLIQ$		-0.0066	-0.0018	-0.0041		-0.0210**	-0.0133	-0.0161
			(-0.15)	(-0.35)		(-2.26)	(-1.31)	(-1.55)
β		0.3169	0.3712	0.3239		1.4262***	1.4551***	1.4206***
		(1.06)	(1.24)	(1.09)		(5.04)	(4.99)	(5.02)
MAX		-0.1585***	-0.1255***	-0.1349***		-0.1701***	-0.1217***	-0.1393***
		(-11.26)	(-5.39)	(-5.97)		(-11.14)	(-4.26)	(-4.65)
VOL			-0.1369				-0.2126*	
			(-1.53)				(-1.92)	
$IVOL$				-0.0912				-0.1309
				(-1.07)				(-1.18)
Constant	0.2527**	1.5332***	1.6341***	1.5990***	0.0776	0.4912*	0.6340**	0.5591**
	(2.47)	(4.62)	(4.72)	(4.74)	(1.13)	(1.91)	(2.40)	(2.13)
OBS.	194,807	194,441	194,384	194,384	133,613	132,104	132,092	132,092
R^2	0.002	0.045	0.047	0.047	0.002	0.052	0.055	0.055
Months	85	85	85	85	83	83	83	83

Table IA.7: Cross-Section Regressions on Idiosyncratic Asymmetry During High and Low Sentiment Period when Excess Return is the Dependent Variable

From July 1965 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables when the lagged month's standardized sentiment index (based on Baker and Wurgler (2006, 2007), extended by Huang et al. (2015) to December 2013)≥ 1 for Model 1 to Model 4 or the lagged month's standardized sentiment index ≤ -1 for Model 5 to Model 8. $ISKEW$ data is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: $ISKEW$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	-0.2035**	-0.0901*	-0.1129**	-0.1058*	0.1549*	0.1377***	0.1390***	0.1384***
	(-2.52)	(-1.84)	(-2.07)	(-1.97)	(1.71)	(3.29)	(3.12)	(3.09)
$SIZE$		-0.1053	-0.1447	-0.1432		-0.3914***	-0.3942***	-0.3900***
		(-1.11)	(-1.51)	(-1.52)		(-3.57)	(-3.63)	(-3.66)
BM		0.4230***	0.4191***	0.4187***		0.4553***	0.4543***	0.4536***
		(3.54)	(3.47)	(3.48)		(2.70)	(2.67)	(2.68)
MOM		0.0159***	0.0160***	0.0160***		0.0023	0.0033	0.0032
		(3.68)	(3.78)	(3.76)		(0.49)	(0.68)	(0.68)
$TURN$		0.1248	0.1401	0.1196		-0.0675	-0.0688	-0.0777
		(1.49)	(1.65)	(1.42)		(-0.69)	(-0.66)	(-0.73)
$ILLIQ$		-0.0139	-0.0012	-0.0049		-0.0242**	-0.0082	-0.0102
		(-1.10)	(-0.09)	(-0.38)		(-2.55)	(-0.77)	(-0.92)
β		-0.3780	-0.2258	-0.3175		1.4921***	1.5290***	1.5029***
		(-0.72)	(-0.44)	(-0.61)		(3.27)	(3.33)	(3.29)
MAX		-0.1584***	-0.0896***	-0.1073***		-0.1614***	-0.1241***	-0.1357***
		(-10.72)	(-3.44)	(-4.17)		(-10.90)	(-4.16)	(-4.19)
VOL			-0.3035***				-0.1729	
			(-2.96)				(-1.57)	
$IVOL$				-0.2280**				-0.1193
				(-2.27)				(-1.01)
Constant	-0.1124	1.9272***	2.3542***	2.3271***	0.9159	2.2085***	2.2893***	2.2410***
	(-0.18)	(2.88)	(3.36)	(3.38)	(1.34)	(2.80)	(2.94)	(2.99)
OBS.	245,524	212,754	205,978	205,978	151,289	134,827	132,347	132,347
R^2	0.004	0.110	0.113	0.113	0.005	0.109	0.112	0.112

Table IA.7 (continued)

From July 1965 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables during high sentiment period when the lagged month's standardized sentiment index (based on Baker and Wurgler (2006, 2007), extended by Huang et al. (2015) to December 2013)≥ 1 for Model 1 to Model 4 or during low sentiment period when the lagged month's standardized sentiment index ≤ -1 for Model 5 to Model 8. IS_{φ} data is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: IS_{φ}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS_{φ}	-2.6933***	-1.6846***	-1.6471***	-1.6513***	-0.2283	-0.8868	-0.8574	-0.8640
	(-3.04)	(-3.25)	(-3.02)	(-3.03)	(-0.27)	(-1.47)	(-1.43)	(-1.43)
$SIZE$		-0.1078	-0.1389	-0.1379		-0.4090***	-0.4143***	-0.4107***
		(-1.12)	(-1.44)	(-1.45)		(-3.71)	(-3.78)	(-3.82)
BM		0.4235***	0.4213***	0.4202***		0.4519***	0.4510***	0.4500***
		(3.52)	(3.47)	(3.47)		(2.68)	(2.65)	(2.66)
MOM		0.0153***	0.0154***	0.0154***		0.0032	0.0041	0.0041
		(3.56)	(3.66)	(3.64)		(0.67)	(0.86)	(0.86)
$TURN$		0.1407*	0.1596*	0.1426*		-0.0655	-0.0643	-0.0723
		(1.67)	(1.87)	(1.69)		(-0.66)	(-0.62)	(-0.68)
$ILLIQ$		-0.0148	-0.0027	-0.0059		-0.0229**	-0.0068	-0.0086
		(-1.16)	(-0.20)	(-0.46)		(-2.50)	(-0.65)	(-0.80)
β		-0.3576	-0.2278	-0.3088		1.5005***	1.5476***	1.5146***
		(-0.67)	(-0.44)	(-0.59)		(3.28)	(3.37)	(3.31)
MAX		-0.1750***	-0.1158***	-0.1308***		-0.1602***	-0.1201***	-0.1316***
		(-11.31)	(-4.69)	(-5.34)		(-11.31)	(-4.25)	(-4.26)
VOL			-0.2642***				-0.1885*	
			(-2.69)				(-1.75)	
$IVOL$				-0.2012**				-0.1374
				(-2.06)				(-1.18)
Constant	-0.1979	1.9686***	2.3066***	2.2887***	0.9950	2.3401***	2.4452***	2.4038***
	(-0.31)	(2.90)	(3.30)	(3.33)	(1.41)	(2.96)	(3.13)	(3.20)
OBS.	238,538	210,036	204,504	204,504	150,055	134,286	131,913	131,913
R^2	0.001	0.110	0.113	0.113	0.002	0.109	0.112	0.112

Table IA.7 (continued)

From July 1965 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables during high sentiment period when the lagged month's standardized sentiment index (based on Baker and Wurgler (2006, 2007), extended by Huang et al. (2015) to December 2013)≥ 1 for Model 1 to Model 4 or during low sentiment period when the lagged month's standardized sentiment index ≤ -1 for Model 5 to Model 8. IE_{φ} data is winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel C: IE_{φ}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IE_{φ}	-8.6049**	-4.3564**	-3.6382*	-3.8058*	-0.3313	-3.6942*	-3.1468	-3.1975
	(-2.21)	(-2.16)	(-1.71)	(-1.80)	(-0.10)	(-1.67)	(-1.41)	(-1.43)
$SIZE$		-0.0999	-0.1338	-0.1323		-0.4033***	-0.4079***	-0.4039***
		(-1.05)	(-1.39)	(-1.40)		(-3.67)	(-3.74)	(-3.78)
BM		0.4250***	0.4247***	0.4237***		0.4545***	0.4532***	0.4521***
		(3.55)	(3.51)	(3.52)		(2.70)	(2.66)	(2.67)
MOM		0.0153***	0.0154***	0.0154***		0.0035	0.0044	0.0043
		(3.58)	(3.68)	(3.66)		(0.72)	(0.91)	(0.91)
$TURN$		0.1368	0.1497*	0.1317		-0.0734	-0.0741	-0.0833
		(1.64)	(1.77)	(1.57)		(-0.76)	(-0.73)	(-0.79)
$ILLIQ$		-0.0143	-0.0025	-0.0059		-0.0236**	-0.0071	-0.0091
		(-1.13)	(-0.19)	(-0.46)		(-2.57)	(-0.68)	(-0.84)
β		-0.3754	-0.2398	-0.3244		1.4834***	1.5309***	1.4975***
		(-0.71)	(-0.46)	(-0.62)		(3.26)	(3.34)	(3.28)
MAX		-0.1647***	-0.1038***	-0.1198***		-0.1521***	-0.1096***	-0.1220***
		(-11.00)	(-4.21)	(-4.92)		(-10.82)	(-3.90)	(-3.96)
VOL			-0.2739***				-0.1958*	
			(-2.78)				(-1.82)	
$IVOL$				-0.2052**				-0.1393
				(-2.11)				(-1.19)
Constant	-0.2001	1.8875***	2.2583***	2.2345***	0.9875	2.2850***	2.3864***	2.3385***
	(-0.32)	(2.82)	(3.25)	(3.27)	(1.41)	(2.89)	(3.06)	(3.12)
OBS.	242,444	211,609	205,075	205,075	150,753	134,634	132,174	132,174
R^2	0.002	0.110	0.112	0.113	0.002	0.108	0.111	0.112

Table IA.8: Asymmetry Proxies Performance Conditional on the Sentiment

The table below presents the results (α_1) of time series regression analysis of the relation between the standardized sentiment indexes and slope coefficients of idiosyncratic asymmetry proxies from cross section regressions from July 1965 to December 2013. Two sentiment indexes: standardized sentiment index from Baker and Wurgler (2006, 2007) (BW, extended by Huang et al. (2015) to December 2013) and standardized sentiment index from Huang et al. (2015) ($HJTZ$), LBW or $LHJTZ$ means the corresponding lagged one month or realized sentiment index). β_{SKEW}, $\beta_{E_{\varphi 1}}$ and $\beta_{S_{\varphi 1}}$ denote the cross section coefficients obtained from univariate regression of the adjusted-return on realized asymmetry proxies, $SKEW$, $E_{\varphi 1}$, and $S_{\varphi 1}$ respectively. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

$$RA_{i,t+1} = \lambda_{0,t} + \beta_{ASYM,t} \times ASYM_{i,t} + \epsilon_{i,t+1},$$

where $ASYM$ is $SKEW$, $E_{\varphi 1}$, or $S_{\varphi 1}$. Then the table below reports the coefficients of following time series regressions.

$$\beta_{ASYM,t} = \alpha_0 + \alpha_1 \times SENT_t + \epsilon_{i,t},$$

where $SENT_t$ is BW, LBW, $HJTZ$ or $LHJTZ$.

	β_{SKEW}	$\beta_{E_{\varphi 1}}$	$\beta_{S_{\varphi 1}}$
BW	-0.0468***	0.1224	-0.1753
	(-2.46)	(0.17)	(-0.87)
LBW	-0.0516***	-0.1054	-0.1492
	(-2.71)	(-0.15)	(-0.74)
$HJTZ$	-0.0631***	0.1757	-0.2710
	(-3.31)	(0.24)	(-1.33)
$LHJTZ$	-0.0703***	0.1287	-0.2804
	(-3.69)	(0.18)	(-1.38)

Table IA.9: Summary Statistics

This table reports the average number, mean, standard deviation, minimum, 25th percentile, median, 75 percentile, and maximum of asymmetry proxies ($E_{\varphi 2}$, $SKEW$, $IE_{\varphi 2}$, $ISKEW$) across the months from January 1962 to December 2013. Here asymmetry proxies are calculated based on the lagged three months daily returns.

Proxy	OBS.	Mean	SD	Min	P25	Median	P75	Max
$E_{\varphi 2}$	3039.414	.0107054	.0203344	-.0509429	-.0027733	.0107211	.0243135	.0697761
$SKEW$	3039.414	.3566377	.9116315	-3.47523	-.0868967	.2981258	.7410399	4.909337
$IE_{\varphi 2}$	3039.303	.0106517	.020175	-.0498071	-.0028459	.0108272	.0242843	.0676051
$ISKEW$	3039.303	.3593567	.9540805	-3.634526	-.1023683	.2997761	.7659897	4.936437

Table IA.10: Summary Statistics for Decile Portfolios of Stocks Sorted by $E_{\varphi 2}$ and $SKEW$

Decile portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the asymmetry measure ($E_{\varphi 2}$ and $SKEW$) calculated based on the lagged three months daily returns. Here $E_{\varphi 2}$, $SKEW$ and excess returns are winsorized at 0.5 percentile and 99.5 percentile. Portfolio 1(10) is the portfolio of stocks with the lowest (highest) realized $E_{\varphi 2}$ ($SKEW$ in Panel B). The table reports for each decile the average across the months in the sample of the median values with in each month of various characteristics for the stocks-the $E_{\varphi 2}$ ($SKEW$ in Panel B), current month excess return (R), the lagged month market capitalization ($SIZE$), the market beta (β),the lagged month book-to-market (BM) ratio, the cumulative pasted six months return (MOM), the measure of lagged month turnover ($TURN$), the measure of illiquidity ($ILLIQ$).

Panel A: $E_{\varphi 2}$

Decile	$E_{\varphi 2}$	R	$SIZE$	β	BM	MOM	$TURN$	$ILLIQ$
Low $E_{\varphi 2}$	-0.023	0.277	5.307	0.721	-0.400	2.666	1.126	1.563
2	-0.010	0.238	5.412	0.783	-0.442	4.143	1.208	1.207
3	-0.003	0.240	5.294	0.793	-0.438	4.653	1.204	1.434
4	0.003	0.166	5.250	0.810	-0.453	5.330	1.224	1.461
5	0.008	0.114	5.273	0.843	-0.469	6.000	1.280	1.279
6	0.013	0.102	5.181	0.858	-0.476	6.333	1.311	1.329
7	0.018	0.028	5.092	0.860	-0.476	7.091	1.323	1.564
8	0.024	-0.087	5.043	0.886	-0.492	7.615	1.370	1.439
9	0.032	-0.124	4.907	0.891	-0.488	8.174	1.387	1.623
High $E_{\varphi 2}$	0.044	-0.303	4.637	0.875	-0.471	9.384	1.379	2.202

Panel B: $SKEW$

Decile	$SKEW$	R	$SIZE$	β	BM	MOM	$TURN$	$ILLIQ$
Low $SKEW$	-0.926	0.143	5.339	0.758	-0.433	0.486	1.315	1.162
2	-0.320	0.296	5.438	0.774	-0.441	4.497	1.171	1.271
3	-0.087	0.297	5.394	0.801	-0.444	5.152	1.174	1.386
4	0.079	0.240	5.340	0.823	-0.453	5.740	1.197	1.449
5	0.226	0.137	5.263	0.843	-0.458	5.974	1.233	1.478
6	0.372	0.093	5.190	0.867	-0.467	6.424	1.280	1.445
7	0.536	0.030	5.093	0.882	-0.478	6.810	1.319	1.447
8	0.741	-0.101	4.969	0.889	-0.479	7.290	1.347	1.550
9	1.056	-0.235	4.813	0.876	-0.479	8.252	1.375	1.796
High $SKEW$	1.836	-0.246	4.615	0.789	-0.466	10.559	1.384	2.378

Table IA.11: Summary Statistics for Decile Portfolios of Stocks Sorted by $IE_{\varphi 2}$ and $ISKEW$

Decile portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the idiosyncratic asymmetry measure ($IE_{\varphi 2}$ and $ISKEW$) calculated based on the lagged three months idiosyncratic daily returns. Here $IE_{\varphi 2}$, $ISKEW$ and excess returns are winsorized at 0.5 percentile and 99.5 percentile. Portfolio 1(10) is the portfolio of stocks with the lowest (highest) realized $IE_{\varphi 2}$ ($ISKEW$ in Panel B). The table reports for each decile the average across the months in the sample of the median values with in each month of various characteristics for the stocks-the $IE_{\varphi 2}$ ($ISKEW$ in Panel B), current month excess return (R), the lagged month market capitalization ($SIZE$), the market beta (β),the lagged month book-to-market (BM) ratio, the cumulative pasted six months return (MOM), the measure of lagged month turnover ($TURN$), the measure of illiquidity ($ILLIQ$).

Panel A: $IE_{\varphi 2}$

Decile	$IE_{\varphi 2}$	R	$SIZE$	β	BM	MOM	$TURN$	$ILLIQ$
Low $IE_{\varphi 2}$	-0.023	0.272	5.387	0.725	-0.407	2.205	1.147	1.356
2	-0.010	0.249	5.414	0.771	-0.433	3.429	1.198	1.221
3	-0.003	0.215	5.312	0.785	-0.434	4.342	1.194	1.360
4	0.003	0.171	5.260	0.805	-0.445	4.908	1.217	1.422
5	0.008	0.067	5.217	0.828	-0.453	5.741	1.254	1.355
6	0.013	0.107	5.146	0.850	-0.465	6.317	1.283	1.435
7	0.019	0.095	5.071	0.862	-0.481	7.274	1.333	1.511
8	0.024	-0.041	5.008	0.885	-0.484	7.984	1.356	1.510
9	0.032	-0.138	4.906	0.906	-0.498	8.965	1.411	1.620
High $IE_{\varphi 2}$	0.044	-0.325	4.697	0.920	-0.508	10.965	1.453	2.029

Panel B: $SKEW$

Decile	$ISKEW$	R	$SIZE$	β	BM	MOM	$TURN$	$ILLIQ$
Low $ISKEW$	-1.016	0.136	5.393	0.772	-0.443	-0.226	1.360	1.075
2	-0.350	0.281	5.436	0.759	-0.429	3.901	1.157	1.283
3	-0.102	0.242	5.365	0.778	-0.432	4.759	1.133	1.442
4	0.071	0.206	5.293	0.800	-0.435	5.421	1.151	1.541
5	0.224	0.146	5.210	0.827	-0.446	5.971	1.195	1.544
6	0.378	0.089	5.132	0.852	-0.458	6.594	1.244	1.516
7	0.550	0.034	5.067	0.878	-0.479	7.226	1.304	1.467
8	0.766	-0.091	4.960	0.901	-0.491	7.972	1.370	1.547
9	1.101	-0.205	4.855	0.904	-0.499	9.010	1.422	1.729
High $ISKEW$	1.931	-0.243	4.711	0.842	-0.493	10.987	1.463	2.192

Table IA.12: The Characteristics of the $E_{\varphi 2}$ and $SKEW$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of $E_{\varphi 2}$ ($IE_{\varphi 2}$) and $SKEW$ ($ISKEW$) measured using daily returns over the lagged one quarter on subsets of lagged predictor variables including size ($SIZE$), book to market ratio (BM), momentum (MOM), turnover ($TURN$), liquidity measure ($ILLIQ$), and market beta (β). In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here idiosyncratic asymmetry measures are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	$E_{\varphi 2}$	$SKEW$	$IE_{\varphi 2}$	$ISKEW$
$SIZE$	-0.0013***	-0.0570***	-0.0014***	-0.0560***
	(-16.86)	(-20.22)	(-17.14)	(-18.34)
BM	-0.0004***	-0.0183***	-0.0005***	-0.0219***
	(-4.88)	(-4.83)	(-6.43)	(-5.75)
MOM	0.0001***	0.0038***	0.0001***	0.0044***
	(21.67)	(21.78)	(26.27)	(23.59)
$TURN$	0.0007***	0.0207***	0.0008***	0.0207***
	(6.76)	(4.17)	(7.55)	(4.12)
$ILLIQ$	0.0001***	0.0016***	0.0001***	0.0019***
	(4.22)	(2.74)	(4.39)	(3.23)
β	0.0025***	0.0032	0.0030***	0.0385***
	(12.61)	(0.34)	(18.67)	(4.14)
Constant	0.0131***	0.5649***	0.0128***	0.5228***
	(23.84)	(24.90)	(24.16)	(22.43)
OBS.	1,638,128	1,638,128	1,638,118	1,638,118
R^2	0.051	0.052	0.059	0.055

Table IA.13: Firm-Level Cross-Sectional Return Regressions with $E_{\varphi 2}$ and $SKEW$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return (the return get rid of the effect of Fama-French three factors, named risk-adjusted return in Brennan, Chordia, and Subrahmanyam (1998), the same definition for following tables' adjusted-return) in that month on subsets of lagged predictor variables including $E_{\varphi 2}$ and $SKEW$ measured over the preceding three months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Adjust Return (RA) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$E_{\varphi 2}$	-4.2118***		-3.6257***	-3.5246***	-3.4399***	-3.4030***	-2.2209***
	(-5.17)		(-4.26)	(-4.65)	(-4.55)	(-4.36)	(-2.87)
$SKEW$		-0.0810***	-0.0293	0.0601***	0.0454**	0.0457**	0.0270
		(-4.39)	(-1.56)	(3.62)	(2.55)	(2.50)	(1.50)
$SIZE$				-0.1192***	-0.1300***	-0.1316***	-0.1208***
				(-9.22)	(-10.03)	(-10.14)	(-9.19)
BM				0.0774**	0.0763**	0.0734*	0.0172
				(2.07)	(2.01)	(1.93)	(0.45)
MOM				0.0084***	0.0091***	0.0089***	0.0082***
				(6.12)	(6.64)	(6.52)	(5.75)
$TURN$				0.1233***	0.1285***	0.1305***	0.1375***
				(3.74)	(4.02)	(3.96)	(4.11)
$ILLIQ$				0.0054	0.0135***	0.0145***	0.0181***
				(1.31)	(2.75)	(3.00)	(3.67)
MAX				-0.1085***	-0.0815***	-0.0763***	0.0230***
				(-17.04)	(-7.33)	(-7.50)	(2.73)
VOL					-0.1123***		
					(-2.96)		
$IVOL$						-0.1370***	-0.3624***
						(-3.96)	(-11.70)
$REVA$							-0.0473***
							(-13.08)
Constant	0.0903***	0.0788**	0.0933***	1.0636***	1.1837***	1.2098***	1.1039***
	(2.70)	(2.31)	(2.77)	(9.88)	(10.39)	(10.61)	(9.40)
OBS.	1,514,285	1,514,285	1,514,285	1,510,401	1,478,013	1,478,013	1,458,077
R^2	0.002	0.001	0.003	0.028	0.031	0.030	0.036

Table IA.13 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables including $E_{\varphi 2}$ and $SKEW$ measured over the preceding three months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$E_{\varphi 2}$	-3.0357**		-3.2426**	-3.9823***	-4.0782***	-3.9780***	-2.8192***
	(-2.30)		(-2.54)	(-5.15)	(-5.15)	(-5.00)	(-3.69)
$SKEW$		-0.0451*	0.0015	0.1075***	0.0452**	0.0605***	0.0410**
		(-1.74)	(0.07)	(6.23)	(2.46)	(3.22)	(2.23)
$SIZE$				-0.1749***	-0.2128***	-0.2114***	-0.2030***
				(-4.44)	(-5.35)	(-5.39)	(-5.15)
BM				0.3022***	0.2938***	0.2946***	0.2483***
				(5.65)	(5.47)	(5.48)	(4.56)
MOM				0.0092***	0.0099***	0.0098***	0.0092***
				(6.23)	(6.75)	(6.66)	(5.92)
$TURN$				-0.0581	-0.0311	-0.0441	-0.0163
				(-1.62)	(-0.88)	(-1.24)	(-0.46)
$ILLIQ$				-0.0040	0.0117**	0.0094*	0.0117**
				(-0.85)	(2.09)	(1.76)	(2.18)
β				0.7916***	0.9177***	0.8621***	0.7885***
				(4.04)	(4.54)	(4.35)	(3.89)
MAX				-0.1230***	-0.0329***	-0.0534***	0.0301***
				(-17.19)	(-2.94)	(-4.88)	(3.47)
VOL					-0.3722***		
					(-8.77)		
$IVOL$						-0.2918***	-0.4744***
						(-7.81)	(-14.71)
REV							-0.0380***
							(-10.16)
Constant	0.6903***	0.6767***	0.6897***	1.6982***	2.0975***	2.0549***	2.0370***
	(3.01)	(2.91)	(3.01)	(5.93)	(7.14)	(7.15)	(6.99)
OBS.	1,896,594	1,896,594	1,896,594	1,638,128	1,602,253	1,602,253	1,602,253
R^2	0.003	0.002	0.004	0.085	0.088	0.088	0.093

Table IA.14: Firm-Level Cross-Sectional Return Regressions with $E_{\varphi 2}$ with 24 Newey-West Lags

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables including $E_{\varphi 2}$ and $SKEW$ measured over the preceding three months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 24-lag adjusted t-statistics (in parentheses). Here idiosyncratic asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Adjust Return (RA) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$E_{\varphi 2}$	-4.2118***		-3.6257***	-3.5246***	-3.4399***	-3.4030***	-2.2209***
	(-4.75)		(-4.33)	(-5.10)	(-4.99)	(-4.78)	(-3.07)
$SKEW$		-0.0810***	-0.0293	0.0601***	0.0454**	0.0457**	0.0270
		(-3.21)	(-1.19)	(3.27)	(2.16)	(2.13)	(1.27)
$SIZE$				-0.1192***	-0.1300***	-0.1316***	-0.1208***
				(-9.50)	(-10.39)	(-10.31)	(-9.24)
BM				0.0774*	0.0763*	0.0734*	0.0172
				(1.84)	(1.75)	(1.69)	(0.39)
MOM				0.0084***	0.0091***	0.0089***	0.0082***
				(5.31)	(5.72)	(5.60)	(5.00)
$TURN$				0.1233***	0.1285***	0.1305***	0.1375***
				(2.87)	(3.23)	(3.17)	(3.20)
$ILLIQ$				0.0054	0.0135**	0.0145**	0.0181***
				(1.18)	(2.39)	(2.51)	(3.19)
MAX				-0.1085***	-0.0815***	-0.0763***	0.0230**
				(-9.39)	(-5.51)	(-5.53)	(2.20)
VOL					-0.1123***		
					(-2.85)		
$IVOL$						-0.1370***	-0.3624***
						(-3.15)	(-8.47)
$REVA$							-0.0473***
							(-11.38)
Constant	0.0903**	0.0788*	0.0933**	1.0636***	1.1837***	1.2098***	1.1039***
	(2.13)	(1.82)	(2.20)	(9.60)	(10.24)	(10.51)	(8.93)
OBS.	1,514,285	1,514,285	1,514,285	1,510,401	1,478,013	1,478,013	1,458,077
R^2	0.002	0.001	0.003	0.028	0.031	0.030	0.036

Table IA.14 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables including $E_{\varphi 2}$ and $SKEW$ measured over the preceding three months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 24-lag adjusted t-statistics (in parentheses). Here idiosyncratic asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$E_{\varphi 2}$	-3.0357**		-3.2426**	-3.9823***	-4.0782***	-3.9780***	-2.8192***
	(-2.01)		(-2.36)	(-6.00)	(-5.98)	(-5.83)	(-4.38)
$SKEW$		-0.0451	0.0015	0.1075***	0.0452**	0.0605***	0.0410*
		(-1.37)	(0.06)	(5.46)	(2.09)	(2.74)	(1.92)
$SIZE$				-0.1749***	-0.2128***	-0.2114***	-0.2030***
				(-3.94)	(-4.79)	(-4.80)	(-4.58)
BM				0.3022***	0.2938***	0.2946***	0.2483***
				(5.18)	(5.03)	(5.04)	(4.17)
MOM				0.0092***	0.0099***	0.0098***	0.0092***
				(5.68)	(6.13)	(6.06)	(5.43)
$TURN$				-0.0581	-0.0311	-0.0441	-0.0163
				(-1.30)	(-0.74)	(-1.03)	(-0.39)
$ILLIQ$				-0.0040	0.0117*	0.0094	0.0117*
				(-0.74)	(1.71)	(1.43)	(1.74)
β				0.7916***	0.9177***	0.8621***	0.7885***
				(3.62)	(3.99)	(3.84)	(3.39)
MAX				-0.1230***	-0.0329**	-0.0534***	0.0301***
				(-9.51)	(-2.36)	(-3.56)	(2.63)
VOL					-0.3722***		
					(-7.44)		
$IVOL$						-0.2918***	-0.4744***
						(-6.39)	(-10.82)
REV							-0.0380***
							(-8.62)
Constant	0.6903***	0.6767***	0.6897***	1.6982***	2.0975***	2.0549***	2.0370***
	(3.41)	(3.29)	(3.42)	(6.03)	(7.19)	(7.21)	(7.03)
OBS.	1,896,594	1,896,594	1,896,594	1,638,128	1,602,253	1,602,253	1,602,253
R^2	0.003	0.002	0.004	0.085	0.088	0.088	0.093

Table IA.15: Firm-Level Cross-Sectional Return Regressions with $IE_{\varphi 2}$ and $ISKEW$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of lagged predictor variables including $IE_{\varphi 2}$ and $ISKEW$ measured over the preceding three months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here idiosyncratic asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Adjust Return (RA) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$IE_{\varphi 2}$	-3.3548***		-2.6063***	-2.9954***	-2.8408***	-2.8462***	-1.1517*
	(-4.36)		(-3.24)	(-4.42)	(-4.11)	(-4.11)	(-1.69)
$ISKEW$		-0.0665***	-0.0298*	0.0605***	0.0495***	0.0470***	0.0282
		(-3.78)	(-1.65)	(3.76)	(2.73)	(2.63)	(1.59)
$SIZE$				-0.1200***	-0.1298***	-0.1312***	-0.1196***
				(-9.30)	(-10.02)	(-10.10)	(-9.10)
BM				0.0759**	0.0756**	0.0721*	0.0165
				(2.03)	(1.99)	(1.90)	(0.43)
MOM				0.0084***	0.0090***	0.0089***	0.0082***
				(6.14)	(6.64)	(6.53)	(5.70)
$TURN$				0.1241***	0.1272***	0.1304***	0.1377***
				(3.76)	(3.98)	(3.96)	(4.11)
$ILLIQ$				0.0054	0.0132***	0.0142***	0.0178***
				(1.32)	(2.68)	(2.95)	(3.61)
MAX				-0.1094***	-0.0849***	-0.0787***	0.0192**
				(-17.26)	(-7.63)	(-7.85)	(2.32)
VOL					-0.1033***		
					(-2.73)		
$IVOL$						-0.1305***	-0.3532***
						(-3.80)	(-11.55)
REV							-0.0473***
							(-13.01)
Constant	0.0831**	0.0742**	0.0858**	1.0675***	1.1747***	1.2042***	1.0915***
	(2.43)	(2.18)	(2.49)	(9.93)	(10.31)	(10.55)	(9.29)
OBS.	1,514,287	1,514,287	1,514,287	1,510,403	1,478,013	1,478,013	1,458,077
R^2	0.002	0.001	0.003	0.028	0.031	0.030	0.036

Table IA.15 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of lagged predictor variables including $IE_{\varphi 2}$ and $ISKEW$ measured over the preceding three months and other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here idiosyncratic asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$IE_{\varphi 2}$	-2.3465*		-2.5872**	-4.1812***	-4.1250***	-4.1060***	-2.5657***
	(-1.73)		(-1.99)	(-6.20)	(-5.98)	(-5.95)	(-4.00)
$ISKEW$		-0.0309	0.0062	0.1066***	0.0466**	0.0607***	0.0438**
		(-1.20)	(0.33)	(6.40)	(2.54)	(3.30)	(2.42)
$SIZE$				-0.1770***	-0.2135***	-0.2122***	-0.2025***
				(-4.49)	(-5.34)	(-5.39)	(-5.12)
BM				0.3007***	0.2925***	0.2934***	0.2477***
				(5.62)	(5.45)	(5.46)	(4.56)
MOM				0.0093***	0.0100***	0.0098***	0.0092***
				(6.27)	(6.78)	(6.69)	(5.90)
$TURN$				-0.0583	-0.0321	-0.0452	-0.0168
				(-1.62)	(-0.91)	(-1.27)	(-0.47)
$ILLIQ$				-0.0040	0.0114**	0.0091*	0.0115**
				(-0.86)	(2.04)	(1.71)	(2.14)
β				0.7966***	0.9186***	0.8697***	0.7946***
				(4.07)	(4.55)	(4.39)	(3.93)
MAX				-0.1232***	-0.0350***	-0.0547***	0.0275***
				(-17.46)	(-3.13)	(-5.05)	(3.22)
VOL					-0.3643***		
					(-8.55)		
$IVOL$						-0.2872***	-0.4672***
						(-7.70)	(-14.51)
REV							-0.0380***
							(-10.09)
Constant	0.6815***	0.6713***	0.6809***	1.7112***	2.0947***	2.0568***	2.0302***
	(2.97)	(2.88)	(2.97)	(5.98)	(7.10)	(7.13)	(6.94)
OBS.	1,896,525	1,896,525	1,896,525	1,638,118	1,602,248	1,602,248	1,602,248
R^2	0.003	0.002	0.004	0.085	0.088	0.088	0.093

Table IA.16: Equal-Weighted Average Monthly Returns of Portfolios Based on Realized $E_{\varphi 2}$ and $SKEW$

Portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the realized $E_{\varphi 2}$ ($SKEW$ for Panel B). Portfolio 1 is the portfolio of stocks with the lowest $E_{\varphi 2}$ ($SKEW$ for Panel B), while Portfolio 5 denotes the highest. And here the excess return and $E_{\varphi 1}$ ($SKEW$ for Panel B) are winsorized at 0.5 percentile and 99.5 percentile.
5-1 spread denotes the average raw return difference between the highest and lowest $E_{\varphi 2}$ ($SKEW$ for Panel B), FF3 alpha denotes the average Fama-French 3-factor alpha difference, and carhart4 alpha denotes the average Carhart 4-factor alpha difference, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: $E_{\varphi 2}$

Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.724***	0.015	0.088*
	(3.58)	(0.29)	(1.76)
2	0.735***	0.015	0.065
	(3.53)	(0.35)	(1.49)
3	0.705***	-0.014	0.029
	(3.29)	(-0.34)	(0.71)
4	0.612***	-0.108***	-0.084**
	(2.78)	(-2.72)	(-2.08)
5(highest)	0.569**	-0.169***	-0.153***
	(2.49)	(-3.79)	(-3.37)
5-1 spread	-0.155**	-0.183***	-0.241***
	(-2.21)	(-3.17)	(-4.12)

Panel B: $SKEW$

Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.671***	-0.032	0.055
	(3.29)	(-0.61)	(1.08)
2	0.801***	0.085**	0.122***
	(3.86)	(2.01)	(2.88)
3	0.704***	-0.020	0.015
	(3.27)	(-0.52)	(0.38)
4	0.635***	-0.096**	-0.066
	(2.83)	(-2.28)	(-1.54)
5(highest)	0.535**	-0.195***	-0.181***
	(2.40)	(-4.38)	(-3.97)
5-1 spread	-0.137**	-0.163***	-0.236***
	(-2.12)	(-2.93)	(-4.25)

Table IA.17: Equal-Weighted Average Monthly Returns of Decile Portfolios Based on Realized $IE_{\varphi 2}$ and $ISKEW$

Portfolios are formed every month from January 1962 to December 2013 by sorting stocks based on the realized $IE_{\varphi 2}$ ($ISKEW$ for Panel B). Portfolio 1 is the portfolio of stocks with the lowest $IE_{\varphi 2}$ ($ISKEW$ for Panel B), while Portfolio 5 denotes the highest. And here the excess return and $IE_{\varphi 1}$ ($ISKEW$ for Panel B) are winsorized at 0.5 percentile and 99.5 percentile.
5-1 spread denotes the average raw return difference between the highest and lowest $IE_{\varphi 2}$ ($ISKEW$ for Panel B), FF3 alpha denotes the average Fama-French 3-factor alpha difference, and carhart4 alpha denotes the average Carhart 4-factor alpha difference, t-statistics are reported in parentheses. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: $IE_{\varphi 2}$

Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.695***	-0.005	0.084*
	(3.46)	(-0.10)	(1.71)
2	0.728***	0.013	0.076*
	(3.52)	(0.30)	(1.79)
3	0.690***	-0.041	0.003
	(3.21)	(-1.00)	(0.08)
4	0.683***	-0.042	-0.025
	(3.09)	(-1.02)	(-0.60)
5(highest)	0.549**	-0.185***	-0.192***
	(2.39)	(-4.20)	(-4.26)
5-1 spread	-0.146**	-0.180***	-0.276***
	(-2.01)	(-3.00)	(-4.70)

Panel B: $ISKEW$

Portfolio	Monthly Excess Return (%)	FF3 Alpha (%)	Carhart4 Alpha (%)
1(lowest)	0.652***	-0.055	0.062
	(3.16)	(-1.05)	(1.25)
2	0.768***	0.062	0.104**
	(3.77)	(2.01)	(2.39)
3	0.738***	0.015	0.043
	(3.46)	(0.36)	(1.05)
4	0.641***	-0.095**	-0.080*
	(2.85)	(-2.27)	(-1.87)
5(highest)	0.546**	-0.185***	-0.184***
	(2.41)	(-4.26)	(-4.12)
5-1 spread	-0.106	-0.130**	-0.245***
	(-1.56)	(-2.24)	(-4.43)

Table IA.18: Cross-Section Regressions with Interaction Terms of Idiosyncratic Asymmetry Proxies and $SIZE$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of $IE_{\varphi 2}$ or $ISKEW$ which measured over the preceding three months, $SIZE$ and the interaction terms of $SIZE$ and $IE_{\varphi 2}$ or $ISKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here idiosyncratic asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} SIZE_{i,t} + \lambda_{2,t} IA_{i,t} + \lambda_{4,t} SIZE_{i,t} \times IA_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $IA_{i,t}$ denote $IE_{\varphi 2}$ or $ISKEW$.

Panel A: Adjusted Return (RA) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SIZE$	-0.0578***	-0.0647***	-0.0708***	-0.0958***	-0.0578***	-0.0637***	-0.0685***	-0.0941***
	(-3.82)	(-4.20)	(-4.68)	(-7.54)	(-3.82)	(-4.17)	(-4.52)	(-7.26)
$IE_{\varphi 2}$		-4.3285***	-9.4061***	-11.0235***				
		(-5.62)	(-5.04)	(-6.37)				
$SIZE \times IE_{\varphi 2}$			1.0859***	1.1844***				
			(3.28)	(3.82)				
$ISKEW$						-0.0884***	-0.2034***	-0.2442***
						(-5.05)	(-4.92)	(-6.51)
$SIZE \times ISKEW$							0.0253***	0.0282***
							(3.44)	(4.13)
BM				0.1276***				0.1292***
				(3.40)				(3.47)
MOM				0.0101***				0.0102***
				(7.55)				(7.59)
$TURN$				-0.0455				-0.0473
				(-1.38)				(-1.43)
$ILLIQ$				-0.0075*				-0.0076*
				(-1.87)				(-1.92)
Constant	0.3673***	0.4386***	0.4710***	0.6649***	0.3673***	0.4216***	0.4461***	0.6471***
	(4.04)	(4.69)	(5.10)	(6.49)	(4.04)	(4.55)	(4.83)	(6.21)
OBS.	1,514,287	1,514,287	1,514,287	1,510,403	1,514,287	1,514,287	1,514,287	1,510,403
R^2	0.004	0.005	0.006	0.025	0.004	0.005	0.006	0.025

Table IA.18 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of $IE_{\varphi 2}$ or $ISKEW$ which measured over the preceding three months, $SIZE$ and the interaction terms of $SIZE$ and $IE_{\varphi 2}$ or $ISKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here idiosyncratic asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}SIZE_{i,t} + \lambda_{3,t}IASYM_{i,t} + \lambda_{4,t}SIZE_{i,t} \times IASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $IASYM_{i,t}$ denote $IE_{\varphi 2}$ or $ISKEW$.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SIZE$	-0.0660**	-0.0717**	-0.0775**	-0.1385***	-0.0660**	-0.0706**	-0.0770**	-0.1367***
	(-2.04)	(-2.23)	(-2.43)	(-3.54)	(-2.04)	(-2.18)	(-2.36)	(-3.48)
$IE_{\varphi 2}$		-3.7172***	-9.1276***	-10.6629***				
		(-3.19)	(-3.97)	(-5.76)				
$SIZE \times IE_{\varphi 2}$			1.1479***	1.0303***				
			(3.02)	(3.18)				
$ISKEW$						-0.0685***	-0.2064***	-0.2286***
						(-3.24)	(-4.44)	(-5.82)
$SIZE \times ISKEW$							0.0308***	0.0270***
							(3.74)	(3.83)
BM				0.3551***				0.3564***
				(6.58)				(6.62)
MOM				0.0112***				0.0111***
				(7.58)				(7.54)
$TURN$				-0.2220***				-0.2229***
				(-5.85)				(-5.84)
$ILLIQ$				-0.0185***				-0.0188***
				(-4.11)				(-4.16)
β				0.6577***				0.6475***
				(3.40)				(3.35)
Constant	1.0026***	1.0601***	1.0921***	1.2950***	1.0026***	1.0435***	1.0771***	1.2762***
	(3.00)	(3.22)	(3.33)	(4.62)	(3.00)	(3.12)	(3.21)	(4.53)
OBS.	1,643,244	1,643,244	1,643,244	1,638,118	1,643,244	1,643,244	1,643,244	1,638,118
R^2	0.014	0.016	0.017	0.082	0.014	0.015	0.016	0.082

Table IA.19: Cross-Section Regressions with Interaction Terms of Idiosyncratic Asymmetry Proxies and MOM

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of $IE_{\varphi 2}$ or $ISKEW$ which measured over the preceding three months, MOM and the interaction terms of MOM and $IE_{\varphi 2}$ or $ISKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} MOM_{i,t} + \lambda_{2,t} IA_{i,t} + \lambda_{3,t} MOM_{i,t} \times IA_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $IA_{i,t}$ denote $IE_{\varphi 2}$ or $ISKEW$.

Panel A: Adjusted Return (RA) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOM	0.0079***	0.0083***	0.0073***	0.0093***	0.0079***	0.0083***	0.0078***	0.0099***
	(5.51)	(5.77)	(4.77)	(6.51)	(5.51)	(5.77)	(5.11)	(6.92)
$IE_{\varphi 2}$		-4.7452***	-4.3946***	-4.9787***				
		(-6.95)	(-6.05)	(-7.30)				
$MOM \times IE_{\varphi 2}$			0.0867***	0.0687***				
			(3.37)	(2.78)				
$ISKEW$						-0.0958***	-0.0784***	-0.0974***
						(-5.95)	(-4.71)	(-6.27)
$MOM \times ISKEW$							0.0016***	0.0010*
							(2.69)	(1.85)
$SIZE$				-0.0877***				-0.0870***
				(-6.89)				(-6.82)
BM				0.1267***				0.1298***
				(3.38)				(3.49)
$TURN$				-0.0472				-0.0514
				(-1.44)				(-1.57)
$ILLIQ$				-0.0078*				-0.0078*
				(-1.96)				(-1.95)
Constant	-0.0418	-0.0043	-0.0082	0.6164***	-0.0418	-0.0154	-0.0261	0.6041***
	(-1.03)	(-0.10)	(-0.19)	(5.97)	(-1.03)	(-0.37)	(-0.62)	(5.83)
OBS.	1,510,403	1,510,403	1,510,403	1,510,403	1,510,403	1,510,403	1,510,403	1,510,403
R^2	0.009	0.010	0.011	0.026	0.009	0.010	0.011	0.026

Table IA.19 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of $IE_{\varphi 2}$ or $ISKEW$ which measured over the preceding three months, MOM and the interaction terms of MOM and $IE_{\varphi 2}$ or $ISKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}MOM_{i,t} + \lambda_{3,t}IASYM_{i,t} + \lambda_{4,t}MOM_{i,t} \times IASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $IASYM_{i,t}$ denote $IE_{\varphi 2}$ or $ISKEW$.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOM	0.0091***	0.0093***	0.0084***	0.0105***	0.0091***	0.0093***	0.0089***	0.0107***
	(4.77)	(4.89)	(4.13)	(6.83)	(4.77)	(4.87)	(4.40)	(6.91)
$IE_{\varphi 2}$		-3.5416***	-2.9069**	-5.1309***				
		(-3.12)	(-2.42)	(-6.89)				
$MOM \times IE_{\varphi 2}$			0.0792***	0.0573**				
			(2.73)	(2.34)				
$ISKEW$						-0.0619***	-0.0356	-0.0826***
						(-2.75)	(-1.52)	(-4.96)
$MOM \times ISKEW$							0.0014**	0.0013**
							(2.19)	(2.48)
$SIZE$				-0.1337***				-0.1311***
				(-3.43)				(-3.36)
BM				0.3539***				0.3568***
				(6.56)				(6.61)
$TURN$				-0.2232***				-0.2264***
				(-5.92)				(-6.01)
$ILLIQ$				-0.0190***				-0.0189***
				(-4.19)				(-4.17)
β				0.6574***				0.6479***
				(3.40)				(3.35)
Constant	0.5510**	0.5730***	0.5686***	1.2646***	0.5510**	0.5639**	0.5515**	1.2405***
	(2.48)	(2.64)	(2.61)	(4.50)	(2.48)	(2.56)	(2.51)	(4.42)
OBS.	1,638,118	1,638,118	1,638,118	1,638,118	1,638,118	1,638,118	1,638,118	1,638,118
R^2	0.015	0.017	0.019	0.083	0.015	0.017	0.018	0.083

Table IA.20: Cross-Section Regressions with Interaction Terms of Idiosyncratic Asymmetry Proxies and $ILLIQ$

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the adjusted-return in that month on subsets of $IE_{\varphi 2}$ or $ISKEW$ which measured over the preceding three months, $ILLIQ$ and the interaction terms of $ILLIQ$ and $IE_{\varphi 2}$ or $ISKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{2,t} ILLIQ_{i,t} + \lambda_{3,t} IA_{i,t} + \lambda_{4,t} ILLIQ_{i,t} \times IA_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $IA_{i,t}$ denote $IE_{\varphi 2}$ or $ISKEW$.

Panel A: Adjusted Return (RA) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ILLIQ$	0.0096*	0.0105**	0.0153***	-0.0037	0.0096*	0.0105**	0.0145***	-0.0044
	(1.91)	(2.06)	(2.83)	(-0.85)	(1.91)	(2.06)	(2.72)	(-1.06)
$IE_{\varphi 2}$		-3.6362***	-1.1158	-3.2473***				
		(-4.73)	(-1.20)	(-4.13)				
$ILLIQ \times IE_{\varphi 2}$			-0.4501***	-0.3776***				
			(-5.19)	(-4.78)				
$ISKEW$						-0.0744***	-0.0250	-0.0689***
						(-4.33)	(-1.25)	(-3.86)
$ILLIQ \times ISKEW$							-0.0097***	-0.0087***
							(-4.66)	(-4.29)
$SIZE$				-0.0869***				-0.0873***
				(-6.83)				(-6.81)
BM				0.1280***				0.1293***
				(3.41)				(3.46)
MOM				0.0101***				0.0101***
				(7.53)				(7.55)
$TURN$				-0.0469				-0.0470
				(-1.42)				(-1.42)
Constant	0.0484	0.0757*	0.0542	0.6015***	0.0484	0.0670	0.0507	0.5958***
	(1.14)	(1.73)	(1.23)	(5.85)	(1.14)	(1.54)	(1.16)	(5.74)
OBS.	1,514,287	1,514,287	1,514,287	1,510,403	1,514,287	1,514,287	1,514,287	1,510,403
R^2	0.004	0.006	0.007	0.025	0.004	0.006	0.007	0.025

Table IA.20 (continued)

Each month from January 1962 to December 2013, we run a firm-level cross-sectional regression of the excess return in that month on subsets of $IE_{\varphi 2}$ or $ISKEW$ which measured over the preceding three months, $ILLIQ$ and the interaction terms of $ILLIQ$ and $IE_{\varphi 2}$ or $ISKEW$ together with other control variables defined in the Appendix. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey and West (1987) 3-lag adjusted t-statistics (in parentheses). Here asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively. The full cross-sectional regression specification is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}ILLIQ_{i,t} + \lambda_{3,t}IASYM_{i,t} + \lambda_{4,t}ILLIQ_{i,t} \times IASYM_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

here $X_{i,t}$ is a vector containing other firm characteristics, and $IASYM_{i,t}$ denote $IE_{\varphi 2}$ or $ISKEW$.

Panel B: Excess Return (R) is the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ILLIQ$	0.0114	0.0120*	0.0179**	-0.0157***	0.0114	0.0119*	0.0171**	-0.0160***
	(1.62)	(1.72)	(2.40)	(-3.33)	(1.62)	(1.71)	(2.28)	(-3.45)
$IE_{\varphi 2}$		-2.3785*	0.2326	-3.7610***				
		(-1.86)	(0.15)	(-4.35)				
$ILLIQ \times IE_{\varphi 2}$			-0.5047***	-0.3271***				
			(-4.92)	(-3.92)				
$ISKEW$						-0.0397*	0.0163	-0.0596***
						(-1.69)	(0.59)	(-3.18)
$ILLIQ \times ISKEW$							-0.0113***	-0.0080***
							(-4.70)	(-3.93)
$SIZE$				-0.1331***				-0.1316***
				(-3.41)				(-3.37)
BM				0.3554***				0.3567***
				(6.58)				(6.61)
MOM				0.0111***				0.0111***
				(7.56)				(7.51)
$TURN$				-0.2223***				-0.2228***
				(-5.87)				(-5.85)
β				0.6543***				0.6466***
				(3.38)				(3.35)
Constant	0.6921***	0.7008***	0.6776***	1.2544***	0.6921***	0.6962***	0.6766***	1.2352***
	(2.94)	(3.05)	(2.96)	(4.48)	(2.94)	(2.99)	(2.91)	(4.39)
OBS.	1,643,244	1,643,244	1,643,244	1,638,118	1,643,244	1,643,244	1,643,244	1,638,118
R^2	0.009	0.012	0.013	0.082	0.009	0.011	0.012	0.082

Table IA.21: Equal-Weighted Bivariate Dependent Sort Portfolio Analysis-$SIZE$ and Idiosyncratic Asymmetry Proxies

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and each of $SIZE$ after controlling for $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B). At the beginning of every month from January 1962 to December 2013, we first sort stocks by $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) into 5 portfolios and then within each $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) portfolio, sort stocks into 5 portfolios by $SIZE$. The table reports the time-series means of the monthly equal-weighted excess returns formed on intersections of $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) and $SIZE$ portfolios. Factor sensitivities for each $SIZE$ High-Low portfolios are presented in the rows labeled β_{MKTRF}, β_{SMB}, β_{HML}, β_{UMD}. Diff denotes the 5-1 return spread difference between highest $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) portfolio and lowest portfolio. t-statistics testing the null hypothesis is equal to zero, are in parentheses. Here the excess return and asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile.

Panel A: Sort By $IE_{\varphi 2}$ then $SIZE$

	$IE_{\varphi 2}$ 1	$IE_{\varphi 2}$ 2	$IE_{\varphi 2}$ 3	$IE_{\varphi 2}$ 4	$IE_{\varphi 2}$ 5	Diff
$SIZE$ 1 (Low)	1.003***	0.894***	0.822***	0.862***	0.651***	NA
	(4.72)	(4.04)	(3.63)	(3.73)	(2.87)	NA
$SIZE$ 2	0.737***	0.784***	0.744***	0.817***	0.612**	NA
	(3.24)	(3.34)	(3.04)	(3.35)	(2.40)	NA
$SIZE$ 3	0.678***	0.781***	0.689***	0.625**	0.556**	NA
	(3.10)	(3.41)	(2.95)	(2.56)	(2.14)	NA
$SIZE$ 4	0.637***	0.702***	0.663***	0.699***	0.585**	NA
	(3.02)	(3.37)	(3.06)	(3.10)	(2.44)	NA
$SIZE$ 5 (High)	0.503***	0.511***	0.537***	0.563**	0.483**	NA
	(2.73)	(2.74)	(2.80)	(2.90)	(2.39)	NA
5-1 spread	-0.500***	-0.383**	-0.286*	-0.299**	-0.167	0.333***
	(-3.40)	(-2.49)	(-1.89)	(-1.96)	(-1.16)	(2.92)
Carhart4 α	-0.378***	-0.178	-0.071	-0.071	0.073	0.451***
	(-3.36)	(-1.53)	(-0.62)	(-0.62)	(0.61)	(3.90)
β_{MKTRF}	0.224***	0.208***	0.212***	0.204***	0.196***	NA
	(8.49)	(7.63)	(7.99)	(7.54)	(6.98)	NA
β_{SMB}	-0.842***	-0.891***	-0.894***	-0.886***	-0.714***	NA
	(-22.73)	(-23.25)	(-23.93)	(-23.20)	(-18.04)	NA
β_{HML}	-0.249***	-0.336***	-0.292***	-0.309***	-0.326***	NA
	(-6.12)	(-7.97)	(-7.11)	(-7.39)	(-7.49)	NA
β_{UMD}	0.095***	0.054**	0.013	0.007	-0.054*	NA
	(3.64)	(1.98)	(0.49)	(0.28)	(-1.94)	NA

Table IA.21 (continued)

Panel B: Sort By $ISKEW$ then $SIZE$	$ISKEW$ 1	$ISKEW$ 2	$ISKEW$ 3	$ISKEW$ 4	$ISKEW$ 5	Diff
$SIZE$ 1 (Low)	0.891***	1.015***	0.933***	0.785***	0.610***	NA
	(4.13)	(4.71)	(4.07)	(3.42)	(2.65)	NA
$SIZE$ 2	0.682***	0.782***	0.853***	0.756***	0.566**	NA
	(2.87)	(3.39)	(3.58)	(2.99)	(2.27)	NA
$SIZE$ 3	0.709***	0.786***	0.814***	0.595**	0.609**	NA
	(3.12)	(3.56)	(3.48)	(2.40)	(2.44)	NA
$SIZE$ 4	0.603***	0.686***	0.692***	0.608***	0.519**	NA
	(2.86)	(3.28)	(3.14)	(2.65)	(2.22)	NA
$SIZE$ 5 (High)	0.475***	0.543***	0.527***	0.520***	0.574***	NA
	(2.55)	(2.90)	(2.76)	(2.66)	(2.88)	NA
5-1 spread	-0.416***	-0.472***	-0.406**	-0.265*	-0.036	0.379***
	(-2.92)	(-3.06)	(-2.55)	(-1.75)	(-0.26)	(3.50)
Carhart4 α	-0.266**	-0.314***	-0.187	-0.032	0.175	0.441***
	(-2.49)	(-2.71)	(-1.57)	(-0.27)	(1.48)	(4.02)
β_{MKTRF}	0.203***	0.250***	0.217***	0.196***	0.172***	NA
	(8.11)	(9.23)	(7.77)	(7.13)	(6.21)	NA
β_{SMB}	-0.832***	-0.887***	-0.937***	-0.836***	-0.667***	NA
	(-23.61)	(-23.29)	(-23.86)	(-21.28)	(-17.09)	NA
β_{HML}	-0.263***	-0.316***	-0.321***	-0.333***	-0.250***	NA
	(-6.80)	(-7.54)	(-7.43)	(-7.71)	(-5.83)	NA
β_{UMD}	0.075***	0.079***	0.035	0.003	-0.054*	NA
	(3.03)	(2.93)	(1.25)	(0.10)	(-1.95)	NA

Table IA.22: Equal-Weighted Bivariate Dependent Sort Portfolio Analysis-MOM and Idiosyncratic Asymmetry Proxies

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and each of MOM after controlling for $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B). At the beginning of every month from January 1962 to December 2013, we first sort stocks by $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) into 5 portfolios and then within each $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) portfolio, sort stocks into 5 portfolios by MOM. The table reports the time-series means of the monthly equal-weighted excess returns formed on intersections of $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) and MOM portfolios. Factor sensitivities for each MOM High-Low portfolios are presented in the rows labeled β_{MKTRF}, β_{SMB}, β_{HML}, β_{UMD}. Diff denotes the 5-1 return spread difference between highest $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) portfolio and lowest portfolio. t-statistics testing the null hypothesis is equal to zero, are in parentheses. Here the excess return and asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile.

Panel A: Sort By $IE_{\varphi 2}$ then MOM

	$IE_{\varphi 2}$ 1	$IE_{\varphi 2}$ 2	$IE_{\varphi 2}$ 3	$IE_{\varphi 2}$ 4	$IE_{\varphi 2}$ 5	Diff
MOM 1 (Low)	0.471*	0.386	0.214	0.090	-0.193	NA
	(1.79)	(1.45)	(0.80)	(0.33)	(-0.70)	NA
MOM 2	0.746***	0.772***	0.671***	0.645***	0.512**	NA
	(3.65)	(3.74)	(3.13)	(2.96)	(2.29)	NA
MOM 3	0.723***	0.780***	0.760***	0.830***	0.669***	NA
	(3.95)	(4.15)	(3.86)	(4.17)	(3.18)	NA
MOM 4	0.705***	0.750***	0.825***	0.913***	0.812***	NA
	(3.86)	(3.94)	(4.16)	(4.41)	(3.67)	NA
MOM 5 (High)	0.913***	0.977***	1.015***	1.088***	1.112***	NA
	(4.21)	(4.31)	(4.22)	(4.41)	(4.25)	NA
5-1 spread	0.442***	0.590***	0.801***	0.998***	1.305***	0.863***
	(2.76)	(3.57)	(4.65)	(5.55)	(7.10)	(6.80)
Carhart4 α	-0.032	0.065	0.210**	0.380***	0.708***	0.740***
	(-0.30)	(0.61)	(1.98)	(3.22)	(5.49)	(5.85)
β_{MKTRF}	-0.043*	-0.036	0.019	-0.038	-0.006	NA
	(-0.71)	(-1.42)	(0.77)	(-1.38)	(-0.18)	NA
β_{SMB}	-0.165***	-0.101***	-0.060*	0.066*	0.091**	NA
	(-4.68)	(-2.86)	(-1.72)	(1.71)	(2.15)	NA
β_{HML}	0.083**	0.077***	0.029	0.089**	0.022	NA
	(2.14)	(1.98)	(0.77)	(2.09)	(0.47)	NA
β_{UMD}	0.712***	0.761***	0.830***	0.832***	0.810***	NA
	(28.55)	(30.51)	(33.67)	(30.32)	(26.97)	NA

Table IA.22 (continued)

Panel B: Sort By $ISKEW$ **then** MOM	$ISKEW$ 1	$ISKEW$ 2	$ISKEW$ 3	$ISKEW$ 4	$ISKEW$ 5	Diff
MOM 1 (Low)	0.454*	0.446*	0.344	0.081	-0.296	NA
	(1.66)	(1.75)	(1.28)	(0.29)	(-1.08)	NA
MOM 2	0.668***	0.731***	0.780***	0.590***	0.500**	NA
	(3.15)	(3.66)	(3.70)	(2.70)	(2.24)	NA
MOM 3	0.685***	0.829***	0.809***	0.764***	0.660***	NA
	(3.61)	(4.48)	(4.16)	(3.75)	(3.15)	NA
MOM 4	0.698***	0.766***	0.786***	0.844***	0.898***	NA
	(3.76)	(4.05)	(3.99)	(4.04)	(4.16)	NA
MOM 5 (High)	0.859***	1.042***	1.113***	1.001***	1.132***	NA
	(3.94)	(4.53)	(4.57)	(3.92)	(4.49)	NA
5-1 spread	0.406**	0.596***	0.769***	0.921***	1.428***	1.022***
	(2.46)	(3.64)	(4.26)	(5.07)	(8.22)	(8.28)
Carhart4 α	-0.107	0.036	0.123	0.302**	0.909***	1.017***
	(-1.02)	(0.34)	(1.09)	(2.51)	(7.15)	(8.20)
β_{MKTRF}	-0.055**	0.023	0.007	-0.000	-0.046	NA
	(-2.24)	(0.92)	(0.26)	(-0.01)	(-1.54)	NA
β_{SMB}	-0.179***	-0.061*	0.011	0.068*	0.070*	NA
	(-5.19)	(-1.76)	(0.30)	(1.73)	(1.68)	NA
β_{HML}	0.135***	0.058	0.076*	0.036	0.025	NA
	(3.54)	(1.51)	(1.87)	(0.83)	(0.54)	NA
β_{UMD}	0.751***	0.768***	0.866***	0.835***	0.731***	NA
	(30.71)	(31.23)	(33.04)	(29.84)	(24.68)	NA

Table IA.23: Equal-Weighted Bivariate Dependent Sort Portfolio Analysis-$ILLIQ$ and Idiosyncratic Asymmetry Proxies

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and each of $ILLIQ$ after controlling for $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B). At the beginning of every month from January 1962 to December 2013, we first sort stocks by $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) into 5 portfolios and then within each $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) portfolio, sort stocks into 5 portfolios by $ILLIQ$. The table reports the time-series means of the monthly equal-weighted excess returns formed on intersections of $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) and $ILLIQ$ portfolios. Factor sensitivities for each $ILLIQ$ High-Low portfolios are presented in the rows labeled β_{MKTRF}, β_{SMB}, β_{HML}, β_{UMD}. Diff denotes the 5-1 return spread difference between highest $IE_{\varphi 2}$ (Panel A, $ISKEW$ for Panel B) portfolio and lowest portfolio. t-statistics testing the null hypothesis is equal to zero, are in parentheses. Here the excess return and asymmetry proxies are winsorized at 0.5 percentile and 99.5 percentile.

Panel A: Sort By $IE_{\varphi 2}$ then $ILLIQ$

	$IE_{\varphi 2}$ 1	$IE_{\varphi 2}$ 2	$IE_{\varphi 2}$ 3	$IE_{\varphi 2}$ 4	$IE_{\varphi 2}$ 5	Diff
$ILLIQ$ 1 (Low)	0.539***	0.585***	0.599***	0.654***	0.517**	NA
	(2.80)	(3.00)	(2.97)	(3.20)	(2.44)	NA
$ILLIQ$ 2	0.615***	0.709***	0.673***	0.726***	0.640**	NA
	(2.82)	(3.25)	(2.99)	(3.08)	(2.56)	NA
$ILLIQ$ 3	0.679***	0.754***	0.687***	0.684***	0.667**	NA
	(3.07)	(3.27)	(2.88)	(2.81)	(2.56)	NA
$ILLIQ$ 4	0.761***	0.831***	0.697***	0.743***	0.614**	NA
	(3.45)	(3.70)	(3.02)	(3.14)	(2.51)	NA
$ILLIQ$ 5 (High)	0.956***	0.801***	0.748***	0.721***	0.495**	NA
	(4.39)	(3.47)	(3.16)	(3.01)	(2.07)	NA
5-1 spread	0.517***	0.311**	0.273*	0.161	-0.056	-0.491***
	(3.61)	(2.05)	(1.86)	(1.11)	(-0.40)	(-4.38)
Carhart4 α	0.369***	0.111	0.142	0.037	-0.163	-0.499***
	(3.42)	(0.97)	(1.28)	(0.32)	(-1.32)	(-4.29)
β_{MKTRF}	-0.300***	-0.294***	-0.288***	-0.275***	-0.227***	NA
	(-11.70)	(-10.90)	(-11.14)	(-10.35)	(-7.98)	NA
β_{SMB}	0.833***	0.898***	0.880***	0.740***	0.538***	NA
	(20.69)	(21.09)	(21.82)	(19.06)	(13.14)	NA
β_{HML}	0.235***	0.235***	0.166***	0.275***	0.301***	NA
	(5.57)	(5.26)	(3.81)	(6.23)	(6.28)	NA
β_{UMD}	-0.047*	-0.031	-0.020	-0.085***	-0.067**	NA
	(-1.73)	(-1.10)	(-0.74)	(-2.97)	(-2.16)	NA

Table IA.23 (continued)

Panel B: Sort By *ISKEW* then *ILLIQ*

	ISKEW 1	*ISKEW* 2	*ISKEW* 3	*ISKEW* 4	*ISKEW* 5	Diff
ILLIQ 1 (Low)	0.521***	0.603***	0.651***	0.597***	0.566***	NA
	(2.66)	(3.09)	(3.22)	(2.90)	(2.73)	NA
ILLIQ 2	0.586***	0.725***	0.715***	0.624***	0.615**	NA
	(2.65)	(3.34)	(3.13)	(2.61)	(2.54)	NA
ILLIQ 3	0.687***	0.781***	0.765***	0.699***	0.705***	NA
	(2.98)	(3.45)	(3.23)	(2.77)	(2.82)	NA
ILLIQ 4	0.692***	0.784***	0.821***	0.695***	0.545**	NA
	(3.07)	(3.57)	(3.59)	(2.94)	(2.24)	NA
ILLIQ 5 (High)	0.889***	0.959***	0.931***	0.680***	0.473**	NA
	(4.24)	(4.11)	(3.60)	(2.85)	(2.03)	NA
5-1 spread	0.382***	0.430***	0.329**	0.175	-0.111	-0.475***
	(2.81)	(2.62)	(1.97)	(1.20)	(-0.90)	(-4.58)
Carhart4 α	0.270***	0.245**	0.171	0.012	-0.176	-0.452***
	(2.64)	(2.01)	(1.35)	(0.10)	(-1.59)	(-4.24)
β_{MKTRF}	-0.277***	-0.356***	-0.317***	-0.245***	-0.171***	NA
	(-11.50)	(-12.37)	(-10.68)	(-8.84)	(-6.59)	NA
β_{SMB}	0.815***	0.884***	0.949***	0.692***	0.501***	NA
	(21.69)	(19.70)	(20.27)	(17.29)	(13.34)	NA
β_{HML}	0.248***	0.264***	0.151***	0.304***	0.221***	NA
	(6.40)	(5.65)	(3.03)	(6.56)	(5.04)	NA
β_{UMD}	-0.037	-0.075**	-0.056*	-0.096***	-0.065**	NA
	(-1.45)	(-2.55)	(-1.78)	(-3.20)	(-2.25)	NA

Table IA.24: Cross Section Correlations of Short Term Asymmetry, Volatility, and Anomalies

Panel A provides the time series average of the correlations of asymmetry measures, volatility, and anomalies for the period from January 1962 to December 2013. Panel B provides the same correlations for the idiosyncratic asymmetry measures.

Panel A: Total Measurement

	$E_{\varphi 2}$	$SKEW$	VOL	$SIZE$	MOM	$ILLIQ$
$E_{\varphi 2}$	1.0000					
$SKEW$	0.5813	1.0000				
VOL	0.0968	0.0838	1.0000			
$SIZE$	-0.1240	-0.1105	-0.2045	1.0000		
MOM	0.1043	0.1311	0.0519	0.0077	1.0000	
$ILLIQ$	0.0153	0.0309	0.2154	-0.5276	-0.0536	1.0000

Panel B: Idiosyncratic Measurement

	$IE_{\varphi 2}$	$ISKEW$	$IVOL$	$SIZE$	MOM	$ILLIQ$
$IE_{\varphi 2}$	1.0000					
$ISKEW$	0.5833	1.0000				
$IVOL$	0.1105	0.0930	1.0000			
$SIZE$	-0.1178	-0.0901	-0.2781	1.0000		
MOM	0.1327	0.1438	0.0578	0.0077	1.0000	
$ILLIQ$	0.0114	0.0217	0.2761	-0.5276	-0.0536	1.0000

Chapter 2

The Wage Premium of Naturalized Citizenship (joint with Esfandiar Maasoumi)

Abstract

We examine the potential effect of naturalization on the U.S. immigrants' earnings. We find the earning gap between naturalized citizens and non-citizens is positive over many years, with a tent shape across the wage distribution. We focus on a normalized metric entropy measure of the gap between distributions, and compare with conventional measures at the mean, median and other quantiles. In addition, naturalized citizen earnings (at least) second order stochastically dominate non-citizen earnings in many of the recent years. We construct two counterfactual distributions to further examine the potential sources of the earning gap, the "wage structure" effect and the "composition" effect. Both of these sources contribute to the gap, but the composition effect, while diminishing somewhat after 2005, accounts for about 3/4 of the gap. The unconditional quantile regression (based on the Recentered Influence Function), and conditional quantile regressions confirm that naturalized citizens have generally higher wages, although the gap varies for different income groups, and has a tent shape in many years.

Keywords: Earning gap, citizenship, Stochastic Dominance tests, RIF regression, entropy measure, immigration.

JEL Classification: C13, J70

2.1 Introduction

Studies of immigrant wages go back to at least Chiswick (1978). Most studies are concerned with the analysis of earnings differences of immigrants compared with natives [see,e.g. Bartolucci (2014); Aldashev, Gernandt, and Thomsen (2012)]. The earning gap between naturalized citizens and non-citizens has received less attention. Besides political and social rights, citizenship provides economic benefits. Most federal, state, local public sector and certain licensed professional jobs are restricted to citizens. These government jobs are stable and offer higher wages. Most private employers prefer citizenship holders as well, due to the risk of knowingly or inadvertently hiring unauthorized immigrants, and the administrative cost of hiring non-citizens. Second, the 1996 US welfare reform sharply reduced welfare eligibility for non-citizens (Permanent residents qualify for these benefits after at least 40 quarters of work with legal status.).

In the literature, economists are interested in three main questions related to citizenship's impact on economic benefits to immigrants. (1) How large is the earning gap? (2) How could one separate out the earning gap due to "the composition effect", or human capital characteristics? (3) and how to evaluate the changes in the distribution and quantiles of the unconditional (marginal) distribution of immigrant log wages? Our paper proposes to offer some answers to these questions, and examines new concepts and techniques for this purpose.

Identification of the "citizenship" effect is more likely by focusing on immigrants alone as a more homogeneous group compared with natives. We also focus on immigrants who are actively in the labor market.

Previous research on wage differentials is often based on certain measures such as means and medians. Sumption and Flamm (2012) reports 50% to 70% gap for the median annual incomes during the period from 1993 to 2010, and naturalized citizens appear to have weathered the effects of the economic crisis more successfully as the median income fell only by 5% from 2006 to 2010, while the decline of non-citizens' median income is 19%[1]. However,

[1]For immigrants with at least ten years of residence in the United States.

the differences at "representative" parts of the earnings distribution (mean, median or any percentile) may not be "representative". This type of heterogeneity challenges the status of any scalar measure of the gap, especially simple aggregators like the mean and median, or any single quantile. Maasoumi and Wang (2015) is the first to utilize a normalized metric entropy measure of the wage gap, adapted from Bhattacharay-Matusita-Hellinger, and developed in Granger, Maasoumi, and Racine (2004). They argue this measure is a more comprehensive welfare-theoretic metric of distance between two earnings distributions. This is important for credible complete, "cardinal rankings". For weaker uniform orderings, they proposed stochastic dominance (SD) tests to rank the earnings distributions over large classes of familiar welfare functions. Maasoumi, Pitts, and Wu (2014) implement similar methods for the wage gap between incumbent and newly hired employees. Our paper employs the same entropy measure and stochastic dominance (SD) tests to explore the earning gap between naturalized citizens with non-citizens in the U.S. from 1994 to 2012. The raw earning gap is often tent shaped in each year, possibly peaking from 1995 to 1997, while the trough appears during 1999-2001. The SD rankings are inferred to a statistical degree of confidence, allowing uniform ranking of naturalized citizens wages over non-citizens for most years. First order SD rankings before 2003 are not statistically significant (significance level considered is 5%), but we find second order significant SD for more than half of time after (including) 2003.

Moving beyond raw wages comparisons, we examine which part of the wage gap may be due to differences in the composition effects (human capital characteristics), and due to wage structure (market returns). The latter is considered by some as an indication of "discrimination" in the context of gender or race gaps. Our paper follows the counterfactual analysis proposed by Maasoumi and Wang (2015) by identifying and estimating two types of counterfactual distributions. This provides a decomposition of the gap into the aforementioned components. This decomposition procedure is described in Firpo, Fortin, and Lemieux (2007) and generalizes the Oaxaca-Blinder type decomposition (at the conditional mean) to the whole distribution.

Based on the counterfactual analysis, the entropy gap estimates suggest a potential very small market structural gap from 1994 to 2012, holding human capital characteristics. SD tests seldom show significant ranking between the (two) non-citizen counterfactual distributions compared with the actual non-citizen wage distributions. Human capital characteristics appear to account for most of the differences in the hourly wage distributions. Entropy estimates quantify the magnitude of this human capital effect over the entire distribution of wages.

Most of the previous studies on the earning gap between naturalized citizens and non-citizens place "citizenship" as an explanatory variable in a Mincer type earnings regression. Based on a linear (conditional mean) regression analysis, Pastor and Scoggins (2012) find that in 2010, naturalized citizens earned 7.9% on average more than non-citizens after controlling for numerous human capital characteristics. Bratsberg, Ragan Jr, and Nasir (2002) track the same young male immigrants group from 1979 through 1991, showing an average wage gain of around 5.6% from naturalization. These results focus on the coefficient of the citizenship variable in the conditional mean. By contrast, we are interested in possibly heterogeneous effect of citizenship at different quantiles. Our paper examines the effect of changing the proportion of naturalization on the τth quantile of the unconditional distribution of log wages. This kind of analysis follows methods that have been developed only recently, such as in Firpo, Fortin, and Lemieux (2009). The approach consists of running a regression of the Recentered Influence Function (RIF) of the unconditional quantile on desired explanatory variables. For each year from 1994 to 2012, we discover a tent shape for the citizenship effect, implying that this effect is different for different levels of income, and is highest between the median and the 75-th percentile . For comparison, we also implement the traditional conditional quantile regressions [Koenker and Bassett Jr (1978); Koenker (2005)].[2] The findings from different methods provide a robustness check, and generally agree, but can differ quantitatively at different quantiles.

[2]The conditional quantile regression coefficient can be interpreted as the marginal effect of citizenship ratio at the τth quantile of the conditional distribution of log wages. Our unconditional quantile approach, following Firpo, Fortin, and Lemieux (2009), provides the marginal effect on the unconditional τth quantile, averaged over conditioning sets.

In section 2, we will present the methods, data description is provided in section 3. In section 4, we provide the results, and conclude our paper in section 5.

2.2 Empirical Methodology

2.2.1 Basic Notation

Let $\ln(\omega^0)$ and $\ln(\omega^1)$ denote the log wages of naturalized citizens and non-citizens respectively. We observe a random sample of $N = N_0+N_1$ immigrants. N_0 and N_1 denote the sample sizes of naturalized citizens and non-citizens respectively. Let $F_0(y) \equiv Pr[\ln(\omega^0) \leq y]$ represents the cumulative density function (CDF) of $\ln(\omega^0)$ (i.e. the log of earning for naturalized citizens) and $f_0(y)$ is the corresponding probability density function (PDF); $F_1(y)$ and $f_1(y)$ are similarly defined for $\ln(\omega^1)$.

Individual earnings are determined by both observable, X_i, and unobservable characteristics ϵ_i via an unknown wage functions g_d

$$\ln(\omega_i^d) = g_d(X_i^d, \epsilon_i^d), \qquad d = 0, 1 \tag{2.1}$$

The wage gap between naturalized citizens and non-citizens stems from two sources in (2.1): (1) differences in the distributions of both observable and unobservable characteristics, X_i^d and ϵ_i^d resp; (2) differences in the wage structures, $g_d(\cdot)$.

2.2.2 Decision-Theoretics: Entropy as a Distributional Measure of the Earnings Gap

The need for careful decision/welfare-theoretic understanding of measures of earnings gap has led to a re-evaluation of suitable functions of the earnings distributions. A brief review of the issues is given in Maasoumi and Wang (2015). Flexible Evaluative Functions (EFs) that account for different outcomes at different parts of the earnings distribution provide better support for functionals that go beyond the mean and median, any single quantile, or merely reporting a set of quantiles. The classical literature on ideal measures of inequality provides the relevant backdrop and guidance. This literature identifies Entropy measure as “ideal” distribution functions.[3] As argued in Maasoumi and Wang (2015), the “gap” between two distribution is conveniently seen as the distance between the entropies (inequality measures) of the relevant distributions. When “metricness” is further required for distance functions (rather than mere divergence), a metric entropy member of the Generalized Entropy family emerges which is a normalization of the Bhattacharya-Matusita-Hellinger measure proposed by Granger, Maasoumi, and Racine (2004). Other entropy measures can be employed with qualitatively consistent results. But only a metric measure that satisfies the triangularity rule may support coherent statements about respective ”distances” amongst three or more distributions.

$$S_\rho = \frac{1}{2}\int_{-\infty}^{\infty}(f_1^{\frac{1}{2}} - f_0^{\frac{1}{2}})^2 dy, \tag{2.2}$$

This entropy measure possess several properties: (1) it can be applied to discrete and continuous variables [4]; (2) if $f_1 = f_0$, the two distribution are equal, then $S_\rho = 0$, and lies between 0 and 1 as it is normalized; (3) it is a metric, accommodating assessment across multiple distributions because triangularity property is satisfied; (4) it is invariant under continuous and strictly increasing transformation on the underlying variables; and (5) it is dimensionless, accommodating multivariable assessments.

Following Granger, Maasoumi, and Racine (2004), Maasoumi and Racine (2002), and Maasoumi and Wang (2015), we consider a kernel-based implementation of (2.2). We use Gaussian kernels and the “normal reference rule-of-thumb” bandwidth ($= 1.06 \cdot \min(\sigma_d, \frac{IQR^d}{1.349}) \cdot n^{-\frac{1}{5}}$, where $\sigma_d, d = 0, 1$ is the sample standard deviation of $\ln(\omega_i^d)_{i=1}^{N_d}$, IRQ^d is the interquartile range of the sample d.) Interestingly, Gaussian kernels also enjoy an entropic justification as the Maximum Entropy choice when only the first two moments of data are utilized.

The entropy values S_ρ may not be statistically significantly different from 0, thus in this

[3]Earlier literature expositing welfare functions associated with entropy measures includes insightful accounts in Cowell and Kuga (1981), and Cowell (1977).

[4]For the discrete variables, $S_\rho = \frac{1}{2}\sum(p_1^{\frac{1}{2}} - p_0^{\frac{1}{2}})^2$

paper, we obtain critical values to test the hypothesis $H_0 : S_\rho = 0$ based on 299 bootstrap re-samples. The critical values are reported in Table (2.1).

[Insert Table 2.1 about here]

2.2.3 Stochastic Dominance

In our paper, we employ statistical tests for first and the second order stochastic dominance. This is motivated by the fact that there is no universally accepted Evaluation Function, and SD rankings, or lack of them, reveal whether (weak) uniform rankings hold across large classes of EFs, or else, how restrictive such functions need to be to provide (cardinal) complete rankings.

First Order Dominance: *Naturalized citizen earnings* $(\ln(\omega^0))$ *first order stochastically dominate non-citizen earnings* $(\ln(\omega^1))$ *(denoted* $\ln(\omega^0)$ *FSD* $\ln(\omega^1)$*) if and only if*

1. $E[u(\ln(\omega^0))] \geq E[u(\ln(\omega^1))]$ *for all* $u \in U_1$ *with strict inequality for some* u*;*

2. Or, $F_0(y) \leq F_1(y)$ *for all* y *with strict inequality for some* y*,*

where U_1 denotes the class of all (increasing) von Neumann-Morgenstern type of social welfare functions u such that welfare is increasing in wages (i.e. $u' \geq 0$).

Second Order Dominance: *Naturalized citizen earnings* $(\ln(\omega^0))$ *second order stochastically dominate non-citizen earnings* $(\ln(\omega^1))$ *(denoted* $\ln(\omega^0)$ *SSD* $\ln(\omega^1)$*) if and only if*

1. $E[u(\ln(\omega^0))] \geq E[u(\ln(\omega^1))]$ *for all* $u \in U_2$ *with strict inequality for some* u*;*

2. Or, $\int_{-\infty}^{y} F_0(t)dt \leq \int_{-\infty}^{y} F_1(t)dt$ *for all* y *with strict inequality for some* y*,*

where U_2 denotes the class of social welfare functions in U_1 such that $u'' \leq 0$ (i.e. concavity).

Then a generalized Kolmogorov-Smirnov test discussed in Linton, Maasoumi, and Whang (2005) and Maasoumi and Heshmati (2000) is used to conduct SD tests. The Kolmogorov-Smirnov test statistics for FSD and SSD are based on empirical counterparts of the following:

$$d = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min\{\sup[F_1(y) - F_0(y)], \sup[F_0(y) - F_1(y)]\}, \tag{2.3}$$

$$s = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min\{\sup \int_{-\infty}^{y} [F_1(t) - F_0(t)]dt, \sup \int_{-\infty}^{y} [F_0(t) - F_1(t)]dt\}. \quad (2.4)$$

To estimate these test statistics, we replace CDFs by empirical CDFs (for example, $\hat{F}_0(y) = \frac{1}{N_0}\sum_{i=1}^{N_0} I(\ln(\omega_i^0) \leq y))$, where $I(\cdot)$ is an indicator function. Additionally, 99 replications of bootstrap technique following the literature (e.g. Maasoumi and Heshmati (2000); Maasoumi and Wang (2015) implemented here to obtain the robustness check of the results. If Probability$[d \leq 0]$ is large enough, say 0.95, and $\hat{d} \leq 0$, then FSD is statistically significant. Similar definition for SSD.

2.2.4 Counterfactual Distributions

The identification of contributing components of the earning gap has been mostly conducted by Oaxaca-Blinder regression decompositions at the conditional mean. In our context, we conduct decompositions that are both robust to wage equation specifications and consider the whole distribution of wages. This is done first by inverse probability techniques, describe immediately below, and later by direct quantile regression and RIF regressions. The goal is to separate wage/market structure and the human capital characteristics components. The different techniques of identifying quantiles/distributions provide a check on robustness of findings. The conditional quantile regressions are further limited by functional specification choices.

Consider two counterfactual cases, as follows:

$$\ln(\omega_i^{c1}) = g_0(X_{i1}, \epsilon_{i1}) \quad (Counterfactual \quad Outcome\#1), \quad (2.5)$$

$$\ln(\omega_i^{c2}) = g_1(X_{i0}, \epsilon_{i0}) \quad (Counterfactual \quad Outcome\#2). \quad (2.6)$$

$F_{c1}(f_{c1})$ represents the corresponding CDF (pdf) of the counterfactual outcome $\ln(\omega_i^{c1})$, thus the differences in the distributions of F_{c1} and F_1 ($\ln(\omega_i^{c1})$ v.s. $\ln(\omega_i^1)$) only come from differences in wage structures or potential discrimination. $F_{c2}(f_{c2})$ represents the corresponding CDF (pdf) of the counterfactual outcome $\ln(\omega_i^{c2})$, as a result, the differences between the distributions of F_{c2} and F_1 ($\ln(\omega_i^{c2})$ v.s. $\ln(\omega_i^1)$) come from the differences in human capital characteristics.

There are many identification strategies for these two counterfactual distributions. We adopt the common assumptions of Ignorability (Unconfoundedness) and Overlapping Support, as employed by Firpo (2007) and Firpo, Fortin, and Lemieux (2007).

Assumption 1: Ignorability *Let (D, X, ϵ) have a joint distribution. For all x in X, ϵ is independent of D given $X = x$; D=1 for non-citizens.*

Assumption 2: Overlapping Support *For all x in X,* $0 < p(x) = Pr[D = 1|X = x] < 1$, here $p(x)$ is called "propensity-score". In practical, we estimate the propensity score using logistic regression.[5]

Consider the following three inverse probability weighing functions:

$$\omega_1(D) = \frac{D}{p}, \quad \omega_0(D) = \frac{1-D}{1-p}, \quad \omega_c(D,X) = (\frac{p(X)}{1-p(X)}) \cdot (\frac{1-D}{p}),$$

here p is the probability that an individual is in group 1.

With these reweighing functions we transform the marginal distribution of $\ln(\omega)$ to the conditional distributions of $\ln(\omega^1)$ given $D = 1$, $\ln(\omega^0)$ given $D = 0$, and $\ln(\omega^0)$ given $D = 1$.

We can identify F_1, F_0, F_{c1} and F_{c2} as follows.

Theorem 2.1: *Under Assumptions 1 and 2:*

(1)

$$F_d(y) = \mathbb{E}[\omega_d(D) \cdot \mathbb{I}(\ln(\omega)) \leq y] \quad d = 0, 1. \tag{2.7}$$

(2)

$$F_{ct}(y) = \mathbb{E}[\omega_{ct}(D,X) \cdot \mathbb{I}(\ln(\omega)) \leq y] \quad t = 1, 2. \tag{2.8}$$

[5]In our paper, we use linear regression, non-parametric regression can be implemented to relieve the parametric functional form restriction.

$\omega_{c2}(D,X) = \omega_c(D,X)$ if we let naturalized citizens to be the treatment group taking dummy value of 1, while $\omega_{c1}(D,X) = \omega_c(D,X)$ if setting non-citizens as the treatment group instead.

2.2.5 Decomposition of the Distributional Statistics

Armed with the conditional distributions $F_d(y), \quad d = 0,1$ and $F_{ct}(y), \quad t = 0,1$, we can decompose the wage gap into two parts, as suggested by Firpo, Fortin, and Lemieux (2007).

Let ν be a functional of the conditional joint distribution of $(\ln(\omega)_0, \ln(\omega)_1)|D$, that is $\nu : \mathcal{F}_\nu \to \mathbb{R}$, and $\mathcal{F}_\nu$ is a class of distribution functions such that $F \in \mathcal{F}_\nu$ if $\|\nu(F)\| < +\infty$. The difference in the ν's between the two groups is called the ν-overall wage gap.

$$\Delta_O^\nu = \nu(F_0) - \nu(F_1) = \nu_0 - \nu_1, \tag{2.9}$$

Then the difference (2.9) in wages can be decomposed into two parts:

$$\Delta_O^\nu = (\nu_0 - \nu_{c2}) + (\nu_{c2} - \nu_1) = \Delta_S^\nu + \Delta_X^\nu. \tag{2.10}$$

The first term Δ_S^ν is the difference in the wage structure, since it is the gap between $g_1(\cdot,\cdot)$ to $g_0(\cdot,\cdot)$ keeping the the distribution of human capital characteristics constant. The second term Δ_X^ν reflects the difference in composition effect. In the last part of this paper, we also provide decompositions of the total difference in mean wages (as in Oaxaca-Blinder decomposition) as well as in at quantiles, based on common index (parametric) specifications. This will provide a check on the consistency of the two different approaches.

2.2.6 Unconditional Quantile Partial Effects (UQPE)

Following the Recentered Influence Function (RIF) regression method provided by Firpo, Fortin, and Lemieux (2009), we can obtain the effect of increasing the proportion of naturalized immigrants on the τth quantile of the unconditional distribution of $\ln(\omega)$.

$$IF(\ln(\omega); q_\tau; F) = \lim_{\varepsilon \to 0} \frac{q_\tau(F_\varepsilon) - q_\tau(F)}{\varepsilon} = \frac{\tau - \mathbb{I}\{\ln(\omega) \leq q_\tau\}}{f(q_\tau)}, \tag{2.11}$$

$$RIF(\ln(\omega); q_\tau; F) = q_\tau + IF(\ln(\omega); q_\tau; F) = q_\tau + \frac{\tau - \mathbb{I}\{\ln(\omega) \leq q_\tau\}}{f(q_\tau)}, \tag{2.12}$$

where q_τ is the τth quantile. $F_\varepsilon(y) = (1-\varepsilon)F + \varepsilon\delta_y, 0 \leq \varepsilon \leq 1$ and δ_y is a distribution that only puts mass at the value y. We use $RIF(\ln(\omega); q_\tau)$ instead of $RIF(\ln(\omega); q_\tau; F)$ to simplify the notation.

The Unconditional Partial Effect (UQPE)

$$\alpha(\tau) = \frac{\partial q_\tau(F_{\ln(\omega), t\cdot G_Y^*})}{\partial t}|_{t=0} = E[\frac{dE[RIF(\ln(\omega), q_\tau)|X]}{dX}], \tag{2.13}$$

here $F_{\ln(\omega), t\cdot G^*_{\ln(\omega)}} = (1-t)\cdot F_{\ln(\omega)} + t\cdot G^*_{\ln(\omega)}$. $G^*_{\ln(\omega)}$ is the counterfactual distribution of $\ln(\omega)$, which can be obtained by replacing $F_X(x)$ with $G_X(x)$. $G_Y^* = \int F_{Y|X}(y|X=x)\cdot dG_X(x)$, The new distribution G_X is the distribution of a random $k \times 1$ vector Z, where $Z_i = X_i$ for $i \neq j$ and $i = 1, ...K$, and $Z_j = X_j + t$, here j is the specific dimension we interested in.

From (2.12),

$$RIF(\ln(\omega); q_\tau) = c_{1,\tau} \cdot I\{\ln(\omega) > q_\tau\} + c_{2,\tau},$$

where $c_{1,\tau} = \frac{1}{f(q_\tau)}$, $c_{2,\tau} = q_\tau - c_{1,\tau}\cdot(1-\tau)$.

Take the expectation,

$$E[RIF(\ln(\omega); q_\tau)|X = x] = c_{1,\tau} \cdot Pr[\ln(\omega) > q_\tau|X = x] + c_{2,\tau},$$

suppose $Pr[\ln(\omega) > q_\tau|X = x]$ is linear in x, then from equation (2.13), we know $\alpha(\tau) = E[\frac{dE[RIF(\ln(\omega), q_\tau)|X]}{dX}]$ is the same as the coefficient of regression RIF on X.

The estimator of RIF is

$$\widehat{RIF}(\ln(\omega); \widehat{q}_\tau) = \widehat{c}_{1,\tau} \cdot \mathbb{I}\{\ln(\omega) > \widehat{q}_\tau\} + \widehat{c}_{2,\tau},$$

here $\widehat{c}_{1,\tau} = \frac{1}{\widehat{f}(\widehat{q}_\tau)}$ and $\widehat{c}_{2,\tau} = \widehat{q}_\tau - \widehat{c}_{1,\tau} \cdot (1-\tau)$. Then the average marginal effect or the Unconditional Quantile Partial Effect(UQPE)-$\alpha(\tau)$ could be obtained by regressing $\widehat{RIF}(\ln(\omega); \widehat{q}_\tau)$ on X, we call it RIF-OLS method. Firpo, Fortin, and Lemieux (2009) also mentioned logistic and polynomial series nonparamentric methods, however the results are very close to the RIF-OLS method for the example in Firpo, Fortin, and Lemieux (2009)'s paper.

2.3 Data

In this paper, we examine the 1994-2012 Integrated Public Use Microdata Series, March Current Population Survey[King et al. (2010)] (IPUMS-CPS). There are 176,164 observations for the 19 years we considered.The average sample size from 1994 to 2012 is 3,706 for naturalized citizens, and 5,566 for non-citizens. The minimum numbers appeared in 1994 for both groups, 1,663 and 3,209 for naturalized and non-citizens respectively. This data source contains detailed information on the labor market outcomes such as earnings and other characteristics. Thus it is widely used in the literature.[6] 1994 is the first year that the citizenship information is collected within immigrants. We restrict our sample to individuals aged 18 to 64, with at least 20 working weeks and 35 working hours (inclusive) per week in the previous year. Hourly wages less than or equals to $1 are excluded.

We use the log of hourly wages, which is obtained by dividing an individual's wage and salary income by the hours worked in the previous year. This is the standard procedure in the literature [e.g. Maasoumi and Wang (2015)]. In our counterfactual analysis, unconditional and conditional quantile regressions, we include age, age squared,[7] education dummies (five education groups: less than high school, high school, some college, college, graduate), current married dummy variable (1 if married and zero otherwise), race dummy (1 if non-white and zero otherwise), region dummies (Northeast, Midwest, South, and West) and three occupations dummies (high-skill for managerial and professional specialty occu-

[6]The IPUMS-USA(IPUMS American Community Survey) provides data from 2001-2011, including information on English proficiency, but is less complete on education level, and covers fewer years.

[7]We include the squared age to reflect the idea that there are declining returns to additional age after some period of time.

pations; medium-skill contains technical, sales, and administrative support occupations; low-skill consists of service, farming, forestry and other occupations)

2.4 Empirical Results

2.4.1 Distributional Comparison and Analysis

First we look at the raw differences measured by the Bhattacharya-Matusita-Hellinger entropy, alongside specific quantile (or moment based) differences of the wage gap between naturalized and non citizens. This is given in Panel A of Table 3.1. Generally speaking, the $S_\rho \times 100$ gap and 10th, 25th, 50th (Median), 75th, 90th percentile gaps including the mean difference are positive and consistent from 1994 to 2012, indicating that naturalized citizens earn more than non-citizens. In addition, from the Panel A, the gap is not constant at different quantiles. For example, at the 10th quantile, the earning gap is 0.24 to 0.36 while it is 0.37 to 0.49 for the 50th quantile. The earning gap increases for above median incomes, and then decreases to 0.21 to 0.38 for the 90th quantile again. Thus, it seems that the association of citizenship is higher for median and above median wages, and generally lower at both tails. A tent shape.

Continuing with the raw entropy differences, nominal peak appears in 1995-1997, while the trough emerges during the period 1999-2001 (shown in Figure 2.2 as well[8]). 2001 is the collapse of the Dot-com bubble. At lower wages (10th quantile), the gap is increasing in the period 2007-2012 compared with the prior period, suggesting the financial crisis may have impacted low income non-citizens more than other income levels. Citizenship may be associated with more stable wages in uncertain economic environments. But this may also be partly due to more active enforcement of immigration laws in some periods.

Figure 2.1 displays the empirical CDFs of naturalized citizens and non-citizens in some years. Predominantly, all non-citizens CDFs are to the left of those of naturalized citizens

[8] Figure 2.2 shows the plot of the normalized values of S_ρ, mean, 10th, 25th, 50th, 75th, and 90th percentiles.

(except Year 1994 when there is a cross at the higher end).[9] These graphical impressions are confirmed statistically. In Table 3.1-we find generally significant Stochastic Dominance of citizen immigrant wages.

[Insert Table 3.1 about here]

[Insert Figure 2.1 about here]

[Insert Figure 2.2 about here]

As just mentioned, in Panel B of Table 3.1, we report SD tests based on 99 bootstrap replications. In all the years 1994-2012, naturalized citizen earnings stochastic dominate non-citizen earnings. Furthermore, we find first order stochastic dominance except for the years 1994 and 1997. The columns labeled d and s are the Kolmogorov-Smirnov test statistics for FSD and SSD respectively (Expressions (2.3-2.4)), while the columns labeled $P[d \leq 0]$ and $P[s \leq 0]$ report the probabilities of first order and second order stochastic dominance, respectively. From Panel B of Table 3.1, FSD is only significant in 2005, but SSD is significant for 2003, 2005, 2008-2010, and 2012. In 2011, the probability is 0.86, which is noteworthy. The earnings distribution of naturalized citizens is found to dominate from 2008 to 2012, indicating non-citizens have not faired well during the recent economic recession. Some regulations may have contributed to this outcome. For example, The U.S. Senate agreed on February, 2009 to set restrictions on the hiring of H-1B workers by financial services firms that received federal bailout funds.

2.4.2 Counterfactual Analysis

Comparing non-citizen counterfactual #1 and non-citizen, measures of earning gap and SD tests are displayed in Table 2.3, and Figure 2.3. Other years graphs are in Appendix A.1 Figure IA.2. Comparison of F_{c1} and F_1 controls for "human capital characteristics", reflecting wage structure components. From Panel B of Table 2.3, there is generally no

[9] graphs for other years are in Appendix A.1 Figure IA.1.

statistically significant first or second order stochastic dominance (except in 1999 and 2008, when probabilities are larger than 0.95). Thus the non-citizen wage distribution #1 and the counterfactual wage distribution #1 are generally unrankable. Market returns cannot account for the wage gap.

In Panel A of Table 2.3 entropy gap S_ρ peaks in 2008 (1.32) but is otherwise quite stable and much smaller than the raw values observed in prior tables. This is consistent with the SD tests. Only other, possibly very narrow decision-theoretic definitions of the gap can possibly order these distributions.

[Insert Table 2.3 about here]

[Insert Figure 2.3 about here]

Table 2.4, and Figure 2.4 show the comparison results for non-citizen counterfactual #2 and non-citizens. Graphs for remaining years are in Figure IA.3 of Appendix A.1. Here, non-citizen counterfactual #2 represents the corresponding earning distributions if we use the distribution of the naturalized citizens' human capital instead of non-citizens' while keeping the wage structure unchanged. The gap is generally positive in Panel A, Table 2.4, accounting for most of the total gap reported in the raw comparisons. There is no discernible general trend in the human capital/characteristics component of the gap. It is stable around 1.33-1.65, with peaks in 2000 and 2005, and troughs in 2009-2012. In the recent recession years, we find the impact of the "skills gap" is declining amongst immigrants. Accordingly, the entropy gap S_ρ has decreased from 1.70 in 2005 to 1.11 in 2012.

The earnings distributions of non-citizen counterfactual #2 graphically FSD the earnings distributions of non-citizen; See Figure 2.4. For FSD, these are not statistically significance except for 2006, as can be seen in Panel B, Table 2.4 for many years. But there is a fairly strong evidence of statistical SSD. The high probabilities for SSD suggest the likelihood of general Third Order SD for all years. This suggests that Evaluative Functions that are (increasingly) inequality averse would order these two outcomes. Skills matter, especially so with increasing inequality aversion, which values upward mobility at lower wages more highly than at higher wages.

[Insert Table 2.4 about here]

[Insert Figure 2.4 about here]

2.4.3 Decomposition of the Gap in Conditional Means and Quantiles

In this section, we examine alternative methods to the nonparametric distribution-based analysis provided so far. Thus we re-examine decompositions of the wage gap based on modeling of the conditional means (Mincer type earnings equations), and conditional quantile regressions. For comparison purposes in this context, we also obtain the corresponding partial effects of "citizenship" on immigrant wages based on the Re-centered Influence Function Regressions described in prior sections.

Table 2.5 reports the gap due to "wage structure" and composition effect. These are reported at the mean and select quantiles. The results at the conditional mean are known as the Oaxaca-Blinder decompositions.

[Insert Table 2.5 about here]

2.4.4 the Unconditional Quantile Partial Effect (UQPE) and the Conditional Quantile Partial Effect (CQPE) of Citizenship

If citizenship effect is "causal", one may wish to find the partial impact of it on immigrants' wages. In this part, we treat citizenship as a factor contributing to immigrants' income. Firpo, Fortin, and Lemieux (2009) suggests a different measure to obtain unconditional quantile partial effects, instead of the coefficient of the factor from the traditional conditional quantile regression. The reason is that the coefficient $\beta_\tau = F^{-1}(\tau|D=1) - F^{-1}(\tau|D=0)$ from a conditional quantile regression is generally different from $dq_\tau(p)/dp, p = P[D=1]$. $D = 1$ for a citizen immigrant. $p = P[D = 1]$ denotes the proportion of naturalized immigrants.

Table 2.6 and Figure 2.5 report unconditional quantile regression estimates (labeled UQR), standard OLS (conditional mean) estimates, and standard (conditional) quantile regression estimates (labeled CQR) of the effect of citizenship status on log wages.[10] The estimates are uniformly positive each year, however the magnitudes are varied for different quantiles. Although the shape of the UQPE is slightly different every year, it is generally the tent shape, illustrating citizenship is more important to middle and upper middle wages, compared to very low-income and high-incomes. This result also indicates that citizenship increases inequality in the lower tail of the distribution while decreases inequality for the upper tail. For example, in year 2012 in Table 2.6, the difference between entries for the 50th and the 10th quantiles is 0.07 (=0.18-0.11), and the difference between the 90th and the 50th quantiles is -0.14 (=0.04-0.18). Thus a 10 percent increase in the citizenship rate is associated with an increase of .007 in the 50-10 gap, but a decrease of the 90-50 gap by 0.014. For comparison, the CQPE results are also positive, but due to the decreasing magnitudes corresponding with larger quantiles, the increase in citizenship ratio will reduce the conditional earning distribution inequality. Bootstrapped standard errors (For UQR and CQR) and robust OLS standard errors are not reported in Table 2.6, since the largest value is $0.00358618 < 0.01$.

[Insert Table 2.6 about here]

[Insert Figure 2.5 about here]

2.5 Conclusions and Future Work

In this paper, we implement entropy and stochastic dominance tests for the comparison of the wage distributions between naturalized and non-citizen immigrants in the US. We construct two counterfactual wage distributions to clarify the sources of the wage gap. In addition, we obtain the estimate of the unconditional quantile partial effect of citizenship.

[10] Other years graphs are in Figure IA.4 of Appendix A.2.

We use CPS data 1994-2012 here. The findings by the two different approaches of inverse probability weighting and quantile regression decompositions are in general agreement. Our main conclusions are as follows:

(1) The wage gap between naturalized and non-citizen is generally stable during 1994 to 2012, and its has a tent shape, suggesting heterogeneity over the wage distribution.

(2) The Raw Naturalized citizen earnings at least SSD non-citizen earnings for most years.

(3) Decomposition of the gap into "wage structure" and "composition" components reveals that human capital characteristics, and skills (observed or otherwise) are the primary source of the wage gap between immigrants.

(4) When wage outcomes cannot be uniformly ranked, as when characteristics are controlled for, our decision-theoretic approach makes clear that only narrow Evaluative Functions would rank wage distributions and outcomes. In such cases, the metric entropy proposed in this paper presents an attractive function of the whole distribution of earnings with a set of weights to different wage earners that is better supported than assessments based on the mean, median, or individual quantiles. Other entropy measures, such as the symmetrized Kullback-Leibler, would provide interesting measures of "divergence", with different underlying welfare functions. The patterns of the gap discovered in this paper are likely to be robust to the choice of entropy functionals.

CPS data does not contain English proficiency information. Neglecting this information may result in overestimates of the effect of "citizenship". Literature on program evaluation that accounts for separate grades in maths and English suggests this is an important distinction. These different skills are also likely differently correlated with length of residency which is often higher for naturalized immigrants.

Appendix

In this appendix, we provide the other years CDF Comparisons between different groups, and unconditional, conditional quantile regression estimates of the effect of citizenship status on log wages.

A.1 CDF Comparisons

Figure IA.1 shows the empirical CDFs of naturalized citizens and non-citizens in other years different from years shown in the main text. Figure IA.2 and IA.3 display the empirical CDFs comparison results for non-citizen counterfactual #1 V.S. non-citizen and non-citizen counterfactual #2 V.S. non-citizens respectively.

[Insert Figure IA.1 about here]

[Insert Figure IA.2 about here]

[Insert Figure IA.3 about here]

A.2 Unconditional and Conditional Quantile Regression Estimates

Figure IA.4 shows the unconditional and conditional quantile regression estimates of the effect of citizenship status on log wages in other years from 1994 to 2012.

[Insert Figure IA.4 about here]

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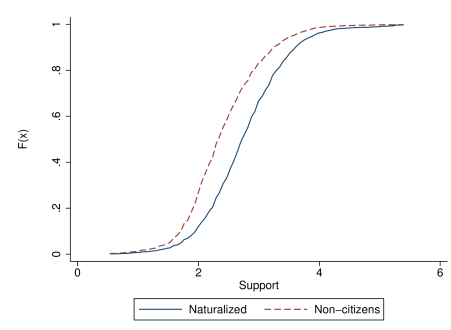

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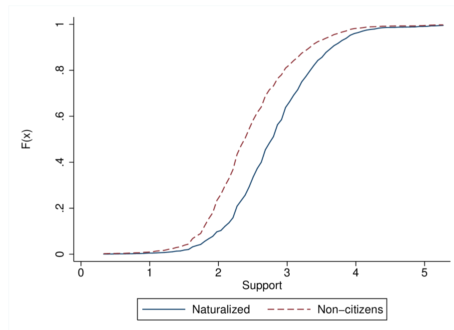

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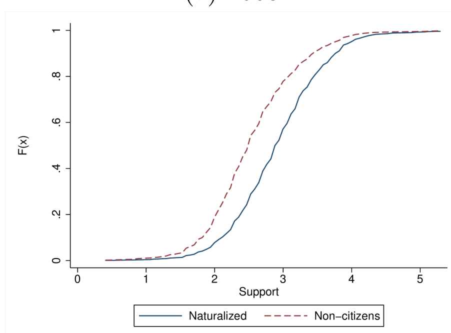

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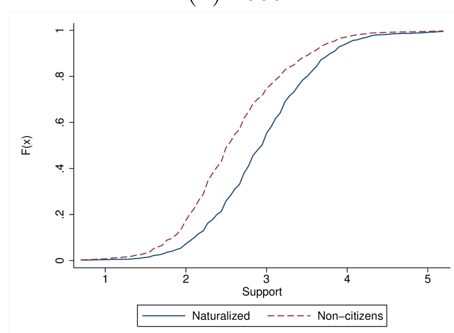

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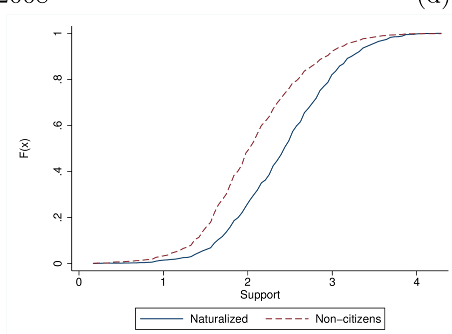


(e) 1994

Figure 2.1: CDF Comparisons of Naturalized Citizen and Non-citizen

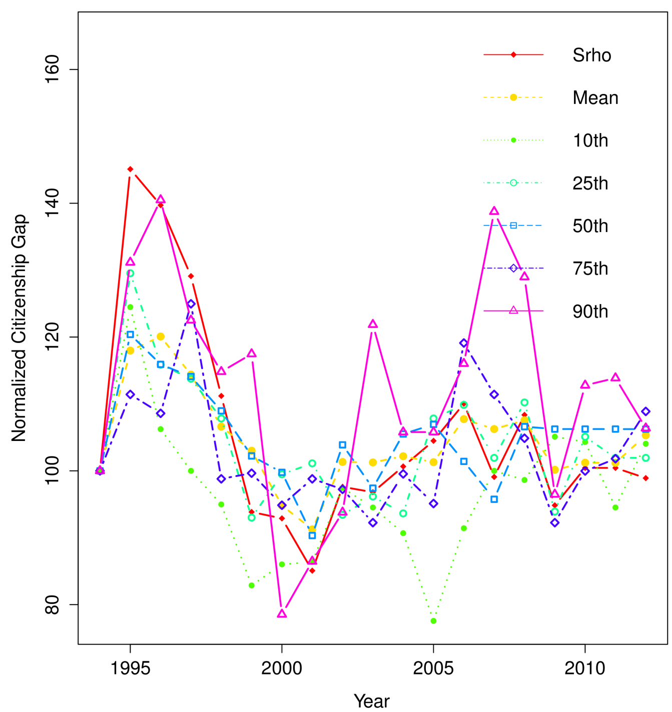
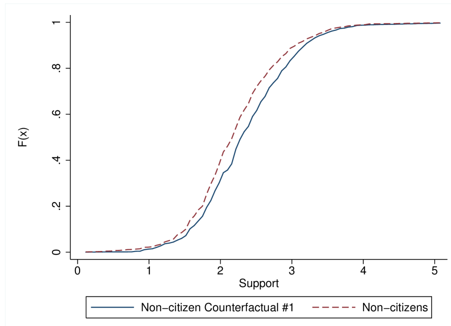


Figure 2.2: The Time Trend of Citizenship Wage Gap



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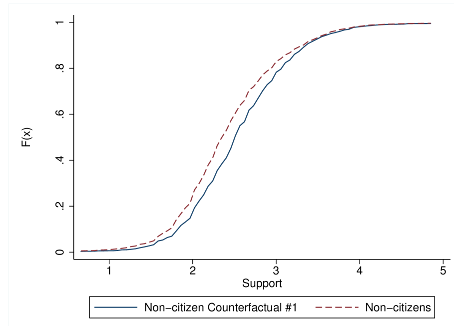

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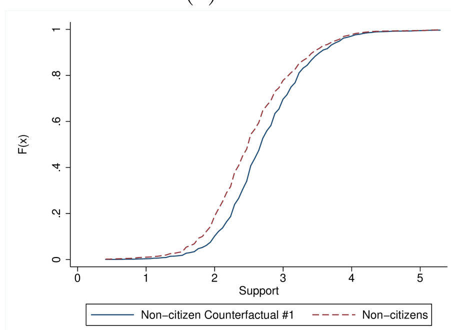

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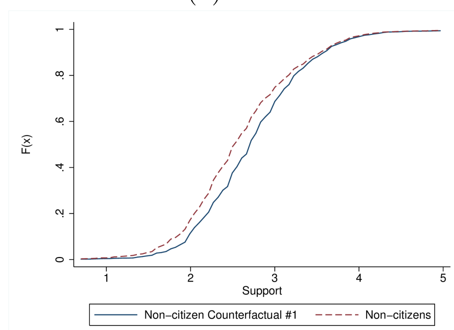

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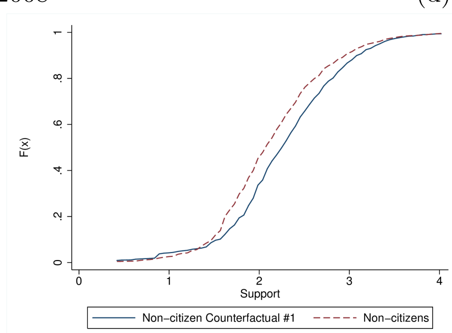

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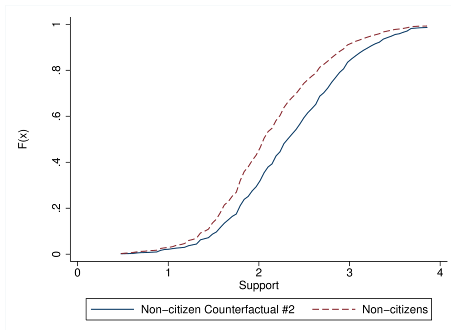
Figure 2.3: CDF Comparisons of Non-citizen Counterfactual # 1 and Non-citizen



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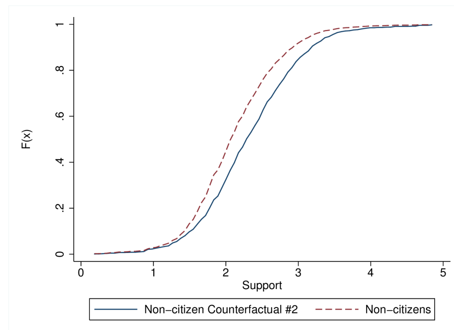

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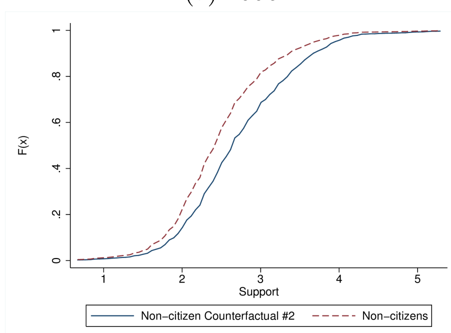

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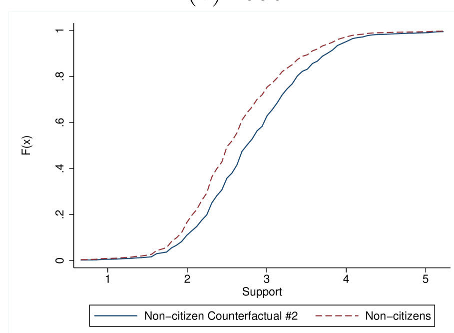

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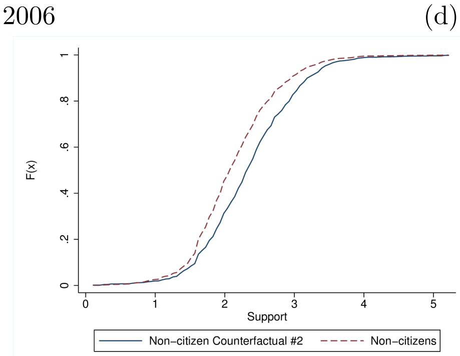
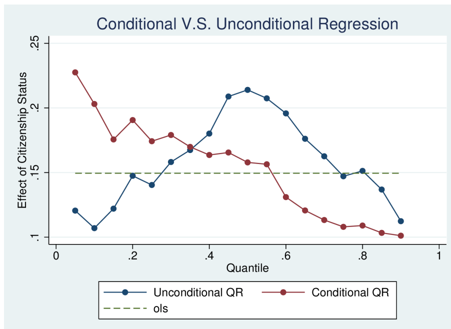


(e) 1997

Figure 2.4: CDF Comparisons of Non-citizen Counterfactual # 2 and Non-citizen



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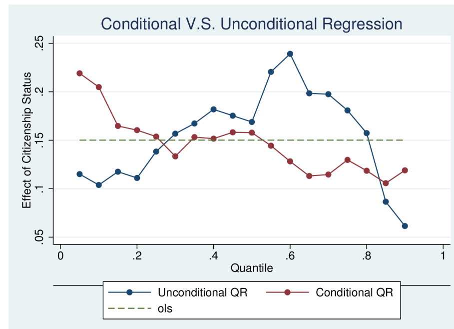

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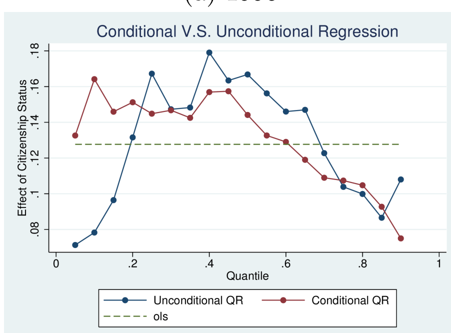

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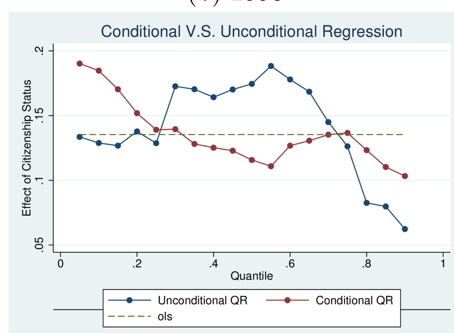
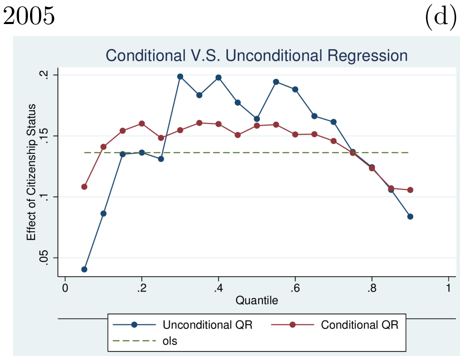


(d) 2009



(e) 2010

Figure 2.5: Unconditional and Conditional Quantile Regression Estimates of the Effect of Citizenship Status on Log Wages

Table 2.1: Critical Values for Testing of $H_0 : S_\rho = 0$

	Non-citizen v.s. Naturalized			C1 v.s. Non-citizen			C2 v.s. Non-citizen		
Year	90th	95th	99th	90th	95th	99th	90th	95th	99th
1994	0.29	0.31	0.35	0.32	0.34	0.40	0.34	0.38	0.49
1995	0.34	0.39	0.45	0.23	0.27	0.34	0.27	0.30	0.37
1996	0.34	0.38	0.44	0.51	0.65	0.78	0.35	0.39	0.44
1997	0.33	0.37	0.44	0.52	0.58	0.79	0.30	0.35	0.42
1998	0.29	0.34	0.40	0.28	0.30	0.38	0.28	0.33	0.41
1999	0.26	0.29	0.36	0.46	0.51	0.60	0.39	0.41	0.51
2000	0.26	0.28	0.37	0.30	0.33	0.39	0.56	0.60	0.75
2001	0.22	0.25	0.29	0.21	0.23	0.28	0.27	0.30	0.34
2002	0.18	0.20	0.23	0.22	0.23	0.28	0.24	0.27	0.35
2003	0.19	0.20	0.24	0.37	0.45	0.53	0.23	0.25	0.30
2004	0.18	0.20	0.25	0.19	0.20	0.27	0.26	0.31	0.37
2005	0.20	0.24	0.28	0.23	0.27	0.30	0.21	0.23	0.27
2006	0.16	0.18	0.24	0.25	0.27	0.33	0.24	0.27	0.32
2007	0.25	0.27	0.31	0.26	0.28	0.33	0.27	0.30	0.36
2008	0.21	0.22	0.29	0.19	0.21	0.27	0.27	0.29	0.33
2009	0.19	0.20	0.29	0.17	0.19	0.24	0.19	0.21	0.30
2010	0.18	0.20	0.24	0.17	0.19	0.22	0.27	0.29	0.36
2011	0.21	0.22	0.28	0.25	0.27	0.35	0.28	0.31	0.37
2012	0.21	0.23	0.28	0.24	0.27	0.31	0.22	0.24	0.27

[1] Data Source: IPUMS CPS (http://cps.ipums.org/cps/). The entropy ($\times 100$) 90th, 95th, and 99th percentile critical values under the null of no entropic difference between two wage distributions.
[2] C1 is Non-citizen Counterfactual #1, C2 is Non-citizen Counterfactual #2.
[3] Critical values obtained from 299 bootstrap re-samples.

Table 2.2: NATURALIZED CITIZEN V.S. NON-CITIZEN WAGE DISTRIBUTIONS

Panel A: The Raw Wage Gap							
Year	$S_\rho \times 100$	Mean	10th	25th	50th	75th	90th
1994	4.00	0.35	0.29	0.35	0.41	0.39	0.27
1995	5.80	0.41	0.36	0.45	0.49	0.43	0.36
1996	5.59	0.42	0.31	0.41	0.47	0.42	0.38
1997	5.16	0.40	0.29	0.40	0.46	0.48	0.33
1998	4.45	0.37	0.27	0.38	0.44	0.38	0.31
1999	3.75	0.36	0.24	0.33	0.41	0.39	0.32
2000	3.71	0.33	0.25	0.35	0.40	0.37	0.21
2001	3.40	0.32	0.25	0.35	0.37	0.38	0.24
2002	3.90	0.36	0.28	0.33	0.42	0.38	0.26
2003	3.87	0.36	0.27	0.34	0.39	0.36	0.33
2004	4.03	0.36	0.26	0.33	0.43	0.38	0.29
2005	4.18	0.36	0.22	0.38	0.43	0.37	0.29
2006	4.40	0.38	0.26	0.38	0.41	0.46	0.32
2007	3.96	0.37	0.29	0.36	0.39	0.43	0.38
2008	4.33	0.38	0.28	0.39	0.43	0.41	0.35
2009	3.79	0.35	0.30	0.33	0.43	0.36	0.26
2010	4.02	0.36	0.30	0.37	0.43	0.39	0.31
2011	4.02	0.36	0.27	0.36	0.43	0.39	0.31
2012	3.96	0.37	0.30	0.36	0.43	0.42	0.29

[1] Data Source: IPUMS CPS (http://cps.ipums.org/cps/). Column 2: Entropy wage gap ($\times$100) is invariant to log transformation. Columns 3-8: conventional measures of the log wage differences.

Table 3.1 (continued)

Panel B: Stochastic Dominance Tests									
Year	OR	$d_{1,max}$	$d_{2,max}$	d	$P[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$P[s \leq 0]$
1994	SSD	0.04	8.44	0.04	0.36	-0.04	250.97	-0.04	0.91
1995	FSD	-0.01	10.50	-0.01	0.30	-0.04	322.73	-0.04	0.77
1996	FSD	-0.04	10.10	-0.04	0.85	-0.04	252.88	-0.04	0.94
1997	SSD	0.00	10.42	0.00	0.28	-0.05	278.53	-0.05	0.68
1998	FSD	-0.01	10.67	-0.01	0.23	-0.04	273.61	-0.04	0.79
1999	FSD	-0.04	9.74	-0.04	0.75	-0.08	236.08	-0.08	0.83
2000	FSD	-0.04	10.45	-0.04	0.76	-0.04	274.21	-0.04	0.86
2001	FSD	-0.05	11.40	-0.05	0.68	-0.05	269.71	-0.05	0.93
2002	FSD	-0.06	12.50	-0.06	0.84	-0.06	322.67	-0.06	0.87
2003	FSD	-0.07	12.61	-0.07	0.94	-0.07	303.39	-0.07	0.98
2004	FSD	-0.08	12.59	-0.08	0.65	-0.09	323.23	-0.09	0.68
2005	FSD	-0.09	12.77	-0.09	0.98	-0.09	298.37	-0.09	1.00
2006	FSD	-0.06	13.41	-0.06	0.55	-0.08	330.51	-0.08	0.57
2007	FSD	-0.06	13.22	-0.06	0.66	-0.07	334.96	-0.07	0.74
2008	FSD	-0.06	13.86	-0.06	0.91	-0.06	328.82	-0.06	1.00
2009	FSD	-0.07	12.83	-0.07	0.92	-0.07	323.90	-0.07	0.98
2010	FSD	-0.02	13.27	-0.02	0.63	-0.06	287.41	-0.06	0.96
2011	FSD	-0.06	13.31	-0.06	0.79	-0.06	273.41	-0.06	0.86
2012	FSD	-0.05	12.67	-0.05	0.83	-0.06	279.47	-0.06	0.98

[1] OR means Observed Ranking.

[2] $P[d] \leq 0$ and $P[s] \leq 0$ results are based on 99 replications of bootstrap re-sampling produce.

Table 2.3: NON-CITIZEN COUNTERFACTUAL #1 V.S NON-CITIZEN Distributions

Panel A: Measures of Wage Differentials							
Year	$S_\rho \times 100$	Mean	10th	25th	50th	75th	90th
1994	0.36	0.07	0.02	0.07	0.09	0.09	0.04
1995	1.23	0.17	0.17	0.15	0.22	0.18	0.12
1996	1.08	0.16	0.14	0.11	0.19	0.22	0.16
1997	1.25	0.14	0.07	0.18	0.21	0.18	0.13
1998	0.75	0.12	0.12	0.12	0.17	0.16	0.07
1999	0.80	0.14	0.06	0.11	0.14	0.17	0.13
2000	0.94	0.13	0.13	0.18	0.14	0.13	0.06
2001	0.68	0.11	0.14	0.13	0.15	0.14	0.03
2002	1.03	0.15	0.12	0.17	0.18	0.16	0.05
2003	0.78	0.12	0.04	0.16	0.17	0.11	0.11
2004	0.77	0.13	0.12	0.13	0.14	0.15	0.05
2005	0.99	0.13	0.08	0.18	0.18	0.13	0.08
2006	0.98	0.14	0.13	0.21	0.15	0.13	0.06
2007	0.90	0.15	0.19	0.16	0.18	0.15	0.13
2008	1.32	0.18	0.17	0.20	0.18	0.16	0.10
2009	0.85	0.14	0.14	0.12	0.16	0.13	0.05
2010	0.81	0.12	0.10	0.13	0.14	0.15	0.07
2011	0.98	0.14	0.08	0.15	0.18	0.14	0.09
2012	0.90	0.14	0.11	0.16	0.18	0.13	0.06

[1] Data Source: IPUMS CPS (http://cps.ipums.org/cps/). Column 2 is entropy gap (×100). Columns 3-8 report conventional measures of the log wages gap.

Table 2.3 (continued)

Panel B: Stochastic Dominance Tests									
Year	OR	$d_{1,max}$	$d_{2,max}$	d	$P[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$P[s \leq 0]$
1994	SSD	0.06	3.24	0.06	0.06	-0.06	81.49	-0.06	0.94
1995	SSD	0.08	7.29	0.08	0.14	-0.07	212.94	-0.07	0.83
1996	None	0.18	6.48	0.18	0.07	0.14	145.28	0.14	0.40
1997	None	0.98	6.61	0.98	0.00	8.85	143.56	8.85	0.06
1998	SSD	0.18	6.81	0.18	0.00	-0.06	137.12	-0.06	0.77
1999	FSD	-0.06	6.18	-0.06	0.45	-0.06	136.05	-0.06	0.97
2000	SSD	0.13	7.74	0.13	0.07	-0.07	150.75	-0.07	0.45
2001	SSD	0.28	7.79	0.28	0.02	-0.09	137.45	-0.09	0.75
2002	None	0.09	9.70	0.09	0.19	0.42	196.17	0.42	0.36
2003	None	0.26	8.10	0.26	0.14	1.52	152.75	1.52	0.37
2004	FSD	-0.05	8.73	-0.05	0.20	-0.16	172.87	-0.16	0.49
2005	SSD	0.07	9.46	0.07	0.15	-0.08	166.08	-0.08	0.70
2006	FSD	-0.03	9.76	-0.03	0.15	-0.15	190.52	-0.15	0.83
2007	None	0.17	9.28	0.17	0.13	0.53	199.70	0.53	0.29
2008	FSD	-0.03	11.25	-0.03	0.66	-0.11	237.46	-0.11	1.00
2009	FSD	-0.05	8.65	-0.05	0.27	-0.11	185.39	-0.11	0.92
2010	SSD	0.10	9.23	0.10	0.05	-0.09	149.57	-0.09	0.75
2011	SSD	0.02	9.92	0.02	0.17	-0.10	161.76	-0.10	0.73
2012	FSD	-0.01	8.91	-0.01	0.19	-0.10	158.71	-0.10	0.77

[1] OR means Observed Ranking.

[2] $P[d] \leq 0$ and $P[s] \leq 0$ results are based on 99 replications of bootstrap re-sampling produce.

Table 2.4: NON-CITIZEN COUNTERFACTUAL #2 V.S NON-CITIZEN Distributions

Panel A: Measures of Wage Differentials							
Year	$S_\rho \times 100$	Mean	10th	25th	50th	75th	90th
1994	1.62	0.23	0.14	0.18	0.25	0.33	0.24
1995	1.60	0.22	0.15	0.17	0.27	0.29	0.26
1996	1.42	0.21	0.08	0.16	0.21	0.29	0.25
1997	1.61	0.22	0.11	0.17	0.26	0.31	0.24
1998	1.39	0.21	0.10	0.16	0.21	0.27	0.25
1999	1.36	0.21	0.07	0.16	0.22	0.26	0.31
2000	1.71	0.24	0.13	0.16	0.26	0.36	0.31
2001	1.34	0.21	0.14	0.15	0.22	0.30	0.26
2002	1.59	0.23	0.10	0.17	0.26	0.29	0.24
2003	1.33	0.20	0.10	0.15	0.25	0.27	0.24
2004	1.50	0.22	0.13	0.15	0.25	0.29	0.27
2005	1.70	0.24	0.13	0.21	0.30	0.34	0.25
2006	1.65	0.24	0.15	0.22	0.26	0.36	0.30
2007	1.65	0.24	0.17	0.16	0.25	0.27	0.29
2008	1.40	0.22	0.16	0.15	0.22	0.26	0.23
2009	1.28	0.21	0.14	0.15	0.24	0.30	0.20
2010	1.23	0.21	0.10	0.15	0.22	0.29	0.24
2011	1.31	0.22	0.08	0.14	0.24	0.31	0.27
2012	1.11	0.20	0.07	0.13	0.23	0.29	0.18

[1] Data Source: IPUMS CPS (http://cps.ipums.org/cps/). Column 2 reports Entropy gap (×100). Columns 3-8 report conventional measures of log wage differences.

Table 2.4 (continued)

Panel B: Stochastic Dominance Tests									
Year	OR	$d_{1,max}$	$d_{2,max}$	d	$P[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$P[s \leq 0]$
1994	FSD	-0.05	8.05	-0.05	0.48	-0.06	240.58	-0.06	0.64
1995	FSD	-0.06	8.60	-0.06	0.60	-0.06	275.01	-0.06	0.94
1996	FSD	-0.04	7.43	-0.04	0.51	-0.06	190.10	-0.06	0.85
1997	None	0.13	8.70	0.13	0.12	1.00	225.37	1.00	0.16
1998	None	0.15	8.02	0.15	0.11	0.77	219.97	0.77	0.20
1999	None	0.07	8.13	0.07	0.13	0.29	201.42	0.29	0.27
2000	FSD	-0.04	9.64	-0.04	0.62	-0.07	274.66	-0.07	0.78
2001	FSD	-0.07	10.63	-0.07	0.34	-0.08	264.87	-0.08	0.51
2002	FSD	-0.08	12.02	-0.08	0.68	-0.08	308.49	-0.08	0.78
2003	None	0.08	10.37	0.08	0.25	0.08	251.36	0.08	0.45
2004	FSD	-0.05	10.80	-0.05	0.58	-0.07	299.83	-0.07	0.88
2005	FSD	-0.10	11.86	-0.10	0.51	-0.10	293.64	-0.10	0.55
2006	FSD	-0.12	11.94	-0.12	0.95	-0.12	331.67	-0.12	0.97
2007	FSD	-0.11	12.38	-0.11	0.37	-0.11	319.73	-0.11	0.60
2008	FSD	-0.08	11.77	-0.08	0.72	-0.10	287.03	-0.10	0.79
2009	FSD	-0.08	11.13	-0.08	0.31	-0.16	292.81	-0.16	0.42
2010	FSD	-0.11	10.63	-0.11	0.84	-0.11	250.11	-0.11	0.90
2011	FSD	-0.09	10.91	-0.09	0.63	-0.10	250.18	-0.10	0.77
2012	FSD	-0.08	9.92	-0.08	0.64	-0.15	228.67	-0.15	0.84

[1] OR means Observed Ranking.

[2] $P[d] \leq 0$ and $P[s] \leq 0$ results are based on 99 replications of bootstrap re-sampling produce.

Table 2.5: Wage Gap Decomposition

Panel A: The Wage Structure Component of the Gap						
Year	Mean	10th	25th	50th	75th	90th
1994	0.12	0.14	0.16	0.16	0.08	0.07
1995	0.17	0.20	0.24	0.20	0.14	0.07
1996	0.21	0.25	0.21	0.24	0.18	0.10
1997	0.18	0.18	0.20	0.20	0.16	0.14
1998	0.17	0.18	0.20	0.21	0.12	0.09
1999	0.15	0.17	0.17	0.18	0.15	0.04
2000	0.11	0.10	0.16	0.18	0.05	-0.01
2001	0.10	0.12	0.20	0.16	0.08	0.01
2002	0.12	0.16	0.12	0.11	0.12	0.06
2003	0.15	0.13	0.17	0.16	0.12	0.11
2004	0.12	0.14	0.14	0.13	0.08	0.06
2005	0.11	0.13	0.14	0.11	0.06	0.06
2006	0.11	0.10	0.15	0.13	0.08	-0.01
2007	0.12	0.11	0.18	0.12	0.13	0.09
2008	0.14	0.13	0.22	0.17	0.11	0.09
2009	0.12	0.13	0.17	0.17	0.05	0.05
2010	0.13	0.18	0.19	0.18	0.09	0.05
2011	0.12	0.18	0.20	0.16	0.05	0.01
2012	0.14	0.19	0.21	0.17	0.09	0.07

[1] Data Source: IPUMS CPS (http://cps.ipums.org/cps/). Column 2-the Standard Oaxaca-Blinder Decomposition. Columns 3-7 are quantile “wage structure“source of the earning gap.

Table 2.5 (continued)

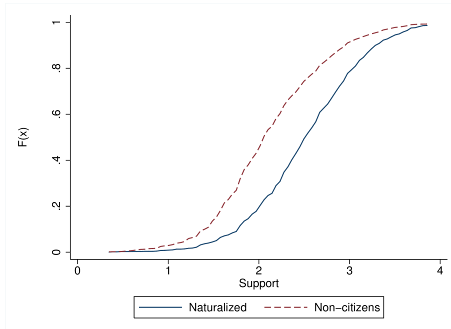
Panel B: Composition Effect Component of the Gap						
Year	Mean	10th	25th	50th	75th	90th
1994	0.23	0.14	0.18	0.25	0.33	0.24
1995	0.22	0.15	0.17	0.27	0.29	0.26
1996	0.21	0.08	0.16	0.21	0.29	0.25
1997	0.22	0.11	0.17	0.26	0.31	0.24
1998	0.21	0.10	0.16	0.21	0.27	0.25
1999	0.21	0.07	0.16	0.22	0.26	0.31
2000	0.24	0.13	0.16	0.26	0.36	0.31
2001	0.21	0.14	0.15	0.22	0.30	0.26
2002	0.23	0.10	0.17	0.26	0.29	0.24
2003	0.20	0.10	0.15	0.25	0.27	0.24
2004	0.22	0.13	0.15	0.25	0.29	0.27
2005	0.24	0.13	0.21	0.30	0.34	0.25
2006	0.24	0.15	0.22	0.26	0.36	0.30
2007	0.24	0.17	0.16	0.25	0.27	0.29
2008	0.22	0.16	0.15	0.22	0.26	0.23
2009	0.21	0.14	0.15	0.24	0.30	0.20
2010	0.21	0.10	0.15	0.22	0.29	0.24
2011	0.22	0.08	0.14	0.24	0.31	0.27
2012	0.20	0.07	0.13	0.23	0.29	0.18

[1] Data Source: IPUMS CPS (http://cps.ipums.org/cps/). Column 2-composition effect from the Standard Oaxaca-Blinder Decomposition. Columns 3-7, composition effects at quantiles.

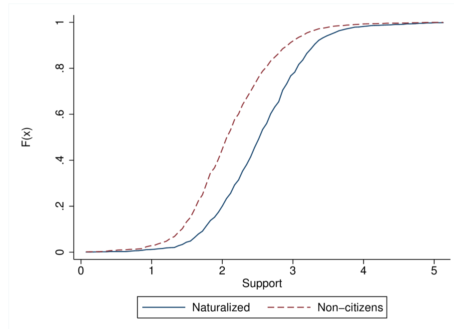
Table 2.6: Comparing OLS, Unconditional Quantile Regressions (UQR), and Conditional Quantile Regressions (CQR) :Citizenship Status Effect

		10th Centile		50th Centile		90th Centile	
Year	OLS	UQR	CQR	UQR	CQR	UQR	CQR
1994	0.13	0.08	0.21	0.16	0.13	0.10	0.09
1995	0.15	0.11	0.20	0.21	0.16	0.11	0.10
1996	0.16	0.13	0.21	0.20	0.17	0.16	0.14
1997	0.14	0.07	0.16	0.19	0.17	0.14	0.11
1998	0.15	0.10	0.20	0.17	0.16	0.06	0.12
1999	0.15	0.10	0.14	0.16	0.14	0.09	0.14
2000	0.13	0.08	0.15	0.17	0.15	0.05	0.09
2001	0.12	0.11	0.15	0.15	0.13	0.06	0.08
2002	0.14	0.10	0.16	0.15	0.15	0.06	0.10
2003	0.14	0.06	0.14	0.18	0.14	0.14	0.11
2004	0.13	0.10	0.15	0.17	0.14	0.09	0.08
2005	0.13	0.08	0.16	0.17	0.14	0.11	0.07
2006	0.12	0.09	0.16	0.15	0.12	0.03	0.09
2007	0.13	0.12	0.16	0.17	0.13	0.10	0.09
2008	0.14	0.11	0.16	0.17	0.15	0.09	0.13
2009	0.14	0.13	0.18	0.17	0.12	0.06	0.10
2010	0.14	0.09	0.14	0.16	0.16	0.08	0.11
2011	0.12	0.09	0.14	0.14	0.14	0.04	0.09
2012	0.14	0.11	0.16	0.18	0.16	0.04	0.11

[1] All robust standard errors (OLS) and bootstrapped standard errors (99 replications) for UQR and CQR are less than .01, thus are neglected in this table.



(a) 1995



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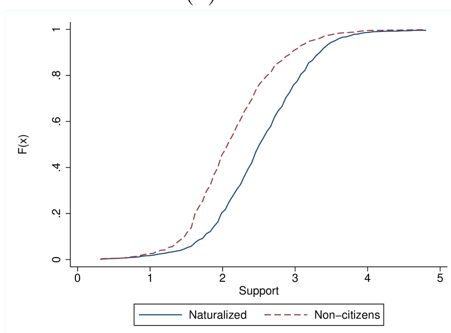
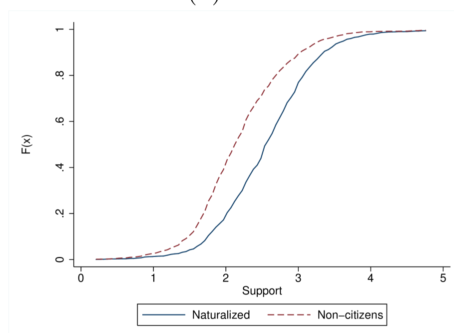
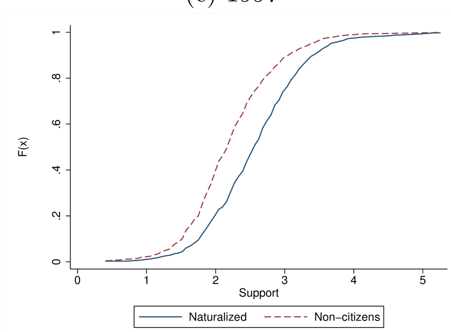


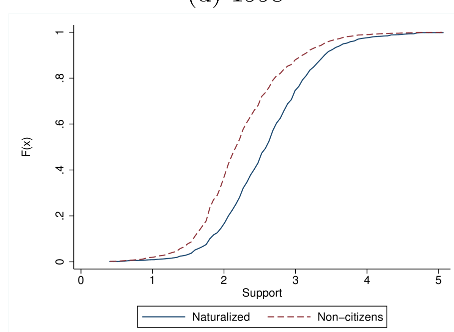
(c) 1997



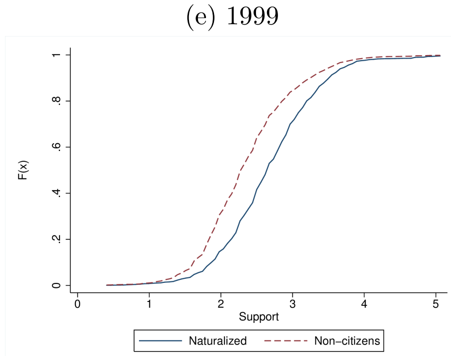
(d) 1998



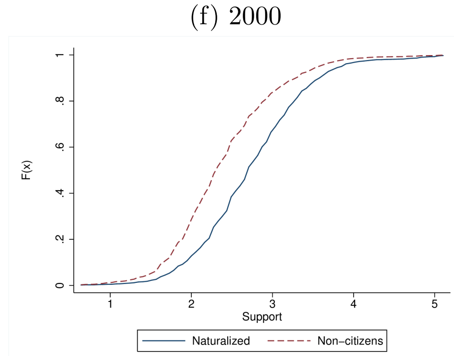
(e) 1999



(f) 2000

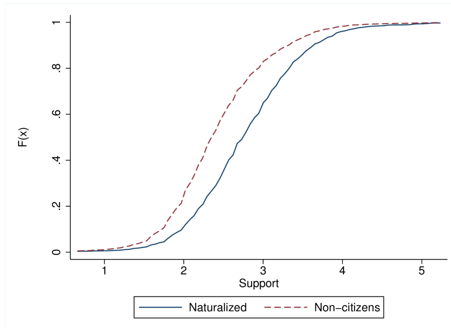


(g) 2001

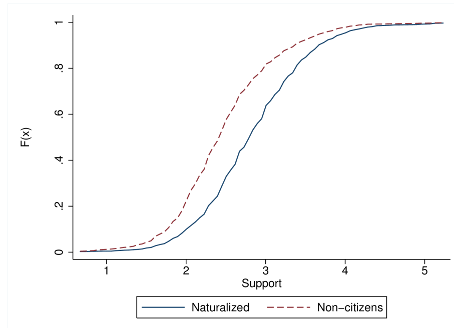


(h) 2002

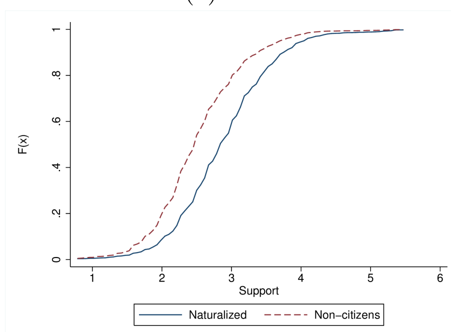
Figure IA.1: CDF Comparisons of Naturalized Citizen and Non-citizen (1994-2012)



(a) 2004



(b) 2006



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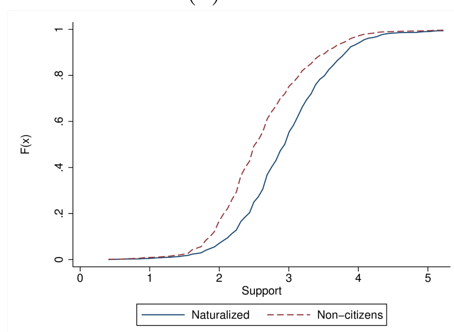

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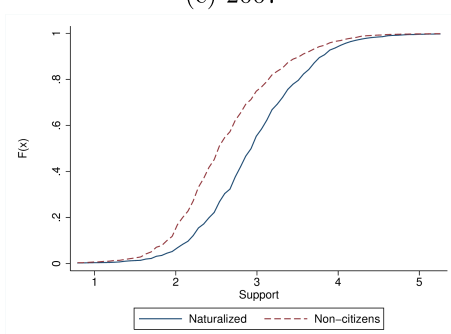

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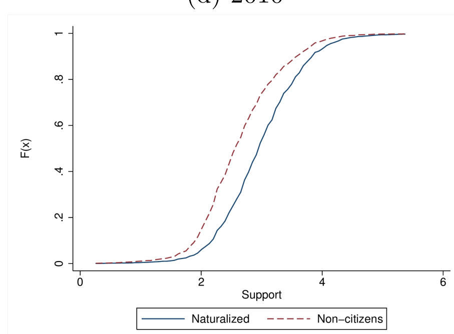

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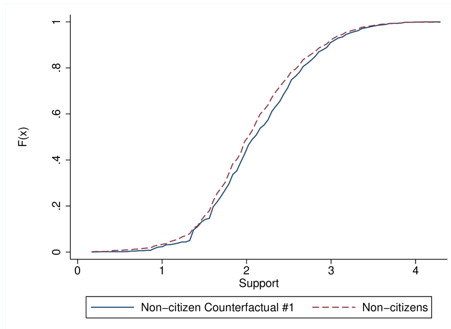
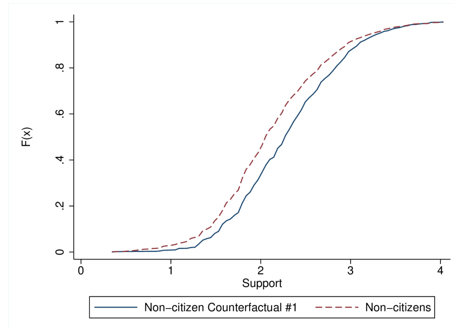
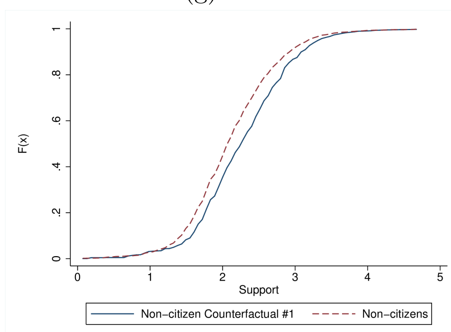
Figure IA.1 (continued)



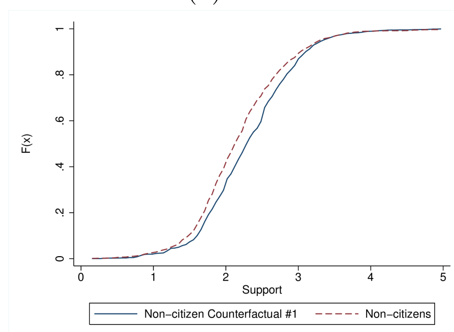
(g) 1994



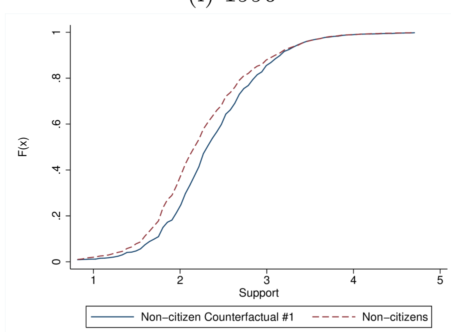
(h) 1995



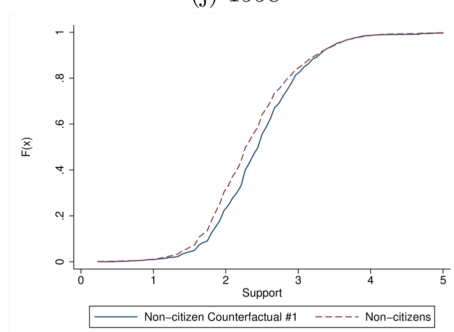
(i) 1996



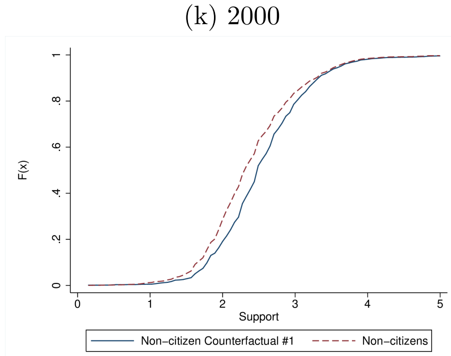
(j) 1998



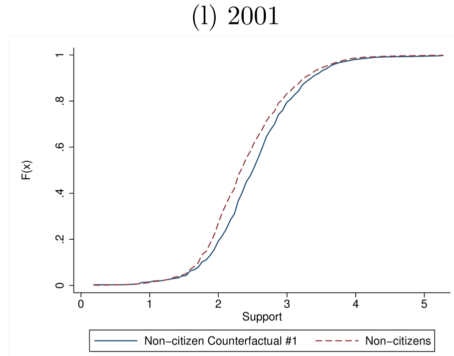
(k) 2000



(l) 2001

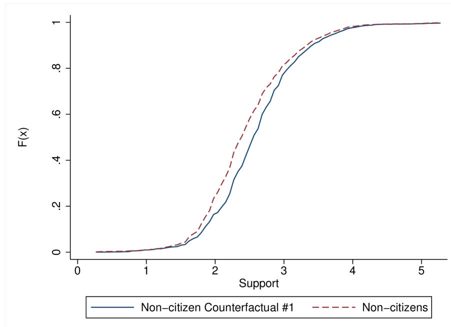


(m) 2002

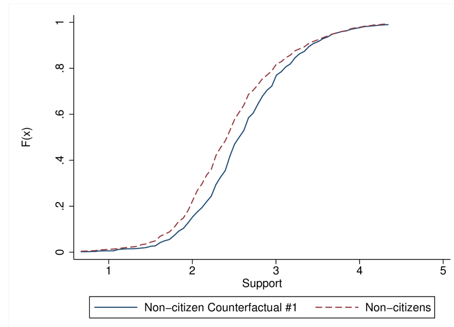


(n) 2003

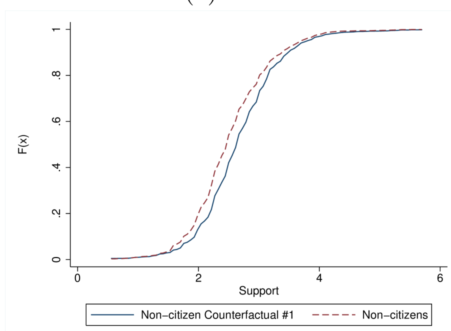
Figure IA.2: CDF Comparisons of Non-citizen Counterfactual # 1 and Non-citizen (1994-2012)



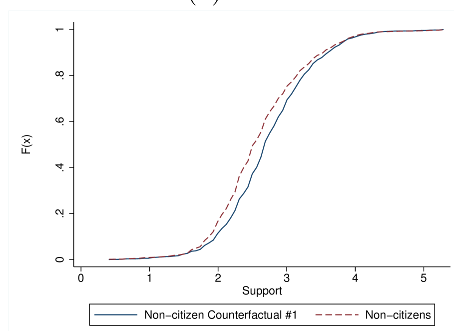
(a) 2005



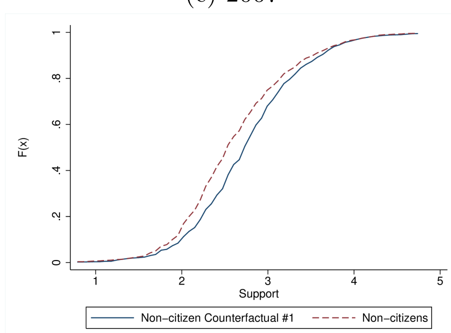
(b) 2006



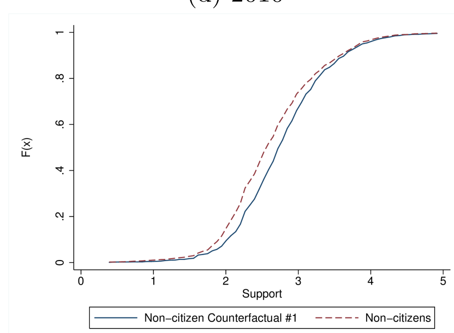
(c) 2007



(d) 2010

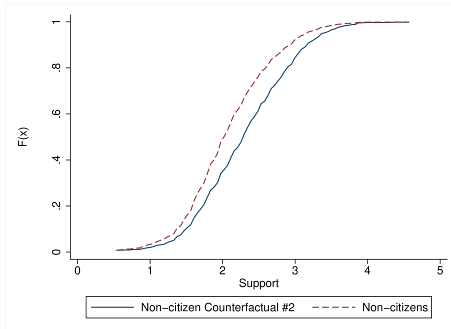


(e) 2011

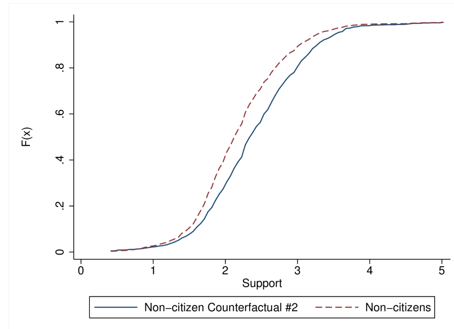


(f) 2012

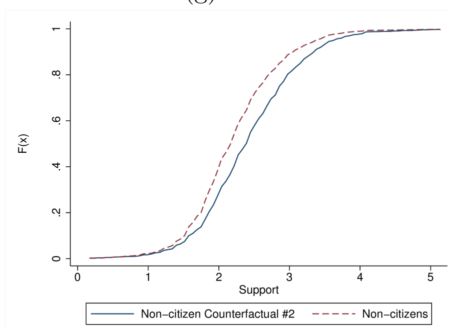
Figure IA.2 (continued)



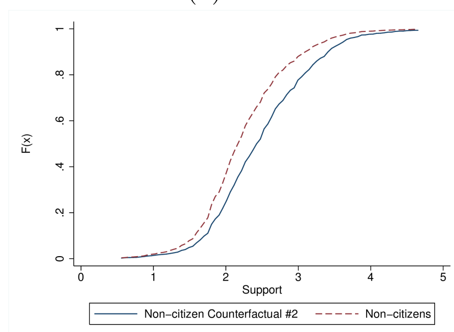
(g) 1994



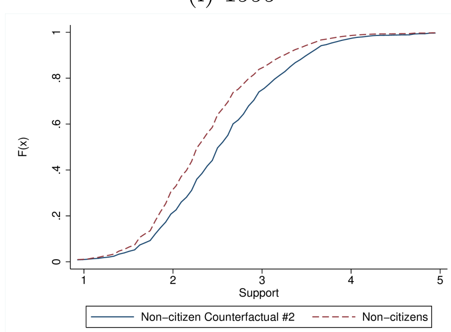
(h) 1998



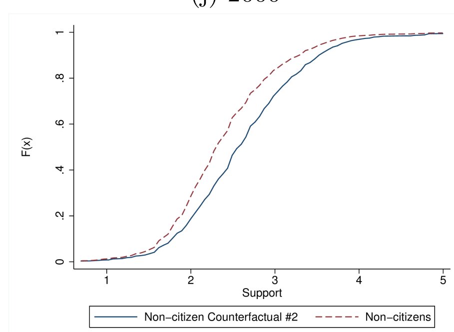
(i) 1999



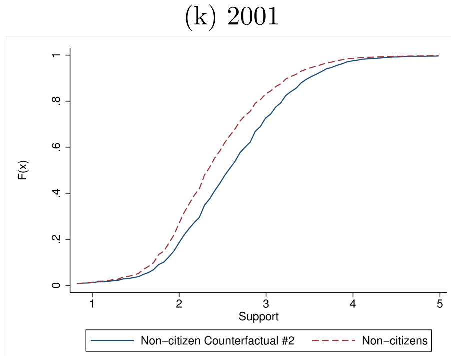
(j) 2000



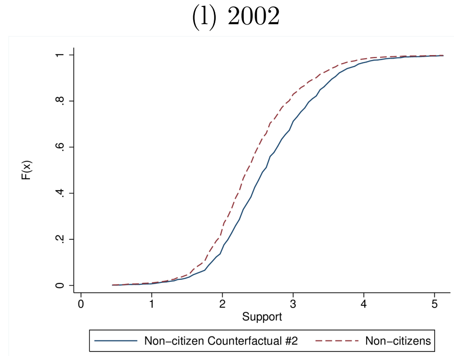
(k) 2001



(l) 2002

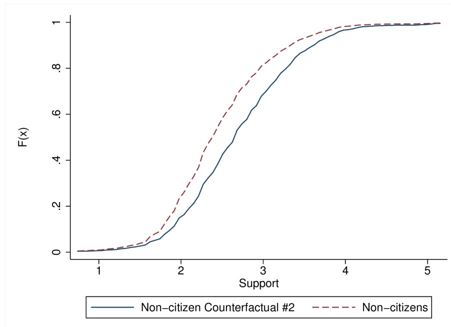


(m) 2003

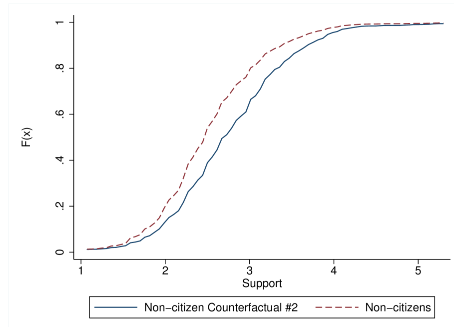


(n) 2004

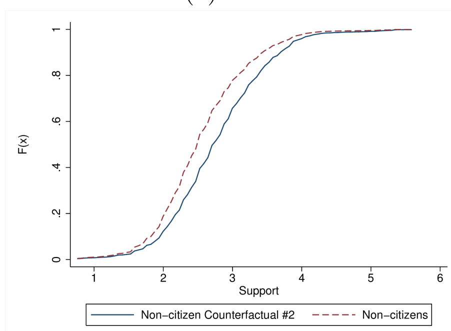
Figure IA.3: CDF Comparisons of Non-citizen Counterfactual # 2 and Non-citizen (1994-2012)



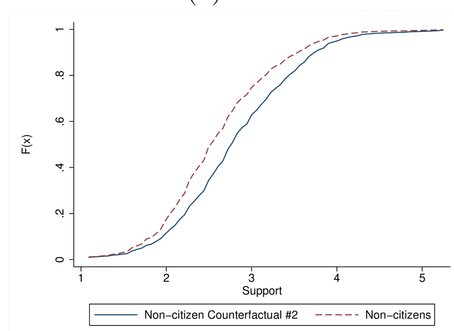
(a) 2005



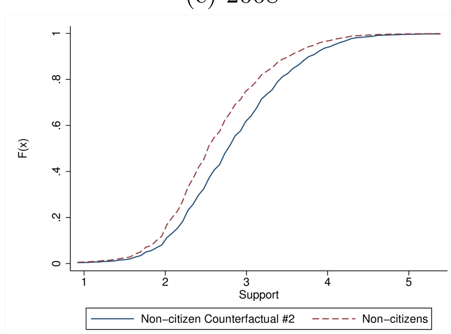
(b) 2007



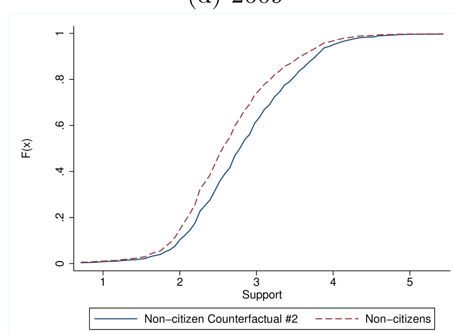
(c) 2008



(d) 2009

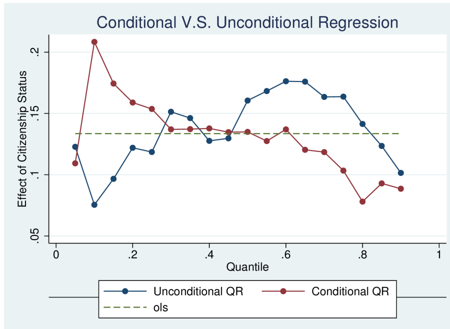


(e) 2011

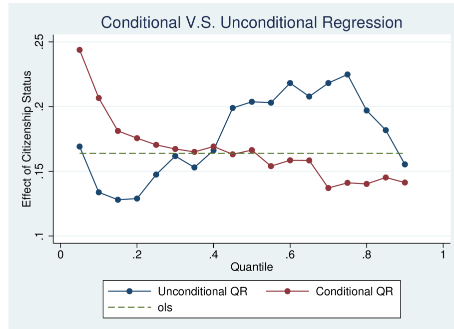


(f) 2012

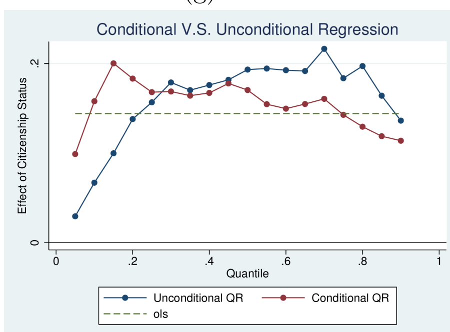
Figure IA.3 (continued)



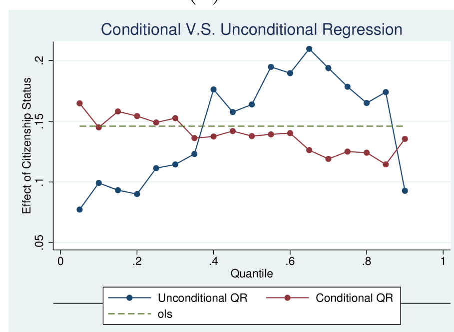
(g) 1994



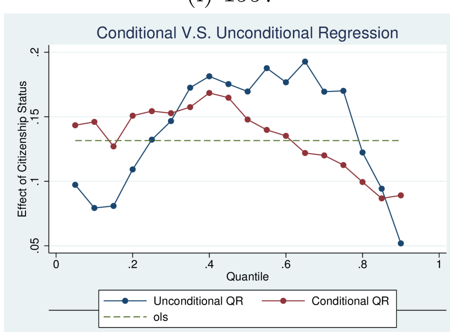
(h) 1996



(i) 1997



(j) 1999



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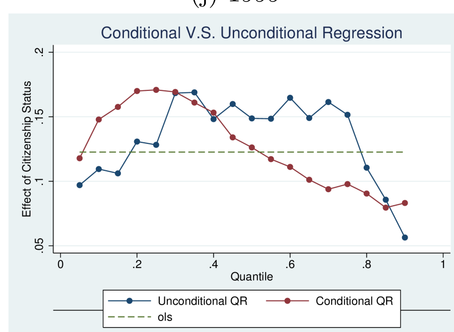
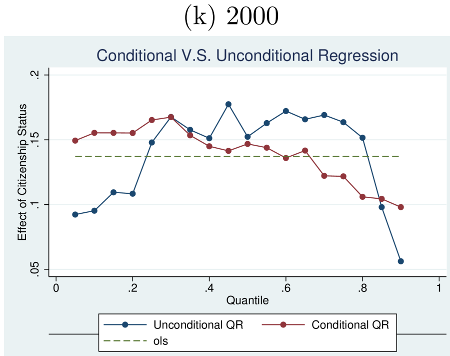


(l) 2001



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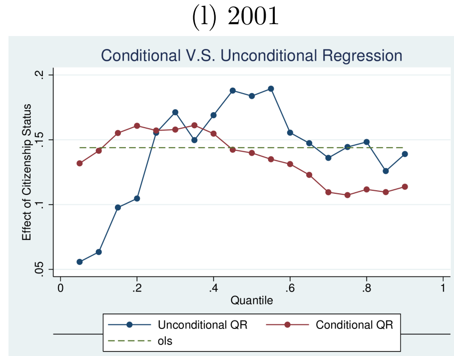
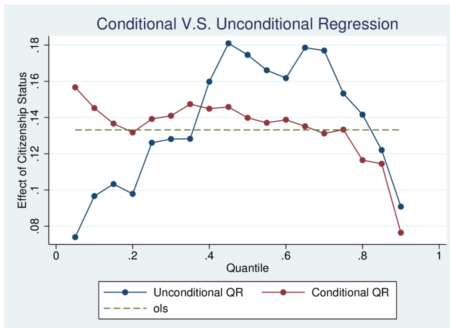
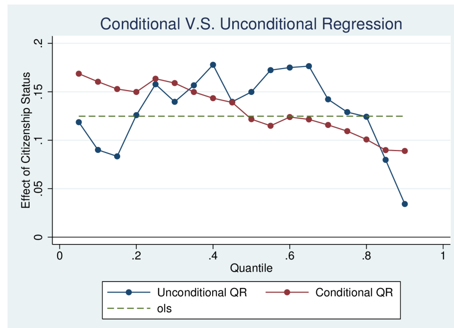


(n) 2003

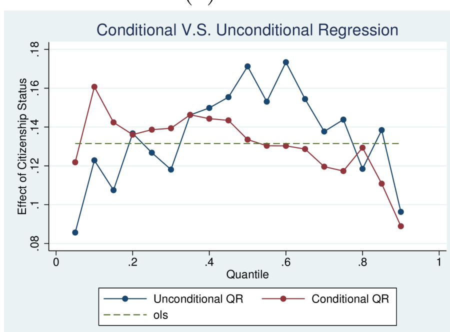
Figure IA.4: Unconditional and Conditional Quantile Regression Estimates of the Effect of Citizenship Status on Log Wages (1994-2012)



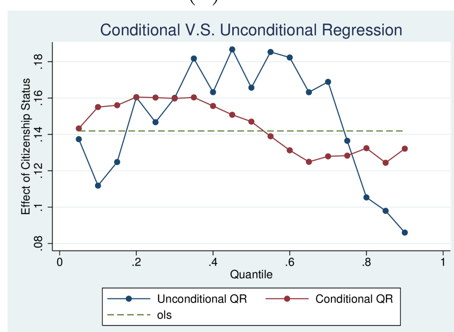
(a) 2004



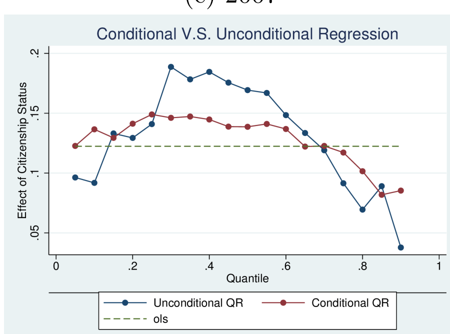
(b) 2006



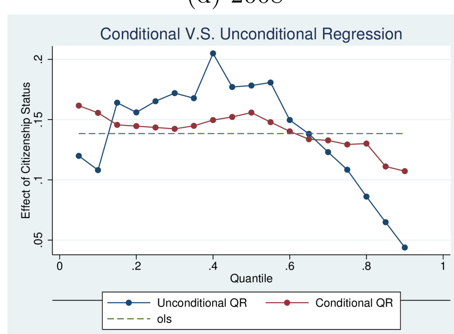
(c) 2007



(d) 2008



(e) 2011



(f) 2012

Figure IA.4 (continued)

Chapter 3

Crude Oil Price Prediction: A Nonparametric Approach

Abstract

In this paper, we propose linear and nonparametric models to predict one month, three months, six months, one year, eighteen months and two years ahead crude oil price in out-of-sample background. Mainly, our forecast depends on three predictor variables, the change in crude oil inventories, its previous prices and product spread. By employing mean-squared prediction error (MSPE) and stochastic dominance (SD) tests, we find that the prediction result of our nonparametric models is significantly better than the random walk model, while the corresponding linear models' performance is better than the random walk model only for longer horizon forecasts (one to two years). In general, for the sample period from 1995.1 to 2015.4, the conclusion is that our model applying nonparametric estimation always outperforms all other models in different horizon forecasting. And for the nonparametric model including all three predictors, we document MSPE reduction as high as 62.6% compared to the random walk model and the directional accuracy ratio as high as 77.5% at the two years horizon.

Keywords: Crude oil price, nonparametric, forecast, random walk, entropy measure, stochastic dominance.

JEL Classification: C53, Q00

3.1 Introduction

There are five main approaches to predict crude oil price. First, professional and survey forecasts. For this method, forecasts can be made on a subjective basis using judgment, intuition, commercial knowledge and any other relevant information. Some academic research focus on the examining the predictability of these professional or survey opinions [see, e.g., Sanders, Manfredo, and Boris (2009); Alquist, Kilian, and Vigfusson (2013)]. Second, oil futures prices forecasts [see, e.g., Knetsch (2007); Alquist and Kilian (2010); Baumeister and Kilian (2012); Alquist, Kilian, and Vigfusson (2013)]. Third, ARMA time series models [see, e.g., Baumeister and Kilian (2012); Alquist, Kilian, and Vigfusson (2013)]. Fourth, predictive regressions including vector auto regressions(VAR). People try to find predictors which could be supported by the economic literature both theoretically and empirically [see, e.g., Ye, Zyren, and Shore (2005); Chen, Rogoff, and Rossi (2010); Baumeister and Kilian (2012); Alquist, Kilian, and Vigfusson (2013); Baumeister and Kilian (2015, 2014a,b); Baumeister, Kilian, and Zhou (2015)]. The last, univariate mixed-data sampling (MIDAS) models which employs distributed lag polynomials to ensure a parsimonious model specification, while allowing for the use of data sampled at different frequencies [see, e.g., Baumeister, Guérin, and Kilian (2015)]. In this paper, we follow the fourth strand of literature while considering about the second and the third as well.

We mainly provide the models with two predictors or three predictors, the inventories, pervious oil prices and including the product spread or not. The inventories can be explained by the economic literature, as the relationship between commodity inventory levels and the short-run price has been studied for nearly a century. Inventories balances supply and demand; it captures seasonality and general trends in production and demand, as well as unexpected supply or demand shifts [see, e.g., Alquist and Kilian (2010); Kilian and Murphy (2014); Kilian and Lee (2014); Baumeister, Guérin, and Kilian (2015)]. We use the crack spread in spot prices to represent the product spread which refers to the approximate ratio in which refined products such as gasoline or heating oil are produced from crude oil. And the most commonly used ratio is 3:2:1 (Following Baumeister, Kilian, and Zhou (2015), they apply product spread models both in futures prices and spot prices), meaning two barrels of gasoline and one barrel of heating oil can be obtained from three barrels of crude oil. The higher the crack spread, the more profit refiners could obtain, more demand for the crude oil to refine.

The regressors we selected are consistent with the current literature. The vector auto regressions(VAR) model includes the percent change in global crude oil production, the Kilian (2009) measure of global real activity (in deviations from trend), the change in global crude oil inventories, and the crude oil price proxy tends to have lower MSPEs compared to the random walk models in short run (1-3 month horizons or 1-2 quarter horizons)forecast[see, e.g., Baumeister and Kilian (2012); Baumeister and Kilian (2014b)]. Baumeister, Kilian, and Zhou (2015) recently found out that some product spread models can predict better than the random walk model does, especially for longer horizon (one to two years).

The one month ahead nonparametric models presented here can predict the crude oil prices very well for the period from 1995.1 to 2015.4.[1] For 3, 6, 12, 18 and 24 months ahead forecasts, nonparametric models' performances are even better which suggesting using non-parametric models instead of linear models for any horizon crude oil forecasting. Although the specific crack spread predictor can not improve the prediction in linear model setting which confirms the finding of Baumeister, Kilian, and Zhou (2015), it can promote the predictability for 6 months beyond horizon forecasting in nonparametric setting according to MSPE and directional accuracy ratio (DAR). Besides linear and nonparametric models, we also provide evaluation and comparison of the forecasts of models including the random walk model and the futures price model. Alquist, Kilian, and Vigfusson (2013) provides a comprehensive evaluation of the forecast accuracy of different types of models. In their paper, they consider the random walk model, the futures price models (We only consider

[1] In the most recent literature, the evaluation period is from 1992.1 to 2012.9[see, e.g., Baumeister and Kilian (2015); Baumeister, Kilian, and Zhou (2015); Baumeister, Guérin, and Kilian (2015); Baumeister, Kilian, and Lee (2014)]. Since we don't have long enough OECD crude oil inventory data points from International Energy Agency(IEA) report, and our models require lag h time period data for h months ahead forecast. The starting time of the out-of-sample evaluation period cannot as early as 1992.1 as it requires more data points for initial estimations.

futures price model in one month ahead prediction since the volume of longer time oil futures' trading is much smaller compared with the one month futures, thus liquidity of longer horizon futures is doubtable which makes them less reliable as predictions), and other predictive models based on the spot price and the futures prices. In addition, Baumeister and Kilian (2015) considers combinations of six existing forecasting models, and demonstrates that this combination model reduces the MSPE by up to 18% at the two-year horizon and significant directional accuracy as high as 77% at 15 month horizon(70% for two-year horizon). Similarly, Baumeister, Kilian, and Lee (2014) also implements the combination of five models, and result in MSPE reduction as high as 29% for two-year horizon and directional accuracy 73% at most. Baumeister, Kilian, and Zhou (2015) and Baumeister, Guérin, and Kilian (2015) document MSPE reductions as high as 20% and 28%; directional accuracy as high as 63% and 70% at the two-year horizon. All last four papers' out-of-sample evaluation periods are the same, from 1992.1 to 2012.9. However, all these complex models considered in Alquist, Kilian, and Vigfusson (2013), Baumeister and Kilian (2015), Baumeister, Kilian, and Lee (2014) and Baumeister, Kilian, and Zhou (2015) including Baumeister and Kilian (2014a,b) are still in specific parametric setting.

Except the linear 3 month ahead models, by employing the entropy method introduced by Maasoumi and Racine (2002), we find that all models introduced here have predictability. And the first order difference linear or nonparametric models including the inventories and pervious prices can provide more accurate predictions than the simple random walk model through the DM-test of Diebold and Mariano (1995)[2]. The reason we utilize the first order difference instead of inventories and pervious prices themselves, is because the unit root tests shows WTI prices (time series till 1994.12) are nonstationary. The entropy method cannot be used for nonstationary series as the empirical distribution for nonstationary is unreliable. Furthermore, the results from Stochastic Dominance (SD) tests (Reference papers are Corradi and Swanson, 2013; Linton, Maasoumi, and Whang, 2005; and Donald and

[2]The CW tests of Clark and West (2006) and Clark and West (2007)(like similar tests in the literature) are biased toward rejecting the null of equal MSPEs [see Alquist, Kilian, and Vigfusson (2013)], It also ignores the real-time nature of the inflation data [see Clark and McCracken (2009)]

Hsu, 2014)suggest only employing nonparametric models instead of all others for different horizons forecasting. Baumeister and Kilian (2015)'s combination model is systematically more accurate than the no-change forecast at all horizons from 1 month to 24 months, which is the first to accomplish this objective. Baumeister, Kilian, and Zhou (2015)'s model is nested inside Baumeister and Kilian (2015)'s model, which could solely beat the random walk model forecast of the real price of crude oil at horizons between one and two years. Here, the nonparametric approach we proposed can beat the the random walk model at all horizons from 1 month to 24 months as well and the results looks even better, MSPE reductions (the real price of oil in levels) as high as 62.6% and directional accuracy as high as 77.5% at the two-year horizon. But the evaluation period runs from 1995.1 to 2015.4.

Following the recent literature on real-time forecast of the real price of oil[see, e.g., Baumeister and Kilian (2012); Baumeister, Kilian, and Zhou (2015); Baumeister and Kilian (2014b); Baumeister and Kilian (2015); Baumeister, Guérin, and Kilian (2015); Baumeister, Kilian, and Lee (2014)], we also adopt to apply real-time data instead of ex-post revised data (Although U.S. CPI index is not the real-time data here). The real-time data is the data released preliminarily, and we don't know whether the performance of the model based on the ex-post revised data is better than the real-time data or not. According to Baumeister and Kilian (2012), not much gains in forecast accuracy when using the ex-post revised data if we use the west Texas Intermediate (WTI) price as the proxy of the crude oil price. WTI spot price is applied as the proxy for the crude oil price here which is commonly used in the literature. Another widely used crude oil price proxy is the U.S. refiner' acquisition cost for crude oil imports which doesn't investigated here.

Whether researchers can provide better forecasts than the random walk model is a hot issue in the literature. This is not just only in the commodities' market. In finance, analysts' earnings per share (EPS) forecasts are commonly used and people believe it is superior to random walk (RW) time-series forecasts[Brown and Rozeff (1978); Fan, So, and Yeh (2006)]. However, Bradshaw et al. (2012) reexamined the result recently and found that this is not always true. Recently, a few papers proposed in the crude oil price literature and point out the naive no-change forecast could be beat[see, e.g., Baumeister, Guérin, and Kilian (2015); Baumeister, Kilian, and Zhou (2015); Baumeister and Kilian (2015); Baumeister, Kilian, and Lee (2014)]. Our paper confirms their results by providing a new econometric forecasting approach and result.

The linear predictive models including inventories and pervious prices predictors are named M1-OLS1, M3-OLS1, M6-OLS1, Y1-OLS1, M18-OLS1 and Y2-OLS1 for 1 month ahead, 3 months ahead, 6 months ahead, 1 year ahead, 18 months ahead and 2 years ahead prediction respectively while M1-NP1, M3-NP1, M6-NP1, Y1-NP1, M18-NP1, and Y2-NP1 are their corresponding nonparametric model versions. When adding the predictor-crack spot spread, the models names are M1-OLS2, M3-OLS2, M6-OLS2, Y1-OLS2, M18-OLS2 and Y2-OLS2 together with M1-NP2, M3-NP2, M6-NP2, Y1-NP2, M18-NP2, and Y2-NP2.

In section 2, we will present our data and one month ahead predictive models and in the following section, the one month ahead models's predictability and comparison of their accuracy will be checked. In section 4, we will provide longer horizon forecasts including 3, 6, 12, 18, and 24 months to check whether we can still obtain better models comparing to the random walk models from 1995.1 to 2015.4. Then in section 5, we utilize stochastic dominance tests to enrich the advantages of our models, especially the nonparametric model. Section 6 concludes.

3.2 Data and One Month Ahead Predictive Models

3.2.1 Data

Data on crude oil prices including spot and futures prices, inventories, and crack spread were collected from 1988 to the beginning of 2015, and we use the data till the December of 1994 as the training set.

In the paper, the real WTI oil price is utilized to represent oil price(Jan. 1986 as the base month for real price). The real WTI oil spot price is obtained by using U.S. CPI(obtained from US. Bureau of Labor Statistics) as the deflator. And since adopting monthly frequency, we utilize monthly averaging WTI crude oil spot price from the Energy Information Administration (EIA) from Jan. 1986 to Apr. 2015 (Cushing, OK WTI spot price FOB, see Figure 3.1 (a)). One month New York Mercantile Exchange (NYMEX) crude oil futures price also could be obtained from EIA for the same period.

Monthly OECD industry of crude oil stock data was collected from Dec. 1987 till Mar. 2015, which denotes inventories' variable. The data is released in Table titled "OECD Industry Stocks and Quarterly Stock Changes" of the International Energy Agency(IEA) monthly oil market report except for the beginning period from Dec. 1987 to Dec. 1991. The data before Jan. 1992 comes from IEA annual report of 1992 as IEA start to release the OECD industry of crude oil stock data in its monthly report from Jan. 1992. The measure system also changes in IEA report. For the original data publication, crude oil stock is measured in millions of tons before May 1994, then switch to millions of barrels. And before Sept. 1992, the monthly report use the opening stock as the monthly stock, then changes to the closing stock level. Thus, we utilize the opening stock before Sept. 1992, and then the closing stock as the monthly crude oil stock proxy. And for the transformation of tons and barrels, we choose IEA 1997 annual report, since it release the stock data in millions of barrels for the period Dec. 1992 to Apr. 1994. And the corresponding millions of tons data observed from the previous monthly reports, then the conversion ratio of the two measure systems is calculated out based on the average ratio of two comparable data, which used to change all data before May 1994 to measure in millions of barrels. The conversion ratio is that 1 ton equals 8.58 barrels for crude oil.

In addition, we generally use real time data or more explicitly, the first time released data. The first time to release monthly crude oil stock data is usually one and half month later. For example, the closing stock of January 2015 will be published in March 2015 IEA monthly report. There are two exceptions, stock data from Dec. 1987 to Dec. 1991 is based on IEA 1992 annual report while Jan. 1992, Feb. 1992, Jun. 1995, and Nov. 1998 month stock data is obtained from first available monthly reports since the first time released month reports are missing.

For calculating the crack spread, we use EIA released New York Harbor conventional gasoline regular price and New York Harbor No.2 heating oil to denote the gasoline and heating oil spot price respectively. Both spot prices periods are from Jun. 1986 to Mar. 2015. The prices for gasoline and heating oil are reported in dollars/gallon, and we use conversion rate 1 barrel = 42 gallons to change the prices measure in dollars/barrel since the crude oil price is measured in dollars/barrel. Then the crack spread spot price (see Figure 3.1 (b)) is expressed as

$$\frac{2}{3}P_t^{gasoline} + \frac{1}{3}P_t^{heatingoil} - WTI_t. \tag{3.1}$$

[Insert Figure 3.1 about here]

3.2.2 Unit Root Test

Furthermore, we impose unit root tests (Augmented Dickey and Fuller (ADF) test and DF-GLS test proposed by Elliott, Rothenberg, and Stock, 1996[3]), Table IA.25 in the Appendix A.2 shows that for the WTI real price, the crack spread and oil inventory, the existence of the unit root cannot be rejected at 5% significance level based on ADF test. Thus, we need to take the first order differences of them to obtain stationary series, which allowing us to employ the entropy measurement for the forecasting performance check.

3.2.3 Predictive Models

At first, we propose two one month ahead out-of-sample forecasting models. The models and the forecasting results are shown as follows (Equation (3.2-3.3) and Fig. (3.2-3.3)).

$$\triangle WTI_{t+1} = g_1(\triangle WTI_t, \triangle Inv_t) + \epsilon_{t+1}, \tag{3.2}$$

[3]We consider DF-GLS test for the detrending time series here as a complement of ADF test, Elliott, Rothenberg, and Stock (1996) and later studies have shown DF-GLS test has greater power than the ADF test.

$$\triangle WTI_{t+1} = g_2(\triangle WTI_t, \triangle Inv_t, \triangle Spread_t) + \epsilon_{t+1}, \tag{3.3}$$

Where WTI_t is the real WTI crude oil spot price, $Spread_t$ is the real spot crack spread and ϵ_{t+1} is the error term. And $\triangle WTI_{t+1} = WTI_{t+1} - WTI_t$.

The data is divided into two subperiod, the first subperiod from 1988.1 to 1994.12 is treated as the training set for the initial estimation and the second subperiod is utilized as a test set. Our method is as follows, using the training set to get the estimation of coefficients of the model, and use it to forecast Jan. 1995's oil price. Then we updated our estimation of coefficients by adding Jan. 1995's observation to the training set, and use it to predict crude oil price in Feb. 1995. By repeating it, we could obtain one-month-ahead out-of-sample predictions from Feb. 1995 to Apr. 2015. This is called a recursive scheme. And we will conduct our forecast for both models including the crack spread or not.

First, we compare our real price predictions by OLS estimations with the actual price in Figure 3.2. The upper part of Figure 3.2 reflects the result for Model (3.2) assuming g_1 is the linear function, and lower one is the result for Model (3.3) assuming g_2 is the linear function. The area between lower bound and higher bound contains 90% confidence intervals([mean-1.645×standard error, mean+1.645×standard error]). Since we apply recursive scheme estimation, the estimation standard error updated after adding each test set month. Then, we repeat the comparison between predictions by using the local linear nonparametric estimation (Li and Racine (2004), briefly described in Appendix A.1) with the actual price in upper part of Figure 3.3, and the area between lower bound and higher bound contains 90% confidence intervals([mean-1.645×standard error, mean+1.645×standard error]).

The lower part of Figure 3.3 shows the forecasting results of the random walk and the futures price model. These two models are alternative prevailing models to predict WTI spot crude oil price. Throughout our paper, the random walk model is the benchmark model, we want to test its predictability by entropy method and comparing it with other models later. Simultaneously, one month futures price provides next month crude oil spot price prediction as well. Examining the result of Figure 3.3, the gap between one month futures price and the current spot price is very tiny as the random walk model prediction almost coincides the prediction by the futures price.

To make the forecasting accuracy more clear, the detailed comparison of different models froecasts is shown in Figure 3.4 and the following section. Figure 3.4 shows the forecast errors for one month's ahead prediction for all models except the futures price model. The black solid line denotes our benchmark model-Random Walk model forecast errors, while blue line and red line denote the linear models and nonparametric models' forecast errors respectively. Intuitively, the nonparametric models' predictions are the best. NP models' performance is especifically better during the high fluctuation period comparing with other models, 2008-2009 for example.

Here we only focus on the out-of-sample forecast, and the result of in-sample-fitting linear model analysis is presented in Table IA.26 of Appendix A.2.

[Insert Figure 3.2 about here]

[Insert Figure 3.3 about here]

[Insert Figure 3.4 about here]

3.3 The Predictability and Model Comparison for One Month Ahead

This section is devoted to compare the predictability between all one month ahead models through utilizing entropy method introduced by Maasoumi and Racine (2002), MSPE and directional accuracy ratio (DAR). All three methods will be used in the following section for longer horizon forecasts performance tests as well. We find that the the all models except the linear 3 months ahead models introduced have predictability as the dependence between the first order difference predictions and the observations is significant due to the entropy results. When using entropy measurement, we implement the bootstrapping method. In addition, we also implement the DM-test of Diebold and Mariano (1995) to check whether the predictions of our one month ahead models are significantly better than the random walk model and the futures price model.

At first, we introduce the nonparametric entropy measure of dependence, as suggested in Granger, Maasoumi, and Racine (2004), Maasoumi and Racine (2002). We believe entropy measure is better in detecting dependence structure than traditional moment-based measures as it is a function of infinite moments of the underlying probability density function (PDF). That is also the reason it requires series to be stationary. The traditional loss functions like mean-squared prediction error (MSPE) can only capture the first and second moments. A normalized Bhattacharya-Matusita-Hellinger measure of dependence is defined as follows:

$$S_{\rho 1} = \frac{1}{2}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(f^{1/2} - f_1^{1/2}f_2^{1/2})^2 dxdy, \tag{3.4}$$

where $f = f(x, y)$ is the joint density and $f_1 = f(x)$ and $f_2 = f(y)$ are the marginal densities of the random variables X and Y. If X and Y are independent, this metric will yield the zero, otherwise it is positive and smaller than 1.

This entropy $S_{\rho 1}$ could be utilized as in-sample goodness-of-fit measure and a test of out-of-sample predictive performance. In our paper, we use it for the out-of-sample predictive performance test, $x = \triangle WTI_t$ is still the actual first order difference of the crude oil prices, but $y = \triangle\widehat{WTI_t}$ now denotes the forecast values. We could rank the model's predictability through $S_{\rho 1}$, the higher the better. In addition, we use the bootstrap resampling approach to obtain our entropy results shown in Table IA.26 and Table 3.1. Bootstrap could improve the asymptotic approximation for our entropy measures.

Based on the result reported in Table 3.1, both nonparametric models have higher entropy $S_{\rho 1}$ and directional accuracy ratios, indicating better out-of-sample forecast performance. And due to the MSPE criterion of Panel B, our nonparametric models have lowest figures among all models. In general, all models including the driftless random walk model and the futures price model have predictability. Both NP models have better performance comparing to our benchmark model(RW model) based on any of three criteria. People may also concern about our specific evaluation period for the documented MSPE result in Table 3.1. Then Figure 3.5 shows the evolution of the recursive MSPE ratio over time, the start time is still 1995.1, but the end time varied from 2000.1 to 2015.4. From the graph, our NP models' MSPE ratios are consistently less than 1 after 2005.

[Insert Table 3.1 about here]

[Insert Figure 3.5 about here]

3.4 The Models for Longer Horizon Forecasts

In this section, we modified previous one month ahead predictive model (3.2) to obtain the 3 months, 6 months, 1 year, 18 months and 2 years ahead out-of-sample forecasting models. (see Equation (3.5-3.6)).

$$WTI_{t+h} - WTI_t = g_1(WTI_t - WTI_{t-h}, Inv_t - Inv_{t-h}) + \epsilon_{t+h}, \quad (3.5)$$

$$WTI_{t+h} - WTI_t = g_2(WTI_t - WTI_{t-h}, Inv_t - Inv_{t-h}, Spread_t - Spread_{t-h}) + \epsilon_{t+h}, \quad (3.6)$$

here $h = 3, 6, 12, 18, 24$ months. WTI_t is the real WTI crude oil spot price, $Spread_t$ is the real spot crack spread and ϵ_{t+1} is the error term.

For longer horizon forecasting, we still utilize the first order difference of the price in the model. Entropy, MSPE and Directional Accuracy Ratio (DAR) methods are used for out-of-sample performance check. We follow the approach introduced before for longer horizon forecasting background to conduct out-of-sample forecasting. The data is divided into two subperiod, the first subperiod from 1987.12 to 1994.12 is treated as the training set and the second subperiod is utilized as the test set. After dividing, from the training set, we obtain the estimation of coefficients of the model, and use it to forecast next month's oil price. Then updating our estimation of coefficients by adding the new observation to the training set, we could predict oil price of the following new month. By repeating it, we could obtain 3, 6, 12, 18, and 24 months out-of-sample predictions till April 2015, respectively. The same recursive scheme we applied in section 2.

The out-of-sample forecasts results are presented in Table (3.2) and Fig. (3.9-3.12). For each specific model, MSPE is increasing when the forecasting horizon becomes longer until 18 months ahead (See Table (3.2)). From Table (3.2), the linear models' predictabilities are significant better compared with the random walk models except for the 3 and 6 months ahead forecasting assuming the level of significance is 5% based on the DM-test of Diebold and Mariano (1995). One of our contribution is that the nonparametric models can always substantially and significantly reduce the MSPE and increase the DAR, recommending us to use nonparametric models instead of linear models for longer horizon forecasts.

To be robust, following the similar recursive scheme report of MSPE ratio as in the previous section, we document the evolution of the recursive MSPE ratio with varied ending time from 2000.1 to 2015.4 in Figure (3.6-3.8). And the start time for out-of-sample squared prediction error calculation is 1995.1. From the graph, our NP models' MSPE ratios are consistently less than 1 except for the 3 months ahead forecast period 2000-2004.

From the Figures (3.9-3.12), there always exist lagged response for linear model predictions. However, the nonparametric setting could solve this situation quite well although it still misses the 2007-2009 spike during the current financial crisis especially for 18 months ahead forecasting. Additionally, Figure (3.13-3.15) show the forecast errors for all our proposed models with the random walk model. Based on the graphs, our NP models' performance is better during the high fluctuation period for any different length horizon forecasts.

[Insert Table 3.2 about here]

[Insert Figure 3.6 about here]

[Insert Figure 3.7 about here]

[Insert Figure 3.8 about here]

[Insert Figure 3.9 about here]

[Insert Figure 3.10 about here]

[Insert Figure 3.11 about here]

[Insert Figure 3.12 about here]

[Insert Figure 3.13 about here]

[Insert Figure 3.14 about here]

[Insert Figure 3.15 about here]

3.5 Robustness Check-Stochastic Dominance

Additionally, we employ tests for the first and second order stochastic dominance (SD) to explore the social welfare comparisons of the negative absolute error. To compare predictive accuracy among forecast models, Corradi and Swanson (2013) suggests using SD tests. In our discussion here, we only concern whether our models such as the linear model, the nonparametric model and the futures price model can predict better results than the random walk model does. Take the first order SD for example, if the linear model's negative absolute error cumulative distribution functions (CDF) lies below the random walk model's, then the linear model is the first order SD the random walk model. The advantage of the SD approach is that the comparison is across the whole distribution, and the inability to infer a dominance relation indicating that any ranking must be based on a particular welfare function, in other words, the conclusion is subjective.

Let X_1 and X_2 be two variables (is the negative absolute prediction error (NAPE) in our case[4]). Let $X_{kt}, k = 1, 2$ denote the not necessarily i.i.d. observations. Let $F_1(x)$ and $F_2(x)$ denote the CDFs, repectively. The definitions of stochastic dominance are as follows:

First Order Dominance: *X_1 First Order Stochastic Dominates X_2 (denoted X_1 FSD X_2) if and only if*

1. $E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_1$ with strict inequality for some u;

2. Or, $F_1(x) \leq F_2(x)$ for all y with strict inequality for some x,

where U_1 denotes the class of all (increasing) von Neumann-Morgenstern type of social welfare functions u such that welfare is increasing in wages (i.e. $u' \geq 0$).

Second Order Dominance: *X_1 Second Order Stochastic Dominates X_2 (denoted X_1 SSD X_2) if and only if*

1. $E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_2$ with strict inequality for some u;

2. Or, $\int_{-\infty}^{x} F_1(t)dt \leq \int_{-\infty}^{x} F_2(t)dt$ for all x with strict inequality for some x,

where U_2 denotes the class of social welfare functions in U_1 such that $u'' \leq 0$ (i.e. concavity).

To test if X_1 FSD (SSD) X_2, we formulate our hypotheses as:

$$H_0 : F_1(x) \leq F_2(x)(H_0 : \int_{-\infty}^{x} F_1(t)dt \leq \int_{-\infty}^{x} F_2(t)dt) \quad for\, all\, x \in X, \tag{3.7}$$

$$H_1 : F_1(x) > F_2(x)(H_0 : \int_{-\infty}^{x} F_1(t)dt > \int_{-\infty}^{x} F_2(t)dt) \quad for\, some\, x \in X. \tag{3.8}$$

Unlike Linton, Maasoumi, and Whang (2005) and Maasoumi and Zhu (2015), we only consider one direction check of SD, which is the same as McFadden (1989) and (Donald and Hsu (2014)).

The Kolmogorov-Smirnov test statistics for X_1 FSD or SSD X_2 is given by

$$d = \sqrt{\frac{N_1 N_2}{N_1 + N_2}} \sup[F_1(x) - F_2(x)], \tag{3.9}$$

$$s = \sqrt{\frac{N_1 N_2}{N_1 + N_2}} \sup \int_{-\infty}^{y} [F_1(x) - F_2(x)]dt. \tag{3.10}$$

[4]SD tests determine the social welfare ranking. For our case, we assume the utility is a function of negative absolute prediction error

Here N_1 and N_2 denote the sample sizes of X_1 and X_2 respectively. To estimate these test statistics, we replace CDF by empirical CDF (for example, $\hat{F}_1(x) = \frac{1}{N_1}\sum_{i=1}^{N_1} I(X_i \leq x)$), where $I(\cdot)$ is an indicator function. Additionally, 299 replications of recentering weakly dependent bootstrap technique [5] following Donald and Hsu (2014)'s method are implemented here to obtain the robustness check of the results. If Probability$[d \leq 0]$ is large enough, say 0.95, and $\hat{d} \leq 0$, then FSD is statistically significant. Similar definition for SSD statistical significance.

Let X_1 denotes the negative absolute forecast error from our models other than the random walk model, and X_2 denotes negative absolute forecast error from the random walk model. If we could find significant SD evidences, we believe our models are better than the random walk model. If not, from SD aspect, our preference is based on the specific welfare function.

The SD results are presented in Table 3.3. And Panel A shows the one month ahead forecasting SD result. Take the linear model M1-OLS1 against RW model for example, Both $d = 0.815$ and $s = 0.122 > 0$, indicating that model M1-OLS1's forecast cannot FSD or SSD RW model's. p value following d equals $0.033 < 5\%$ even reject the H_0 M1-OLS1 FSD RW assuming 5% significance level. But for the M1-NP1 versus RW model, $s = -0.012$, and $P[s \leq 0] = 0.950 >= 95\%$, meaning that model M1-NP1's forecast SSD RW model's.

In general, based on Table 3.3, the nonparametric models (Except for the model without crack spread predictor for six months ahead) significantly SSD (5% significance level) the random walk model for one month, three months, and six months ahead forecasting. The performance of the nonparametric models is even better for longer horizon forecasting, as the nonparametric model including the crack spread significantly FSD the random walk model. This finding is consistent with entropy, MSPE and DAR results pointed out above. However, we can not find the linear models or the futures price model first or second order significantly SD the random walk model for 1 month to 18 month ahead forecasting, suggesting us using nonparametric model instead of the linear model. Additionally, Figures

[5] By using entropy $S_{\rho 1}$ introduced by Maasoumi and Racine (2002), the independence of NAPEs is rejected. I wonder like to thank Tong Xu to provide the code.

(3.16-3.19) display the empirical cumulative distribution functions of the negative absolute forecast error between the random walk model with other mentioned models.

[Insert Table 3.3 about here]

[Insert Figure 3.16 about here]

[Insert Figure 3.17 about here]

[Insert Figure 3.18 about here]

[Insert Figure 3.19 about here]

3.6 Conclusions

In this paper, we develop linear and nonparametric models based on the previous prices, inventories and crack spot spread to conduct 1 month, 3 months, 6 months, 1 year, 18 months and 2 years ahead out-of-sample forecasting for WTI real prices. Both OLS and nonparametric estimations are implemented. Except for 3 month linear forecast models, all these models have predictability based on the entropy measure. And for longer horizon forecasts (one to two years), all linear and nonparametric models perform better compared to the random walk model. For the specific period from 1995.1 to 2015.4 considered in our paper, nonparametric models' performance is the best among all models for any horizon forecast, 1 months, 3 months, 6 months, 1 year, 18 months and 2 years ahead.

In the literature, Researchers also include other predictors to predict, such as excess production capacity, or capacity utilization rate, cumulative excess capacity, exchange rate, and aforemention global crude oil production, global real economic activity together with other product spreads. The papers [Dixit and Pindyck (1998); Dahl and Yücel (1991); Kaufmann et al. (2004)] confirm excess production capacity could be an important explanatory variable. Enzler, Johnson, and Paulus (1976), and Stevens and Adams (1986) use the cumulative excess capacity in their models. Ye, Zyren, and Shore (2006), and Ye et al. (2009) use both of them for forecasting oil price besides inventory. Energy Information Administration (EIA) releases monthly reports of OPEC's expected near future's surplus of crude oil production which can be used as a proxy of excess production capacity expectation after 2007.10. The data available time period is still too short weaken its effectiveness test. Chen, Rogoff, and Rossi (2010) discovered that the "commodity currency" exchange rates have surprisingly robust power in predicting commodity prices inspire us considering exchange rate as the regressor. Recently, Baumeister and Kilian (2012), Baumeister and Kilian (2014b), and Baumeister and Kilian (2015) show out the importance of global crude oil production and global real economic activity for more accurate forecasting in linear model setting. In addition, through an empirical test, Baumeister, Kilian, and Zhou (2015) find that other product spread such as gasoline spread can predict better than the random walk model does, especially for longer horizon (one to two years). Adding or replacing our current predictors with these predictors in our nonparametric models may further increase the predictability power in specific periods.

Appendix

A.1 Nonparametric Method

The nonparametric method implemented in this article is the local linear nonparametric method proposed by Li and Racine (2004)[Li and Racine (2004)]. The method is based on the following minimization problem:

The general regression model form is

$$Y_i = g(X_i) + u_i, \quad i = 1, ..., n, \tag{3.11}$$

here (Y_i, X_i) are sample realizations.

$$\min_{a,b} \sum_{i=1}^{n} (Y_i - a - (X_i - x)'b)^2 K(\frac{X_i - x}{h}), \tag{3.12}$$

here $K(\cdot)$ is the kernel function, h is the bandwidth.

The optimal bandwidth selection for (3.12) here is crucial, we use least squares cross-validation to choose h to minimizes the integrated squared error of the resulting estimate. And for our paper, we always update the new optimal bandwidth after adding the new test month as recursive scheme is applied.

The integrated squared difference between $\hat{f}$ and f is

$$\int [\hat{f}(x) - f(x)]^2 dx, \tag{3.13}$$

$$CV_f(h_1, ..., h_s) = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \bar{K}_h(X_i, X_j) - \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j \neq i, j=1}^{n} K_h(X_i, X_j), \tag{3.14}$$

where

$$K_h(X_i, X_j) = \prod_{s=1}^{q} h_s^{-1} k(\frac{X_{is} - X_{js}}{h_s}),$$

$$\bar{K}_h(X_i, X_j) = \prod_{s=1}^{q} h_s^{-1} \bar{k}(\frac{X_{is} - X_{js}}{h_s}),$$

and $\bar{k}(v) = \int k(u)k(v-u)du$ is the twofold convolution kernel derived from univariate kernel function $k(\cdot)$.

Interested researchers could read [Li and Racine (2007)] for details.

A.2 Unit Root Test and In-Sample-Fitting

We impose unit root tests (Augmented Dickey and Fuller (ADF) test and DF-GLS test proposed by Elliott, Rothenberg, and Stock, 1996, Table IA.25 shows that for the WTI real price and the crack spread, the existence of the unit root cannot be rejected at 1% significance level. And for inventory variable series, we cannot reject unit roots at 1% significance level based on ADF test too. Thus, we need to take the first order differences of WTI prices to obtain stationary series, which allow us employing the entropy measurement for the forecasting performance check.

[Insert Table IA.25 about here]

Table IA.26 provides the OLS estimation results based on the linear specification in equation (3.2-3.3) for the sample period from Dec. 1987 to Apr. 2015. As expected, the change of the WTI price is positively related with WTI price change of the most recent month, while positive changing inventory level has a negative impact on the spot prices. The positive changing spread has a positive impact on the spot price coincide common sense, higher spread means more profits for refiners, then the demand of the crude oil will increase. However, both two predictors, inventory level and the spread are insignificant at 5% significance level. Adj. R^2 helps us to measure the goodness-of-fit [6].

[Insert Table IA.26 about here]

The OLS estimation results for longer horizon in-sample-fitting are reported in Table

[6] Adj. R^2 in Table IA.26 is low due to the first order difference treatment while unit root cannot be rejected

IA.27, which expresses three vital messages. First, except for the 3 month ahead, the negative coefficients in front of previous price changes imply the negative relationship between current price changes and previous ones, and all coefficients results are significant at 5% significance level. Second, for long horizon forecasting models (1 year, 18 months and 2 years ahead), the positive coefficients of the change of inventories suggest that the oil price will go up when the inventory level increases, but for 6 months ahead forecasting models, this relationship is significantly negative if assuming 5% is the level of significance. Third, the crack spot spread predictor is insignificant for most of the models except for the 1 year ahead model. However, the crack spread helps in nonparametric setting.

[Insert Table IA.27 about here]

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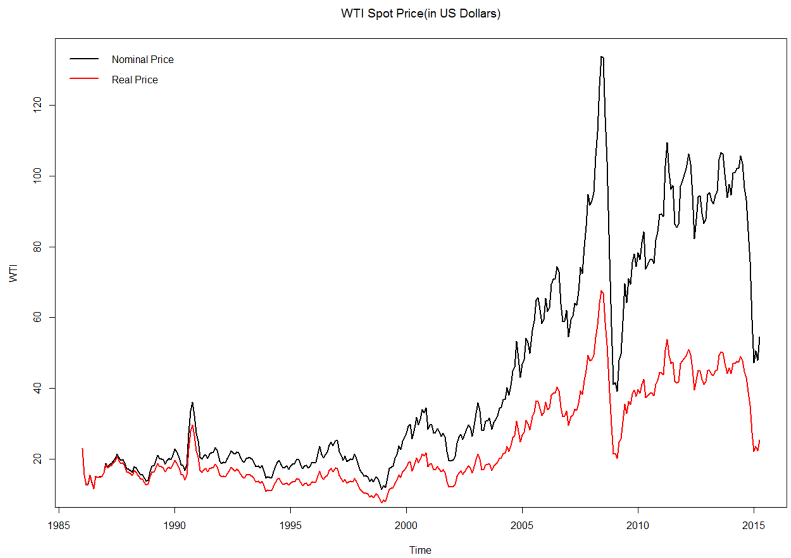
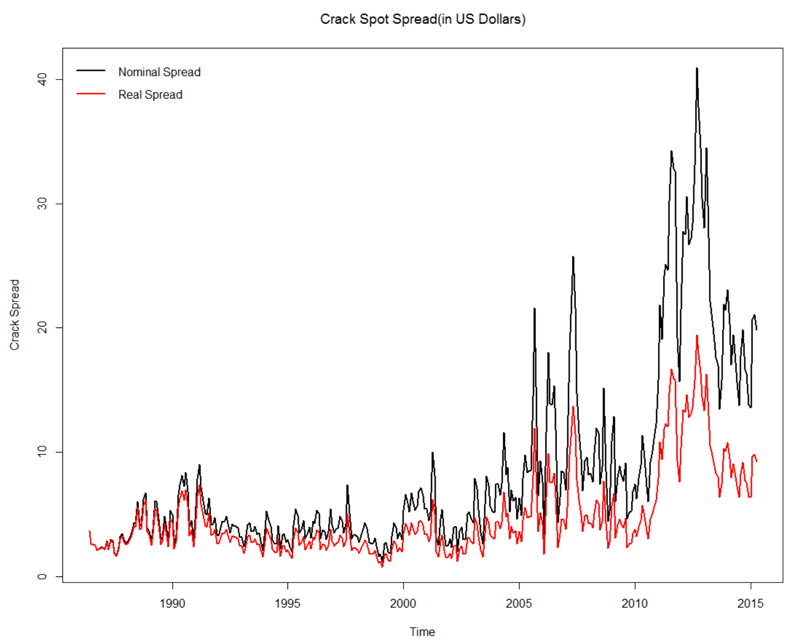
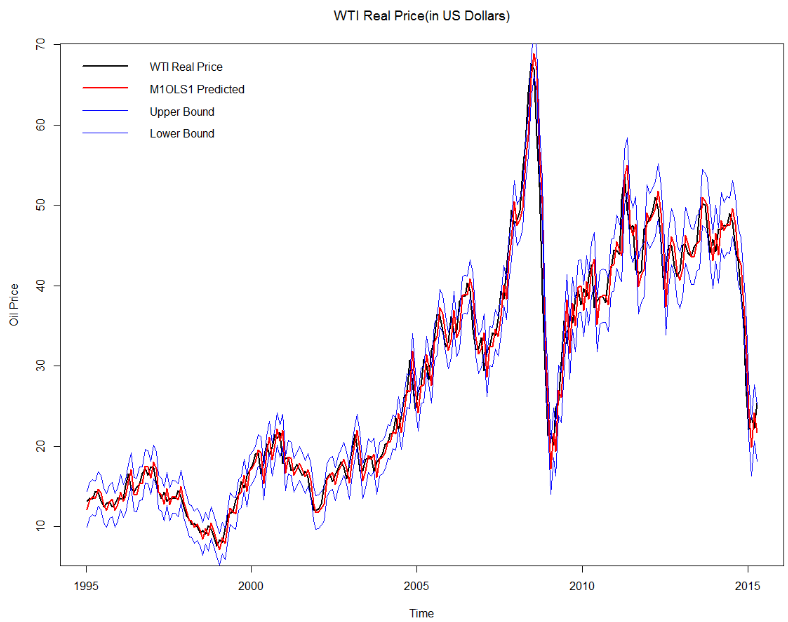


(a) WTI(US Dollar Per Barrel)

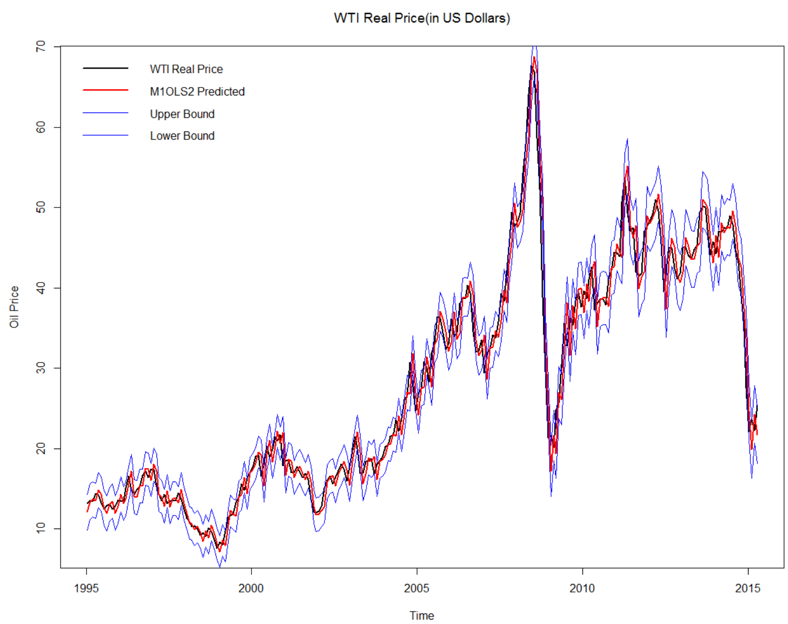


(b) Crack Spread(US Dollar Per Barrel)

Figure 3.1: Nominal and Real Spot Prices

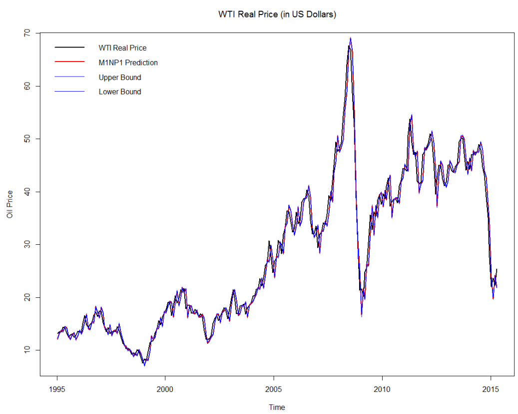


(a) M1OLS1

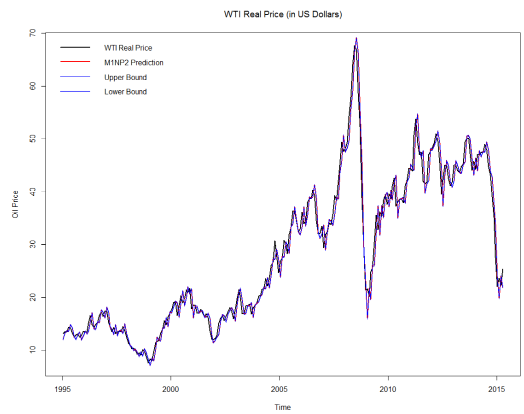


(b) M1OLS2

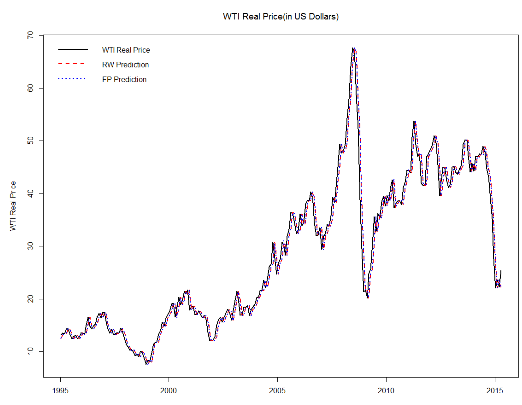
Figure 3.2: WTI One-month-ahead Out-of-sample's Predictions



(a) M1NP1



(b) M1NP2



(c) M1RWFP

Figure 3.3: WTI One-month-ahead Out-of-sample's Predictions

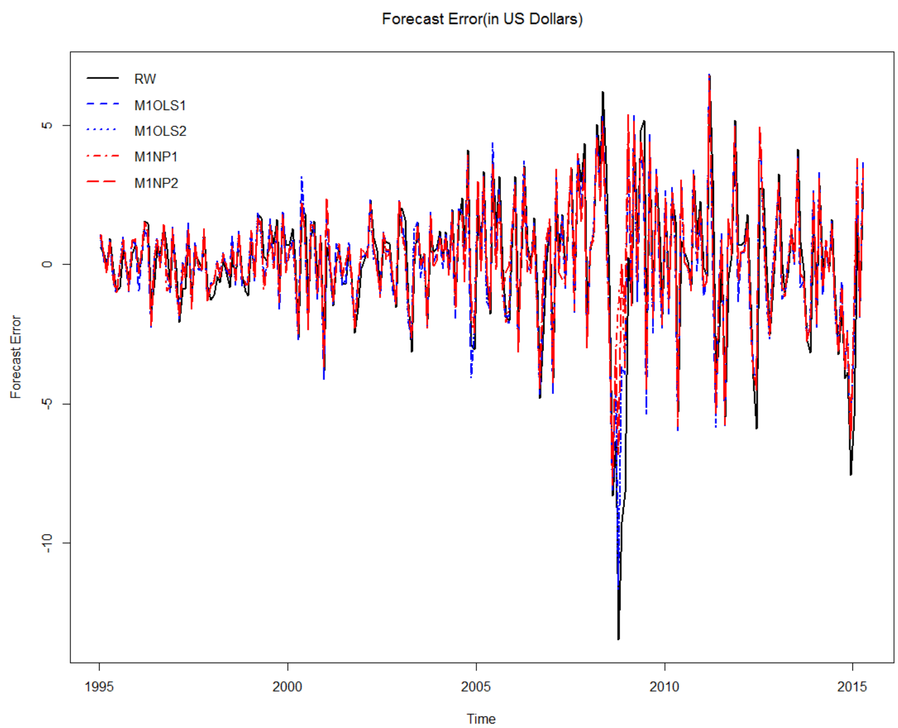


Figure 3.4: Forecast Errors for One Month's Ahead Prediction(in US Dollars)

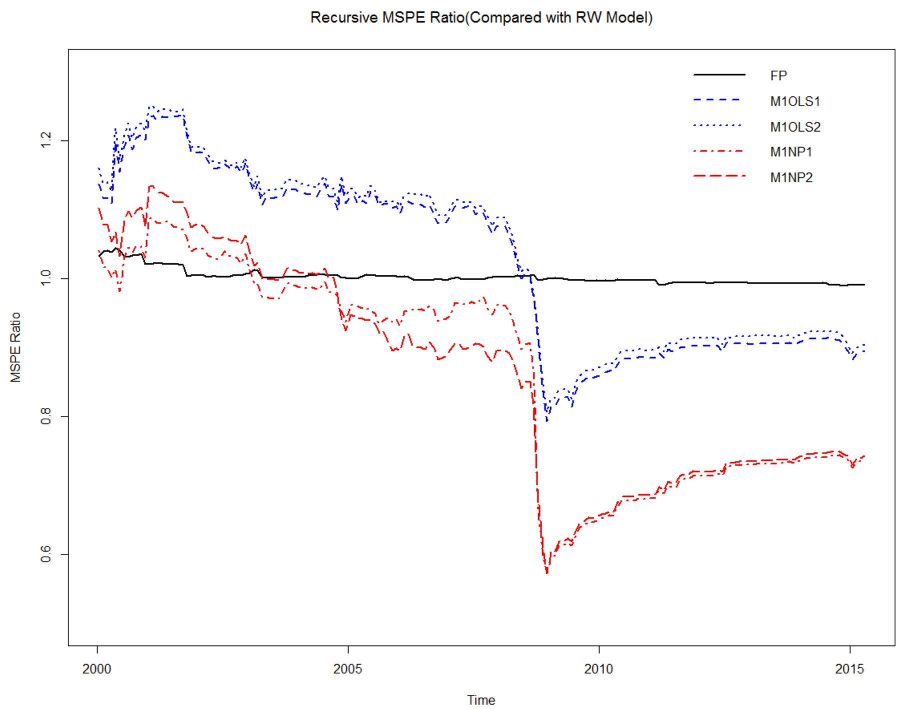
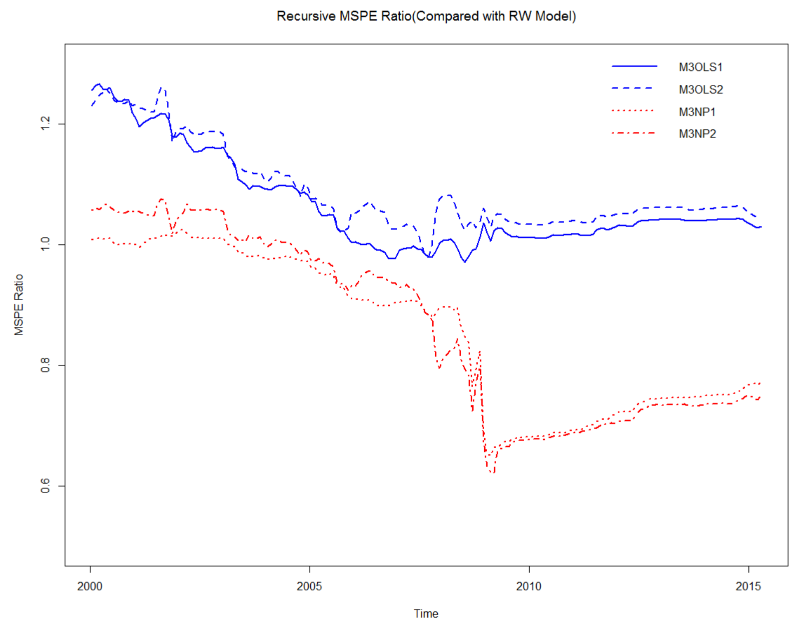
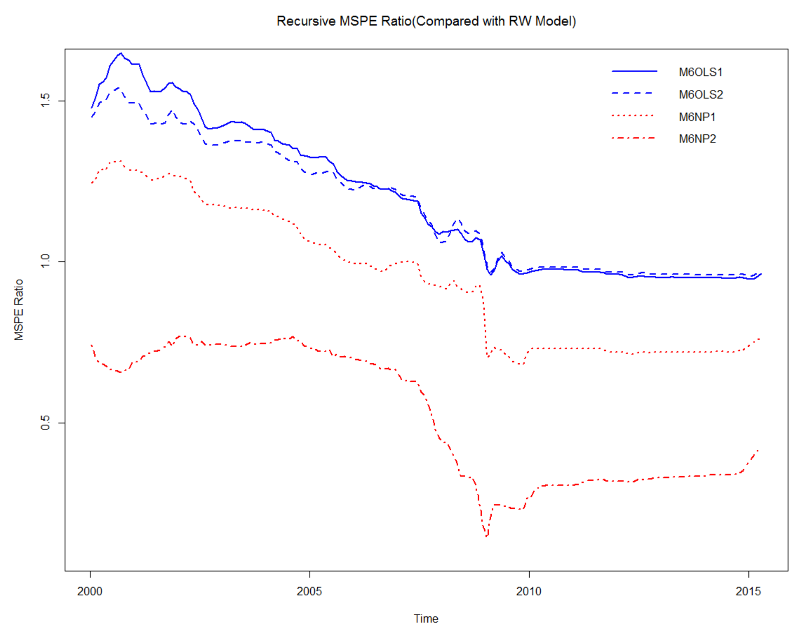


Figure 3.5: Recursive MSPE ratio for One Month's Ahead Prediction

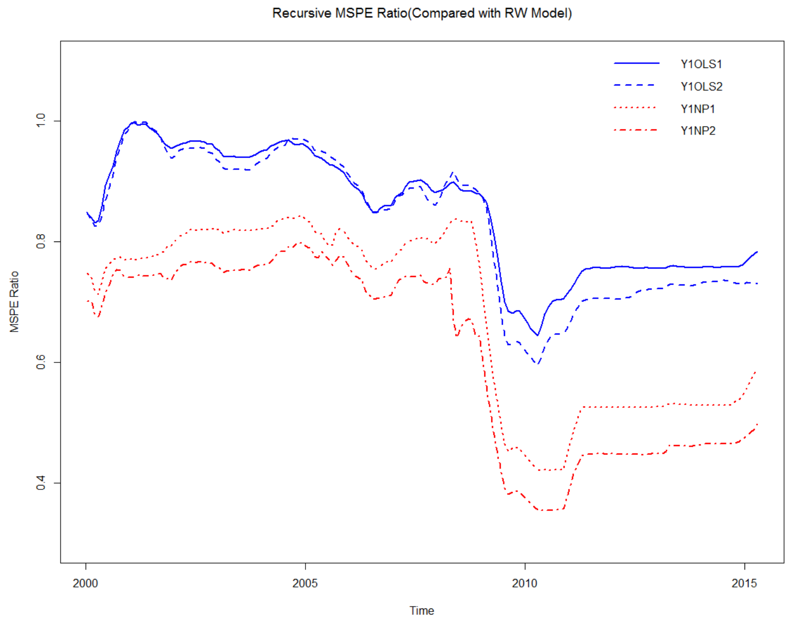


(a) 3 Months

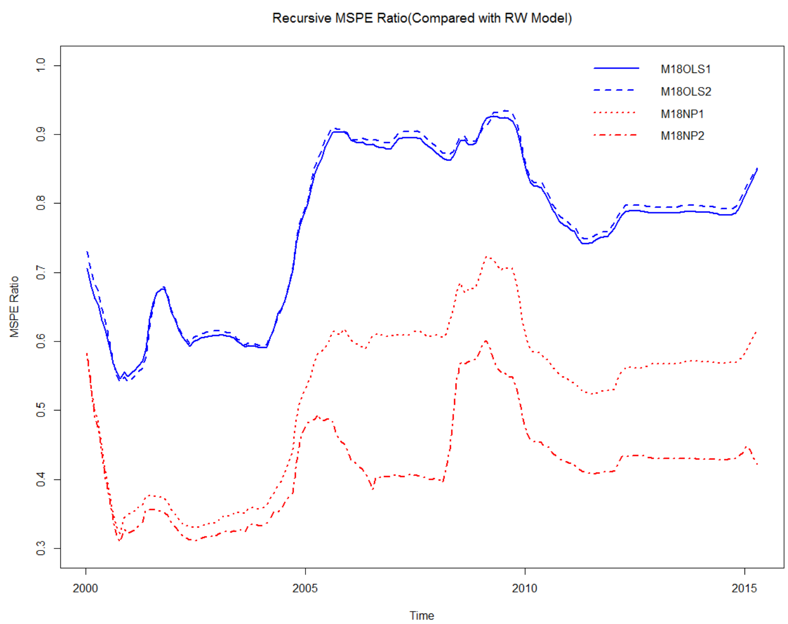


(b) 6 Months

Figure 3.6: Recursive MSPE ratio for 3, and 6 Months Ahead Prediction(in US Dollars)



(a) 1 Year



(b) 18 Months

Figure 3.7: Recursive MSPE ratio for 12, and 18 Months Ahead Prediction(in US Dollars)

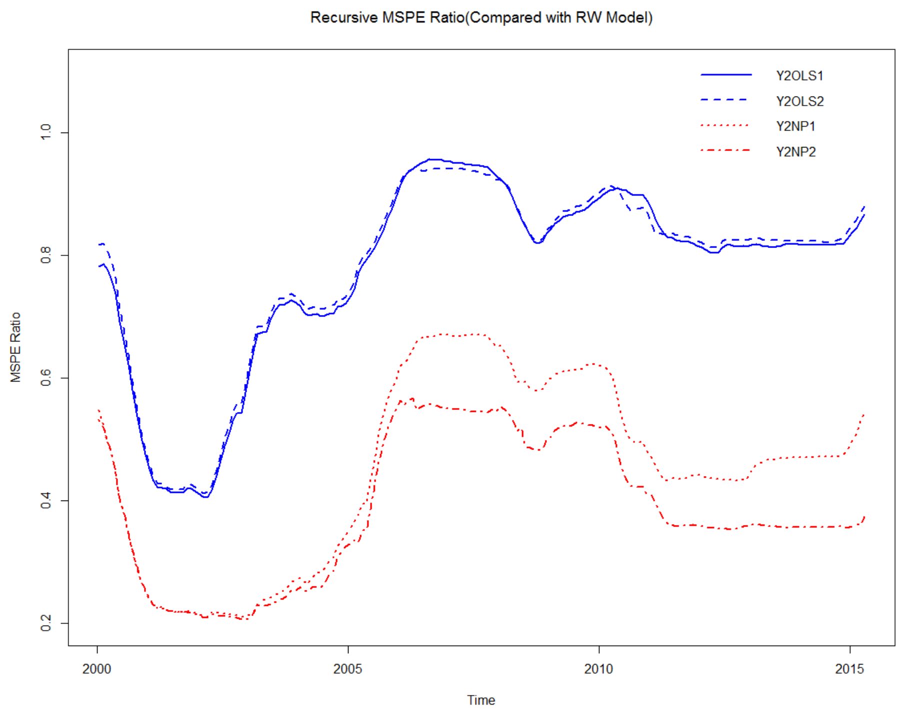
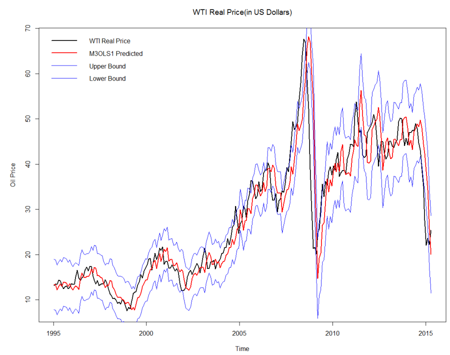
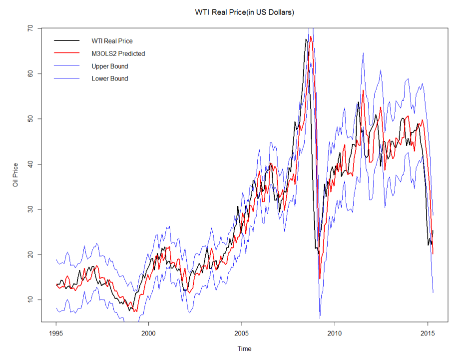


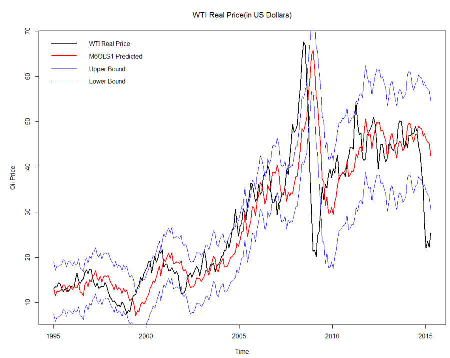
Figure 3.8: Recursive MSPE ratio for 2 Years Ahead Prediction(in US Dollars)



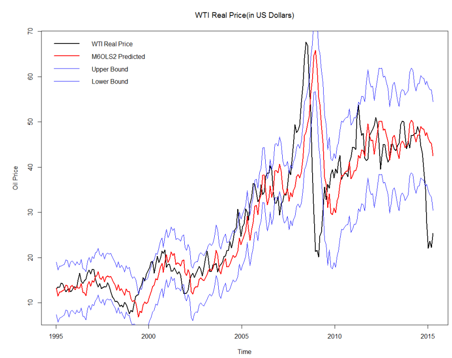
(a) 3 months



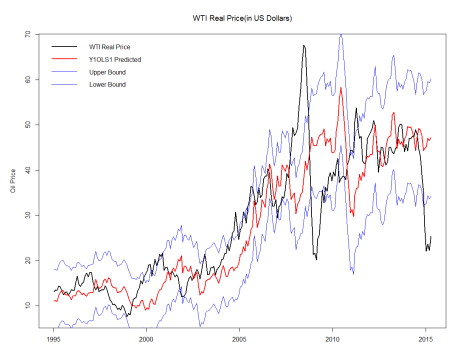
(b) 3 months



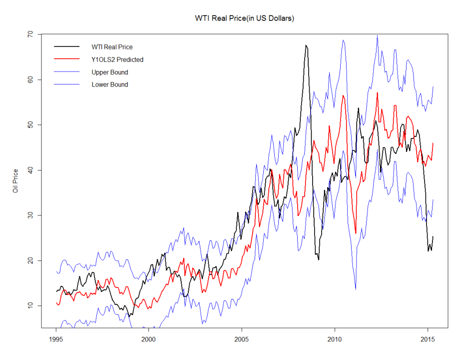
(c) 6 months



(d) 6 months

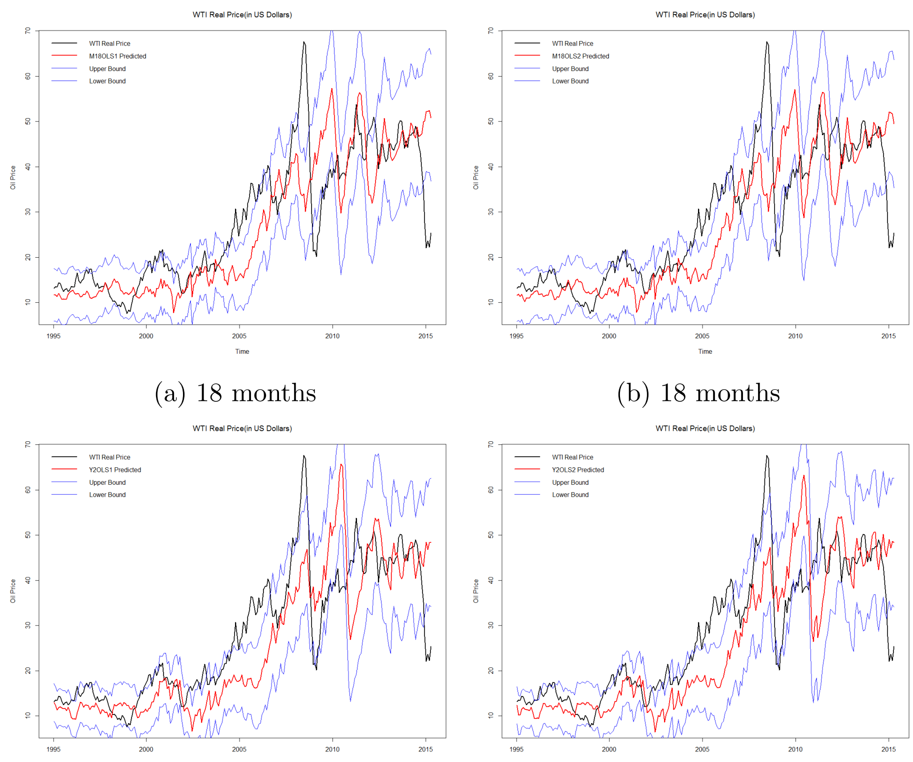


(e) 12 months



(f) 12 months

Figure 3.9: 3, 6, and 12 Months' Predictions by Linear Models



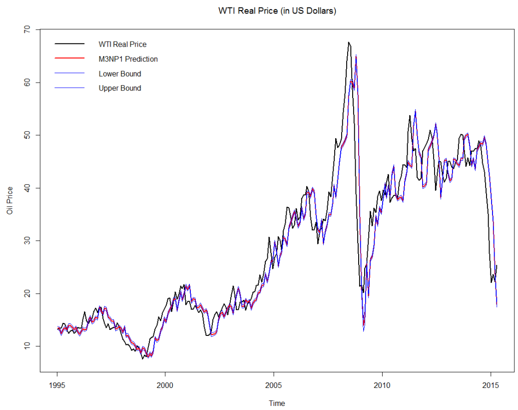
(a) 18 months

(b) 18 months

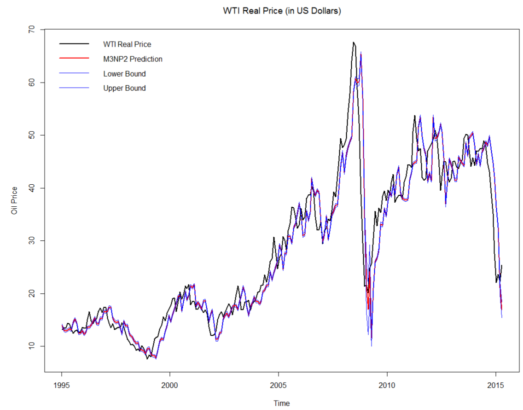
(c) 24 months

(d) 24 months

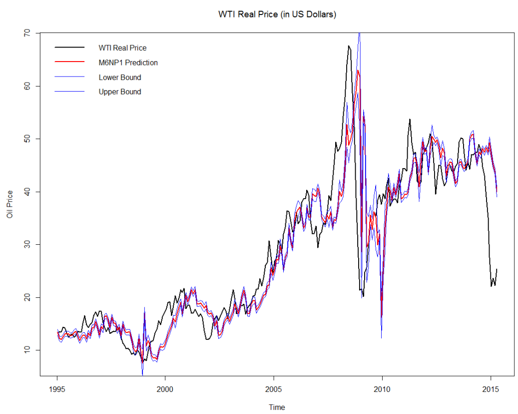
Figure 3.10: 18 and 24 Months' Predictions by Linear Models



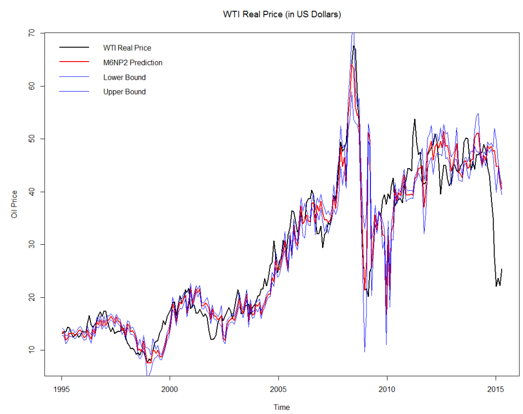
(a) 3 months



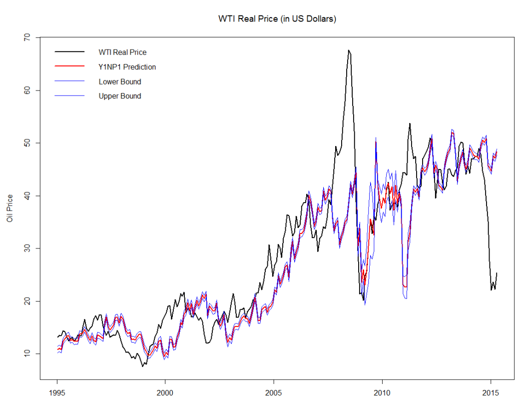
(b) 3 months



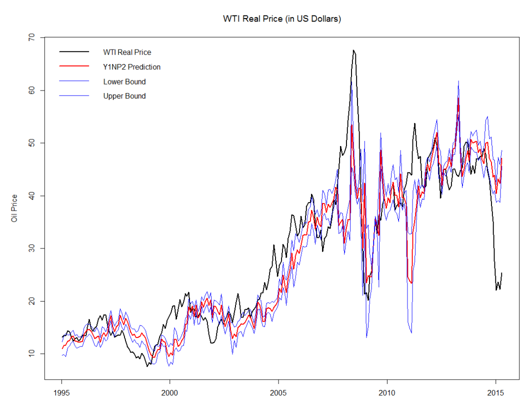
(c) 6 months



(d) 6 months

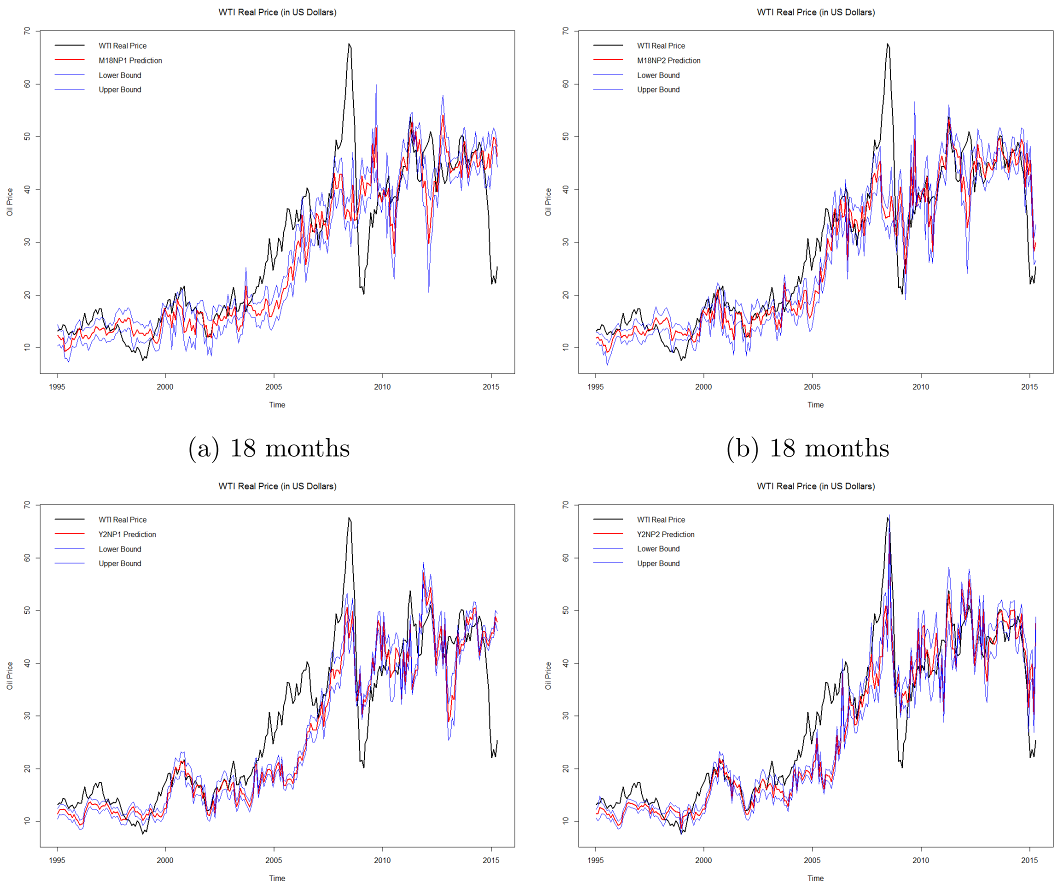


(e) 12 months



(f) 12 months

Figure 3.11: 3, 6, and 12 Months' Predictions by Nonparametric Models



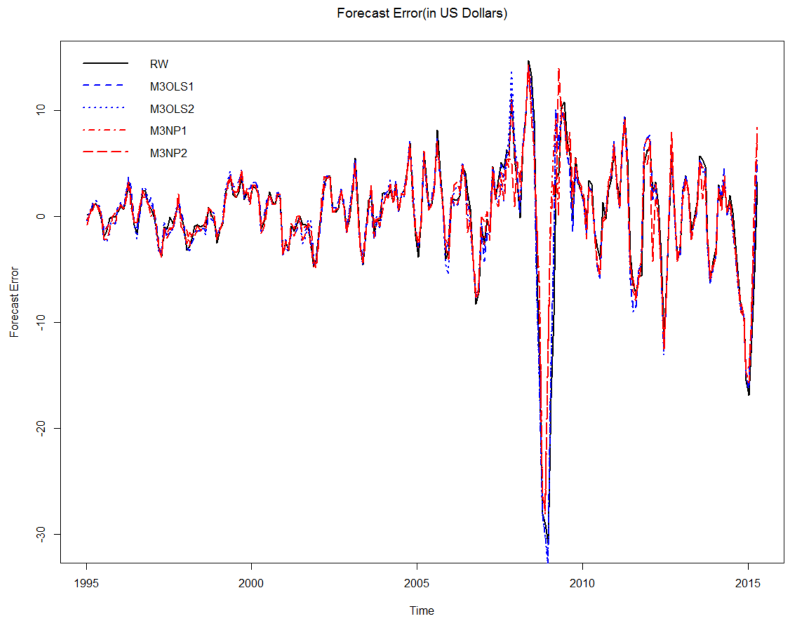
(a) 18 months

(b) 18 months

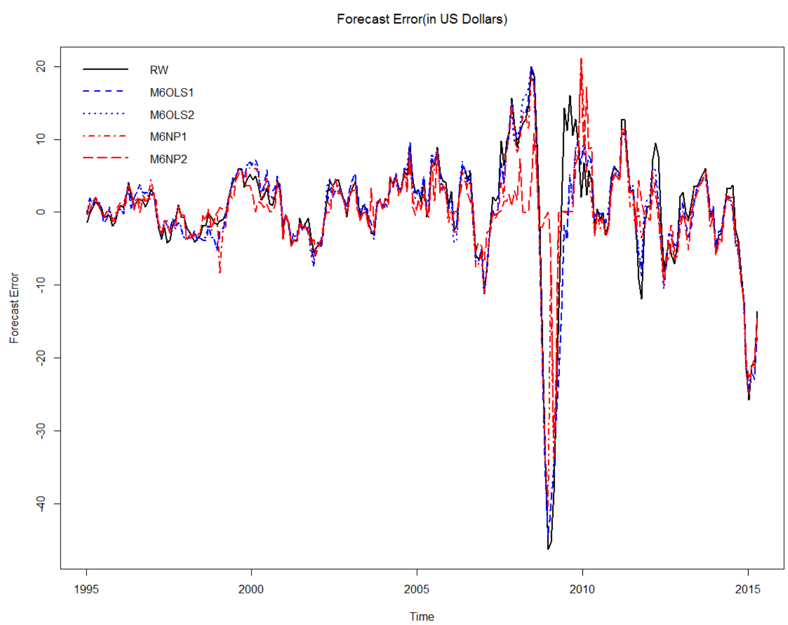
(c) 24 months

(d) 24 months

Figure 3.12: 18, and 24 Months' Predictions by Nonparametric Models

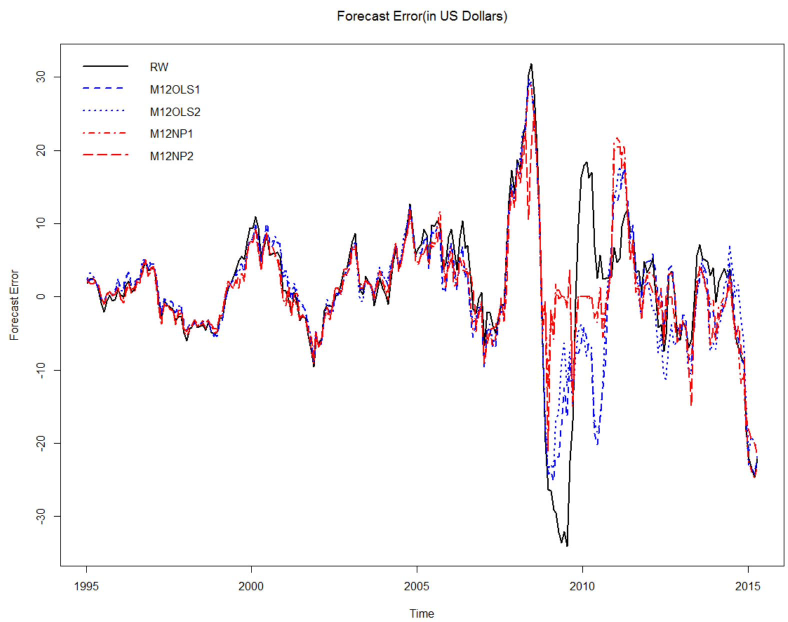


(a) 3 Months

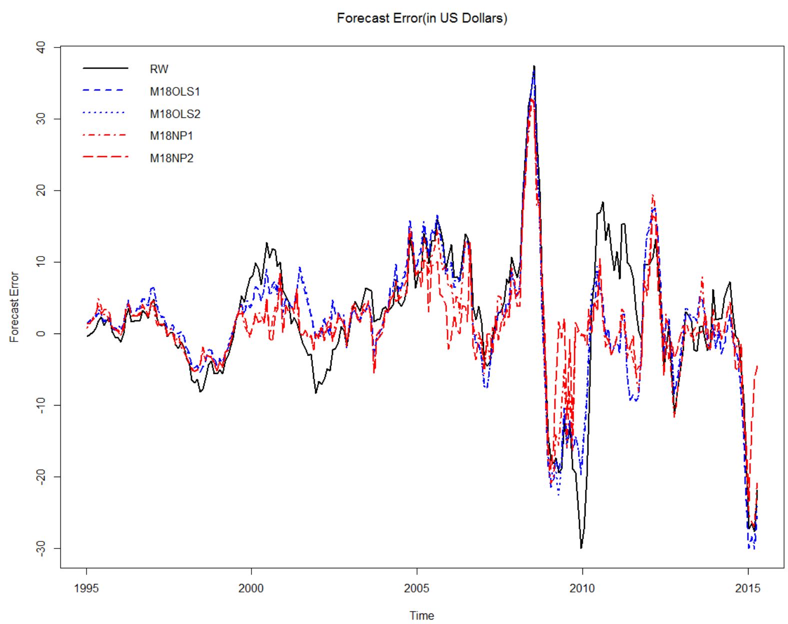


(b) 6 Months

Figure 3.13: Forecast Errors for 3, and 6 Months Ahead Prediction(in US Dollars)



(a) 1 Year



(b) 18 Months

Figure 3.14: Forecast Errors for 12, and 18 Months Ahead Prediction(in US Dollars)

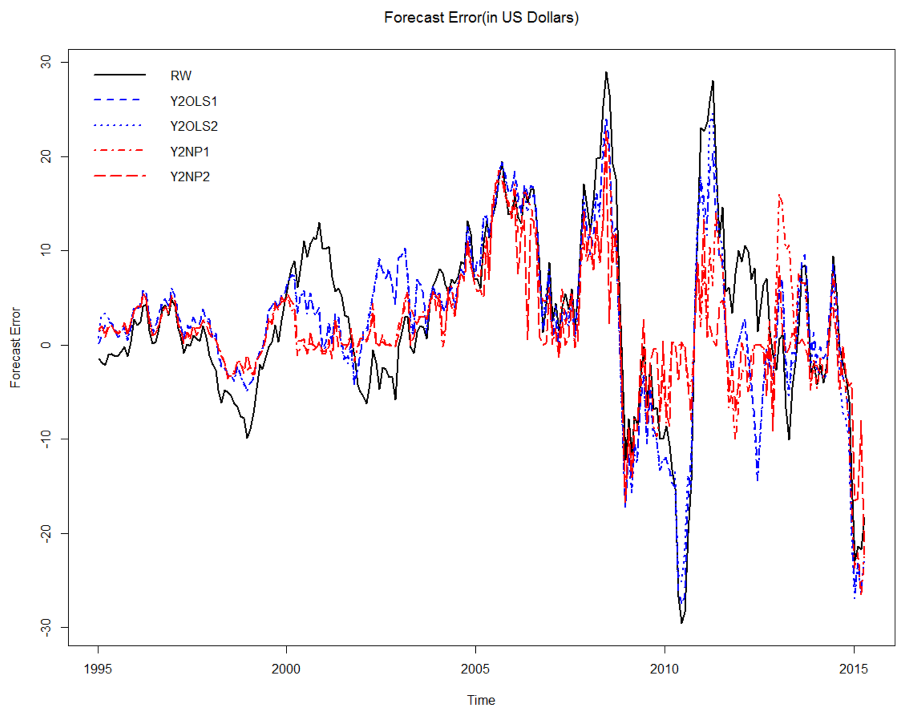
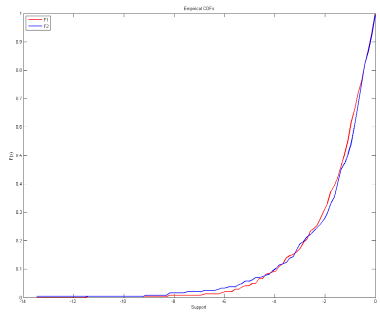
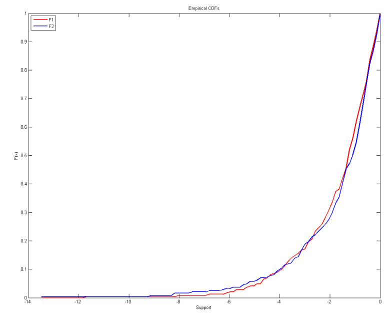


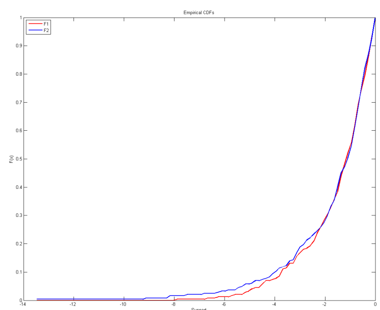
Figure 3.15: Forecast Errors for 2 Years Ahead Prediction(in US Dollars)



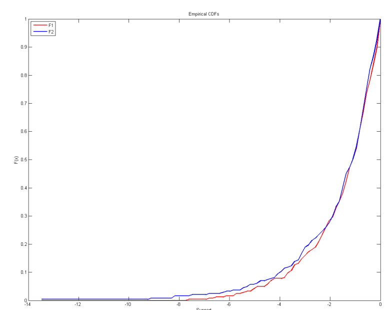
(a) M1-OLS1 V.S. RW



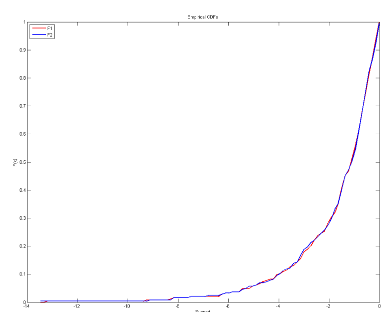
(b) M1-OLS2 V.S. RW



(c) M1-NP1 V.S. RW

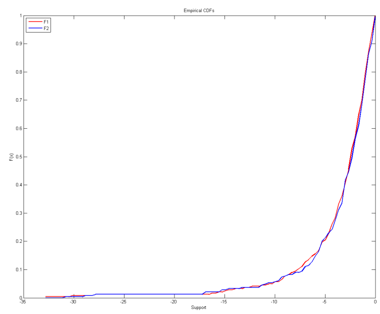


(d) M1-NP2 V.S. RW

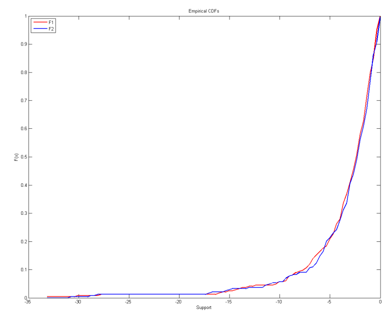


(e) M1-FP V.S. RW

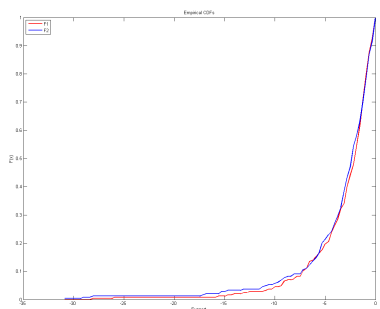
Figure 3.16: CDF Comparisons of the Negative Absolute Forecast Error (1995.1-2015.4)



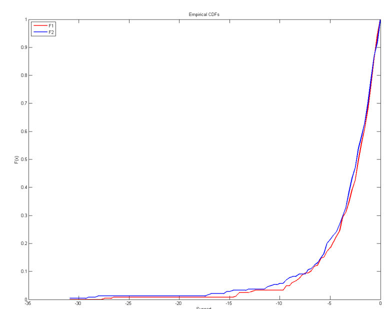
(a) M3-OLS1 V.S. RW



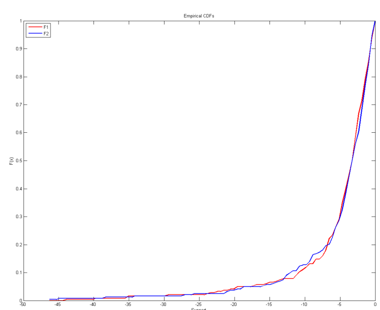
(b) M3-OLS2 V.S. RW



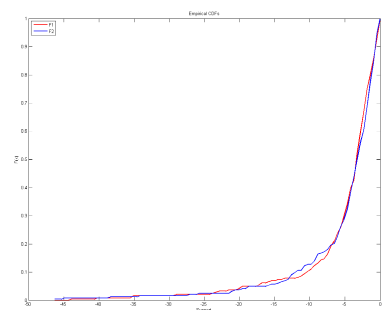
(c) M3-NP1 V.S. RW



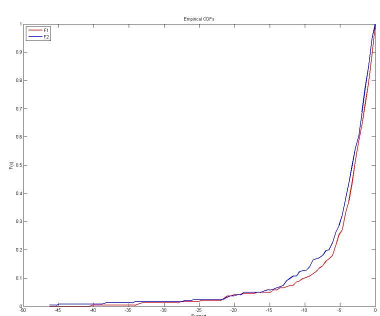
(d) M3-NP2 V.S. RW



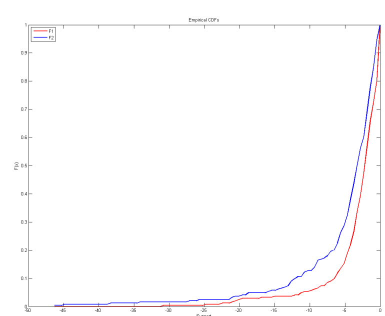
(e) M6-OLS1 V.S. RW



(f) M6-OLS2 V.S. RW

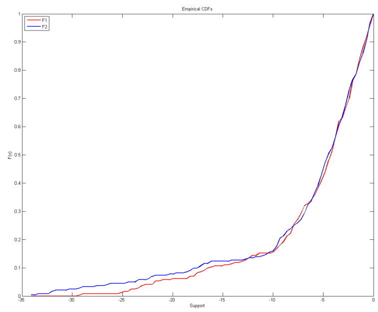


(g) M6-NP1 V.S. RW

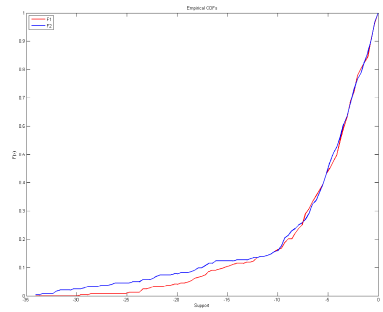


(h) M6-NP2 V.S. RW

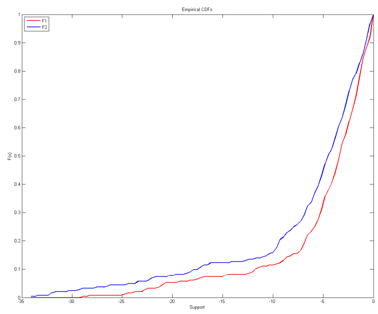
Figure 3.17: CDF Comparisons of the Negative Absolute Forecast Error (1995.1-2015.4)



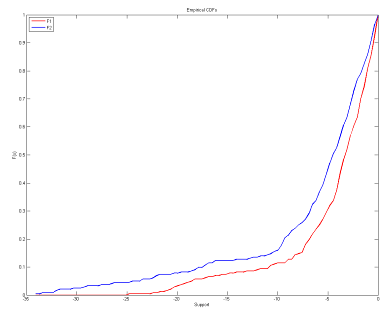
(a) M12-OLS1 V.S. RW



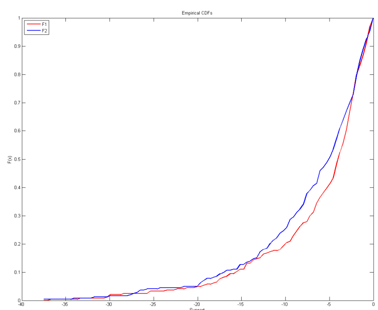
(b) M12-OLS2 V.S. RW



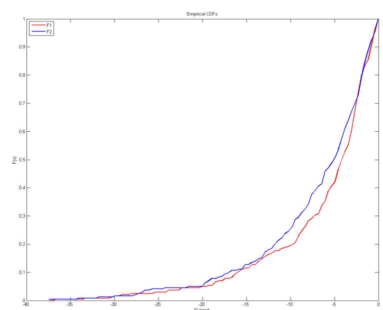
(c) M12-NP1 V.S. RW



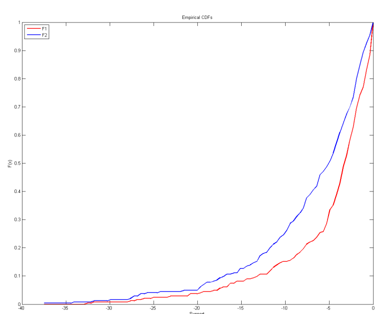
(d) M12-NP2 V.S. RW



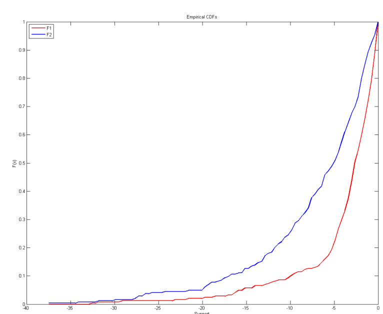
(e) M18-OLS1 V.S. RW



(f) M18-OLS2 V.S. RW

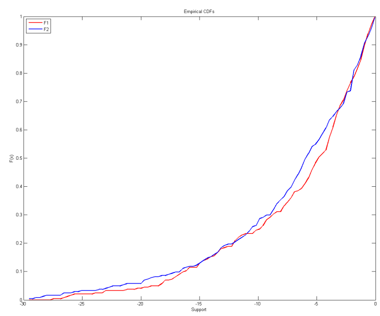


(g) M18-NP1 V.S. RW

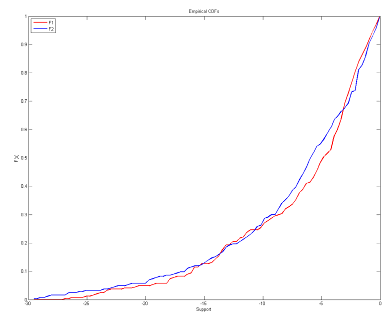


(h) M18-NP2 V.S. RW

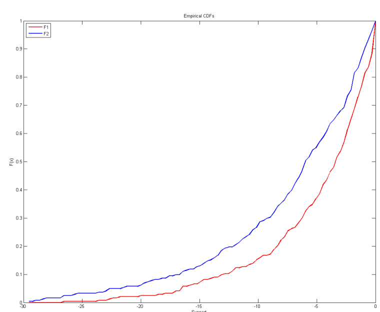
Figure 3.18: CDF Comparisons of the Negative Absolute Forecast Error (1995.1-2015.4)



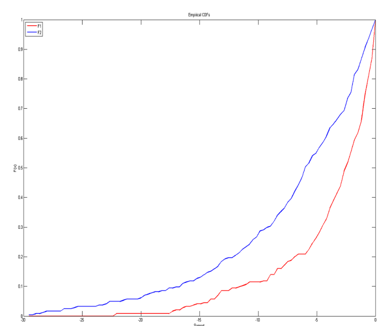
(a) M24-OLS1 V.S. RW



(b) M24-OLS2 V.S. RW



(c) M24-NP1 V.S. RW



(d) M24-NP2 V.S. RW

Figure 3.19: CDF Comparisons of the Negative Absolute Forecast Error (1995.1-2015.4)

Table 3.1: Out-of-sample One Month Ahead Forecast Performance

Panel A: Entropy $S_{\rho 1}$

	M1-OLS1	M1-OLS2	M1-NP1	M1-NP2	RW	Futures
$S_{\rho 1}$	0.015	0.015	0.018	0.022	0.016	0.017
p value	0	0	0	0	0	0

Panel B: MSPE

	M1-OLS1	M1-OLS2	M1-NP1	M1-NP2	RW	Futures
MSPE	5.607	5.668	4.626	4.656	6.266	6.207
MSPE Ratio	0.895	0.905	0.738	0.743	1	0.991
p value	0.096	0.113	0.033	0.018	NA	0.100

Panel C: Directional Accuracy Ratio

	M1-OLS1	M1-OLS2	M1-NP1	M1-NP2	RW	Futures
DAR	0.500	0.504	0.566	0.562	NA	0.549

[1] Forecasting period for oil price from 1995.1 to 2015.4
[2] For Panel A, all results are significant; for Panel B, Comparisons of models are based on the DM-test of Diebold and Mariano (1995), and the alternative hypothesis is that random walk method is less accurate than the other method. MSPE evaluates the real price of oil in levels.
[3] p-values of Panel A, is generated with 99 bootstrap replications. Under the null, $S_{\rho 1}$ takes the value of zero, which means the actual series and the forecasts are independent.

Table 3.2: Out-of-sample 3, 6, 12, 18 and 24 Months Ahead Forecast Performance

Panel A: 3 Months Ahead					
Entropy $S_{\rho 1}$	M3-OLS1	M3-OLS2	M3-NP1	M3-NP2	RW
$S_{\rho 1}$	0.017	0.016	0.038	0.042	0.032
p value	0.091	0.333	0	0	0
MSPE	M3-OLS1	M3-OLS2	M3-NP1	M3-NP2	RW
MSPE	31.410	31.939	23.594	22.916	30.496
MSPE Ratio	1.030	1.047	0.774	0.751	1
p value	0.837	0.917	0.028	0.022	NA
	M3-OLS1	M3-OLS2	M3-NP1	M3-NP2	RW
DAR	0.496	0.459	0.603	0.570	NA
Panel B: 6 Months Ahead					
Entropy $S_{\rho 1}$	M6-OLS1	M6-OLS2	M6-NP1	M6-NP2	RW
$S_{\rho 1}$	0.021	0.024	0.039	0.081	0.029
p value	0	0	0.010	0	0
MSPE	M6-OLS1	M6-OLS2	M6-NP1	M6-NP2	RW
MSPE	67.596	68.254	38.807	31.779	70.255
MSPE Ratio	0.962	0.972	0.552	0.452	1
p value	0.219	0.282	0.033	0.002	NA
	M6-OLS1	M6-OLS2	M6-NP1	M6-NP2	RW
DAR	0.500	0.484	0.611	0.705	NA

[1] Forecasting period for oil price from 1995.1 to 2015.4, DAR represents Directional Accuracy Ratio.
[2] For entropy $S_{\rho 1}$ in Panel A, all results except linear models are significant, while for entropy $S_{\rho 1}$ in Panel B, all results are significant; for MSPE, Comparisons of models are based on the DM-test of Diebold and Mariano (1995), and the alternative hypothesis is that random walk method is less accurate than the other method. MSPE evaluates the real price of oil in levels.
[3] p-values are generated with 99 bootstrap replications. Under the null, $S_{\rho 1}$ takes the value of zero, which means the actual series and the forecasts are independent.

Table 3.2 (continued)

Panel C: 1 Year Ahead					
Entropy $S_{\rho 1}$	Y1-OLS1	Y1-OLS2	Y1-NP1	Y1-NP2	RW
$S_{\rho 1}$	0.054	0.059	0.085	0.093	0.056
p value	0	0	0	0	0
MSPE	Y1-OLS1	Y1-OLS2	Y1-NP1	Y1-NP2	RW
MSPE	76.004	70.992	57.251	48.328	97.041
MSPE Ratio	0.783	0.732	0.590	0.498	1
p value	0.005	0.003	0.000	0	NA
	Y1-OLS1	Y1-OLS2	Y1-NP1	Y1-NP2	RW
DAR	0.619	0.656	0.660	0.738	NA
Panel D: 18 Months Ahead					
Entropy $S_{\rho 1}$	M18-OLS1	M18-OLS2	M18-NP1	M18-NP2	RW
$S_{\rho 1}$	0.056	0.050	0.074	0.139	0.057
p value	0	0	0	0	0
MSPE	M18-OLS1	M18-OLS2	M18-NP1	M18-NP2	RW
MSPE	86.886	87.162	62.971	43.253	102.357
MSPE Ratio	0.849	0.852	0.615	0.423	1
p value	0.002	0.002	0	0	NA
DAR	M18-OLS1	M18-OLS2	M18-NP1	M18-NP2	RW
DAR	0.648	0.631	0.717	0.775	NA

[1] Forecasting period for oil price from 1995.1 to 2015.4, DAR represents Directional Accuracy Ratio.
[2] For entropy $S_{\rho 1}$ in Both panels, all results are significant; for MSPE, Comparisons of models are based on the DM-test of Diebold and Mariano (1995), and the alternative hypothesis is that random walk method is less accurate than the other method. MSPE evaluates the real price of oil in levels.
[3] p-values are generated with 99 bootstrap replications. Under the null, $S_{\rho 1}$ takes the value of zero, which means the actual series and the forecasts are independent.

Table 3.2 (continued)

Panel E: 2 Years Ahead					
Entropy $S_{\rho 1}$	Y2-OLS1	Y2-OLS2	Y2-NP1	Y2-NP2	RW
$S_{\rho 1}$	0.082	0.074	0.136	0.152	0.069
p value	0	0	0	0	0
MSPE	Y2-OLS1	Y2-OLS2	Y2-NP1	Y2-NP2	RW
MSPE	86.499	87.811	54.047	37.350	99.773
MSPE Ratio	0.867	0.880	0.542	0.374	1
p value	0.004	0.010	0	0	NA
DAR	Y2-OLS1	Y2-OLS2	Y2-NP1	Y2-NP2	RW
DAR	0.623	0.615	0.676	0.775	NA

[1] Forecasting period for oil price from 1995.1 to 2015.4

[2] For entropy $S_{\rho 1}$, all results are significant; for MSPE, Comparisons of models are based on the DM-test of Diebold and Mariano (1995), and the alternative hypothesis is that random walk method is less accurate than the other method. MSPE evaluates the real price of oil in levels.

[3] p-values are generated with 99 bootstrap replications. Under the null, $S_{\rho 1}$ takes the value of zero, which means the actual series and the forecasts are independent.

Table 3.3: Stochastic Dominance Test Results

	OR	d	$P[d \leq 0]$/p	s	$P[s \leq 0]$/p
Panel A: For 1 Month Ahead					
OLS1 V.S. RW	None	0.815	0.033	0.122	0.478
OLS2 V.S. RW	None	0.815	0.027	0.192	0.378
NP1 V.S. RW	SSD	0.181	0.806	-0.012	0.950
NP2 V.S. RW	SSD	0.091	0.910	-0.012	0.963
FP V.S. RW	SSD	0.136	0.779	-0.012	0.438
Panel B: For 3 Months Ahead					
OLS1 V.S. RW	None	0.407	0.171	1.079	0.057
OLS2 V.S. RW	None	0.498	0.130	1.431	0.020
NP1 V.S. RW	SSD	0.181	0.686	-0.014	0.990
NP2 V.S. RW	SSD	0.272	0.331	-0.014	0.977
Panel C: For 6 Months					
OLS1 V.S. RW	None	0.724	0.023	0.212	0.632
OLS2 V.S. RW	None	0.724	0.040	0.442	0.508
NP1 V.S. RW	SSD	0.045	0.756	-0.021	0.880
NP2 V.S. RW	FSD	-0.045	0.903	-0.021	0.993
Panel D: For 1 Year Ahead					
OLS1 V.S. RW	SSD	0.317	0.572	-0.016	0.973
OLS2 V.S. RW	SSD	0.226	0.789	-0.016	0.993
NP1 V.S. RW	FSD	-0.045	0.676	-0.016	0.997
NP2 V.S. RW	FSD	-0.045	0.940	-0.016	1.000
Panel E: For 18 Months Ahead					
OLS1 V.S. RW	None	0.181	0.635	0.046	0.619
OLS2 V.S. RW	SSD	0.136	0.876	-0.003	0.415
NP1 V.S. RW	FSD	-0.045	0.906	-0.017	1.000
NP2 V.S. RW	FSD	-0.045	1.000	-0.017	1.000
Panel F: For 2 Years Ahead					
OLS1 V.S. RW	SSD	0.317	0.619	-0.013	0.953
OLS2 V.S. RW	SSD	0.724	0.077	-0.013	0.943
NP1 V.S. RW	FSD	-0.045	0.967	-0.014	0.980
NP2 V.S. RW	FSD	-0.045	0.993	-0.014	1.000

[1] Forecasting period for oil price from 1995.1 to 2015.4.

[2] OR means Observed Ranking. If the Kolmogorov-Smirnov test statistics is negative, $P[d] \leq 0$ or $P[s] \leq 0$ is obtained by 299 replications of bootstrap re-sampling produce. Otherwise, we use 299 replications of recentering weakly dependent bootstrap technique of Donald and Hsu (2014) to get the p value of H_0: X_1 FSD (SSD) X_2.

Table IA.25

Unit Root Tests						
	WTI	Inventory	Crack Spread	1% Critical Value	5% Critical Value	10% Critical Value
ADF test	-0.6321	-0.2131	-1.4077	-2.58	-1.95	-1.62
DF-GLS test	-1.1859	-2.6157	-2.4418	-2.57	-1.94	-1.62

[1] The null is the existence of the unit root for the time series till 1994.12.
[2] ADF test means Augmented Dickey and Fuller unit root test; DF-GLS test performs the modified Dickey-Fuller t test proposed by Elliott, Rothenberg, and Stock (1996).

Table IA.26: Estimated Coefficients for One Month Ahead in Sample Model

Panel A: Not Including The Spread				
	Coefficient	SE	t value	Probability
Intercept	0.022	0.118	0.186	0.853
△ WTI_t	0.377	0.052	7.279	0***
△ Inv_t	-0.001	0.006	-0.208	0.835
Panel B: Including The Spread				
	Coefficient	SE	t value	Probability
Intercept	0.022	0.118	0.182	0.855
△ WTI_t	0.376	0.052	7.23	0***
△ Inv_t	-0.001	0.006	-0.24	0.814
△ $Spread_t$	0.023	0.084	0.278	0.781

[1] Estimating period for oil price from 1987.12 to 2015.4

[2] Adj. $R^2 = 0.137$, Residual SE = 2.131 for Panel A; Adj. $R^2 = 0.134$, Residual SE = 2.134 for Panel B

Table IA.27: Estimated Coefficients for 3, 6, 12, 18 and 24 Months Ahead in Sample Model

	Coefficient	SE	t value	Probability
Panel A: Not Including The Spread for 3 Month Ahead				
Intercept	0.042	0.282	0.149	0.882
WTI_t-WTI_{t-3}	0.128	0.057	2.267	0.024**
Inv_t-Inv_{t-3}	0.012	0.008	1.461	0.145
Panel B: Including The Spread for 3 Month Ahead				
Intercept	0.043	0.282	0.153	0.879
WTI_t-WTI_{t-3}	0.130	0.057	2.294	0.023**
Inv_t-Inv_{t-3}	0.013	0.009	1.537	0.125
$Spread_t$-$Spread_{t-3}$	-0.065	0.127	-0.511	0.610
Panel C: Not Including The Spread for 6 Month Ahead				
Intercept	0.467	0.412	1.135	0.257
WTI_t-WTI_{t-6}	-0.333	0.059	-5.671	0***
Inv_t-Inv_{t-6}	-0.023	0.010	-2.203	0.028**
Panel D: Including The Spread for 6 Month Ahead				
Intercept	0.464	0.412	1.126	0.261
WTI_t-WTI_{t-6}	-0.333	0.059	-5.671	0***
Inv_t-Inv_{t-6}	-0.024	0.011	-2.228	0.027**
$Spread_t$-$Spread_{t-6}$	0.057	0.157	0.363	0.717
Panel E: Not Including The Spread for 1 Year Ahead				
Intercept	1.164	0.465	2.501	0.013**
WTI_t-WTI_{t-12}	-0.442	0.058	-7.589	0***
Inv_t-Inv_{t-12}	0.027	0.012	2.331	0.0204**
Panel F: Including The Spread for 1 Year Ahead				
Intercept	1.013	0.450	2.251	0.025**
WTI_t-WTI_{t-12}	-0.444	0.056	-7.913	0***
Inv_t-Inv_{t-12}	0.030	0.011	2.701	0.007***
$Spread_t$-$Spread_{t-12}$	0.723	0.148	4.895	0***

[1] Estimating period for oil price from 1988.6 to 2015.4 for 3 month ahead in sample model, from 1988.12 to 2015.4 for 3 month ahead in sample model, from 1989.12 to 2015.4 for 1 year ahead in sample model

[2] Adj. $R^2 = 0.014$, Residual SE = 5.064 for Panel A; Adj. $R^2 = 0.011$, Residual SE = 5.07 for Panel B; Adj. $R^2 = 0.090$, Residual SE = 7.286 for Panel C; Adj. $R^2 = 0.088$, Residual SE = 7.296 for Panel D; Adj. $R^2 = 0.223$, Residual SE = 7.928 for Panel E; Adj. $R^2 = 0.278$, Residual SE = 7.643 for Panel F. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Table IA.27 (continued)

Panel G: Not Including The Spread for 18 Months Ahead				
	Coefficient	SE	t value	Probability
Intercept	1.804	0.521	3.464	0.001***
WTI_t-WTI_{t-18}	-0.400	0.059	-6.787	0***
Inv_t-Inv_{t-18}	0.016	0.010	1.701	0.090*
Panel H: Including The Spread for 18 Months Ahead				
Intercept	1.725	0.522	3.302	0.001***
WTI_t-WTI_{t-18}	-0.426	0.061	-6.949	0***
Inv_t-Inv_{t-18}	0.016	0.010	1.676	0.095*
$Spread_t$-$Spread_{t-18}$	0.241	0.160	1.506	0.133
Panel I: Not Including The Spread for 2 Years Ahead				
Intercept	1.885	0.554	3.403	0.001***
WTI_t-WTI_{t-24}	-0.198	0.060	-3.280	0.001***
Inv_t-Inv_{t-24}	0.052	0.011	4.888	0***
Panel J: Including The Spread for 2 Years Ahead				
Intercept	1.886	0.562	3.354	0.001***
WTI_t-WTI_{t-24}	-0.198	0.064	-3.095	0.002***
Inv_t-Inv_{t-24}	0.052	0.011	4.864	0***
$Spread_t$-$Spread_{t-24}$	-0.003	0.157	-0.019	0.985

[1] Estimating period for oil price from 1990.12 to 2015.4 for 18 months ahead in sample model, from 1991.12 to 2015.4 for 2 years ahead in sample model
[2] Adj. $R^2 = 0.156$, Residual SE = 8.572 for Panel G; Adj. $R^2 = 0.160$, Residual SE = 8.553 for Panel H; Adj. $R^2 = 0.136$, Residual SE = 8.644 for Panel I; Adj. $R^2 = 0.132$, Residual SE = 8.66 for Panel J. Significance at 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.