Can High-Frequency Traders Game Futures?

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High-frequency trading (HFT) is a boon for some market participants and a worry for others. Gomber et al. [2011] used a survey to conclude that most academic literature to date finds only positive effects of HFT, particularly on such variables as liquidity and volatility, which are crucial to healthy functioning of securities markets. Several studies have shown that HFT adds liquidity to markets and reduces market volatility (see, for example, Jarnecic and Snape [2010], Brogaard [2010], and Hasbrouck and Saar [2010]).

Despite reassurances from these authors, many traders still fret about the ability of HFTs to understand traders' intentions and increase the costs of trading through lightning-fast moves. A September 12, 2011, article in *The Financial Times*, for instance, said that two-thirds of institutional market participants worried about the possible ramifications of high-frequency trading.

The current study seeks to ascertain the influence high-frequency traders exert on other trades in Eurobund futures. Specifically, we pose and answer the following question: Can high-frequency traders deploy the so-called "pump-and-dump" strategies to disadvantage large traders? We show that such strategies are not economical in the Eurobund futures market. The Eurobund futures market was chosen for this study based on the futures' copious liquidity, the ready availability of tick data, and the scarcity of other HFT research in the futures space.

High-frequency trading has been a catalyst behind major structural changes in the markets, as well as a subject of much controversy. While many common HFT strategies are benign (see Aldridge [2009] for an HFT strategy summary), some market participants remain unconvinced. In the high-frequency pump and dump evaluated in this study, computer-assisted traders are thought to momentarily drive up or down the prices of securities, only to promptly reverse their positions and capitalize on false momentum at the expense of other traders.

Throughout this article, we will use the notion of market impact to evaluate various hypotheses. We formally define the market impact of a trade as the change in price following the trade and use the obtained metric to assess the likelihood of HF pump and dump based on theoretical predictions of Huberman and Stanzl [2004] and Gatheral [2010]. The latter specifies conditions necessary for the absence of high-frequency pump-and-dump opportunities: The post-trade permanent market impact function should be symmetric in size for buyer-initiated and seller-initiated trades. If the post-trade permanent market impact for buyer-initiated trades exceeds that for seller-initiated trades, for example, a high-frequency trader could "pump" the security price through repeated purchases to a new high level and then "dump" the security, thereby incurring less market impact when disposing of a position and generating a profit. In our analysis, however, we find that such high-frequency pump-and-dump strategies are not feasible once trading costs are taken into account.

This article proceeds as follows. I first establish the theoretical foundation of market impact and survey the related literature. I then describe the key methodologies deployed and the data used in the study and summarize the results. After analyzing optimization of execution and delivering analysis-based suggestions for better executional performance, I present my conclusions and directions for future research.

METHODOLOGY

Huberman and Stanzl [2004] and Gatheral [2010] analyzed the theoretical underpinnings of pump-and-dump strategies and concluded that pump and dump is feasible whenever the permanent market impact functions are not symmetric for buys and sells. In other words, when pump and dump is *not* feasible, the price change following a sell-initiated trade of size V is equal to the negative of the price change following a buy-initiated trade of size V. When this "no-pump, no-dump" condition is violated, an arbitrage opportunity exists.

We formally describe pump-and-dump strategies using a measure of permanent market impact $f(V_t)$ of a trade of size V_t processed at time t, where $V_t > 0$ indicates a buyer-initiated trade and $V_t < 0$ describes a seller-initiated trade. If $f(V) > -f(-V)$, a trader could artificially pump and then dump by first buying and then selling at the same trade size V. Conversely, if $f(V) < -f(-V)$, the trader could manipulate the markets by first selling and then buying the securities back.

To examine the evolution of market impact over time, we consider market impact within different "event windows," for which the length of the window is determined by a number of trade ticks before and after the market order event, as shown in Exhibit 1.

Denoting market impact function f, we obtain the following specification:

$$f_{t+1} = \ln[P_{t+1}] - \ln[P_{t-1}]$$
$$\vdots$$
$$f_{t+\tau} = \ln[P_{t+\tau}] - \ln[P_{t-1}]$$

To evaluate the feasibility of the pump and dump, we use a linear specification for the market impact as a function of trading volume, V, consistent with Breen, Hodrick, and Korajczyk [2002]; Kissell and Glantz [2002]; and Lillo, Farmer, and Mantegna [2003]; and following Huberman and Stanzl [2004] and Gatheral [2010]:

$$f_{t+\tau}(V_t) = \alpha_\tau + \beta_\tau V_t + \varepsilon_{t+\tau} \tag{1}$$

where V_t is the size of trade executed at time t, β_τ is the trade size–dependent market impact, and α_τ is the trade size-independent impact of each trade, measured τ ticks after time t. If the high-frequency pump and dump is feasible, β_τ for buyer-initiated trades will be different from $-\beta_\tau$ estimated for seller-initiated trades. The null hypothesis, that pump and dump exists in Eurobund futures, can then be specified as follows:

$$H_0 : \beta_\tau|_{\textit{buyer-initiated trades}} \neq -\beta_\tau|_{\textit{seller-initiated trades}} \tag{2}$$

And the alternative hypothesis ruling out pump and dump can be specified as:

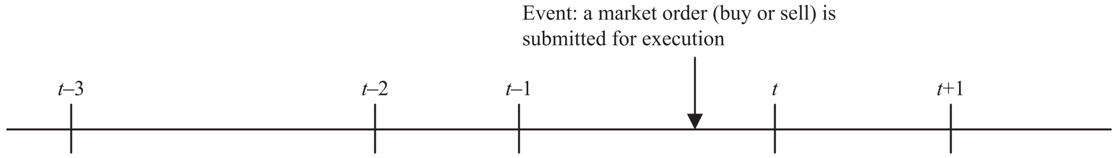
$$H_A : \beta_\tau|_{\textit{buyer-initiated trades}} = -\beta_\tau|_{\textit{seller-initiated trades}} \tag{3}$$

We now proceed to the discussion of estimation and interpretation of results.

DATA

The data used in the analysis are a sequence of Eurex Eurobund futures (symbol FGBL) trades, recorded and time-stamped with millisecond granularity. In addition to the timestamp, the data include the trade price and trade size. The data, the "official" copy of the Eurex trading tape, are commercially distributed to traders.

EXHIBIT 1
Sequence of Events Used in Market Impact Computation



The data are voluminous: As Exhibit 2 shows, any given day witnesses anywhere from 10,000 to 80,000 trades. Trades come in various trade sizes. While the median trade size tends to be just five contracts, the maximum trade size easily reaches 20,000 units (see Exhibits 3 and 4). The median trade size tends to rise by just one contract in end-of-quarter months. Within each day, median trade sizes change from one hour to the next, but not by much, as Panels A and B of Exhibit 5 illustrate. We further confirm the lack of time-of-day effects using the vector autoregressive (VAR) specification of Hasbrouck [1991] and Dufour and Engle [2000] with dummy variables—the results ascribe little statistical significance to times of day from one month to the next. In the intraday data, directional trading is detected during hours when major economic announcements take place, but even then, the statistical significance of these time-of-day effects is low.

Exhibit 6 notes the peculiarity specific to futures markets: In the last few days of each quarter, the average trade size spikes. This observation is likely related to position rollovers during futures expiration months. Exhibit 7 shows trade count per order size and trader's preference for round lot numbers: Multiples of 50 contracts are common.

The data do not contain best bid/offer information or identification of whether the trades were initiated by the buyer or seller. To identify whether the trade was initiated by a market buy or a market sell, we use a tick rule. A tick rule is one of the three most popular methodologies used to determine whether a buyer or seller initiated a given trade, in the absence of such information in the

EXHIBIT 2
Distribution of Daily Number of Trades

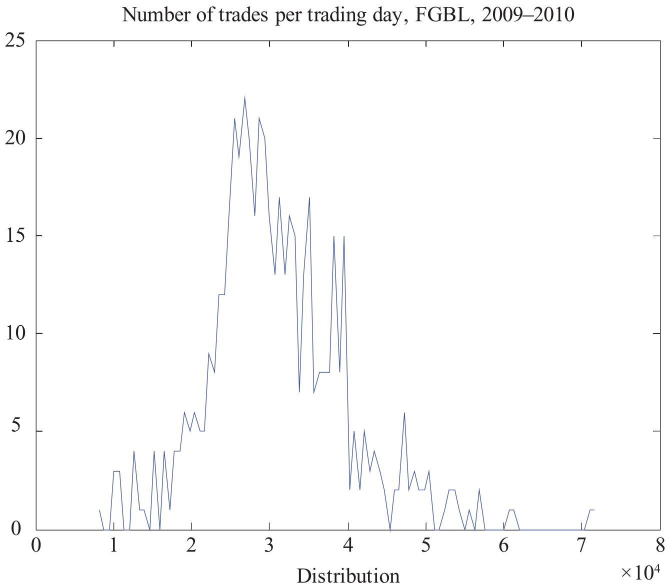


EXHIBIT 3
Maximum Daily Trade Sizes

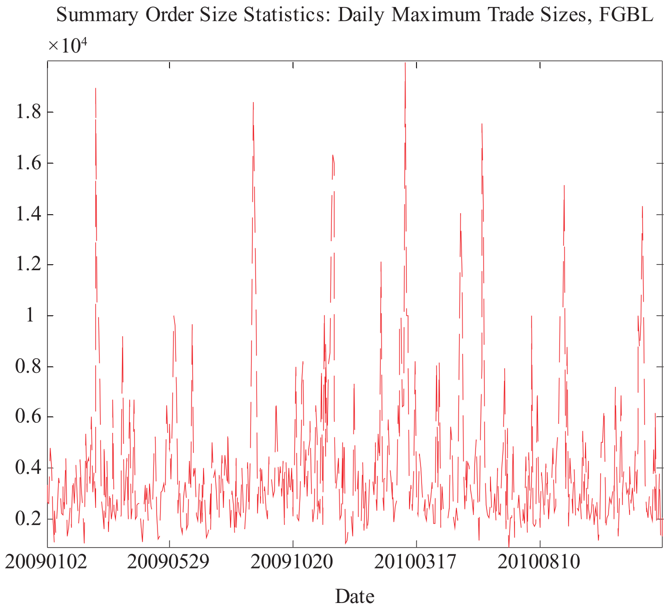


EXHIBIT 4
Median Daily Trade Sizes

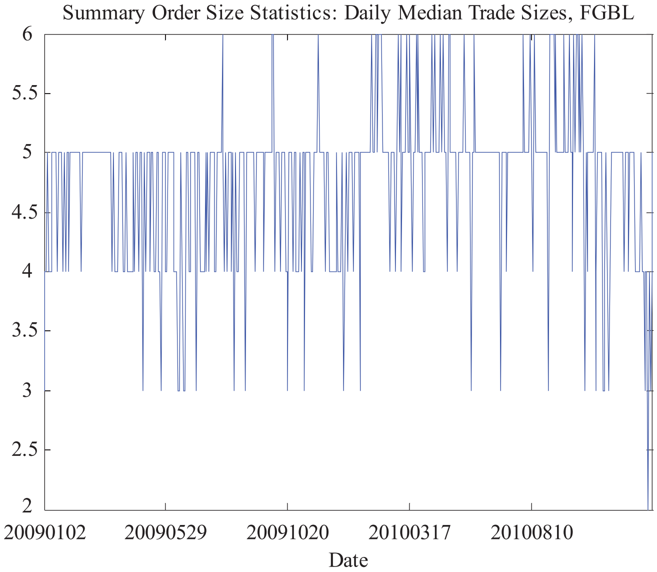
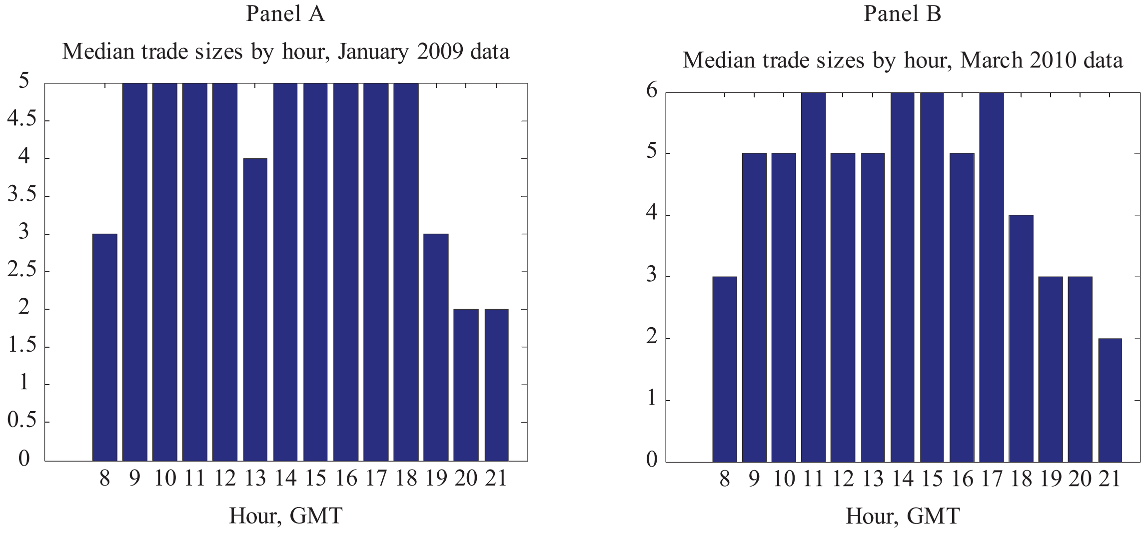


Exhibit 5

Median Trade Sizes by Hour of the Day, Observed in FGBL Trade Data in January 2009 and March 2010



dataset. The other two popular methods are the quote rule and the Lee–Ready rule, after Lee and Ready [1991].

According to the tick rule, the classification of a trade is performed by comparing the price of the trade with the price of the preceding trade; no bid or offer quote information is taken into account. Each trade is then classified into one of four categories:

- an uptick, if the trade price is higher than the price of the previous trade
- a downtick, if the trade price is lower than the price of the previous trade
- a zero-uptick, if the price has not moved, but the last recorded move was an uptick
- a zero-downtick, if the price has not moved, but the last recorded move was a downtick

Exhibit 6

Average Daily Trade Sizes, 2009–2010

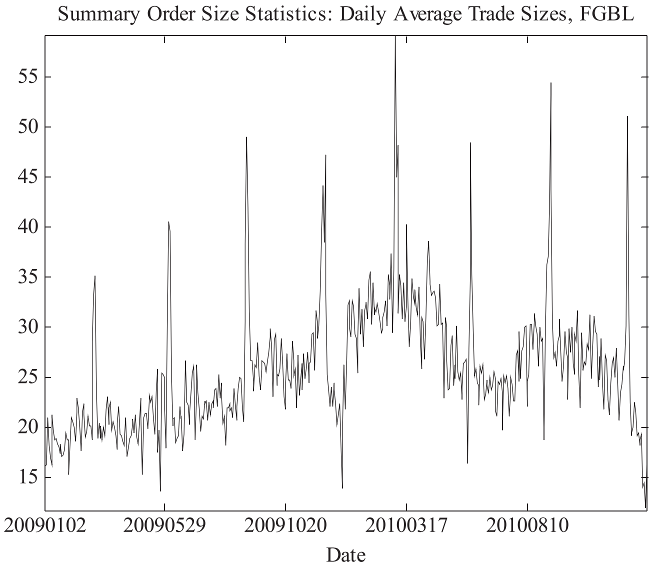
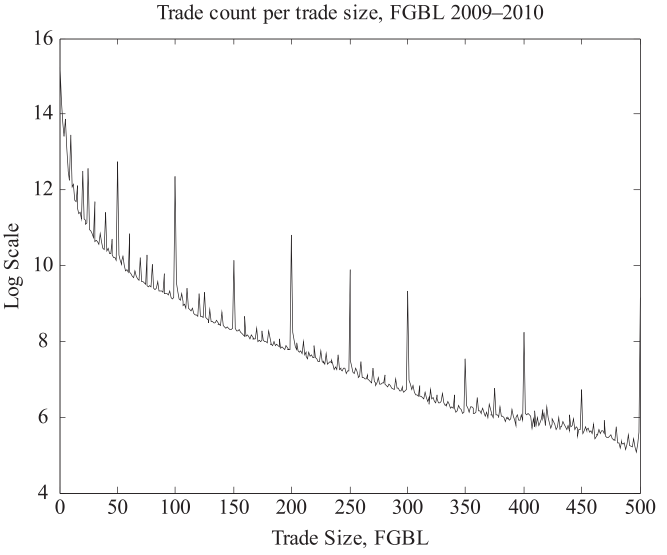


Exhibit 7

Trade Count per Trade Size, 2009–2010



If the trade's price differs from that of the previous trade, the last trade is classified as an uptick or a downtick, depending on whether the price has moved up or moved down. If the price has not moved, the trade is classified as a zero-uptick or a zero-downtick, depending on the direction of the last nonzero price change.

According to Ellis, Michaely, and O'Hara [2000], in 1997–1998, the tick rule correctly classified 77.66% of all NASDAQ trades. The alternative order classification rules deliver comparable accuracy of classification. The often-used quote rule has been shown to correctly classify 76.4% of all trades on NASDAQ (see Ellis, Michaely, and O'Hara [2000]). Ellis, Michaely, and O'Hara [2000] show that the Lee–Ready rule correctly classifies just 81.05% of all trades as either buy or sell initiated, a small improvement over the tick classification. The Lee–Ready rule, however, requires bid and offer quotes, the data we do not possess for this analysis.

Most of the tests related to accuracy of order classification rules have been conducted on equities only. As a result, the proportion of correctly classified trades may be due specifically to short sale–related regulatory issues in equities (see Asquith, Oman, and Safaya [2008]). In the absence of short-sale constraints in the Eurobund futures data, our tick rule–based trade classification is likely to be much more precise.

In computing market impact, we treat overnight returns as missing values, thus ensuring that the market impact on a specific day is a function of data recorded on that day only.

ESTIMATION RESULTS

We estimate Equation (1) using ordinary least squares (OLS) and present results for $\tau = 5$, corresponding to five trade ticks following the trade of interest. The five-tick cutoff, which has been used in other studies of market impact such as Dufour and Engle [2000], has been deemed a sufficient indicator of market dynamics. Other, higher, values of τ studied produce results similar to those with $\tau = 5$.

Exhibit 8 reports estimates of Equation (1) for trades of all sizes by month for the 2009–2010 period. Exhibit 9 graphically illustrates the relationship of volume coefficients for buy and sell trades. Exhibit 10 shows the results of the difference tests of volume coefficients observed for buy and sell trades.

Coefficients for the entire sample, large trades and small trades, were estimated using the following linear regression: $MI_{t+\tau}(V) = \alpha_\tau + \beta_\tau V_t + \varepsilon_{t+\tau}$, where the observations were separated into buys and sells.

The observed differences in buyer- and seller-initiated market impact change from month to month and lack statistical significance. On the basis of the results, we conclude that the FGBL futures data do not support the possibility of high-frequency pump and dump.

The results presented in Exhibit 8 indicate another interesting phenomenon: Trade size–related market impact does not begin to register until the trade size rises to about 100 contracts. Since the unexplained variation, intercept α, in the market impact equation is large (on the order of 10^{-5}), and the trade-related market impact is on the order of 10^{-7}, a single trade of up to 100 contracts may incur as much impact as a trade of 1 contract. This is great news for institutions and other large fund managers who are concerned about the impact of their trades—in the FGBL futures market, a single trade of a size considerably larger than the median trading size leaves no trace, on average. Unlike the equities markets, the Eurex FGBL market is resilient to a much larger capacity.

ROBUSTNESS CHECKS

To check whether the results are robust, we considered several auxiliary explanatory variables: volatility, spread, and intertrade duration. Other studies found such additional explanatory variables for temporary market impact.

For example, in futures, Burghardt, Hanweck, and Lei [2006] show that post-trade market impact is also dependent on liquidity characteristics, such as the market depth. Other studies have focused on equities. Breen, Hodrick, and Korajchyk [2002], Lillo, Farmer, and Mantegna [2003], and Almgren et al. [2005] show that the permanent market impact function in equities is dependent on stock-specific liquidity characteristics. Dufour and Engle [2000] find that longer intertrade duration leads to lower market impact, and vice versa. Ferraris [2008] reports that several commercial models for equity market impact use volatility and the bid–ask spread prevailing at the time of the trade as predictive inputs to forecast the market impact of the trade. In the current study, we find that volatility, spread, and intertrade duration help explain market impact in futures as well. None of the auxiliary variables, however, change the

Exhibit 8

Estimation of Size-Dependent Market Impact for Large and Small Trades in Eurobund Futures, by Month

	Buys, all trade sizes					Sells, all trade sizes				
	# obs	α_5	*t*-stat	β_5	*t*-stat	# obs	α_5	*t*-stat	β_5	*t*-stat
200901	373631	1.6E–5	50.7	1.6E–7	24.1	367857	–2E–5	–50.5	–1.4E–7	–18.6
200902	332584	1.4E–5	37.4	1.3E–7	20.0	334078	–1.7E–5	–46.0	–1.1E–7	–17.6
200903	400829	1.5E–5	54.8	3E–8	11.8	402137	–1.6E–5	–55.5	–4.8E–8	–17.4
200904	319454	1.0E–5	39.5	1.8E–7	37.3	318556	–1.4E–5	–46.2	–1E–7	–21.8
200905	298859	1.2E–5	37.1	1.1E–7	23.3	300020	–1.4E–5	–41.4	–1.2E–7	–23.4
200906	348640	1.2E–5	32.4	3.8E–8	11.9	341341	–1.5E–5	–38.5	–2.6E–8	–7.7
200907	310745	7.5E–6	20.8	1.4E–7	22.8	303278	–1.2E–5	–29.3	–1.1E–7	–17.1
200908	284896	8.6E–6	23.1	1.2E–7	20.1	285690	–1.3E–5	–30.3	–1.2E–7	–17.0
200909	331673	9.5E–6	43.5	1.8E–8	12.4	325211	–1.1E–5	–42.5	–2.9E–8	–15.0
200910	337226	7.2E–6	35.6	8.4E–8	32.4	330927	–8.1E–6	–38.2	–8.3E–8	–28.9
200911	283547	7.5E–6	35.1	7.6E–8	29.6	281327	–9.6E–6	–39.2	–5E–8	–18.6
200912	249533	8.6E–6	23.2	1.4E–8	6.4	248061	–1.3E–5	–36.1	–1.1E–8	–5.1
201001	247741	5.7E–6	14.9	9.9E–8	21.0	247258	–1.1E–5	–22.7	–6.9E–8	–12.1
201002	298294	6.5E–6	16.9	8.1E–8	19.8	295019	–1.1E–5	–29.5	–5.4E–8	–14.1
201003	295452	6.6E–6	26.4	2.9E–8	16.4	297502	–9.5E–6	–34.8	–1.9E–8	–11.9
201004	297115	6.4E–6	23.1	8.3E–8	26.2	298106	–8.3E–6	–31.7	–7.3E–8	–24.6
201005	413507	1.1E–5	33.5	1.1E–7	22.9	409226	–1.3E–5	–45.1	–8E–8	–20.3
201006	393351	1.1E–5	41.1	2.5E–8	11.8	387231	–1.4E–5	–45.8	–2.1E–8	–9.0
201007	314054	6.3E–6	18.5	1.2E–7	23.9	307322	–1.1E–5	–29.4	–1.1E–7	–20.4
201008	299741	7.1E–6	17.4	9.9E–8	18.6	296117	–1.2E–5	–26.9	–6.6E–8	–12.4
201009	422772	1.3E–5	61.0	2.5E–8	15.5	419480	–1.4E–5	–55.0	–2.9E–8	–17.0
201010	345432	8.7E–6	41.6	1.0E–7	35.5	328033	–9.6E–6	–42.2	–1.1E–7	–35.2
201011	447795	1.1E–5	55.6	1.0E–7	33.8	426999	–1.3E–5	–52.9	–9.3E–8	–27.8
201012	305279	1.4E–5	45.2	2.2E–8	8.8	302936	–1.8E–5	–49.3	–3E–8	–9.3

Exhibit 9

Volume Coefficients of Market Impact of Buy and Sell Trades, FGBL Futures, 2009–2010

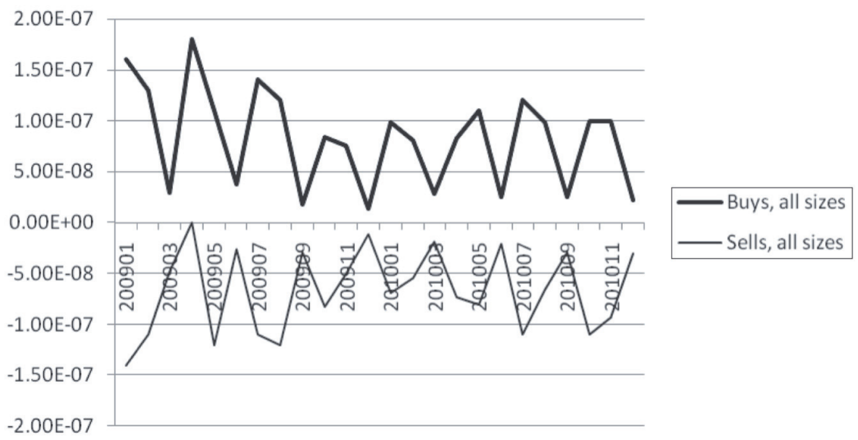
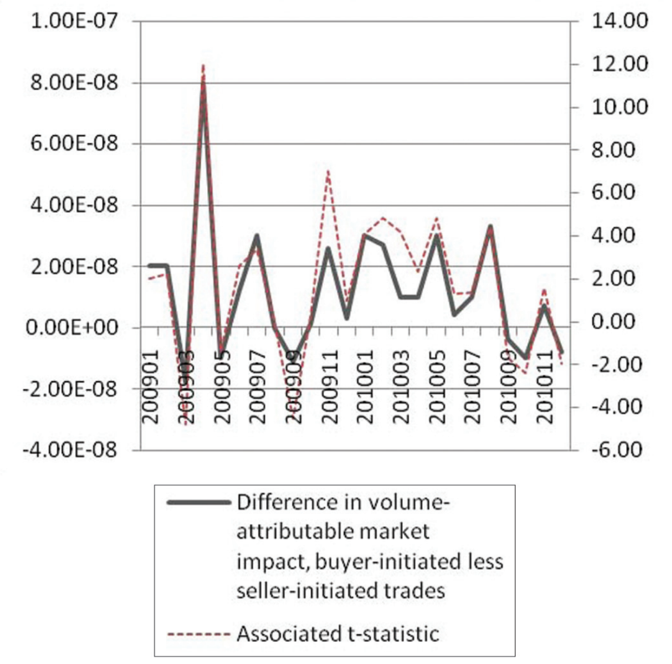


EXHIBIT 10

Difference in Volume-Attributable Market Impact of Buyer-Initiated Trades Less That of Seller-Initiated Trades



symmetry between the volume-dependent market impact coefficient created by buyer- and seller-initiated trades. The auxiliary variables also do not alter the value or the statistical significance of the trade size–independent component, the intercept, thus leaving the dominant size-independent market impact unexplained.

CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

Current research shows that large traders' concerns of adverse pump-and-dump activity by high-frequency traders do not find support in Eurobund futures data. Instead, individual trades of 100 contracts or smaller carry little size-dependent market impact. Due to a trade-size independent market impact that is large relative to the trade size-dependent impact, trades of up to 100 contracts incur market impact similar to that of median-size trades of 5 contracts. The trade-size independent market impact cannot be explained by volatility, spread, or the inter-trade duration preceding each trade. Understanding the drivers of the observed size-independent market impact would compose an interesting future investigation.

ENDNOTE

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