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The Imbalance-Based Trading Strategies on Taiwan Exchange Rate Market

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Abstract

The paper examines short-run exchange rate dynamics in a small open economy, Taiwan, based on the microstructure framework of foreign exchange markets. This study develops a contrarian imbalance-based trading strategy given the negative interaction between lagged order imbalances and current returns. We find that imbalance-based strategy with large order imbalance consistently outperforms the benchmark, and an asymmetry trading performance in the currency appreciations versus depreciations period. These results could interpret as reflecting the official intervention behavior. Furthermore, the performance of our daily strategies could dominate that of the intraday strategies. A nested causality approach, which examines the dynamic return-order imbalance relationship during the price-formation process, confirms the results.

JEL classification numbers: G12; G14; G15
Keywords: order imbalance, intraday, NTD/USD exchange rate, causality relation.

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1. Introduction

The paper examines short-run exchange rate dynamics in a small open economy, Taiwan with a managed floating exchange rate regime for local currency, i.e. the New Taiwan Dollar (NTD), based on the recent microstructure framework of foreign exchange markets where the main explanatory variable is the order imbalance. Given the significant and negative relationship between current returns and lagged order imbalances [18], which is possibly related to the price stabilization mechanism executed by Taiwan's central bank[2], we try to develop a contrarian imbalance-based trading strategy, and interpret the performance results as reflecting the intervention behavior. In addition, we use a nested causality approach, which examines the dynamic return-order imbalance relationship during the price-formation process, to explain the profitability results.

The exchange rate issue is essential for policy makers of small open economies for several reasons. First, the exchange rate is perhaps the most important asset price in the globalizing economy [39]. Osorio et al. [38] show that economies with a relatively greater contribution from exchange rate and equity movements in the overall financial conditions, such as Hong Kong, Taiwan, and Singapore, tend to experience greater volatility in GDP growth. Second, it is also important to note that exchange rate management and interventions occur mostly in emerging economies market participates and can actively use monetary regulation and operating practices [42].

Before the 1990s, the papers about the causes of exchange rate movements focus on macroeconomics arguments. Nonetheless, the asset market models of exchange rate with low frequency data on exchange rates and macroeconomic fundamentals cannot explain exchange rate movements in the short run. Therefore,

[2] Taiwan is an export-dependent economy with adopting a managed floating exchange rate system. Taiwan's central bank claim the NTD exchange rate is in principle guided by market mechanism, the Bank only steps in when there's excessive exchange volatility. As Taiwan central bank didn't provide details (the size and the time persistence) of its intervention activities, it's difficult to measure the accurate level and volatility of intervention effect. However, Yan and Shea [44] indirectly confirm the policy consideration, such as exchange rate stabilization, play an important role in influencing the NTD/USD exchange rate trend, and have driven the Taiwan's central bank to undertake significant intervention into the market. Furthermore, Wu et al. [43] adopt a monetary model with Balassa-Samuelson effects to investigate Taiwan's exchange rate policies since 1980. They found central bank adopted exchange rate stabilization policies during the post Asian financial crisis period, 1997:12–2010:06, which covered the sample period, 2008, of Chen et al. [17].

in the last decade, many papers about the models of exchange rate determination are based on market microstructure arguments. The main result of the new market microstructure approach is that order imbalance has the considerable explanatory power for exchange rate dynamics in the short term, from 5 minute to daily interval. Order imbalance, a measure of net buying pressure, is defined as the net of buyer-initiated and seller-initiated currency transactions [34].[3] The relationship between return dynamics and order imbalances comes from two channels of market micro-structure theory. First, an information channel emerges when market makers change price in response to order flows that may reflect private information.[4] [31] [20] [40] Second, an inventory-control channel emerges when market makers adjust price to control inventory risk due to order flows.[5] [5] Both channels indicate that buyer-initiated trades result in price increasing, while seller-initiated trades push price down.

In contrast to early work by Evans and Lyons [23], which describe the relation between exchange rate changes and order imbalance by OLS regression model, we propose a GARCH(1,1) model which can capture the time-variant property of the relation. Because of the evidence of time-varying liquidity in the foreign exchange market [24], the liquidity measured by the relation between price changes and order flows [3] through OLS regression model, which presumes that the variance of the samples is constant, might be revised. As liquidity depends on volatility, [15] [2] estimate market activity variable such as the intensity of quote arrivals on the conditional variance equation, we run the time-varying GARCH(1,1)

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[3] The definition of order imbalance for foreign exchange markets is similar to that for other financial markets. For example, [33] define the order imbalance as the net of buyer-initiated and seller-initiated equity transactions.

[4] According to the information-based channel in the field of foreign exchange rate, [8] distinguish two classes of traders: rational investors and unsophisticated customers. Rational investors represent all foreign exchange traders, such as dealers, hedge funds and of other actively traded funds, which have direct and full access to the trading platforms. Unsophisticated customers correspond to traders, such as industrial corporations or institutional investors, which do not have direct access to trading platforms. These traders must phone up dealer brokers to get trading prices and complete a transaction. Thus, there exists asymmetric information between foreign exchange traders, so that, order imbalances can have the information content.

[5] Regarding the liquidity channel in the field of foreign exchange rate, foreign exchange dealers are willing to absorb an excess demand (supply) of foreign currency from their customers only if compensated by a shift in the exchange rate. [8] [23]

model by simultaneously incorporating order imbalance in the conditional mean and variance equations to model NTD/USD dynamics and discuss whether the relationship between order imbalances and foreign exchange returns should consider the linkage with volatility.

Furthermore, due to the limited availability of high frequency foreign exchange trading data, studies analyzing profitability in intraday foreign exchange rarely exist.[6] In this study, we try to form a trading strategy based on the return-order imbalance relationship [18] to examine whether the imbalance-based trading strategy can earn a positive return and beat the open-to-close return on the daily and intraday basis. Moreover, because the relation between the price impact and the size in order flow/volume in the foreign exchange market is contentious[7], and previous studies [35] find that Taiwan's central bank tends to steps in the foreign exchange market when the exchange rate changes dramatically either in the appreciation or depreciation period, we are particularly interested in investigating whether larger order imbalances tend to produce better trading performance. We trade strategies based on three scenarios: 0%, 50% and 90% truncations of order imbalances.

Because prior literatures indicate a strong association between order imbalance and exchange rate return, it is also possible that the correlation between order flow and exchange rate movements comes from the opposite causality, with exchange rates movements driving order flow. Some studies investigate this possibility.[8] In this study, we follow Chen and Wu [10] nested causality approach

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[6] For example, Neely and Weller [37] examine the out-of-sample performance of intraday technical trading strategies selected using two methodologies, a genetic program and an optimized linear forecasting model. When transaction costs and trading hours are taken into account, they find no evidence of excess returns to the trading rules derived with either methodology. Nonetheless, Della Corte et al. [21] show that the currency volatility risk premium (VRP) has substantial predictive power for the cross section of currency returns. A portfolio of currencies (VRP) constructed by going long cheap volatility insurance currencies and short expensive volatility insurance currencies generates economically and statistically significant returns.

[7] Evans [22]) finds a strong positive relation between the price impact of order flow and trading volume in the foreign exchange market, which is consistent with the evidence from the stock market, for example, Chan and Fong [11] find that the order imbalance in large trade size categories affects the return more than in smaller size categories. However, Berger et al. [6] find that the price impact is inversely related to trading volume on an intraday basis in the foreign exchange market. Overall, the relation between the price impact of order flow and trading volume in the foreign exchange market is not clear.

[8] For example, Evans and Lyons [25] find that the influence of order flow on exchange rate

to identify the robust causal relation, including independency, the contemporaneous, unidirectional and feedback relations, between order imbalance and high frequency NTD/USD return. Constructing the causal relations between order imbalance and return may help us to figure out the main source of a profitable order imbalance based trading strategy.

The main results of the study are stated as follows. First, we employ a GARCH (1,1) model to confirm not only the impact of order imbalances on returns but also the impact of order imbalances on volatility. Moreover, the decreases in significance between volatility and order imbalance with shorter sample lengths implies that market maker (the central bank can be the candidate) have more dominate power in reducing the volatility via the order adjustments over a shorter time interval. Secondly, we find that all imbalance-based trading strategy yields a positive return, and the 90% truncation strategy consistently dominates the buy-and-hold strategy. The success of the contrarian trading strategy with larger order imbalance is a possible result from central bank using larger order intervention responses to the dramatic changes in NTD/USD. Our empirical finding appears to support Taiwan's central bank attempts to manage when there's excessive exchange volatility [35]. Besides, the existence of an asymmetry trading performance in the currency appreciations versus depreciations period appear to be consistent with the literature of an asymmetry in central bank foreign exchange intervention in Taiwan [18]. Finally, we find a unidirectional relationship from order imbalances to returns in our daily data, while a contemporaneous relationship between returns and order imbalances in our intraday data. This result could explain why our daily order imbalance strategies could dominate the intraday order imbalance strategies.

Our study relates to market microstructure argument of exchange rate determination and makes marginal contributions to the literature as follows. First of all, despite lacking of intervention details, we examine the imbalance-based trading strategy in the foreign exchange market, and interpret the performance results as reflecting intervention behavior. We argue that central bank's behavior in stabilizing exchange rates during the exchange rate dramatic changes plays a very

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survives intact after controlling for feedback trading; Danielsson and Love [19] also find that the influence becomes stronger after controlling for feedback trading.

important role in pricing, particularly in the appreciation period, and we could exploit this policy consideration to make profits by executing the contrarian trading strategy with larger imbalances. Secondly, since order flow data are usually available at daily frequencies, the direction of causation on an intraday basis is hard to prove. We use a specific intraday NTD/USD dataset to investigate the nested causality between order imbalances and returns. Fourthly, compared to previous high-frequency NTD/USD dynamics studies, our dataset covers recent trading records[9] while previous studies are limited to the trading records before 2001[10]. Our new dataset will be helpful for generating more reliable results on the intraday NTD/USD dynamics following the further liberalizing and maturing in the local foreign exchange market[11].

The remainder of this study is organized as follows. Section 2 describes data. Section 3 presents the dynamic relation between return, volatility and order imbalance. The trading strategy based on return-order imbalance relation is discussed in Section 4. Section 5 presents the dynamic causal relation between return and order imbalance. Section 6 concludes.

2. Data

We obtain our sample intraday dataset including the trade prices and volume on the interbank spot NTD/USD exchange rate at a 15-minute frequency from the Taipei Foreign Exchange Brokerage Inc. page on Reuters' screen.[12] Our sample covers 251 consecutive trading days, from 2 January 2008 through 31 December

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[9] Relevant literatures include [27] [29].

[10] Our dataset is the same as in Chen et al [17].

[11] In the past years, with further liberalizing in the Taipei foreign exchange market, the trading scale and the trading share of interbanks have grown rapidly. After deducting double counting on the part of interbank transactions, total net trading volume on spot NTD/USD exchange rate grew from US$ 759 billion in 2001 to US$ 2,455 billion in 2008. The interbank transactions as opposed to bank to non-bank customer transactions accounted for 68.9 percent of the total net turnover in 2008, while only 56.2 percent in 2001.

[12] The Taipei Foreign Exchange Brokerage Inc. is the larger of two brokerage firms at the Taipei interbank foreign exchange market. About 70% of the interbank FX transactions are matched by Taipei Foreign Exchange Brokerage Inc., which disclosures the trade information on the interbank spot NTD/USD exchange rate at a 15-minute frequency. However, since Feb. 12, 2010, the company disclosures the morning's transactions at noon and all day's transactions at pm 4 instead of spot information.

2008.

The NTD/USD exchange rate experienced a noticeable fluctuation for 2008[13]. Considering the central bank may use orders intervention responses to currency appreciations versus depreciations asymmetrically[14], we further explore how the market states influence the dynamic relations between order imbalance, volatility and return of intraday NTD/USD foreign exchange rates, and our trading performance. We segment the entire sample period into two sub-samples: NTD appreciation (i.e. USD depreciation) and NTD depreciation (i.e. USD appreciation) periods. There is no common definition of up and down markets. In this study, we follow Fabozzi and Francis [26] assignment algorithm to define bear and bull markets. The appreciation (depreciation) period is designated as those months with the average rate of monthly returns above (below) zero. Using the nonnegative criteria and maintaining a continuous empirical period, NTD appreciation period covers from 2 January 2008 to 30 June 2008, whereas NTD depreciation period covers from 1 July 2008 to 31 December 2008.[15] Figure 1 illustrates how to define two market periods.

The intraday returns of NTD/USD exchange rate are defined as logarithms of trade price change, $R_t = [\ln(P_t/P_{t-1})]\times 10000$,[16] where P_t denotes the spot NTD/USD exchange rate at the end of the 15-minute interval. The Taipei foreign exchange market opens from 9:00 to 16:00, with a lunch break from 12:00 to 14:00, from Mondays to Fridays. To maintain a continuous empirical series, we include the close-to-open or overnight returns. From the opening of the foreign exchange

13 The NT dollar against the US dollar started the year strong and hit a yearly high in March due to a weak US dollar, reflecting the impact of the US subprime mortgage crisis. From July onwards, due to some US big financial groups facing financial distress, US investors sold their foreign assets and repatriated the proceeds, causing the US dollar to become stronger in the international markets. The NT dollar against the US dollar depreciated. See Central Bank of the Republic of China (Taiwan) (2009) for details.

14 For example, Chen [18] confirms the existence of an asymmetry in central bank foreign exchange intervention responses to currency appreciations versus depreciations in Taiwan by identifying the structural exchange rate shocks using a structural VAR model. He finds the clear evidence that after March 1998, Taiwan’s central bank aggressively aimed at preventing the value of the NT dollar rising, while inactively reacted to the value of the NT dollar depreciating.

15 In the NTD appreciation period of our research, the rate of return on May 2008 do not exceed zero.

16 Considering the readability of our empirical results, the calculation of returns in this paper is scaled by hundredfold.

market through the closing, we get 20 return observations during a trading day, for a total of 20×251 days = 5,020 high frequency foreign exchange return observations in our sample. The 1st and the 13th observations of each trading day denote the close-to-open change and the morning close-to-afternoon open change, respectively.[17] The daily NTD/USD return is defined

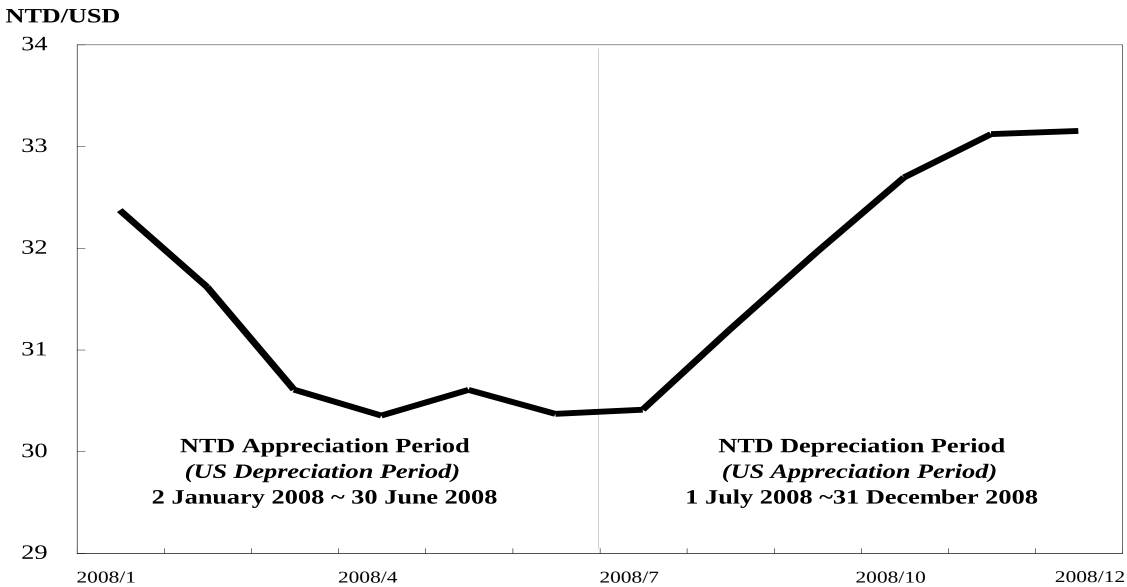

Figure 1. The NTD/USD exchange rate trend of the sample period

This figure describes the monthly spot NTD/USD exchange rate from 2 January 2008 through 31 December 2008. Based on the Fabozzi and Francis (1977) assignment algorithm, we define the bull and bear markets. The appreciation (depreciation) period is designated as those months with the average rate of monthly return above (below) zero. Using the nonnegative criteria and maintaining a continuous empirical period, NTD appreciation period covers from 2 January 2008 to 30 June 2008, whereas NTD depreciation period covers from 1 July 2008 to 31 December 2008.

as logarithms of the open-to-close change, $R_t = [\ln(P_{\text{closing of } t} / P_{\text{opening of } t})] \times 10000$.

To measure the intraday order imbalance, we segment the volume as either buyer-initiated or seller-initiated. Although our dataset does not indicate whether a trade is initiated by the buyer or the seller, nor does it provide intraday bid and ask

[17] Because the price information at 9:00 (morning opening) may contain more noise and tend to produce autocorrelated returns [41], and the Taipei Foreign Exchange Brokerage, Inc. does not disclosure the trade information at 14:00 (afternoon opening), the 1st and the 13th observations are calculated by previous day's close-to-9:15 changes and 12:00-to-14:15 changes, respectively.

quotes,[18] the availability of trade price data allows us to distinguish between buyer-initiated and seller-initiated trades. Following the tick rule adopted by Booth et al. (2002) [4], each trade will be identified as buyer- or seller-initiated by comparing the trade price to previous trade price. In this study, if a trade at the end of the 15-minute interval occurs at a price higher (lower) than the previous trade price, the corresponding 15-minute volume is classified as a buyer (seller)-initiated transaction. If order imbalance is designated as a buyer-initiated order, and it is the positive sign, and vice versa. Order imbalance and volume are measured in millions of U.S. dollars. Besides, we construct the measure of daily order imbalances, $OIBACC_t$. It is computed as the accumulation of 15-minute order imbalance over a-day window.

In Table 1, we present descriptive statistics of the 15-minute NTD/USD exchange rate return, absolute return, and the corresponding volume as well as order imbalance for the entire sample and two sub-samples. We report sample moments, and the normal distribution test statistics for relevant variables. The average 15- minute return in the entire period is close to zero (0.03%, scaled by hundredfold), whereas the average order imbalance is -US$ 0.78 millions. The average standard deviation of 15-minute order imbalance in the entire period is really high, reaching for US$ 80.52 million. For two sub-samples sorted by market states, the average 15-minute return in NTD (quotation in the basis of USD) appreciation period is –0.27% (scaled by hundredfold) while is 0.31% (scaled by hundredfold) in NTD depreciation period. In addition, volume and order imbalances in NTD appreciation period have greater fluctuations than those in NTD depreciation period.

3. Dynamic relation between return, volatility and order imbalance

In contrast to Evans and Lyons [22], which describe the relation between exchange rate returns and order imbalance by OLS regression model, we employ a

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[18] According to Lee and Ready [33] assignment algorithm, if a transaction occurs above the prevailing quote mid-point, it is regarded as a buyer-initiated trade and vice versa. If a transaction occurs exactly at the quote mid-point, it is signed using the previous transaction price according to the tick test (i.e., buys if the sign of the last non-zero price change is positive and vice versa).

GARCH(1,1) model by simultaneously incorporating order imbalance in the conditional mean and variance equations to investigate the short-run NTD/USD exchange rate dynamics. The reason using the GARCH (1,1) model is stated as follows. First, by the ARCH LM test, we find that there exists ARCH effect among residual series in the OLS regressions of intraday NTD/USD exchange return on the imbalances (The results are available upon request).

Table 1: Descriptive statistics of the intraday NTD/USD exchange rate return, absolute return, volume and order imbalance

The summary statistics represent the time-series statistics of the 15-minute NTD/USD exchange rate return, the absolute return, and the corresponding volume as well as order imbalance. The return is calculated as $[\ln(P_t/P_{t-1})]\times 10000$, where P_t denotes the spot exchange rate at the end of the 15-minute interval. The trading volume is segmented as buyer-initiated or seller-initiated to measure the order imbalance. If a trade at the end of the 15-minute interval occurs at a price higher (lower) than the previous trade price, the corresponding 15-minute volume is classified as a buyer (seller)-initiated transaction. If order imbalance is a buyer-initiated order, and it is the positive sign, and vice versa. Order imbalance and trading volume are measured in millions of U.S. dollars.

(i) Entire sample period: 2 January 2008 ~ 31 December 2008 (5,020 observations)

	Return	Absolute Return	Trading Volume	Order Imbalance
Mean	0.03	4.10	59.85	-0.78
Std. Dev.	7.62	6.43	53.87	80.52
Skewness	0.08	5.45	3.53	-0.49
Kurtosis	34.28	51.33	28.32	10.59

(ii) NTD appreciation period: 2 January 2008 ~ 30 June 2008 (2,440 observations)

	Return	Absolute Return	Trading Volume	Order Imbalance
Mean	-0.27	4.00	65.83	-0.32
Std. Dev.	7.03	5.79	60.80	89.62
Skewness	-1.28	4.94	3.91	-0.64
Kurtosis	27.60	43.74	30.80	11.89

(iii) NTD depreciation period: 1 July 2008 ~ 31 December 2008 (2,580 observations)

	Return	Absolute Return	Trading Volume	Order Imbalance
Mean	0.31	4.20	54.19	-1.21
Std. Dev.	8.14	6.98	45.67	70.86
Skewness	0.87	5.62	2.26	-0.20
Kurtosis	36.64	52.20	11.49	5.62

Second, the GARCH (1,1) model is often used as describing high-frequency foreign exchange rate dynamics in the empirical studies such as Chang and Taylor [9]; Andersen et al. [1]. Third, the time-varying liquidity evidence in the foreign exchange market [23] implies the liquidity measured by the relation between price changes and order flows [3] in a linear model might be revised. As liquidity depends on volatility [15], and Bollerslev and Domowits [2] estimate market activity variable such as the intensity of quote arrivals on the conditional variance equation, we run a GARCH(1,1) model to capture the time-variant property of relation.

According to the approach in Huang et al [30] [19], the dynamic return-volatility-order imbalance GARCH (1,1) model is specified as follow,

$$R_t = \alpha_0 + \alpha_1 OI_t + \alpha_2 OI_{t-1} + \alpha_3 R_{t-1} + \alpha_4 \varepsilon_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t \,|\, \Omega_{t-1} \sim N(0, h_t) \tag{2}$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \beta_3 OI_{t-1} \tag{3}$$

In equation (1), R_t denotes the 15-minute logarithms returns of spot NTD/USD exchange rate, as previously defined. Based on the effect of autocorrelated order imbalances [31] [28], we include the contemporaneous and lagged-one order imbalances (labeled OI) as explanatory variables to capture intraday return. In equation (2), the disturbances ε_t are modeled as normally distributed conditional on the information set Ω_{t-1} available at time t-1, with zero mean and variance h_t. The variance h_t in equation (3) depends on the lagged conditional variance h_{t-1}, past disturbance ε_{t-1}, and lagged-one order imbalance, where β_3 is the coefficient describing the impacts of order imbalance on exchange rate volatility.

By the ARCH LM test in the GARCH (1,1) model, we find that there does not exist ARCH effect among residual series (The results are available upon request). Thus, the GARCH (1,1) model could resolve the weakness embedded in the OLS regression model. Parameter estimates of the GARCH (1,1) model are reported in Table 2 for the entire period and two sub-samples. There are some findings for all three samples. The current intraday order imbalances have significantly positive relations with NTD/USD returns for all samples. Moreover, all our samples have significantly positive relations between volatility and order imbalances, implying

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[19] Huang et al [30] have found some evidences between order imbalances and returns in U.S. stock markets.

that higher order imbalances cause higher volatility.

Table 2: The dynamic relationships between order imbalances, volatility and returns of intraday NTD/USD exchange rates

This table presents the coefficients from GARCH (1,1) models for the intraday returns of NTD/USD exchange rate.

$$R_t = \alpha_0 + \alpha_1 OI_t + \alpha_2 OI_{t-1} + \alpha_3 R_{t-1} + \alpha_4 \varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \beta_3 OI_{t-1}$$

We segment the trading volume as buyer- initiated or seller-initiated to measure the order imbalance. If a trade at the end of the 15-minute interval occurs at a price higher (lower) than the previous trade price, the corresponding 15-minute volume is classified as a buyer (seller)-initiated transaction. If order imbalance is a buyer-initiated order, and it is the positive sign, and vice versa. * denotes significant at the 5% level (two-tailed test).

Panel A: Entire period

In mean equation	α_0	α_1	α_2	α_3	α_4
Coefficient	-0.049	0.035	0.003	0.001	0.077
T-statistics	(-0.53)	(120.61)*	(0.20)	(0.00)	(0.37)
In variance equation	β_0	β_1	β_2	β_3	
Coefficient	0.428	0.982	0.007	0.002	
T-statistics	(9.74)*	(683.34)*	(15.76)*	(4.77)*	

Panel B: NTD appreciation period

In mean equation	α_0	α_1	α_2	α_3	α_4
Coefficient	-0.268	0.030	0.001	0.011	-0.109
T-statistics	(-2.03)*	(123.93)*	(0.00)	(0.06)	(-0.56)
In variance equation	β_0	β_1	β_2	β_3	
Coefficient	0.07816	0.99087	0.00263	0.00059	
T-statistics	(6.43)*	(1430.68)*	(8.54)*	(2.42)*	

Panel C: NTD depreciation period

In mean equation	α_0	α_1	α_2	α_3	α_4
Coefficient	0.627	0.062	0.011	-0.087	-0.075
T-statistics	(1.77)	(251.11)*	(0.17)	(-0.15)	(-0.13)
In variance equation	β_0	β_1	β_2	β_3	
Coefficient	0.001	0.886	0.113	0.002	
T-statistics	(0.00)	(2783.08)*	(46.69)*	(2.88)*	

Furthermore, the lagged-one order imbalance-return effect, measured by α_2, become insignificant after controlling for the imbalances on the conditional variance equation, when compared to the results of OLS regression model (Chen et al.,2014) [18].[20] It suggests that the price impact of interbank order flow decrease after considering the volatility impact.[21]

For robustness check, we run the specified GARCH models under different sample lengths, from weekly to yearly. The significances of estimated parameters are given in Table 3. We find the current intraday order imbalances have significantly positive relations with NTD/USD returns regardless of sample lengths. Nevertheless, the percentage of positive significances in volatility-order imbalance relation decreases as the interval lengthens. The decreases in significance between volatility and intraday order imbalance with shorter sample lengths might imply that market maker (the central bank can be the candidate) have more dominate power in reducing the volatility over a shorter time interval.

4. Trading strategy based on return-order imbalance relation

Order imbalance could be a predictor of price if it conveys information that currency markets need to aggregate.[22] In a typical rational expectation model of asset pricing, foreign currencies traders collect from various sources information and trade accordingly. Equilibrium exchange rates are then reached via the trading process, in that information contained in order flow is progressively shared among market participants and incorporated into exchange rates. Although we find that the lagged-one order imbalance-return effects are insignificant after controlling for the imbalances on the conditional variance equation in section 3, there is still a predictive negative relationship between lagged order imbalances and returns when current imbalances and volatility are not included in the regression [18].

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[20] Chen et al. [17] find lagged order imbalance exerts a significant negative effect on the current intraday return after controlling for the contemporaneous order imbalance in the NTD/USD exchange rate market. This is consistent with Chordia et al. [12] findings on the stock market index.

[21] Berger et al. [6] document that the price impact of interbank order flow is inversely related to volatility on an intraday basis.

[22] The information includes anything pertaining to the realization of uncertain demands, such as differential interpretation of news, shocks to hedging demands and shocks to liquidity demands, etc. [22].

Table 3: Significances in order imbalances in intraday GARCH (1,1) models

This table presents the number of significances in parameters in intraday GARCH(1,1) models for NTD/USD returns under yearly, half-yearly, monthly and weekly sample lengths.

$$R_t = \alpha_0 + \alpha_1 OI_t + \alpha_2 OI_{t-1} + \alpha_3 R_{t-1} + \alpha_4 \varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t), \quad h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \beta_3 OI_{t-1}$$

We segment the trading volume as buyer-initiated or seller-initiated to measure the order imbalance. If a trade at the end of the 15-minute interval occurs at a price higher (lower) than the previous trade price, the corresponding 15-minute volume is classified as a buyer (seller)-initiated transaction. If order imbalance is a buyer-initiated order, and it is the positive sign, and vice versa. α_1 and α_2 measure the impacts of current and lag-one order imbalances on returns; α_3 measures the effect of autocorrelation of returns; and β_3 measures the impact of order imbalances on volatilities. "Significant" denotes significant at the 5% level (two-tailed test).

Panel A: In mean equation

Parameter		α_0	α_1	α_2	α_3	α_4
(i) yearly period:						
Significant Positive	number	0	1	0	0	0
Significant Negative	number	0	0	0	0	0
(i) half-yearly period:						
Significant Positive	number	0	2	0	0	0
Significant Negative	number	1	0	0	0	0
(iii) monthly period:						
Significant Positive	*percentage*	*25%*	*100%*	*17%*	*8%*	*8%*
Significant Negative	*percentage*	*33%*	*0%*	*0%*	*0%*	*17%*
(iv) weekly period:						
Significant Positive	*percentage*	*2%*	*100%*	*9%*	*8%*	*13%*
Significant Negative	*percentage*	*4%*	*0%*	*2%*	*2%*	*8%*

Panel B: In variance equation

Parameter		β_0	β_1	β_2	β_3
(i) yearly period:					
Significant Positive	number	1	1	1	1
Significant Negative	number	0	0	0	0
(i) half-yearly period:					
Significant Positive	number	1	2	2	2
Significant Negative	number	0	0	0	0
(iii) monthly period:					
Significant Positive	*percentage*	*42%*	*100%*	*100%*	*58%*
Significant Negative	*percentage*	*0%*	*0%*	*0%*	*0%*
(iv) weekly period:					
Significant Positive	*percentage*	*17%*	*92%*	*47%*	*23%*
Significant Negative	*percentage*	*0%*	*0%*	*0%*	*0%*

Therefore, we form a contrarian trading strategy based on the signs of order imbalances, which is a reversed trading rule by Chordia and Subrahmanyam [14].[23] For daily study, we execute a trading strategy that sells US dollar (NTD is quoted in the basis of USD) at the opening and buys at the closing if the previous day's imbalance was positive, and vice versa. For intraday study, we do a trading strategy that sells US dollar after the first corresponding positive intraday order imbalance shown up in anytime (in the morning) or in the afternoon of each day and buys back after the first corresponding negative order imbalance appeared, and vice versa.

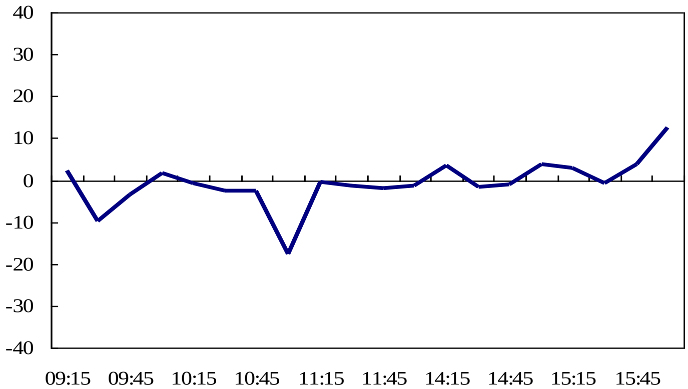
Moreover, to investigate whether larger order imbalances have better predictability [22] [11] [32] [16] and thus produce better trading performance, we trade the above strategy based on three scenarios: 0% truncation, 50% truncation, and 90% truncation. The 50% truncation strategy sieves out 50% of smaller daily/intraday order imbalances in the absolute size by using the data from the entire sample period of order imbalances. Likewise, the 90% truncation strategy trims 90% of smaller daily/intraday order imbalances by using the data from the entire sample period of order imbalances.

To test whether our strategy can beat the pure buy-and-hold strategy, we also form benchmark strategy. From Figure 2, we know that order imbalances in the opening and the closing appear the opposite signs regardless of an up or down market, therefore we form two kinds of benchmark strategy: (i) pure buy-and-hold strategy- buys US dollar at the opening and sells at the closing for the entire sample period. (ii) the hindsight strategy- sells US dollar at the opening and buys at the closing in the NTD appreciation (USD depreciation) period, and buys US dollar at the opening and sells at the closing basis of trade prices instead of quote data.[24]

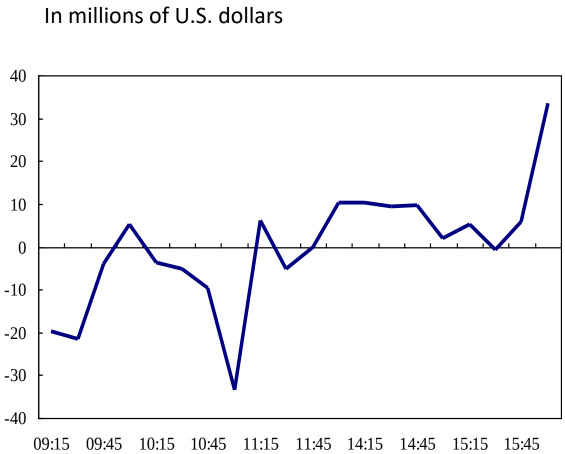
[23] Chordia and Subrahmanyam [14] find a predictive positive relation between lagged imbalances and returns in individual stocks, and form the trading strategy that buys at the opening and sells at the closing if the previous day's imbalance was positive to yield positive and significant profits.

[24] Due to lacking the quote prices, it's unclear whether the returns obtained using trade prices will be higher/lower than those received using quote prices.

(i) Entire sample period



(ii) NTD appreciation period



(iii) NTD depreciation period

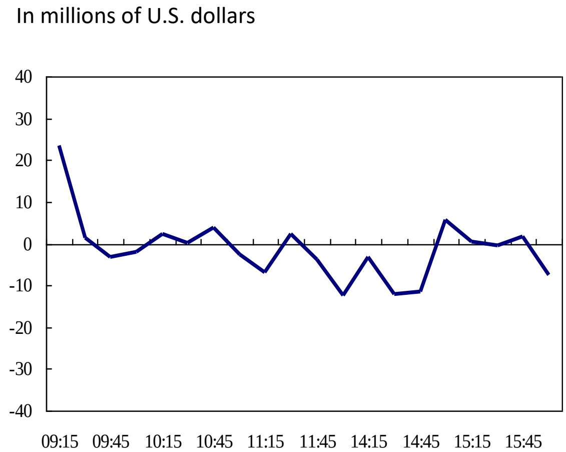


Figure 2. Average order imbalance of intraday NTD/USD exchange rates at 15-minute interval

We segment the trading volume as either buyer-initiated or seller-initiated to measure the order imbalance. If a trade at the end of the 15-minute interval occurs at a price higher (lower) than the previous trade price, the corresponding 15-minute volume is classified as a buyer (seller)-initiated transaction. If order imbalance is a buyer-initiated order, and it is the positive sign, and vice versa. Order imbalance and trading volume are measured in millions of U.S. dollars.

Panel A of Table 4 presents the profit from the benchmark and trading strategy based on daily lagged imbalances, OIBACC. The average daily returns (scaled by hundredfold) of 0%, 50%, and 90% truncation strategies for the entire period are 1.984%, 1.068%, and 6.718% (scaled by hundredfold), respectively. Only the 50% truncation strategy has smaller return than that of the hindsight benchmark (ii), 1.535% (scaled by hundredfold). To sum up, order imbalance trading strategies always yield positive returns, and the 90% truncation strategy consistently dominates the benchmark[25]. The success of the contrarian trading strategy with larger order imbalance is a possible result from the advance adjustment in market participants' quotes in line with the central bank using larger order intervention responses to the dramatic changes in NTD/USD. This result tend to indirectly support Taiwan's central bank claims to manage when there's excessive exchange volatility.

In particular, we observe there is the existence of an asymmetry trading performance in the currency appreciations versus depreciations period. The returns obtained from the contrarian trading strategy based on the 50% and 90% truncation in the appreciations period are much higher than those received in the depreciations period.

Our empirical finding appears to be consistent with the asymmetry in central bank foreign exchange intervention responses to currency appreciations versus depreciations in Taiwan [18]. Chen [18] finds Taiwan's central bank actively fights against a trend appreciation of the NTD, while adapts a let-it-go policy reacted to a trend depreciation of the NTD. The success of the contrarian trading strategy possibly comes from the advance adjustment in market participants' quotes in line with the price stabilization mechanism executed by Taiwan's central bank; thus, the more active interventions (in the appreciation phase), the more profitable might be earned. That is, whatever the nature of the link between order flows and exchange rates, it appears to be clearly affected by the presence of central banks in the market [36].

[25] Nevertheless, if we consider the impact of transaction costs (spread and fees) on returns, the profitability might disappear.

Table 4: Profits from trading strategy based on lagged order imbalance

This table reports the average returns resulting from a contrarian trading strategy based on the signs of order imbalances under three scenarios: 0% truncation, 50% truncation, and 90% truncation of order imbalances (sieving out the absolute daily order imbalance with 50% or 90% by using the data from the entire sample period). Panel A present the trading strategy based on daily lagged order imbalance, i.e. sells US dollar (NTD is quoted in the basis of USD) at the opening and buys at the closing if the previous day's imbalance was positive, and vice versa. Panel B shows the trading strategy based on intraday lagged order imbalance, i.e. sells US dollar after the first corresponding positive intraday order imbalance shown up in anytime or in the afternoon of each day and buys back after the first corresponding negative order imbalance appeared, and vice versa. The average returns of benchmark strategy come from: (i) pure buy-and-hold strategy- buys US dollar at the opening and sells at the closing for the entire sample period. (ii) the hindsight strategy- sells US dollar at the opening and buys at the closing in the NTD appreciation period, and buys US dollar at the opening and sells at the closing in the NTD depreciation period. Our trading strategy is on the basis of trade prices instead of quote data.

Panel A: Based on daily lagged order imbalance

	Trading strategy independent of lagged OI		Trading strategy based on lagged OI		
Average Daily Return (scaled by hundredfold)	Benchmark (i)	Benchmark (ii)	0% truncated	50% truncated	90% truncated
Entire period	**-0.116**	**1.535**	**1.984**	**1.068**	**6.718**
NTD appreciation period	-1.698	1.698	1.401	2.281	14.202
NTD depreciation period	1.380	1.380	2.534	-0.635	-3.486
Number of Trading for entire period	*251*	*251*	*251*	*125*	*26*

Panel B: Based on intraday lagged order imbalance

	Trading strategy independent of lagged OI		Trading strategy based on lag-one OI			
Average Daily Return (scaled by hundredfold)	Benchmark (i)	Benchmark (ii)	0% truncated truncated trading in anytime	0% truncated truncated trading in the afternoon	50% truncated	90% truncated
Entire period	**-0.116**	**1.535**	**0.125**	**0.140**	**0.439**	**2.079**
NTD appreciation period	-1.698	1.698	0.267	1.060	0.348	2.096
NTD depreciation period	1.380	1.380	0.015	-0.736	0.557	2.251
Number of Trading for entire period	*251*	*251*	*251*	*250*	*241*	*74*

Panel B of Table 4 presents the profit from trading strategy based on intraday lagged imbalances.[26] We also observe the trend that when trimming the smaller order imbalances, the strategy yields a higher average return. The average daily returns (scaled by hundredfold) of 0% truncation with trading in anytime as well as in the afternoon, 50%, and 90% truncation strategies for the entire period are 0.125%, 0.140%, 0.439%, and 2.079% (scaled by hundredfold), respectively. Although all the order imbalance strategies yield positive return and beat the benchmark (i) pure buy-and-hold strategy; only 90% truncation strategy dominates the hindsight benchmark (ii), 1.535% (scaled by hundredfold).

Furthermore, we find that average returns of the intraday order imbalance strategies are generally smaller than those of the daily order imbalance strategies. A possible explanation is as follows. Although Taiwan central bank didn't provide detail (the size and the time persistence) of its intervention activities, most news reported it intervened with large and frequent at the day's closing (16:00). Since the intraday contrarian imbalance-based strategies are always finished before the day's closing, they possibly cannot catch as the benefit from central bank's stabilization mechanism as the daily contrarian strategies.

5. Dynamic causality relations in explaining the successful trading strategy

In order to explain the story behind an imbalance-based trading strategy, we employ a nested causality to explore the dynamic causal relationship between returns and order imbalances. According to Chen and Wu [10], we construct a VAR model to describe the temporal behaviors of return (labeled x_1) and order imbalance (labeled x_2), and then use a systematic multiple hypotheses testing method for identifying the dynamic relations between them. We define four relations between two random variables, x_1 and x_2, in terms of constraints on the conditional variances of $x_{1(T+1)}$ and $x_{2(T+1)}$ based on various available information sets, where $x_i=(x_{i1} , x_{i2} , ..., x_{iT})$, i=1, 2, are vectors of observations up to time period T.

Definition 1: Independency, $x_1 \wedge x_2$: x_1 and x_2 are independent if and only if

[26] Transaction costs (i.e. spread and fee) and risk should also be considered. This part is left for future research.

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{2(T+1)}})$$

and (4)

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) = Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) = Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{1(T+1)}})$$

Definition 2: Contemporaneous relation, x_1 < - > x_2: x_1 and x_2 are contemporaneously related if and only if

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2})$$

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) > Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{2(T+1)}})$$

and (5)

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) = Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2})$$

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) > Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{1(T+1)}})$$

Definition 3: Unidirectional relation, x_1= > x_2: There is a unidirectional relationship from x_1 to x_2 if and only if

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2})$$

and (6)

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) > Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2})$$

Definition 4: Feedback relation, x_1 < = > x_2: There is a feedback relation between x_1 and x_2 if and only if

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) > Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2})$$

and (7)

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) > Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2})$$

To explore the dynamic causality of a bivariate system (e.g. returns and order imbalances), five statistical hypotheses (H_1 through H_4) are formed in the Table 5, where the necessary and sufficient conditions corresponding to each hypothesis are given in terms of constraints on the parameter values of the VAR model. We use a systematic multiple-hypotheses testing method to determine a specific causal relation. Unlike the traditional pairwise hypothesis testing, this testing method avoids the potential bias induced by restricting the causal relation to a single alternative hypothesis. In implementing this method, results of several pairwise hypothesis tests need to be employed.

Table 5: Test flow chart of a multiple hypothesis testing procedure

---

Test Sequence I
(a) H_3 vs. H_4
(b) H_3^* vs. H_4

→ E_1 : (a) reject H_3, (b) reject H_3^* → $x_1 <=> x_2$

→ E_2 : (a) reject H_3, (b) not reject H_3^* → $x_1 \Rightarrow x_2$

→ E_3 : (a) not reject H_3, (b) reject H_3^* → $x_1 \Leftarrow x_2$

↓

E_4 : (a) not reject H_3
(b) not reject H_3^*

↓

Test Sequence II
(c) H_2 vs. H_3
(d) H_2 vs. H_3^*

→ E_5 : (c) reject H_2, (d) not reject H_2 → $x_1 \Leftarrow x_2$

→ E_6 : (c) not reject H_2, (d) reject H_2 → $x_1 \Rightarrow x_2$

↓

E_8 : (c) not reject H_2, (d) not reject H_2 → Test Sequence IV

E_7 : (c) reject H_2
(d) reject H_2

↓

Test Sequence III
(e) H_2 vs. H_4

→ E_{10} : (e) not reject H_2 → Test Sequence IV
(f) H_1 vs. H_2

↓

E_9 : (e) reject H_2

E_{11} :(f) reject H_1 E_{12} :(f) not reject H_1

↓ ↓ ↓

$x_1 <=> x_2$	$x_1 \leftrightarrow x_2$	$x_1 \wedge x_2$

Note : Five groups of dynamic relations are identified: independency ($\wedge$) , the contemporaneous relation ($\leftrightarrow$) , unidirectional relation ($\Rightarrow$ or $\Leftarrow$) and feedback relation ($<=>$). To determine a specific causal relation, we use a systematic multiple hypotheses testing method. Unlike the traditional pairwise hypothesis testing, this testing method avoids the potential bias induced by restricting the causal relation to a single alternative hypothesis. In implementing this method, we need to employ results of several pairwise hypothesis tests.
Source: Chen and Wu [10].

Panel A of Table 6 presents results for the daily sample. For the entire period, we show that a unidirectional relationship from order imbalances to returns with OIBACC measure. Panel B of Table 6 presents results for the intraday sample under different sample lengths, from weekly to yearly. For weekly length, the contemporaneous relation accounts for 87%, whereas the unidirectional relationship from order imbalances to returns is 8% and the unidirectional relationship from returns to order imbalances is 6%. For monthly length, the contemporaneous relation occupies 92% while the unidirectional relationship from order imbalances to returns is 8%. For half-yearly length, there exists the contemporaneous relation in NTD appreciation period while the unidirectional relationship from order imbalances to returns in NTD depreciation period. For yearly length, we find a contemporaneous relationship between intraday returns and order imbalances. Overall, a contemporaneous relationship between intraday returns and order imbalances seems to dominate the other relations regardless of sample lengths in intraday study. This result could explain why our daily order imbalance strategies could dominate the intraday order imbalance strategies.

6. Conclusion

In this study, we utilize a specific intraday dataset on NTD/USD exchange rate to explore the role of order imbalance in the high frequency exchange rate dynamics of the small open economies. It is unique in that instead of directly analyzing the effect of intervention on the value or volatility of the exchange rate due to lacking of the detail of its intervention activities, we propose a GARCH (1,1) model to examine the linkage of relations between order imbalances and foreign exchange returns with volatility. Furthermore, we investigate the performance of the imbalance-based trading strategy, and interpret these empirical findings as reflecting official intervention behavior.

We first employ the GARCH (1,1) model by simultaneously incorporating order imbalance in the conditional mean and variance equations to capture the time-variant property of the order imbalance-return relation. We find there exist significantly positive relations between volatility and order imbalance, and the lagged-one order imbalance-return effect become insignificant when compared to that of OLS regression model [18].

Table 6. Dynamic nested causality relations between NTD/USD returns and order imbalances under different sample lengths

This table reports the results for tests of hypotheses on dynamic causal relations between NTD/USD returns, denoted as x_1, and order imbalances, denoted as x_2. Five groups of causal relations are defined as follows: independency ($\wedge$), the contemporaneous relation ($<->$), unidirectional relation ($\Rightarrow$ or $\Leftarrow$), , and feedback relation ($<=>$). Panel A presents the relations between daily NTD/USD returns and order imbalances. Panel B presents the relations between intraday NTD/USD returns and order imbalances. In Panel B, the first return and the corresponding order imbalance of each day is discarded since it would have been correlated with a lagged interval from the previous trading day. The relation is based on the 5% significant level of the test.

Panel A: Dynamic causality relations between daily returns (x_1) and order imbalances (x_2)

Relations		$x_1 \wedge x_2$	$x_1 <-> x_2$	$x_1 \Rightarrow x_2$	$x_1 \Leftarrow x_2$	$x_1 <=> x_2$
yearly period (OIBACC$_t$ measure):						
	Number	0	0	0	1	0

Panel B: Dynamic causality relations between intraday returns (x_1) and order imbalances (x_2)

Relations		$x_1 \wedge x_2$	$x_1 <-> x_2$	$x_1 \Rightarrow x_2$	$x_1 \Leftarrow x_2$	$x_1 <=> x_2$
(i) yearly period:						
	number	0	1	0	0	0
(i) half-yearly period:						
	number	0	1	0	1	0
(iii) monthly period:						
	number	0	11	0	1	0
	percentage	*0%*	*92%*	*0%*	*8%*	*0%*
(iv) weekly period:						
	number	0	46	3	4	0
	percentage	*0%*	*87%*	*6%*	*8%*	*0%*

Taken together, these findings suggest that the price impact of interbank order flow decrease after considering the volatility impact. Because the GARCH (1,1) model controls volatility more appropriately, some of the explanatory power of imbalances in the OLS regression model comes from volatility, and not the order imbalance itself. Furthermore, we note the decreases in significance between volatility and intraday order imbalance with shorter sample lengths. This might imply the effectiveness of price stabilization by the central bank, aiming at reducing exchange rate volatility via the order adjustments, could be judged as being successful over a shorter time interval.

The second part of our analysis reveals the performance of the contrarian trading strategies based on the signs of order imbalances with different order imbalance truncations. We document that imbalance-based trading strategies earn positive returns no matter what kinds of scenarios we choose, and the 90% truncation strategy consistently dominates the benchmark. In line with the Taiwan's central bank claim it only steps in when there exists excessive exchange volatility, the success of the contrarian trading strategy with larger order imbalance is a natural result from central bank using larger order intervention responses to the dramatic changes in currency.

Besides, on the daily strategy, we observe an asymmetry trading performance in the currency appreciations versus depreciations period. Our empirical finding tends to argue previous findings of the asymmetry in central bank foreign exchange intervention responses to currency appreciations versus depreciations in Taiwan. [18] Moreover, we find the average returns of the intraday imbalance-based strategies are generally smaller than those of the daily strategies. We attribute this to central bank intervention patterns. Most news reported it intervened with large and frequent pattern at the day's closing. Because the intraday strategies are always finished before the day's closing, they cannot catch as the benefit from central bank's stabilization mechanism as the daily strategies.

Finally, we have looked at the dynamic causality relation between return and order imbalance to explore why our imbalance-based trading strategy earns a positive return. Our approach based on Chen and Wu [10] shows that there is a unidirectional relationship from order imbalances to returns in our daily data, while a contemporaneous relationship between returns and order imbalances in our intraday data. This result confirms the dominance of our daily imbalance-based strategies over the intraday strategies.

Our comprehensive empirical analysis has both implications for empirical modeling of foreign exchange rates under the microstructure framework and for policy making at central banks in emerging economies. The studies on the imbalance-based strategies tend to support the informational approach of the microstructure literature and indirectly confirm that interventions convey some valuable information for foreign exchange traders, which is consistent with Beine et al. [7]. For a policy purpose, as exchange rate management occurs mostly in emerging economies, figuring out the link the order imbalances (or imbalance-based trading strategy) of foreign exchange traders with the interventions would be relevant to the effectiveness of central bank policy.

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