Volatility Anomalies and the Drivers Behind: Evidence from Emerging Markets

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Abstract

The question remains as to the drivers responsible for the widely documented volatility anomalies. For the purpose, this study attempts to gauge the volatilities that better capture investors' demand unrelated to fundamentals, and examines for emerging markets how such demands harm financial market efficiency. To extract the impact attributable to uninformed/speculative demand, this study adjusts those IVOL and MAX metrics by price movements from differing trading hours along with other adaptations. Results strongly suggest that the regular trading hour (open-to-close) measures best capture the demands led to anomalies. In addition, the risk metrics estimated using unlevered returns generally show less anomaly effects, and the scaled-MAX indeed helps to reduce the confounding effect arising from the size of volatility. This study further examines whether the presence of such investors' demand unrelated to fundamentals indeed harms the financial market efficiency, and finds results related to country-level institutional factors. This research expects to contribute to the understanding of the drivers behind the volatility anomalies.

Keywords: Financial market efficiency; Idiosyncratic volatility; MAX; Price informativeness; Uninformed demand

JEL classifications: F30; G12; G15

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1. Introduciton

The primary role that a financial market serves is to offer a guidance to properly allocate ownership of an economy's capital (Fama, 1970). With the increasing development of technology, one would expect stock prices to become more informative due to greater information production, and more efficient capital allocation in the economy. Nevertheless, the presence of uninformed trades, which could be a result of institutions and/or investor preference for non-wealth factors, greatly influences the price informativeness. In particular, investors may well trade for purposes unrelated to firm fundamentals. The primary purposes of this study are therefore two folds. One is to find measures that capture investors demand unrelated to fundamentals. The second is then to examine for emerging markets how such investor demand harm stock price informativeness in terms of real efficiency.

Extreme price movements are likely driven by irrational demand from investors. Those stocks are thus natural candidates revealing investors' demand deviating from firm fundamentals. This study employs MAX (highest daily returns in a month) and IVOL (idiosyncratic volatility) to characterize stocks with extreme movements and to assess investors' irrational demand. Stocks with high MAX or high IVOL have been widely documented to exhibit mis-pricing.[1] These metrics of extreme movements however are confounded by possible other drives of stock prices. Further treatments are required to better isolate the irrational demand.

Specifically, this study aims to understand whether there is any loss in price informativeness owing to the presence of stocks with extreme volatility. To answer the question, one needs to first identify the part induced by irrational demand, and then one could examine how the isolated return movements affect price informativeness in terms of real efficiency. This study addresses the following concerns when using these risk metrics to identify pricing unrelated to firm fundamentals. First, as suggested by French and Roll (1986), the information content embedded in price changes during

[1] For MAX effects, see for example Doran Jiang, and Peterson (2011), Carpenter, Lu, and Whitelaw (2015), Conrad, Kapadia, and Xing (2014), and Bali, Brown, Murray, and Tang (2017). For IVOL effects, see for example Bali and Cakici (2008), Fu (2009), Chen et al. (2012), and Ewens, Jones, and Rhodes-Kropf (2013).

regular trading hours or overnight hours is largely different. One would reasonably assume that public information mostly reveals after market close or before the next day open, while private information and noise trading induce price movements mostly over regular trading hours through investors' trading. To better capture the effect of noise trades, one should focus on the price movements occurring during the regular trading hours. This consideration is relevant for studies that attempt to differentiate the information content driven by distinct sources (e.g., see Boudoukh, et al. (2018)).

Second, now that stock prices respond to non-fundamental as well as fundamental shocks, the impact of uninformed trades can only be better estimated by first properly accounting for the price movements reflecting firm fundamentals. There is an extensive empirical literature suggesting a role for financial leverage in explaining the cross-sectional dispersion in expected stock returns. Some studies also find leverage-related anomalies.[2] Researchers suggest that a proper measure assessing firm fundamental changes should be based on "unlevered" asset returns. In a recent study, Doshi, Jacobs, Kumar and Rabinovitch (2019) particularly point out the importance of finding unlevered returns prior to cross-sectional return tests. In view of these findings, the focus measures of extreme volatility, MAX and IVOL, are estimated with unlevered returns.

This study re-visits the MAX effect and IVOL effect for emerging markets based on the aforementioned revised risk metrics, which consider returns measured over different intervals of a day, and using unlevered returns to properly account for financial leverage risk. Our findings indicate that the speculative demand for lottery-type payoffs or payoffs unrelated to fundamentals is indeed stronger during the trading hours, which is evidenced by that the noise demand in the trading hour (open-to-close) exhibit a reversal much stronger than that from after-hour price movements. If MAX effect or IVOL effect is driven by demand unrelated to fundamentals, the associated anomaly should be

[2] Studies finding the role of leverage in cross-sectional stock pricing include Bhandari (1988), Chan and Chen (1991), Fama and French (1992), Vassalou and Xing (2004), and Choi (2013)). Studies identifying leverage-related anomalies include Jegadeesh and Titman (1993), Zhang (2005), Asness, Moskowitz, and Pedersen (2013), Frazzini and Pedersen (2014), Novy-Marx (2013), and Fama and French (2015). Penman, Richardson, and Tuna (2007) and Engle and Siriwardane (2017) attempt to isolate the leverage component when testing the cross-sectional relation.

most pronounced for MAX/IVOL measured using open-to-close returns. Findings of this research are consistent with such claim. Meanwhile, our evidence also shows that MAX/IVOL effect is weakened when using pre-scaled unlevered return for estimation. Our results for emerging markets are consistent with the finding by Doshi et al. (2019) for the IVOL effect in U.S. market. The results are believed to aid future tests for stock return anomalies.

The next objective of this study is then to examine whether investors' demand unrelated to fundamentals, as assessed by the revised MAX/IVOL anomalies, lead to a loss in price informativeness for emerging markets. There is a large literature analyzing price informativeness, tracing back to Grossman and Stiglitz (1980), Stiglitz and Weiss (1981), Admati (1985) and Kyle (1985). When stock prices are informative, investors suffer less information asymmetry and are thus able to allocate their capital more efficiently. The measurement however is subject to variations when it comes to empirical testing. Bai, Philippon and Savov (2016) derive a welfare-based measure of price informativeness, forecast price efficiency (FPE), which assesses the predicted variation of future cash flows from current market prices at different horizons. This study follows Bai, et al. (2016) to estimate price informativeness and test whether there is a loss of FPE due to extreme price movements.

For this purpose, this study takes advantage of the multi-market platform to compare the FPE across emerging markets. On one hand, country characteristics that may influence price informativeness vary widely across markets. On the other hand, some of the markets, as compared to developed markets, are endowed with great investment opportunities. The greater investment opportunities coupled with relatively inferior information environment, one would expect managerial real investment decisions to be more sensitive to mis-pricing due to investor noise trades, which means greater loss in economic efficiency. This study finds a loss of price informativeness from the trading of stocks with extreme price behavior while the loss varies with sample period, which results may arise from the industry affiliations of sample emerging markets.

Results of this study are believed to contribute to the literature in the following perspectives. First, this research computes various versions of MAX and IVOL metrics for emerging market stocks when considering price changes over different intra-day intervals and when being revised to unlevered returns. For the MAX metric, we also follow Asness, Frazzini, and Gormsen (2019) to scale the maximum return of a stock by its ex-ante volatility. The purpose is to isolate the right skewed distribution in MAX and expects to better capture investors' demand for lottery-type payoffs. This study then re-tests the MAX effect and the IVOL effect for emerging markets based on revised measures of these two metrics. To our best knowledge, there are yet other studies, on the US market or international market, simultaneously considering all these aforementioned issues for adjusting MAX and IVOL and testing their relationship with cross-sectional stock returns. The findings of this research indicate significant differences in MAX or IVOL anomalies when using revised metrics.

Second, this study measures price informativness using the FPE suggested by Bai et al. (2016) for sample emerging markets. When it comes to the operational definition of price informativeness, the channel moves from market price to real investment (FPEINV) and then to the realization of earnings (FPE). This study compares the FPE-based price informativeness for the whole market against that for the group that excludes those stocks exhibiting extreme price movements in terms of various MAX and IVOL metrics. A significant spread in FPE between these two groups will indicate that the presence of MAX or IVOL affects the price informativeness for the market. This study finds that the cross-country FPE is indeed decreased due to the presence of high-MAX and high-IVOL stocks.

Last, this study finds robust evidence that investors' preference (overpricing) for high IVOL stocks exhibits a significantly negative relation with the FPE. This result indicates that the presence of investors exhibiting great preference for speculative payoffs harms a market's price informativeness in terms of real efficiency, i.e., FPE.

There is a large literature testing price efficiency in the sense that stock prices fully and immediately reflect information relevant for the firm. Nonetheless, price informativeness in terms of real efficiency, takes the next step to reveal whether market prices leading to efficient resource allocation. There has not yet been a consensus as to an operational definition to measure such economic efficiency. Along the channel, from market pricing, to real investment decisions, and to the realization of earnings, firms may experience a loss in efficiency during each stage. This study applies the revised risk metrics, MAX and IVOL, that better capture the irrational demand from investors to explore their relation to investment decisions and to firm earnings (as measured by FPE). Since the early theoretical development, there have been yet many empirical studies on real efficiencies until more recently (e.g., see Baker, Stein, and Wurgler, 2003; Chen, Goldstein, and Jiang, 2006; Edmans, Goldstein and Jiang, 2012; Bai, Philippon and Savov, 2016; Edmans, Jayaraman and Schneemeier, 2017; Binsbergen and Opp, 2019). More interesting findings are expected from this growing literature.

2. Research Hypothesis Development

The primary goal of this study is to examine whether investors' demand unrelated to fundamentals, as revealed by extreme price movements, show negative impact on price informativeness of a market. The selected metrics for extreme price movements include MAX and IVOL, which have been widely studied for their associated anomalies in the US and in the international markets. One major difference that this research expects to make is to apply revised measures of MAX and IVOL that consider different trade hours due to the response to different information content, and the heteroscedasticity induced by financial leverage. In addition, the price informativeness used in the study is related to real efficiency. Empirical studies on real efficiency are relatively few but growing recently. This section reviews the related studies and develops research hypotheses.

2.1 MAX, IVOL and the Associated Anomalies

The literature documents extensive evidence on volatility related anomalies, including beta anomaly and idiosyncratic volatility anomaly, finding low returns to prior period IVOL.[3] The literature has

[3] For studies on beta anomaly, see Black (1972), Fama and MacBeth (1973), Fama and French (1992), Baker and Wurgler

offered a wide range of explanations for these phenomena (e.g., see Baker and Wurgler, 2006; Zhang, 2006; Bali and Cakici, 2008; Barberis and Huang, 2008; Fu, 2009; Jiang, Xu and Yao, 2009; Huang, Liu, Rhee and Zhang, 2010; Han and Lesmond, 2011; Stambaugh, Yu and Yuan, 2015; Hong and Sraer, 2016). To reconcile such pricing anomalies, there are risk-based explanations, which suggest possible missing factors, as well as behavioral based explanations (e.g., see Barberis and Huang, 2008; Baker et al., 2011; Shen and Yu, 2013; An, Wang, Wang, and Yu, 2015; Wang, Yan, and Yu, 2017). Under behavioral models, market participants are irrational. Preferences for lotteries plus the biases of representativeness and overconfidence give rise to the over-pricing of stocks with extreme or volatile payoffs (Fischhoff, Slovic and Lichtenstein, 1977; Kahneman and Tverky, 1979; Alpert and Raiffa, 1982; Tversky and Kahneman, 1983). Such irrational demand could be arbitraged away if there are enough rational investors capitalize on such anomaly when arbitrages are feasible or not costly. In relation to behavioral explanations, recent studies have also suggested that social connections or cultural related factors play a role in those anomalies (e.g., see Heimer, 2016).

This study focuses on the impact on price informativeness in a market due to investors' demand shocks unrelated to firm fundamentals. For the purpose, this research expects such irrational demand shock to be revealed from stocks with extreme price movements. This study follows the definition of lottery-type stocks by Bali, Cakici and Whitelaw (2011) and Bali et al. (2017), which studies use highest daily returns in a month (MAX) to measure the demand for lottery-type stocks and idiosyncratic volatility (IVOL) as proxies for the impact from noise trades. The heightened demand for lottery-type stocks or stocks with high IVOL may be driven by information or by irrational motives. Jiang and Zhu (2017) find overnight jumps have most significant predictive power for subsequent stock returns, and they suggest that one can properly interpret a price jump, especially an overnight jump, as an information event. Inspired by the finding of Jiang and Zhu (2017) and suggestions from French and Roll (1986) and Boudoukh, et al. (2018), this study computes MAX and IVOL based on different

(2014), and Frazzini and Pedersen (2014). For studies on idiosyncratic volatility anomaly, see for example Bali and Cakici (2008), Fu (2009), Chen et al. (2012), and Ewens, Jones, and Rhodes-Kropf (2013), among others..

trading intervals in a day in anticipation to better capture differential impact of noise trades.

2.2 Unlevered Returns - Financial Leverage Risk and Cross-Sectional Returns

Firm leverage has long played a role in explaining the cross-sectional stock returns. Nonetheless, the effect of financial leverage on the cross-sectional returns still remains unresolved, and a group of researchers also find anomalies to be related to leverage.[4] In the empirical literature, most studies tackle the impact by including the leverage characteristic in the regression model for the analysis. However, financial leverage induces heteroscedasticity in stock returns and such heteroscedasticity is highly nonlinear and difficult to be controlled for by simply including the leverage variable in regressions (Harvey, 1976). There are studies attempting to isolate the leverage component when testing the cross-sectional relation (e.g., see Penman, Richardson, and Tuna, 2007; Engle and Siriwardane, 2017). In a recent study, Doshi, Jacobs, Kumar, and Rabinovitch (2019) examine whether some well-documented anomalies are attributable to financial leverage risk. They propose to test those anomalies through the cross-section of "unlevered" equity returns. They suggest approaches to infer "unlevered returns" from the directly observed "levered returns" prior to the cross-sectional tests. Doshi et al. re-examine anomalies associated with beta, size, BM, and IVOL, and find that the unlevered market beta better explains the cross-section of unlevered returns, the size effect weakens, and the value premium and the IVOL puzzle both substantially weaken.

This study follows the approach suggested by Doshi et al. (2019) and computes unlevered returns before proceeding to compute the risk metrics, to examine the associated anomalies and investigate their impact on pricing.

2.3 Price Informativeness in Terms of Real Efficiency

[4] For examples, see Bhandari (1988), Chan and Chen (1991), Fama and French (1992), Vassalou and Xing (2004) and Choi (2013) on the relation between leverage and return. See Jegadeesh and Titman (1993), Zhang (2005), Asness, Moskowitz, and Pedersen (2013), Novy-Marx (2013), Frazzini and Pedersen (2014), Fama and French (2015) for researches on leverage related anomalies.

There is a large literature analyzing information efficiency of stock prices, that is, the extent to which the firm fundamental information is incorporated into stock prices. The pioneer theoretical works include studies by Grossman and Stiglitz (1980), Stiglitz and Weiss (1981), Admati (1985) and Kyle (1985). Researchers advocate that when stock prices are informative, investors suffer less information asymmetry and are thus able to allocate their capital more efficiently. This is the conventional view of linking financial market efficiency to efficient real decisions. Theoretical researches may choose different forms of feedback from investment to market prices.[5]

There have been limited empirical researches studying the real effects of financial market transactions (Baker, Stein, and Wurgler, 2003; Chen, Goldstein, and Jiang, 2006; Bakke and Whited, 2010; Edmans, Goldstein and Jiang, 2012; Bai, Philippon and Savov, 2016; Edmans, Jayaraman and Schneemeier, 2017). Bond, Edmans and Goldstein (2012) term the price efficiency in secondary markets as forecasting price efficiency (FPE), which assesses the extent to which market prices predict firm fundamental values. They derive a welfare-based measure of price informativeness, forecast price efficiency (FPE), which assesses the predicted variation of future cash flows from current market prices at different horizons.

This study follows Bai, et al. (2016) to estimate price informativeness and test whether there is a loss of FPE due to extreme price movements. FPE measures the linkage between current market prices and future earnings. Current market prices are moved by public information, private information and noise trades. In order to successfully translate the information carried by market prices to firm earnings, it requires that managers have the ability to isolate relevant public and private information from noises and then properly utilize the information for real investment decisions. In a recent study, Dessaint, Foucault, Fresard and Matray (2018) point out that noise in stock prices show real impact for firm investment decisions even after controlling for possible agency issues and financial constraints.

[5] Recent theoretical work on asset prices and real efficiency includes Bond, Goldstein, and Prescott (2010), Goldstein and Guembel (2008), Goldstein, Ozdenoren, and Yuan (2013), Kurlat and Veldkamp (2015), Ozdenoren and Yuan (2008), Subrahmanyam and Titman (1999), and Edmans, Goldstein, and Jiang (2012).

2.4 MAX and IVOL Effects – Re-Visit with Revised Measures

This study re-examines the MAX and IVOL effect for emerging market stocks, when MAX and IVOL are re-computed based on returns over different trading intervals, namely close-to-close, close-to-open, and open-to-close. The information content is largely different among these returns. It is expected that public information mostly releases after market close and before market open, while private information is revealed and noise trades are active during the regular trading hours. This suggests that the risk metrics measured over the open-to-close hours are relatively more influenced by noise trades, and thus more likely to exhibit mis-pricing. This study will test the following hypothesis.

H1: (MAX Effect and IVOL Effect – Measures Based on Different Trading Intervals)

The volatility anomalies expect to be most pronounced when the risk metric is measured using the trading hour returns (i.e., from open to close).

Meanwhile, this study also appeals to the argument on the leverage impact and applies unlevered returns to compute those risk metrics, MAX and IVOL. Such adjustment expects to better measure firm fundamental values and the anomalies will be mitigated.

H2: (MAX Effect and IVOL Effect – Measures Based on Unlevered Returns)

The volatility anomalies expect to be mitigated when the risk metric is measured based on unlevered returns.

2.5 Stocks with Extreme Movements and Price Informativeness

Market prices contain information disclosed by firms (i.e., public information), information produced by investors through their trading (i.e., private information), and mis-information driven by noise trades or irrational demand shocks from investors. Forecast price efficiency (FPE) measures the extent to which the market prices could predict future firm cash flows. That is, the magnitude of FPE reflects both public information and private information in market prices that are relevant to future firm earnings.

The following issues are involved in the channel between current market prices and future firm earnings. The first issue is whether the stock prices fully reflect all available information. One also needs to know whether stock prices provide information accurately and relevant for resource allocation. The possibility is that noise trades distort the messages carried by market prices, which then mislead managers in their real investment decisions. Then, with stock prices being informative, the role of aiding efficient allocation of resources still ultimately relies on managerial decisions. More informative prices do not necessarily imply contribution to economic efficiency on the part of financial markets. The preceding issues are often intertwined theoretically and, more so, empirically. There should be an effective link between current stock prices and managerial decisions on investment, and then one could expect the investment decisions leading to future earnings.

Bali et al. (2011) find that stocks to deliver lottery-like payoffs in the portfolio formation month continue to exhibit this behavior in the future. Their findings point to that MAX is a characteristic, rather than a short term statistic, for a stock. The persistence of the anomaly is likely to show impact on real efficiency. Indeed, Binsbergen and Opp (2019) indicate that one important condition that financial market anomalies lead to real economic distortions is persistence of the abnormal returns. For the aggregate economy, a small but persistent abnormal return harms more in terms of economic efficiency than a short-lived but large abnormal return.

The focus of this study is to examine whether investors' demand unrelated to firm fundamentals harm price informativeness of a market. To answer the question, one needs to identify the part of information content of stock prices induced by irrational demand, and then examine how the return movements affect price informativeness in terms of the linkage to firm earnings. Specifically, this study will test the following hypothesis.

H3: (Stocks with extreme returns and price informativeness)

The presence of stocks exhibiting extreme price movements will harm the price informativeness of the market, in terms of weakened linkage between market prices and future earnings.

If the risk metrics measured over the open-to-close hours better capture the noise trades, the associated risk metrics expect to lead to greater mis-pricing and harm price informativeness. In addition, this study also applies unlevered returns to compute those risk metrics, MAX and IVOL. Returns with such adjustment expect to better measure market price responses to firm fundamentals. It follows that the anomalies, if partially attributable to leverage, should be mitigated when unlevered returns are employed for the tests.

Results of this study contribute to the understanding of the formation of anomaly associated with MAX and IVOL, but also shed light on the information content carried by those extreme price movements.

3. Estimation of MAX and IVOL to Capture Noise Demands

To examine how investors' demand unrelated to firm fundamentals harm price informativeness, one has to properly measure the extent to which investors' irrational trades reflected from stock price changes. This study addresses the following issues regarding these metrics. First, to better capture the impact of noise trading, we focus on the part of price movements occurring during the (regular) trading hours. Second, unlevered returns can properly measure the price changes to firm fundamentals. We follow the approach suggested by Doshi et al. (2019) to infer unlevered returns from the directly observed levered returns. The focus measures of extreme volatility, MAX and idiosyncratic volatility (IVOL), are estimated to incorporate these aforementioned concerns.

3.1 Volatility metrics considering trading intervals and unlevered returns

Return volatility could arise from the revelation of public information, the release of private information, or shocks to investors' demand for liquidity or noise trading. In order to better understand the drivers of return volatility, French and Roll (1986) compare variance ratios of stock returns during periods of regular trading hours and overnight. The idea is that public information is mostly released after market close or before market open (i.e., overnight) while private information is revealed through trading, which mostly occur during regular trading hours. Their finding suggests that private information driven rational trading is responsible for the most part of price movements. Some later studies made consistent conclusions (e.g., see Barclay and Hendershott, 2003; Chordia, Roll and Subrahmanyam, 2011). In a more recent study by Boudoukh, Feldman, Kogan and Richardson (2018), they attempt to find the information content that induces return volatility of US stocks through the linkage between news and stock price movements. Similarly, they consider three periods covering news and returns, namely, the full trading day (from close to close), the regular trading hours (from open to close), and the overnight hours (from close to open).

Accordingly, this study computes the risk metrics based on close-to-close, open-to-close, and close-to-open returns, to track the type of information content driving the extreme volatility. Note that while many markets nowadays allow trades after regular trading hours, the trades are comparatively much less frequent and noise trading has little impact after the close of regular market. The following specifications of MAX and IVOL consider this issue.

Doshi et al. (2019) propose alternative approaches to infer the unlevered returns from levered returns. Their first approach simply scales excess levered equity returns by the leverage ratio. Their second approach then unlevers returns using a parametric model derived from Merton (1974) or more sophisticatedly from Leland and Toft (1986). Doshi et al. show that these two approaches are related. Considering that the application of the second parametric model requires more company-level data, which are not available for our subjects, emerging market companies, this study adopts their first approach to scale unlevered returns.

Specifically, this study scales the levered return to unlevered return as below:

$$R_{i,t}^{U} = R_{E,i,t} \times (1 - L_{i,t-1}) = R_{E,i,t} \times (1 - \left(\frac{BVD_{i,t-1}}{BVD_{i,t-1} + MVE_{i,t-1}}\right)) \quad (1)$$

In the above equation, $R_{i,t}^{U}$ denotes the unlevered return (asset return) for stock i at time t, and $R_{E,i,t}$ denotes the levered return (i.e., the directly observed equity stock return) for stock *i* at time *t*. Leverage ($L_{i,t-1}$) is computed as the ratio of the book value of total liabilities ($BVD_{i,t-1}$) to the sum of the book value of total liabilities ($BVD_{i,t-1}$) and the market value of equity ($MVE_{i,t-1}$). The leverage ratio is re-estimated every month based on the recent month of market value and prior year book value data. The volatility metrics are adapted accordingly and detailed below.

3.2 Revised Metrics of Extreme Price Movements - MAX and IVOL

Bali et al. (2011) propose a more direct measure, MAX, which assesses the average of k highest daily returns in a month, with k being equal to 1 to 5. This non-parametric measure has been widely applied in recent studies on stocks with extreme payments. In this study, the focus is on stocks showing prices likely to be affected by investors' demand unrelated to firm fundamental. Stocks with extreme volatilities, which have been widely documented to exhibit mis-pricing, are the subjects of the study. In particular, $MAX_{i,t}$ measures the average of the *k* highest daily returns for stock *i* during month *t*, and this study sets k equal to 3.

The MAX measures are adapted to incorporate the impact of trading hours and financial leverage. The efforts of those treatments aim to isolate the part of price movement driven by demand unrelated to firm fundamentals. In brief, the MAX metric are revised by considering different trading interval, by purging the volatility from MAX, and by adjusting the directly observed levered returns with leverage.

As discussed above, this study follows French and Roll (1986) and Boudoukh, et al (2018), among others, and consider three periods of returns, namely, the full trading day (from close to close), the regular trading hours (from open to close), and the overnight hours (from close to open). This study computes the MAX also based on close-to-close, open-to-close, and close-to-open returns, such that we can trace the type of information content driving the extreme volatility. This study applies three different trading periods for computing MAX metric, and we have

$$MAXCC_{i,t} = \frac{1}{h}(\sum_{k=1}^{h} \max h((R_{CC\,i,d}, d = 1, D_t)), \tag{2a}$$

$$MAXOC_{i,t} = \frac{1}{h}(\sum_{k=1}^{h} \max h((R_{OC\,i,d}, d = 1, D_t)), \tag{2b}$$

$$MAXCO_{i,t} = \frac{1}{h}(\sum_{k=1}^{h} \max h((R_{CO\,i,d}, d = 1, D_t)), \tag{2c}$$

where $maxh(R_{CC,i,d})$, $maxh(R_{OC,i,d})$, and $maxh(R_{CO,i,d})$ respectively denotes the h-th maximum daily return in month t, with daily return being calculated using closing prices on day d-1 and day d, opening price and closing price on day d, and closing price on day $d-1$ and opening price on day d, and D_t is the number of trading days in month t.

This approach distinguishes the MAX return by the trading hour MAX (MAXOC) and the overnight MAX (MAXCO). If following the interpretations of French and Roll (1986) and Boudoukh et al. (2018), among others, MAXCO expects to capture mostly max returns induced by public information while MAXOC captures mostly the movement attributable to private information or noise trading. Since the study by Bali et al. (2011), most studies employ the raw MAX (i.e., MAXCC) to measure lottery demand from investors and the MAX effect is estimated accordingly. MAXCC is a confounded measure to gauge investors' speculative demand in that the metric MAXCC may well capture not only lottery demand but also price movements responding to public information and private information. Alternatively, the trading hour MAXOC expects to better reflect the movements due to investors noise trading, which can be more likely triggered by their demand for lottery-type payoffs.

Asness et al. (2019) test whether the volatility effect (i.e., high volatility stocks yielding low next-period abnormal return) for various risk metrics, including total volatility, beta, IVOL and MAX, is driven by leverage constraints. The authors point out that a stock has a high MAX return could be attributable to either having a high volatility or its return distribution is right-skewed. To decompose these effects, they propose a new measure, SMAX, which is the MAX return divided by its ex-ante volatility. In particular, for each stock, we calculate the MAX value (the average of the k highest daily returns) over the month, divided by the stock's ex-ante volatility. Volatilities, $\hat{\sigma}_{i,t}$, are estimated using one-year rolling windows of log daily returns. A minimum of 120 trading days of non-missing return data are required to estimate the volatilities. That is, we have $SMAXCC_{i,t}$, $SMAXOC_{i,t}$ and $SMAXCO_{i,t}$. These measures capture a stock's realized return distribution and further isolate lottery demand from volatility.

For MAX measures, the unlevered MAX is now computed using the unlevered return $R_{i,t}^{U}$ adjusted for the directly observed levered stock return, $R_{E,i,t}$, using prior year leverage ratio, as specified in equation (1). Specifically, in equations (2a) to (2c), the three returns measured over different hours, *Rcc*, *Roc*, and *Rco*, are now replaced with the adjusted unlevered return according to equation (1), and we have correspondingly, R_{cc}^{U}, R_{oc}^{U}, and R_{co}^{U}. Since the adjusted factor (leverage) varies at monthly frequency (monthly market value and annual book value), the monthly unlevered MAX can be obtained by multiplying the levered MAX values (MAXCC, MAXOC, MAXCO) in equations (2a)-(2c) by $(1\text{-}L_{i,t-1})$. Those unlevered MAXs are denoted as $MAXCC^{UR}$, $MAXOC^{UR}$, $MAXCO^{UR}$ respectively, for later applications and discussions. The values of unlevered MAXs are different from those of levered MAXs across stocks and over time.

In the case of unlevered SMAX, the numerator is levered-MAX times $(1\text{-}L_{i,t-1})$ adjusted monthly. The denominator is now the unlevered volatility, which is estimated using one-year rolling windows of log "unlevered" returns, with the daily returns being adjusted differently each month. It follows that these two factors will not be cancelled out. The unlevered SMAX, are denoted as $SMAXCC^{UR}$, $SMAXOC^{UR}$, and $SMAXCO^{UR}$, respectively.

This study considers returns of three intraday intervals, namely, the full trading day (from close to close), the regular trading hours (from open to close), and the overnight hours (from close to open). The idiosyncratic volatility (IVOL) is estimated using the residual returns, $\varepsilon_{CC,i,d}, \varepsilon_{OC,i,d}, \varepsilon_{CO,i,d}$, obtained from a one-factor market model regression (including fixed effects). The monthly IVOL over different intervals, *IVOLCC*, *IVOLOC*, and *IVOLCO*, respectively is the sum of squared daily idiosyncratic returns $\varepsilon_{CC,i,d}, \varepsilon_{OC,i,d}, and\ \ \varepsilon_{CO,i,d}$.

The unlevered IVOL is estimated using the unlevered return $R^{U}_{i,t}$, adjusted for the levered stock return, $R_{E,i,t}$, using prior year leverage ratio, as specified in equation (1). In the market model, the dependent variable is the unlevered return, $R^{U}_{i,t}$, and the market portfolio return is the return on the portfolio that aggregates the rescaled returns, $R^{U}_{i,t}$, for all stocks in the market. The resulting monthly IVOL is the sum of squared daily unlevered residual returns when the returns are measured over different intervals. And, we will have unlevered IVOLs when using close-to-close, open-to-close, and close-to-open intervals, which are denoted as $IVOLCC^{UR}$, $IVOLOC^{UR}$, and $IVOLCO^{UR}$, respectively.

3.3 Data

This study assembles 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 31 emerging markets from Europe, America, Africa and Asia.[6]

[6] The sample markets include Argentina, Brazil, Czech Republic, Chili, China, Colombia, Egypt, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Jordan, Korea (South), Malaysia, Mexico, Morocco, Pakistan, Peru, the Philippines, Poland, Portugal, the Russian Federation, Singapore, Sri Lanka, Taiwan, Thailand, and Turkey, South Africa, and Venezuela. Jordan and Venezuela are later dropped due to insufficient data. Argentina, Jordan and Venezuela are later dropped due to insufficient available data.

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, the main results rely on data from 1990 to 2016.

Only common stocks listed on the major exchange of the country with data available from Datastream and Worldscope will be 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. We 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.[7] The company-level accounting data will be collected from Worldscope. All the price and return data are converted into US dollars. Most of the macroeconomic data for sampled markets are obtained from the World Bank database (WDI-online), FRED, and Datastream.

3.4 Preliminary Statistics

Table 1 describes firm-level variables of sample stocks aggregated across 31 emerging markets. To better understand the contrasting characteristics of stocks with extreme movements, the sample is partitioned in to those stocks exhibiting high extreme movements, in terms of IVOL and MAX, and the remaining. For each market, stocks are classified as those showing extreme movements if their IVOLs or MAXs are among the top 20 percentile for the year in the market. Panel A contrasts those stocks

[7] This study imposes 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, We will implement a filter for reversals in the data that could be caused by incorrect stock prices. In particular, we 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%. We further winsorize 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.

with High-IVOL and those without. Panel B, C and D then lists firm characteristics for those stocks with High MAX1, MAX2 and MAX3, respectively.

[Insert Table 1 Here]

As expected, those stocks with high IVOL or high MAXs tend to be those of smaller size firms, in terms of both market capitalization and total asset value, those with low analyst coverage, higher total return volatility, lower prior 11-month returns, higher MB ratios and lower earnings. Those with high IVOL also tend to show higher MAX values, and the reverse also holds.

Table 2 lists the descriptive statistics for the IVOL and MAX metrics when calculated using different trading hour returns, using unlevered returns and adjusting for volatilities. Panel A lists those results using raw returns, i.e., prior to the application of unlevered returns. Column (1) lists statistics for the IVOL estimates. Columns (2), (3) and (4) list the statistics for traditional measures of MAX, including MAX1, MAX2 and MAX3. Column (5), (6) and (7) then reports the statistics respectively for SMAX1, SMAX2 and SMAX3, which are MAX values scaled by return volatilities.

In the Panel, these metrics are computed using (a) close-to-close daily returns, (b) open-to-close intra-day returns, or (c) close-to-open (prior day close to next day open) returns. As expected, a comparison of volatility metrics calculated with returns over these three daily intervals indicates that the metrics based on close-to-close returns are largest in magnitude. More interestingly, metrics based on price movements over regular trading hour (open-to-close) are larger than those obtained using price movements over after hours (close-to-open). This finding is consistent with the conjecture that noise demand is stronger during regular trading hours. Note that such relation does not hold for scaled-MAXs. Columns (5) to (7) show that the open-to-close SMAX is similar in size to close-to-open SMAX, while close-to-close SMAX remains as the highest. This observation suggests either that the after-hour noise demand is not low as expected or that scaling by return volatility may also purge some noise demand away from the metrics.

[Insert Table 2 Here]

Panel B repeats the IVOL and MAX metrics measured over different trading hours while the returns are first unlevered as suggested by Doshi et al. (2019). As expected, the average estimates for those metrics obtained using unlevered returns are lower attributable to the calculations per se. Similar to the results of Panel A, the relative sizes of open-to-close IVOL and MAX measures are again larger than the corresponding close-to-open ones, and SMAXs again show similar in size between two intraday hours. .

4. Re-visit of MAX effect and IVOL effect – Using Revised Metrics

This study applies various versions of the risk metrics, MAX and IVOL, to examine the associated anomalies across emerging markets. Note however that while the MAX effect and IVOL effect, in their original forms, are well-documented for the US market and also quite robust for developed markets (e.g, see Bail et al., 2017), the literature exhibits inconsistent results regarding the MAX effect and IVOL across emerging markets. Most of the inconsistencies may be attributable to the insufficient valid data for some markets.

Liu, Stambaugh and Yuan (2019) find 83% of the reverse mergers in China involve shells from the smallest stocks. The authors thus exclude the bottom 30% of stocks from their sample to avoid shell-value contamination. In order to apply same standard across sample markets, this study re-examines the MAX and IVOL effect by excluding the smallest 10% of firms from the sample.

This study performs a fixed effects analysis by combining all sample markets in the regression. In the fixed-effects model, this study applies the procedure of Petersen (2009) to correct the standard errors for possible serial correlation within a firm and for cross-sectional correlation across firms in a given time. The MAX-effect and IVOL-effect is re-tested by apply the revised measures in the regressions. The anomaly associated with each MAX metrics is estimated each month by running the following regressions:

$$R_{c,i,t} = b_{0,c,t} + b_{IVOL,c,t} \times IVOL_{c,i,t-1} + \ b_{MAX\ \ c,t} \times MAX_{c,i,t-1} + b_{size\ \ c,t} \times lnMV_{c,i,t-1} + b_{mb,c,t} \times lnMB_{c,i,t-1}$$
$$+b_{mom\ \ c,t} \times MOM_{c,i,t-1} + b_{tnv,c,t} \times Turnover_{c,i,t-1} + b_{p,c,t} \times lnP_{c,i,t-1} + b_{beta,c,t} \times BETA_{c,i,t-1}$$
$$+b_{cov,c,t} \times Coverage_{c,i,t-1} + b_{rev,c,t} \times R_{c,i,t-1} + b_{vol,c,t} \times Volatility_{c,i,t-1} + e_{\ c,i,t}$$
(3)

where $R_{c,i,t}$ is the excess return on stock *i* in country *c* during month *t*. The regressions are performed on the one-month lagged values of IVOL, MAX, firm market value (lnMV), market-to-book ratio (lnMB), prior 11-month returns (MOM), turnover ratio (Turnover), share price (lnP), market beta (BETA), analyst coverage (Coverage) and lagged returns ($R_{c,i,t-1}$). All continuous variables are winsorized at their 1st and 99th percentiles. The result of $b_{IVOL,c}$ assesses the magnitude of IVOL effect, and $b_{MAX,c}$ evaluates the size of the anomaly associated with lottery-type demand measured by MAX. Similar settings are also used in Bali et al. (2011, 2017) and Yu and Yuan (2016), among others.

4.1 Anomalies from Trading-Hour (Open-to-Close) versus After-Hour (Close-to-Open) Price Movements

In the revisit of the anomalies, this study applies various versions of IVOL metrics that consider different intraday intervals and unlevered returns. The MAX metrics further consider the cases when MAX measures are further scaled by return volatility. Table 3 reports the regression results using different daily hours. Panel A reports the results for the sample period starting from year 1994. This study requires daily open prices for sample stocks to compute our primary metrics. In view of the insufficient data of the opening price for the sample emerging market stocks, this study selects a later year to mitigate the problem of unbalanced sample for certain markets. Panel B reports the results when the starting year is selected to be year 2000.

[Insert Table 3 Here]

In each Panel of Table 3, results are separately estimated with risk metrics computed using three different daily intervals. In Panel A, Columns (1) to (3) list results when the traditional close-to-close returns are used as base for the calculations. During the sample period, the aggregated emerging market stocks exhibit robust IVOL puzzle as widely documented in the literature. The MAX effect is significant only when MAX1 is applied. Columns (4) to (6) then report the results for metrics estimated using open-to-close trading hour returns, which are considered to capture the most impact from noise trades. In comparison to the close-to-close results, the IVOL effect remains strong and evident and the MAX effect is more robust when all MAX1, MAX2 and MAX3 show statistically significant effect. Columns (7) to (9) list the estimated regression coefficients for after-hour (close-to-open) metrics. The results are strikingly different here. The IVOL coefficients now switched from negative to positive and significant. The MAX effects now disappear for all three MAXs. This finding is consistent with the conjecture that the trading hour returns better capture the noise trades, which lead to the mispricing. That the open-to-close results demonstrate the strongest IVOL and MAX effect suggests that the traditional close-to-close returns are confounded measures.

Panel B repeats the same estimation while using a later sample period that starts from year 2000. A comparison of the results from these three groups of regressions still indicates that the open-to-close returns exhibit the strongest IVOL and MAX anomalies. Nonetheless, the close-to-close cases now become stronger and closer to the open-to-close returns. The close-to-open results now show significant MAX effects while the coefficients of IVOL remain positive. This result seems to suggest that the close-to-open hours carry increasingly more noise trades over time.

[Insert Table 4 Here]

To better contrast the impact from two intraday intervals, Table 4 reports the results of regressions that simultaneously include both the open-to-close risk metrics and the close-to-open ones. Results are also repeated for different sample periods. A comparison of the results across Columns (1), (2) and (3) suggests that the open-to-close anomaly seems unrelated to the close-to-open anomaly as the coefficient estimates of IVOL or MAX remain similar regardless of whether the alternative intraday hour metrics (*IVOL_OC* and *IVOL_CO*, or *MAX_OC* and *MAX_CO*) are included in the regression. This observation, which holds for both Panel A and Panel B, suggests that the impacts from these two intervals are not much correlated.

4.2 Anomalies from Unlevered-Return-Metrics and Volatility-Scaled-MAX

Doshi et al. (2019) use their proposed unlevered return and find the IVOL effect to become weak and almost disappear. They claim that unlevered returns can properly measure the price changes reflecting the firm fundamentals. It can then better reflect the true cross-sectional relations. To proceed, the regressions are performed with returns and risk-metrics calculated by first being "unlevered" through the conversion shown in Equation (1). The IVOL and MAX anomalies are re-tested accordingly. Table 5 reports the results.

[Insert Table 5 Here]

Panel A of Table 5 reports the regression results when all metrics and returns are unlevered. Columns (1) to (3) list the results for close-to-close interval returns. The IVOL effect still remains but in a smaller magnitude, and the MAX effect disappears. This finding partially supports the claim by Doshi et al. (2019). Next, Columns (4) to (6) and Columns (7) to (9) respectively report the results of open-to-close and close-to-open returns. The open-to-close metrics still present robust IVOL as well as MAX effects. Note however that the previously unfounded close-to-open IVOL effect in Table 3 and Table 4 now re-appears.

Panel B of Table 5 lists the traditional levered-return results while the MAX metrics are now scaled by prior return volatilities. SMAX expects to better isolate lottery demand from volatility. Columns (1) to (3) show that the MAX effects are now reversed for close-to-close metrics and Columns (4) to (6) find that the MAX effects though still exist but weakened in comparison to Panel A of Table 3. The close-to-open results in Columns (7) to (9) also do not present significant MAX effects. In all, SMAX purges the volatility effect from the measure and thus better captures the pure lottery demand. On one hand, the close-to-close results indicate that such volatility scaling is important when examining effects from lottery demand. On the other hand, the significant results from open-to-close metrics suggest that the noise demand for lottery-type payoffs indeed leads to overpricing.[8]

Panel C presents results when considering both unlevered return metrics and volatility-scaled MAX. The findings are consistent with those discussed for Panel A and Panel B. In brief, the unlevered return metrics still reveal IVOL anomalies when close-to-close returns are applied. However, the resurging IVOL effect from the after hour returns (close-to-open) is puzzling and requires further explorations to offer a better explanation.

4.3 Regional Results

The above findings may arise from the impact form large countries or may be limited to specific geographic regions. This study examines the results by four geographic regions, namely Asia, Europe, America and Middle East & Africa.[9] Table 6 reports the findings when three alternative daily interval returns are applied. Panel A reports the traditional close-to-close results. First, the IVOL effect remains strong and consistent across four regions. The MAX effects however only prevail in Asia and somewhat in America (South America in this sample).

[Insert Table 6 Here]

The open-to-close results in Panel B expect to best reveal the noise trade effects and show the strongest IVOL and MAX anomalies. The MAX effect is now present in Asian, American and Middle East & African markets. The IVOL effect remains strong across three out of four regions but

[8] Note that the positive and significant IVOL results in Columns (7) to (9) are similar to the corresponding results in Table (3). That is, this observation is not attributable to SMAX.

[9] The Asian region includes China, Hong Kong, India, Indonesia, South Korea, Malaysia, Philippines, Pakistan, Singapore, Sri Lanka, Taiwan and Thailand. The European region includes Czech Republic, Egypt, Greece, Hungary, Ireland, Poland, Portugal and Russian Federation. The American region includes Argentina, Brazil, Chili, Colombia, Mexico and Peru. The Middle-East & African region includes Israel, Turkey, Morocco and South Africa.

disappears for America. The possibility is that the MAX effect now absorbs the previously found IVOL effect.

5. Price Informativeness

One of the major functions that financial markets serve is to offer a guide to allocate ownership of an economy's capital. Any increased price informativeness thus expects to deliver more efficient capital allocation in the economy. Several issues should be addressed in the channel between market pricing and future firm earnings. The first issue is whether the stock prices fully reflect all available information. The associated question is whether stock prices provide information accurately and relevant for resource allocation, as noise trades may distort the messages carried by market prices, which then mislead managers in their real investment decisions. Last, even with stock prices being informative, the role of efficient allocation of resources still ultimately relies on managerial decisions. More informative prices do not necessarily lead to economic efficiency. There should be an effective link between stock pricing and managerial decisions on investment, and then one could expect the investment decisions leading to future earnings (Tobin, 1969, Fama, 1970, Bai et al., 2016).

Having addressed the issues of measuring the impact of trades unrelated to fundamentals, we now proceed to examine the second question, i.e., whether investors' demand unrelated to firm fundamentals harm price informativeness of a market in this section.

5.1 Forecast Price Efficiency (FPE)

This study follows Bai, Philippon and Savov (2016) to estimate price informativeness and then compares the price informativeness across partitioned samples based on the values of volatility metrics. Bai et al derive a welfare-based measure of price informativeness, forecast price efficiency (FPE), which assesses the predicted variation of future cash flows from current market prices at different horizons.

Market prices contain information disclosed by firms (i.e., public information), information produced by investors through their trading (i.e., private information), and mis-information driven by noise trades or irrational demand shocks from investors. Forecast price efficiency (FPE) measures the extent to which the market prices could predict future firm cash flows. That is, the magnitude of FPE reflects both public information and private information in market prices that are relevant to future firm earnings. This study aims to examine any loss in price informativeness, as measured by FPE, owing to the presence of stocks with extreme volatility.

Estimation of price informativeness (FPE)

Following Bai et al. (2016), the measure of price informativeness (FPE) is estimated through running cross-sectional regressions of future earnings on current market prices with proper controls. In particular, for each market, each year *t*, the following cross-section regression is performed at different horizons *h*=1, 2, 3 years:

$$\frac{EBIT_{i,t+h}}{TA_{i,t}} = a_{t,h} + \quad b_{t,h} \times \ln\left(\frac{MVE_{i,t}}{TA_{i,t}}\right) + c_{t,h} \times \left(\frac{EBIT_{i,t}}{TA_{i,t}}\right) + \sum_k^K f_{t,h}^k \times D_{i,t}^k \quad + e_{i,t,h} \qquad (4)$$

In the above equation, $MVE_{i,t}$ is market capitalization for firm *i* at the end of year *t*, $TA_{i,t}$ is total assets for firm *i* in year *t*, $EBIT_{i,t}$ is earnings before interest and taxes for firm *i* in year *t*, and $D_{i,t}^k$ are the industry indicators (based on ICB classifications).

For each market, the price informativeness (FPE) is the predicted standard deviation of future cash flows, as measured by earnings, from market prices. That is, price informativeness in year *t* at horizon *h* (h=1, 2, and 3), $FPE_{t,h}$, is the regression coefficient in the above equation, $b_{t,h}$, times the cross-sectional standard deviation of ln(MVE/TA) in year *t*:

$$FPE_{t,h} = \quad b_{t,h} \times \sigma_t\left(\ln\left(\frac{MVE_{i,t}}{TA_{i,t}}\right)\right) \qquad (5)$$

Predicted variation of investment from prices (FPEINV)

Following Bai et al. (2016), this study also examines how the price informativeness leads to firm investment decisions. That is, FPE measures the predicted variation of earnings (as proxied by firm EBIT) from market prices (as gauged by firm market value MVE). Similar forecasting regression is performed to find how market prices could predict future investment, which can be proxied by firm R&D and/or capital expenditure.[10]

$$\frac{INV_{i,t+h}}{TA_{i,t}} = a'_{t,h} + b'_{t,h} \times \ln\left(\frac{MVE_{i,t}}{TA_{i,t}}\right) + c'_{t,h} \times \left(\frac{EBIT_{i,t}}{TA_{i,t}}\right) + d'_{t,h} \times \left(\frac{INV_{i,t}}{TA_{i,t}}\right) + \sum_k^K f'^k_{t,h} \times D^k_{i,t} + e_{i,t,h} \quad (6)$$

In the above equation, $INV_{i,t+h}$ denotes the future investment, as measured by R&D and/or capital expenditure of firm i in year t, and current earnings and investments are included as controls. The predicted variation of investment form prices is then

$$FPEINV_{t,h} = b'_{t,h} \times \sigma_t\left(\ln\left(\frac{MVE_{i,t}}{TA_{i,t}}\right)\right) \quad (7)$$

Theoretically, the real efficiency of market prices (*FPE*) could achieve only when managers make proper investment decisions based on information embedded in market prices (as measured by *FPEINV*), and then earnings realize as a result of investment. That is, high *FPE* implies high *FPEINV*. However, high *FPEINV* does not necessarily translate into high *FPE*, as whether investment results in earnings is subject to further uncertainty.

5.2 Price informativeness and Stocks with Extreme Volatility – Cross-Market Analysis

To test whether the presence of stocks with extreme volatility harms a market's price informativeness, we form two groups of stocks each year in each market. One group (Full_Sample) contains the whole sample firms. Another group (ExHimax or ExHiIVOL) excludes those stocks showing extreme volatility, which are defined as those with top 20 percentile of MAX or IVOL during the year. We then apply the forecasting regression (4) separately for each group and compute their FPE

[10] Due to the insufficiency of R&D data for emerging market stocks, we resort to capital expenditures as the investment variable.

according to equation (5). Prices of stocks with extreme volatility expect to carry more noises, as those volatilities are entailed from investors' demand unrelated to fundamentals. If firm managers are unable to filter out noises from market prices, this will lead to ineffective real investment decisions and poor earnings. The consequence is then a lower FPE for the group of Full_Sample compared to the FPE for the group of ExHiMax (or ExHiIVOL).

[Insert Table 7 Here]

Table 7 reports the cross-market average results of FPE for the full sample period (Panel A) and for the two sub-sample periods (Panel B and Panel C) at different forecasting horizons (h=1, 2 or 3 years). In each Panel, Column (1) lists the cross year-market mean and median values of FPE with a forecast horizon of one year, two years or three years. Column (2) reports the corresponding FPE estimates when excluding those stocks in the top 20 percentile IVOL values. Column (3), (4) and (5) respectively reports the FPE estimates when excluding those stocks in the top 20 percentile MAX1, MAX2 or MAX3 values. One would expect the FPE values to increase after excluding those stocks exhibiting extreme volatilities. For the entire sample period (Panel A), all the one-year ahead and two-year ahead FPE values are increased after excluding those stocks with extreme volatilities in terms of IVOL or MAX, and the increases are statistically significant. Nonetheless, two cases for the three-year ahead FPE for the market failed to improve after excluding stocks with extreme volatilities.

We further examine whether such pattern varies over time. Panel B shows the results for the earlier sample period (1990 to 1999) and only one in 12 cases that we observe a significant increase in FPE. Panel C shows those for the more recent sub-period (2000-2016) and the results are much different from those found in earlier period. One can see that for all 12 cases the market FPEs are significantly improved after excluding those stocks with extreme volatilities. Results for FPE are generally consistent with our Hypothesis 2, i.e., stocks with extreme volatilities indeed harm the market's price informativeness in terms of real efficiency.

The univariate tests in Table 7 do not control for other country-level factors that may affect FPE.

We thus employ regression analysis to find whether the cross-market values of FPE exhibit a relation with the market's preference for extreme payoffs. This approach allows us to control for temporal and cross-market variations in macroeconomic variables. Table 8 reports the results.

[Insert Table 8 Here]

To proceed, one needs a proxy variable assessing investors' preference for extreme payoffs, which can be measured by the additional premium investors are willing to (over)pay for such stocks. Specifically, the regression coefficient of MAX (or IVOL) in Equation (3) indicates the size of anomaly per unit of MAX (or IVOL). This study thus proxy the investors' preference unrelated to fundamentals by multiplying the regression coefficient of MAX (or IVOL) by the its cross-sectional standard deviation, which is denoted as PremMAX (or PremIVOL) Results are reported in Table 8.

Note that the company information for emerging market stocks is relatively limited during the earlier period. We therefore focus on the results starting from year 1995 (Panel A) and those from year 2000 (Panel B). The focus variables are PremMAX and PremIVOL, and their negative coefficient suggests that investors' strong preference for stocks with extreme payoffs, in terms of MAX or IVOL, tends to harm the market's price informativeness in terms of real efficiency (i.e., FPE). One can find that the coefficients of PremIVOL are mostly negative and significant. On the other hand, the coefficients of PremMAX do not show a consistent relation with FPE . The overall results in Table 8 suggest that a strong presence of stocks with high IVOL tend to decrease FPE while similar evidence for MAX is relatively weak. These results indicate that a financial market with investors exhibiting greater preference for stocks paying extreme payoffs harm price informativeness in terms of real efficiency, i.e., FPE..

6. Conclusions

This study examines the impact on price informativeness from investor trades deviating from firm fundamentals. We first identify measures that capture investors' demand unrelated to fundamentals.

Then, we proceed to examine for emerging markets how such demands harm price informativeness in terms of real efficiency. Extreme price movements are likely results from irrational demand from investors. Stocks with extreme price movements are thus candidates to reveal participating traders' demand or preference for payoffs unrelated to firm fundamentals. The focus measures of this study include the well applied idiosyncratic volatility (IVOL) and MAX values. In order to better capture the impact from noise trades, the IVOL and MAX metrics are revised by applying returns from different intraday intervals and by returns adjusted for leverage. The MAX measures are also scaled by return volatility in order to purge the volatility effect from MAX and obtain a better measure for lottery demand.

This study revisits the IVOL and MAX anomalies by applying those revised metrics. The evidence finds that the regular trading hour (open-to-close) measures, which are considered to carry most noise demands, entail greater mispricing. The volatility-scaled MAX exhibits less anomaly returns, when the confounding volatility-effect is being controlled for. More importantly, the risk metrics estimated using unlevered returns generally show less IVOL or MAX effects, suggesting that leverage is at least partially responsible for the raw-return-anomalies.

We then proceed to examine whether the presence of such investors' demand unrelated to fundamentals indeed harm the market efficiency in terms of forecast price efficiency (FPE). Our cross-market regression results, which control for country factors, find weak evidence consistent with this claim.

This study contributes to the literature in that various evidences are offered to suggest and to confirm approaches to capture the magnitude of noise trades. In addition, while researches on emerging markets are relatively challenging due to the disadvantage in sufficient data availability, the ever changing dynamics also offer researchers interesting topics to explore.

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Table 1 Firm Characteristics of Stocks with Extreme Returns in Terms of High IVOL or High MAX
This table reports the mean and the median of firm characteristics for stocks with extreme returns versus those without extreme returns. Panel A compares the characteristics of stocks that have top 20 percentile of idiosyncratic volatility in own market and the remaining stocks. Panel B, C and D compares the characteristics of those stocks with those stocks with high MAX1, MAX2, and MAX3 values and the remaining stocks. Listed results are based on monthly observations of firm characteristics or annual observations of book value terms of 31 cross-country sample stocks for the period from 1990 to 2016.

Panel A. Partitioned by Top-20% IVOL

	IVOL	MAX1	MAX2	MAX3	MktCap.	Coverage	Turnover	Beta	TotVol	Mom	Tot Asset	MB	ROA	Debt/Eq	R&D	Cap Exp
Hi-IVOL																
mean	0.046	0.082	0.063	0.051	184.7	3.0	0.267	0.768	0.0051	-0.010	324.0	14.520	0.006	0.424	0.025	0.044
median	0.039	0.072	0.060	0.049	20.1	0	0.020	0.743	0.0017	-0.022	0.8	1.140	0.020	0.071	0.005	0.017
Std.dev	0.051	0.066	0.074	0.030	1753.9	14.4	0.792	1.107	0.6524	0.347	4600.0	509.756	0.108	1.067	0.090	0.073
firm*mth (or yr)	410982	529115	528671	522731	480941	527544	475660	410982	405120	429980	27351	288871	27170	319524	6731	25736
Non-Hi-IVOL																
mean	0.025	0.053	0.044	0.037	881.9	13.4	0.219	0.780	0.0010	0.003	995.0	8.520	0.054	0.413	0.016	0.060
median	0.023	0.051	0.042	0.036	90.4	0	0.027	0.768	0.0007	-0.003	2.8	1.407	0.051	0.120	0.004	0.033
Std.dev	0.013	0.024	0.027	0.016	5210.4	34.9	0.741	0.586	0.0015	0.241	12600.0	452.008	0.078	0.909	0.050	0.079
firm*mth (or yr)	1866552	2097538	2091716	2086646	1993862	2091420	1946534	1866552	1857220	1873820	129796	1437337	125266	1560897	34606	119465

Panel B. Partitioned by Top-20% MAX1

	IVOL	MAX1	MAX2	MAX3	MktCap.	Coverage	Turnover	Beta	TotVol	Mom	Tot Asset	MB	ROA	Debt/Eq	R&D	Cap Exp
Hi-MAX1																
mean	0.042	0.090	0.073	0.054	349.8	5.7	0.288	0.898	0.0041	-0.001	470.0	15.095	0.020	0.460	0.026	0.051
median	0.035	0.079	0.064	0.052	31.1	0	0.031	0.889	0.0015	-0.014	1.3	1.222	0.030	0.096	0.004	0.022
Std.dev	0.046	0.061	0.050	0.028	2727.6	21.2	0.843	1.001	0.5895	0.332	5450.0	635.781	0.104	1.104	0.094	0.079
firm*mth (or yr)	500825	591362	587714	583124	539866	589572	530138	500825	496234	500579	32915	347776	31911	385958	8104	30387
Non-Hi-MAX1																
mean	0.025	0.047	0.039	0.035	809.9	11.3	0.195	0.744	0.0010	0.001	918.0	10.786	0.051	0.404	0.015	0.058
median	0.023	0.047	0.040	0.034	73.3	0	0.019	0.737	0.0007	-0.004	2.4	1.361	0.050	0.110	0.003	0.031
Std.dev	0.015	0.027	0.038	0.018	5341.1	32.4	0.694	0.597	0.0027	0.247	12100.0	1103.078	0.080	0.903	0.046	0.078
firm*mth (or yr)	1776709	2345117	2291551	2241966	2090942	2338200	2100343	1776709	1766106	1865758	131489	1458983	132219	1643973	34751	125674

Panel C. Partitioned by Top-20% MAX2

	IVOL	MAX1	MAX2	MAX3	MktCap.	Coverage	Turnover	Beta	TotVol	Mom	Tot Asset	MB	ROA	Debt/Eq	R&D	Cap Exp
Hi-MAX2																
mean	0.041	0.087	0.076	0.057	345.3	6.0	0.297	0.909	0.0041	0.003	420.0	15.422	0.022	0.457	0.026	0.051
median	0.035	0.077	0.066	0.054	32.1	0	0.033	0.904	0.0015	-0.010	1.3	1.266	0.031	0.097	0.005	0.022
Std.dev	0.046	0.061	0.054	0.028	2421.4	21.6	0.857	1.000	0.5964	0.336	5220.0	641.164	0.104	1.098	0.089	0.080
firm*mth (or yr)	491427	579646	579646	574425	530669	577884	521649	491427	484736	490473	32293	341823	31311	378223	8052	29783
Non-Hi-MAX2																
mean	0.026	0.049	0.038	0.034	814.8	11.5	0.194	0.744	0.0011	0.000	937.0	10.570	0.051	0.404	0.015	0.058
median	0.023	0.048	0.039	0.034	73.5	0	0.019	0.736	0.0007	-0.005	2.4	1.356	0.049	0.110	0.003	0.032
Std.dev	0.015	0.025	0.036	0.017	5387.5	32.7	0.693	0.599	0.0028	0.244	12200.0	1098.270	0.080	0.903	0.048	0.078
firm*mth (or yr)	1782140	2299619	2299619	2250665	2080100	2292792	2078612	1782140	1777405	1869556	131191	1454605	130830	1626256	34492	124425

	Panel D. Partitioned by Top-20% MAX3															
	IVOL	MAX1	MAX2	MAX3	MktCap.	Coverage	Turnover	Beta	TotVol	Mom	Tot Asset	MB	ROA	Debt/Eq	R&D	Cap Exp
Hi-MAX3																
mean	0.032	0.070	0.057	0.046	544.3	9.6	0.285	0.852	0.0021	0.000	775.0	9.506	0.039	0.433	0.019	0.057
median	0.028	0.063	0.052	0.043	57.2	0	0.036	0.852	0.0010	-0.010	2.0	1.369	0.042	0.111	0.004	0.029
Std.dev	0.029	0.040	0.034	0.021	3179.4	28.5	0.846	0.750	0.3313	0.283	9310.0	398.140	0.091	0.990	0.064	0.080
firm*mth (or yr)	1578151	1799344	1799344	1799344	1690312	1793460	1651968	1578151	1571297	1583679	106399	1153166	102810	1265938	29014	98126
Non-Hi-MAX3																
mean	0.021	0.036	0.031	0.026	1069.8	12.3	0.092	0.615	0.0007	0.003	966.0	15.291	0.059	0.377	0.013	0.057
median	0.018	0.036	0.030	0.026	77.3	0	0.009	0.599	0.0004	-0.001	2.3	1.313	0.055	0.102	0.003	0.032
Std.dev	0.012	0.017	0.018	0.017	7200.9	35.1	0.431	0.530	0.0012	0.222	14200.0	1649.575	0.075	0.839	0.043	0.074
firm*mth (or yr)	689380	1025746	1025746	1025746	893012	1023144	911516	689380	687992	766300	55794	629157	57229	712725	13135	54109

Table 2
Idiosyncratic Volatility and MAX - When Calculated with Regular-Trading-Hour Returns vs. After-Hour-Returns & Transaction Returns vs. Unlevered Returns

This table presents descriptive statistics for IVOL and MAX which are calculated with different returns. Panel A presents those statistics when traditional transaction returns are used. The returns are then measured using (a) regular close-to-close returns, (b) open-to-close trading hour returns, and (c) close-to-open after hour returns. Panel B presents statistics for corresponding IVOL-UR and MAX-UR while the returns are first converted to unlevered returns. In each panel, MAX values are estimated using the average h-highest daily returns, with h equal to 1, 2, or 3, as denoted as MAX1, MAX2, and MAX3. The corresponding SMAX values are MAX scaled by return standard deviations. The samples consist of more than 1.5 million firm-month observations in 31 emerging markets covered in Datastream and Worldscope from 1990 to 2016.

Panel A. IVOL/MAX Calculated using Traded Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IVOL	*MAX1*	*MAX2*	*MAX3*	*SMAX1*	*SMAX2*	*SMAX3*
(a) Close-to-Close Return (CC)							
Mean	0.028	0.056	0.047	0.040	1.943	1.601	1.358
Median	0.025	0.050	0.043	0.036	1.872	1.583	1.365
Stdev	0.016	0.040	0.032	0.026	0.894	0.716	0.619
Firm*month	2,277,534	2,589,332	2,463,392	2,376,382	2,262,340	2,233,621	2,202,817
(b) Open-to-Close Return (OC)							
Mean	0.028	0.050	0.043	0.037	1.784	1.456	1.246
Median	0.024	0.041	0.036	0.032	1.757	1.507	1.322
Stdev	0.017	0.045	0.036	0.031	6.053	5.583	5.508
Firm*month	2,069,645	2,281,714	2,146,544	2,066,461	2,061,403	2,036,344	2,000,256
(c) Close-to-Open Return (CO)							
Mean	0.024	0.043	0.035	0.030	1.803	1.468	1.249
Median	0.018	0.031	0.026	0.022	1.726	1.477	1.291
Stdev	0.019	0.043	0.034	0.029	8.596	8.572	8.577
Firm*month	1,925,904	2,179,338	2,113,679	2,062,040	1,925,830	1,920,952	1,913,176
Panel B. IVOL/MAX Calculated using Converted Unlevered Returns							
	IVOL-UR	*MAX1-UR*	*MAX2-UR*	*MAX3-UR*	*SMAX1-UR*	*SMAX2-UR*	*SMAX3-UR*
(a) Close-to-Close Return (CC)							
Mean	0.017	0.037	0.031	0.026	1.974	1.630	1.388
Median	0.015	0.031	0.026	0.023	1.893	1.603	1.385
Stdev	0.010	0.028	0.022	0.019	0.885	0.699	0.601
Firm*month	1,680,197	1,827,819	1,768,575	1,725,987	1,670,478	1,652,869	1,634,438
(b) Open-to-Close Return (OC)							
Mean	0.017	0.033	0.027	0.024	1.834	1.513	1.302
Median	0.015	0.026	0.022	0.020	1.769	1.520	1.337
Stdev	0.011	0.028	0.023	0.020	4.137	3.092	2.835
Firm*month	1,566,214	1,660,336	1,613,972	1,576,893	1,562,673	1,551,635	1,533,925
(c) Close-to-Open Return (CO)							
Mean	0.013	0.025	0.021	0.018	1.866	1.528	1.308
Median	0.010	0.018	0.015	0.013	1.749	1.496	1.307
Stdev	0.011	0.025	0.019	0.016	2.662	2.578	2.552
Firm*month	1,492,056	1,627,767	1,599,005	1,573,479	1,492,017	1,489,547	1,485,508

Table 3 Revisit IVOL and MAX Anomalies - Using Trading-Hour Returns versus After-Hour Returns

This table presents estimates of ordinary least squares (OLS) regressions in which the dependent variables are the next month returns of stocks across emerging markets. The focus variables, IVOL (idiosyncratic volatilities) and MAX, are measured using different daily hours. Model group (I) presents the traditional case where daily returns are estimated using closing prices. Model group (II) presents results when IVOL and MAX metrics are estimated using daily trading-hour returns, i.e., from open to close price changes. Model group (III) then presents the results when IVOL and MAX metrics are estimated using after-hour returns, i.e., percentage changes from prior closing price to next day opening price. Firm level control variables are included in the regressions, including firm market value, MB ration, momentum return (prior 11-month return), turnover ratio, price level, market beta, logarithm of one plus analyst coverage, return reversal (prior-month return), and prior-quarter total volatility. The whole sample consists of firm-month observations in 31 emerging markets covered in Datastream and Worldscope from 1990 to 2016. To mitigate the unbalanced effect due to insufficient price data in early years, Panel A presents results from regressions using data starting from 1994. Panel B then presents the results for the more recent sample period, i.e., from year 2000. *p*-values based on the standard errors clustered at firm level are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A. Sample Period from Year 1994								
	(I) *Close-to-Close (CC)*			(II) *Open-to-Close (OC)*			(III) *Close-to-Open (CO)*		
Independent var	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL	-0.879***	-1.027***	-1.151***	-0.450***	-0.458***	-0.476***	0.189***	0.207***	0.209***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MAX1	-0.031***			-0.033***			0.006		
	(0.000)			(0.000)			(0.558)		
MAX2		-0.015			-0.040***			-0.008	
		(0.181)			(0.001)			(0.544)	
MAX3			-0.000			-0.044***			-0.011
			(0.992)			(0.001)			(0.478)
Market Value	-0.044	-0.077	-0.119	0.007	0.011	0.005	0.156**	0.157**	0.156**
	(0.582)	(0.339)	(0.138)	(0.931)	(0.888)	(0.954)	(0.049)	(0.047)	(0.048)
MB ratio	-0.379***	-0.367***	-0.380***	-0.308***	-0.307***	-0.304***	-0.313***	-0.313***	-0.312***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum	-1.708***	-1.679***	-1.633***	-2.170***	-2.163***	-2.156***	-2.110***	-2.108***	-2.104***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	3.575***	3.653***	3.524***	3.574***	3.576***	3.613***	2.992***	3.007***	2.998***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price	0.030**	0.035***	0.040***	0.048***	0.048***	0.049***	0.047***	0.046***	0.046***
	(0.011)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Beta	-0.007***	-0.008***	-0.008***	-0.004***	-0.005***	-0.005***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Analyst Coverage	-2.330***	-2.366***	-2.414***	-2.525***	-2.548***	-2.559***	-2.224***	-2.219***	-2.226***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return Reversal	0.019***	0.019***	0.022***	0.013***	0.013***	0.013***	0.015***	0.015***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	1.143***	1.239***	1.299***	0.589***	0.597***	0.605***	0.138***	0.140***	0.139***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	573789	569097	565375	539471	538273	537325	539330	539119	538709
Adj. R2	0.038	0.039	0.039	0.038	0.038	0.038	0.038	0.038	0.038
F-Stat	355.046	358.730	360.828	335.594	335.527	335.119	331.463	331.777	331.718

	Panel B. Sample Period from Year 2000								
	(I) *Close-to-Close (CC)*			**(II) *Open-to-Close (OC)***			**(III) *Close-to-Open (CO)***		
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL	-1.532***	-1.685***	-1.839***	-0.264***	-0.277***	-0.311***	0.141***	0.139***	0.117***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
MAX1	-0.054***			-0.069***			-0.032***		
	(0.000)			(0.000)			(0.002)		
MAX2		-0.061***			-0.078***			-0.040***	
		(0.000)			(0.000)			(0.004)	
MAX3			-0.022			-0.076***			-0.025
			(0.110)			(0.000)			(0.128)
Market Value	-0.421***	-0.450***	-0.488***	-0.211***	-0.206***	-0.211***	-0.110	-0.109	-0.110
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.124)	(0.128)	(0.125)
MB ratio	-0.456***	-0.441***	-0.446***	-0.388***	-0.387***	-0.385***	-0.402***	-0.402***	-0.402***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum	-0.750***	-0.715***	-0.663***	-1.304***	-1.295***	-1.288***	-1.286***	-1.288***	-1.291***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	-0.442	-0.366	-0.701	1.704***	1.700***	1.709***	0.793	0.805	0.781
	(0.435)	(0.522)	(0.223)	(0.004)	(0.004)	(0.004)	(0.180)	(0.173)	(0.187)
Price	0.012	0.013	0.017	0.051***	0.052***	0.052***	0.049***	0.049***	0.049***
	(0.424)	(0.381)	(0.253)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Market Beta	-0.008***	-0.008***	-0.009***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Analyst Coverage	-1.505***	-1.558***	-1.586***	-1.729***	-1.745***	-1.758***	-1.549***	-1.547***	-1.561***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return Reversal	0.015***	0.016***	0.018***	0.011***	0.011***	0.011***	0.015***	0.015***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	1.806***	1.930***	1.988***	0.520***	0.527***	0.535***	0.225***	0.227***	0.223***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	476865	472738	469738	461461	460625	459966	461429	461286	461013
Adj. R2	0.038	0.039	0.039	0.037	0.037	0.038	0.037	0.037	0.037
F-Stat	328.050	332.008	333.817	310.600	310.342	310.018	307.686	307.637	307.366

Table 4 IVOL and MAX Anomalies – Simultaneous Consideration of Metrics Using Trading-Hour Returns and After-Hour Returns

This table presents estimates of ordinary least squares (OLS) regressions in which the dependent variables are the next month returns of stocks across emerging markets. The focus variables, IVOL (idiosyncratic volatilities) and MAX, are measured using different daily hours. This table compares the effect of extreme returns occurring in different hours of the day. IVOL_OC and MAX_OC are measured with open-to-close daily returns, while IVOL_CO and MAX_CO are measured with close-to-open returns. Columns (3), (6) and (9) include extreme return metrics over different hours and contrast their impact on next period stock returns. Year fixed-effects and country fixed effects are incorporated. Firm level control variables and country-level variables are also included in each regression. Panel A presents results from regressions using data starting from 1994. Panel B then presents the results for the more recent sample period, i.e., from year 2000. The whole sample consists of firm-month observations in 31 emerging markets covered in Datastream and Worldscope from 1990 to 2016. *p*-values based on the standard errors clustered at firm level are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Sample Period from Year 1994

	MAX1			***MAX2***			***MAX3***		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL OC	-0.450***		-0.470***	-0.458***		-0.493***	-0.476***		-0.508***
	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
IVOL CO		0.189***	0.207***		0.207***	0.224***		0.209***	0.214***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
MAX OC	-0.033***		-0.029***	-0.040***		-0.026**	-0.044***		-0.027*
	(0.000)		(0.004)	(0.001)		(0.044)	(0.001)		(0.081)
MAX CO		0.006	0.003		-0.008	-0.013		-0.011	-0.015
		(0.558)	(0.771)		(0.544)	(0.359)		(0.478)	(0.392)
Firm factor cntrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	573789	569097	565375	539471	538273	537325	539330	539119	538709
Adj. R2	0.038	0.039	0.039	0.038	0.038	0.038	0.038	0.038	0.038
F-Stat	355.046	358.730	360.828	335.594	335.527	335.119	331.463	331.777	331.718

Panel B. Sample Period from Year 2000

	MAX1			***MAX2***			***MAX3***		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL OC	-0.264***		-0.283***	-0.277***		-0.296***	-0.311***		-0.311***
	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
IVOL CO		0.141***	0.118***		0.139***	0.109***		0.117***	0.071*
		(0.000)	(0.001)		(0.000)	(0.003)		(0.001)	(0.057)
MAX OC	-0.069***		-0.061***	-0.078***		-0.066***	-0.076***		-0.073***
	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
MAX CO		-0.032***	-0.019*		-0.040***	-0.023		-0.025	-0.000
		(0.002)	(0.084)		(0.004)	(0.119)		(0.128)	(0.987)
Firm factor cntrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	461461	461429	461429	460625	461286	460477	459966	461013	459672
Adj. R2	0.037	0.037	0.037	0.037	0.037	0.038	0.038	0.037	0.037
F-Stat	310.600	307.686	300.451	310.342	307.637	300.065	310.018	307.366	299.471

Table 5 IVOL and MAX Anomalies - Using Un-levered Returns & Volatility-Scaled MAX for Trading-Hour and After-Hour Metrics

This table presents estimates of ordinary least squares (OLS) regressions in which the dependent variables are the next month returns of stocks across emerging markets. The focus variables, IVOL (idiosyncratic volatilities) and MAX, are measured using different daily hours. Model group (I) presents the traditional case where daily returns are estimated using closing prices. Model group (II) presents results when IVOL and MAX metrics are estimated using daily trading-hour returns, i.e., from open to close price changes. Model group (III) then presents the results when IVOL and MAX metrics are estimated using after-hour returns, i.e., percentage changes from prior closing price to next day opening price. Panel A reports the anomaly effects when IVOL-UR and MAX-UR are calculated with returns measured over different hours and further being unlevered. Panel B reports the anomaly effects when SMAX-UR are obtained by being further scaled by prior return volatility. Panel C then reports the results when using both levered return metrics and scaled MAX. In each regression, year and country fixed effects are considered. Firm level control variables and country-level variables are also included in the regressions. The whole sample consists of firm-month observations in 31 emerging markets covered in Datastream and Worldscope from 1990 to 2016. To mitigate the unbalanced effect due to insufficient price data in early years, this table presents results from regressions using data starting from 1994. *p*-values based on the standard errors clustered at firm level are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. IVOL / MAX Estimated Using Unlevered Returns									
	(I) *Close-to-Close (CC)*			**(II) *Open-to-Close (OC)***			**(III) *Close-to-Open (CO)***		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL-UR	-0.381***	-0.417***	-0.442***	-0.402***	-0.419***	-0.433***	-0.129***	-0.079*	-0.074*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.057)	(0.074)
MAX1-UR	-0.012			-0.051***			-0.031**		
	(0.299)			(0.000)			(0.032)		
MAX2-UR		0.008			-0.050***			-0.072***	
		(0.631)			(0.002)			(0.000)	
MAX3-UR			0.034**			-0.047**			-0.088***
			(0.049)			(0.016)			(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed eff	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	572655	567978	564271	538591	537396	536449	538450	538240	537832
Adj. R2	0.038	0.039	0.039	0.038	0.038	0.038	0.038	0.038	0.038
F-Stat	354.690	357.571	358.801	336.427	336.233	335.512	331.361	331.807	331.722

Panel B. IVOL / MAX Estimated Using Levered Returns & MAX is Volatility-Scaled									
	(I) *Close-to-Close (CC)*			(II) *Open-to-Close (OC)*			(III) *Close-to-Open (CO)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL	-0.888***	-1.026***	-1.134***	-0.507***	-0.514***	-0.528***	0.199***	0.202***	0.207***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMAX1	0.001***			-0.001**			0.000		
	(0.005)			(0.013)			(0.114)		
SMAX2		0.002***			-0.001**			0.000	
		(0.000)			(0.031)			(0.143)	
SMAX3			0.002***			-0.001*			0.001**
			(0.000)			(0.068)			(0.040)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed eff	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	572458	569097	565375	538796	538270	537325	539330	539119	538709
Adj. R2	0.038	0.039	0.039	0.038	0.038	0.038	0.038	0.038	0.038
F-Stat	355.455	359.092	361.413	335.396	335.419	335.006	331.498	331.806	331.779

Panel C. IVOL / MAX Estimated Using Unlevered Returns & MAX is Volatility-Scaled									
	(I) *Close-to-Close (CC)*			(II) *Open-to-Close (OC)*			(III) *Close-to-Open (CO)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL-UR	-0.409***	-0.407***	-0.396***	-0.500***	-0.501***	-0.500***	-0.184***	-0.183***	-0.179***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMAX1-UR	0.000			-0.001***			-0.000		
	(0.397)			(0.000)			(0.895)		
SMAX2-UR		0.001***			-0.001***			-0.000	
		(0.001)			(0.000)			(0.414)	
SMAX3-UR			0.002***			-0.001***			-0.000
			(0.000)			(0.000)			(0.532)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed eff	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	571226	567875	564168	537815	537295	536352	538347	538137	537729
Adj. R2	0.038	0.039	0.039	0.038	0.038	0.038	0.038	0.038	0.038
F-Stat	355.287	357.814	359.196	336.469	336.419	335.704	331.360	331.667	331.567

Table 6 IVOL and MAX Anomalies – Regional Effects when Metrics Measured Using Trading-Hour versus After-Hour Returns

This table presents regional estimates of ordinary least squares (OLS) regressions in which the dependent variables are the next month returns of stocks across emerging markets. The focus variables, IVOL (idiosyncratic volatilities) and MAX, are measured using different daily hours. Panel A presents the traditional case where daily returns are estimated using closing prices. Panel B presents results when IVOL and MAX metrics are estimated using daily trading-hour returns, i.e., from open to close price changes. Panel C then presents the results when IVOL and MAX metrics are estimated using after-hour returns, i.e., percentage changes from prior closing price to next day opening price. In each regression, year and country fixed effects are considered. Firm level control variables and country-level variables are also included in the regressions. The whole sample consists of firm-month observations in 31 emerging markets covered in Datastream and Worldscope from 1990 to 2016. To mitigate the unbalanced effect due to insufficient price data in early years, this table presents results from regressions using data starting from 1994. *p*-values based on the standard errors clustered at firm level are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A. IVOL & MAX Estimated with Close-to-Close Price Changes											
	Asia			*Europe*			*America*			*Middle East & Africa*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IVOL_CC	-1.847***	-2.104***	-2.377***	-1.764***	-1.784***	-1.741***	-2.725***	-2.778***	-2.726***	-0.817***	-0.837***	-0.818***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MAX1_CC	-0.052***			0.030			-0.044			0.015		
	(0.000)			(0.333)			(0.240)			(0.604)		
MAX2_CC		-0.067***			0.110***			-0.077			0.056	
		(0.000)			(0.008)			(0.127)			(0.157)	
MAX3_CC			-0.020			0.161***			-0.097*			0.092**
			(0.169)			(0.001)			(0.098)			(0.048)
FirmFactor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFact	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	371156	367040	364210	49494	49462	49380	27262	26984	26708	59229	59195	59132
Adj. R2	0.033	0.034	0.035	0.058	0.058	0.058	0.076	0.076	0.077	0.046	0.046	0.046
F-Stat	344.659	351.626	355.427	93.587	93.786	93.861	72.909	73.099	72.762	92.370	92.588	92.686

	Panel B. IVOL & MAX Estimated with Open-to-Close Price Changes											
	Asia			*Europe*			*America*			*Middle East & Africa*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IVOL_OC	-0.188***	-0.202***	-0.228***	-0.332***	-0.330***	-0.351***	-0.075	-0.030	-0.036	-0.381***	-0.430***	-0.476***
	(0.000)	(0.000)	(0.000)	(0.007)	(0.007)	(0.004)	(0.689)	(0.872)	(0.849)	(0.000)	(0.000)	(0.000)
MAX1_OC	-0.030***			-0.011			-0.219***			-0.078***		
	(0.005)			(0.702)			(0.000)			(0.005)		
MAX2_OC		-0.024*			-0.019			-0.311***			-0.091**	
		(0.092)			(0.625)			(0.000)			(0.013)	
MAX3_OC			-0.017			-0.010			-0.358***			-0.091**
			(0.294)			(0.818)			(0.000)			(0.035)
FirmFactor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFact	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	370899	370256	369826	43199	43176	43143	23813	23784	23710	53665	53524	53401
Adj. R2	0.032	0.032	0.032	0.059	0.059	0.059	0.074	0.074	0.074	0.057	0.057	0.057
F-Stat	327.675	327.485	327.242	83.202	83.207	83.206	62.020	62.279	62.110	105.083	104.782	104.920

	Panel C. IVOL & MAX Estimated with Close-to-Open Price Changes											
	Asia			*Europe*			*America*			*Middle East & Africa*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IVOL_CO	0.101***	0.106***	0.081**	0.091	0.062	0.028	-0.219	-0.210	-0.220	-0.201*	-0.249**	-0.226*
	(0.008)	(0.005)	(0.033)	(0.460)	(0.620)	(0.820)	(0.227)	(0.247)	(0.222)	(0.095)	(0.039)	(0.059)
MAX1_CO	-0.041***			0.002			-0.037			0.179***		
	(0.000)			(0.964)			(0.450)			(0.000)		
MAX2_CO		-0.056***			0.025			-0.057			0.257***	
		(0.000)			(0.595)			(0.389)			(0.000)	
MAX3_CO			-0.044**			0.071			-0.052			0.322***
			(0.014)			(0.195)			(0.513)			(0.000)
FirmFactor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFact	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*firm*month*	370869	370754	370555	43199	43194	43174	23812	23807	23787	53664	53642	53594
Adj. R2	0.031	0.031	0.031	0.059	0.059	0.059	0.073	0.073	0.073	0.057	0.057	0.057
F-Stat	326.689	326.649	326.181	82.889	82.880	82.807	61.182	61.179	61.198	105.030	105.301	105.382

Table 7 Forecast Price Efficiency of Emerging Market
This table reports the descriptive statistics for FPE for the entire sample period (Panel A) and for the first sub-period (Panel B), and for the later sub-period (Panel C) across emerging markets. Column (1) lists the FPE values for the full sample. Column (2), (3), (4) and (5) reports the FPE values calculated by excluding those stocks with the top 20 percentile IVOL, MAX1, MAX2 and MAX3, respectively.

Panel A. FPE Values for Emerging Markets (1990-2016)					
	I. FPE – One-Year Ahead				
	(1)	(2)	(3)	(4)	(5)
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0110	0.0123***	0.0124***	0.0123***	0.0121***
median.	0.0097	0.0111	0.0108	0.0111	0.0104
Std dev	0.0131	0.0124	0.0130	0.0127	0.0133
	II. FPE – Two-Years Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0103	0.0119***	0.0113***	0.0111***	0.0106***
median.	0.0092	0.0111	0.0106	0.0109	0.0105
Std dev	0.0125	0.0127	0.0124	0.0123	0.0134
	III. FPE – Three-Years Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0086	0.0096***	0.0085	0.0085	0.0092**
median.	0.0082	0.0098	0.0088	0.0093	0.0094
Std dev	0.0125	0.0119	0.0119	0.0127	0.0145
Panel B. FPE Values for Emerging Markets (1990-1999)					
	I. FPE – One-Year Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0123	0.0137	0.0137	0.0137	0.0157
median.	0.0106	0.0117	0.0119	0.0125	0.0114
Std dev	0.0143	0.0143	0.0145	0.0146	0.0171
	II. FPE – Two-Years Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0128	0.0127	0.0115	0.0110	0.0128
median.	0.0122	0.0127	0.0117	0.0118	0.0096
Std dev	0.0140	0.0140	0.0143	0.0143	0.0170
	III. FPE – Three-Years Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0096	0.0098*	0.0084	0.0076	0.0090
median.	0.0102	0.0106	0.0088	0.0102	0.0074
Std dev	0.0160	0.0131	0.0138	0.0147	0.0189
Panel C. FPE Values for Emerging Markets (2000-2016)					
	I. FPE – One-Year Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0102	0.0116***	0.0117***	0.0116***	0.0109***
median.	0.0095	0.0108	0.0108	0.0105	0.0100
Std dev	0.0122	0.0116	0.0124	0.0120	0.0118
	II. FPE – Two-Years Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0093	0.0114***	0.0111***	0.0108***	0.0097**
median.	0.0086	0.0106	0.0103	0.0105	0.0106
Std dev	0.0116	0.0120	0.0119	0.0115	0.0123
	III. FPE – Three-Years Ahead				
	Full Sample	Ex HiIVOL	Ex HiMAX1	Ex HiMAX2	Ex HiMAX3
mean	0.0080	0.0095***	0.0087*	0.0089**	0.0088*
median.	0.0078	0.0094	0.0088	0.0093	0.0094
Std dev	0.0105	0.0117	0.0112	0.0118	0.0130

Table 8 Forecast Price Efficiency (FPE) and Preference for IVOL & Lottery-Type Payoffs

This table presents estimates of ordinary least squares (OLS) regressions in which the dependent variables are FPE for the market with one-, two- or three-year forecasting horizons. The major independent variables are the premiums investors are willing to overpay for stocks with high MAX or IVOL (PremMAX or PremIVOL). Panel A presents results for the period between 1995 and 2016 for FPEs, which are estimated using one-year ahead, two-years ahead and three-years ahead forecasting. Panel B presents the corresponding results for the period between 2000 and 2016. The whole sample consists of country-year observations across 31 emerging markets from 1990 to 2016, while sample sizes are losing due to lack of data. *p*-values based on the standard errors clustered at firm level are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. FPE and Preference for Extreme Payoffs (1995-2016)

	(I) FPE – 1-year ahead			**(II) FPE – 2-years ahead**			**(III) FPE – 3-years ahead**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PrmIVOL	-0.095***	-0.092**	-0.098**	-0.060*	-0.072**	-0.074**	0.015	-0.006	-0.010
	(0.006)	(0.012)	(0.015)	(0.067)	(0.032)	(0.042)	(0.660)	(0.856)	(0.787)
PrmMAX1	-0.184**			0.043			0.027		
	(0.012)			(0.585)			(0.725)		
PrmMAX2		-0.016			-0.088			0.066	
		(0.878)			(0.348)			(0.474)	
PrmMAX3			-0.025			-0.112			0.044
			(0.790)			(0.198)			(0.604)
GDP growth	-0.084***	-0.082***	-0.082***	-0.077***	-0.079***	-0.079***	-0.036*	-0.035*	-0.036*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.091)	(0.099)	(0.089)
StockMktVal/GDP	0.001*	0.001	0.001	0.000	0.000	0.000	0.001	0.001	0.001
	(0.081)	(0.105)	(0.101)	(0.726)	(0.727)	(0.734)	(0.154)	(0.156)	(0.154)
GDP per cap	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
Good Gov Index	0.001**	0.001**	0.001**	0.001*	0.001*	0.001*	0.001	0.001	0.001
	(0.025)	(0.023)	(0.024)	(0.066)	(0.066)	(0.066)	(0.140)	(0.140)	(0.140)
Patents/Population	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.444)	(0.499)	(0.490)	(0.348)	(0.344)	(0.348)	(0.263)	(0.257)	(0.255)
Fixed Effect (Yr)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*Country*year*	335	335	335	312	312	312	289	289	289
Adj. R2	0.106	0.095	0.095	0.109	0.112	0.115	0.048	0.049	0.048
F-Stat	2.473	2.295	2.295	2.470	2.510	2.558	1.583	1.597	1.586

	Panel B. FPE and Preference for Extreme Payoffs (2000-2016)								
	(IV) FPE – 1-year ahead			**(V) FPE – 2-years ahead**			**(VI) FPE – 3-years ahead**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PremIVOL	-0.088***	-0.102***	-0.108***	-0.052	-0.069**	-0.070*	0.024	0.008	0.012
	(0.009)	(0.004)	(0.006)	(0.104)	(0.037)	(0.056)	(0.448)	(0.801)	(0.737)
PremMAX1	-0.120			0.081			0.032		
	(0.101)			(0.312)			(0.678)		
PremMAX2		0.130			-0.082			0.035	
		(0.208)			(0.405)			(0.703)	
PremMAX3			0.072			-0.115			-0.012
			(0.447)			(0.193)			(0.890)
GDP growth	-0.041	-0.038	-0.039	-0.060**	-0.061**	-0.061**	-0.043*	-0.043*	-0.043*
	(0.112)	(0.140)	(0.126)	(0.019)	(0.017)	(0.016)	(0.095)	(0.095)	(0.089)
StockMktVal/GDP	0.001	0.001	0.001	0.000	0.000	0.000	0.001*	0.001*	0.001*
	(0.214)	(0.280)	(0.253)	(0.843)	(0.810)	(0.812)	(0.067)	(0.067)	(0.066)
GDP per cap	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.019)	(0.020)	(0.020)
Good Gov Index	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**	0.000	0.000	0.000
	(0.005)	(0.003)	(0.003)	(0.020)	(0.025)	(0.025)	(0.340)	(0.344)	(0.350)
Patents/Population	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.647)	(0.706)	(0.681)	(0.434)	(0.410)	(0.412)	(0.282)	(0.275)	(0.279)
Fixed Effect (Yr)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*Country*year*	274	274	274	251	251	251	229	229	229
Adj. R2	0.058	0.064	0.058	0.066	0.066	0.070	0.048	0.046	0.046
F-Stat	1.765	1.847	1.766	1.843	1.837	1.896	1.575	1.555	1.548