Sentiment, Market Order Choice, and Returns

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Sentiment, Market Order Choice, and Returns

Abstract
We use a unique data set over a crisis period obtained from the Taiwan Futures Exchange (TAIFEX) to investigate the order type choices made by retail and institutional investors. The results indicate that individual investors submit more market orders and sell orders during periods when market sentiment is highly fearful. In contrast, institutional investors are less sensitive to market sentiment and sometimes display the opposite trading behavior, especially when the market is liquid. Institutional trades can alleviate, but not reverse, individuals’ market orders during market panics, and actually exacerbate price drops at the intraday level. Furthermore, we find that retail investors’ market order choices, which are measured in market order ratios, have significant impact on contemporaneous and future price movements, both directly and indirectly through the influence on order imbalance. The pattern is particularly strong for sell orders and for intraday high-frequency horizons. In sum, our research provides important insight into market stability and microstructure.

JEL Classification: G14, G15

Keywords: Market Sentiment, Market Order, Order Submission and Imbalance, Individual and Institutional Investors.
1. INTRODUCTION

U.S. stocks and stock index futures experienced an unusually speedy crash and recovery (flash crash) on May 6th, 2010, and subsequent regulatory investigations pointed to market sentiment as an important factor in explaining the market turmoil. Theoretical and empirical studies agree that order imbalances by different types of investors contain information and are responsible for such sharp asset price movements. For example, Barber et al. (2009) and Lee et al. (2004) point out that order imbalances by retail investors can reveal information that predicts future market returns. Consistent with theoretical predictions, Kaniel et al. (2008) and Boehmer and Wu (2008) show that retail investors tend to provide liquidity, whereas other types of investors demand liquidity under normal market conditions. Such differences in liquidity need can partly explain the variation in order imbalances across investor types, asset prices, and volatilities.

What remains largely unknown is whether different types of investors change their trading behavior in differing directions during specific market conditions, especially market turmoil. For example, the regulators propose that the use of market orders might have contributed to market instability and a temporary breakdown in orderly trading during the flash crash of May 6th, 2010. Extant studies suggest and speculate that the choices between order types (market orders vs. limit orders) by different investor types (institutional vs. retail investors) vary over time and may have profound influence on order imbalances, liquidity, and asset prices (Harris and Hasbrouck, 1996;...
Bae et al., 2003; Anand et al., 2005; Chung et al., 1999; Chung and Zhao, 2004), whereas data limitations have, until now, hindered scholars from studying the order type choice by different types of investors over time, especially during financial crises. Answers to such questions not only help better understand extreme market volatility, but also alleviate a resulting market crash. To this end, we consider three years of high-frequency order and trade data from the Taiwan Futures Exchange (TAIFEX), and study how order type choices by the respective investor types shift over time, especially during a market crash. As a result, we have three major discoveries.

First, we find that retail investors submit more and larger market orders during fearful market periods, (i.e., market panics). Specifically, a one standard deviation increase in the TVIX, the official index of market fear in Taiwan (Taiwanese counterpart of VIX), leads retail investors to increase the fraction of their ask-side market orders (in volume) by about 1.538 percentage points. However, it only leads to an increase of 0.724 percentage points in the number of submissions\(^6\). Furthermore, this pattern is weaker for bid-side market orders since a one standard deviation increase in the TVIX leads retail investors to increase the fraction of their orders by only 1.086% in volume and 0.271% in number of submissions.

Second, in contrast to the above result, market sentiment does not significantly influence order choices made by institutional investors. We find that TVIX influences neither the fraction of market orders nor the size of market orders. As a matter of fact, during fearful market conditions and panics, institutional investors execute less aggressive transactions through limit orders, if the market is sufficiently liquid.

Third, we show that these changes in order types during market turmoil have an important influence on the market returns and volatility. The fraction of market orders among all orders by retail investors has significant explanatory power for contemporaneous and future returns. One

\(^6\)These values are estimated by model (1) in subsection 3.1 with daily data.
possible mechanism through which the choice of order type affects returns is through order imbalance.

Our results hold when we control for the potential endogeneity issue. That is, market order submissions by retail and institutional investors vary over time, especially during fearful market sentiment. In addition, our results remain robust when we examine market microstructure effects that may affect order submission behaviors. Our results also hold when we control for potentially endogenous relationships between the sentiment index and spot returns, and other factors known to influence investors’ order submission decisions, such as market conditions, investor behavior, trading mechanism, and measurement horizons.

In sum, we make three primary contributions to the literature. Firstly, we find evidence supporting some theoretical assumptions that investors choose different ways to submit their orders depending on market conditions (Biais et al., 1995; Parlour, 1998). Our findings support the view that order submission decisions are strategic and influenced by factors such as market level sentiment and liquidity. In particular, we find that order submission decisions of retail and institutional investors are affected by market sentiment differently. Such results highlight the importance of making more realistic assumptions about retail and institutional investors in future theoretical studies with asset pricing and market microstructure models.

More importantly, we are among the first to provide empirical evidence on how different types of investors adjust their order submission decisions over time and under various market conditions. We show that in the aggregate market, there is only a modest temporal shift in the choice between market and limit order types. However, the patterns are distinctly different depending on investor type, i.e., individual investors trade substantially more through market orders, whereas institutions partially reverse that trend. Our results also indicate that retail and
institutional investors are both responsible for market crashes, yet through different mechanisms. Highly fearful sentiment induces retail investors to shift from limit orders to market orders, which partly explains why retail investors are responsible for exacerbating market crashes once they start (i.e., once market sentiment turns fearful). On the other hand, we demonstrate that institutional investors continuously modify their order submission decisions largely depending on market liquidity. During periods of market crashes when liquidity is scarce, it is not clear that institutional investors can play their expected stabilizing role to diffuse market turmoil.

Secondly, we show that trading by institutions and retail investors has a disparate impact on asset price formation over different periods. Furthermore, even for the same type of investor, the choice to submit orders through market orders or limit orders has a varying impact on asset prices. This is especially important to the asset pricing and market microstructure literature given our above finding that the same type of investor may switch their order submission choices depending on market conditions. Our findings are among the first to point out that, in addition to changes in order imbalance in general, changes in order direction (buy vs. sell) and order submission methods (market order vs. limit order) can have an important influence on asset prices over time. Such findings provide important implications for future research on crashes and market volatility.

Finally, our findings relate to the behavioral finance literature and suggest that the composition of investor clientele is important to understanding asset returns and volatility. Investors’ varying responses to fearful sentiment and sharp market downturns can explain why some younger securities markets (i.e., derivatives markets) and international markets with a strong retail investor presence (i.e., many Asian stock markets) are more susceptible to market
turmoil and excess volatility. Hence, our findings call for future research to better understand the dynamics of investor clientele in financial markets.

The remainder of the paper is organized as follows: Section 2 presents the data from the TAIFEX and introduces our methodology; Section 3 provides empirical findings regarding investors’ choices of order submission methods; Section 4 illustrates empirical findings regarding how order submission choice affects asset prices; and Section 5 summarizes the results and concludes the article with a brief discussion. We provide detailed explanations of parameter estimations in the Appendix.

2. DATA
2.1. Data Description
Since its establishment in 1998, the Taiwan Futures Exchange (TAIFEX) has become a high-volume exchange in the derivatives market. By the end of 2009, stock index, interest rate, and gold futures (as well as options) are all traded on the TAIFEX. The number of trading accounts has grown from 75,035 in July 1998 to 1,268,199 at the end of 2009\(^7\). Individual investors hold 99.38% of the trading accounts and are responsible for 44.39% of total trading volume. Although individual investors display higher turnover than institutions (Barber et al., 2009), less than 1 percent of individual investors are classified as day traders by the TAIFEX’s margin requirement during 2007 and 2008 (Kuo and Lin, 2013). In addition, foreign institutions are responsible for about 10% of institutional investors’ trading volume and thus play an important role on the TAIFEX, although almost all individual investors are domestic. It is worth noting that the annual trading volume of 136,719,777 contracts in 2009 makes the TAIFEX the 18\(^{th}\) largest derivatives exchange in the world (Futures Industry Association (FIA), 2009).

\(^7\) The population of Taiwan is 23,119,772 at the end of 2009 according to government statistics, which are available at http://www.stat.gov.tw/ct.asp?xItem=15408&CtNode=3623&mp=4.
Among several futures contracts traded on the TAIFEX, the Taiwan Stock Exchange Capitalization Weighted Stock Index Futures (ticker: TX) is the most important. The underlying asset for TX is the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX)\(^8\) of the Taiwan Stock Exchange (TWSE). The contract size of the TX is 200 New Taiwan Dollars\(^9\) (TWD) per index point, and the tick size (minimum price fluctuation) is 1 index point. In addition to the minimum initial and maintenance margin requirements, the TAIFEX regulates the maximum position limit for trading TX. However, to compete for commissions, most Futures Commodity Merchants (FCMs) make exceptions and lower such requirements in practice.\(^10\) The total trading volume of the TX was 24,625,062 contracts in 2009. Institutional investors and retail investors both play important roles in TX trading and account for 29.38% and 70.62% of trading volume\(^11\), respectively. Such a mix of investors offers us a good opportunity to explore the effects of market sentiment on distinct types of investors.

In this study, the sample\(^12\) period ranges from January 2\(^{\text{nd}}\), 2007 to December 31\(^{\text{st}}\), 2009 (747 trading days), which includes the 2007\(^13\) global financial downturn. The database includes all trades, orders, and quotes for the TX. The transaction database includes the contract code,\(^8\) The TAIEX is similar to the Standard & Poor’s 500 and the most widely quoted of all TWSE indices. The base year value of 1966 was set at 100. The TAIEX is adjusted in the event of a new listing, a de-listing, or a new share offering, to offset the influence on the TAIEX of non-trading activities. The TAIEX covers all of the listed stocks excluding preferred stocks, full-delivery stocks, and stocks that have only been listed for less than one calendar month.
\(^9\) The currency rate is about 33 TWD per USD at the end of 2009.
\(^10\) For example, on December 31\(^{\text{st}}\), 2009, the nominal value of a TX contract was TWD 1,641,000, but the initial and maintenance margin requirements for trading TX were only TWD 77,000 and TWD 59,000, respectively. The trading volume and the open interest of TX were 67,209 and 48,234 contracts, respectively, but the position limits of TX for retail and institutional investors were as high as 5,000 and 10,000 contracts, respectively. In addition, institutional investors may apply for an exemption from the upper limit on trading accounts for hedging purposes, and position limits are not applicable to omnibus accounts. Thus, such regulations are unlikely to be burdensome for retail or institutional investors. These regulations are available from TAIFEX’s website, http://www.taifex.com.tw.
\(^11\) The ratio of individual investors to institutional investors in TAIFEX is similar to that on TWSE. Individual investors account for 72.05% of total trading volume in 2009.
\(^12\) The sample covers the most adjacent maturing contract and switches to the next adjacent maturing contract 5 days before the nearby contract maturity.
\(^13\) The Global Financial Crisis in 2007 may have changed investors’ attitudes to financial risk taking, and submission choices may have changed as well. Therefore, we perform sub-sample analysis for data within each year between 2007 and 2009. We obtain very consistent results, which are available from the authors upon request.
transaction date, time, order type (i.e., market or limit order), price, buy and sell volumes, and an identifier for whether the investor is an institution or individual. The order database includes contract code, order date, time, order type, price, buy and sell volumes, a code for new order/cancellation/emendation, and an identifier for the investor in the trade database. The quotes database includes contract code, date, time, and the five best bid/ask quotes with their corresponding depths (unexecuted volumes).

To measure market sentiment, we use TVIX\textsuperscript{14}, the most widely used fear index in Taiwan. The TAIFEX launched the TVIX in December, 2006, in collaboration with the Chicago Board Options Exchange (CBOE), and the TVIX follows the same methodology as the VIX at the CBOE. Like the VIX, TVIX is also the investor ‘fear gauge,’ with higher values indicating greater fear in the market (Whaley, 2000 and 2009). In addition, the TAIFEX makes available the best five quoted bid/ask prices, their corresponding depths (unexecuted volumes), and the TVIX level, to all investors on a real-time basis during trading hours.

2.2. Summary Statistics

We first provide summary statistics on the order submissions by individual and institutional investors\textsuperscript{15}, respectively. As Table 1 reveals, on an average trading day, 13,450 (14,032) contracts, or 7.34\% (7.78\%), are placed through market order on the bid (ask) side and 178,509 (177,879) contracts, or 92.66\% (92.22\%),\textsuperscript{16} are placed through limit orders on the bid (ask) side. It is interesting to notice that individual investors and institutional investors display distinctly different preferences for market and limit orders. For individual investors, about 15.55\% (16.18\%) of buy (sell) orders are submitted through market orders in volume of submissions. In

\textsuperscript{14} There is no tradable instrument on TVIX.

\textsuperscript{15} The classification of investor types is similar to Barber et al. (2008), Griffin et al. (2003) and Kuo and Lin (2013), because there is no market maker on the TX market.

\textsuperscript{16} In Table 1, the percentages are calculated from the ratios of corresponding means, medians, standard deviations, maximums, and minimums, respectively.
contrast, only less than 1 %, i.e., 0.70% (0.75%), of institutional buy (sell) orders are submitted through market orders in volume of submissions. Given their respective order submissions, individual investors account for 39.36% of submitted limit orders (in volume) from the bid side on an average trading day. Such findings are largely in line with the common notion that institutional investors may be concerned with the price impact of their trades and tend to avoid market orders.

In addition to trading volume, we also perform a similar analysis on the number of order submissions. Table 1 reports results that are consistent with those based on order volume. Indeed, the pattern that individual investors submit a far greater proportion of their trades through market orders is even stronger, partly because individual investors submit fewer orders as measured in number of trades than as measured in trade volume.

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Next, we examine the properties of the TVIX and its ability to track market sentiment. As Table 2 shows, the distribution of the daily close level of the TVIX is right skewed (coefficient of skewness = 0.440) and platykurtotic (coefficient of kurtosis = 0.222) during the sample period, suggesting that market sentiment, as measured by TVIX, is normally calm but highly fearful during states of turmoil. In unreported analysis, we find that the properties of the TVIX are qualitatively and quantitatively similar to those of the VIX (Whaley, 2000 and 2009). In addition, Figure 1 shows the TVIX moves against TAIEX index in general and usually spikes upward when the stock index TAIEX crashes in response to unexpected market and world events. Such results are consistent with the notion that the TVIX reflects market panic (i.e., sentiment) in the Taiwanese market, and maps closely with what Whaley (2009) finds for the VIX in the U.S.

The detailed analysis of the TVIX is available from the authors upon request.
After reporting the summary statistics of the order submissions and the TVIX measure, we investigate how market sentiment, as proxied by the TVIX, influences order type choices (i.e., market orders versus limit orders) for individual and institutional investors, respectively. In particular, we investigate the daily and intraday relationship between the TVIX and the market order ratio for individual investors and institutional investors separately.

We first calculate the coefficients of correlation between market sentiment and market order ratios for individual and institutional investors separately, to obtain a general picture of how market sentiment influences investors’ order type choices. Panel A in Table 3 shows that for both the bid and ask sides, the coefficients of correlation between the TVIX and the market order ratio are positive for individual investors. However, on the bid (ask) side, the coefficient of correlation between the market order and TVIX, measured in volume of submissions, is 0.237 (0.330), far greater than that coefficient, measured in number of submissions, 0.129 (0.197).

Further, these daily interval coefficient of correlations for the bid (ask) side, i.e., 0.237 (0.330) measured in volume of submissions and 0.129 (0.197) measured in number of submissions, are both stronger than the corresponding 5-minute intraday interval coefficient of correlations, i.e., 0.106 (0.138) measured in volume of submissions and 0.055 (0.076) measured in number of submissions.

In contrast, the coefficients for institutional investors are much smaller and do not clearly lead to a consistent direction. Specifically, the absolute value of the coefficients is less than 5% and the results show mixed signs for institutional investors. Our preliminary results thus indicate that market sentiment seems to have a strong influence on how individual investors choose
between market orders and limit orders to submit their trades, whereas institutional investors are not much influenced by market sentiment.

Moving beyond the coefficients of correlation, we divide the trading days into five categories based on market sentiment as measured by the TVIX level at market close. The 1st quintile includes those trading days when the market is most calm and the 5th quintile consists of those trading days when the market is most fearful.\(^\text{18}\) With such a classification, we can find out whether the market order ratio for the entire market and for individual and institutional investors, respectively, varies over time along with market sentiment.

As Panel B of Table 3 shows, the average market order ratio for individual investors increases as the TVIX increases. For the measure by order volume, the average market order ratio increases from 13.87% (13.65%) of the buy (sell) orders during the least fearful period to 15.97% (17.31%) percent during the most fearful periods. These results are significant at the 1% level with \(t = 4.978\) (8.369). Consistently, for the measure by order number, the market order ratio increases from 17.39% (18.44%) of the buy (sell) orders to 18.19% (19.74%), from the least to the most fearful market regimes.

Interestingly, although the market order ratio measured by order number increases between \(P_1\) and \(P_5\) for institutional trades on the ask side, this increase is not statistically significant. Because the market order ratio is a proxy for the demand for immediacy (Lee et al., 2004), our results suggest that individual investors increase their demand for immediacy as market sentiment becomes more fearful.

\(^{18}\) The cutoffs for the 20th, 40th, 60th, and 80th percentiles for the daily close TVIX level are 21.616, 27.496, 31.542, and 36.844, respectively.
Due to the fact that the entire market comprises trades submitted by both individual and institutional investors, the aggregate market-level pattern lies somewhat between the patterns for individual and institutional investors. Indeed, the market order ratio increases, albeit modestly, at the market level. Our analysis by investor type hence reveals the limitation of studying order submission methods at the aggregate level without distinguishing between investor types; our findings stress the importance of studying retail and institutional investors separately in addition to together.

So far, our analysis of the summary statistics regarding market sentiment and market order ratios provides strong support for two conjectures. First, individual and institutional investors choose different types of orders to submit their trades, and second, their preferences for market orders vary drastically, depending on the market sentiment. Because the dynamics of order type choices across investor types change with market sentiment, this calls into question the common assumption of constant order type choices by different investors, employed in the extant theoretical studies (e.g., see Biais et al., 1995; Parlour, 1998; Chung et al., 1999; Chung and Zhao, 2004).

3. Regression Analysis

3.1. Methodology

Having completed the precursory analysis, we now explore the relationship between market sentiment and market order ratios for individual investors and institutional investors, through regression analysis. To examine the influence of market sentiment\(^\text{19}\) on order type choices, we calculate market order ratios in terms of the volume of submissions and in terms of the number

\(^{19}\) To measure market sentiment in this analysis, we follow Whaley’s (2000, 2009) approach and use a specification involving the level of TVIX. Our results remain robust when we use a specification involving the change in TVIX.
of submissions. To conserve space, we only report the results based on volume. The results obtained for the number of submissions are materially the same and available upon request.

In this study, we mainly focus on market order submissions because they are more reflective of sentiment than are limit orders (Barber et al., 2009). To this end, we define market order submission ratios for individual and institutional investors, respectively:

\[ \text{ind} \text{mkt} \text{SV} \text{RV} + \text{inst} \text{mkt} \text{SV} \text{RV} \]

where \( \text{ind} \text{mkt} \text{SV} \) is the volume of market orders submitted by individual investors, \( \text{inst} \text{mkt} \text{SV} \) is the volume of market orders submitted by institutional investors, and \( \text{inst} \text{SV} \text{lim} \) is the volume of limit orders submitted by institutional investors.

Because some studies find asymmetry between the bid-side and ask-side orders (e.g., Chiyachantana et al., 2004; Samarakoon, 2010; Chou et al., 2011), we define the dummy variable \( D_{AS} \) (i.e., \( D_{AS} = 1 \) for the ask side and \( D_{AS} = 0 \) for the bid side). Furthermore, we use the interaction term \( D_{AS} \cdot TVIX \) to verify whether there is asymmetry towards market sentiment on the bid and ask sides. The resulting linear regression takes the following specifications for daily data:

\[ \text{ind} \text{mkt} \text{RV} = \alpha_1 + \beta_{1,1} D_{AS} + \beta_{1,2} D_{AS} TVIX + \beta_{1,3} TVIX + \epsilon, \]

\[ \text{inst} \text{mkt} \text{RV} = \alpha_2 + \beta_{2,1} D_{AS} + \beta_{2,2} D_{AS} TVIX + \beta_{2,3} TVIX + \eta. \]  

(1)

20 To take into account the effects of heteroscedasticity and an AR(1) process, we employ the generalized method of moments (GMM) approach to separately estimate two linear regression equations. For the sake of simplicity, we omit the subscript "t" representing the t-th observation from each of variables and random errors. In addition, we assume that the mean of the vector of random errors with the length N (the sample size) is \( 0 \_\text{N x 1} \). Moreover, we assume that the variance of this vector is a positive definite matrix, which allows for the possibility of heteroscedasticity and an AR(1) process (e.g., see Tsai, 1986). Finally, the orthogonality conditions are satisfied (i.e., \( E[D_{AS} \cdot \epsilon = 0], E[D_{AS} TVIX \cdot \epsilon = 0], \) and \( E[TVIX \cdot \epsilon = 0] \)). The methodology is also referred to as OLS with Newey-West standard errors (Greene, 2002). The analogous setting and assumptions are applied to models (2), (5), and (6).
For intraday analysis, we set up an opening-time trading period dummy, $D_{\text{open}}$ (i.e., $D_{\text{open}} = 1$ for orders submitted during 8:45–9:00 a.m. and $D_{\text{open}} = 0$, otherwise), and a closing-time trading period dummy, $D_{\text{close}}$ (i.e., $D_{\text{close}} = 1$ for orders submitted during 1:30–1:45 p.m. and $D_{\text{close}} = 0$, otherwise), to detect the intraday effect of investors’ order submissions (Harris, 1998; Anand et al., 2005). Accordingly, the linear regression takes the following specifications for intraday data:

$$
\text{mkt} \, RV_{\text{ind}} = \alpha_1 + \beta_{1,1} D_{\text{open}} + \beta_{1,2} D_{\text{close}} + \beta_{1,3} D_{\text{AS}} + \beta_{1,4} D_{\text{AS}} \, TVIX + \beta_{1,5} TVIX + \epsilon,
$$

$$
\text{mkt} \, RV_{\text{inst}} = \alpha_2 + \beta_{2,1} D_{\text{open}} + \beta_{2,2} D_{\text{close}} + \beta_{2,3} D_{\text{AS}} + \beta_{2,4} D_{\text{AS}} \, TVIX + \beta_{2,5} TVIX + \eta. \tag{2}
$$

It is noteworthy that there are 5-minute intervals in which investors do not submit any market orders (especially for institutional investors). Hence, we may face the potential problem of sample selection bias (Heckman, 1979; Heckman et al., 1997; Heckman et al., 1998). In particular, the quoted spread and the quoted depth may influence investors’ tendency to trade in the market during any particular 5-minute interval (Chung et al., 1999) and are therefore included in the first-stage selection regression in a two-stage sample selection approach (Greene, 2002; Toomet and Henningsen, 2008). Specifically, we first employ the selection regression to estimate the probability of observing a non-zero observation (i.e., some investors choose to trade through market orders in that 5-minute interval), and then we employ a second-stage regression that estimates the impact of market sentiment on investors’ choice of market and limit orders.

Accordingly, we take a snapshot of the limit order book for the TX in each 5-minute interval to obtain the quoted spread in index points, $\text{spread}$. For ask (bid) side market order ratios, we further define $bdep$, the difference between the depths resulting from their corresponding best ask (bid) and bid (ask) prices, and $adep$, the difference between the two sums of the 2nd to 5th depths resulting from their corresponding ask (bid) and bid (ask) prices. We include these

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**21** The trading of the TX begins fifteen minutes earlier (8:45 a.m. versus 9:00 a.m.) and closes fifteen minutes later (1:45 p.m. versus 1:30 p.m.).
variables in the selection equation to reflect the potential influence of market depth on our sample selection.

From the above discussions, the sample selection models for individual investors in volume of submissions are given below:

Selection eq. \( m^{\text{ind}}P_{V}^{*} = \lambda_1 + \gamma_{1,1}D_{\text{open}} + \gamma_{1,2}D_{\text{close}} + \gamma_{1,3}\text{spread} + \gamma_{1,4}\text{bdep} + \gamma_{1,5}\text{adep} + \eta, \)

Regression eq. \( m^{\text{ind}}RV_{\text{ind}} = \alpha_1 + \beta_{1,1}D_{\text{open}} + \beta_{1,2}D_{\text{close}} + \beta_{1,3}D_{\text{ask}} + \beta_{1,4}D_{\text{ask TVIX}} + \beta_{1,5}\text{TVIX} + \varepsilon, \) (3)

where \( m^{\text{ind}}RV_{\text{ind}} \) is the market order ratio for individual investors, \( D_{\text{open}} \) is the opening time dummy, \( D_{\text{close}} \) is the closing time dummy, \( D_{\text{ask}} \) is the ask side dummy, and \( \text{TVIX} \) is the close level in 5-minute intervals. Then, let \( m^{\text{ind}}PV_{\text{ind}}^{*} \) be the latent endogenous variable for individual investors, under market conditions of \( D_{\text{open}}, D_{\text{close}}, \text{spread}, \text{bdep}, \) and \( \text{adep}, \) such that \( m^{\text{ind}}PV_{\text{ind}}^{*} = 1 \) if \( m^{\text{ind}}PV_{\text{ind}}^{*} > 0 \) and \( m^{\text{ind}}PV_{\text{ind}}^{*} = 0 \) otherwise. In addition, let

\[
\Pr\{m^{\text{ind}}PV_{\text{ind}}^{*} = 1 \mid D_{\text{open}}, D_{\text{close}}, \text{spread}, \text{bdep}, \text{adep}\} = \\
\Phi(\lambda_1 + \gamma_{1,1}D_{\text{open}} + \gamma_{1,2}D_{\text{close}} + \gamma_{1,3}\text{spread} + \gamma_{1,4}\text{bdep} + \gamma_{1,5}\text{adep})
\]

and

\[
\Pr\{m^{\text{ind}}PV_{\text{ind}}^{*} = 0 \mid D_{\text{open}}, D_{\text{close}}, \text{spread}, \text{bdep}, \text{adep}\} = \\
1 - \Phi(\lambda_1 + \gamma_{1,1}D_{\text{open}} + \gamma_{1,2}D_{\text{close}} + \gamma_{1,3}\text{spread} + \gamma_{1,4}\text{bdep} + \gamma_{1,5}\text{adep}),
\]

where \( \Phi \) is the cumulative Normal distribution function. Moreover, \( \varepsilon \) and \( \eta \) are assumed to be bivariate normal, with mean zero and covariance matrix \[
\begin{bmatrix}
\sigma_{\varepsilon}^2 & \sigma_{\varepsilon\eta} \\
\sigma_{\varepsilon\eta} & 1
\end{bmatrix}
\]. Subsequently, we replace \( m^{\text{inst}}RV_{\text{ind}} \) and \( m^{\text{inst}}PV_{\text{ind}}^{*} \) in model (3) with \( m^{\text{inst}}RV_{\text{inst}} \) and \( m^{\text{inst}}PV_{\text{inst}}^{*} \), respectively, to analyze the relationship for institutional investors. Detailed estimation procedures can be found in Greene (2002) and Toomet and Henningsen (2008).
3.2. Daily Analysis

Consistent with our summary statistics, Table 4 reveals that the relationship between market sentiment and market order ratio is positive for individual investors and such results are highly significant at the 1% level. These results provide strong support for our hypothesis that individual investors submit more market orders during market turmoil. This finding is also consistent with our previous summary statistics; the coefficient for market sentiment is insignificant and indeed sometimes negative for institutional investors.

The above differences in their choices of order type depict the interplay between individual investors and institutional investors under various market conditions. These discoveries confirm that individual investors are far more sensitive to market sentiment than are institutional investors, which suggests that retail investors may be more responsible than institutional investors for exacerbating market volatility when market sentiment begins to deteriorate.

<<Insert Table 4 about Here>>

3.3. Intraday Analysis

Intraday analysis is important not only for researchers in the market microstructure field, but also for regulators concerned with intraday volatilities and flash crashes (e.g., the events of May 6, 2010). Hence, we study the relationship between sentiment and market order choice at an intraday frequency.

Consistent with the daily results, we find that individual investors increase their market orders when facing more fearful market conditions, whereas institutions are indifferent to sentiment at the intraday level. In addition, intraday results reveal that the interaction between ask-side orders and market sentiment is significantly positive for individual investors. This suggests that individual investors favor market orders, particularly when executing sell orders.
Such market sell orders by individual investors add additional panic to an already fearful market and contribute to further price drops and fear within the same trading day.

Next, because liquidity may influence an investor’s tendency to trade in the market (Chung et al., 1999), we report the sample selection models in Table 5 to address the impact of liquidity on order submissions, where liquidity is measured by quoted spread and market depth. The left side of Panel A in Table 5 presents the results of our sample selection models for individual investors. It indicates that the coefficients for the two measures of market depth are both highly significantly negative, indicating that individual investors display a higher tendency to submit market orders during more illiquid market periods.

After taking into account the potential selection bias, Panel A of Table 5 presents the results from the regression of market order ratio on market sentiment with the 5-minute interval data. To the focal interest of the paper, $\hat{\beta}_{1,5}$ is positive at the 1% significance level, confirming prior results that individual investors trade more through market orders during more fearful market periods. This relationship is not only statistically significant, but also economically important: a one standard deviation increase in the TVIX measure can lead to a 1.181% increase in the ask-side market order ratio.

<<Insert Table 5 about Here>>

As for the control variables, we find that individual investors submit a lower fraction of their trades through market orders during the market opening period (i.e., $\hat{\beta}_{1,1}$ is significantly negative at the 1% level) and a higher fraction of trades in the market closing period ($\hat{\beta}_{1,2}$ is significantly positive at the 1% level). This result is consistent with the conjecture in the extant

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22 We perform unconditional linear regression and obtain consistent results. These results are available from the authors upon request.
literature that individual investors are likely to be at an informational disadvantage during the market opening period and therefore decide to submit fewer market orders (e.g., Harris, 1998; Anand et al., 2005). In addition, the market order ratio for individual investors is more sensitive to market sentiment on the ask side, as reflected by $\hat{\beta}_{1,4}$ on the interaction term $D_{SS} \cdot TVIX$ being positive and highly significant. This finding implies that individual investors submit more market sell orders when the TVIX is high, which would aggravate a sudden market slump.

In contrast to individual investors, institutional investors submit fewer market orders when market sentiment is fearful (i.e., $\hat{\beta}_{1,5}$ is significantly negative at the 1% level). In addition, $\hat{\beta}_{1,4}$ is negative (marginally significant), suggesting that institutional investors are particularly averse to market orders in their selling trades during market turmoil. It is noteworthy that, unlike individual investors, institutional investors are more likely to submit market orders during both the opening and closing periods. Moreover, institutional investors seem to be more sensitive to market liquidity conditions; they are more likely to submit market orders when the spread is relatively narrower (which indicates the market being more liquid).

We are among the first to document how market sentiment can substantially influence individual and institutional investors’ choices between market and limit orders, at both daily and intraday intervals. On one hand, our results show that institutional investors opt for fewer market orders when submitting trades during a market panic. This means institutional investors’ greater reliance on limit orders can somewhat alleviate the otherwise negative impact from retail investors on the market during a time of turmoil.

At the same time, it is important to point out that the coefficient for institutional investors is far smaller than that for individual investors, in absolute value, implying that institutional investors’ choices between market and limit orders are less sensitive to market sentiment than are
individual investors’ choices, given the same shift in TVIX. This suggests that, even though institutional investors can play a stabilizing role in preventing market crashes, their actions are not strong enough to prevent or avert a sudden market drop aggravated by individual investor selling.

Finally, we show that the ability of institutional investors to reverse the impact of individual investors depends on market liquidity conditions. Institutional investors do not appear on the opposing side of the market from retail investors at times when market liquidity is low and the institutional investors’ stability is most needed. Hence, our findings question the argument that institutional investors can stabilize the market by countering individual investors’ irrational behavior or trading mistakes.

3.4 Alternative explanations

Apart from sentiment, several other factors may affect investors’ order type choices. One possibility is that, because institutions hold larger portfolios and trade in larger volumes, they may sometimes choose to trade with market orders to better leverage liquidity from retail investors. This being the case, we should expect to observe smaller market orders by institutions, as they try to divide their large trades and hide their identity (Barber et al., 2008). However, we indeed observe the opposite in Table 6. Institutional investors submit much larger market orders than limit orders, indicating that institutional investors’ market order submissions are not more ‘strategic’ than their limit order submissions. This confirms that such a motivation cannot be driving institutions’ choice between market and limit orders.

<<Insert Table 6 about Here>>

In addition, given that institutional investors hold large portfolios, which may be harder to execute, some institutional investors, such as hedge fund and proprietary trading desks, use
‘iceberg’ orders (i.e., hidden-size orders) to obtain market information and optimize trading in the U.S. market. An ‘iceberg’ trading mechanism may lead to a systematic bias in the distribution of market vs. limit orders for institutional investors. We verify with the Taiwan regulatory authorities that ‘iceberg’ trades are not allowed in the TX market.

Finally, the need for institutional investors to roll over their hedge positions may cause different submission behaviors surrounding the maturity date (the 3rd Wednesday). For this matter, our sample covers the most adjacent maturing contract and switches to the next adjacent maturing contract 5 days before the nearby contract maturity. This rolling-over avoids the possible effects surrounding the maturity date (the third Wednesday of the delivery month) for investors to reconstruct and maintain their portfolios.

4. Market Order Ratio and Asset Prices

Our study has shown that retail and institutional investors adjust their market order choices in response to market sentiment. A natural subsequent question is whether the market order choices of these two different types of investors affect asset prices. To this end, we employ two distinct channels to investigate their impact. First, we examine the direct relationship between market order ratios and market-level returns, to gain some novel insights into how investors’ choices between order submission types affect asset prices. Furthermore, we investigate whether the changes in market order choices by different types of investors could provide additional help in explaining price movements through order imbalances, as documented in the extant literature (e.g., Easley et al., 1998; Chordia et al., 2002; Chordia and Subrahmanyam, 2004). This exercise

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23 In some exchanges (e.g., CME Globex, Euronext, and Eurex), traders are allowed to submit iceberg orders, which specify a price, a total order size, and a peak size (smaller than the total size). At the beginning, only the peak size is displayed in the limit order book and the rest of the order is hidden. After the peak size has been fully executed, the hidden size is automatically displayed in the limit order book.
can provide a more comprehensive understanding of how changes in market order choices impact the market.

4.1. Market Order Ratios and Returns

We start by studying the direct impact of market order ratios on market returns. Since we have demonstrated that the relationship between market order ratios on the bid side and the ask side differs for individual and institutional investors, we regress the market-level returns on the bid-side and ask-side market order ratios to examine their respective impact on asset prices. To further capture the respective directional impact, we separate the market order ratio on the bid side from that of the ask side in our analysis. In addition, we add one-period lagged variables to assess their predictive power on market returns. As a result, we have the following regression model:

\[ r_t = \alpha + \beta r_{t-1} + \lambda_{1,4} RV_{ind,t}^{buy} + \lambda_{1,2} RV_{ind,t-1}^{buy} + \lambda_{1,3} RV_{ind,t}^{sell} + \lambda_{1,4} RV_{ind,t-1}^{sell} + \lambda_{1,5} RV_{inst,t}^{buy} + \lambda_{1,6} RV_{inst,t-1}^{buy} + \lambda_{1,7} RV_{inst,t}^{sell} + \lambda_{1,8} RV_{inst,t-1}^{sell} + \epsilon_t, \]  

where \( r_t \) is the contemporaneous price movement of TX measured in the natural logarithm, \( RV_{ind,t}^{buy} (RV_{ind,t}^{sell}) \) is the contemporaneous market order ratio in volume of submissions for individual investors on the bid (ask) side, \( RV_{inst,t}^{buy} (RV_{inst,t}^{sell}) \) is the contemporaneous market order ratio in volume of submissions for institutional investors on the bid (ask) side, and the subscript \( t-1 \) denotes a one-period lag. In addition, we assume that the \( \epsilon_t \) are independent and identically distributed according to a normal distribution with mean zero and constant variance for \( t=1,...,N \).

The results in Table 7 reveal that market order ratios play an important role in predicting market returns. Specifically, the market order ratios on both the bid side and ask side each have a

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To take into account the lagged variable, we employ the techniques of Enders (2004) and Harvey (1990) to estimate regression coefficients in the dynamic time series model. We also applied this approach to model (9).
significant impact on market returns; the market order ratio on bid-side orders has a significantly positive impact on market returns, whereas that on ask-side orders has a significantly negative impact on market returns. Such findings are consistent with the view that market orders tend to be more aggressive and less patient than limit orders, and therefore have greater potential for moving asset prices (Harris, 1998). It is also noteworthy that the magnitude of the coefficients on the market order ratio (both for the bid side and ask side) for individual investors are much bigger (and highly statistically significant) than those of institutional investors. Combined with our findings that the market order choice for individual investors is much more highly influenced by market sentiment, Table 7 shows that the choice between market and limit orders for individual investors may be an important channel through which market sentiment affects market returns and volatility.

From Table 7, we further find that the impact of market order ratios is much stronger when measured on an intraday horizon than on a daily horizon. The magnitude and significance of the respective variables are much stronger for intraday analysis than for daily analysis. Even though the market order ratio for institutional investors is marginally significant at the daily level, it is highly significant at the intraday level. Such findings stress the importance of examining intraday changes in market order ratios when attempting to better understand the flash crash phenomenon due to panicky market sentiment.

Besides contemporaneous market order ratios, we also included the one-period lag in equation (4) to better assess the causality of the relationship and predictive power by lagged market order ratios. For both retail and institutional investors, the one-period lagged market order ratio on the bid side has a negative impact on next-period returns, in addition to the strong positive correlation between market returns and contemporaneous market order ratios. In contrast,
the coefficient on one-period lagged market order ratio is significantly positive, reducing the negative impact from the contemporaneous market order ratio on the ask side.

It is worth noting that, although the market order ratio for institutional investors on the bid side does not shift considerably in response to external shocks, the market order ratio on the ask side indeed responds to sentiment in a similar way as that of individual investors. This means that institutions can add additional selling pressure when prices start dropping and fear starts escalating. Hence, our findings again challenge the capacity of institutions to stabilize intraday price drops.

4.2 Transmission between TVIX and TAIEX

One potential motivation behind trading on the stock index TAIEX is that investors may take hedging positions in stock index futures TX, by tracking TVIX, or take synthetic arbitrage positions between TX and the spots markets in response to fluctuations in TVIX. As a result, market order ratios may be influenced by the TAIEX spot market, and in turn influence TVIX (because TVIX is calculated based on TAIEX put and call contract prices).

To examine such a confounding factor, we further perform regressions of the four market order ratios against TVIX and TAIEX price movement, given that we previously find that the four market order ratios have different impacts on TX returns. In particular, the regression specification in the daily data is as follows:

\[
\begin{align*}
RV_{\text{buy}}^{\text{sell}} &= \alpha_1 + \beta_{1,1}CPM + \beta_{1,2}TVIX + \epsilon_1, \\
RV_{\text{sell}}^{\text{buy}} &= \alpha_2 + \beta_{2,1}CPM + \beta_{2,2}TVIX + \epsilon_2, \\
RV_{\text{inst}}^{\text{buy}} &= \alpha_3 + \beta_{3,1}CPM + \beta_{3,2}TVIX + \epsilon_3, \\
RV_{\text{inst}}^{\text{sell}} &= \alpha_4 + \beta_{4,1}CPM + \beta_{4,2}TVIX + \epsilon_4,
\end{align*}
\]  

(5)

25 For the sake of simplicity, we omit the subscript “t”, representing the t-th observation from each of the variables and random errors in equation (5). The analogous setting is applied to the models (5) and (5*). In addition, the data before spot market open time (9:00 a.m.) and after spot market close time (1:30 p.m.) are omitted.
where \( RV_{ind}^{buy} \), \( RV_{ind}^{sell} \), \( RV_{inst}^{buy} \), and \( RV_{inst}^{sell} \) are market order ratios in volume of submissions, as defined previously, \( CPM \) is the contemporaneous price movement of the TAIEX measured in the natural logarithm to control the transmission, and \( TVIX \) is the daily close level to measure market sentiment. In intraday analysis, we replace the variables in model (5) with their corresponding variables at the 5-minute interval, and then label the resulting model (5*).

Panel A of Table 8 shows that even when we explicitly control for fluctuations in the TAIEX market, the changes in market order ratio over time depend on TAIEX returns and investor type. After we control for the impact of TAIEX returns on market order ratios, the findings are similar to those on market order ratios in Section 3. Individual investors tend to submit more market orders when the market is highly fearful, reflected by the positive coefficient of \( \hat{\beta}_{1,2} \) and \( \hat{\beta}_{2,2} \) (significant at the 1% level). In contrast, the patterns between market order ratios and market sentiment are slightly negative for institutional investors, as reflected by insignificant \( \hat{\beta}_{3,2} \) and \( \hat{\beta}_{4,2} \) in regression (5).

Panel B of Table 8 shows the results of the intraday analysis. Consistent with the daily results, individual investors submit more market orders during periods of market panic, as reflected by significantly positive \( \hat{\beta}_{1,2} \) and \( \hat{\beta}_{2,2} \). In contrast with the daily results, institutional investors also submit more market buy (sell) orders, when spot market is rising (falling), as reflected by \( \hat{\beta}_{3,1} \) (\( \hat{\beta}_{4,1} \)) being highly significant in (5*). That is, unlike the weaker influence of transmission mechanism on institutional investors’ market order choice at a daily horizon, institutional investors trade in a similar pattern to retail investors on an intraday basis. Accordingly, they may aggravate intraday volatility and reinforce a market slump during a relatively short time period.
In sum, we find that individual investors submit more market sell orders during highly fearful periods, even when controlling for market movement in the TAIEX spot market. Such selling by individual investors could potentially exacerbate a market slump and corresponding fluctuation. At the same time, institutional investors display the opposite trading pattern to the individual investors.

4.3. Market Order Choices, Order Imbalances, and Market Returns

Our above studies demonstrate that market sentiment has a strong influence on the market order choices made by both types of investors. This motivates us to study whether the changes in market order choices by different types of investors could provide additional help in explaining price movements through order imbalance, as documented in the extant literature (e.g., Easley et al., 1998; Chordia et al., 2002; Chordia and Subrahmanyam, 2004).

For the dependent variable, we define four different proxies for order imbalance,

\[ SV_{ind}^{mkt} = \text{sell}_{ind}^{mkt} - \text{buy}_{ind}^{mkt}, \quad \text{lim}_{ind} SV = \text{sell}_{ind}^{lim} - \text{buy}_{ind}^{lim}, \quad SV_{inst}^{mkt} = \text{sell}_{inst}^{mkt} - \text{buy}_{inst}^{mkt}, \]

\[ \text{lim}_{inst} SV = \text{sell}_{inst}^{lim} - \text{buy}_{inst}^{lim}, \]

in our daily analysis. Because market level trading volume and liquidity shift considerably over time, we normalize all daily order imbalances by the respective sum of the daily buy and sell order submissions.\(^{26}\) For example, the normalized market order imbalance in volume for individual investors is

\[ \text{sell}_{ind}^{mkt} SV_{norm}^{ind} = \frac{\text{sell}_{ind}^{mkt} SV_{ind} - \text{buy}_{ind}^{mkt} SV_{ind}}{\text{sell}_{ind}^{mkt} SV_{ind} + \text{buy}_{ind}^{mkt} SV_{ind}}. \]

To facilitate our analysis, we propose the following two-stage approach\(^{27}\):

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\(^{26}\) The results remain almost the same, indeed stronger, when we use the unadjusted order imbalance measures.

\(^{27}\) In unreported analysis, we include both the opening time trading period dummy (\(D_{\text{open}}\)) and the closing time trading period dummy (\(D_{\text{close}}\)) as independent variables in stage 1, which yields similar results. They can be obtained from the authors upon request.
Stage 1

\[ RV_{\text{buy}}^{\text{ind}} = \alpha_1 + \beta_{1,1} \text{SV}_{\text{norm}} + \beta_{1,2} \text{lim SV}_{\text{ind}} + \beta_{1,3} \text{SV}_{\text{norm}} + \beta_{1,4} \text{lim SV}_{\text{inst}} + \varepsilon_1, \]

\[ RV_{\text{sell}}^{\text{ind}} = \alpha_2 + \beta_{2,1} \text{SV}_{\text{norm}} + \beta_{2,2} \text{lim SV}_{\text{ind}} + \beta_{2,3} \text{SV}_{\text{norm}} + \beta_{2,4} \text{lim SV}_{\text{inst}} + \varepsilon_2, \]

\[ RV_{\text{buy}}^{\text{inst}} = \alpha_3 + \beta_{3,1} \text{SV}_{\text{norm}} + \beta_{3,2} \text{lim SV}_{\text{ind}} + \beta_{3,3} \text{SV}_{\text{norm}} + \beta_{3,4} \text{lim SV}_{\text{inst}} + \varepsilon_3, \]

\[ RV_{\text{sell}}^{\text{inst}} = \alpha_4 + \beta_{4,1} \text{SV}_{\text{norm}} + \beta_{4,2} \text{lim SV}_{\text{ind}} + \beta_{4,3} \text{SV}_{\text{norm}} + \beta_{4,4} \text{lim SV}_{\text{inst}} + \varepsilon_4, \]

Stage 2

\[ r = \alpha_5 + \beta_1 \text{SV}_{\text{norm}} + \beta_2 \text{lim SV}_{\text{ind}} + \beta_3 \text{SV}_{\text{norm}} + \beta_4 \text{lim SV}_{\text{inst}} + \beta_5 \text{SV}_{\text{norm}} + \beta_6 \text{lim SV}_{\text{inst}} + \beta_7 \text{SV}_{\text{norm}} + \beta_8 \text{lim SV}_{\text{inst}} + \varepsilon, \]  

where \( \varepsilon_1, \varepsilon_2, \varepsilon_3, \) and \( \varepsilon_4 \) are residuals obtained, respectively, by fitting the four regressions in Stage 1. Note that Stage 1 enables us to understand the relationship between market order ratios and order imbalances, while Stage 2 allows us to assess the incremental contribution of market order ratios on market returns, after removing the effects of order imbalances.

<<Insert Table 9 about Here>>

Panel A of Table 9 (Stage 1) reports that order imbalances and market order ratios are indeed highly related. However, the relationship between the two is very different for individual investors and institutional investors, and for market order imbalances as opposed to limit order imbalances. As for market orders, the market order ratio and individual investors’ order imbalance are closely related as evidenced by the adjusted R-squared in the regression being close to 40% in the intraday analysis. However, the relationship between market order ratio and order imbalance is less strong for institutional investors, with a much smaller adjusted R-squared of about 20%.

At the same time, the limit order imbalance does not have much explanatory power for market order ratios, especially in the daily analysis. Our discoveries are consistent with the extant literature that market orders have a greater price impact than do limit orders (Bae et al., 2003; Anand et al., 2005). In addition, our new findings reveal that market orders have a stronger
impact on the market during fearful market conditions than during calm market conditions. Individual investors, who submit more orders through market orders during market crashes, should hence be given more attention by researchers and regulators trying to better understand extreme volatility and market crashes.

The results in Panel B (Stage 2) of Table 9 show that, consistent with the literature, market-wide order imbalance is highly related to market returns. Except for the limit orders by retail investors, who are more likely to play the role of a liquidity trader (Lee et al., 2004), all three other order imbalances are positively related to market returns. These results hold at both the daily and intraday horizons. However, regression residuals from the first stage are different for the daily and intraday horizons. On the daily horizon, none of the four market order ratio residuals is significant, suggesting that most of the information in the market order ratios has already been captured by order imbalance.

In contrast, there is a distinct pattern at the intraday level. Three of the four coefficients on market order ratio residuals are highly significant, indicating that at this higher frequency, market order ratios have a separate and stronger influence on market returns. In addition, the information contained in investors’ order choices provides additional explanatory power for market returns.

Comparing the model in Stage 2 of equation (6) with its subset model by excluding the residuals, we find that the adjusted R-squared increases by about 50 percent (from 0.36 to 0.53 at the daily level and from 0.16 to 0.25 at the intraday level). This indicates that, in addition to order imbalance (which is known to the literature), the market order ratio itself has a distinct and considerable impact on asset prices, especially during volatile market conditions.

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28 Adjusted R-squared of 36% (16%) is obtained by fitting the daily (5-minute) data with the subset model. The detailed results are available from the authors upon request.
In sum, the above findings offer at least three important policy implications. First, individual investors’ choice of different order types can have a profound impact on market order imbalances. Second, market orders by institutional investors do not sufficiently reverse or alleviate the actions of individual investors and indeed can exacerbate market crashes at a high frequency intraday level. Finally, given that market order ratios may affect order imbalance and are known to influence returns, market orders and market order ratio may have a greater indirect impact on asset prices than limit orders do, especially during periods of market panic. We will formally investigate the last point in the next subsection.

4.4. Re-examination: Market Order Choices and Market Returns

Based on our previous analysis, we speculate that the order imbalances and market order ratios for different types of investors may have a different impact on market returns. To this end, we include contemporaneous and one-period lagged order imbalances and market order ratios for individual investors and institutional investors, respectively, in the regression model to assess their respective influence on asset returns. Specifically, we add order imbalance variables into equation (4) and yield the following model:

\[
 r_t = \alpha + \beta_{r,t-1} + \lambda_1 RV_{buy}^{ind,t} + \lambda_2 RV_{buy}^{ind,t-1} + \lambda_3 RV_{sell}^{ind,t} + \lambda_4 RV_{sell}^{ind,t-1} + \lambda_5 RV_{buy}^{inst,t} + \lambda_6 RV_{buy}^{inst,t-1} + \lambda_7 RV_{sell}^{inst,t} + \lambda_8 RV_{sell}^{inst,t-1} + \lambda_9 \text{norm}^{SV}_{ind,t} + \lambda_{10} \text{norm}^{SV}_{ind,t-1} + \lambda_{11} \text{norm}^{SV}_{ind,t} + \lambda_{12} \text{norm}^{SV}_{ind,t-1} + \lambda_{13} \text{norm}^{SV}_{ind,t} + \lambda_{14} \text{norm}^{SV}_{ind,t-1} + \lambda_{15} \text{norm}^{SV}_{ind,t} + \lambda_{16} \text{norm}^{SV}_{ind,t-1} + \epsilon_t. 
\]

Table 10 reports three interesting findings. First, order imbalances seem to have a stronger explanatory power than market order ratios, for both individual and institutional investors. Most of the coefficients on contemporaneous order imbalance variables are highly

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29 We estimate the Variance Inflation Factor (VIF) for the independent variables and there is no serious multicollinearity among independent variables.
significant and much bigger in magnitude than the coefficients on market order ratios. In addition, consistent with the extant literature, the contemporaneous order imbalance has stronger influence on returns than does the lagged order imbalance.

Second, market order ratios have a greater influence on market returns at the intraday horizon than at the daily horizon. The coefficients are significant for all four contemporaneous market order ratio variables in intraday analysis, confirming our previous finding that market order ratios have independent direct explanatory power for returns. In contrast, none of the coefficients on the market order ratios are significant at the 1% level on a daily basis. These results are consistent with our prior finding that market order ratios have a particularly strong impact on the market at the higher frequency.

Third, we notice an interesting reversal of sign for the coefficient on the market order ratio of individual investors. Whereas, in Table 6, we find that the bid-side market order ratio positively contributes to returns, the ask-side market order ratio negatively contributes to returns, for both individual and institutional investors. After including the order imbalance in equation (7), Table 10 shows that this pattern is reversed for individual investors: the bid-side market order ratio contributes negatively, and the ask-side market order ratio contributes positively to market returns, in opposition to our earlier findings. This result suggests that, once we control for the interaction between order imbalances and market order ratios, the latter can indeed attenuate some of the impact of order imbalances on market returns.

In sum, our above findings reveal that market order ratios, especially those of retail investors, are highly related to order imbalances for each respective investor type. On one hand, this influence may be caused by the same source, i.e., market sentiment. On the other hand, it seems that market order ratios alone have strong explanatory power for order imbalances,
implying that individual investors’ choice between different types of order submissions is related to their intention to move in or out of the market, especially at the high frequency daily horizon. Our findings call for attention to the importance of order type choice, especially by individual investors. In short, market order ratios at different horizons and by different types of investors can be very different, and some market order ratios can have an important influence on determining intraday order imbalance and price movements.

5. CONCLUSIONS

Recently, the finance literature has paid increasing attention to understanding the impact of sentiment. In this study, we demonstrate how sentiment influences financial markets. By assembling a unique dataset of trades, orders, and quotes on the TAIEX futures from Taiwan, we show that individual investors and institutional investors choose different types of orders (market vs. limit orders) to trade during periods of market turmoil. Individual investors are more likely to trade through market orders, and submit more sell orders through market order during fearful market conditions. In contrast, institutional investors’ choices between market and limit orders are minimally influenced by market sentiment. In some cases on a daily basis, institutional trades can be counter-individual traders and stabilize the market.

We also show that, although the sentiment’s impact on the aggregate order type choice may be muted, sentiment has considerable impact on the order type choice by separate groups of investors, especially during market panics. In turn, the order type choice and order imbalance by individual and institutional investors separately contributes to asset price formation over time.

In conclusion, our results demonstrate that, other than information and liquidity considerations, the composition of investor types within a market can also influence market volatility and the tendency to experience extreme market price movements. Our findings indicate the importance of the effect of market sentiment on order submissions and order imbalances, as
practitioners emphasize. Accordingly, our novel discoveries on how sentiment affects market stability could allow regulators to be better prepared for preventing market crashes by using leading indicators other than the range of price decline.\textsuperscript{30}

\textsuperscript{30} One example of a stock exchange circuit breaker tied to price decline is the NYSE’s Rule 80B (Trading Halts Due to Extraordinary Market Volatility): The trigger levels for a market-wide trading halt are set at 10\%, 20\% and 30\% of the DJIA, calculated at the beginning of each calendar quarter, using the average closing value of the DJIA for the prior month, thereby establishing specific point values for the quarter. Each trigger value is rounded to the nearest 50 points. The halt for a 10\% decline is one hour if it occurs before 2 p.m., 30 minutes if it occurs between 2 p.m. and 2:30 p.m., and no halt at all if it occurs after 2:30 p.m. The halt for a 20\% decline is two hours if it occurs before 1 p.m., one hour if it occurs between 1 p.m. and 2 p.m., and covers the rest of the day if it occurs after 2 p.m. If the market declines by 30\% at any time, trading is halted for the remainder of the day.
References

- 33 -
Appendix. Parameter Estimations and Model Assumptions in Regression Analysis

To take heteroscedasticity and autocorrelation into account, we consider the method of Generalized Method of Moments (GMM) for daily and intraday analysis (e.g., Bodurtha and Mark, 1991; Wei and Chiang, 2004) in models (1), (2), (5), and (6). Specifically, we employ the GMM approach to first estimate the regression coefficients and then their resulting asymptotic covariance matrix is estimated via the Newey and West (1987) method. Subsequently, we compute their corresponding t-statistics for testing each coefficient. It is noteworthy that GMM makes no strong distributional assumptions. In model (1), for example, we assume that the orthogonality conditions are satisfied (i.e., $E[D_{AS} \cdot \varepsilon = 0], E[D_{TVIX} \cdot \varepsilon = 0]$, and $E[TVIX \cdot \varepsilon = 0]$).

In addition, we assume that the variance of the vector of random errors with length N (the sample size) is a positive definite matrix, which allows for the possibility of heteroscedasticity or an AR(1) process (e.g., see Tsai, 1986). The methodology is also referred to as OLS with Newey-West standard errors (Greene, 2002).

To avoid a sample selection bias, we also fit the sample selection models (Heckman, 1979; Heckman et al., 1997; Heckman et al., 1998) for individual and institutional investors (model (3)), respectively. In short, the selection models include an observation if and only if the latent endogenous variable is greater than 0 and the selection equation provides such an indication. Note that the sample bias is especially important for institutional investors because their market order ratio is particularly low, and there are 5-minute intervals with no market orders submitted by institutional investors. Finally, we use the packages in R to conduct all analyses, including the gmm package (Chaussé, 2010), the sampleSelection package (Toomet and Henningsen, 2008), and the dynlm package (Chapter 3 of Kleiber and Zeileis, 2008).
Table 1. Basic Statistics of Daily Order Submissions of TX Contracts

This table presents the basic statistics of daily order submissions of individual investors, institutional investors, and the entire market, respectively. The period covers January 2nd, 2007 through December 31st, 2009 (747 trading days).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Trader Type</th>
<th>Bid Side</th>
<th></th>
<th>Ask Side</th>
<th></th>
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<td></td>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Standard Deviation</td>
<td>Max</td>
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<td>Volume of Market Order Submissions</td>
<td>Individual Investors</td>
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<td>12324</td>
<td>5498</td>
<td>44089</td>
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<td>Institutional Investors</td>
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<td>523</td>
<td>779</td>
<td>17287</td>
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<td></td>
<td>Entire Market</td>
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<tr>
<td>Volume of Limit Order Submissions</td>
<td>Individual Investors</td>
<td>70263</td>
<td>64695</td>
<td>29388</td>
<td>156172</td>
</tr>
<tr>
<td></td>
<td>Institutional Investors</td>
<td>108247</td>
<td>98012</td>
<td>57626</td>
<td>289584</td>
</tr>
<tr>
<td></td>
<td>Entire Market</td>
<td>178509</td>
<td>165930</td>
<td>82624</td>
<td>404210</td>
</tr>
<tr>
<td>Market Order Ratio in Volume of Submissions</td>
<td>Individual Investors</td>
<td>15.55%</td>
<td>15.55%</td>
<td>0.05%</td>
<td>50.55%</td>
</tr>
<tr>
<td></td>
<td>Institutional Investors</td>
<td>0.70%</td>
<td>0.52%</td>
<td>0.88%</td>
<td>17.49%</td>
</tr>
<tr>
<td></td>
<td>Entire Market</td>
<td>7.34%</td>
<td>7.12%</td>
<td>2.01%</td>
<td>28.21%</td>
</tr>
<tr>
<td>Number of Market Order Submissions</td>
<td>Individual Investors</td>
<td>6590</td>
<td>6416</td>
<td>2996</td>
<td>36158</td>
</tr>
<tr>
<td></td>
<td>Institutional Investors</td>
<td>184</td>
<td>134</td>
<td>281</td>
<td>6431</td>
</tr>
<tr>
<td></td>
<td>Entire Market</td>
<td>6774</td>
<td>6573</td>
<td>3070</td>
<td>36261</td>
</tr>
<tr>
<td>Number of Limit Order Submissions</td>
<td>Individual Investors</td>
<td>30931</td>
<td>29229</td>
<td>13055</td>
<td>69100</td>
</tr>
<tr>
<td></td>
<td>Institutional Investors</td>
<td>38287</td>
<td>31294</td>
<td>26210</td>
<td>136246</td>
</tr>
<tr>
<td></td>
<td>Entire Market</td>
<td>69218</td>
<td>62376</td>
<td>37569</td>
<td>188533</td>
</tr>
<tr>
<td>Market Order Ratio in Number of Submissions</td>
<td>Individual Investors</td>
<td>17.64%</td>
<td>17.32%</td>
<td>2.93%</td>
<td>67.78%</td>
</tr>
<tr>
<td></td>
<td>Institutional Investors</td>
<td>0.65%</td>
<td>0.42%</td>
<td>1.21%</td>
<td>25.52%</td>
</tr>
<tr>
<td></td>
<td>Entire Market</td>
<td>9.64%</td>
<td>9.70%</td>
<td>2.79%</td>
<td>47.22%</td>
</tr>
</tbody>
</table>

Table 2. Summary Statistics for TVIX, Daily Close Level

This table presents summary statistics for the daily close level of the Taiwan Volatility Index (TVIX) during the sample period, from January 2, 2007 through December 31, 2009, a total of 747 trading days.

<table>
<thead>
<tr>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>5th Percentile</th>
<th>20th Percentile</th>
<th>40th Percentile</th>
<th>60th Percentile</th>
<th>80th Percentile</th>
<th>95th Percentile</th>
<th>Max</th>
<th>Coef. of Skewness</th>
<th>Coef. of Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>29.796</td>
<td>29.390</td>
<td>9.048</td>
<td>11.740</td>
<td>15.896</td>
<td>21.616</td>
<td>27.496</td>
<td>31.542</td>
<td>36.844</td>
<td>44.602</td>
<td>60.410</td>
<td>0.440</td>
<td>0.222</td>
</tr>
</tbody>
</table>
Table 3. Market Order Ratio and TVIX

This table presents the relationship between market order ratio and TVIX for individual investors, institutional investors, and the entire market, respectively. Panel A presents the coefficients of correlation between market order ratios and TVIX, measured daily and at 5-minute intervals. For 5-minute interval analysis, each of the 747 trading days is divided into 60 5-minute intervals between 8:45 a.m. and 1:45 p.m., allowing for 61 intraday observations. Panel B presents market order ratio average by TVIX quintiles for individual investors, institutional investors, and the entire market, respectively. During the sample period (747 trading days), the 20th, 40th, 60th, and 80th percentiles in the daily close level of TVIX are 21.616, 27.496, 31.542, and 36.844, respectively. These 4 values divide the trading days into quintiles in panel B, and market order ratio averages of each quintile, $P_1$, $P_2$, $P_3$, $P_4$, and $P_5$ are shown. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Coefficients of Correlation between Market Order Ratios and TVIX

<table>
<thead>
<tr>
<th></th>
<th>Individual Investors</th>
<th>Institutional Investors</th>
<th>Entire Market</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bid Side</td>
<td>Ask Side</td>
<td>Bid Side</td>
</tr>
<tr>
<td></td>
<td>In Volume of</td>
<td>In Number of Submissions</td>
<td>In Volume of</td>
</tr>
<tr>
<td>Daily (N=747)</td>
<td></td>
<td></td>
<td>Submissions</td>
</tr>
<tr>
<td>0.237</td>
<td>0.129</td>
<td>0.330</td>
<td>0.197</td>
</tr>
<tr>
<td>0.106</td>
<td>0.055</td>
<td>0.138</td>
<td>0.076</td>
</tr>
<tr>
<td>5-minute (N=45,567)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B. Market Order Ratio Average by TVIX Quintiles

<table>
<thead>
<tr>
<th></th>
<th>Individual Investors</th>
<th>Institutional Investors</th>
<th>Entire Market</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bid Side</td>
<td>Ask Side</td>
<td>Bid Side</td>
</tr>
<tr>
<td>$P_1$, TVIX&lt;21.616 (N=150)</td>
<td>13.87%</td>
<td>0.88%</td>
<td>0.98%</td>
</tr>
<tr>
<td>$P_2$, 21.616&lt;=TVIX&lt;27.496 (N=149)</td>
<td>15.54%</td>
<td>0.57%</td>
<td>0.58%</td>
</tr>
<tr>
<td>$P_3$, 27.496&lt;=TVIX&lt;31.542 (N=149)</td>
<td>16.53%</td>
<td>0.62%</td>
<td>0.65%</td>
</tr>
<tr>
<td>$P_4$, 31.542&lt;=TVIX&lt;36.844 (N=149)</td>
<td>15.86%</td>
<td>0.61%</td>
<td>0.60%</td>
</tr>
<tr>
<td>$P_5$, TVIX&gt;=36.844 (N=150)</td>
<td>15.97%</td>
<td>0.84%</td>
<td>0.93%</td>
</tr>
<tr>
<td>$P_5 - P_1$</td>
<td>2.10%</td>
<td>-0.04%</td>
<td>-0.05%</td>
</tr>
<tr>
<td>t value</td>
<td>4.978***</td>
<td>8.369***</td>
<td>-0.254</td>
</tr>
</tbody>
</table>
### Table 4. Market Order Ratio and Market Sentiment

This table presents the daily and intraday analysis of market order and market sentiment for individual and institutional investors, respectively. We present parameter estimates and the corresponding t values by fitting the data with GMM. For daily data, the regression specifications in Panel A are:

\[
\begin{align*}
\text{in\_mkt\_RV} &= \alpha_1 + \beta_{1,1} D_{A5} + \beta_{1,2} D_{A5} TVIX + \beta_{1,3} TVIX + \epsilon, \\
\text{inst\_mkt\_RV} &= \alpha_2 + \beta_{2,1} D_{A5} + \beta_{2,2} D_{A5} TVIX + \beta_{2,3} TVIX + \eta,
\end{align*}
\]

where \( \text{in\_mkt\_RV} \) (\( \text{inst\_mkt\_RV} \)) is the market order ratio in volume of submissions submitted by individual (institutional) investors, \( D_{A5} \) is the ask side dummy, and \( TVIX \) is the close level of the trading day (5-minute interval).

For intraday data, the regression specifications in panel B are:

\[
\begin{align*}
\text{in\_mkt\_RV} &= \alpha_1 + \beta_{1,1} D_{open} + \beta_{1,2} D_{close} + \beta_{1,3} D_{A5} + \beta_{1,4} D_{A5} TVIX + \beta_{1,5} TVIX + \epsilon, \\
\text{inst\_mkt\_RV} &= \alpha_2 + \beta_{2,1} D_{open} + \beta_{2,2} D_{close} + \beta_{2,3} D_{A5} + \beta_{2,4} D_{A5} TVIX + \beta_{2,5} TVIX + \eta.
\end{align*}
\]

where \( \text{in\_mkt\_RV} \) (\( \text{inst\_mkt\_RV} \)) is the market order ratio in volume of submissions submitted by individual (institutional) investors, \( D_{open} \) is the opening time trading period dummy, \( D_{close} \) is the closing time trading period dummy, \( D_{A5} \) is the ask side dummy, and \( TVIX \) is the close level in the 5-minute interval data. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

#### Panel A. Daily Results

<table>
<thead>
<tr>
<th></th>
<th>Individual Investors</th>
<th>Institutional Investors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.1254</td>
<td>0.0094</td>
</tr>
<tr>
<td>( \beta_{1,1} )</td>
<td>-0.0094</td>
<td>0.0126</td>
</tr>
<tr>
<td>( \beta_{1,2} )</td>
<td>0.0005</td>
<td>0.0004</td>
</tr>
<tr>
<td>( \beta_{1,3} )</td>
<td>0.0012</td>
<td>0.0003</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Panel B. Intraday Results

<table>
<thead>
<tr>
<th></th>
<th>Individual Investors</th>
<th>Institutional Investors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.1138</td>
<td>0.0032</td>
</tr>
<tr>
<td>( \beta_{1,1} )</td>
<td>-0.0245</td>
<td>0.0011</td>
</tr>
<tr>
<td>( \beta_{1,2} )</td>
<td>0.0543</td>
<td>0.0016</td>
</tr>
<tr>
<td>( \beta_{1,3} )</td>
<td>-0.0046</td>
<td>0.0044</td>
</tr>
<tr>
<td>( \beta_{1,4} )</td>
<td>0.0004</td>
<td>0.0002</td>
</tr>
<tr>
<td>( \beta_{1,5} )</td>
<td>0.0014</td>
<td>0.0001</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.0002

- 39 -
Table 5. Sample Selection Models: Intraday Market Order Ratio and Market Sentiment with the State of the Limit Order Book, by Investor Type

This table presents results by fitting sample selection models (3) (Heckman, 1979; Heckman et al., 1997; Heckman et al., 1998). For example, the following regression equation and selection equation are fitted for individual investors.

Selection eq. \[ \hat{m}_{it} PV_{it} = \hat{\lambda}_i + \gamma_{1it} D_{open} + \gamma_{1it} D_{close} + \gamma_{1it} spread + \gamma_{1it} bdep + \gamma_{1it} adel + \eta. \]

Regression eq. \[ \hat{o}_{it} RV_{it} = \alpha_i + \beta_{1it} D_{open} + \beta_{1it} D_{close} + \beta_{1it} D_{ask} + \beta_{1it} D_{ask} TVIX + \beta_{1it} TVIX + \epsilon. \]

where \( \hat{o}_{it} RV_{it} \) is the market order ratio in volume of submissions submitted by individual investors, \( D_{open} \) is the opening time trading period dummy, \( D_{close} \) is the closing time trading period dummy, \( D_{ask} \) is the ask side dummy, and \( TVIX \) is the close level of the 5-minute interval in the regression equation.

In the selection equation, \( \hat{m}_{it} PV_{it} \) is the latent endogenous variable for individual investors, under market conditions of \( D_{open} \), \( D_{close} \), \( spread \), \( bdep \), and \( adel \), such that \( \hat{m}_{it} PV_{it} = 1 \) if \( \hat{m}_{it} PV_{it}^* > 0 \) and \( \hat{m}_{it} PV_{it} = 0 \) otherwise; \( spread \) is the quoted spread in index points. For ask (bid) side market order ratios, we further define \( bdep \), the difference between the depths resulted from their corresponding best ask (bid) and bid (ask) prices, and \( adel \), the difference between the two sums of the 2nd to 5th depths resulted from their corresponding bid (ask) and ask (bid) prices. Detailed estimation procedures can be found in Greene (2002) and Toomet and Henningsen (2008). The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>Individual Investors</th>
<th>Institutional Investors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel A. Regression Equation</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>( \hat{\alpha}_1 ) &amp; 0.1177 &amp; 0.0013 &amp; 87.487*** &amp; 0.0317 &amp; 0.0012 &amp; 27.056***</td>
<td></td>
</tr>
<tr>
<td>( \hat{\beta}_{1,1} ) &amp; -0.0247 &amp; 0.0011 &amp; -22.164*** &amp; 0.0142 &amp; 0.0008 &amp; 17.751***</td>
<td></td>
</tr>
<tr>
<td>( \hat{\beta}_{1,2} ) &amp; 0.0536 &amp; 0.0011 &amp; 48.085*** &amp; 0.0150 &amp; 0.0008 &amp; 19.230***</td>
<td></td>
</tr>
<tr>
<td>( \hat{\beta}_{1,3} ) &amp; -0.0015 &amp; 0.0019 &amp; -0.799 &amp; 0.0017 &amp; 0.0014 &amp; 1.151</td>
<td></td>
</tr>
<tr>
<td>( \hat{\beta}_{1,4} ) &amp; 0.0003 &amp; 0.0001 &amp; 4.442*** &amp; -0.0001 &amp; 0.0000 &amp; -1.821</td>
<td></td>
</tr>
<tr>
<td>( \hat{\beta}_{1,5} ) &amp; 0.0010 &amp; 0.0000 &amp; 23.925*** &amp; -0.0003 &amp; 0.0000 &amp; -9.609***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel B. Selection Equation</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>( \hat{\lambda}_1 ) &amp; 2.5700 &amp; 0.0174 &amp; 148.062*** &amp; 0.0243 &amp; 0.0045 &amp; 5.407***</td>
<td></td>
</tr>
<tr>
<td>( \hat{\gamma}_{1,1} ) &amp; 0.1105 &amp; 0.0728 &amp; 1.518 &amp; 0.2947 &amp; 0.0172 &amp; 17.138</td>
<td></td>
</tr>
<tr>
<td>( \hat{\gamma}_{1,2} ) &amp; 0.4745 &amp; 0.1120 &amp; 4.238 &amp; 0.4988 &amp; 0.0178 &amp; 28.098</td>
<td></td>
</tr>
<tr>
<td>( \hat{\gamma}_{1,3} ) &amp; -0.0001 &amp; 0.0001 &amp; -1.526 &amp; -0.0001 &amp; 0.0000 &amp; -2.422</td>
<td></td>
</tr>
<tr>
<td>( \hat{\gamma}_{1,4} ) &amp; -0.0008 &amp; 0.0002 &amp; -3.908*** &amp; -0.0004 &amp; 0.0001 &amp; -3.637***</td>
<td></td>
</tr>
<tr>
<td>( \hat{\gamma}_{1,5} ) &amp; -0.0013 &amp; 0.0001 &amp; -9.683 &amp; -0.0011 &amp; 0.0001 &amp; -19.575***</td>
<td></td>
</tr>
</tbody>
</table>
Table 6. Size of Market and Limit Orders by Investor Type

This table presents size of market and limit orders average by bid and ask sides for individual investors and institutional investors, respectively. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Individual Investors</th>
<th></th>
<th>Institutional Investors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bid Side</td>
<td>Ask Side</td>
<td></td>
<td>Bid Side</td>
</tr>
<tr>
<td></td>
<td>Market</td>
<td>Limit</td>
<td>Market</td>
<td>Limit</td>
</tr>
<tr>
<td>Order Size</td>
<td>1.956</td>
<td>2.312</td>
<td>1.965</td>
<td>2.465</td>
</tr>
<tr>
<td>Difference</td>
<td>-0.356</td>
<td>-0.500</td>
<td>0.838</td>
<td>0.940</td>
</tr>
<tr>
<td>t-value</td>
<td>-23.634  ***</td>
<td>-25.990 ***</td>
<td>12.492 ***</td>
<td>13.038 ***</td>
</tr>
</tbody>
</table>

Table 7. Price Movement, Contemporaneous and Lagged Market Order Ratio

This table presents results of a regression of price movement against contemporaneous and lagged buy/sell market order ratio on a daily and an intraday (5-minute) basis, respectively. The regressions are specified as:

\[ r_t = \alpha + \beta r_{t-1} + \lambda_{1,1} RV_{buy,t-1} + \lambda_{1,2} RV_{buy,ind,t-1} + \lambda_{1,3} RV_{sell,t-1} + \lambda_{1,4} RV_{sell,ind,t-1} + \lambda_{1,5} RV_{buy,inst,t} + \lambda_{1,6} RV_{buy,inst,t-1} + \lambda_{1,7} RV_{sell,inst,t} + \lambda_{1,8} RV_{sell,inst,t-1} + \varepsilon_t, \]

where \( r_t \) is contemporaneous price movement, \( RV_{buy,ind,t} \) (\( RV_{sell,ind,t} \)) is contemporaneous market order ratio in volume of submissions of individual investors on bid (ask) side, and the subscript \( t-1 \) denotes a one-period lag.

In addition, we assume that \( \varepsilon_t \) are independent and identically distributed according to a normal distribution with mean zero and constant variance for \( t=1,...,N \). The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Daily Data</th>
<th></th>
<th>Intraday Data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
<td>t value</td>
<td>Estimate</td>
</tr>
<tr>
<td>^\alpha</td>
<td>-0.001691</td>
<td>0.003754</td>
<td>-0.450</td>
<td>0.000098</td>
</tr>
<tr>
<td>^\beta</td>
<td>0.003459</td>
<td>0.036777</td>
<td>0.094</td>
<td>-0.035320</td>
</tr>
<tr>
<td>^\lambda_{1,1}</td>
<td>0.354215</td>
<td>0.024275</td>
<td>14.592</td>
<td>0.009756</td>
</tr>
<tr>
<td>^\lambda_{1,2}</td>
<td>-0.096886</td>
<td>0.026232</td>
<td>-3.693</td>
<td>-0.001896</td>
</tr>
<tr>
<td>^\lambda_{1,3}</td>
<td>-0.314588</td>
<td>0.022362</td>
<td>-14.068 ***</td>
<td>-0.009225</td>
</tr>
<tr>
<td>^\lambda_{1,4}</td>
<td>0.070698</td>
<td>0.025507</td>
<td>2.772</td>
<td>0.002244</td>
</tr>
<tr>
<td>^\lambda_{1,5}</td>
<td>0.089858</td>
<td>0.049743</td>
<td>1.806</td>
<td>0.005658</td>
</tr>
<tr>
<td>^\lambda_{1,6}</td>
<td>0.048769</td>
<td>0.050946</td>
<td>0.957</td>
<td>-0.000713</td>
</tr>
<tr>
<td>^\lambda_{1,7}</td>
<td>0.118651</td>
<td>0.042714</td>
<td>2.778</td>
<td>-0.005201</td>
</tr>
<tr>
<td>^\lambda_{1,8}</td>
<td>-0.116869</td>
<td>0.042684</td>
<td>-2.738</td>
<td>0.001536</td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.3816  Adjusted R-squared: 0.2010
Table 8. Market Order Ratio, TAIEX returns, and Market Sentiment

This table presents results of a regression of order imbalance against market sentiment on a daily basis. The regressions are specified as:

\[
RV_{\text{buy}} = \alpha_1 + \beta_1 CPM + \beta_2 TVIX + \epsilon_1,
\]
\[
RV_{\text{sell}} = \alpha_2 + \beta_3 CPM + \beta_4 TVIX + \epsilon_2,
\]
\[
RV_{\text{buy}} = \alpha_3 + \beta_5 CPM + \beta_6 TVIX + \epsilon_3,
\]
\[
RV_{\text{sell}} = \alpha_4 + \beta_7 CPM + \beta_8 TVIX + \epsilon_4,
\]

where \(RV_{\text{buy}}, RV_{\text{sell}}, RV_{\text{buy}}\), and \(RV_{\text{sell}}\) are market order ratios, \(CPM\) is the contemporaneous price movement of TAIEX in natural logarithm, and \(TVIX\) is the close level. We present parameter estimates and the corresponding t values by fitting the data with GMM. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Daily Results by Investor Type

<table>
<thead>
<tr>
<th></th>
<th>Individual Investors</th>
<th>Institutional Investors</th>
<th>Institutional Investors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
<td>t value</td>
</tr>
<tr>
<td>(\hat{\alpha}_1)</td>
<td>0.137130</td>
<td>0.008155</td>
<td>16.814***</td>
</tr>
<tr>
<td>(\hat{\beta}_{1,1})</td>
<td>0.497880</td>
<td>0.077380</td>
<td>6.434***</td>
</tr>
<tr>
<td>(\hat{\beta}_{1,2})</td>
<td>0.000638</td>
<td>0.000260</td>
<td>2.452***</td>
</tr>
<tr>
<td>Adjusted R-squared:</td>
<td>0.08020</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B. Intraday Results by Investor Type

<table>
<thead>
<tr>
<th></th>
<th>Individual Investors</th>
<th>Institutional Investors</th>
<th>Institutional Investors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
<td>t value</td>
</tr>
<tr>
<td>(\hat{\alpha}_2)</td>
<td>0.114820</td>
<td>0.003179</td>
<td>36.114***</td>
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<tr>
<td>(\hat{\beta}_{2,1})</td>
<td>-0.680310</td>
<td>0.113060</td>
<td>-6.017***</td>
</tr>
<tr>
<td>(\hat{\beta}_{2,2})</td>
<td>0.001316</td>
<td>0.000299</td>
<td>4.403***</td>
</tr>
<tr>
<td>Adjusted R-squared:</td>
<td>0.08961</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.08961

Adjusted R-squared: -0.001019
Table 9. Price Movement, Order Imbalance and Market Order Ratio

In this table, we perform two stage regressions in daily and 5-minute data, respectively. Stage 1 controls for the effects of order imbalances, and Stage 2 shows the net effects of market order ratio on price movement. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Stage 1

\[
R_{\text{buy}}^{\text{inst}} = \alpha_1 + \lambda_{1,1} \text{mkt} \text{SV}_{\text{norm}}^{\text{inst}} + \lambda_{1,2} \lim \text{SV}_{\text{norm}}^{\text{inst}} + \lambda_{1,3} \text{mkt} \text{SV}_{\text{norm}}^{\text{inst}} + \lambda_{1,4} \lim \text{SV}_{\text{norm}}^{\text{inst}} + \epsilon_1, \\
R_{\text{sell}}^{\text{inst}} = \alpha_2 + \lambda_{2,1} \text{mkt} \text{SV}_{\text{norm}}^{\text{inst}} + \lambda_{2,2} \lim \text{SV}_{\text{norm}}^{\text{inst}} + \lambda_{2,3} \text{mkt} \text{SV}_{\text{norm}}^{\text{inst}} + \lambda_{2,4} \lim \text{SV}_{\text{norm}}^{\text{inst}} + \epsilon_2, \\
R_{\text{buy}}^{\text{ind}} = \alpha_3 + \lambda_{3,1} \text{mkt} \text{SV}_{\text{norm}}^{\text{ind}} + \lambda_{3,2} \lim \text{SV}_{\text{norm}}^{\text{ind}} + \lambda_{3,3} \text{mkt} \text{SV}_{\text{norm}}^{\text{ind}} + \lambda_{3,4} \lim \text{SV}_{\text{norm}}^{\text{ind}} + \epsilon_3, \\
R_{\text{sell}}^{\text{ind}} = \alpha_4 + \lambda_{4,1} \text{mkt} \text{SV}_{\text{norm}}^{\text{ind}} + \lambda_{4,2} \lim \text{SV}_{\text{norm}}^{\text{ind}} + \lambda_{4,3} \text{mkt} \text{SV}_{\text{norm}}^{\text{ind}} + \lambda_{4,4} \lim \text{SV}_{\text{norm}}^{\text{ind}} + \epsilon_4,
\]

Stage 2

\[r = \alpha_5 + \beta_1 \text{mkt} \text{SV}_{\text{norm}}^{\text{ind}} + \beta_2 \lim \text{SV}_{\text{norm}}^{\text{ind}} + \beta_3 \text{mkt} \text{SV}_{\text{norm}}^{\text{ind}} + \beta_4 \lim \text{SV}_{\text{norm}}^{\text{ind}} + \beta_5 \hat{\epsilon}_1 + \beta_6 \hat{\epsilon}_2 + \beta_7 \hat{\epsilon}_3 + \beta_8 \hat{\epsilon}_4 + \epsilon,
\]

where \( r \) is price movement of TX in natural logarithm, \( R_{\text{buy}}^{\text{inst}} \) (\( R_{\text{sell}}^{\text{inst}} \)) is market order ratio in volume of submissions of individual investors on bid (ask) side, \( R_{\text{buy}}^{\text{ind}} \) (\( R_{\text{sell}}^{\text{ind}} \)) is market order ratio in volume of submissions of institutional investors on bid (ask) side, \( \text{mkt} \text{SV}_{\text{norm}}^{\text{ind}}, \lim \text{SV}_{\text{norm}}^{\text{ind}}, \text{mkt} \text{SV}_{\text{norm}}^{\text{inst}}, \) and \( \lim \text{SV}_{\text{norm}}^{\text{inst}} \) are normalized order imbalances and \( \hat{\epsilon}_1, \hat{\epsilon}_2, \hat{\epsilon}_3, \) and \( \hat{\epsilon}_4 \) are residuals obtained, respectively, by fitting the four regressions in Stage 1.

Using Daily Data

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_1 )</td>
<td>0.1580</td>
<td>0.0030</td>
<td>52.553 ***</td>
<td>0.1509</td>
<td>0.0009</td>
</tr>
<tr>
<td>( \lambda_{1,1} )</td>
<td>0.1207</td>
<td>0.0356</td>
<td>3.386 ***</td>
<td>0.1273</td>
<td>0.0017</td>
</tr>
<tr>
<td>( \lambda_{1,2} )</td>
<td>-0.0752</td>
<td>0.0216</td>
<td>-3.478 ***</td>
<td>-0.0773</td>
<td>0.0087</td>
</tr>
<tr>
<td>( \lambda_{1,3} )</td>
<td>0.0062</td>
<td>0.0037</td>
<td>1.672 *</td>
<td>0.0023</td>
<td>0.0006</td>
</tr>
<tr>
<td>( \lambda_{1,4} )</td>
<td>0.0066</td>
<td>0.0097</td>
<td>0.685</td>
<td>0.0133</td>
<td>0.0061</td>
</tr>
<tr>
<td>Adjusted R-squared: 0.2213</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Using Intraday Data

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_2 )</td>
<td>0.1583</td>
<td>0.0028</td>
<td>55.701 ***</td>
<td>0.1531</td>
<td>0.0007</td>
</tr>
<tr>
<td>( \lambda_{2,1} )</td>
<td>-0.1990</td>
<td>0.0301</td>
<td>-6.609 ***</td>
<td>-0.1379</td>
<td>0.0016</td>
</tr>
<tr>
<td>( \lambda_{2,2} )</td>
<td>0.1471</td>
<td>0.0270</td>
<td>5.439 ***</td>
<td>0.1304</td>
<td>0.0065</td>
</tr>
<tr>
<td>( \lambda_{2,3} )</td>
<td>0.0062</td>
<td>0.0036</td>
<td>1.694 *</td>
<td>-0.0010</td>
<td>0.0005</td>
</tr>
<tr>
<td>( \lambda_{2,4} )</td>
<td>-0.0097</td>
<td>0.0138</td>
<td>-0.698</td>
<td>-0.0133</td>
<td>0.0041</td>
</tr>
<tr>
<td>Adjusted R-squared: 0.3950</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- 43 -
Table 9. Price Movement, Order Imbalance and Market Order Ratio (cont.)

<table>
<thead>
<tr>
<th></th>
<th>Estimate 1</th>
<th>Std. Error 1</th>
<th>t value 1</th>
<th>Estimate 2</th>
<th>Std. Error 2</th>
<th>t value 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_3$</td>
<td>-0.1385</td>
<td>0.0757</td>
<td>-1.830 *</td>
<td>-0.0217</td>
<td>0.0187</td>
<td>-1.164</td>
</tr>
<tr>
<td>$\lambda_{3,1}$</td>
<td>1.6675</td>
<td>0.3484</td>
<td>4.786 ***</td>
<td>1.3416</td>
<td>0.0756</td>
<td>17.737 ***</td>
</tr>
<tr>
<td>$\lambda_{3,2}$</td>
<td>-1.0908</td>
<td>0.2923</td>
<td>-3.733 ***</td>
<td>-1.1669</td>
<td>0.0667</td>
<td>-17.491 ***</td>
</tr>
<tr>
<td>$\lambda_{3,3}$</td>
<td>9.4512</td>
<td>2.6216</td>
<td>3.605 ***</td>
<td>6.2170</td>
<td>0.5462</td>
<td>11.382 ***</td>
</tr>
<tr>
<td>$\lambda_{3,4}$</td>
<td>-6.4590</td>
<td>3.6043</td>
<td>-1.792 *</td>
<td>-5.9661</td>
<td>0.6633</td>
<td>-8.994 ***</td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.2829

Panel B. Stage 2

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_4$</td>
<td>0.0119</td>
<td>0.0007</td>
<td>16.995 ***</td>
</tr>
<tr>
<td>$\lambda_{4,1}$</td>
<td>-0.0333</td>
<td>0.0242</td>
<td>-1.377</td>
</tr>
<tr>
<td>$\lambda_{4,2}$</td>
<td>-0.0240</td>
<td>0.0184</td>
<td>-1.301</td>
</tr>
<tr>
<td>$\lambda_{4,3}$</td>
<td>-0.0106</td>
<td>0.0018</td>
<td>-5.841 ***</td>
</tr>
<tr>
<td>$\lambda_{4,4}$</td>
<td>-0.0150</td>
<td>0.0131</td>
<td>-1.144</td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.1830

Adjusted R-squared: 0.2400

Adjusted R-squared: 0.0863
Table 10. Price Movement, Contemporaneous and Lagged Market Order Ratios, and Contemporaneous and Lagged Order Imbalances

In this table, we conduct a regression of price movement against lagged price movement, individual and institutional investors’ market order ratios, and lagged market order ratios in daily and 5-minute data, respectively. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

\[ r_t = \alpha + \beta r_{t-1} + \lambda_1 RV_{buy,ind,t} + \lambda_2 RV_{buy,inst,t} + \lambda_3 RV_{sell,ind,t} + \lambda_4 RV_{sell,inst,t} + \lambda_5 RV_{norm,ind,t-1} + \lambda_6 RV_{norm,inst,t-1} + \lambda_7 SV_{mkt,t} + \lambda_8 SV_{ind,t} + \lambda_9 SV_{norm,ind,t-1} + \lambda_{10} SV_{norm,inst,t-1} + \lambda_{11} limSV_{ind,t} + \lambda_{12} limSV_{inst,t} + \lambda_{13} imSV_{ind,t} + \lambda_{14} imSV_{norm,ind,t-1} + \lambda_{15} imSV_{norm,inst,t-1} + \lambda_{16} imSV_{norm,inst,t-1} + \epsilon_t, \]

where \( r_t \) is contemporaneous price movement of TX in natural logarithm, \( RV_{buy,ind,t} (RV_{sell,ind,t}) \) is contemporaneous market order ratio in volume of submissions of individual investors on bid (ask) side, \( RV_{buy,inst,t} (RV_{sell,inst,t}) \) is contemporaneous market order ratio in volume of submissions of institutional investors on bid (ask) side, \( SV_{mkt,t}, SV_{ind,t}, SV_{norm,ind,t}, SV_{norm,inst,t} \) and \( limSV_{ind,t}, limSV_{inst,t} \) are contemporaneously normalized order imbalances, and subscript \( t-1 \) denotes a one-period lag.

<table>
<thead>
<tr>
<th>Daily Data</th>
<th>Intraday Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>**</td>
<td>** Estimate</td>
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<tr>
<td>^</td>
<td>0.000391</td>
</tr>
<tr>
<td>^</td>
<td>-0.005925</td>
</tr>
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<td>^</td>
<td>-0.046935</td>
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<tr>
<td>^</td>
<td>0.057069</td>
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<tr>
<td>^</td>
<td>0.086139</td>
</tr>
<tr>
<td>^</td>
<td>-0.090914</td>
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<td>-0.062922</td>
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<td>^</td>
<td>0.059536</td>
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<td>^</td>
<td>0.124166</td>
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<td>^</td>
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<td>^</td>
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<td>-0.047743</td>
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<td>^</td>
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<td>0.018560</td>
</tr>
<tr>
<td>^</td>
<td>0.001411</td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.5328

Adjusted R-squared: 0.3255
Figure 1. TAIEX and TVIX Daily Close Level, December 1st, 2006~ December 31st, 2009