Are price and trade-size substitutable liquidity measures in foreign exchange swap market?

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ABSTRACT

Using a foreign exchange swaps dataset between New Taiwan Dollar (TWD) and U.S. Dollar (USD) from Taiwan, this paper provides evidence that price and trade size are substitutable liquidity measures in the foreign exchange swap market. Moreover, this paper shows that a bank's nationality would influence the degree of price and size precision. When more foreign banks are involved in trading, price and size tend to be more clustered. Foreign exchange swaps is the globally most traded financial contract reported by the Bank for International Settlements. This paper shows how price and size are related and their determinants in the foreign exchange swap market.

Keywords: foreign exchange swaps, price clustering, size clustering, bank's nationality

1. INTRODUCTION

In financial markets, liquidity can be measured in 3 ways including timing, price, and quantity (Hodrick and Moulton, 2009). Timing measures how fast a transaction can be completed at a desired price level. Price measures the distance between bid and ask prices. Quantity measures the amount of trading interest at a certain price level. The level of liquidity would affect a trader's profitability and therefore drive the market behavior. For example, during the real estate bubble period, the market price was wide (i.e., the level of liquidity is low), buyers did not want to increase prices while sellers were hesitant to sell at prices below the market level. The low level of liquidity, in terms of price, resulted in either no transaction, when buyers and sellers refused to converge their prices, or market crashes, when sellers decided to sell at the buyer's prices.

One trading behavior related to the level of liquidity is "price clustering". It refers to the fact that traders adopt an imprecise pricing strategy, so that prices tend to be quoted at certain ending numbers. Price clustering results in prices jumping in a larger interval. For example, in the foreign exchange market, where there is no pricing regulation, studies show that instead of demonstrating a uniform distribution in pricing, the last number of most transaction prices was either 0 or 5 (e.g., Liu, 2011). In literature, price clustering behavior is documented in financial markets such as stock, gold, foreign exchange, interest rate markets, etc. (e.g., Ball et al., 1985; Grossman et al., 1997; Kahn et al., 1999; Liu and Witte, 2013; Schwartz et al., 2004).

To explain these clustering behaviors, the most popularly proposed hypotheses include price resolution hypothesis (Ball et al., 1985), attraction hypothesis (Goodhart and Curcio, 1991), and negotiation hypothesis (Harris, 1991). Ball et al. (1985) attribute the imprecise pricing strategy to the level of market uncertainty. Goodhart and Curcio (1991) state that it is human nature to be attracted to certain numbers. Harris (1991) proposes that imprecise prices reduce the number of prices to be negotiated with between buyers and sellers, and therefore increase transaction speed and decrease the chance of miscommunication. Price clustering reduces market liquidity because it widens the distance between buying and selling prices. In the case of price clustering at 0 or 5, prices move by the unit of 5 instead of 1, therefore, resulting in potential profit concession.

Likewise, any imprecise behavior in any liquidity dimension will result in deviation from the optimal portfolio. Since traders may not be able to obtain liquidity in all dimensions, they may use one liquidity dimension to substitute the insufficiency of another. One of the liquidity measures is trade size. It measures if traders can trade at their desired quantities. Barclay and Warner (1993) find that medium-size trades tend to have a higher price impact on NYSE. They argue that informed traders hide their identities with the medium-size trades, resulting in a higher price impact. The behavior of hiding trades with medium-size trades is called "Stealth-trading". Alexander and Peterson (2007) find similar results on NYSE and NASDAQ. Ligon and Liu (2013) find evidence of stealth-trading behavior in foreign exchange market. Some recent studies investigated whether trade size can be a liquidity substitution for price. Using foreign exchange market data, Moulton (2005) finds that traders use more distinct sizes in trading at quarter-end. The paper argues that since there are more heterogeneous uninformed traders in the market during the quarter-end, their desire to satisfy the quantity demands makes trade size less clustered. The evidence of size clustering was also documented in futures market (see ap Gwilym and Meng, 2010). Meng et al. (2013) show that price and size are substitutable liquidity measures in the credit default swap (CDS) market.

The remainder of the paper is structured into the following sections. Section 2 describes the sample. Section 3 discusses the methodology. Section 4 reports the results. Section 5 concludes.

2. SAMPLE DESCRIPTION

Using a foreign exchange swaps dataset, this study examines whether there exists a substitution effect between price and trade size. Based on the daily trading volume reported by the Bank of International Settlements, foreign exchange swaps is the globally most traded financial contract. In 2022, the daily foreign exchange trading volume has reached $7.5 trillion, in which foreign exchange swaps accounted for $3.8 trillion. The currency pair under this study is between New Taiwan Dollar (TWD) and U.S. Dollar (USD). The dataset comes from a leading foreign exchange swap brokerage firm in Taiwan. The sample covers a 2-year period from August 2001 to July 2003, or 489 trading days.

Table 1 (Appendix) provides the sample description. The total number of observations is 3,692. The size of transactions (Size) ranges from 1 to 50 million with the mean of 10 million. The mean contract duration (Duration) is 123 days, ranging from as short as 3 days to as long as 547 days. The exchange rate between USD and TWD is quoted indirectly, i.e., the price of USD in terms of TWD. The mean spot rate (SP) is TWD 34.588 per USD and the mean swap rate (SW) is TWD 34.548 per USD. The mean daily number of transactions (NUM) is 7.55, ranging from 1 trade to as many as 28 trades.

A unique aspect of the sample is that it includes the bank's nationality for each transaction. All participants in this sample are banks, a total of 56 banks including 31 domestic banks and 25 foreign banks. Among all transactions, 45% are between 2 foreign banks, 12% are between 2 domestic banks, 43% are between a domestic bank and a foreign bank. Previous studies show that the amount of information obtained by domestic and foreign banks could be discriminatory (see Peiers, 1997; Eun and Sabherwal, 2002), resulting in different trading behavior. Liu and Witte (2013) show an increased tendency of clustered pricing behavior when a trade involves a foreign bank. This study hypothesizes that in a day when more foreign banks are participating, both price and size will tend to be more clustered.

3. METHODOLOGY

A trade is categorized as a price-clustered trade if the following two criteria are met. First, the ending number of a swap rate is either zero or five, and second, the number of decimal places used in pricing is less than or equal to three. In the USD/TWD market, the normal number of decimal places used in pricing is three. Therefore, a trade with more than three decimal places used in pricing is considered as a non-clustered trade. A trade is categorized as a size-clustered trade if the size of a transaction is in the increment of five, e.g., 5 million, 10 million, etc.

Figures 1 and 2 (Appendix) show the frequency of price clustering in the sample. Figure 1 (Appendix) shows the number of decimal places used in pricing. Clearly, most of the transactions used exactly three decimal places in pricing. 58% of the transactions in this sample used three decimal places. Figure 2 (Appendix) shows that zero and five are the most used ending numbers in pricing. Out of the 3,692 transactions in this sample, transactions with an ending number of zero or five account for 56% of trades. When combining the two price clustering criteria, 48% of transactions in this sample are categorized as price-clustered trades.

Figure 3 (Appendix) shows the number of trades in different trading sizes. The most frequently traded size is USD 10 million, which accounts for 48% of trades in the sample. The second most traded size is USD 5 million, which accounts for 28% of trades, followed by USD 20 million (9%), USD 15 million (5%), and USD 30 million (2%).

Table 2 (Appendix) shows the percentage of price-clustered and size-clustered trades under different contract duration categories including 1 month or less, 1 to 2 months, 2 to 3 months, 3 to 6 months, 6 to 9 months, and more than 9 months. There exists a positive relation between price clustering and contract duration. On the other hand, the level of size clustering is consistent across the different contract duration categories.

Table 3 (Appendix) shows the percentage of price-clustered and size-clustered trades based on the absolute return of each transaction. For each transaction, the absolute rate of return is calculated by taking the absolute value of the percentage deviation of the actual swap rate, SW, from the implied swap rate, SW*, as follows.

$$Absolute\ rate\ of\ return = \left|\frac{SW - SW^*}{SW^*}\right|$$

where SW* is derived by using interest rate parity formula.

$$SW^* = SP \times \frac{(1 + i_{TWD})}{(1 + i_{USD})}$$

where SP is the spot rate between USD and TWD, i_{TWD} and i_{USD} are interest rates in Taiwan and U.S., respectively. Liu and Witte (2013) show that a trade with a higher rate of return is more likely to be clustered because traders care more about transaction speed than price precision. Therefore, there is the expectation of a positive relation between the size of return and level of clustering. Table 3 (Appendix) shows the absolute percentage return in six categories from as low as 0.2 percent and below to as high as 1% and above. The table illustrates a clear positive relation between the absolute percentage return and price clustering. For size clustering, the relation is less clear. The percentages of size-clustered trades are between 91% and 94%.

To examine if price and size are substitutable liquidity measures, the daily clustering percentages of price and size are calculated as follows.

$$PC_t = \frac{TPC_t}{N_t}$$

$$SC_t = \frac{TSC_t}{N_t}$$

where PC_t is the daily percentage of price-clustered trades on day t, SC_t is the daily percentage of size-clustered trades on day t, TPC_t is the total number of price-clustered trades on day t, TSC_t is the total number of size-clustered trades on day t, and N_t is the total number of trades on day t. Of the 489 trading days, 13 days have only 1 transaction. These days are deleted from the dataset, making the total number of days 476. Figures 4 and 5 (Appendix) show the daily clustering percentages of price and size. Consistent with the results in Table 2, the percentage of daily size-clustering tends to be higher than that of price-clustering.

To examine if price and size are substitutable liquidity measures, following Meng et al. (2013), three-stage least squares (3SLS) is performed to simultaneously estimate the daily clustering percentages of price and size.

$$PC_t = \alpha + \beta_1 SC_t + \beta_2 IQ_t + \beta_3 DAYS_t + \beta_4 MR_t + \beta_5 IRC^{USD,\ before} + \beta_6\ IRC^{USD,\ after} + \beta_7\ IRC^{TWD,\ before} + \beta_8 IRC^{TWD,\ after} + \beta_9 QE_t + \beta_{10} BN_t + e_{1t}$$

$$SC_t = \alpha + \beta_{11}PC_t + \beta_{12}NUM_t + \beta_{13}SIZE_t + \beta_{14}DAY_t + \beta_{15}MR_t + \beta_{16}QE + \beta_{17}BN_t + e_{2t}$$

IQ is the inverse square root of the total number of trades per day. Previous study shows that higher trade frequency reduces market uncertainty, and therefore increases the level of price precision (Harris, 1991). On the other hand, ap Gwilym et al. (1998) and Meng et al. (2013) show the opposite. They argue that in a high-volume day, to speed up transactions, prices tend to be more clustered. DAYS is the daily average contract duration. The longer a contract is, the lower the level of information is available, making trades more likely to be clustered. MR is the annualized absolute mean return per day. A positive relation should be observed between return and clustering. QE is a categorical variable which equals one if the spot date of a trade lands on the first or last week of a quarter. Quarter-end market irregularity is well documented (Kotomin and Winters, 2006; Kotomin et al., 2008). The frequency of clustering should be higher at quarter-end. Following Liu and Witte (2013), interest rate variables, $IRC^{USD,\ before}$, $IRC^{USD,\ after}$, $IRC^{TWD,\ before}$, and $IRC^{TWD,\ after}$ are included in the equations. When the U.S. and Taiwan central banks changed the discount rates, these variables equal one if transaction dates land within seven days prior to or after the change. BN is a bank's nationality variable. It is the percentage of daily transactions that involve foreign banks on both the buying and selling sides. Since foreign banks have information disadvantage, it is hypothesized that trades completed by foreign banks are less precise and therefore are more likely to be clustered.

4. RESULTS

Table 4 (Appendix) reports the results. If price and trade size are substitutable liquidity measures, negative coefficients of PC and SC are expected. The coefficients of PC and SC are both negative and significant at the 1% level. The results demonstrate that if there are more size-clustered trades, prices are less precise and vice versa. No evidence is found regarding the relation between transaction frequency and the level of price and size clustering. Both the coefficients of IQ and NUM are not statistically significant. Clustering and number of days in contract, on the other hand, are positively related. Both coefficients of the variable, DAYS, are positive and significant at 1% and 5% levels for price and size clustering, respectively. The coefficients of the annualized absolute mean return, MR, are both positive and statistically significant at the 1% level. This result is consistent with the previous studies, in that volatility positively influences the level of clustering in price and size. Regarding the quarter-end effect, the coefficients of QE in both price and size equations are positive and significant at 1% and 5% levels, respectively, which show similar results found by Liu and Witte (2013). Finally, the coefficients of bank's nationality, BN, are both positive and statistically significant at 5% and 1% levels for pricing and size clustering, respectively. The result is consistent with the hypothesis that the amount of information obtained by domestic and foreign banks is discriminatory (see Peiers, 1997; Eun and Sabherwal, 2002). When more foreign banks participate in the market, both price and size tend to be clustered more.

5. CONCLUSION

In this study, foreign exchange swap data is used to examine if price and size are substitutable liquidity measures. Based on the daily trading volume reported by the Bank of

International Settlements, foreign exchange swaps is the globally most traded financial contract. The result of this paper shows that the daily clustering percentages of price and size are inversely related. In any given day, when prices are more clustered, trade sizes are more precise, and vice versa. In addition, price and size clustering are positively related to contract duration, rate of return, and end-of-quarter. This paper also provides insight on the effect of a bank's nationality in trading. When there are more foreign banks trading in the market, trades tend to be clustered more in both price and size.

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Table 1 – Sample descriptions

Table 1 summarizes the data sample. Size is the trade size of each transaction in millions of USD. Duration is the number of days of each transaction. SP is the spot rate. SW is the forward rate. Both spot and swap rates are the prices of USD in terms of TWD NUM is the daily number of trades.

	Size	Duration	SP	SW	NUM
Mean	10.078	123	34.588	34.548	7.55
Std dev	5.7421	122.198	0.3779	0.3914	4.7072
Min	1	3	32.943	32.859	1
Max	50	547	35.220	35.220	28
N	3692	3692	3692	3692	489

Table 2 – Contract days and clustering

Table 2 shows the percentage of trades that are price-clustered and size-clustered based on contract days.

Contract days	Observations	Price-clustered	Size-clustered
Less than 1 month	612	16%	93%
1 to 2 months	885	24%	94%
2 to 3 months	288	37%	92%
3 to 6 months	682	48%	91%
6 to 9 months	536	71%	90%
More than 9 months	689	94%	94%

Table 3 – Absolute percentage return and clustering

Table 3 shows the percentage of trades that are price-clustered and size-clustered based on the absolute percentage returns.

Absolute percentage returns	Observations	Price-clustered	Size-clustered
0.2 and below	1108	25%	91%
0.21-0.4	701	42%	94%
0.41-0.6	674	52%	93%
0.61-0.8	500	58%	92%
0.81-1	411	67%	94%
1 and above	298	92%	94%

Table 4 – Three-stage least squares estimation of price clustering and size clustering in foreign exchange swap market

Table 4 shows the results of the three-stage least squares estimation of the daily clustering percentages of price (PC) and size (SC).

PC	Coefficient	T-Statistics
SC	-1.020***	3.13
IQ	0.047	0.57
DAYS	0.002***	9.64
MR	0.366***	8.48
$IRC^{NTD, before}$	0.051	1.11
$IRC^{NTD, after}$	0.010	0.39
$IRC^{USD, before}$	-0.035	1.03
$IRC^{USD, after}$	-0.002	0.11
QE	0.067**	2.12
BN	0.117**	2.15
Constant	0.945***	2.98
SC	**Coefficient**	**T-Statistics**
PC	-0.580***	2.72
NUM	-1.00E-04	0.07
SIZE	0.004	1.49
DAYS	0.001**	2.27
MR	0.230***	3.11
QE	0.047*	1.85
BN	0.101***	3.13
Constant	0.881***	21.33

*** significant at 1%; ** significant at 5%; * significant at 10%

Figure 1 – Number of decimal places used in pricing

Figure 1 shows the number of decimal places used in pricing, ranging from 1 to 5 decimal places.

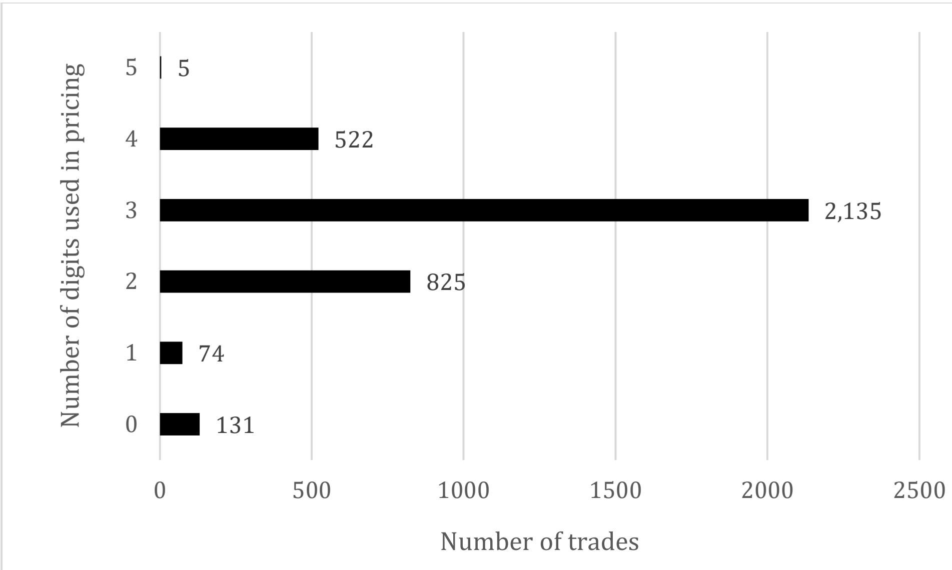

Figure 2 - Ending number used in pricing

Figure 2 shows the ending number used in swap pricing, ranging from 0 to 9.

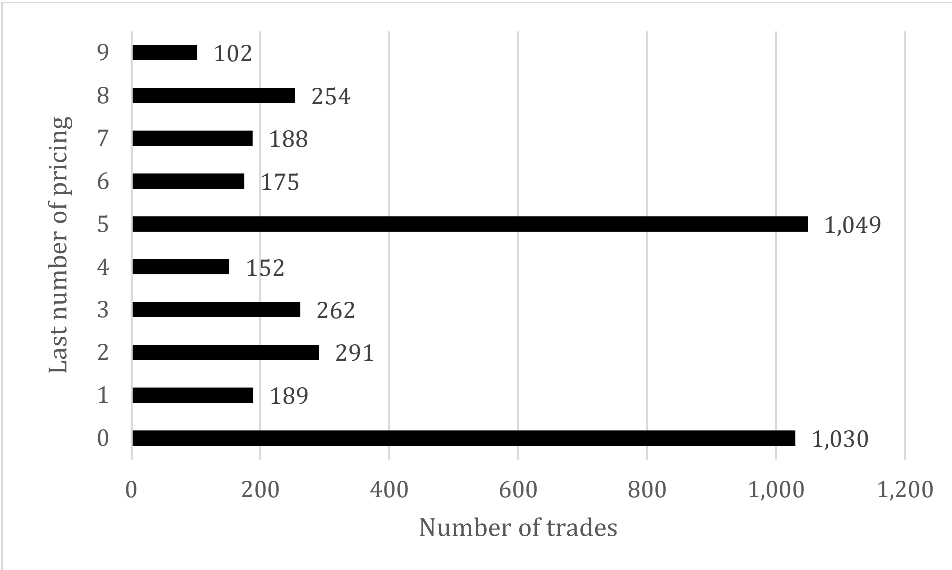

Figure 3 – Trade size clustering

Figure 3 shows the number of trades in different trading sizes, ranging from USD 1 million to USD 50 million, in the increment of USD 5 million.

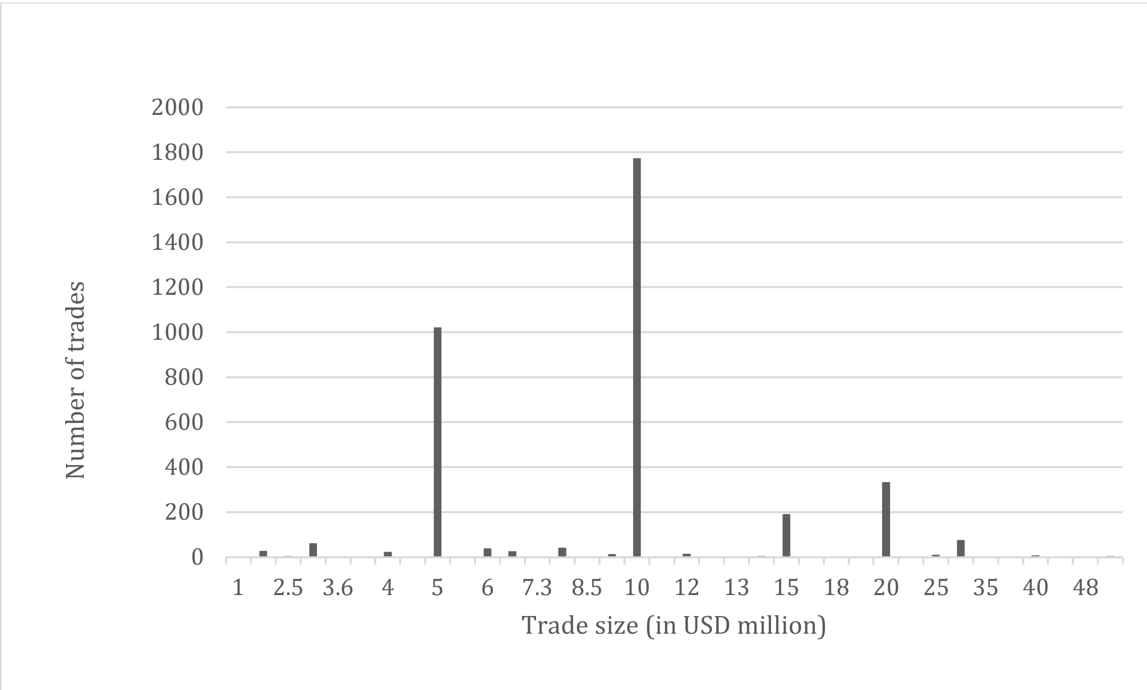

Figure 4 – Daily price clustering percentage

Figure 4 shows the percentage of price-clustered trades in each sample day. A trade is categorized as price-clustered if the following two criteria are met. First, the number of decimal places used in pricing is 3, and second, the last digit in pricing is either 0 or 5. Daily price clustering percentage is the total number of price-clustered trades divided by the total number of trades in each day.

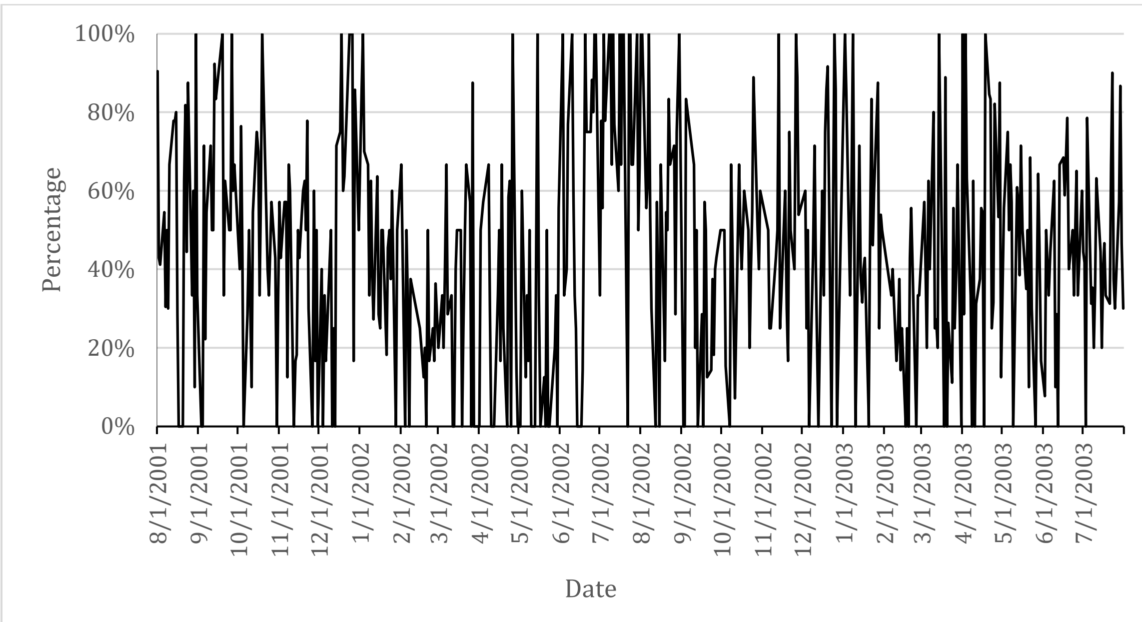

Figure 5 – Daily size clustering percentage

Figure 5 shows the percentage of size-clustered trades in each sample day. A trade is categorized as size-clustered if the size of a trade is in the increment of five. Daily size clustering percentage is the total number of size-clustered trades divided by the total number of trades in each day.