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Highlights:

- First analysis of performance of trade classification rules for the interbank currency market.
- Broad set of classification rules and large sample.
- MEMO rule performs best.
- Bulk classification rules do not provide large benefits.

The Accuracy of Trade Classification Systems on the Foreign Exchange Market: Evidence from the RUB/USD Market*

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Abstract

To the best of our knowledge we are the first to test a broad set of trade classification rules on the foreign exchange interbank market. A unique data set on the Russian Rouble/US Dollar trade includes the true trade initiator. The modified EMO (Ellis, Michaely and O'Hara) rule is currently the best choice at classifying trades. When quote data is not present, the tick rule yields a considerably lower accuracy. Yearly variations in the accuracy can be attributed to the difference in the location where trades occurred. Not surprisingly, trades executed at the quotes are the most informative.

Keywords: microstructure, foreign exchange, trade classification, Russian Rouble, tick rule, quote rule, bulk classification

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1. Introduction

The trade indicator is a binary variable stating whether the buyer or seller of an asset has initiated the trade by submitting a market order or an immediately executed limit order. Typical applications include the order flow (signed transaction volume, interpreted as buying or selling pressure, see inter alia Boyer and Van Norden 2006, Frömmel et al. 2008, Zhang 2018), bid-ask spread decomposition models such as those by Huang and Stoll (1997), tests for informed trading (Yung 2005, Elaut et al. 2018, Pöppe et al. 2016).

Despite its widespread empirical applications, the trade indicator is often not included in data sets. Therefore, trade classification rules (TCR) have been developed in order to classify trades as buyer- or seller-initiated, when the true originator is unknown. While the accuracy of those TCRs has been subject of various studies, the vast majority focuses on equity markets, whereas the foreign exchange market remains uncovered. The main reason is that classified data for the foreign exchange market is rare compared to equity markets. To the best of our knowledge, the currency market has only been analyzed by Omrane and Welch (2016), but for an Electronic Communication Network (ECN)[1], which is designed for non-reporting dealers and with very specific characteristics.

Our contribution to the literature is twofold: First, we compare broader set of TCR than most other studies. Second, we do this for the foreign exchange market. As Theissen (2001) points out markets' microstructure substantially affects the accuracy of TCR. The foreign exchange market substantially differs from equity markets, which previous studies have almost exclusively covered (Omrane and Welch 2016). It is a two-tier market, separated into the interbank market, where professional currency traders deal with each other and where price discovery takes place, on the one hand, and the customer market, where customers trade with the banks and submit their orders, which will finally be executed on the interbank

[1] An ECN is a computerized network for trading currencies outside traditional trading platforms. Due to their lack of liquidity most ECN are crossing networks and obtain prices from other trading venues without own price discovery. As Omrane and Welch (2016) state, "ECN data has poorer classification success across all the algorithms and because of the dominance of electronic markets today, recent studies like Chakrabarty et al (2007) are perhaps more relevant."

market. Different from Omrane and Welsh (2016) our data set covers the interbank market, where price discovery takes place, and we apply more TCRs to a longer data set.

The remainder of the paper proceeds as follows. Section 2 introduces the classification rules and briefly reviews the literature. Section 3 describes the data. Section 4 discusses the results and section 5 summarizes and concludes.

2. Trade Classification Rules (TCR)

2.1 Classification of TCR

The research concerning trade classification algorithms or trade classification systems is not very wide-ranging, nor is it very old. Lee and Ready (1991) were the first to systematically compare and analyze the performance of TCRs. We can distinguish two groups of TCRs: trade-by-trade classification rules, which classify every single trade, and bulk-classification rules, which assign a probability for being buyer- or seller-initiated to a bulk of trades. The trade-by trade classification rules analyzed are briefly introduced in Table 1. They include the tick rule (TR), the quote rule (QR) and combinations of both, with research showing better results for the more recent EMO (**E**llis, **M**ichaely and **O**'Hara) and MEMO (**m**odified **EMO**) rules.

The proposition of Easley et al. (2012) to rethink trade classification can thus be seen as revolutionary. **Bulk Volume Classification (BVC)** allocates a bulk of trades into buy and sell order flow, which is obviously very different to assigning an individual trade as either a buy or a sell. To do this, they use trade volume over intervals of either fixed time, fixed volume or fixed numbers of trades (for details see Easley et al. 2013). The standardized price change between the beginning and the end of the interval is then calculated to estimate the share of buy and sell volume. It should be intuitively clear that the larger (more positive) this price change is, the more probable that the underlying trades were buys and vice versa. Their conclusion is that BVC is superior to the incumbent TCR on index and commodity futures data, both in accuracy and resource requirements.

2.2 The Performance of TCR

A couple of studies empirically test the performance of TCRs. These studies, however, almost exclusively focus on equity and commodity markets. Furthermore, they are often restricted to a subset of TCRs. We provide a summary in Table 2.

Most studies find a performance (fraction of correctly classified trades) of trade-by-trade rules between 75 and 90%. The accuracy, however, seems to depend on the markets under consideration and on the location of trades. To the best of our knowledge, there is only one previous study on the foreign exchange market, but none on the interbank market, where price discovery occurs. *Omrane and Welch* (2016) studied the accuracy of the tick rule and BVC on EUR/USD, JPY/USD and GBP/USD from Hotspot (an electronic communication network). They have to deal with asynchronous trade and quote records and accordingly the tick rule's performance deteriorates. The accuracy is with 65.9%, 69.8% and 66.3% for the three currency pairs remarkably low and even falls substantially for zero ticks.

3. Data

The study uses a unique data set on the US Dollar-Russian Rouble market[2], and covers the period from mid-2011 to 2014. The RUB/USD rate is one of the more heavily traded exchanges rates and during our sample period ranked as the 11th most important currency pair with a share in global turnover of 1.5% (BIS 2013). Table 3 gives some descriptive statistics of our data set, while Figure 1 displays the price evolution through our sample. Our data set exceeds all existing studies in terms of sample length and allows studying subsamples under varying market conditions. Nevertheless, the number of observations is close to the average in existing studies, because we can only observe one currency pair, while studies on equity markets typically focus on a sample of stocks. Omrane and Welsh (2016) analyze three currency pairs with together 1,232,816 trades over two years, whereas our sample consists of 5,212,904 trades for one currency pair over a sample period of 3.5 years.

4. Results

4.1 Tick-by-tick Rules

Table 4 summarizes the performance of the trade-by-trade rules over the whole sample period in the first row. It is striking that the RTR substantially underperforms with an accuracy of only 46.42 %. In addition, the tick rule correctly classifies only 70.58% whereas the remaining rules all

[2] This is the same data set as used in Frömmel and Lampaert (2016). For the representativeness of the data, see Elaut et al. (2018), p39.

reach an accuracy of more than 85%. While this is lower than what is usually found on equity markets, it is in line with the study by Omrane and Welch (2016), who attribute the underperformance of the tick rules to the specific structure of the FX market. The remaining rules perform quite similarly with accuracies between 85.78% (QR) and 86.85% (MEMO), which is in line with Chakrabarty et al. (2007), although the differences are smaller for our sample. Furthermore our accuracy is similar to studies based on NYSE data (Lee and Radhakrishna 2000, Odders-White 2000, Finucane 2000), but better than those for NASDAQ data (Ellis et al. 2000, Chakrabarty et al. 2007) and the Frankfurt Stock Exchange (Theissen 2001). The low number of prices inside the spread, including trades at the midpoint, can explain the relatively small improvement of the LR, EMO and MEMO rules over the quote rule.

Table 5 displays the performance under varying market conditions. In 2011, characterized by a large fraction of trades outside the quotes, all rules but the RTR perform worse than in the other years. In contrast, for 2012 and 2013, characterized by low volatility and a high share of trades executed at the quotes, the accuracy generally increases. In 2014, finally we observe more than 40% of trades inside the quotes, which again deteriorates the accuracy. Only the tick rule shows a higher accuracy in 2014. While this contradicts the lower performance of the tick rule in volatile and trending markets as found by Aitkin and Frino (1996), it may be due to the higher share of non-zero ticks in 2014.

Finally we examine the accuracy of the rules conditional on the characteristics of the trades, i.e. separately for the buy and sell side (Aitkin and Frino 1996, Omrane and Welsh 2016), for trades inside the quote (Ellis et al. 2000)[3], and for zero versus non-zero ticks (Aitkin and Frino, 1996; Theissen, 2001; Omrane and Welch, 2016).

The results are displayed in Table 5. First, we confirm the asymmetry in buyer and seller-initiated trades found by Aitkin and Frino (1996) and Omrane and Welsh (2016), with seller-initiated trades performing remarkably better than buyer-initiated trades (the average difference is 7.46% for all TCR compared to 9.49% in Omrane and Welsh 2016). Second, for all quote-based rules we find lower accuracy for trades inside the quotes. Again, our results corroborate with the empirical literature. Third and finally, we find a substantial underperformance of the tick rule for zero tick trades, which is 9.33 percentage points lower than for non-zero ticks, compared to only 3.67 percentage points for the quote based rules.

[3] The EMO and MEMO rule were specifically created to cope with this problem and their superior performance should thus imply that this bias is also present in this study. Odders-White (2000) and Theissen (2000) also reported worse performances for trades occurring on the midpoint of the b/a spread, which is a specific case of trades occurring inside the quotes. We do, however, not look at trades at the midpoint, because there are too few of them in our sample.

4.2 Bulk Volume Classification (BVC)

We now turn to the evaluation of the BVC. Before we compare it to the tick-by-tick rules as discussed in the previous section, we will perform some considerations on the BVC, such as the choice of the bar size, the distribution and the treatment of overnight returns.

The impact of trade bar size on the BVC's accuracy is given in Table 6. There is no theoretical guideline on how many trades should form one bar. Based on our results and the average number of daily trades of around 4500 to 8000, bar sizes of 250, 500 and 1000 trades seem to be most suitable for further study. The found accuracies are in line with the 88.97% to 93.57% found by Easley et al. (2013), but substantial higher than the 71.1% to 78.2% of Chakrabarty et al. (2013).

Second, the accuracy of the BVC depends on the supposed underlying distribution of price changes. Easley et al. (2013) suggest a Student t-distribution with df = 0.25, while Chakrabarty et al. (2013) opt for a normal distribution. As the results in Table 7 show, using the normal distribution leads to a substantially weaker performance of the BVC[4], whereas for the t-distribution the performance slightly improves for lower degrees of freedom, so we rely on the same distribution as Easley et al. (2013).

Third, since there is no substantial effect by excluding overnight returns[5] we follow Chakrabarty et al. (2013) and include them in our analysis.

The main advantage of BVC is its resource efficiency and especially time saving (Easley et al. 2013). We therefore briefly scrutinize this claim. For fully utilizing the power of BVC, it is necessary to work with vendor-compressed data. When dealing with individual trade data as in Chakrabarty et al. 2013 and in our study, we need to aggregate the data first before applying BVC. If solely the application of the TCR for the signing of trades is considered, as would be the case for vendor-compressed data, we find a duration of 0.22s for BVC and an average of 1.07s for trade-by-trade TCR[6]. This corresponds with a time efficiency ratio of 20.5%, i.e. BVC is five times faster than the average tick-by-tick TCR. However, when the preparatory work of aggregating trades in bars is also considered, the total computational time for BVC becomes 0.58s and the efficiency ratio declines to 54.3% compared to 25% reported by Chakrabarty et al. (2013). We therefore conclude that the time saved by BVC are not as large as suggested by Easley et al. (2013) and further depend on the data available to the researcher.

In a final step we compare the BVC to the incumbent trade-by-trade TCRs. As already discussed, this comparison requires adapting the trade-by-trade TCR so that they also aggregate

[4] This also holds for other bar sizes.
[5] The results are not displayed here, but available from the authors on request.
[6] Since these computational times can be slightly differ for different runs, they should only be seen as a rough indication for the sake of comparison.

the classifications in bars. As this allows for offsetting, the BAR or the fraction of overall volume correctly classified within bars of all TCR are then comparable. Table 8 displays the results. The BVC does not increase the accuracy over aggregated trade-by-trade TCRs: It performs slightly worse than the tick rule, but is clearly outperformed by the quote-based rules. Easley et al. (2013) report similar results, but conclude that the underperformance is acceptable in the light of the BVC's other advantages. Chakrabarty et al. (2013) report much larger performance differences.

5. Conclusion

This paper reviews the literature on trade classification rules and applies them to a unique data set of tick-by-tick trades in the RUB/USD market. This is the first evaluation of TCRs on the FX interbank market and at the same time the most exhaustive comparison of TCRs.

We find an accuracy of tick-by-tick rules in line with existing literature. The MEMO improves on all previous TCR and is currently the best choice at classifying trades. When quote data is not present, the TR yields a considerably lower accuracy. Its ease-of-use makes it nonetheless very useful for many researchers. Yearly variations in the accuracy can be attributed to different locations where trades occurred. Not surprisingly, trades executed at the quotes are the most informative ones.

Furthermore, the most important biases encountered in the literature have been confirmed in this study: Seller-initiated trades perform remarkably better than buyer-initiated trades. The EMO rule, and especially the MEMO rule, offer substantial improvements over LR as they have far more power for classifying trades that occurred inside the quotes. The biggest disadvantage of the TR is its poor performance for zero ticks.

The recently suggested Bulk Volume Classification slightly underperforms tick-by-tick rules. BVC provides some time saving, which, however, substantially declines, if the available data first needs to be aggregated.

Altogether, for our data set all quote-based rules perform similarly well, with the MEMO rule providing the highest accuracy.

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TABLE 1. TRADE-BY-TRADE CLASSIFICATION RULES

	Requirement	Classification	Remarks
Tick rule (TR)	Transaction data	If price higher (lower) than previous: buy (sell) If no price change same as previous	Blume, MacKinlay and Tercker (1989)
Reverse Tick rule (RTR)	Transaction data	If price higher (lower) than subsequent: buy (sell) If no price change same as subsequent	Differs from TR only, if there are subsequent price movements in the same direction
Quote rule (QR)	Transaction data and midpoint	If price above (below) midpoint: buy (sell) Prices at midpoint unclassified	Hasbrouck (1988)
Lee and Ready rule (LR rule)	Transaction data and midpoint	If price above (below) midpoint: buy (sell), for prices at midpoint: use tick rule	Lee and Ready (1991) Widely used
EMO rule	Transaction data, bid and ask	Trades at the quote: Quote rule For all quotes inside the spread: Tick rule	Ellis, Michaely and O'Hara (2000)
Modified EMO	Transaction data, bid and ask	Trades at the quote and up to 30% below the ask or above the bid: Quote rule, for all trades in the inner 40% of the spread: Tick rule	Chakrabarty et al. (2007)

TABLE 2. Research on the Accuracy of Trade Classification Rules

Author(s)	Data	TCR	Accuracy	Benchmark	Additional results
Lee and Ready (1991)	150 NYSE firms in 1988	LR rule	90.9%	True classification	
Aitken and Frino (1996)	ASX, 1993-1994, 4,022,339 trades	TR	75%	Quote rule	90% for non-zero ticks
Lee and Radhakrishna (2000)	TORQ[7] (NYSE) 11/1990-1/1991 687,980 trades	LR rule	93% for classified trades (i.e. 60% of the sample)	True classification	
Odders-White (2000)	TORQ (NYSE) 11/1990-1/1991 318,364 trades	LR rule	85% for LR rule	True classification	
Finucane (2000)	TORQ (NYSE) 11/1990-1/1991 337,667 trades	LR rule and RT rule	84% for LR 83% for RTR	True classification	
Ellis et al. (2000)	313 NASDAQ stocks 9/1996-9/1997 2,433,019 trades	QR, TR, LR rule, and EMO rule	76.4% for QR 77.7% for TR 81.1% for LR rule 81.9% for the EMO rule	True classification	All rules perform poorly for trades inside the quotes, and introduce a bias when classifying large trades, trades during high volume periods, and ECN trades. The effective spread is systematically overestimated.
Theissen (2001)	15 stocks from the Frankfurt Stock Exchange (5 from DAX and 10 from MDAX), 21 trading days	TR, LR rule	72.2% for the TR 72.8% for the LR rule	Based on the position taken by the specialist ("Makler")	Only slight increase of accuracy when trades at midpoint are excluded
Savickas and Wilson (2003)	Option trading from CBOE for 826 securities from NYSE and NASDAQ, 1,425,767 customer-market maker trades	TR, QR, LR rule, EMO rule	59% for the TR 83% for the QR 80% for the LR rule 78% for the EMO rule	True classification (matched)	Filtering out critical trades leads to performance in line with other studies.
Chakrabarty et al. (2007)	750 NASDAQ stocks traded on two ECNs (INET and	TR, LR rule, EMO	75.4% for TR 74.4% for LR rule	True classification	MEMO rule more advantageous for trades inside quotes (76.32%, compared to 71.85%

[7] The TORQ dataset is a subsample of detailed trade data on 144 firms listed on the NYSE. It was collected under supervision of Joel Hasbrouck, see Lee and Rahdhakrishna (2000).

	ArcaEx), 4-6/2005, 17,464,049 trades	rule, MEMO rule	75.8% for EMO rule 76.5% for MEMO rule		for the LR rule and 71.35% for both the tick and the EMO rule).
Lu and Wei (2009)	684 TWSE stocks traded on an ECN, 1-6/2006, 17,272,235 trades	TR, QR, LR rule (modified) and EMO rule	74% for TR 93% for QR 97% for modified LR 95% for EMO rule	Matched orders	
Chakrabarty et al. (2013)	300 stocks traded on INET over 3 months in 2005, and three months in 2006	TR and BVC	Time bars: 77.5-94.4% for TR 62.3-78.1% for BVC Volume bars: 80.7-93.5% for TR 67.9-77.8% for BVC	True classification	TR without offsetting is significantly outperformed by BVC for bars for time bars of 1,800 sec and above, and for volume bars of 8,000 shares or above respectively. BVC performs better for large caps.
Panayides et al. (2019)	Euronext Paris, 100 stocks over 3 months (4/2007, 2/2008, 4/2008) LSE, 125 stocks over 2 months (2 and 4/2008)	TR, LR rule and BVC	Time bars: up to 96.57% for TR up to 95.73% for LR up to 90.90% for BVC Volume bars: up to 96.26% for TR up to 95.79% for LR up to 90.58% for BVC	True classification	Low-latency trading decreases performance of LR rule
Omrane and Welch (2016)	Hotspot data (ECN) on EUR/USD, JPY/USD and GBP/USD, 1,232,816 trades	TR, BVC	TR: 65.9% (EUR/USD), 69.8% (JPY/USD) 66.3% (GBP/USD) 57.4-60% group TR 53.5-57.4% (BVC)	True classification	Differences in accuracy between currency pairs

TABLE 3. Descriptive Statistics on our Data Set

	2011	2012	2013	2014
Num	499 779	1 189 595	1 524 877	1 998 651
Volume				
Av. Volume/trade				
Max	32.831	34.198	33.504	80.200
Min	27.392	28.834	29.870	33.025
Mean	30.109	31.174	32.009	40.605
Median	30.530	31.180	32.264	36.220
Range	5.440	5.364	3.634	47.175
Std	1.502	1.061	0.946	8.124

Location	**Obs 2011-2014**	2011-2014	**2011**	**2012**	**2013**	**2014**
Outside quotes	510,790	9.80%	30.39%	13.33%	11.12%	1.54%
Ask	2,025,326	38.85%	33.94%	42.38%	47.26%	31.60%
Bid	1,843,291	35.36%	33.74%	43.84%	41.34%	26.18%
Inside quotes	833,497	15.99%	1.93%	0.45%	0.28%	40.68%
Midpoint[20]	23,128	0.44%	0.03%	0.00%	0.02%	1.13%
Total	**5,212,904**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Zero ticks	2,553,135	48.98%	52.58%	52.64%	52.41%	43.32%
Non-zero ticks	2,659,766	51.02%	47.42%	47.36%	47.59%	56.77%

FIGURE 2. Evolution of the RUB/USD Rate during the Sample Period

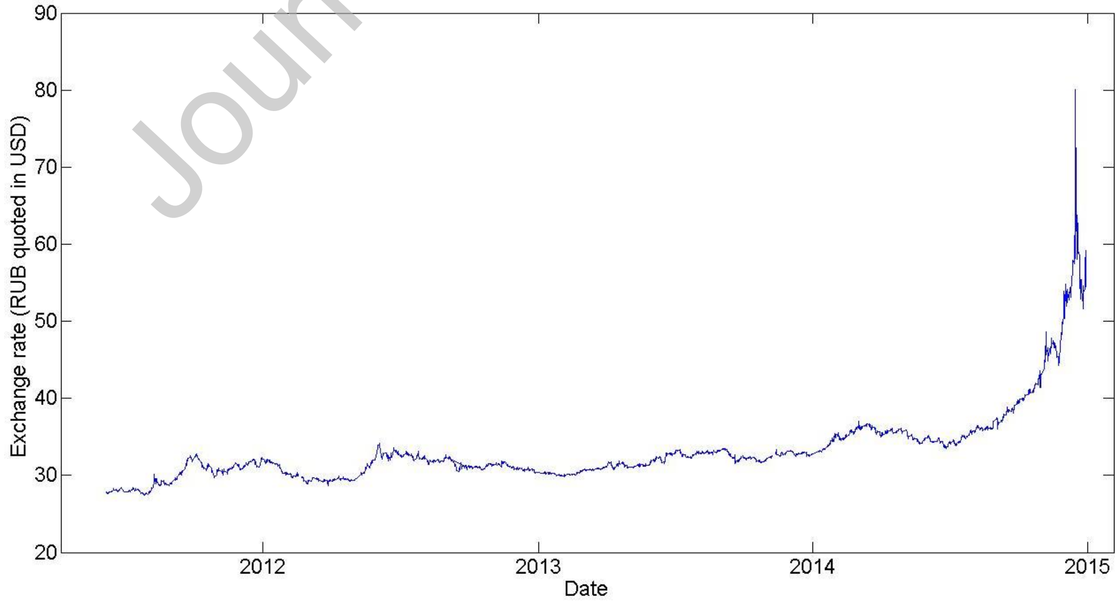

TABLE 4. Accuracy of Trade-by-trade TCRs

	RTR	TR	QR	LR	EMO	MEMO
2011-2014	46.42%	70.58%	85.78%	86.10%	86.26%	86.85%
2011	49.10%	62.32%	78.10%	78.11%	75.49%	75.89%
2012	48.62%	66.17%	89.42%	89.42%	89.07%	89.19%
2013	49.36%	68.58%	90.27%	90.27%	90.16%	90.22%
2014	42.21%	76.79%	82.11%	82.93%	84.32%	85.63%

TABLE 5. Accuracy of Trade-by-trade TCRs and Location of the Trades

	TR	QR	LR	EMO	MEMO
Buy	67,46%	82,91%	83,14%	82,62%	83,55%
Sell	74,78%	89,64%	90,08%	91,17%	91,29%
Inside quotes	69,57%	67,01%	69,00%	69,57%	73,24%
Zero ticks	65,82%	83,80%	84,07%	84,88%	84,74%
Non-zero ticks	75,15%	87,68%	88,04%	87,59%	88,87%
Total	**70,58%**	**85,78%**	**86,10%**	**86,26%**	**86,85%**

TABLE 6. Accuracy of BVC

Trade bar size	BVC	Trade bar size	BVC	Trade bar size	BVC
10	76.50%	250	88.72%	5000	90.45%
25	81.96%	500	89.58%	10000	89.87%
50	84.88%	1000	90.10%	20000	89.64%
100	86.97%	2500	90.45%		

TABLE 7. BVC and Alternative Distributions

	Student t-distribution							Normal distribution
Bar size	**Df=0.05**	**0.1**	**0,25**	**0,5**	**1**	**100**	**10000**	
250	89.02%	89.03%	88.72%	88.19%	87.60%	86.53%	86.52%	69.51%
500	90.09%	90.04%	89.58%	88.94%	88.27%	87.07%	87.06%	74.22%
1000	90.85%	90.72%	90.10%	89.34%	88.55%	87.18%	87.16%	77.78%

TABLE 8. Performance of BVC vs. Trade-by-trade TCRs

	BVC	TR	QR	LR	EMO	MEMO
250	88,72%	89,79%	92,17%	92,09%	92,41%	92,25%
500	89,58%	90,68%	92,36%	92,25%	92,62%	92,39%
1000	90,10%	91,22%	92,48%	92,34%	92,78%	92,48%

Author statement

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