Unrealized Gains and Return-Volatility Anomalies

Chin-Wen Hsin

Abstract

This study examines the role of investors' propensity to sell, measured by unrealized capital gains (CGO), in affecting the return-volatility anomaly. Using disposition effect as a channel, this study finds the following evidence in emerging markets. First, the aggregate fixed effects results show that CGO as well as its decomposed GO (gains overhang) have positive relation with next period returns, an evidence consistent with the disposition effect, which suggests that stocks with greater unrealized gains tend to be subject to greater propensity to sell and thus underpricing, and yield higher next period returns. Next, this study finds unrealized gains/losses indeed influence the IVOL effect. Stocks with greater CGO exhibit more negative IVOL anomaly. Further dissection shows that unrealized gains (GO) aggravate the negative IVOL anomaly while unrealized losses (|LO|) tends to reverse or weaken the anomaly, suggesting investors to exhibit diverse propensity to sell over different ranges of capital gains/losses. The results are partially in support of the asymmetric V-shaped disposition effect in that a large |LO| serves as a decelerator for the IVOL effect. The absence of similar impact from investors' propensity to sell on MAX anomaly implicates that the mechanism leading to these two anomalies are likely to differ. Last, the regional analysis finds that the impact of unrealized gains/losses on returns or on IVOL effect does not apply for Latin American markets. This suggests that the diverse propensity to speculate across markets plays a role in investors' selling schedule relative to unrealized gains/losses.

Keywords: Disposition effect; Emerging market; IVOL anomaly; MAX anomaly; Propensity to sell

JEL Classification: G14, G15

---

*College of Management, Yuan Ze University, 135 Yuan-Tung Road, Chung-Li, Taoyuan, Taiwan 32003. Email: fncwhsin@saturn.yzu.edu.tw

1. Introduction

Traditional asset pricing theory implies a positive relation between risk and expected returns. The literature however finds various measures of risk present evidence in conflict with the basic principle. Black, Jensen and Scholes (1972) first find that low-risk firms tend to earn higher average returns when risk is measured by CAPM beta. Later studies find robust evidence of flat or even negatively sloped SML in the US market and in international markets[1] This "beta anomaly" has attracted a large literature attempting to resolve this puzzle. Another risk measure, idiosyncratic volatility (IVOL), also presents a puzzle. Classical asset pricing theory asserts that only systematic risk should be priced and expected return of a stock is not supposed to depend on idiosyncratic volatility. Starting with Ang, Hodrick, Xing and Zang (2006), recent empirical studies generally find a negative cross-sectional relation between idiosyncratic volatility and next period return for U.S. market as well as international markets, while with a few exceptions (e.g., Bali and Cakici, 2008). Various explanations have been afforded to explain such phenomenon.[2]

More recently, Kumar (2009) and Kumar et al. (2011) define stocks as lottery-type stocks as those having the feature of paying low while having very low probability of very high payoff. They find those lottery-type stocks tend to be over-priced and are associated with lower expected return. Such phenomenon is interpreted as the result of investors preference for skewness. There has been increasing evidence documented for the US market [Doran et al. (2011), Han and Kumar (2013), and An, Wang, Wang, and Yu (2015)] and for the international markets [Doran et al. (2011), Carpenter, Lu, and Whitelaw (2014), Annaert, De Ceuster, and Verstegen (2013), Walkshwausl (2014), Zhong and Gray (2014), Hsin and Peng (2016)]. Bali et al. (2011) propose a more direct measure, MAX, which assesses the magnitude of prior highest return of a stock. This over-pricing of lottery-type stocks thus can be termed as MAX anomaly.

These aforementioned anomalies, from the long-existing beta anomaly to IVOL anomaly and then the more recent MAX anomaly, present inverted or flat relations between risk and returns and have attracted researchers to afford explanations to reconcile these puzzles. The high correlations among these measures also imply inter-connections among their associated anomalies. One may thus expect that these anomalies are shared with similar driving forces. The literature

[1] For example, see Black (1972), Fama and MacBeth (1973), Fama and French (1992), and Baker and Wurgler (2014), and Frazzini and Pedersen (2014). In particular, Baker, Bradley, and Wurgler (2011) and Frazzini and Pedersen (2014) both find a strategy by buying low-beta and selling high-beta stocks (Betting-Against-Beta) yields significant abnormal returns.

[2] For example, see Baker and Wurgler (2006), Zhang (2006), Bali and Cakici (2008), Fu (2009), Jiang, Xu and Yao (2009), Huang, Liu, Rhee and Zhang (2010), Han and Lesmond (2011), and Stambaugh, Yu and Yuan (2015).

generally offers two approaches to explaining these anomalies, risk-based or behavioral. This study borrows one of the behavioral explanations to find the commonality, i.e., the disposition effect. In particular, Shefrin and Statman (1985) describes that investors tend to sell securities with potential capital gains rather than those with capital losses. Researchers have since documented evidence of investor trading behavior in support of this effect in the US market as well as in the international markets.[3] The suggestion that investors have heterogeneous propensity to sell conditional on unrealized gains and losses offers possible explanations for pricing anomalies. Note however that any price impact can only result from aggregated investor behavior. For this purpose, Grinblatt and Han (2005) design a measure to estimate the aggregated unrealized capital gains (CGO) and find that the investor behavioral pattern suggested by disposition effect serves as a source of price momentum.

The primary research purpose of this study is to examine the role of investors' propensity to sell in affecting the relation between return and these risk metrics, primarily IVOL and MAX. This study attempts to test the implications from disposition effect, in the form of both the traditional binary version (Shefrin and Statman, 1985) and the V-shaped version (Ben-David and Hirshleifer, 2012), on the anomalies associated with IVOL and MAX. In particular, currently documented IVOL or MAX anomalies are monotonic and unconditional. The asymmetric V-shaped selling schedule expects to yield implications that are non-monotonic and state-dependent, and shed further light on the heterogeneity of risk-return relations.

Under binary disposition effect (Shefrin and Statman, 1985), investors tend to sell securities whose prices have increased since purchase rather than those that have fallen in value. <u>It follows that investors' selling propensity is monotonically increasing relative to unrealized profit.</u> On the other hand, under the asymmetric V-shaped disposition effect (Ben-David and Hirshleifer, 2012), investors' selling propensity is an asymmetric V-shaped function of unrealized profits, implying that selling probability increases with the magnitude of gains or losses and that the gain side has a larger slope than the loss side. <u>It follows that the average selling propensity is higher for gains than losses, which therefore still results in selling more gains than losses</u>.

That is, holding other things constant, the impact of large unrealized gains or losses on stock pricing depends on the

[3] For example, see Odean (1998), Grinblatt and Keloharju (2001), Locke and Mann (2005), Shapira and Venezia (2001), Coval and Shumway (2005) for US market and Grinblatt and Keloharju (2001), Shapira and Venezia (2001), Feng and Seasholes (2005) for international markets.

assumed relation between propensity to sell and unrealized gains/losses. Under binary disposition effect, investors' selling propensity is monotonically increasing with unrealized profit. It follows that stocks with larger unrealized gains (losses) expect to experience higher (less) selling pressure, leading to lower (higher) current prices and higher (lower) next period returns. Under asymmetric V-shaped disposition effect, stocks with either large unrealized gains or large losses experience higher selling pressure, leading to lower current price and higher next period return. However, since the selling propensity is asymmetrically higher for gains than for losses, the underpricing due to unrealized losses expects to be of lesser extent to the underpricing due to unrealized gains. The analysis calls for dissected measures of unrealized capital gains and capital losses. Our first research question addresses the relation between unrealized gains/losses (GO, LO, CGO) and cross-sectional returns in a market. The empirical results for emerging markets generally conform to the binary disposition effect, which evidence is inconsistent with An (2016) for the US market..

Our second research question then relates the propensity to sell to the inverted return-volatility relation, namely the IVOL effect and the MAX effect. Following the binary disposition effect, stocks with greater unrealized net capital gains (CGO) tend to be underpriced due to greater selling pressure, which will lessen or reverse the negative IVOL effect. That is, under binary disposition effect, stocks with lower CGO or larger |LO| tend to show greater IVOL effect than those with higher CGO or lower |LO|. Under the V-shaped disposition effect, stocks experienced with greater unrealized capital gains (GO) or greater unrealized losses in absolute value (|LO|) tend to have greater propensity to sell and greater selling pressure, and are likely to be underpriced. That is, under the asymmetric V-shaped disposition effect, a larger GO or a larger |LO| serves as a decelerator of the IVOL effect, while with the influence from GO being greater. The implications from these two versions of disposition effect differ in the relation between |LO| and the IVOL effect. The contrasting inferences offer us a venue to empirically test which version of disposition effect prevails in our sample emerging markets.

Moreover, studies have suggested that speculative trading plays a role in these anomalies (e.g., Ben-David and Hirshleifer, 2012). Investors' speculative characteristics, such as trading behavior, demographic attributes and culture factors may well contribute to the observed anomalies. This study will take advantage of the multi-market platform to examine this issue.

Accordingly, this study documents the following evidence in the emerging markets. First, in view of the high correlations among IVOL, MAX and BETA, this study constructs risk metrics that are orthogonalized against each other. I then use those orthogonalized IVOL, MAX and BETA for further investigations. The anomaly associated with IVOL generally remains robust in most emerging markets. However, the MAX anomaly is weakened and the BETA anomaly has become insignificant in most markets and in aggregation.

Next, this study computes measures of unrealized capital gains (GO), capital losses (LO), and net capital gains (CGO) for individual stocks across 32 emerging markets. The mean/median GO and LO vary significantly across markets. The mean/median GO and |LO| are, as expected, greater when using longer estimation window, i.e., 36 months versus 12 months. When aggregating all stocks across all sample emerging markets while controlling for country factors, the fixed effects results show that CGO as well as its decomposed components, GO and |LO|, have positive relation with next period returns. The evidence is consistent with the argument that stocks with greater unrealized gains or losses tend to be subject to greater propensity to sell and thus underpriced, and yield higher next period returns.

Most importantly, this study finds results regarding the impact of propensity to sell on IVOL/MAX anomalies. The empirical results indicate that stocks with greater CGO tend to exhibit even greater negative IVOL anomaly while similar impact is absent in the case of MAX anomaly. The results are not consistent with the predictions from disposition effect. Note that stocks with greater propensity to sell are subject to contrasting forces on their IVOL anomaly. On one hand, those stocks are likely to be underpriced and the negative IVOL anomaly expects to be weakened. On the other hand, those stocks are subject to greater arbitrage risk as well as greater arbitrage asymmetry (i.e., greater likelihood being short due to their high unrealized capital gains). Such factors then expect to aggravate the negative IVOL effect. The CGO results suggest in aggregation the latter effect dominates.

To better dissect the effects, the decomposed components are applied. Results show that GO aggravates the negative IVOL anomaly while |LO| tends to reverse or weaken the anomaly. This provides evidence consistent with the V-shaped disposition effect, suggesting investors to have diverse propensity to sell over different ranges of unrealized capital gains/losses. It should however be noted that this study does not find widespread evidence of significant impact of propensity to sell on these anomalies for individual markets. Meanwhile, the absence of similar impact from investors' propensity to sell, whether measured by GO, LO, or CGO, on MAX anomaly, suggests that the mechanism leading to these two anomalies are likely to differ.

Last, this study also performs regional analysis in view of the diverse propensity to speculation across markets of distinct cultures. Results find that the impact of CGO and GO on the IVOL anomaly disappear for Latin American markets while the impact of |LO| remains robust in the region. This result suggests that investors in different regions exhibit different functional forms of preferences for capital gains.

Studies on propensity to sell are still relatively scant in current literature, which primarily is attributable to the requirement of account data for such type of studies. The proposed measure of CGO by Grinblatt and Han (2005) offers a venue to perform studies in relation to behavioral finance over wider samples and in international markets. More evidence expects to be documented with these measures. Results of this study suggest that the IVOL anomaly and the MAX anomaly, though are correlated, may well be generated via different mechanisms, which suggestion is revealed from the different findings with propensity to sell. More interesting investigations are expected by tracking such differences.

The remainder of this report is organized as follows. In Section 2, I will review the literature relating to the impact of derivative usage and earnings management on firm value, and develop the research hypotheses. Section 3 describes the sample, proxy measures and presents the diagnostics. Section 4 reports the empirical results. Section 5 concludes.

2. Literature Review and Research Hypothesis Development

2.1 Anomalies on Risk-Return Relations

<u>Beta Anomaly</u>

CAPM of Sharpe (1964) and Lintner (1965) implies a positive relation between beta-risk and expected returns. Black, Jensen and Scholes (1972) first find that low- risk firms tend to earn higher average returns when risk is measured by CAPM beta. Later studies find robust evidence of flat or even negatively sloped SML in the US market and in international markets [Black (1972), Fama and MacBeth (1973), Fama and French (1992), and Baker and Wurgler (2014), Frazzini and Pedersen (2014)]. Baker, Bradley, and Wurgler (2011) recently show that the cumulative performance of stocks has been declining with beta since 1968. Baker, Bradley, and Wurgler (2011) and Frazzini and Pedersen (2014) both find a strategy by buying low-beta and selling high-beta stocks (Betting-Against-Beta) yields significant abnormal returns as high as the value premium or the momentum profits. Asness, Frazzini, and Pedersen (2014), Bali et al. (2014), Huang, Lou, and Polk (2014), Novy-Marx (2014), Boguth and Simutin (2015), and Malkhozov et al. (2015) all examine this betting-against-beta (BAB) strategy.

Indeed, researchers have long attempted to reconcile this flat or downward-sloped SML by relaxing assumptions of CAPM [e.g., Black (1972), Delong et al. (1990), Campbell, Grossman, and Wang (1993)]. More recently, Hong and Saer (2016) suggest that relaxing the assumption of short sales and homogeneous expectations may explain the negatively sloped SML. There is recently also a strand of literature emphasizing that conditional beta or conditional alpha can be used to resolve the beta anomaly (e.g., see Cederburg and O'Doherty (2016) and Babenko, Boguth and Tserlukevich (2016)). Also, Bali, Cakici, and Whitelaw (2011), Barberis and Huang (2008), and Bali, Brown, Murray, and Tang (2016) argue that the demand for lottery-type stocks can partially explain the beta anomaly.

<u>Idiosyncratic Risk (IVOL) Anomaly</u>

Idiosyncratic volatility of stock returns has become one of the most actively researched topics since the pioneer works of Roll (1988) and Campbell, Lettau, Malkiel, and Xu (2001). Classical asset pricing theory asserts that only systematic risk should be priced and expected return of a stock is not supposed to depend on idiosyncratic volatility. More recently, Ang, Hodrick, Xing, and Zhang (2006) finds stocks with high idiosyncratic volatilities tend to have lower next period returns in cross sections. This ignites a strand of researches investigating this idiosyncratic volatility puzzle, which has become a notable anomaly or source of mis-pricing in finance researches. Empirical studies generally find a negative cross-sectional relation between idiosyncratic volatility and next period return for U.S. market as well as international markets (e.g., see Fu 2009; Chen et al., 2012; Ewens, Jones, and Rhodes-Kropf, 2013), while with a few exceptions (e.g., Bali and Cakici, 2008). Various explanations have been afforded to explain such phenomenon (e.g., see Baker and Wurgler, 2006; Zhang, 2006; Bali and Cakici, 2008; Fu, 2009; Jiang, Xu and Yao, 2009; Huang, Liu, Rhee and Zhang, 2010; Han and Lesmond, 2011).

Many researchers consider idiosyncratic volatility to represent arbitrage risk. Recently, Stambaugh, Yu and Yuan

(2015) suggest that this idiosyncratic volatility puzzle is a product of arbitrage risk born by idiosyncratic risk combined with arbitrage asymmetry arising from investors being unable or unwilling to short sell. Stocks with greater idiosyncratic volatility are more susceptible to mispricing. Among over-priced (under-priced) stocks, those with greater idiosyncratic volatility are subject to greater over-pricing (under-pricing). Next, Stambaugh et al. introduce arbitrage asymmetry to the scenario. Empirical evidence shows that investors are usually unable to short sell stocks due to institutional factors or unwilling to short simply due to personal preference (e.g., see Boehmer, Jones, and Zhang, 2009; Boulton and Braga-Alves, 2010; Saffi and Sigurdsson, 2011). This then makes over-pricing harder to be arbitraged away than under-pricing. In aggregation, the negative idiosyncratic volatility effect prevails over the positive one at market level. The empirical evidence of Stambaugh et al. (2015) over the U.S. market supports their hypothesis.

Anomaly associated with Lottery-Type Stocks (MAX Anomaly)

Kumar (2009) and Kumar et al. (2011) define stocks as lottery-type stocks as those having the feature of paying low while having very low probability of very high payoff. They find those lottery-type stocks tend to be over-priced and are associated with lower expected return. Kumar (2009) explains the phenomenon with investors' preference for skewness, which leads to overpricing for lottery type stocks and then a lower next period return. There has been increasing evidence documented for the US market [Doran et al. (2011), Han and Kumar (2013), and An, Wang, Wang, and Yu (2015)] and for the international markets [Doran et al. (2011), Carpenter, Lu, and Whitelaw (2014), Annaert, De Ceuster, and Verstegen (2013), Walkshwausl (2014), Zhong and Gray (2014), Hsin and Peng (2016)].

Among those studies, Bali et al. (2011) propose a more direct measure, MAX, which assesses the magnitude of prior highest return of a stock. Hsin and Peng (2016) test the over-pricing for lottery-type stocks for 30 emerging markets by portfolio sorts on MAX, as well as by performing a Fama-MacBeth (1973) cross-sectional regression of predictive returns while controlling for other factors affecting the cross-sectional returns. Both the results of portfolio sorts and those of Fama and MacBeth procedure find robust evidence of lower next-month return for stocks with higher prior MAX values.

2.2 Disposition Effect – Classic Binary Version and V-Shaped Version

The disposition effect proposed by Shefrin and Statman (1985) describes that investors tend to sell securities with potential capital gains rather than those with capital losses. Researchers have since documented evidence of investor trading behavior in support of this effect in the US market as well as in the international markets [e.g., see Odean (1998) and Grinblatt and Keloharju (2001), Feng and Seasholes (2005), and Barber and Odean (2013)]. The suggestion that investors have heterogeneous propensity to sell conditional on unrealized gains and losses offers possible explanations for pricing anomalies. Note however that any price impact can only result from aggregated investor behavior. For this purpose, Grinblatt and Han (2005) design a measure to estimate the aggregated unrealized capital gains (CGO, which will be discussed in details in the methodology section) and find that the investor behavioral pattern suggested by disposition effect serves as a source of price momentum.

More recently, Ben-David and Hirshleifer (2012) examine the trading data and find that investors' propensity to sell is not a monotonic function, but instead, a V-shaped function of unrealized gains with the gain side having a larger slope than the loss side in terms of absolute value (see Figure 2B of Ben-David and Hirshleifer). Under this asymmetric V-shaped function for propensity to sell, investors still on average tend to sell more winners than losers due to the asymmetric slopes. However, unlike the classic binary disposition effect, the V-shaped function suggests that investors will exhibit heterogeneous trading behavior not just between gain domain and loss domain but also across different ranges of gains and losses. An (2016) is one of the first studies testing the empirical implication of this V-shaped disposition effect on asset pricing. An (2016) finds that U.S. stocks with extreme unrealized gains or losses have higher next period returns than the remaining stocks, an evidence in support of the V-shaped function for selling propensity.

This proposed study attempts to test the implications from disposition effect, in the form of both the traditional binary version and the V-shaped version, on the anomalies associated with IVOL and MAX. In particular, currently documented IVOL or MAX anomalies are monotonic and unconditional. The asymmetric V-shaped selling schedule expects to yield implications that are non-monotonic and state-dependent, and hopefully shed further light on the heterogeneity of risk-return relations.

2.3 Research Hypothesis Development

IVOL Anomaly and Investors' Propensity to Sell (Unrealized Capital Gains/Losses)

Various researchers have offered explanation for the IVOL anomaly. Among them, Stambaugh, Yu and Yuan (2015) analyze the IVOL effect through two forces, arbitrage risk and arbitrage asymmetry. Among over-priced (under-priced) stocks, those with greater idiosyncratic volatility are subject to greater over-pricing (under-pricing) due to higher arbitrage risk. At the same time, the short sales constraints make over-pricing harder to be arbitraged away than under-pricing. In aggregation, the negative idiosyncratic volatility effect prevails over the positive one at market level. The framework of Stambaugh et al. suggests that the magnitude of the IVOL anomaly depends on the likelihood of over-pricing versus under-pricing, the likelihood of short-sales, and the magnitude of arbitrage risk. Their empirical evidence over the U.S. market indicates a positive IVOL effect among most underpriced stocks and a negative while stronger effect among the most overpriced stocks.

Following the binary disposition effect, stocks with greater unrealized net capital gains (CGO) tend to be underpriced due to greater selling pressure, which will lessen or reverse the negative IVOL effect. That is, under binary disposition effect, a greater CGO or GO posits as a decelerator for the IVOL effect.[4] On the other hand, stocks with strong capital losses (i.e., negative CGO) tend to have less selling pressure and are likely to be over-priced, which scenario tends to aggravate the IVOL effect. That is, under binary disposition effect, stocks with lower CGO or larger |LO| tend to show greater IVOL effect than those with higher CGO or lower |LO|. Note that Wang Yan and Yu (2017) find that the risk-return relation is positive among stocks with high CGO while negative among stocks with low CGO.

Under the V-shaped disposition effect, stocks experienced with greater unrealized capital gains (GO) or greater unrealized losses in absolute value (|LO|) tend to have greater propensity to sell and greater selling pressure, and are likely to be underpriced, while the degree of underpricing over the range of negative CGO should be less than that over the range of positive CGO. Such impact from propensity to sell then serves to lessen the IVOL effect. That is, under the asymmetric V-shaped disposition effect, a larger GO or a larger |LO| serves as a decelerator of the IVOL effect, while with the influence from GO being greater.

The implications from these two versions of disposition effect differ in the relation between |LO| and the IVOL effect.

[4] While stocks with greater CGO are likely to be subject to greater arbitrage risk, it still requires the presence of arbitrage asymmetry to establish the negative IVOL effect.

The binary disposition effect predicts that a large |LO| tends to aggravate the IVOL effect, <u>while the V-shaped disposition effect predicts the opposite direction for stocks with large |LO|.</u> The contrasting inferences offer us a venue to empirically test which version of disposition effect prevails in our sample emerging markets.

Furthermore, Ben-David and Hirshleifer (2012) find that the strength of the V-shape in the disposition effect is related to investors' speculative characteristics, such as trading behavior and demographic characteristics of investors. It follows that the difference in the relation between IVOL and next period return across different ranges of GO and |LO| depends upon the speculative characteristics of the market. This proposed study employs 30 emerging markets as the sample, which provides a platform to study the impact of country-specific factors, including trading behavior and culture factors, on the pattern of the relationship of risk measures and expected returns.

That is, based on the V-shaped disposition effect, we hypothesize that the heterogeneity of the IVOL effect across various ranges of unrealized capital gains and losses (GO and LO) becomes widened for those markets with investors characterized as being more speculative.

<u>MAX Anomaly and Investors' Propensity to Sell (Unrealized Capital Gains/Losses)</u>

Based on the V-shaped disposition effect, investors sell more when they have larger gains and losses. It follows that stocks with larger unrealized gains and losses will experience greater selling pressure, which will drive down current price and lead to higher next period returns when prices are restored to their fundamental values. Note that the existing explanations for the over-pricing of lottery type stocks focus on the demand side of investors. The introduction of disposition effect will add the selling side story to the picture.

First, if we assume lottery-type stocks to be those with greater unrealized gains, then V-shaped disposition effect suggests that lottery-type stocks, or stocks with higher prior MAX, tend to experience larger selling pressure and lead to higher next period return, which is inconsistent with the current finding for high-MAX stocks. In fact, stocks with greater prior one-month MAX values do not necessarily have greater unrealized capital gains. The possibility is that for stocks with high MAX, a history of price increase and large unrealized capital gains (high GO) may lead to selling pressure and higher next period return, as long as the demand for lottery-type stocks do not dominate the disposition effect. On the other hand, if those stocks with high MAX have a history of price path that yields unrealized capital losses or small capital gains, which situation yields low likelihood of selling pressure. It follows that the effect from demand for lottery-type stocks will prevail and drive up current price, leading to lower next period return, i.e., the presence of MAX anomaly.

Specifically, based on the V-shaped disposition effect, the MAX effect depends on stocks' unrealized capital gains. The result is a horse race between the demand for the lottery-type payoffs and the stockholders' selling propensity. Those stocks with high MAX while having high unrealized capital gains (GO) tend to have a selling pressure that offsets the effect of demand for lottery-type stocks, leading to insignificant MAX anomaly. On the other hand, for those stocks with high MAX but only mild level of GO or |LO|, the effect of demand for lottery-type stocks will prevail and lead to over-pricing and then lower next period return, i.e., a presence of MAX anomaly.

This study tests the following two hypotheses state the predictions respectively from the V-shaped disposition effect and the binary version disposition effect. First, the magnitude of MAX anomaly depends non-monotonically on stocks' unrealized net capital gains. The MAX anomaly is greatest for those with mild level of unrealized capital gains or losses (GO and |LO|), then for those with large magnitude of capital losses (|LO|), and the anomaly may become insignificant for those with high unrealized capital gains (GO). Second, the magnitude of MAX anomaly decreases monotonically with stocks' unrealized net capital gains. The MAX anomaly is greater for those with unrealized capital losses (CGO < 0) and becomes less or insignificant for those with net capital gains (CGO>0).

Ben-David and Hirshleifer (2012) have emphasized that the slopes of the V-shape depends on the speculative characteristics of investors. An (2016) also find the effects of unrealized gains and losses are stronger in more speculative subsamples. This study will take advantage of the sample of multiple markets, which are expected to have different investor traading characteristics due to the diverse institutional factors and culture factors, to test the impact of speculative characteristics on the MAX anomaly. However, the speculative characteristics may well show their impact on the demand side (i.e., greater preference for lottery type stocks) as well as on their selling schedule (i.e., more dependent on their unrealized capital gains). It is simply an empirical issue when it comes to the trade-offs between these two forces. Based on the V-shaped disposition effect, the magnitude of MAX anomaly depends on the stocks' unrealized net capital gains, with the sensitivity determined by the markets institutional and culture factors.

Recently, An et al. (2015) also find the anomaly associated with lottery type stocks to depend on prior unrealized gains/losses in the US market. The difference is that An et al. adopt a preference-based explanation, i.e., reference-dependent preference (RDP) for their finding. This study proposes the above research hypotheses, which specifically consider both the buying behavior (demand for lottery type payoffs) and the non-linear selling schedule implied by the disposition effect. Furthermore, this proposed study has the advantage of a multi-market sample and provides us with an opportunity to test the relation between the investors speculative characteristics and the sensitivity of MAX anomaly relative to the unrealized gains/losses.

3. Method and Data

3.1. Measures of Risk Metrics

Measure of Idiosyncratic Volatility (IVOL)

This study estimates the idiosyncratic risk of stocks based on the method used by Goyal and Santa-Clara (2003), among others, and calculates the monthly idiosyncratic risk by regressing stock *i*'s daily dollar returns within month *t* on the local market index return of the home market of stock *i*, $R_{m,t}$. Daily stock returns are in US dollars for all sample stocks. The idiosyncratic risk of stock *i* for month *t* is measured by the standard deviation of the residuals, which will be denoted as $IVOL_{i,t}$. A minimum of 10 days data are required for the computation. An alternative approach applies the above regression each month over a three-month moving window. That is, the monthly idiosyncratic volatility for month *t* will be estimated using daily returns during month *t-2* to *t*. The purpose is to avoid losing too many sample stocks due to insufficient daily returns for computing idiosyncratic volatility. I also estimate the idiosyncratic risk of stocks by additionally incorporating global market index return, $R_{w,t}$, in the regression. Such application follows Bekaert, Hodrick and Zhang (2009) by considering the comovement with the world market also as a part of systematic risk. Accordingly, the standard deviation of the residuals in equation (2) serves as an alternative version of idiosyncratic volatility considering global factors.

In this study, idiosyncratic volatilities (IVOL) is computed for each month *t* using the daily return data from month t to month t-T, with T equal to 11 based on the market model in equation (1) and the global version in equation (2). That is, the monthly series of IVOL is computed with moving windows with a window length of one year. The idiosyncratic volatility anomaly (IVOL effect) for my sample of emerging markets will be re-tested through Fama-MacBeth cross-sectional equation, where the relevant firm characteristics can be controlled for.

<u>Measure of Market Beta</u>

The market beta (BETA) of stock *i* in month *t* is estimated by applying a modified market model, that includes the lead and the lag of the market portfolio return, in addition to the current market portfolio return in the regression [e.g., see Scholes and Williams (1977)]. The market beta is estimated with daily return data for the 11 months before the end of month *t*, and is re-estimated each month using a moving window.

<u>Measure of MAX</u>

Kumar (2009) and Kumar et al. (2011) define stocks as lottery-type stocks as those having the feature of paying low while having very low probability of very high payoff. Bali et al. (2011) propose a more direct measure, MAX, which assesses the magnitude of prior highest return of a stock. This study follows Bali et al. (2011) and define '$MAX(k)_{i,t}$' as the average of the k highest daily returns for stock i during month t, i.e.,

$$MAX(k)_{i,t} = \frac{1}{k}\left[\sum_{h=1}^{k} \max h(R_{i,d})\right], d=1, D_t, \tag{1}$$

where $maxh(R_{i,d})$ denotes the *h*-th maximum daily return of month *t* and D_t is the number of trading days in month *t*.

Hsin and Peng (2016) test the over-pricing for lottery-type stocks for 30 emerging markets by portfolio sorts on MAX, as well as by performing a Fama-MacBeth (1973) cross-sectional regression of predictive returns while controlling for other factors affecting the cross-sectional returns, including market beta, firm size, market-to-book ratio, turnover ratio, and the price level of a stock as controls [also see Kumar (2009) and Bali et al. (2011)]. Both the results of portfolio sorts and those of Fama and MacBeth procedure find robust evidence of lower next-month return for stocks with higher prior MAX values.

Table 1 reports the descriptive statistics of IVOL, BETA and MAX, in addition to other firm-level and country-level variables to be used in this study.

[Insert Table 1 about Here]

Orthogonalized Risk Measures

Table 2 shows that across all emerging markets, there is a monotonically increasing relation between MAX and beta/IVOL. Those stocks in the high-MAX portfolio exhibit greater mean/median values of market beta and IVOL. This implies that the anomalies associated with MAX, beta and IVOL could well be inter-related. Indeed, Bali, Brown, Murray and Tang (2016) have recently found the demand for lottery-type stocks could explain away a significant portion of the beta anomaly in the US market.

[Insert Table 2 about Here]

In order to disentangle these anomalies and sort out their sources, this study measures the orthogonalized beta, IVOL and MAX. The orthogonalized measures of Beta, IVOL and MAX is obtained by running separate cross-sectional regressions. At the end of each month *t*, we perform the following cross-sectional regressions for all stocks in the same market:

$$Beta_{i,t} = c_{Beta} + c_1\ IVOL_{i,t} + c_2\ MAX_{i,t} + e_{Beta,i,t} \tag{2a}$$

$$IVOL_{i,t} = c_{IVOL} + c_1\ Beta_{i,t} + c_2\ MAX_{i,t} + e_{IVOL,i,t} \tag{2b}$$

$$MAX_{i,t} = c_{MAX} + c_1\ Beta_{i,t} + c_2\ IVOL_{i,t} + e_{MAX,i,t} \tag{2c}$$

The portion of Beta that is orthogonal to IVOL and MAX is denoted as Beta⊥, which is equal to the intercept c_{Beta} plus the residual terms e_{Beta}. Similarly, we obtain the orthogonalized measures for Beta, IVOL and MAX, denoted respectively as Beta⊥, IVOL⊥ and MAX⊥, as the intercept plus the residual term in the corresponding regression. These orthogonalized measures will be used for all later tests in this study.

3.2 Estimates of Propensity to Sell - Unrealized Capital Gains / Losses at Stock Level

Grinblatt and Han (2005) propose an empirical estimate for unrealized capital gains of individual stocks, which is termed as capital gain overhang (CGO). The CGO measures the difference between the current stock price and a reference purchase price, which is estimated based on historical prices and turnovers. The CGO serves as a proxy measure for the net unrealized capital gains aggregated over all investors for each stock. Frazzini (2006) later applies a similar measure based on mutual fund holdings. Wang et al. (2016) also employ the measure to distinguish states of prior gains/losses for investors. A recent study by An (2016) further decomposes the CGO into a capital gains component and capital loss component in order to study the asymmetry of investors propensity to sell. Considering the likelihood of investors' asymmetric responses, this proposed study will adopt the decomposed measures proposed by An (2016).

In particular, this study will calculate the "Gain Overhang" (GO) component as follows:

$$GO_{i,t} = \sum_{n=1}^{T} w_{i,t-n} \, [gain_{i,t-n}]$$

$$gain_{i,t-n} = \frac{P_{i,t} - P_{i,t-n}}{P_{i,t-n}} \times D^{+} \qquad (3)$$

$$w_{i,t-n} = \frac{1}{k} V_{i,t-n} \times \prod_{j=1}^{n-1} [1 - V_{i,t-n+j}]$$

where $V_{i,t}$ is the turnover ratio of stock *i* at time t, D+ is equal to 1 if $P_t \geq P_{t-n}$ (i.e., a non-negative capital gain) and is zero otherwise. This GO is essentially a turnover-weighted average of unrealized capital gains for investors holding stock *i*, with the weight serving as a proxy for the percentage of stocks purchased at time *t-n* that are not traded later. This study will compute this GO measure at each month end while using daily prices and turnover ratios in the above equations. Note that Grinblatt and Han (2005) and Wang et al. (2016) use weekly prices/turnover ratios instead. However, considering that investors in emerging markets tend to be dominated by retail investors and tend to trade on short horizon, this study will apply daily price/turnover ratios instead.

Similarly, the aggregated unrealized capital loss for each stock, i.e., the capital Loss Overhang (LO) is estimated as follows:

$$LO_{i,t} = \sum_{n=1}^{T} w_{i,t-n} \, [loss_{i,t-n}]$$

$$loss_{i,t-n} = \frac{P_{i,t} - P_{i,t-n}}{P_{i,t-n}} \times D^{-} \qquad (4)$$

$$w_{i,t-n} = \frac{1}{k} V_{i,t-n} \times \prod_{j=1}^{n-1} [1 - V_{i,t-n+j}]$$

where D- is equal to 1 if $P_t < P_{t-n}$ (i.e., a capital loss) and is zero otherwise, and all other variables are the same as those defined for GO. In the above equations for GO and LO, This study computes two sets of GO, LO, and CGO based on two different lengths of window, 36 months and 12 months. Accordingly, the normalizing factor '*k*' in the equation is set to make the sum of weights over the window equal to 1.

Note that all the current studies that employ CGO measures use US stocks as their sample and choose a five-year window for their researches. Considering that emerging market stocks generally suffer from short histories of price data, this study selects a shortened window. In addition, according to Ben-David and Hirshleifer (2012), their researched disposition effect flattens after one year. Also, some studies find that most emerging market investors have relatively shorter holding periods for their stock holdings.

Corresponding to the original variable defined by Grinblatt and Han (2005), CGO, a net unrealized capital gain, is simply the sum of Gain Overhang (GO) and Loss Overhang (LO):

$$CGO_{i,t} = GO_{i,t} + LO_{i,t} \qquad (5)$$

CGO could be positive or negative for a stock at a given time, depending on the relative magnitude of *GO* and |*LO*| at the time. A positive CGO means a positive net capital gain, while a negative CGO means a net capital loss for the stock at the time.

The descriptive statistics of CGO, GO and LO for the 32 sample emerging markets are reported in Table 3. As one can see, the mean and media values of propensity to sell vary significantly across markets.

[Insert Table 3 about Here]

These three measures, *GO*, *LO*, and *CGO*, are applied in the study to serve as proxies for unrealized capital gains and losses, built on which different theories, being preference-based or belief-based, will make inferences on next period stock pricing. According to the V-shaped disposition effect suggested by Ben-David and Hirshleifer (2012), investors' propensity to sell is an asymmetric V-shaped function of unrealized profits, with the gain side assuming a steeper slope than the loss side. Ben-David and Hirshleifer test their theory using investors' trading data and find evidence in support of their hypothesis that investors tend to sell more when facing larger profits or larger losses, while with the likelihood increasing more over the gain side. Their V-shaped disposition effect is thus different from the traditional binary disposition effect, which only suggests the difference in the probability of selling between the gain side and the loss side.

Note that the actual price impact of the propensity to sell derived from the disposition effect argument depends on the aggregated propensity over all investors in the market equilibrium. Grinblatt and Han (2005) therefore propose the CGO measure to estimate the aggregated unrealized capital gains/losses at stock level and apply the measure to test the classic (binary) disposition effect, which states that investors tend to sell winners and hold losers. Accordingly, stocks with high and positive CGO expect to experience higher selling pressure and become underpriced, and are conjectured to have higher next period return. On the other hand, stocks with low and negative CGO are relatively overpriced and expect to yield lower next period return. Frazzini (2006) later also use similar CGO measure for testing mutual fund holdings. More recently, Wang, Yan and Yu (2016) apply the CGO measure to test their reference-dependent preference (RDP) explanation by applying the prospect theory [(Tversky and Kahneman (1992) and Barberis and Huang (2008)] for the reversed risk-return relation. An (2016) apply the decomposed CGO measures, GO and LO, and find that stocks with both large unrealized gains (GO) and large unrealized losses (|LO|) have larger next month returns. An (2016) interprets the results as supporting evidence for the V-shaped disposition effect proposed by Ben-David and Hirshleifer (2012).

The binary disposition effect suggests that stocks with high and positive CGO expect to experience higher selling pressure and become underpriced, are thus conjectured to yield higher next period. The aggregated results of emerging market stocks indeed indicate a positive relation between CGO and next period returns.

Meanwhile, the V-shaped disposition effect by Ben-David and Hirshleifer (2012) suggests that investors tend to sell more when facing larger profits or larger losses, while with the likelihood increasing more over the gain side. That is, the decomposed GO and LO expect to show different results, with GO having even stronger relation with next period return that LO. Consistent with the implication from the V-shaped disposition effect, the aggregated results of this study in fact indicate that GO and |LO| work in the opposite directions on next period return. In particular, this study finds that .

3.3 Data

This study will assemble a sample of emerging markets based on those defined by *Morgan Stanley Capital International*. This study selects those emerging markets in the sample also takes into account their data availability, including the sufficiency of firm-level data provided by Datastream and Worldscope. Our sample thus covers 30 emerging markets from Europe, America, Africa and Asia. Note that some countries, e.g., Hong Kong and Singapore, are also included for their emerging market history during our sample period. Considering limited data availability during earlier years from Datastream, I will apply a sample period extending from January 1980 to December 2016. However, it expects the main results will rely on data from 1990 to 2016, as the emerging market data are limited prior to 1990.

Only common stocks listed on the major exchange of the country with data available from Datastream and Worldscope will be included (one exception is China, where Shanghai exchange and Shengzheng exchange listed stocks are both included). That is, stocks must have a type of instrument indicator equal to 'Equity'. Sampled stocks should be domestically incorporated based on their home country and traded in local currency. The prices of suspended stocks will be dropped from the sample. I also exclude the initial six months' trading data for those newly listed or re-listed stocks. Daily prices including dividends (RI) are used. To enter the final sample, stocks must have return data available (after filtering) for at least 120 days in the sample year. This study will exclude country-months where fewer than 10 firms have available data. The company-level accounting data will be collected from Worldscope.

Global market data is calculated based on the World Market Index (at Level 1). Global industry data are from Datastream Global Equity Sector Indices. All the index data will be converted into US dollars. Most of the macroeconomic data for sampled markets are obtained from the World Bank database (WDI-online), FRED, and Datastream. ICRG data are available from PRS Group at monthly frequency. World Values Survey database is used to collect those social culture data (trust, hierarchy, and individualism), which are available from *World Values Survey Association (www.worldvaluessurvey.org).*

This study will impose a number of filters for those price data collected from Datastream. The sample includes only stocks listed on primary exchanges of the country and traded in local currency. Those leading and trailing zeros in the Datastream return series will be set to missing values. To address issues on coding errors of Datastream data, I will implement a filter for reversals in the data that could be caused by incorrect stock prices. In particular, I set R_t and R_{t-1} to missing if $|R_t| > 200\%$ or $|R_{t-1}| > 200\%$ and $R_{t-1} + R_t < 50\%$. I further windsorize the top and bottom 0.1% of the final sample of stock returns. The study by Ince and Porter (2006) presents a detailed discussion on the treatment of coding errors in Datastream and provides possible solutions. To enter the sample, stocks must have available return data for at least 120 days in the sample year. This study will exclude country-years where fewer than 10 firms have available data.

3.4. Time-Varying and Cross-Market Variables

This section provides details on those country level variables, which are applied in explaining or serving as control variables for time-varying common idiosyncratic volatility across markets as well as for explaining the idiosyncratic volatility effect. Empirical values of selected variables are listed in Table 1 for those sample markets.

Cultural Dimensions of Investors

This study follows prior researches including, La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997), Guiso, Sapienza and Zingales (2008b), and Pevzner, Xi and Xin. (2015) and captures a country's level of societal trust, hierarchy and individualism by its citizens' response to questions in World Values Surveys (WVS). This study will calculate three dimensions of culture measures of trust, hierarchy and individualism by closely following the procedure of Pevzner et al. (2015). The World Values Surveys (WVS) were undertaken in six waves in 1981–1984, 1989–1993, 1994–1998, 1999–2004, 2005–2008, and 2010-2014 (see http://www.wvsevsdb.com/wvs/WVSData.jsp). The scores are based on citizens' response to questions in the survey. The most recent cultural values will be matched to my country-level variables. This study will use the WVS information to assess three dimensions of societal culture, including trust, hierarchy and individualism.

Country Factors for Institutions and Market Development

The international finance literature has applied a variety of county-specific variables to evaluate the level of institutions quality, which expects to affect how investors process corporate information and price stocks. Bartram et al. (2012) also discuss those variables in determining a market's volatility. In this research, those variables expect to be related with the common idiosyncratic volatility as well. This class of variables generally assesses both the hardware (infrastructure) and software (laws, governance, disclosure and enforcement standards) of the corporate environment. The former may be directly measured, while the latter are usually indexed and sometimes obtained through survey.

Among those candidate variables, the mostly widely used variables are those from the following series of studies: LaPorta, Lopez-de-Silanes, Shleifer, and Vishny, 1997, 1998; LaPorta, Lopez-de-Silanes, and Shleifer, 2006; and Djankov, LaPorta, Lopez-de-Silanes, and Shleifer, 2008. Those values are mostly time invariant, as they are collected through survey during one particular historical year. Also widely cited are indexes from the ICRG (International Country Risk Guide) with values mostly available at monthly frequency. In addition, researchers also compute scores to assess corporate information quality/efficiency based on company-level information (e.g., Collins, Kothari, Shanken and Sloan, 1994; Durnev, Morck, Yeung and Zarowin, 2003; Leuz, Nanda and Wysocki, 2003).

4. Disposition Effect and the Beta, IVOL, MAX Anomalies

4.1 Measuring Beta-, IVOL- and MAX- Anomalies

I measure anomalies associated with Beta, IVOL and MAX using Fama-MacBetah (1973) cross-sectional regression. In the following discussions, I use 'RISK' to denote any of the three risk measures, Beta, IVOL and MAX. I perform a series of Fama-MacBeth (1973) cross-sectional regressions, which can easily incorporate additional control variables. Within each country, the anomaly associated with each risk metrics is estimated each month by running the following cross-sectional regressions:

$$\begin{aligned} R_{i,t} = {} & b_{0,t} + b_{BETA,t} BETA_{i,t-1} + b_{IVOL,t} IVOL_{i,t-1} + b_{MAX,t} MAX_{i,t-1} + b_{1,t} \ln SIZE_{i,t-1} + b_{2,t} \ln MB_{i,t-1} \\ & + b_{3,t} \ln P_{i,t-1} + b_{4,t} LIQ_{i,t-1} + b_{5,t} R_{i,t-1} + \varepsilon_{i,t+1} \end{aligned} \quad , \quad (6)$$

where $R_{i,t}$ is the return on stock i in month t. The cross-sectional regressions are performed on the one-month lagged values of BETA, IVOL, MAX and controlling for firm size, market-book ratio, share price, share turnover and lagged returns. All variables are winsorized at their 1st and 99th percentiles.

I then follow the standard Fama-MacBeth approach and compute the time-series averages of the slope coefficients from the regressions of stock returns. Results are reported in Table 4. The empirical results indicate that the negative anomaly for the orthogonalzied IVOL remains robust for 18 out of 31 sample markets, while the MAX anomaly has become relatively weakened presents significance for 13 markets. The anomaly for the orthogonalized BETA is significance for only three markets. .

[Insert Table 4 about Here]

4.2 Individual Market Analysis with Fama-MacBeth Approach

This section tests our main research hypotheses involving the explanations offered by disposition effect. These tests will be conducted with Fama-MacBeth cross-sectional regressions. In particular, I perform the monthly Fama-MacBeth cross-sectional regressions of stock returns on lagged risk metrics, measures for unrealized capital gains/losses, and other controls. The regressions are specified as follows.

$$\begin{aligned} R_{i,t} &= b_{0,t} + b_{1,t}CGO_{i,t-1} + b_{2,t}RISK_{i,t-1} + b_{3,t}CGO_{i,t-1} \times RISK_{i,t-1} \\ &\quad + b_{4,t}\ln SIZE_{i,t-1} + b_{5,t}\ln MB_{i,t-1} + b_{6,t}\ln P_{i,t-1} + b_{7,t}LIQ_{i,t-1} + b_{8,t}R(-12,-1)_{i,t-1} + b_{9,t}R_{i,t-1} + \varepsilon_{i,t+1} \end{aligned} \tag{7}$$

$$\begin{aligned} R_{i,t} &= b_{0,t} + b_{1,t}GO_{i,t-1} + b_{2,t}\,|\,LO_{i,t-1}\,| + b_{3,t}RISK_{i,t-1} + b_{4,t}GO_{i,t-1} \times RISK_{i,t-1} + b_{5,t}\,|\,LO_{i,t-1}\,| \times RISK_{i,t-1} \\ &\quad + b_{6,t}\ln SIZE_{i,t-1} + b_{7,t}\ln MB_{i,t-1} + b_{8,t}\ln P_{i,t-1} + b_{9,t}LIQ_{i,t-1} + b_{10,t}R(-12,-1)_{i,t-1} + b_{11,t}R_{i,t-1} + \varepsilon_{i,t+1} \end{aligned} \tag{8}$$

In the above regressions, RISK represents one of the risk metrics, i.e., BETA, IVOL and MAX. In addition, RISK will also be replaced with the orthogonalzied risk metrics, i.e., Beta⊥, IVOL⊥ and MAX⊥, respectively. The significance and magnitude of the regression coefficient for the inter-action terms between GO, |LO|, CGO and the risk metric will be used to test the hypotheses.

[Insert Table 5 about Here]

Results indicate that at market level, investors' propensity to sell, as measured by CGO, only shows significant negative impact on the IVOL anomaly for China, Morocco, Russian, and South Africa. Further explorations will be conducted by aggregating stocks across all sample markets.

4.3 Cross-Market Analysis with Fixed-Effects Model

One of the primary research purposes of this proposed study is to take advantage of the multi-market platform and examine the impact of cross-market differences in speculative characteristics of investors. For this purpose, a cross-market analysis will be performed. In addition to those country-specific institutional factors, this study will employ culture factors that may well affect market investors' speculative trading behavior. This study follows prior researches to apply the survey data from World Value Surveys (WVS) (e.g., see La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1997; Guiso, Sapienza and Zingales, 2008; Chui, Titman and Wei, 2010; Pevzner, Xi and Xin, 2015) as well as the data of Hofstede's cultural dimensions. The summary statistics of those cultural variables are listed in Table 2. This study performs the following fixed effects regressions:

$$
\begin{aligned}
R_{i,t} = {} & b_0 + b_1 CGO_{i,t-1} + b_2 RISK_{i,t-1} + b_3 CGO_{i,t-1} \times RISK_{i,t-1} + b_4\ Culture_{c,t} \\
& + b_5 Culture_{c,t} \times CGO_{i,t-1} + b_6 Culture_{c,t} \times RISK_{i,t-1} + b_7 Culture_{c,t} \times CGO_{i,t-1} \times RISK_{i,t-1} \\
& + b_{6,t} \ln SIZE_{i,t-1} + b_{7,t} \ln MB_{i,t-1} + b_{8,t} \ln P_{i,t-1} + b_{9,t} LIQ_{i,t-1} + b_{10,t} R(-12,-1)_{i,t-1} + b_{11,t} R_{i,t-1} \\
& + \sum_{q=1}^{Q} h_q\ [MACRO_{q,c,t}] + \sum_{j=1}^{J} s_j\ [Controls_{j,c,t}] + \varepsilon_{i,t+1}
\end{aligned}
\tag{11}
$$

where *MACROS* refer to those variables applied in the literature to affect returns. The remaining variables are as described in the preceding section. I will follow the procedure of Petersen (2009) to correct the standard errors for possible serial correlation within a given country and for cross-sectional correlation across countries in a given time.

The focus again is the regression coefficients for the inter-active terms. In particular, the regression coefficient for the interactive term among Culture, CGO, and RISK will serve for testing our research hypotheses. Again, the RISK metrics will be set as BETA, IVOL and MAX. In addition, RISK is replaced with the orthogonalzied risk metrics, i.e., Beta$_{\perp}$, IVOL$_{\perp}$ and MAX$_{\perp}$, respectively.

[Insert Table 6 about Here]

Results are reported in Table 6, which lists the aggregated results with fixed effects model for the IVOL and MAX effect. Dependent variable is the one-month ahead individual stock returns across all sample emerging markets. The model considers possible impact from investors' propensity to sell, as proxied by CGO (capital gains overhang), GO (gains overhang) and LO (loss overhang), in addition to controls for other prior-period firm characteristics, including market value (lnSize), MB ratio (lnMB), illiquidity (Illiq), prior six-month return (Mom), prior month return (Reversal), and price per share (lnPrice). Among those reported models, models [3], [4] and [7] consider the impact of propensity to sell using CGO, while models [5], [6], and [8] apply the decomposed variables, GO and LO for the examination. Panel A lists the results when 36 month windows are used to estimate CGO, GO and LO, while Panel B lists those when 12-month windows are used for the estimation. The risk metrics (IVOL, MAX, and Beta) have been first orthogonalized against each other via monthly cross-sectional regressions within each market. Reported models also differ in terms of consideration of country-specific factors or not. The sample period is from 1980 to 2016, with most markets running with sufficient data starting from 1990. Month fixed effects are included in all regressions.

The fixed effects results show that CGO as well as its decomposed components, GO and |LO|, have positive relation with next period returns. The evidence is consistent with the argument that stocks with greater unrealized gains or losses tend to be subject to greater propensity to sell and thus underpriced, and yielding higher next period returns.

This study finds results regarding the impact of propensity to sell on IVOL/MAX anomalies. The empirical results indicate that stocks with greater CGO tend to exhibit even greater negative IVOL anomaly while similar impact is absent in the case of MAX anomaly. Note that stocks with greater propensity to sell are subject to contrasting forces on their IVOL anomaly. On one hand, those stocks are likely to be underpriced and the negative IVOL anomaly expects to be weakened. On the other hand, those stocks are subject to greater arbitrage risk as well as greater arbitrage asymmetry (i.e., greater likelihood being short due to their high unrealized capital gains). Such factors then expect to aggravate the negative IVOL effect. The CGO results suggest in aggregation the latter effect dominates.

To better dissect the effects, the decomposed components are applied. Results show that GO aggravates the negative IVOL anomaly while |LO| tends to reverse or weaken the anomaly. This provides evidence consistent with the V-shaped disposition effect, suggesting investors to have diverse propensity to sell over different ranges of unrealized capital gains/losses. It should however be noted that this study does not find widespread evidence of significant impact of propensity to sell on these anomalies for individual markets. Meanwhile, the absence of similar impact from investors' propensity to sell, whether measured by GO, LO, or CGO, on MAX anomaly, suggests that the mechanism leading to these two anomalies are likely to differ.

[Insert Table 7 about Here]

This study also performs regional analysis in view of the diverse propensity to speculation across markets of distinct cultures. The 32 markets are classified into three regions: i) Asia, ii) Latin America, and iii) Europe-Africa-SouthernAsia. Results are reported in Table 7, which show that the impact of CGO and GO on the IVOL anomaly disappear for Latin American markets while the impact of |LO| remains robust in the region. This result suggests that investors in different regions exhibit different functional forms of preferences for capital gains.

5. Conclusion

The primary purpose of this study is to examine the role of investors' propensity to sell in affecting the relation between return and risk metrics. This study attempts to test the implications from disposition effect, in the form of the traditional binary version and the V-shaped version, on the anomalies associated with IVOL and MAX.

This study finds the following evidence in the emerging markets. First, we orthogonalize risk metrics against each other to extract the pure effect. After orthogonalization, the IVOL effect generally remains robust in most emerging markets, while the MAX anomaly is weakened and the BETA anomaly has become insignificant in most markets and in aggregation.

Second, when aggregating all stocks across sample emerging markets while controlling for country factors, the fixed effects results show that CGO as well as its decomposed components, GO, have positive relation with next period returns.

The evidence is consistent with the argument by disposition effect that stocks with greater unrealized gains tend to be subject to greater propensity to sell and thus underpricing, and yield higher next period returns.

Third, the empirical results indicate that stocks with greater CGO tend to exhibit even greater negative IVOL anomaly while similar impact is absent in the case of MAX anomaly. To better dissect the effects, the decomposed components are applied. Results show that GO aggravates the negative IVOL anomaly while |LO| tends to reverse or weaken the anomaly. This provides evidence suggesting that investors have diverse propensity to sell over different ranges of unrealized capital gains/losses. Our results are partially in support of the asymmetric V-shaped disposition effect in that a large |LO| serves as a decelerator for the IVOL effect. The absence of similar impact from investors' propensity to sell, whether measured by GO, LO, or CGO, on MAX anomaly, suggests that the mechanism leading to these two anomalies are likely to differ.

Last, this study also performs regional analysis in view of the diverse propensity to speculate across markets of distinct cultures. Results find that the impact of CGO and GO on the IVOL anomaly disappear for Latin American markets while the impact of |LO| remains robust in the region. This result suggests that investors in different regions exhibit different functional forms of preferences for capital gains.

Studies on propensity to sell are still relatively scant in current literature. The proposed measure of CGO by Grinblatt and Han (2005) offers a venue to perform studies in relation to behavioral finance over wider samples and in international markets. Results of this study suggest that the IVOL anomaly and the MAX anomaly, though are correlated, may well be generated via different mechanisms, which suggestion is revealed from the different findings with propensity to sell. More interesting investigations are expected by tracking such differences.

References

An, L., 2016. Asset Pricing When Traders Sell Extreme Winners and Losers. Review of Financial Studies 29, 823-861.

An, L., Wang., H., Wang, J., Yu, J. 2015. Lottery-Related Anomalies: The Role of Reference-Dependent Preferences. Federal Reserve Bank of Dallas, Working Paper No. 259.

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

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

Avramov, D., Chordia, T., Jostova, G., Philipov, A. 2013. Anomalies and financial distress, Journal of Financial Economics 108, 139-159.

Babenko, I., Boguth, O., Tserlukevich, Y. 2016. Idiosyncratic Cash Flows and Systematic Risk. Journal of Finance 111, 425-456.

Bailey, W., Karolyi, A., Salva, C., 2006. The economic consequences of increased disclosure: evidence from international cross-listings. Journal of Financial Economics 81,175–213.

Bali, T. G., Brown, S., Murray, S., Tang,Y., 2016. A Lottery Demand-Based Explanation of the Beta Anomaly. Journal of Quantitative Finance and Accounting, forthcoming.

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

Baker, M. and J. Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, Journal of Finance, 61 (4), 1645-1680.

Bansal, R., Kiku, D., Shaliastovich, I., Yaron, A., 2014. Volatilty, the macoeconomy, and asset prices. Journal of Finance 69, 2471-2511.

Bansal, R., Yaron, A. 2004 Risks for the long run: A potential resolution of asset pricing puzzles, Journal of Finance 59, 1481–1509.

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

Barberis, Nicholas, and Wei Xiong, 2009, What drives the disposition e_ect? An analysis of a long-standing preference-based explanation, Journal of Finance 64, 751-784.

Bartram, S., G. Brown and R. M. Stulz, 2012, Why are U.S. stocks more volatile? Journal of Finance, 67, 1329–1370.

Bekaert, G., Hodrick, R., Zhang, X. 2009. International Stock Return Comovements, Journal of Finance 64, 2591-2626.

Ben-David, I. , Hirshleifer, D. , 2012. Are investors really reluctant to real- ized their losses? Trading responses to past returns and the disposi- tion effect. Review of Financial Studies 25, 2485–2532 .

Benartzi, S. , Thaler, R. , 1995. Myopic loss aversion and the equity premium puzzle quarterly. Journal of Economics 110, 73–92 .

Black, F. , 1972. Capital market equilibrium with restricted borrowing. Jour- nal of Business 45, 4 4 4–455 .

Bennett, J. A., Sias, R. W., Starks, L. T. 2003. Greener Pastures and the Impact of Dynamic Institutional Preferences, Review of Financial Studies 16, 1203-1238.

Bloom, Nick, 2009, The impact of uncertainty shocks, Econometrica 77, 623–689.

Boehmer, E., Jones, C., Zhang, X., 2009. Shackling the short sellers: the 2008 shorting ban. Unpublished working paper, EDHEC Business School, Columbia University, and Purdue University.

Boulton, T., Braga-Alves, M., 2010. The skinny on the 2008 naked short- sale restrictions. Journal of Financial Markets 13, 397–421.

Brandt, M. W., Brav, A., Graham, J. R., Kumar, A. 2010. The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episodes?, Review of Financial Studies 23, 863-899.

Bris, A., Goetzmann, W. N., Zhu, N., 2007. Efficiency and the bear: short sales and markets around the world. Journal of Finance 62, 1029–1079.

Brockman, P., Liebenberg, I., Schutte, M., 2010. Comovement, information production, and the business cycle. Journal of Financial Economics 97, 107–129.

Brown, G., Kapadia, N. 2007. Firm-specific risk and equity market development, Journal of Financial Economics 84, 358-388.

Campbell, J.Y., Lettau, M., Malkiel, B., Xu, Y. 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, Journal of Finance 56, 1-43.

Carrieri, F., Chaieb, I., Errunza, V., 2013. Do implicit barriers matter for globalization? Review of Financial Studies 26,

1694-1739.
Chan, K., and A. Hameed. 2006. Stock price synchronicity and analyst coverage in emerging markets. Journal of Financial Economics 80, 115–147.
Chen, Z., Petkova, R. 2012. Does idiosyncratic volatility proxy for risk exposure? Review of Financial Studies 25(9): 2745-2787.
Djankov, S., La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2008. The law and economics of self-dealing. Journal of Financial Economics 88, 430–465.
Doidge, Craig, C., Andrew Karolyi, and René M. Stulz, 2013, The U.S. left behind? Financial globalization and the rise of IPOs outside the U.S. Journal of Financial Economics 110, 546-573..
Durnev, A., Morck, R., Yeung, B., Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797-836.
Ewens, M., Jones, C., Rhodes-Kropf, M. 2013. The price of diversifiable risk in venture capital and private equity, Review of Financial Studies 26, 1854–1889.
Fernandes, N., Ferreira, M. 2008. Does international cross-listing improve the information environment? Journal of Financial Economics 88: 216–244.
Ferreira, D., Ferreira, M., Raposo, C. 2011. Board structure and price informativeness. Journal of Financial Economics 99: 523–545.
Ferreira, M., and P. Laux. 2007. Corporate governance, idiosyncratic risk, and information flow. The Journal of Finance 2: 951–989.
Fink, J., Fink, K. E., Grullon, G. and Weston, J. P. (2010). What drove the increase in idiosyncratic volatility during the internet boom?, Journal of Financial and Quantitative Analysis 45: 1253-1278.
Fu, F. 2009. Idiosyncratic risk and the cross-section of expected stock returns, Journal of Financial Economics 91, 24-37.
Frazzini, Andrea, 2006, The disposition effect and underreaction to news, Journal of Finance, 61, 2017 2046.
Frazzini, A. , Pedersen, L. , 2014. Betting against beta. Journal of Financial Economics 111, 1–25 .
Goetzmann, W.N., Kumar, A., 2008. Equity portfolio diversification. Review of Finance 12, 433–463.
Goyal, A., Santa-Clara, P., 2003. Idiosyncratic risk matters!. Journal of Finance 58, 975–1007.
Grinblatt, M. , Han, B. , 2005. Prospect theory, mental accounting, and mo- mentum. Journal of Financial Economics 78, 311–339 .
Grundy, B. D., Martin, J. S., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. Review of Financial Studies 14, 29-78.
Gul, F., Ng, A., Srinidhi, B. 2011. Does board gender diversity improve the informativeness of stock prices? Journal of Accounting and Economics 51, 314–338.
Guo, H., Savickas, R. 2010. Relation between time-series and cross-sectional effects of idiosyncratic variance on stock returns, Journal of Banking & Finance 34(7): 1637-1649.
Han, Y., Lesmond, D. 2011. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility, Review of Financial Studies 24, 1590-1629.
Herskovic, B., Bryan, K., Lustig, H., Van Nieuwerburgh, S., 2015. The common factor in idiosyncratic volatility: Quantitative asset pricing implications. Journal of Financial Economics, http://dx.doi.org/10.1016/j.jfineco.2015.09.010
Hsin, C., Peng, S., 2016. Informational Efficiency and Investor Preference for Lottery-Type Stocks in Emerging Markets. Working Paper, FMA 2016.
Hong, H. , Sraer, D. , 2011. Speculative betas. Unpublished working paper. Princeton University .
Huang, W., Liu, Q., Rhee, S. G., Zhang, L. 2010. Return Reversals, Idiosyncratic Risk, and Expected Returns, Review of Financial Studies 23, 147-168.
Hutton, A., A. Marcus, and H. Tehranian. 2009. Opaque financial reports, R2, and crash risk. Journal of Financial Economics 94, 67–86.
Ince, O., Porter, R., 2006. Individual equity return data from Thomson Datastream: handle with care! Journal of Financial Research 29, 463–479.
Irvine, P. J. and Pontif, J. (2009). Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition, Review of Financial Studies 22, 1149{1177.
Jiang, G. J., Xu, D., Yao, T. 2009. The information content of idiosyncratic volatility, Journal of Financial and Quantitative Analysis 44, 1-28.
Kumar, A., 2007. Do the diversification choices of individual investors influence stock returns? Journal of Financial Markets 10. 362–390.

Kumar, A., 2009. Who gambles in the stock market? Journal of Finance 64, 1889–1933.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W., 1997. Legal determinants of external finance, Journal of Finance 52, 1131-1150.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W., 1998. Law and finance, Journal of Political Economy 106, 1113–1155.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2006. What works in securities laws? Journal of Finance 61, 1–32.
Li, K., Morck, R., Yang, F., Yeung, B., 2004. Firm-specific variation and openness in emerging markets. The Review of Economics and Statistics 86(3), 658–669.
Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: Why do emerging markets have synchronous stock price movements? Journal of Financial Economics 58, 215-260.
Odean, T. , 1998. Are investors reluctant to realize their losses? Journal of Finance 53, 1775–1798 .
Pástor, L.,Veronesi,P., 2003. Stock valuation and learning about profitability. Journal of Finance 58, 1749–1789.
Pástor, L., Veronesi, P., 2009. Technological revolutions and stock prices. American Economic Review 99, 1451–1483.
Petersen, M. A., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, Review of Financial Studies, 22, 435-480.
Pevzner, M., Xie, F., Xin, X., 2015. When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements. Journal of Financial Economics 117, 190-223.
Quinn, D., 1997, The correlates of changes in international financial regulation, American Political Science Review 91, 531-551.
Rajgopal, S., and M. Venkatachalam. 2011. Financial reporting quality and idiosyncratic return volatility Journal of Accounting and Economics 51: 1–20.
Roll, R. 1988. R2, Journal of Finance 43, 541–566.
Saffi, P., Sigurdsson, K., 2011. Price efficiency and short selling. Review of Financial Studies 24, 821–852.
Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride

losers too long: Theory and evidence, Journal of Finance 40, 777{791.
Stambaugh, R., Yu, J., Yuan, Y. 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70 (5), 1903-1948.
Stulz, R. 2005. The limits of financial globalization. Journal of Finance 60:1595–638.
Thaler, R. , 1980. Toward a positive theory of consumer choice. Journal of Economic Behavior and Organization 1, 39–60 .
Thaler, R. , 1985. Mental accounting and consumer choice. Marketing Sci- ence 4, 199–214.
Wang, H., Yan, J., Yu, J., 2016, Reference-dependent preferences and the risk-return trade-off, Journal of Financial Economics, forthcoming, http://dx.doi.org/10.1016/j.jfineco.2016.09.010
Wei, S., Zhang, C. 2006. Why did individual stocks become more volatile? Journal of Business 79, 259–292.
Xu, Y., Malkiel, B. G. 2003. Investigating the behavior of idiosyncratic volatility, The Journal of Business 76, 613{645.
Zhang, X. F. 2006. Information uncertainty and stock returns, The Journal of Finance 61, 105-137.

Table 1 Summary Statistics by Country

This table reports country-level median values of firm-year observations. Panel A reports mean value for firm-level variables and Panel B reports mean value for country-level variables. The sample period is from 1990 to 2016. The definitions of variables are described in Appendix. All continuous variables except for *Max* measures are winsorized at the 1% and 99% levels.

Panel A. Firm Level Characteristics

Country	Exchange	# of Firms	IVOL	Max	Beta	MV ($mil USD)	M/B	Illiq.	MOM(%)	Price	ROA %	Lev %
Argentina	Buenos Aires	111	0.028	0.051	0.74	814	1.90	0.036	1.05	0.99	7.01	25.4
Brazil	São Paulo	344	0.029	0.058	0.73	3052	2.31	0.644	1.16	5.70	6.18	28.4
Chile	Santiago	203	0.021	0.039	1.05	1516	2.46	0.026	2.16	0.71	7.01	25.7
China	Shanghai	1131	0.027	0.051	1.08	1215	5.19	0.471	1.17	0.92	3.60	26.8
Colombia	Bogota	57	0.029	0.050	0.99	2654	36.7	0.028	1.80	1.77	5.59	16.2
Czech Republic	Prague	185	0.019	0.035	0.52	3308	5.64	0.092	0.97	29.97	6.74	18.9
Egypt	Cairo & Alexandria	164	0.023	0.040	0.78	423	2.73	0.226	0.79	3.76	7.29	15.8
Greece	Athens	403	0.031	0.058	0.88	310	24.6	0.090	-0.09	2.61	5.69	22.8
Hong Kong	Hong Kong	1799	0.028	0.055	0.60	1011	3.00	0.052	0.52	0.10	3.19	18.4
Hungary	Budapest	81	0.032	0.061	0.68	690	5.72	0.110	-0.25	7.81	3.87	17.7
India	NSE	2514	0.047	0.073	0.93	62	3.68	0.034	-0.44	1.41	5.33	27.4
Indonesia	Indonesia	597	0.034	0.067	0.85	645	2.73	0.213	0.07	0.06	7.46	30.0
Ireland	Dublin	107	0.022	0.052	0.59	2298	4.02	0.055	0.40	1.40	4.95	24.6
Israel	Tel Avia	812	0.028	0.045	0.94	469	2.47	0.025	0.35	2.61	2.21	28.0
Jordan	Amman	125	0.023	0.035	0.90	80	1.25	0.123	-1.36		1.54	11.6
South Korea	Korea	1351	0.040	0.076	0.79	640	1.36	0.404	0.61	8.03	5.29	32.6
Malaysia	Bursa Malaysia	1062	0.025	0.050	1.01	406	2.31	0.067	0.37	0.34	5.75	19.0
Mexico	BMV	268	0.022	0.044	0.82	2695	1.82	0.133	1.51	1.40	8.53	25.7
Morocco	Casablanca	95	0.017	0.033	0.88	1014	2.71	0.022	0.65	73.1	6.38	17.0
Pakistan	Karachi	303	0.029	0.050	0.90	230	2.84	0.201	1.95	0.60	10.28	26.1
Peru	Lima	150	0.025	0.047	0.97	675	1.84	0.122	2.79	0.74	9.55	20.7
Philippines	Philippine	349	0.032	0.059	0.80	592	8.48	0.134	0.45	0.05	4.51	20.3
Poland	Warsaw	952	0.033	0.061	0.85	354	2.92	0.113	-0.53	2.58	2.71	16.1
Portugal	Lisbon	166	0.022	0.040	0.84	1311	2.43	0.113	0.24	5.88	1.97	40.0
Russian Federation	MICEX	217	0.029	0.057	0.74	6993	2.40	0.061	2.34	0.79	9.07	23.0
Singapore	Singapore	716	0.024	0.048	0.95	834	2.03	0.060	0.84	0.19	4.68	18.0
South Africa	Johannesburg	866	0.026	0.051	0.77	1318	4.14	0.049	0.37	0.69	10.27	14.8
Sri Lanka	Colombo	306	0.030	0.054	1.26	60	2.01	0.080	0.30	0.43	5.80	25.8
Taiwan	Taiwan	1067	0.025	0.046	0.93	827	2.16	0.242	0.54	0.62	4.81	23.0
Thailand	Thailand	828	0.028	0.051	0.67	379	2.54	0.325	0.42	0.32	5.12	29.1
Turkey	Istanbul	451	0.035	0.068	0.82	507	3.49	1.901	0.29	2.72	10.08	22.1
Venezuela	Caracas	23	0.034	0.058	0.81	1457	1.54	0.011	1.18	--	5.81	9.6

Table 1—*Continued*

Panel B. Country Level Characteristics

Country	GDP per capita	Trade (% of GDP)	Market Cap (% of GDP)	GDP Growth %	Turnover ratio %	Legal	Good Gov Index	Patent (% Pop)	Individualism	Masculinity	Tnover %
Argentina	8083	28.1	14.4	2.1	36.5	0	8.9	0.001	46	56	12.2
Brazil	6283	22.7	34.6	1.0	55.6	0	9.6	0.001	38	49	46.8
Chile	8084	63.0	91.1	3.6	11.6	0	13.8	0.001	23	28	11.1
China	2702	42.9	34.7	8.8	187.8	0	9.2	0.001	20	66	147.4
Colombia	3838	35.9	27.4	2.3	15.2	0	9.8	0.000	13	64	9.5
Czech Republic	11789	108.7	18.0	1.8	52.3	0	12.5	0.005	58	57	47.0
Egypt	1710	48.9	30.8	2.2	47.2	0	9.0	0.000	25	45	22.2
Greece	18185	50.1	37.3	0.6	46.0	0	11.5	0.003	35	57	39.1
Hong Kong	28071	310.6	542.4	2.8	51.6	1	13.9	0.038	25	57	49.4
Hungary	8931	124.1	18.0	2.2	70.4	0	12.6	0.007	80	88	73.8
India	791	34.9	48.2	4.9	73.3	1	9.6	0.001	48	56	84.6
Indonesia	1712	55.7	26.7	3.5	36.5	0	9.4	0.000	14	46	42.3
Ireland	38010	159.3	52.3	4.5	19.9	1	13.3	0.040	70	68	40.5
Israel	23474	67.3	56.4	1.9	39.6	1	12.3	0.170	54	47	56.4
Jordan	2416	122.8	99.3	1.0	26.1		11.5	0.000			
South Korea	16424	72.6	55.4	4.5	164.8	0	11.9	0.119	18	39	174.1
Malaysia	6068	176.0	149.1	3.6	27.2	1	11.4	0.003	26	50	32.5
Mexico	7186	52.8	27.5	1.2	30.1	0	11.3	0.001	30	69	31.1
Morocco	2021	64.4	37.6	2.5	6.7	0	11.1	0.000	46	53	9.9
Pakistan	771	33.5	19.5	1.8	162.5	1	7.8	0.000	14	50	94.6
Peru	3321	40.6	28.5	2.9	9.7	0	10.1	0.000	16	42	9.3
Philippines	1518	81.1	52.0	2.3	21.6	0	10.3	0.000	32	64	22.5
Poland	7640	66.9	20.3	3.7	40.8	0	12.5	0.001	60	64	47.6
Portugal	16138	66.2	30.7	1.3	57.1	0	13.2	0.002	27	31	48.0
Russian Federation	6313	54.5	34.9	0.7	45.0	0	9.0	0.001	39	36	45.6
Singapore	32629	358.2	177.2	3.6	52.1	1	14.7	0.074	20	48	51.6
South Africa	4630	53.0	181.8	0.8	21.9	0	12.0	0.002	65	63	36.5
Sri Lanka	1641	68.2	17.4	4.6	15.0	1	10.2	0.000	--	--	14.5
Taiwan	15860	93.0	115.2	5.6	207.5	0	13.2	231.177	17	45	194.1
Thailand	3418	112.7	58.3	3.7	74.0	1	9.6	0.000	20	34	81.7
Turkey	6617	44.9	21.7	3.1	146.3	0	9.5	0.000	37	45	138.5
Venezuela	6408	51.3	7.3	0.9	16.6	0	6.4	0.001	12	73	10.0

Table 2 Risk Metrics Across MAX-sorted Portfolios

This table lists the mean values of assorted risk metrics of portfolios sorted on MAX in each individual emerging market. Panel A lists the mean MAX values in each decile portfolios sorted on MAX. For the same MAX-sorted decile portfolios, Panel B, C, and D respectively reports the mean Beta, IVOL, and total volatility values in each portfolio.

Panel A. Mean MAX Values

	P- 1	*P- 2*	*P- 3*	*P- 4*	*P- 5*	*P- 6*	*P- 7*	*P- 8*	*P- 9*	*P- 10*	*P10-P1*
Braz	0.012	0.034	0.046	0.059	0.098	0.062	0.072	0.087	0.115	0.244	0.223**
Chil	0.004	0.015	0.022	0.028	0.034	0.037	0.043	0.052	0.066	0.125	0.119**
ChinF	0.030	0.039	0.045	0.048	0.055	0.057	0.063	0.071	0.082	0.103	0.075**
CzRe	0.015	0.038	0.055	0.056	0.073	0.058	0.062	0.069	0.081	0.134	0.089**
Egyp	0.019	0.034	0.043	0.049	0.079	0.051	0.058	0.066	0.078	0.118	0.083**
Gree	0.020	0.037	0.047	0.056	0.069	0.066	0.074	0.085	0.100	0.141	0.122**
HoKo	0.016	0.031	0.040	0.050	0.068	0.064	0.076	0.092	0.119	0.212	0.183**
IndiS	0.024	0.040	0.049	0.057	0.065	0.073	0.084	0.102	0.129	0.202	0.178**
Indo	0.013	0.036	0.048	0.060	0.077	0.084	0.101	0.123	0.160	0.258	0.236**
Isra	0.015	0.031	0.040	0.047	0.055	0.063	0.073	0.085	0.102	0.169	0.154**
KoreF	0.023	0.035	0.043	0.050	0.056	0.063	0.072	0.082	0.099	0.130	0.107**
Mala	0.016	0.029	0.037	0.045	0.053	0.062	0.073	0.087	0.110	0.183	0.166**
Mexi	0.012	0.032	0.048	0.054	0.096	0.056	0.064	0.075	0.092	0.152	0.111**
Paki	0.007	0.028	0.039	0.047	0.056	0.063	0.074	0.092	0.128	0.249	0.242**
Phil	0.010	0.031	0.044	0.057	0.080	0.074	0.089	0.112	0.153	0.272	0.247**
Pola	0.028	0.046	0.061	0.076	0.113	0.073	0.086	0.107	0.139	0.246	0.175**
RussS	0.021	0.038	0.058	0.069	0.139	0.079	0.094	0.118	0.157	0.269	0.213**
Sing	0.015	0.028	0.036	0.045	0.058	0.059	0.070	0.085	0.109	0.182	0.153**
SoAf	0.015	0.030	0.044	0.049	0.069	0.060	0.074	0.097	0.138	0.287	0.195**
SrLa	0.010	0.032	0.052	0.059	0.090	0.074	0.087	0.106	0.136	0.232	0.210**
Taiw	0.024	0.034	0.041	0.044	0.050	0.056	0.062	0.068	0.074	0.092	0.067**
Thai	0.015	0.031	0.040	0.048	0.058	0.064	0.075	0.089	0.109	0.166	0.146**
Turk	0.036	0.051	0.060	0.064	0.075	0.077	0.087	0.100	0.118	0.172	0.131**

Panel B. Mean Beta Values

	P- 1	*P- 2*	*P- 3*	*P- 4*	*P- 5*	*P- 6*	*P- 7*	*P- 8*	*P- 9*	*P- 10*	*P10-P1*
Braz	0.647	0.694	0.737	0.758	0.758	0.777	0.795	0.800	0.813	0.812	0.146**
Chil	0.951	0.969	0.990	1.051	1.066	1.099	1.111	1.122	1.129	1.105	0.155**
ChinF	0.891	0.952	0.977	0.992	1.007	1.014	1.009	1.017	1.027	1.024	0.127**
CzRe	0.631	0.684	0.644	0.758	0.767	0.893	0.865	0.904	0.931	0.950	0.066**
Egyp	0.686	0.771	0.780	0.804	0.846	0.994	1.012	0.983	0.994	0.950	0.157**
Gree	0.714	0.851	0.904	0.945	0.962	0.970	0.977	0.989	1.013	1.031	0.317**
HoKo	0.571	0.681	0.740	0.763	0.788	0.788	0.793	0.796	0.780	0.779	0.208**
IndiS	0.837	0.907	0.948	0.967	0.990	1.001	1.018	1.031	1.061	1.074	0.237**
Indo	0.765	0.827	0.866	0.912	0.916	0.944	0.962	0.976	0.979	0.980	0.195**
Isra	0.842	0.895	0.928	0.946	0.960	0.952	0.955	0.936	0.939	0.932	0.087**
KoreF	0.612	0.715	0.747	0.767	0.784	0.797	0.798	0.798	0.786	0.779	0.167**
Mala	0.820	0.923	1.007	1.064	1.111	1.155	1.187	1.209	1.234	1.285	0.465**
Mexi	0.696	0.820	0.873	0.872	0.877	0.935	0.938	0.951	0.962	0.972	0.204**
Paki	0.932	0.938	0.983	1.036	1.043	1.063	1.088	1.161	1.254	1.385	0.453**
Phil	0.776	0.827	0.884	0.914	0.972	1.012	1.029	1.067	1.074	1.189	0.357**
Pola	0.765	0.803	0.820	0.807	0.837	0.880	0.891	0.885	0.925	0.982	0.141**
RussS	0.703	0.742	0.737	0.726	0.739	0.722	0.695	0.762	0.743	0.764	0.061**
Sing	0.783	0.905	0.987	1.037	1.073	1.073	1.090	1.114	1.132	1.149	0.363**
SoAf	0.744	0.782	0.863	0.938	0.955	0.877	0.890	0.920	0.999	1.122	0.361**
SrLa	1.376	1.354	1.393	1.419	1.462	1.481	1.486	1.557	1.578	1.634	0.260**
Taiw	0.772	0.869	0.914	0.940	0.963	0.988	0.997	1.007	1.011	1.006	0.232**
Thai	0.656	0.753	0.829	0.871	0.894	0.916	0.935	0.949	0.946	0.950	0.299**
Turk	0.744	0.829	0.843	0.856	0.855	0.860	0.859	0.841	0.835	0.806	0.059**

Panel C. Mean IVOL Values

	P- 1	*P- 2*	*P- 3*	*P- 4*	*P- 5*	*P- 6*	*P- 7*	*P- 8*	*P- 9*	*P- 10*	*P10-P1*
Braz	0.230	0.140	0.130	0.170	0.240	0.150	0.180	0.230	0.330	0.660	0.430
Chil	0.080	0.050	0.050	0.040	0.050	0.050	0.060	0.070	0.080	0.150	0.070
ChinF	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.080	0.010
CzRe	0.140	0.110	0.130	0.150	0.170	0.230	0.240	0.260	0.300	0.340	0.200
Egyp	0.080	0.090	0.090	0.100	0.120	0.080	0.090	0.090	0.110	0.160	0.080
Gree	0.110	0.090	0.090	0.110	0.130	0.150	0.170	0.200	0.250	0.300	0.190
HoKo	0.120	0.100	0.110	0.130	0.140	0.160	0.190	0.220	0.260	0.330	0.210
IndiS	0.130	0.130	0.140	0.160	0.170	0.180	0.210	0.250	0.320	0.440	0.310
Indo	0.270	0.200	0.220	0.250	0.270	0.300	0.350	0.410	0.490	0.640	0.370
Isra	0.200	0.140	0.130	0.140	0.160	0.170	0.190	0.220	0.250	0.340	0.140
KoreF	0.080	0.090	0.100	0.110	0.120	0.120	0.130	0.150	0.170	0.210	0.130
Mala	0.080	0.070	0.080	0.090	0.110	0.120	0.140	0.150	0.190	0.250	0.170
Mexi	0.120	0.090	0.090	0.100	0.160	0.110	0.120	0.130	0.140	0.240	0.120
Paki	0.240	0.130	0.140	0.160	0.160	0.180	0.210	0.290	0.470	0.920	0.680
Phil	0.280	0.160	0.170	0.190	0.240	0.260	0.310	0.370	0.490	0.690	0.410
Pola	0.170	0.140	0.180	0.220	0.280	0.180	0.230	0.280	0.370	0.560	0.390
RussS	0.180	0.190	0.240	0.310	0.480	0.360	0.470	0.620	0.750	0.920	0.740
Sing	0.090	0.070	0.080	0.090	0.110	0.130	0.160	0.190	0.250	0.400	0.310
SoAf	0.190	0.090	0.080	0.100	0.120	0.160	0.220	0.330	0.570	1.280	1.090
SrLa	0.230	0.170	0.190	0.200	0.230	0.230	0.250	0.280	0.340	0.440	0.210
Taiw	0.050	0.050	0.060	0.060	0.060	0.070	0.070	0.080	0.080	0.090	0.040
Thai	0.130	0.110	0.110	0.120	0.130	0.150	0.160	0.180	0.210	0.270	0.140
Turk	0.130	0.130	0.130	0.130	0.140	0.140	0.140	0.150	0.160	0.190	0.060

Panel D. Mean Volatility Values

	P- 1	*P- 2*	*P- 3*	*P- 4*	*P- 5*	*P- 6*	*P- 7*	*P- 8*	*P- 9*	*P- 10*	*P10-P1*
Braz	0.086	0.075	0.076	0.080	0.085	0.081	0.086	0.092	0.102	0.124	0.033**
Chil	0.052	0.047	0.046	0.047	0.049	0.050	0.051	0.054	0.056	0.066	0.013**
ChinF	0.069	0.071	0.071	0.072	0.073	0.071	0.071	0.071	0.072	0.073	0.005**
CzRe	0.091	0.088	0.090	0.098	0.094	0.120	0.130	0.133	0.137	0.137	0.005*
Egyp	0.060	0.065	0.068	0.069	0.072	0.076	0.076	0.077	0.080	0.081	0.013**
Gree	0.070	0.071	0.073	0.076	0.079	0.080	0.082	0.085	0.090	0.094	0.024**
HoKo	0.064	0.065	0.069	0.073	0.077	0.081	0.085	0.089	0.095	0.102	0.037**
IndiS	0.076	0.079	0.083	0.086	0.088	0.090	0.093	0.097	0.103	0.112	0.035**
Indo	0.093	0.088	0.090	0.094	0.095	0.098	0.103	0.107	0.112	0.120	0.026**
Isra	0.081	0.075	0.075	0.077	0.080	0.081	0.085	0.088	0.093	0.102	0.021**
KoreF	0.066	0.071	0.072	0.075	0.076	0.078	0.080	0.082	0.085	0.092	0.026**
Mala	0.054	0.057	0.061	0.064	0.067	0.070	0.073	0.076	0.079	0.084	0.030**
Mexi	0.063	0.063	0.066	0.066	0.075	0.072	0.073	0.073	0.076	0.081	0.017**
Paki	0.080	0.070	0.072	0.074	0.075	0.077	0.081	0.090	0.105	0.132	0.052**
Phil	0.086	0.076	0.080	0.085	0.090	0.095	0.100	0.106	0.117	0.133	0.041**
Pola	0.077	0.075	0.080	0.083	0.087	0.085	0.091	0.096	0.105	0.116	0.026**
RussS	0.081	0.087	0.094	0.103	0.115	0.127	0.127	0.139	0.166	0.173	0.067**
Sing	0.051	0.053	0.057	0.061	0.064	0.068	0.071	0.074	0.078	0.086	0.030**
SoAf	0.065	0.057	0.060	0.062	0.066	0.071	0.078	0.090	0.108	0.144	0.049**
SrLa	0.082	0.076	0.079	0.082	0.084	0.082	0.084	0.088	0.092	0.100	0.018**
Taiw	0.061	0.066	0.068	0.067	0.068	0.070	0.071	0.073	0.074	0.076	0.016**
Thai	0.065	0.067	0.071	0.073	0.075	0.077	0.078	0.081	0.083	0.088	0.024**
Turk	0.091	0.096	0.097	0.097	0.097	0.099	0.099	0.100	0.102	0.105	0.013**

Table 3 Descriptive Statistics of Capital Gains Overhang (CGO), Gains Overhang (GO) and Loss Overhang (LO)

This table reports the descriptive statistics of CGO (Capital Gains Overhang), and its components GO (Gains Overhang) and LO (Loss overhang) for the sample of emerging markets. Results reported are based on the time series average of cross-sectional measures with each individual emerging market from the period from 1980 to 2016, while the actual starting month varies across markets due to data availability. Panel A reports the measures when the cumulative returns are computed over 36-month moving windows, while Panel B reports the measures when the window length is 12 months.

Panel A. Length of Estimation Window Period = 36 months																
	Argentin	*Brazil*	*Chili*	*China*	*Colomb*	*Ch.Rep*	*Egypt*	*Greece*	*HKong*	*Hungary*	*India*	*Indonesi*	*Israel*	*Ireland*	*Jordan*	*Korea*
Start Month	199309	199004	198909	199103	199203	199309	199412	198803	198708	199103	199503	199006	200008	199212	200512	198003
CGO																
Mean	0.359	0.131	0.200	-0.034	0.191	-0.004	0.025	0.127	0.013	0.155	0.140	0.131	0.086	0.195	0.043	0.067
Median	0.265	0.045	0.112	-0.043	0.091	-0.009	-0.015	0.007	-0.022	0.068	-0.026	0.027	0.064	0.099	0.005	0.014
GO																
Mean	0.407	0.169	0.232	0.058	0.230	0.065	0.119	0.267	0.165	0.238	0.318	0.238	0.182	0.288	0.127	0.155
Median	0.285	0.061	0.127	0.033	0.110	0.010	0.048	0.107	0.073	0.106	0.086	0.085	0.107	0.144	0.045	0.069
LO																
Mean	-0.048	-0.038	-0.033	-0.092	-0.040	-0.069	-0.095	-0.140	-0.151	-0.083	-0.177	-0.108	-0.095	-0.092	-0.084	-0.089
Median	-0.014	-0.008	-0.005	-0.077	-0.011	-0.020	-0.063	-0.100	-0.099	-0.034	-0.117	-0.055	-0.039	-0.037	-0.040	-0.056
	Malay	*Mexico*	*Morocco*	*Pakista*	*Peru*	*Philippi*	*Poland*	*Portug*	*Russia*	*Singapor*	*S. Africa*	*SriLanka*	*Taiwan*	*Thaila*	*Turkey*	*Venezuel*
Start Month	198405	198803	199310	198903	199103	198001	199106	198803	199511	198303	199003	198703	198902	198703	198803	199003
CGO																
Mean	0.030	0.220	0.097	0.178	0.221	0.185	0.070	0.090	0.096	0.082	0.131	0.112	-0.043	0.061	0.039	0.528
Median	-0.011	0.119	0.050	0.092	0.103	0.141	-0.009	0.043	0.032	0.043	0.062	0.046	-0.047	0.005	-0.010	0.301
GO																
Mean	0.153	0.261	0.154	0.248	0.250	0.259	0.202	0.163	0.163	0.180	0.215	0.177	0.068	0.148	0.118	0.598
Median	0.074	0.136	0.081	0.121	0.117	0.179	0.081	0.072	0.058	0.098	0.103	0.074	0.037	0.053	0.038	0.353
LO																
Mean	-0.123	-0.041	-0.057	-0.070	-0.029	-0.073	-0.132	-0.072	-0.067	-0.098	-0.084	-0.065	-0.111	-0.087	-0.079	-0.070
Median	-0.086	-0.008	-0.025	-0.026	-0.003	-0.036	-0.091	-0.023	-0.020	-0.056	-0.036	-0.025	-0.085	-0.048	-0.048	-0.043

Table 3 (continued)

Panel B. Length of Estimation Window Period = 12 months																
	Argentin	*Brazil*	*Chili*	*China*	*Colomb*	*Ch.Rep*	*Egypt*	*Greece*	*HKong*	*Hungary*	*India*	*Indonesi*	*Israel*	*Ireland*	*Jordan*	*Korea*
Start Month	199309	199004	198909	199103	199203	199309	199412	198803	198708	199103	199503	199006	200008	199212	200512	198003
CGO																
Mean	0.118	0.050	0.067	-0.025	0.064	0.000	-0.002	0.041	-0.006	0.051	0.038	0.036	0.037	0.064	0.002	0.021
Median	0.092	0.022	0.038	-0.036	0.035	-0.002	-0.017	0.007	-0.015	0.026	-0.020	0.003	0.033	0.040	-0.007	-0.001
GO																
Mean	0.162	0.079	0.093	0.053	0.096	0.045	0.068	0.133	0.097	0.113	0.159	0.113	0.103	0.128	0.062	0.094
Median	0.117	0.035	0.048	0.032	0.051	0.013	0.032	0.072	0.050	0.058	0.055	0.047	0.064	0.073	0.023	0.046
LO																
Mean	-0.044	-0.030	-0.025	-0.078	-0.032	-0.045	-0.070	-0.092	-0.103	-0.061	-0.121	-0.077	-0.066	-0.064	-0.060	-0.073
Median	-0.020	-0.009	-0.005	-0.068	-0.012	-0.014	-0.049	-0.063	-0.066	-0.028	-0.077	-0.040	-0.029	-0.029	-0.028	-0.048
	Malay	*Mexico*	*Morocco*	*Pakista*	*Peru*	*Philippi*	*Poland*	*Portug*	*Russia*	*Singapor*	*S. Africa*	*SriLanka*	*Taiwan*	*Thaila*	*Turkey*	*Venezuel*
Start Month	198405	198803	199310	198903	199103	198001	199106	198803	199511	198303	199003	198703	198902	198703	198803	199003
CGO																
Mean	-0.005	0.081	0.034	0.051	0.079	0.061	0.022	0.030	0.044	0.022	0.049	0.033	-0.031	0.015	0.019	0.148
Median	-0.016	0.052	0.020	0.029	0.037	0.046	-0.007	0.017	0.021	0.014	0.029	0.014	-0.036	-0.002	-0.009	0.086
GO																
Mean	0.082	0.115	0.069	0.107	0.103	0.110	0.117	0.080	0.095	0.091	0.108	0.079	0.055	0.083	0.087	0.208
Median	0.046	0.067	0.038	0.053	0.047	0.071	0.059	0.040	0.041	0.054	0.058	0.035	0.033	0.037	0.036	0.133
LO																
Mean	-0.087	-0.034	-0.036	-0.056	-0.024	-0.049	-0.095	-0.050	-0.051	-0.069	-0.059	-0.046	-0.086	-0.068	-0.068	-0.060
Median	-0.063	-0.009	-0.016	-0.024	-0.004	-0.023	-0.066	-0.021	-0.017	-0.040	-0.027	-0.019	-0.069	-0.040	-0.045	-0.043

Table 4 Analysis of Price Anomaly for Various Risk Metrics, IVOL, MAX, and Beta.

This table reports the Fama-MacBeth results of monthly returns relative to prior period risk metrics, including IVOL, MAX and Beta, while controlling for other prior-period firm characteristics, including market value (ln*Size*), MB ratio (ln*MB*), illiquidity (Illiq), prior six-month return (Mom), prior month return (Reversal), and price per share (ln*Price*). Note that the risk metrics (IVOL, MAX, and Beta) have been first orthogonalized against each other via monthly cross-sectional regressions within each market. The sample period is from 1980 to 2016, with most markets running with sufficient data starting from 1990. Each cross-sectional regression is performed for each month within each individual emerging market. Statistical significance at the 10, 5, and 1% level is indicated by +, *, and **, respectively.

	Argent.	*Brazil*	*Chili*	*China*	*Colomb*	*CzRep*	*Egypt*	*Greece*	*HKong*	*Hungary*	*India*	*Indon.*	*Ireland*	*Israel*	*Jordan*	*Korea*
IVOL	-1.429**	-0.641+	-0.591*	-1.390**	-1.621	-6.806	-0.77	-0.944**	-0.621**	-2.116**	-0.227	-0.655	-3.189**	-1.069**	-0.782+	-0.062
p-val	0.001	0.088	0.044	0.000	0.731	0.365	0.139	0.001	0.002	0.009	0.299	0.186	0.000	0.000	0.096	0.545
MAX	-0.134	-0.173	-0.177*	-0.224**	-0.338	-4.018	-0.078	-0.264**	-0.083*	-0.750**	-0.081	-0.02	-0.817**	-0.117+	-0.341+	-0.035
p-val	0.194	0.111	0.033	0.000	0.758	0.360	0.587	0.000	0.030	0.003	0.147	0.683	0.001	0.086	0.061	0.265
Beta	-0.005	-0.01	-0.004+	0.013**	0.028	0.19	-0.006	-0.008+	-0.003	-0.015	-0.001	-0.002	-0.004	-0.007*	-0.005	0.001
p-val	0.573	0.105	0.075	0.000	0.532	0.445	0.513	0.061	0.163	0.214	0.747	0.569	0.640	0.040	0.107	0.632
lnSize	1.229	0.453	-0.458	-2.417*	-0.986	48.362	-0.498	8.971+	0.434	1.057	-33.420*	3.019	-0.634	-0.768	0.594	0.919+
p-val	0.318	0.241	0.539	0.035	0.122	0.386	0.888	0.095	0.116	0.502	0.020	0.197	0.401	0.47	0.943	0.091
lnMB	-0.002	-0.004+	0.000	0.000	0.004	-0.01	-0.004+	-0.003**	-0.005**	-0.001	-0.001	-0.006**	0.003	-0.003+	-0.006	-0.007**
p-val	0.424	0.058	0.929	0.882	0.849	0.793	0.062	0.001	0.000	0.807	0.632	0.000	0.303	0.056	0.228	0.000
Mom	0.040**	0.007	0.043**	0.016*	0.170*	-0.092	0.005	0.007	0.014**	0.026	0.005	0.005	0.054**	0.034**	0.003	0.002
p-val	0.000	0.522	0.000	0.021	0.038	0.642	0.663	0.426	0.001	0.198	0.463	0.483	0.000	0.000	0.824	0.778
Illiquidity	0.055	0.031	0.013	0.001	1.059	-1.539	0.002	0.003	0.022**	-0.070+	0.053	0.010*	0.039	0.028	-0.005	0.001
p-val	0.164	0.330	0.749	0.621	0.245	0.421	0.745	0.909	0.001	0.078	0.333	0.028	0.323	0.532	0.658	0.342
Reversal	-0.012	-0.004	-0.054**	-0.063**	-0.031	-0.189	0.008	-0.050**	0.001	-0.011	-0.053**	-0.007	-0.012	-0.047**	0.026	-0.115**
p-val	0.480	0.800	0.001	0.000	0.919	0.360	0.709	0.000	0.855	0.700	0.000	0.527	0.591	0.001	0.255	0.000
lnPrice	-0.002	0.002	0.000	-0.006+	0.002	0.021**	0.002	-0.001	0.000	0.000	0.000	0.004+	-0.003	0.000	-0.001	0.004*
p-val	0.378	0.126	0.490	0.053	0.468	0.003	0.23	0.465	0.701	0.864	0.872	0.063	0.118	0.577	0.829	0.036
Avg obs	42.6	74.3	59.1	604.4	25.0	25.6	83.7	148.2	592.9	27.9	328.6	161.6	32.6	179.2	65.3	437.2
Avg adjR^2	0.118	0.129	0.138	0.134	0.245	-0.04	0.186	0.127	0.074	0.23	0.096	0.075	0.184	0.096	0.122	0.115

Table 4 (continued)

	Malay	*Mexico*	*Morocco*	*Pakistan*	*Peru*	*Philippines*	*Poland*	*Portugal*	*Russia*	*Singapore*	*SAfrica*	*SriLanka*	*Taiwan*	*Thailand*	*Turkey*
IVOL	-0.768**	4.888	0.045	-0.435	-1.900*	-0.357	-0.622*	-1.048*	0.185	-0.300	-0.690**	-0.101	-1.152**	-0.760**	-0.844*
p-val	0.004	0.214	0.917	0.200	0.012	0.138	0.017	0.019	0.665	0.158	0.007	0.733	0.000	0.000	0.023
MAX	-0.121*	-0.134	0.025	-0.031	-0.412+	-0.046	-0.032	-0.133	-0.002	-0.061	-0.100	0.002	-0.292**	-0.086+	-0.152*
p-val	0.031	0.111	0.869	0.778	0.060	0.428	0.614	0.286	0.988	0.238	0.110	0.981	0.001	0.081	0.041
Beta	-0.002	-0.008+	0.000	-0.002	0.005	-0.002	0.004	-0.004	0.000	0.000	0.002	-0.005	0.002	-0.002	0.004
p-val	0.423	0.072	0.936	0.718	0.629	0.561	0.379	0.386	0.969	0.897	0.457	0.234	0.529	0.478	0.569
lnSize	0.532	1.447+	0.173	-4.678	-2.718	1.366	6.725	0.615	-0.01	0.251	-0.168	15.893	0.894+	3.309+	2.505
p-val	0.808	0.077	0.733	0.123	0.436	0.381	0.178	0.480	0.924	0.648	0.702	0.626	0.066	0.06	0.238
lnMB	-0.004**	-0.001	-0.003	-0.003	0.000	-0.003*	0.000	-0.002	-0.005*	-0.002+	-0.002*	-0.006*	-0.006**	-0.005**	-0.006**
p-val	0.000	0.458	0.242	0.201	0.871	0.021	0.930	0.26	0.018	0.054	0.036	0.031	0.001	0.001	0.000
Mom	0.010+	0.044**	0.037*	0.012	0.01	0.013+	0.029**	0.030*	0.024*	0.018**	0.030**	0.000	0.019**	0.019**	-0.014+
p-val	0.085	0.000	0.026	0.241	0.551	0.098	0.000	0.016	0.040	0.002	0.000	0.984	0.009	0.001	0.054
Illiquidity	-0.008	0.02	0.157	-0.002	-0.007	-0.003	0.004	-0.046	-0.057	-0.009	0.012	-0.002	0.001	0.004*	-0.001
p-val	0.438	0.142	0.3	0.827	0.907	0.93	0.674	0.147	0.284	0.194	0.214	0.913	0.868	0.019	0.205
Reversal	-0.038**	0.002	-0.034	-0.040**	0.042	-0.016	0.007	0.025	-0.003	-0.019+	-0.044**	-0.070*	-0.004	0.016+	-0.026*
p-val	0.000	0.907	0.229	0.009	0.129	0.196	0.544	0.182	0.892	0.067	0.000	0.022	0.713	0.087	0.014
lnPrice	0.002	0.001	0.003*	0.002	0.001	0.001	-0.001	0.002	0.001	0.000	0.001	0.001	0.001	0.001	0.001
p-val	0.314	0.233	0.035	0.175	0.723	0.132	0.384	0.347	0.144	0.813	0.449	0.606	0.672	0.628	0.507
Avg obs	412.9	61.8	41.3	101.9	33.6	101.9	201.4	37.2	67.4	206.8	166.6	118.8	541.9	286.3	183.8
Avg $adjR^2$	0.123	0.125	0.107	0.126	0.146	0.107	0.076	0.13	0.107	0.096	0.107	0.117	0.131	0.105	0.084

Table 5 Analysis of Price Anomaly for Various Risk Metrics – with the Consideration of Propensity to Sell.

This table reports the Fama-MacBeth results of monthly returns relative to prior period risk metrics, including IVOL, MAX and Beta, while controlling for other prior-period firm characteristics, including CGO (Capital Gains Overhang), market value (ln*Size*), MB ratio (ln*MB*), illiquidity (Illiq), prior six-month return (Mom), prior month return (Reversal), and price per share (ln*Price*). Note that the risk metrics (IVOL, MAX, and Beta) have been first orthogonalized against each other via monthly cross-sectional regressions within each market. The sample period is from 1980 to 2016, with most markets running with sufficient data starting from 1990. Each cross-sectional regression is performed for each month within each individual emerging market. Statistical significance at the 10, 5, and 1% level is indicated by +, *, and **, respectively.

	Argent.	*Brazil*	*Chili*	*China*	*Colomb*	*CzRep*	*Egypt*	*Greece*	*HKong*	*Hungary*	*India*	*Indon.*	*Ireland*	*Israel*	*Jordan*	*Korea*
IVOL	-1.193+	-0.569	-0.179	-1.474**	-0.847	-15.102	-0.76	-1.124**	-0.560*	-1.797+	-0.361	-0.318	-2.883**	-0.954**	-1.018*	0.014
p-val	0.062	0.211	0.604	0.000	0.806	0.313	0.211	0.000	0.011	0.074	0.121	0.193	0.000	0.003	0.047	0.922
MAX	-0.121	-0.128	-0.141	-0.236**	-0.203	-7.726	-0.005	-0.259**	-0.034	-0.569+	-0.126+	-0.016	-0.842**	-0.108	-0.411*	0.005
p-val	0.403	0.336	0.149	0.000	0.818	0.307	0.976	0.006	0.425	0.085	0.059	0.798	0.004	0.174	0.033	0.917
CGO	-0.005	0.017	0.019+	0.057**	0.067	-0.252	0.009	-0.002	0.012	0.005	-0.010	-0.017	-0.009	0.016	0.058+	0.000
p-val	0.748	0.439	0.068	0.003	0.222	0.552	0.682	0.859	0.129	0.872	0.518	0.432	0.782	0.196	0.061	0.956
CGOxIVOL	0.831	0.192	-0.733	-2.145*	-3.369	-4.173	-0.015	0.776	-0.461	0.780	0.418	0.303	0.774	-0.522	-1.211	0.361
p-val	0.342	0.855	0.353	0.023	0.623	0.807	0.991	0.238	0.485	0.720	0.581	0.628	0.628	0.488	0.504	0.433
CGOxMAX	0.249	0.276	0.247	-0.195	-0.795	1.29	-0.053	0.269	0.136	-0.100	-0.169	0.098	0.96	0.132	-1.247	0.131
p-val	0.311	0.521	0.311	0.369	0.679	0.924	0.92	0.19	0.361	0.899	0.559	0.457	0.111	0.58	0.136	0.364
Beta	-0.002	-0.017+	-0.003	0.012**	0.026	0.205	-0.004	-0.009+	-0.003	-0.014	-0.002	0.000	0.001	-0.005	-0.005	0.001
p-val	0.801	0.053	0.225	0.000	0.568	0.505	0.694	0.076	0.165	0.301	0.557	0.914	0.913	0.114	0.179	0.559
lnSize	1.755	1.175	-0.884	-2.667*	-0.889	44.627	-1.010	9.900+	0.498+	1.498	-38.154**	4.529*	-0.559	-0.652	3.936	1.086*
p-val	0.193	0.161	0.295	0.031	0.359	0.386	0.788	0.083	0.071	0.391	0.009	0.022	0.494	0.485	0.662	0.046
lnMB	-0.002	-0.005*	-0.001	0.000	0.009	-0.002	-0.005+	-0.003**	-0.005**	-0.004	-0.001	-0.007**	0.003	-0.003*	-0.004	-0.007**
p-val	0.277	0.019	0.709	0.851	0.696	0.971	0.055	0.000	0.000	0.232	0.668	0.000	0.307	0.035	0.45	0.000
Mom	0.043**	0.000	0.040**	0.011+	0.179	-0.105	0.001	0.004	0.009*	0.017	0.008	0.000	0.053**	0.022**	-0.01	-0.001
p-val	0.001	0.967	0.000	0.082	0.252	0.602	0.944	0.648	0.043	0.420	0.289	0.976	0.002	0.009	0.448	0.903
Illiquidity	0.076+	0.049	0.002	0.000	1.095	-1.507	0.002	0.003	0.025**	-0.057	0.063	0.012**	0.06	0.042	-0.002	0.001
p-val	0.068	0.156	0.958	0.834	0.241	0.451	0.774	0.894	0.000	0.105	0.259	0.009	0.149	0.375	0.861	0.315
Reversal	-0.007	-0.002	-0.045**	-0.062**	0.043	-0.127	0.01	-0.054**	0.000	-0.033	-0.050**	-0.008	-0.018	-0.044**	0.016	-0.114**
p-val	0.675	0.923	0.005	0.000	0.883	0.476	0.659	0.000	0.962	0.261	0.000	0.478	0.439	0.001	0.487	0.000
lnPrice	-0.002	0.001	0.000	-0.008*	0.001	0.02	0.002	-0.002	-0.001	0.001	-0.001	0.002	-0.004+	-0.001	-0.007	0.004*
p-val	0.29	0.402	0.889	0.014	0.806	0.316	0.383	0.27	0.536	0.753	0.536	0.299	0.073	0.296	0.141	0.044
Avg obs	42.7	74.2	59.1	604.4	25.0	25.7	83.8	148.2	596.1	27.9	329.6	161.9	32.6	181.3	65.4	437.2
Avg $adjR^2$	0.131	0.138	0.17	0.14	0.408	-0.094	0.192	0.143	0.085	0.282	0.116	0.093	0.227	0.115	0.135	0.127

Table 5 (continued)

	Malay	*Mexico*	*Morocco*	*Pakistan*	*Peru*	*Philippines*	*Poland*	*Portugal*	*Russia*	*Singapore*	*SAfrica*	*SriLanka*	*Taiwan*	*Thailand*	*Turkey*
IVOL	-0.914**	-0.523	0.041	-0.49	-2.182*	-0.369	-0.510+	-0.406	0.905*	-0.389	-0.553*	-0.124	-1.062**	-0.759**	-0.682
p-val	0.001	0.243	0.933	0.216	0.023	0.151	0.086	0.460	0.043	0.165	0.033	0.706	0.001	0.000	0.225
MAX	-0.196**	-0.079	-0.169	-0.005	-0.465	-0.068	0.052	0.118	0.212	-0.059	-0.066	0.053	-0.262**	-0.068	-0.161*
p-val	0.005	0.44	0.355	0.973	0.111	0.324	0.475	0.470	0.105	0.383	0.321	0.599	0.007	0.192	0.039
CGO	0.016+	-0.004	0.036*	0.012	0.047	-0.003	-0.014	0.033	0.052**	0.004	0.023**	0.030+	-0.018	0.006	0.089
p-val	0.084	0.779	0.049	0.381	0.193	0.767	0.416	0.109	0.009	0.661	0.002	0.057	0.356	0.612	0.65
CGOxIVOL	-0.506	0.324	-2.208+	-0.146	-2.661	-0.088	0.723	-1.278	-2.357*	0.663	-1.004*	-1.129	0.98	0.352	-1.874
p-val	0.347	0.721	0.059	0.81	0.185	0.861	0.334	0.385	0.012	0.300	0.043	0.173	0.483	0.556	0.669
CGOxMAX	0.064	-0.057	0.061	0.244	-0.218	-0.104	0.398*	-0.737	-0.338	0.254	-0.14	-0.254	0.427	0.273+	-0.536
p-val	0.670	0.815	0.912	0.309	0.628	0.479	0.033	0.17	0.277	0.106	0.427	0.306	0.304	0.092	0.171
Beta	-0.001	-0.009+	-0.001	0.000	0.006	-0.002	0.005	-0.007	-0.004	0.000	0.002	-0.006	0.002	-0.003	0.002
p-val	0.583	0.059	0.811	0.977	0.602	0.423	0.278	0.221	0.643	0.899	0.454	0.259	0.623	0.37	0.823
lnSize	0.062	0.37	0.383	-3.687	-5.166	1.599	7.235	0.616	-0.02	0.649	-0.044	49.436	0.563	3.502*	2.939
p-val	0.975	0.179	0.482	0.218	0.248	0.350	0.163	0.504	0.841	0.332	0.918	0.171	0.242	0.034	0.224
lnMB	-0.004**	0.000	-0.005+	-0.004	0.002	-0.003*	0.000	-0.003	-0.006*	-0.003**	-0.002**	-0.008*	-0.006**	-0.006**	-0.007**
p-val	0.000	0.725	0.054	0.114	0.621	0.019	0.924	0.139	0.016	0.006	0.004	0.012	0.001	0.000	0.000
Mom	0.007	0.037**	0.035*	0.007	0.013	0.01	0.030**	0.017	0.030*	0.012+	0.025**	-0.005	0.016*	0.012*	-0.012
p-val	0.27	0.000	0.047	0.502	0.479	0.194	0.001	0.223	0.015	0.055	0.000	0.746	0.036	0.024	0.105
Illiquidity	-0.003	0.027+	0.227	0.000	-0.037	0.001	0.005	-0.037	-0.045	-0.003	0.023*	0.007	0.001	0.005**	-0.001
p-val	0.714	0.054	0.138	0.971	0.586	0.98	0.59	0.249	0.38	0.663	0.017	0.726	0.807	0.009	0.215
Reversal	-0.038**	0.006	-0.034	-0.038*	0.036	-0.015	0.008	0.035+	0.001	-0.019+	-0.044**	-0.073*	-0.003	0.017+	-0.027*
p-val	0.000	0.697	0.239	0.013	0.202	0.255	0.491	0.091	0.966	0.082	0.000	0.027	0.736	0.078	0.015
lnPrice	0.001	0.001	0.002	0.002	-0.001	0.001	-0.002	0.001	0.001	-0.001	0.000	0.000	0.001	0.000	0.002
p-val	0.706	0.667	0.16	0.245	0.738	0.105	0.106	0.472	0.13	0.556	0.557	0.934	0.648	0.869	0.253
Avg obs	413.0	61.9	41.4	101.9	33.7	101.9	201.1	37.3	67.5	206.8	167.3	118.8	541.9	286.4	183.9
Avg adjR^2	0.135	0.141	0.12	0.132	0.169	0.125	0.084	0.153	0.126	0.108	0.122	0.128	0.141	0.114	0.1

Table 6 Fixed-Effects Analysis of IVOL / MAX Effects across Emerging Markets – When Considering the Impact of Propensity to Sell

This table reports the aggregated results with fixed effects model for the IVOL and MAX effect. Dependent variable is the one-month ahead individual stock returns across all sample emerging markets. The model considers possible impact from investors' propensity to sell, as proxied by CGO (capital gains overhang), GO (gains overhang) and LO (loss overhang), in addition to controls for other prior-period firm characteristics, including market value (ln*Size*), MB ratio (ln*MB*), illiquidity (Illiq), prior six-month return (Mom), prior month return (Reversal), and price per share (ln*Price*). Among those reported models, models [3], [4] and [7] consider the impact of propensity to sell using CGO, while models [5], [6], and [8] apply the decomposed variables, GO and LO for the examination. Panel A lists the results when 36 month windows are used to estimate CGO, GO and LO, while Panel B lists those when 12-month windows are used for the estimation. The risk metrics (IVOL, MAX, and Beta) have been first orthogonalized against each other via monthly cross-sectional regressions within each market. Reported models also differ in terms of consideration of country-specific factors or not. The sample period is from 1980 to 2016, with most markets running with sufficient data starting from 1990. Month fixed effects are included in all regressions. The p-values based on the robust standard errors clustering at the country level are reported below the regression coefficient.

Panel A. Estimation window for CGO, GO, LO = 36 months								
model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
IVOL	-0.221	-0.211	-0.201	-0.193	-0.137	-0.174	-1.195	-1.488
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
MAX	-0.010	-0.006	-0.005	-0.002	0.011	0.012	-0.269	-0.328
	0.134	0.365	0.440	0.827	0.294	0.280	0.000	0.000
CGO			0.018	0.022			0.022	
			0.000	0.000			0.000	
CGOxIVOL			-0.318	-0.451			-0.475	
			0.000	0.000			0.000	
CGOxMAX			0.021	0.007			-0.005	
			0.257	0.705			0.808	
GO					0.010	0.013		0.012
					0.000	0.000		0.000
GOxIVOL					-0.350	-0.419		-0.382
					0.000	0.000		0.000
GOxMAX					0.002	-0.012		-0.002
					0.938	0.672		0.954
|LO|					-0.052	-0.056		-0.060
					0.000	0.000		0.000
|LO|xIVOL					0.626	0.876		1.050
					0.000	0.000		0.000
|LO|xMAX					0.000	0.013		0.078
					0.992	0.750		0.058
FnRskxIVOL							0.025	0.032
							0.000	0.000
FnRskxMAX							0.007	0.008
							0.000	0.000
Beta	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.476	0.707	0.549	0.702	0.487	0.675	0.761	0.721
lnSize	0.107	0.044	0.055	-0.030	-0.035	-0.104	-0.013	-0.091
	0.036	0.459	0.279	0.611	0.478	0.070	0.820	0.109
lnMB	-0.005	-0.006	-0.005	-0.007	-0.006	-0.007	-0.007	-0.007
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mom	0.011	0.010	0.005	0.005	0.003	0.003	0.004	0.002
	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.012
Illiquidity	0.002	0.001	0.003	0.002	0.001	0.000	0.002	0.000
p-val	0.000	0.001	0.000	0.000	0.063	0.349	0.000	0.242
Reversal	-0.007	-0.009	-0.007	-0.010	-0.007	-0.010	-0.010	-0.010
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lnPrice	0.001	0.001	0.000	0.001	0.000	0.000	0.001	0.000
p-val	0.000	0.000	0.591	0.000	0.000	0.003	0.000	0.001
Country Factors	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	0.16	0.18	0.17	0.18	0.17	0.18	0.18	0.18
F-statistic	915.67	906.97	913.41	905.23	908.76	899.95	900.17	895.16
F-prob	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
nobs (firms*mth)	1534405	1376807	1533939	1376459	1533939	1376459	1376459	1376459

Panel B. Estimation window for CGO, GO, LO = 12 months								
model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
IVOL	-0.221	-0.211	-0.221	-0.220	-0.105	-0.147	-1.169	-1.303
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
MAX	-0.010	-0.006	-0.006	-0.003	0.025	0.028	-0.268	-0.287
	0.134	0.365	0.367	0.698	0.022	0.016	0.000	0.000
CGO			0.041	0.047			0.048	
			0.000	0.000			0.000	
CGOxIVOL			-0.568	-0.824			-0.871	
			0.000	0.000			0.000	
CGOxMAX			0.016	0.001			-0.022	
			0.556	0.969			0.444	
GO					0.023	0.028		0.026
					0.000	0.000		0.000
GOxIVOL					-0.684	-0.812		-0.717
					0.000	0.000		0.000
GOxMAX					-0.054	-0.078		-0.050
					0.276	0.138		0.351
|LO|					-0.077	-0.083		-0.089
					0.000	0.000		0.000
|LO|xIVOL					0.700	1.093		1.332
					0.000	0.000		0.000
|LO|xMAX					-0.067	-0.059		0.031
					0.211	0.282		0.582
FnRskxIVOL							0.024	0.028
							0.000	0.000
FnRskxMAX							0.007	0.008
							0.000	0.000
Beta	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.476	0.707	0.648	0.762	0.468	0.596	0.818	0.633
lnSize	0.107	0.044	0.005	-0.078	-0.055	-0.130	-0.063	-0.120
	0.036	0.459	0.917	0.181	0.264	0.023	0.281	0.036
lnMB	-0.005	-0.006	-0.005	-0.007	-0.005	-0.006	-0.007	-0.006
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mom	0.011	0.010	-0.001	-0.002	-0.003	-0.003	-0.002	-0.003
	0.000	0.000	0.156	0.058	0.005	0.002	0.033	0.001
Illiquidity	0.002	0.001	0.003	0.002	0.001	0.001	0.002	0.001
p-val	0.000	0.001	0.000	0.000	0.012	0.137	0.000	0.087
Reversal	-0.007	-0.009	-0.008	-0.010	-0.008	-0.011	-0.011	-0.011
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
lnPrice	0.001	0.001	0.000	0.001	0.000	0.000	0.001	0.000
p-val	0.000	0.000	0.859	0.000	0.021	0.000	0.000	0.000
Country Factors	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	0.16	0.18	0.17	0.18	0.17	0.18	0.18	0.18
F-statistic	915.67	906.97	915.96	907.61	910.81	901.84	902.52	896.92
F-prob	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
nobs (firms*mth)	1534405	1376807	1533888	1376423	1533888	1376423	1376423	1376423

Table 7 Regional Analysis of IVOL / MAX Effects in Emerging Markets – When Considering the Impact of Propensity to Sell

This table reports the aggregated regional results with fixed effects model for the IVOL and MAX effect. Dependent variable is the one-month ahead individual stock returns for the markets in one of three regions, Asia, Latin America, and Euro-Africa-S.Asia. The model considers possible impact from investors' propensity to sell, as proxied by CGO (capital gains overhang), GO (gains overhang) and LO (loss overhang), in addition to controls for other prior-period firm characteristics, including market value (ln*Size*), MB ratio (ln*MB*), illiquidity (Illiq), prior six-month return (Mom), prior month return (Reversal), and price per share (ln*Price*). Among those reported models, models [3], [4] and [7] consider the impact of propensity to sell using CGO, while models [5], [6], and [8] apply the decomposed variables, GO and LO for the examination. The risk metrics (IVOL, MAX, and Beta) have been first orthogonalized against each other via monthly cross-sectional regressions within each market. Reported models also differ in terms of consideration of country-specific factors or not. The sample period is from 1980 to 2016, with most markets running with sufficient data starting from 1990. Month fixed effects are included in all regressions. The p-values based on the robust standard errors clustering at the country level are reported below the regression coefficient.

.

model	(A) Asia [1]	(A) Asia [2]	(B) Latin America [3]	(B) Latin America [4]	(C) Euro-Africa-S.Asia [5]	(C) Euro-Africa-S.Asia [6]
IVOL	-0.948	-1.189	-3.111	-3.593	0.369	0.343
	0.001	0.000	0.001	0.000	0.221	0.256
MAX	-0.336	-0.394	-0.712	-0.810	0.094	0.149
	0.000	0.000	0.003	0.001	0.438	0.220
CGO	0.025		0.010		0.018	
	0.000		0.000		0.000	
CGOxIVOL	-0.473		-0.220		-0.412	
	0.000		0.154		0.000	
CGOxMAX	-0.032		-0.037		0.038	
	0.252		0.440		0.162	
GO		0.015		0.003		0.008
		0.000		0.293		0.000
GOxIVOL		-0.462		0.041		-0.327
		0.000		0.826		0.000
GOxMAX		-0.029		0.024		-0.009
		0.532		0.670		0.791
|LO|		-0.053		-0.077		-0.067
		0.000		0.000		0.000
|LO|xIVOL		0.771		2.330		1.227
		0.000		0.001		0.000
|LO|xMAX		0.081		0.436		-0.021
		0.104		0.086		0.797
FnRskxIVOL	0.022	0.029	0.074	0.082	-0.015	-0.015
	0.001	0.000	0.003	0.001	0.061	0.051
FnRskxMAX	0.008	0.010	0.018	0.020	-0.002	-0.002
	0.000	0.000	0.003	0.002	0.607	0.489
Beta	0.000	0.000	-0.005	-0.005	0.003	0.003
	0.505	0.594	0.000	0.000	0.000	0.000
lnSize	-0.195	-0.192	-0.053	-0.080	0.831	0.517
	0.015	0.014	0.523	0.320	0.000	0.002
lnMB	-0.007	-0.007	-0.001	-0.001	-0.006	-0.007
	0.000	0.000	0.061	0.027	0.000	0.000
Mom	0.003	0.002	0.019	0.018	0.013	0.010
	0.007	0.125	0.000	0.000	0.000	0.000
Illiquidity	0.000	-0.001	0.004	0.003	0.002	0.001
p-val	0.398	0.042	0.009	0.049	0.000	0.062
Reversal	-0.024	-0.024	-0.009	-0.010	-0.005	-0.005
p-val	0.000	0.000	0.132	0.119	0.113	0.096
lnPrice	0.000	0.000	0.000	0.000	0.001	0.000
p-val	0.001	0.292	0.664	0.303	0.000	0.066
Country Factors	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	0.21	0.21	0.31	0.31	0.18	0.18
F-statistic	730.9	725.7	91.3	90.7	259.0	258.1
F-prob	0.000	0.000	0.000	0.000	0.000	0.000
nobs (firms*mth)	939336	939336	68257	68257	368866	368866