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Tick test accuracy in foreign exchange ECN markets

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ABSTRACT

Recent computer quoting activity has increased the allure of the tick test because the quote rule and its variants require matching asynchronous trade and quote records. We find tick test accuracy of 1.2 million forex trades is about 67% which falls to 63% for zerotick trades (half the sample). Accuracy declines as quoted spreads decrease and as time to the previous trade increases. We observe extreme asymmetry for midquote changes, where buyer accuracy is 96% (27%) for up (down) changes, respectively. The quote rule is about 77% accurate. The group tick test is superior to the bulk volume classification method.

1. Introduction

Since most databases do not indicate the trade initiator, many research papers assign trade direction based on the tick test, the quote rule, LR (Lee and Ready, 1991), or EMO (Ellis et al., 2000), with the latter two using a combination of the tick and quote rules. Consequently, the tick rule is used to sign a portion of the trades in a significant amount of microstructure research. An early example in the foreign exchange market is Lyons (1995) who uses the tick rule to support an inventory control effect on the USD/Deutsche Mark. The tick rule is easy to use as only trade data is required; as such, it avoids the empirical errors caused by matching quotes to trades with delayed time stamps. This issue may be particularly important for newer data with its increase in quoting activity per trade. The tick rule can be fairly accurate but errors increase for some subsamples such as zerotick trades. To our knowledge there has been no formal examination of the tick test in the foreign exchange (forex) market; consequently, this is our primary purpose.

Since our 2005/6 ECN (electronic communication network) trade/quote data on the euro, pound, and yen exchange rates is signed as buyer or seller initiated, we can definitively test the accuracy of the tick and quote rules. However, all forex trades occur 'on quote' so our results indirectly pertain to LR and EMO since they both use the quote rule for 'at quote trades'. Since trade data is not usually found in academic forex research,[1] much less signed as buyer/seller initiated, this paper is

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[1] For example see Kenourgios et al. (2015) and Evans and Speight (2010) who use 5 min forex quote data.

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not only the first to examine the tick rule for foreign exchange rates, but also one of the few papers to have signed data in the market microstructure literature.

We find the tick test is 67%, 65%, and 67% accurate for the euro, pound, and yen respectively, which compares to 77%, 78%, and 79% for the quote rule.[2] The euro, pound, and yen comprise 55%, 19%, and 26% of our sample of 1, 248,494 signed trades with over 100 million quotes. Tick test accuracy increases for larger quoted spreads and for shorter time intervals between trades. Zerotick accuracy averages about 62% and declines with the number of zeroticks, but varies considerably. For the euro it rises above 73% for a single zerotick that has no intervening quote and falls under 50% for more than twenty zeroticks. A midquote change reveals severe asymmetry in tick test accuracy. For example, euro buyer accuracy is 95% (29%) for an up (down) midquote change, respectively. Unique to forex are the 3.7% of trades that have a zero spread (bid equals ask), for which the quote rule cannot assign direction but the tick test has only a 55% success rate.

Increased computer trading has moved forex closer to current equity markets, making our results more pertinent. However, forex trading still differs from most equity venues. It is decentralized, self-regulated with no formal market making requirements, no margins, and no restrictions on short selling. Trading is concentrated on servers in London and New York with about 44% of trades involving the USD. Global forex trading per day averaged $5.3 trillion in April (2013), $4 trillion (2010), and $3.3 trillion (2007) according to the Triennial Central Bank Survey (2013).

An overview of signing algorithm tests, which focuses on equities, is in Appendix. Our 67% average tick test accuracy is lower than the 76% average in equity markets (range of 72% to 83%) but is higher than the 59% for 1995 option trades in Savickas and Wilson (2003), who note a large error rate for complex trades not executed on the automated execution system. Poor subsample performance is common across many studies. For example, correct classification rates are lower across NYSE equity studies for zerotick trades (60% in Odders-White (2000) and (77)% in Finucane (2000)) and midquote trades (63% Odders-White, 61% Ellis et al., and 66% Finucane).

Many papers find biases in microstructure research because of incorrectly signed trades. For example, Chakrabarty et al. (2007) reveal the biases in estimating effective spreads and the price impact of trades for both LR and EMO. Finucane (2000) shows biases in signed volume and effective spreads (particularly if zerotick trades are excluded), but the tick test is not as biased as LR. Ellis et al. (2000) find that LR significantly overstates the effective spread, which is partly due to a poor (55%) classification accuracy for trades inside the spread that are prevalent for large trades, high volume periods, and ECN trades. Boehmer et al. (2007) find that LR causes significant downward bias in estimating the PIN (probability of informed trades).[3]

Signed data reveals the 'true' classification (initiator) which implies more accuracy for signing tests and related research. For example, Chakrabarty et al. (2012a) find equity (NASDAQ) short sales are predominantly buyer initiated which is contrary to conventional views (see Asquith et al., 2008). Chakrabarty uses the same 2 months in 2005 as Asquith, but has INET order data with a buy/sell indicator and designates the 'true' trade initiator as the last person to place their order chronologically. In general, not all transactions are classifiable by this method as Odders-White (2000) notes that 25.1% of her trade transactions were unclassifiable because of missing order records. Another 'true' classification method requires knowledge of both traders' identities. For example, a retail customer trading with a specialist, market maker, or broker is assumed to be the initiator. However, not all trades can be signed with this method either; for instance, inter-broker or inter-dealer trades (EMO exclude 24.6% of their sample and Finucane cannot identify trader types for 25% of TORQ trades). In addition, recent literature questions the assumption that intermediaries are passive liquidity providers (see Anand and Subrahmanyam, 2008; Chaboud et al., 2014). A forex example of the importance of the true initiator is Bjønnes and Rime (2005), who use the latest chronological time stamp and do not find the inventory effect (based on the tick test) of Lyons (1995).[4] Initiator classifications based on the latest chronological order or knowledge of the participants are more accurate but there may still be some error and/or data loss. Consequently, knowledge of the true trade classification is an important advantage.

A related issue for the quote rule, LR, and EMO involves the matching of trade and quote data. Delayed matching is often necessary because (equity) trade data are not recorded as quickly as quotes. Depending on the type and age of the data, various authors recommend delays from zero to 5 s[5] to reduce signing errors when matching trades to quotes.[6] For newer data, Chakrabarty et al. (2012a) recommends returning to a one second delay instead of the contemporaneous quotes recommended by Bessembinder (2003) and Petersen and Sirri (2003). This matching issue may also affect the 'true' classification of buyer/seller initiated trades with proprietary data (see Boehmer et al., 2007; Bessembinder, 2003), including ECN order data. Holden and Jacobsen (2011) examine the difficulties in matching trades to quotes with modern equity tick data. The tick rule has greater appeal because it avoids these matching problems.

Computer trading in automated markets (ECNs) has substantially altered market microstructure and changed the role of financial intermediaries (see Angel et al. (2011) and Holden and Jacobsen (2011) regarding the breakdown of standard

[2] These quote rule success rates subtract the matching zero spreads (bid = ask).

[3] Other relevant papers are Bessembinder (2003), Petersen and Sirri (2003), Theissen (2001) and Odders-White (2000).

[4] Berger et al. (2008) also use the 'latest time stamp' to sign forex trades to relate order flow and exchange rates and find partial support for Evans and Lyons (2002, 2008) with respect to high frequency rate movements.

[5] See Lee and Ready (1991), Piwowar and Wei (2006) and Bessembinder (2003).

[6] Delays using the LR algorithm to sign trades are one second in Anand et al. (2008) and two seconds in Huh (2014).