Robust microstructure: #fincap

June 14, 2021

1 Methodology

To examine how key market microstructure measures changed between 2002 and 2018[1] for the EURO STOXX 50® Index Futures, we estimate the following regression using monthly observations:

$$log(Y_t) = \alpha + \beta X_t + \varepsilon_t, \tag{1}$$

where $log(Y_t)$ is the log value of our measure and X_t is a time variable equal to 1/12 for the first observation and increasing by 1/12 each month. The $\widehat{\beta}$ estimate can be interpreted as the per-year change in %. We compute Heteroskedasticity and Autocorrelation-Consistent (HAC) standard errors with 6 lags. Figure 1 shows the time-series of each measures and Table 1 reports our regression estimates.

2 Results

2.1 Null hypothesis 1: Market efficiency has not changed over time.

If informationally-efficient log prices follow a random walk ($p_t = p_{t-1} + \varepsilon_t$) and assuming that $E\left(\varepsilon_t \varepsilon_{t-j}\right) = 0 \; \forall j$, we have that $Var\left(p_t - p_{t-n}\right) = n\sigma_\varepsilon^2$.

We define the Variance Ratio (Lo and MacKinlay, 1988) as:

$$VR\left(n,k\right) = \frac{kVar\left(p_t - p_{t-n}\right)}{nVar\left(p_t - p_{t-k}\right)} \tag{2}$$

Under the null, prices follow a random walk, $VR\left(n,k\right) = 1$. To test for *changes* in market efficiency, we follow O'Hara and Ye (2011) and compute the absolute difference between 1 and $VR\left(n,k\right)$:

$$ABS\_VR\left(n,k\right) = \left|1 - VR\left(n,k\right)\right| \tag{3}$$

Low values of $ABS\_VR\left(n,k\right)$ are associated with an efficient market and prices behaving like a random walk. Choices for n and k are up to the econometrician, and values used

[1] For measures requiring signed trades, our sample period is Nov. 2009 to Dec. 2018.

in the literature vary. For example, Lo and MacKinlay (1988) use 2 to 8 weeks over 1 week while Comerton-Forde, Grégoire, and Zhong (2019) use 1 minute over 15 seconds. In modern markets, choosing higher frequency measures is more reasonable. Variance ratios are estimated from midquote prices, but our data only contains trades. To mitigate issues from using trade prices (see, e.g. Gregoire and Martineau, 2021), we use n =30 minutes and k =5 minutes, and only consider trades on the front-most contract.[2] We compute daily ABS_VRs and then take the monthly average for our regressions.

We do not reject the null of no change as our measure ABS_VR increased by 0.531% on average per year where the standard error of this change is 0.449% and the resulting t-statistic is 1.182 (p-value is 0.237).

2.2 Null hypothesis 2: The realized spread on market orders has not changed over time.

We define the realized spread as in Goyenko, Holden, and Trzcinka (2009):

$$REAL\_SPREAD(\Delta) = \begin{cases} 2(p_t - m_{t+\Delta}) & \text{for buyer-initiated trades,} \\ 2(m_{t+\Delta} - p_t) & \text{for seller-initiated trades,} \end{cases} \tag{4}$$

where p_t is the log traded price for the transaction at time t, and m_t is the prevailing log midquote at time t. Since our data only contains trade prices, we approximate $m_{t+\Delta}$ with the price of the last transaction at time $t+\Delta$. To mitigate issues associated with sparse trading, we use $\Delta = 5$ minutes and only consider trades on the front-most contract. We estimate realized spread for individual trades and winsorize the top and bottom 0.5% trades in each month. We thencompute the monthly realized spread as the quantity-weighted average for all trades in the month.

We do not reject the null of no change as our measure REAL_SPREAD declined by 1.534% on average per year where the standard error of this change is 3.459% and the resulting t-statistic is -0.444 (p-value is 0.657).

[2] We roll over to the next contract on the expiry date, we do not consider a contract on the day it expires.

2.3 Null hypothesis 3: Client share volume as a fraction of total volume has not changed over time.

We compute the monthly share of client volume in total volume using all trades for all maturities as:

$$SHR\_CLIENT\_VOL = \frac{\sum_{n=1}^{N} q_n \times \mathbb{1}_{n,\text{client}}}{\sum_{n=1}^{N} q_n} \tag{5}$$

where q_n is the quantity of trade n and $\mathbb{1}_{n,\text{client}}$ is an indicator variable equal to one if trade n is a client trade and zero otherwise.

We reject the null of no change. We find that the share of client volume in total volume declined as our measure SHR_CLIENT_VOL declined by 3.723% on average per year where the standard error of this change is 0.270% and the resulting t-statistic is -13.812 (p-value is < 0.001).

This result shows that client trades make up a much smaller fraction of total volume than they did 20 years ago. This is consistent with our observations from Panel C of Figure 1 showing a gradual decrease over the sample period with a sharp decrease around the GFC.

2.4 Null hypothesis 4: Client realized spreads have not changed over time.

We compute the realized bid-ask spreads that clients paid ($REAL\_SPREAD\_CLIENTS$) similarly to $REAL\_SPREAD$ in Section 2.2 but using client trades only.

We do not reject the null of no change as our measure CLIENTS_REAL_SPREAD increased by 5.578% on average per year where the standard error of this change is 4.462% and the resulting t-statistic is 1.250 (p-value is 0.211).

2.5 Null hypothesis 5: The fraction of client trades executed via market orders and marketable limit orders has not changed over time.

We compute the monthly fraction of client trades executed via market orders and marketable limit orders using all trades for all maturities as:

$$SHR\_CLIENT\_VOL = \frac{\sum_{n=1}^{N} \mathbb{1}_{n,\text{client}}}{N}, \tag{6}$$

where N is the total number of trades and $\mathbb{1}_{n,\text{client}}$ is an indicator variable equal to one if trade n is a client trade and zero otherwise.

We do not reject the null of no change as our measure FRAC_CLIENTS_MKT increased by 0.059% on average per year where the standard error of this change is 0.192% and the resulting t-statistic is 0.309 (p-value is 0.757).

2.6 Null hypothesis 6: Relative gross trading revenue (GTR) for clients has not changed over time.

We compute our measure $CLIENTS\_GTR$ as:

$$CLIENTS\_GTR = \frac{\sum_i s_i q_i (C - P_i)}{\sum_i q_i P_i} \tag{7}$$

where P_i is the traded price for transaction i, q_i is the quantity and s_i is the trade direction (+1 for buys, -1 for sells) and C is the last transaction price of the day. To mitigate issues associated with sparse trading, we only consider trades on the front-most contract. We compute the monthly GTR as the dollar volume-weighted average for all trades in the month.

We do not reject the null of no change as our measure CLIENTS_GTR declined by 4.914% on average per year where the standard error of this change is 4.647% and the resulting t-statistic is -1.057 (p-value is 0.290).

References

Comerton-Forde, Carole, Vincent Grégoire, and Zhuo Zhong, 2019, Inverted fee structures, tick size, and market quality, *Journal of Financial Economics* 134, 141–164.

Goyenko, Ruslan Y, Craig W Holden, and Charles A Trzcinka, 2009, Do liquidity measures measure liquidity?, *Journal of Financial Economics* 92, 153–181.

Gregoire, Vincent, and Charles Martineau, 2021, How is earnings news transmitted to stock prices?, *Available at SSRN.*

Lo, Andrew W, and A Craig MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *The Review of Financial Studies* 1, 41–66.

O'Hara, Maureen, and Mao Ye, 2011, Is market fragmentation harming market quality?, *Journal of Financial Economics* 100, 459–474.

Table 1
Regression output

	Coef.	Std. err.	t stat.	p-value	C.I. lower bound	C.I. upper bound
ABS_VR	0.531%	0.449%	1.182	0.237	-0.349%	1.412%
REAL_SPREAD	-1.534%	3.459%	-0.444	0.657	-8.313%	5.245%
SHR_CLIENT_VOL	-3.723%	0.270%	-13.812	< 0.001	-4.252%	-3.195%
CLIENTS_REAL_SPREAD	5.578%	4.462%	1.250	0.211	-3.166%	14.323%
FRAC_CLIENTS_MKT	0.059%	0.192%	0.309	0.757	-0.318%	0.437%
CLIENTS_GTR	-4.914%	4.647%	-1.057	0.290	-14.023%	4.194%

Figure 1. Time-series of the microstructure measures