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High frequency trading and end-of-day manipulation

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High frequency trading and end-of-day manipulation

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Abstract

We examine the impact of higher frequency trading on the frequency and severity of suspected end of day price dislocation cases in 22 stock exchanges around the world over the period January 2003 – June 2011. Controlling for country, market, legal and other differences across exchanges and over time, and using a variety of robustness checks including difference-in-differences tests, we show that the presence of high frequency trading in some markets has significantly *mitigated* the frequency and severity of end-of-day manipulation, counter to recent concerns expressed in the media. The effect of HFT is more pronounced than the role of trading rules, surveillance, enforcement and legal conditions in curtailing the frequency and severity of end-of-day manipulation.

Keywords: High frequency trading, End-of-day Manipulation, Trading Rules, Surveillance, Law and Finance

JEL Codes: G12, G14, G18, K22

"There is nothing so terrible as activity without insight."

Johann Wolfgang von Goethe

1. Introduction

High frequency trading (HFT) has become commonplace in many exchanges around the world. HFT involves implementing proprietary trading strategies through the use computerized algorithms. HFTs rapidly trade in and out of positions thousands of times a day without holding positions at the end of the day, and profit by competing for consistent albeit small profits on each trade. While estimates vary due to the difficulty in ascertaining whether each trade is an HFT, recent estimates suggest HFT accounts for 50-70% of equity trades in the U.S., 40% in Canada, and 35% in London (Chang, 2010 ; Grant, 2011 ; O'Reilly, 2012). The growth in HFT activities has generated plenty of attention from financial market regulators and commentators,[2] particularly as HFTs were found to have contributed to the May 6, 2010 Flash Crash by withdrawing liquidity (Easley et al., 2010). Some commentators have likewise expressed concern that HFT might increase the prevalence of market manipulation (Biasis and Woolley, 2011). However, prior work has not empirically examined the impact of HFT on specific forms of manipulation.

In this paper, we directly examine the link between HFT and one very important and specific form of manipulation: end-of-day price dislocation. 'Closing' or 'end-of-day' [hereafter EOD] prices are extremely important for a number of reasons, including the fact that they are often

[2] See, e.g., Huw Jones, "EU Lawmaker Turns Screws on Ultra-Fast Trading", Reuters (March 26, 2012); Lucas Mearian, "SEC Probes High-Speed Traders," Compterworld (March 26, 2012); Chlistalla (2011). FINRA even asked high frequency trading firms to disclose computer codes in order to check for manipulative strategies; see http://www.reuters.com/article/2011/09/01/us-financial-regulation-algos-idUSTRE7806J420110901

used to determine the expiration value of derivative instruments and directors' options, price of seasoned equity issues, evaluate broker performance, compute net asset values of mutual funds, and compute stock indices (Comerton-Forde and Putnins, 2011).[3] As such, there is massive incentive to manipulate closing price by ramping up end of day trading to push the closing price to an artificial level.

Specifically, we examine closing price manipulation from 22 stock exchanges around the world from January 2003 – June 2011. We construct a monthly panel dataset of the frequency and severity of EOD manipulation cases. Suspected cases on EOD manipulation are based on consideration of a significant increase in the EOD returns, trading activity in the last part of the day, and bid-ask spreads, as well as a reversion to natural price level the following morning (Cahart et al., 2002; Hillion and Suominen, 2004; Comerton-Forde and Putnins, 2011). These cases considered herein were in fact developed with market surveillance authorities and their software developers for the respective countries, including Capital Markets CRC, and SMARTS, Inc.

We relate the frequency and severity of EOD manipulation across markets and over time to the introduction of high-frequency trading. The actual start date of HFT, if at all, is not known with precise accuracy across all markets around the world. Nevertheless, HFT is usually characterized by large number of orders with smaller order quantities and tending to have short position-holding periods with almost no overnight position (Aldridge, 2009; Henrikson, 2011; Brogaard, 2010). To this end, we examine when there were unusual changes in market trading patterns over the January 2003 – June 2011 to identify when, if at all, HFT was likely having a significant influence in the marketplace. Moreover, we consider other factors such as whether or not the exchange has direct market access (DMA), which is a requirement for HFT. We examine the robustness of our findings to different proxies to identify the material presence of HFT in a marketplace.

The data examined in this paper show that marketplaces with a significant presence of HFT are substantially less likely to experience EOD manipulation and more severe EOD manipulation. In particular, the number of suspected EOD price manipulation cases decrease by 27.85 cases per month due to HFT in the most conservative estimate; given the average number of cases per month in the data is 35.78, this means that HFT decreases the probability of EOD manipulation by 77.8%. This effect is statistically significant regardless of the empirical methods and control variables. Moreover, HFT is associated with a decrease in the total trading value surrounding per suspected dislocating the EOD price case by the most conservative estimate of 35.85% relative to the average size of the total trading value surrounding per suspected dislocating the EOD price case; the least conservative estimate is 54.71%.

It is noteworthy that policy mechanisms, including trading rules, surveillance and enforcement, appear to have had less of an effect in mitigating EOD manipulation. This is surprising, since these mechanisms have been shown to improve market quality in terms of increased liquidity, lower bid-ask spreads, improved market capitalization and greater numbers IPOs (Aitken and Siow, 2003; La Porta et al., 2006; Cumming and Johan, 2008; Jackson and Roe, 2009;

[3] For related work on market manipulation and exchange governance, see Aggarwal and Wu (2006), Carhart et al. (2002), Merrick et al. (2005), O'Hara (2001), O'Hara and Mendiola (2003), Peng and Röell (2009), Pirrong (1999, 2004), Röell (1993),

Cumming et al., 2011). By contrast, HFT is prevalent only on the most liquid exchanges around the world, and yet policy mechanisms have had less of an effect in curtailing the positive outcomes of HFT in terms of less pronounced and less frequent EOD manipulation.

Our paper is related to a small but growing literature on HFT. The benefits and costs of HFT are nicely summarized by Biais and Woolley (2011). Potential benefits of HFT include: (1) HFT can help ensure that related assets remain consistently priced due to increased liquidity (Chaboud et al, 2009); (2) HFT algorithms can help traders cope with market fragmentation by fostering competition between trading mechanisms, including exchanges and other platforms; and (3) HFT algorithms can mitigate traders' cognition limits and traders' limited rationality. Brogaard (2010) found that the participation rate of HFT in the sample NASDAQ equity trading data used in his study is approximately 77% and he concluded that HFT play a vital role in the price efficiency and price discovery process. Hendershott and Riordan (2010) and Hendershott et al. (2011) find consistent evidence from NASDAQ on the important role of HFT in price discovery and liquidity.

Biasis and Woolley (2011) also note that potential costs of HFT include: (1) manipulation in various ways that are described in section 2 below; (2) adverse selection in the sense that non-HFT trades are slower and less well informed that HFT trades, thereby leading to a reduced market participation among non non-HFT traders (i.e., HFT trades impose a negative externality of adverse selection on non-HFT traders); (3) imperfect competition among HFT traders and non-HFT traders due to the large fixed costs of establishing HFTs; and (4) systematic risk, which might increase if HFT algorithms rely on similar strategies which are correlated. In respect of the first point, we are not aware of any systematic evidence on the effect of HFT on market manipulation. In respect of the latter point, there is mixed evidence on the impact of HFT on volatility depending on the context. Focused on the recent Flash Crash in the United States financial market that occurred on May 6th, 2010, Kirilenko, et al. (2011) argue that High-frequency traders (HFTrs) did not activate the Flash Crash but rather intensified the market volatility. However, Brogaard (2010) finds that, rather than increasing stock volatility due to more frequent trading, HFT reduces stock volatility.

Our paper does not weight-in on each of these specific benefits or costs, but rather focuses on the narrow question of whether or not HFT affects the frequency and magnitude of EOD price dislocation. Overall, our findings imply HFT makes it more difficult for market manipulators to manipulate EOD closing prices. Our central finding is therefore consistent with the extant evidence and results in Brogaard (2010), Hendershott and Riordan (2010) and Hendershott et al. (2011) on the valuable role for HFT in facilitating price discovery. Our findings do not imply that HFT makes it more or less difficult to manipulate prices or volume in other ways, as those issues are beyond the scope of our paper. It may well be the case that future efforts in monitoring HFT are warranted among policymakers and surveillance authorities, but such efforts should not inhibit the role of HFT in facilitating a reduction in EOD manipulation.

This paper is organized as follows. Section 2 discusses EOD manipulation in relation to HFT as well as various policy mechanisms designed to curb manipulation. Section 3 describes end of day trading manipulation and high frequency trading. The data are introduced in Section 4. Section 5 presents multivariate analyses of the relation between the end of day manipulation and high frequency trading. Concluding remarks follow in the last section.

2. Market manipulation

2.1. HFT and market manipulation

There are theoretical reasons either way in terms of whether or not HFT mitigates market manipulation or exacerbates market manipulation. In this subsection, we first describe the possibility of HFT exacerbating manipulation, and then consider with some arguments as to why HFT might mitigate manipulation.

HFT, by virtue of the speed of the entering orders and execution of transactions, have the potential scope for facilitating manipulation more easily in a number of ways. First, HFT can be used to enter purchase orders at successively higher prices to create the appearance of active interest in a security, which is also termed as ramping/gouging. This type of HFT strategy is sometime referred to as ‘smoking’, or luring non-HFT orders (Biasis and Woolley, 2011). This can also take the form of pump and dump schemes whereby HFT is used to generate a significant increase in price and volume for a security, carry out a quick flip, and the securities are then sold (often to retail customers) at the higher price. Another similar type of price manipulation takes the form of pre-arranged trading. Pre-arranged trades involve colluding parties simultaneously entering orders at an identical price and volume, which might be easier to coordinate with across HFT systems. Because pre-arranged trades avoid the order queue, they can influence the price of a security. Similarly, market setting is a form of manipulation whereby HFT could be used to cross-orders at the short-term high or low to effect the volume weighted average price, or to set the price in one market for the purpose of a cross in another market. These forms of price manipulation are often geared towards EOD trades to manipulate the closing market price of the security, particularly since the EOD price affect the expiration value of derivative instruments and directors’ options, the price of seasoned equity issues, broker performance evaluation, the net asset values of mutual funds, and the value of stock indices.

HFT can also be used to exacerbate spoofing. Spoofing, also known as “painting the tape”, is a form of market manipulation that involves actions taken by market participants to give an improper or false impression of unusual activity or price movement in a security. Spoofing may take the form of fictitious orders, giving up priority, layering of bids-asks, and switches. The more general act of entering fictitious orders involve entering orders on one side of the market, then completing orders on the other side of the market and deleting the original order after the trade occurs. Giving up priority refers to deleting orders on one side of the market as they approach priority and then entering the order again on the same side of the market. Layering of bids-asks refers to traders or brokers that stagger orders from the same client reference at different price and volume levels to give the misleading impression of greater interest in the security from a more diverse set of exchange participants, and might be viewed as being carried out for the purpose of manipulation. Switches involve deleting orders on one side of the market as they approach priority and then entering the order again on the opposite side of the market.

Finally, the presence of HFT may manipulate markets by ‘stuffing’ orders, thereby making it more difficult for non-HFT orders to execute. HFT has an obvious speed advantage, and regular traders entering non-HFT orders suffer a technological disadvantage from not being able to have orders reach the exchange in the same time period. Moreover, there are large fixed costs of setting up HFT systems, and regular market participants, particularly retail participants, are less able to incur such fixed costs.

On the other hand, there are at least two reasons to believe that HFT will on average curtail market manipulation for the following reasons. First, exchange surveillance systems are designed to pick up patterns of illegal manipulation, and not one-off manipulation. HFT orders are by definition following a computer algorithm, and therefore HFT systems set with the view towards manipulation are much more likely to set off a real-time alert to a securities surveillance officer (Cumming and Johan, 2008). Second, HFT has been reported to have significance benefits of increasing liquidity, reducing bid-ask spreads and facilitating price discovery (Brogaard, 2010; Hendershott and Riordan, 2010; Hendershott et al., 2011). It is much more difficult for manipulators to engage in market manipulation in the presence of greater market efficiency (Aitken and Siow (2003).

Overall, given the theoretical reasons either way in terms of whether HFT mitigates or exacerbates manipulation, it is necessary to test the effect with the use of large sample data from many exchanges around the world. For the first time, we provide such tests in the empirical analyses in the subsequent sections of this paper.

2.2. Trading rules, surveillance and other factors pertinent to manipulation

Apart from HFT, there are a number of factors that can affect the likelihood of manipulation across exchanges and over time. First, surveillance systems are not of equal quality across countries, and superior systems are more likely to curtail the presence of manipulators (Cumming and Johan, 2008). Second, exchange trading rules have the ability to improve market liquidity (Cumming et al., 2011) and have the ability to signal to market participants that specific types of illegal activity are illegal. Third, the quality of enforcement of illegal activity varies across countries (La Porta et al., 1998, 2006 ; Jackson and Roe, 2009), which in turn can influence the likelihood that manipulators will be present in a marketplace.

In addition to rules, surveillance and enforcement, there are other market wide differences across countries and exchanges. In particular, some exchanges are much more liquid for reasons related to the development of the particular exchange or national economy. To this end, when assessing the presence of market manipulation, it is important to account for market condition differences across exchanges as well as over time. We consider these factors in our empirical tests below.

3. Data

Our sample comprises 22 stock exchanges whose trading data are included in commonly used data sources such as Thomson Reuters Datastream. The sample comprises Australia, Canada, China (Shanghai and Shenzhen), Germany, Hong Kong, India (Bombay and the National Stock Exchange of India), Japan, Malaysia, New Zealand, Norway, Singapore, South Korea, Sweden, Switzerland, Taiwan, the U.K., and the U.S. (NASDAQ and NYSE). The start date of HFT in the sample was determined with the methods described in the Appendix of this paper.

The definitions and source of the variables used in the analyses are provided in Table 1. Our main dependent variables are the number of suspected dislocating the EOD price cases and the average trading value surrounding per suspected dislocating the EOD price case. The dependent variables are based on actual identified suspected cases from surveillance authorities via SMARTS Group, Inc., and CMCRC. SMARTS provides surveillance software to over 40 exchanges around the world. Table 2 indicates that the average (median) number of suspected dislocating the EOD price cases 35.78 (14) per exchange month in the sample, with a range from minimum zero to maximum of 1645. The average (median) total trading value surrounding per suspected dislocating the EOD price case is US$670,971.8($136,814.2).

Table 1. Definition of variables. This table defines our independent, dependent and control variables.

Variable Name	Definition
HFT	Dummy variable indicates when HFT starts in the market, as described in the Appendix.
Trading Rule Index	
Total Trading Rules Index	Sum of insider trading rules index, price manipulation rules index, volume manipulation rules index, spoofing rules index, false disclosure rules index, false disclosure rules index, market manipulation rules index, and broker-agency rules index. Source: Cumming, Johan, and Li (2011).
Surveillance, Enforcements, Efficiency of Judiciary, and Rule of Law indices	
Surveillance Index	The principal component of (1) single market surveillance and (2) cross market surveillance. Source: Cumming and Johan (2008). Available for a subset of countries, and provided contingent on maintaining confidentiality and anonymity as exchanges do not want market participants to know all of the things they do and do not look for in their surveillance. Source: Cumming, Johan, and Li (2011).
Efficiency of the Judiciary Index	Assessment of the efficiency and integrity of the legal environment. Scale from zero to ten; with lower scores, lower efficiency levels. Source: La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998).
Staff per million population(extrapolated sample)	The 2005 size of the securities regulator's staff, divided by the country's population in millions. Source: Jackson, and Roe (2009).
DLLS Public enforcement index	Public enforcement here is an index aggregating whether Public enforcement here is an index aggregating whether jail sentences for the approving body, or fine or jail sentence for the principal wrongdoer.

Variable Name	Definition
	Source: Djankov, La Porta, Lopez-de-Silanes, and Shleifer (2008a).
Market Statistics	
Log (Market Capitalization)	Log of domestic market capitalization in USD millions. Market capitalization is from World Federation of Exchanges (2003/01-2011/06). Source: WFE.
Log (Volume)	Log of total value of shares trading in USD millions. Total value of share trading data is from World Federation of Exchanges (2003/01–2011/06). Source: WFE.
Log (Number of Trades)	Log of total number of trades in thousands in the same period. Numbers of trades are from World Federation of Exchanges (2003/01–2011/06). Source: WFE.
Log (1+MSCI)	Log of one plus the MSCI index in the lagged period. Source: MSCI.COM (2003/01-2011/06).
Log (GDP)	Log of gross domestic product (GDP) per capita in the lagged period. Source: GlobalInsight. (2003/01-2011/06).
Log (Average Market Trade Size)	Log of average market trade size in the same period. Source: Capital Markets Cooperative Research Centre (CMCRC).
Evidenced Measures of Market Quality	
Suspected Dislocating the EOD Price Cases	Total number of suspected dislocating of the end of day price cases. Source: Capital Markets Cooperative Research Centre (CMCRC).
Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case	Average trading value surrounding each suspected dislocating EOD price case. Source: Capital Markets Cooperative Research Centre (CMCRC).

Table 2. Descriptive statistics. This table presents statistics for the full sample of country-month observations in the data. The data span the months from January 2003 – June 2011, and the exchanges listed in Table 2. World Federation of Exchanges (WFE) data are not available for Korea (KOSDAQ), Germany (XET), Sweden (OMX), and London (CHIX). Also, WFE are incomplete data for the number of trades, market capitalization and volume for New Zealand (NSX) and China (SSE and SZSE). Index from LaPorta (1998, 20006) are not available for China.

	Mean	Median	Standard Deviation	Minimum	Maximum	Number of Observations
Suspected Dislocating the EOD Price Cases	35.78	14	85.27	0	1645	2244
Total Trading Value Surrounding Per Suspected Dislocating the EOD Price Case	670971.8	136814.2	2384730	0	5.72e+07	2244
HFT Dummy	0.47	0	0.50	0	1	2244
Total Trading Rule Index	18.70	18	9.23	4	37	2244
Surveillance	19.00	15	13.93	3	41	2244
Resource-based measures of public enforcement (Jackson and Roe, 2009)	20.49	15.79	19.19	.43	88.74	2040
Public enforcement index (DLLS, 2008)	0.46	0.5	0.42	0	1	2040
Rule of Law	8.32	8.78	1.98	4.17	10	2040

	Mean	Median	Standard Deviation	Minimum	Maximum	Number of Observations
Efficiency of the Judiciary	9.10	10	1.36	6	10	2040
log(Market Capitalization)	13.60	13.63	1.35	9.88	16.63	1817
log(Volume)	11	11.11	1.91	4.94	14.99	1731
log(Number of Trades)	9.47	9.68	2.15	3.19	12.95	1121
log(MSCI)	0.01	0.01	0.07	-0.41	0.31	2186
Log(Average Market Trade Size)	7.96	7.87	1.62	5.16	12.88	2196
log(GDP)	9.58	10.21	1.38	6.14	11.44	2244

We use several exchange level variables covering monthly observations from January 2003 to June 2011, the period considered by this study. The domestic market capitalization at the end of each month, monthly total trading volume, and data for the total number of trades for each stock exchange are obtained from World Federation of Exchanges (WFE). Some observations are missing, such as data from the WFE and index values from La Porta et al. (1998) and Jackson and Roe (2009). We obtained missing WFE values using Reuters exchange data from Capital Markets CRC for WFE and compared results with those values to results that skip missing observations in the regressions reported below, and our results were not materially different. Similarly, we filled in missing values for the indices based on taking the median and mean values of the indices for the missing countries based on the countries of the same legal origin. Again, the results were not materially different. We discuss these different sets of results explicitly below.

Surveillance data are used from Cumming and Johan (2008) and updated to 2011. Cumming and Johan surveyed 25 exchanges around the world to ascertain the extent of single- and cross-market surveillance. The data were obtained confidentially because a would-be manipulator might trade in ways that could not be detected if precise information about surveillance activity was available. The data are based on an equally weighted index that adds one every time a different type of single- and cross-market manipulation is monitored.

Exchange trading rule indices are obtained from Cumming et al. (2011), as summarized in Table 3. Trading rules for these stock exchanges are found on the each exchange's webpage, with the sole exception of China, where the pertinent trading rules for the Shanghai and Shenzhen exchange are found on the China Securities and Regulatory Commission webpage. There are three primary legal indices introduced: the Insider Trading Rules Index, the Market Manipulation Rules Index, and the Broker-Agency Conflict Rules Index. The Market Manipulation Rules Index consists of four subcomponents: the Price Manipulation Rules Index, the Volume Manipulation Rules Index, the Spoofing Manipulation Rules Index, and the False Disclosure Rules Index. These indices are summarized in Table 2 for the pre- and post-MiFID periods for January 2003- June 2011. The indices are created by summing up the number of specific provisions in the exchange trading rules in each country. In the post-MiFID period the Insider Trading Rules Index varies from a low value of zero (for a number of exchanges listed in Table 2) to ten (for NASDAQ). The Market Manipulation Rules Index varies from a low value of two (for Malaysia, Taiwan and Tokyo) to 13 (for London, NYSE). The Broker-Agency Conflict Rules Index varies from a low value of zero (for Australia, Hong Kong, Germany, Shanghai, Shenzhen, Taiwan, Tokyo and OSLO) to five (for NASDAQ). The total trading rule index is the sum of the Insider Trading Rules Index, the Market Manipulation Index, and the Broker-Agency Conflict Rules Index. While present results in our regressions with the use of the Total Rules Index, the use of sub-indices does not materially impact our conclusions and findings herein.

Table 3. Trading rule indices. This table summarizes the index values for the trading rules for each exchange, as defined in Table 1. Panel A presents the trading rule index values for post-MiFID (Nov. 2007 – Jun. 2011; and in brackets are values for Jan. 2003 – Oct. 2007). Panel B compares the mean of trading rule index among different legal origin. The Cochran and Cox (1950) t-statistics are shown in Panel B and the *, **, * denote significance at the 10%, 5%, and 1% levels, respectively.**

Panel A

Exchange	Price Manipulation Index	Volume Manipulation Index	Spoofing Index	False Disclosure Index	Market Manipulation Index	Insider Trading Index	Broker Agency Index
English Legal Origin							
Australia	3 (3)	1 (1)	2 (2)	0 (0)	6 (6)	2 (2)	0 (0)
Bombay	0 (0)	1 (1)	1 (1)	1 (1)	3 (3)	2 (2)	3 (3)
Canada	7 (7)	2 (2)	3 (3)	0 (0)	12 (12)	2 (2)	1 (1)
Hong Kong	3 (3)	2 (2)	1 (1)	1 (1)	7 (7)	0 (0)	0 (0)
India NSE	3 (3)	1 (1)	1 (1)	1 (1)	6 (6)	3 (3)	3 (3)
London	7 (6)	2 (2)	3 (3)	1 (1)	13 (12)	3 (2)	0 (0)
Malaysia	0 (0)	0 (0)	1 (1)	1 (1)	2 (2)	7 (7)	2 (2)
NASDAQ	5 (5)	1 (1)	3 (3)	2 (2)	11 (11)	10 (10)	5 (5)
NYSE	6 (6)	2 (2)	3 (3)	2 (2)	13 (13)	7 (7)	3 (3)

Exchange	Price Manipulation Index	Volume Manipulation Index	Spoofing Index	False Disclosure Index	Market Manipulation Index	Insider Trading Index	Broker Agency Index
Singapore	3 (3)	1 (1)	2 (2)	1 (1)	7 (7)	2 (2)	2 (2)
Average English Legal Origin	3.83 (3.67)	1.25 (1.25)	2.00 (2.00)	1.00 (1.00)	8.08 (7.92)	3.67 (3.50)	1.83 (1.83)
Median English Legal Origin	3.00 (3.00)	1.00 (1.00)	2.00 (2.00)	1.00 (1.00)	7.00 (7.00)	3.00 (2.00)	2.00 (2.00)
German Legal Origin							
Germany	7 (0)	1 (0)	3 (1)	1 (0)	12 (1)	3 (2)	0 (1)
Korea	4 (4)	2 (2)	2 (2)	1 (1)	9 (9)	3 (3)	2 (2)
Shanghai	2 (2)	1 (1)	1 (1)	1 (1)	5 (5)	2 (2)	0 (0)
Shenzhen	2 (2)	1 (1)	1 (1)	1 (1)	5 (5)	2 (2)	0 (0)
Switzerland	7 (2)	1 (1)	3 (1)	1 (1)	12 (5)	3 (2)	1 (1)
Taiwan	2 (2)	0 (0)	0 (0)	0 (0)	2 (2)	0 (0)	0 (0)

Exchange	Price Manipulation Index	Volume Manipulation Index	Spoofing Index	False Disclosure Index	Market Manipulation Index	Insider Trading Index	Broker Agency Index
Tokyo	1 (1)	0 (0)	1 (1)	0 (0)	2 (2)	1 (1)	0 (0)
Average German Legal Origin	3.63 (2.13)	1.00 (0.88)	1.63 (1.13)	0.75 (0.63)	7.00 (4.75)	2.13 (1.88)	0.63 (0.75)
Median German Legal Origin	3.00 (2.00)	1.00 (1.00)	1.50 (1.00)	1.00 (1.00)	7.00 (5.00)	2.50 (2.00)	0.00 (0.50)
Scandinavian Legal Origin							
OMX	7 (2)	1 (1)	3 (2)	1 (1)	12 (6)	5 (4)	2 (2)
Oslo	7 (2)	1 (1)	3 (1)	1 (0)	12 (4)	4 (3)	0 (0)
Average Scandinavian Legal Origin	7.00 (2.00)	1.00 (1.00)	3.00 (1.50)	1.00 (0.50)	12.00 (5.00)	4.50 (3.50)	1.00 (1.00)
Median	7.00 (2.00)	1.00 (1.00)	3.00	1.00 (0.50)	12.00 (5.00)	4.50	1.00 (1.00)

Exchange	Price Manipulation Index	Volume Manipulation Index	Spoofing Index	False Disclosure Index	Market Manipulation Index	Insider Trading Index	Broker Agency Index
Scandinavian Legal Origin			(1.50)			(3.50)	

Panel B

Tests of Means	Price Manipulation Index	Volume Manipulation Index	Spoofing Index	False Disclosure Index	Market Manipulation Index	Insider Trading Index	Broker Agency Index
English versus Civil Law	-3.01*** (16.07***)	5.74*** (8.76***)	1.57 (18.75***)	6.33*** (13.37***)	0.33 (17.44***)	7.90*** (11.33***)	14.02*** (14.81***)
English versus German	1.32 (14.87***)	5.09*** (8.25***)	5.66*** (19.69***)	7.32*** (11.94***)	4.07*** (16.26***)	11.76*** (14.25***)	14.67** (15.26***)
English versus Scandinavian	-29.75*** (19.54***)	7.95*** (9.13***)	-25.15*** (8.61***)	0.00 (9.71***)	-22.78*** (17.14***)	-6.41*** (0.00)	6.55** (7.53***)

Tests of Means	Price Manipulation Index	Volume Manipulation Index	Spoofing Index	False Disclosure Index	Market Manipulation Index	Insider Trading Index	Broker Agency Index
German versus Scandinavian	-29.06*** (2.12**)	0.00 (-3.45***)	-25.96*** (-6.90***)	-10.82*** (2.41**)	-24.60*** (-1.54)	-30.57*** (-25.60***)	-3.22*** (-2.48**)

We also acquire a series of law and finance indices from La Porta et al. (1998, 2006) and Spamann (2010), which includes the rule of law and efficiency of the judiciary. Other legal indices were considered, but they did not impact the empirical tests reported below and are therefore excluded for conciseness. Although we do have information on surveillance mentioned immediately above, we do not have data on enforcement of the trading rules that we analyze in this article; nevertheless, our understanding from our data sources for surveillance in Cumming and Johan (2008) is that enforcement is highly correlated with surveillance because otherwise exchanges would not bother to carry out surveillance. To further proxy enforcement, we use prior indices of enforcement such as efficiency of the judiciary. In other work, note that La Porta et al. (2006) finds evidence that private enforcement facilitates the development of stock markets, while Jackson and Roe (2009) find stronger evidence on the value of liability standards and public enforcement. The difference in Jackson and Roe is that they employ more detailed resource-based measures such as budgets/GDP and staffing/population to study enforcement. These enforcement measures differ significantly across countries, but not over time. We have considered all of the indices in the La Porta et al. (2006) and Jackson and Roe (2009); inclusion/exclusion of these indices does not materially affect the conclusions regarding HFT and other things presented herein.

To control for the influence of market specific changes, we draw from a series MSCI Global Standard Index from Morgan Stanley Capital International's webpage. Also, we include both exchange and year-dummy variables in our multivariate analyses in section 4 below.

4. Univariate tests

Table 4 provides a comparison of means and medians tests for the number of suspected dislocating the EOD price cases in Panel A, and the total trading value surrounding per suspected dislocating the EOD price case in Panel B.

Table 4. Comparison tests. This table presents the comparison of mean and median tests for number of suspected dislocating the EOD price cases (Panel A) and total trading value surrounding per suspected dislocating the EOD price cause (Panel B) from January 2003 to December 2006 before the financial crisis period. We have removed the four exchanges that have HFT starting date at the beginning of our dataset. There are total of 17 exchanges in our test. 7 exchanges are from the HFT countries and 10 exchanges are from the nonHFT countries. The *, ** and * denote significance at the 10%, 5% and 1% level, respectively.**

Panel A: Suspected Dislocating the EOD Price Cases					Panel B: Total Trading Value Surrounding Per Suspected Dislocating the EOD Price Case				
	All Countries		HFT Countries			All Countries		HFT Countries	
	HFT Countries	NonHFT Countries	Post -HFT	Pre-HFT		HFT Countries	NonHFT Countries	Post -HFT	Pre-HFT
Number of Observations	384	480	164	220	Number of Observations	384	480	164	220
Mean	21.76	41.33	18.24	24.37	Mean	8.30E+05	1.82E+05	4.36E+05	6.12E+05
Standard Deviation	28.60	107.43	21.67	32.65	Standard Deviation	2.24E+06	4.91E+05	5.58E+05	8.32E+05
Median	12.5	14.00	12	13	Median	2.26E+05	5.34E+04	2.11E+05	2.42E+05
Difference in means	3.83***		2.21**		Difference in means	-5.57***		2.47**	
Difference in medians	P<0.042**		P=0.230		Difference in medians	P<0.000***		P=0.2216	

Table 4 Panel A shows that the average (median) number of suspected dislocating the EOD price cases is 21.76 (12.5) in HFT exchange time periods, which is lower than 41.33 (21.67) average number of cases in non HFT-exchange time periods. This difference is means (medians) is significant at the 1% (5%) level. Moreover, considering the impact of introducing HFT in a market, Table 4 Panel A shows that post-HFT exchanges had on average (median) 18.24 (12) cases, which is lower than the average (median) of 24.27 (13) in pre-HFT time periods. This difference in means is significant at the 5% level, but the difference in median is not statistically significant.

Figure 1 plots the indexed average number of EOD manipulation cases for HFT and non-HFT exchanges. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. Figure 1 is consistent with the tests in Table 4 Panel A highlighting the fact that EOD manipulation cases are less frequently associated with HFT both in terms of comparing pre- and post-HFT time periods and HFT and non-HFT exchanges.

Figure 1. Plot of indexed of average EOD price case. Mean of suspected EOD price dislocation cases of HFT countries and non-HFT countries are shown here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. . For nonHFT countries, the zero month is January 2005. The values for the nonHFT countries are also indexed to the zero date.

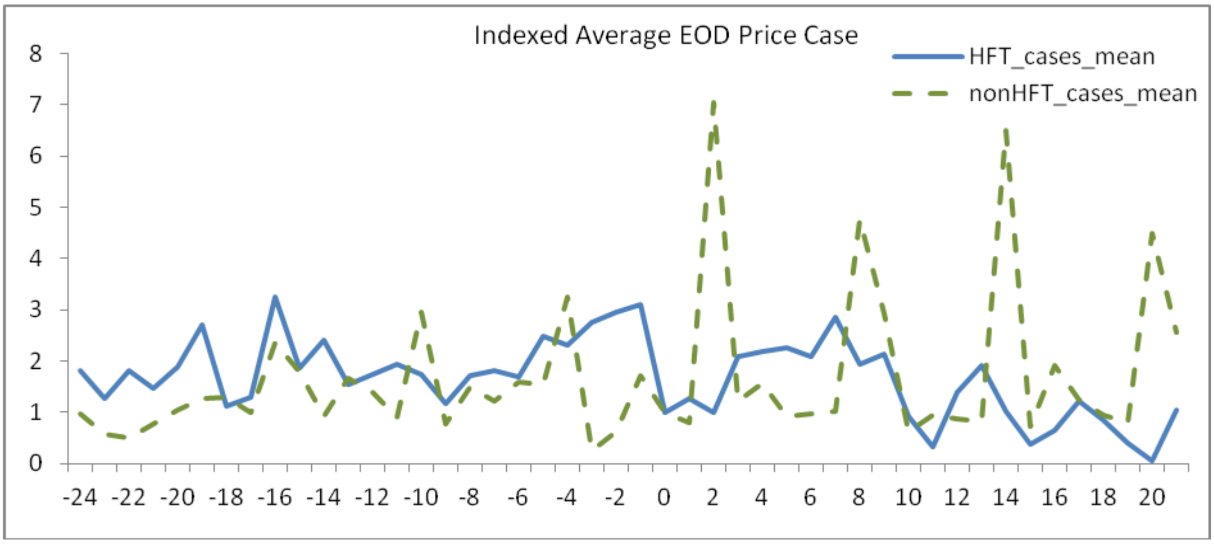
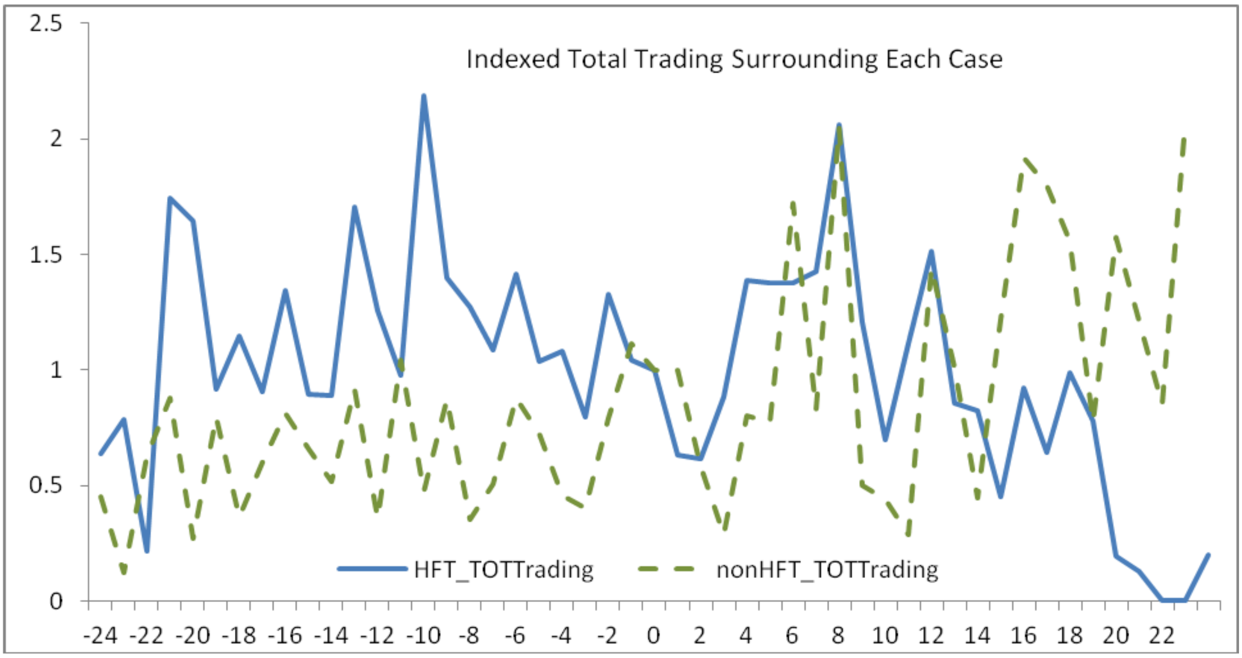


Table 4 Panel B shows that the average (median) trading value surrounding suspected discloating the EOD price cases is 8.30^{E}+05 (2.26^{E}+05) in HFT exchange time periods, which is higher than the 1.82^{E}+05 (5.34^{E}+04) average (median) trading value surrounding cases in non HFT-exchange time periods. This difference is means (medians) is significant at the 1% (5%) level. This difference in values suggests that there is a more pronounced value of trading surrounding EOD manipulation under HFT. However, we note that HFT exchanges are in substantially more developed countries with larger trading values (Appendix). Therefore, we also compare the values pre- and post-introduction of HFT. Considering the impact of introducing HFT in a market, Table 4 Panel B shows that post-HFT exchanges had on average (median) 4.36^{E}+05 (2.11^{E}+05) trading value surrounding cases, which is lower than the average (median) of 6.12^{E}+05 (2.42^{E}+05) in pre-HFT time periods. This difference in means is significant at the 5% level, but the difference in median is not statistically significant.

Figure 2 plots the indexed total trading value surrounding EOD manipulation cases for HFT and non-HFT exchanges. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. Moreover, the indexing of the values negates the scale effect in Table 4 Panel B for comparing HFT and non-HFT countries discussed above. Figure 2 clearly shows that EOD manipulation cases are less frequently associated with HFT both in terms of comparing pre- and post-HFT time periods and HFT and non-HFT exchanges.

Figure 2. Plot of indexed of average total trading surrounding per EOD price case. Total trading value surrounding per suspected EOD dislocation case of HFT countries and non-HFT countries are shown here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. For nonHFT countries, the zero month is January 2005. The values for the nonHFT countries are also indexed to the zero date.



Overall, these comparison tests support the view that HFT is associated with a lower frequency of EOD manipulation. Further, the pre- versus post-HFT tests support the view that there is less trading value surrounding EOD manipulation cases. The HFT versus non-HFT value tests highlight the need to control for other things being equal across exchanges, as done in the next section with the multivariate tests.

Table 5 presents a correlation matrix for the main variables used in the multivariate tests provided in the next section. The correlations highlight similar trends as in the comparison tests. As well, the correlations show areas in which collinearity is potentially problematic for regression analyses, and as such we present alternative specifications with and without collinear variables in the regressions in the subsequent section.

Table 5. Correlation matrix. This Table presents Pearson Correlation coefficients for the full sample of exchange-months in the data. The *, ** and * indicate the correlations are statistically significant at the 10%, 5% and 1% level, respectively.**

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Suspected Dislocating the EOD Price Cases	1														
2	Total Trading Value Surrounding Per Suspected Dislocating the EOD Price Case	0.02	1													
3	HFT Dummy	-0.04	0.205***	1												
4	Total Trading Rule Index	0.06	0.300***	0.525***	1											
5	Surveillance	-0.0945**	0.328***	0.178***	0.657***	1										
6	Resource-based measures of public enforcement (Jackson and Roe, 2009)	-0.197***	0.151***	0.04	0.217***	0.221***	1									
7	Public enforcement index (DLLS, 2008)	-0.06	-0.135***	0.04	-0.121***	-0.580***	0.02	1								
8	Rule of Law	-0.328***	0.217***	0.565***	0.371***	0.372***	0.482***	-0.0680*	1							
9	Efficiency of the Judiciary	-0.104**	0.255***	0.646***	0.484***	0.210***	0.416***	0.01	0.644***	1						
10	log(Market Capitalization)	0.102**	0.322***	0.317***	0.584***	0.694***	0.253***	-0.468***	0.195***	0.270***	1					
11	log(Volume)	0.0896**	0.307***	0.298***	0.625***	0.756***	0.247***	-0.463***	0.304***	0.208***	0.923***	1				
12	log(Number of Trades)	0.330***	0.113***	-0.01	0.400***	0.454***	-0.04	-0.450***	-0.269***	-0.248***	0.747***	0.778***	1			
13	log(MSCI)	-0.0992**	-0.156***	-0.02	-0.04	-0.03	-0.04	0.05	-0.0693*	-0.05	0.02	-0.02	0.01	1		
14	Log(Average Market Trade Size)	-0.280***	-0.117***	-0.537***	-0.631***	-0.284***	0.354***	-0.05	0.01	-0.145***	-0.434***	-0.434***	-0.475***	0.01	1	
15	log(GDP)	-0.324***	0.227***	0.336***	0.356***	0.405***	0.623***	-0.218***	0.737***	0.413***	0.215***	0.343***	-0.0714*	-0.0705*	0.230***	1

5. Multivariate tests

5.1. Primary results

Table 6 presents panel data regression results with 7 alternative econometric models for the two dependent variables for the number of EOD manipulation cases and the average trading value surrounding such cases. The seven models include different sets of explanatory variables to highlight robustness. Model 1 includes the HFT variable along with microstructure control variables in terms of exchange characteristics such as market capitalization, dollar volume, and the number of trades. Model 1 also includes country control variables for GDP per capita, and fixed effects for exchanges and years. Model 1 uses a difference-in-differences estimator with the time period for the introduction of HFT at the average date for the exchanges in the sample. Models 2-7, by contrast, use a simple dummy variable equal to one for the specific start date of HFT in the exchange in the sample (if at all for the exchange). Models 2-6 differ from Model 1 by the inclusion of different sets of trading rule and enforcement variables, which is useful to show explicitly since many of these variables are highly correlated. Model 7 includes a complete set of variables all at once. All models use two-way clustering of errors by year and exchange (Petersen, 2009).

Table 6. Regression results. This table presents Ordinary Least Square panel regressions of determinates of the number of suspected EOD price cases and the trading value surrounding such cases. Variables are as defined in Table 1. Standard errors are clustered by exchange. Panel A presents regression results for the suspected dislocating the end of day (EOD) price cases. Panel B presents regression results for average trading value surrounding per suspected dislocating the EOD price case where the dependent variable is winsorized at the 95%, and Panel C uses the same dependent variable winsorized at the 99%. Model 1 presents results of a difference-in-difference measure. Model 2 presents a regression results with Total Trading Index from Cumming, et al. (2010). Model 3 presents a regression results with surveillance index. Model 4 presents the results with Public Enforcement Index from Jackson and Roe, (2009) and from Djankov, et al. (2008). Model 5 and Model 6 present the regression results with Efficiency of Law and with Rule of Law from LLSV (1998, 2006), respectively. The Model 7 presents the results with all index and control variables. The *, ** and * are statistically significant at the 10%, 5% and 1% level, respectively.**

Panel A: Suspected Dislocating the EOD Price Case														
Independent Variables	Model 1:		Model 2:		Model3:		Model 4:		Model5:		Model6:		Model7:	
	Difference-in-difference		Trading Rule Index		Surveillance		Public Enforcements		Efficiency Of Law		Rule of Laws		All Jointly	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	96.25	0.23	94.21	0.23	238.14	0.67	332.35	0.52	89.69	0.12	34.91	0.08	521.19	0.59
HFT Dummy	-33.53	-2.58**	-33.00	-2.42**	-33.53	-2.58**	-30.62	-2.51**	-30.62	-2.51**	-27.85	-1.91*	-29.09	-1.97**
Trading														

Panel A: Suspected Dislocating the EOD Price Case														
Rules														
Total Trading Rule Index			0.28	0.43									0.52	0.59
Enforcement														
Surveillance					-3.87	-1.49							-5.64	-4.56***
Public enforcement (Jackson and Roe, 2009)							-1.49	-0.71					0.67	0.21
Public enforcement (DLLS, 2008)							8.41	0.21					36.82	1.27
Efficiency of the									22.9	0.91			-1.49	-0.04

Panel A: Suspected Dislocating the EOD Price Case														
Judiciary									3					
Rule of Law											22.93	0.63	-18.17	-1.68*
Microstructure Control Variables														
Log Market Capitalization	-22.38	-0.96	-22.51	-0.95	-22.38	-0.96	-34.06	-0.92	-34.06	-0.92	3.10	0.15	-34.99	-0.92
Log Volume	36.59	1.82*	37.82	1.70*	36.59	1.82*	48.65	1.87*	48.65	1.87*			51.20	1.77*
Log Number of Trades	-12.13	-1.30	-13.4	-1.23	-12.13	-1.30	-15.00	-1.07	-15.00	-1.07	18.22	1.42	-17.84	-1.04

Panel A: Suspected Dislocating the EOD Price Case														
			9											
Log MSCI	-110.89	-3.17***	-111.18	-3.22***	-110.89	-3.17***	-114.91	-2.45**	-114.91	-2.45**	-115.82	-2.21**	-115.02	-2.46**
Log Average Market Trade Size											-6.48	-0.47		
Country Control Variables														
Log GDP	1.10	0.04	0.77	0.03	1.10	0.04	-14.45	-0.36	-14.46	-0.36	-27.44	-0.61	-16.44	-0.39
Fixed Effect on	Yes		Yes		Yes		Yes		Yes		Yes		Yes	

Panel A: Suspected Dislocating the EOD Price Case							
Exchanges							
Fixed Effect on Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Control	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year
Number of Observations	1051	1051	1051	895	895	931	895
R2	0.39	0.39	0.39	0.38	0.38	0.36	0.38

Panel B: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 95%)														
Independent Variables	Model 1:		Model 2:		Model3:		Model 4:		Model5:		Model6:		Model7:	
	Difference-in-difference		Trading Rule Index		Surveillance		Public Enforcements		Efficiency Of Law		Rule of Laws		All Jointly	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	-1.70E+07	-2.41**	-1.70E+07	-2.39**	-8.29E+06	-2.68***	-1.28E+07	-1.48	-1.39E+07	-2.46**	-9.82E+06	-2.60***	-2.57E+05	-1.89*
HFT Dummy	-2.11E+05	-1.99**	-2.27E+05	-1.65*	-2.11E+05	-1.99*	-2.25E+05	-1.93*	-2.25E+05	-1.93**	-2.50E+05	-1.77*	-2.57E+05	-1.89*

Panel B: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 95%)														
Trading Rules														
Total Trading Rule Index			-8.38E+03	-0.60									-1.07E+04	-0.87
Enforcement														
Surveillance					-2.46E+05	-2.18**							-1.10E+03	-0.03
Public enforcement (Jackson and Roe, 2009)							-1.27E+04	-0.83					-9.36E+04	-1.46
Public enforcement (DLLS, 2008)							-5.05E+05	-1.84*					-2.04E+05	-0.26

Panel B: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 95%)														
Efficiency of the Judiciary									9.81E+04	0.32			1.35E+06	1.74*
Rule of Law											-4.61E+05	-0.69	-4.51E+05	-1.08
Microstructure Control Variables														
Log Market Capitalization	-6.80E+05	-1.71*	-6.76E+05	-1.67*	-6.80E+05	-1.71*	-2.64E+05	-0.73	-2.64E+05	-0.73	-2.34E+04	-0.15	-2.45E+05	0.64
Log Volume	5.98E+05	1.71*	5.62E+05	1.46	5.98E+05	1.71*	3.20E+05	0.93	3.20E+05	0.93			2.67E+05	0.69
Log Number of Trades	-1.12E+05	-0.50	-7.13E+04	-0.27	-1.12E+05	-0.50	2.25E+04	0.09	2.25E+04	0.09	2.72E+05	1.79*	8.07E+04	0.30

Panel B: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 95%)														
Log MSCI	-1.11E+06	-2.55**	-1.10E+06	-2.53*	-1.11E+06	-2.55**	-1.52E+06	-2.38**	-1.52E+06	-2.38**	-1.55E+06	-2.30**	-1.52E+06	-2.36**
Log Average Market Trade Size											-7.73E+03	-0.09		
Country Control Variables														
Log GDP	2.07E+06	2.25**	2.08E+06	2.27**	2.07E+06	2.25**	1.34E+06	1.29	1.34E+06	1.29	1.34E+06	1.32	1.38E+06	1.36
Fixed Effect on Exchanges	Yes		Yes		Yes		Yes		Yes		Yes		Yes	

Panel B: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 95%)							
Fixed Effect on Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Control	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year
Number of Observations	1051	1051	1051	895	895	931	895
R2	0.28	0.28	0.28	0.26	0.26	0.26	0.26

Panel C: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 99%)														
Independent Variables	Model 1:		Model 2:		Model3:		Model 4:		Model5:		Model6:		Model7:	
	Difference-in-difference		Trading Rule Index		Surveillance		Public Enforcements		Efficiency Of Law		Rule of Laws		All Jointly	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	-1.52E+07	-2.46**	-1.52E+07	-2.44**	-6.72E+06	-2.64***	-1.23E+07	-1.44	-1.32E+07	-2.15**	-8.88E+06	-2.26**	-1.99E+06	-1.33
HFT Dummy	-2.23E+	-2.44**	-2.31E+05	-1.96**	-2.23E+	-2.44**	-2.69E+05	-2.09**	-2.69E+	-2.09**	-3.22E+05	-1.97*	-2.87E+	-1.95*

Panel C: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 99%)														
	05				05			*	05			*	05	
Trading Rules														
Total Trading Rule Index			-3.97E+03	-0.32									-6.16E+03	-0.58
Enforcement														
Surveillance					-2.28E+05	-2.34**							-1.19E+04	-0.38
Public enforcement (Jackson and Roe, 2009)							-9.84E+03	-0.77					-9.01E+04	-1.49
Public enforcement							-3.96E	-1.93					-2.4	-0.3

Panel C: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 99%)														
(DLLS, 2008)							+05	**					8E+05	6
Efficiency of the Judiciary									7.32E+04	0.25			1.29E+06	1.78*
Rule of Law											-4.82E+05	-0.77	-4.62E+05	-1.19
Microstructure Control Variables														
Log Market Capitalization	-7.04E+05	-2.12**	-7.02E+05	-2.09**	-7.04E+05	-2.12**	-3.26E+05	-0.95	-3.26E+05	-0.95	-5.17E+04	-0.35	-3.15E+05	-0.89
Log Volume	5.53E+05	1.77**	5.36E+05	1.59	5.53E+05	1.77*	3.42E+05	1.00	3.42E+	1.00			3.12E+05	0.86

Panel C: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 99%)														
									05					
Log Number of Trades	-1.09E+05	-0.49	-9.00E+04	-0.35	-1.09E+05	-0.49	8.17E+03	0.03	8.17E+03	0.03	2.53E+05	1.91*	4.16E+04	0.14
Log MSCI	-1.06E+06	-2.47**	-1.06E+06	-2.45**	-1.06E+06	-2.47**	-1.41E+06	-2.40**	-1.41E+06	-2.40**	-1.43E+06	-2.35**	-1.41E+06	-2.38**
Log Average Market Trade Size											-5.16E+04	-0.50		
Country Control Variables														
Log GDP	1.94E+06	2.42**	1.94E+06	2.44**	1.94E+06	2.42**	1.35E+06	1.38	1.35E+	1.38	1.34E+06	1.39	1.38E+06	1.43

Panel C: Average Trading Value Surrounding Per Suspected Dislocating the EOD Price Case (Winsorized 99%)							
					06		
Fixed Effect on Exchanges	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect on Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Control	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year	Exchange and Year
Number of Observations	1051	1051	1051	895	895	931	895
R2	0.33	0.33	0.33	0.30	0.40	0.30	0.30

Table 6 Panel A presents the regression results for the number of suspected EOD price cases. The data show HFT is negatively associated with the number of suspected EOD cases, and in each model the effect is significant at the 5% level of significance (with the sole exception of Model 6 where it is significant at the 10% level). In terms of the economic significance, the data indicate that HFT gives rise to an average of 27.85 fewer cases in the most conservative estimate in Model 6, and up to a reduction in cases by 33.53. Given that the average number of cases per month per exchange is 35.78, this is equivalent to a conservative estimate of a reduction by 77.8% in the number of cases with HFT.

The control variables in Table 6 Panel A show very little statistical significance, with a few exceptions. First, EOD manipulation is less common among exchanges in times of weak market conditions as proxied by the MSCI index performance in the country, and this effect is statistically significant in all of the models. Second, there is evidence that EOD manipulation is more common when dollar trading volume is higher, and this effect is significant at the 10% level in all models. Third, EOD manipulation is less common among countries with more surveillance; this effect is statistically significant at the 1% level, but significant in Model 7 only. Model 7 likewise shows EOD manipulation is less common in countries with a higher rule of law index, but again this effect is significant in Model 7 only.

Table 6 Panels B and C presents the regression results for the number of suspected EOD price cases winsorized at the 95% and 99% levels, respectively. Both 95% and 99% are used to show robustness, as well as the role of HFT in curtailing the more extreme outliers. The data indicate that HFT has a very pronounced role in mitigating the trading value surrounding EOD dislocating cases, and this effect is statistically significant at the 5% (Model 1) and 10% (Models 2-7) levels in Panel B, and at the 5% (Models 1-6) and 10% (Model 7) levels in Panel C. The economic significance is consistently higher in Panel C than in Panel B for each Model, which shows that HFT curtails extreme events with EOD manipulation cases. The most conservative estimate is from Model 1 in Panel B, which shows a reduction by $2.11^{E}+05$. Given the average trading value surrounding EOD cases is $5.89^{E}+05$, this reduction is economically significant at 35.85% of the average value. The least conservative estimate is from Model 6 in Panel C which shows a reduction by $3.22^{E}+05$, or 54.71%.

The most significant control variable is the MSCI returns in Panels B and C, consistent with that in Panel A. Worse market conditions in terms of MSCI performance are associated with less pronounced manipulation. The other control variables are not as consistently significant relative to the HFT variable in Panels B and C, but do show some significant effects. Higher market capitalization is associated with a reduction in the value (Models 1-3 in Panels B and C), and higher dollar volume is associated with a higher trading value (Models 1 and 3 in Panels B and C). There is some evidence that surveillance reduces the trading value surrounding manipulation (Model 3 in Panels B and C), as does public enforcement (Model 4 in Panels B and C), but these effects are not robust in the other models. More efficient judiciary is positive and significant in Model 7, but only at the 10% level and significant in a spurious way due to collinearity with other variables, and this effect is again not robust in Model 5.

5.2. Robustness checks

In the course of our empirical analyses we carried out a number of robustness checks. First, we considered different specifications of the dependent variables, such as without winsorizing and winsorizing at different levels, different time periods, etc. Second, instead of using total trading rules, we used subsets of the trading rules indices. Third, we considered other measures of law quality such as antidirector rights (La Porta et al., 1998; Spamann, 2010), disclosure (La Porta et al., 2006) and other proxies for the resources devoted to securities regulation (Jackson and Roe, 2009). Fourth, we considered other instrumental variable and difference-in-differences specifications, such as with lagged dependent variables and other specifications. Fifth, we considered possible outlier time periods and outlier exchanges. Sixth, we considered other proxies for HFT, such as trending variables instead of a binary variable, to account for increases in HFT over time. Seventh, we have considered other explanatory variables, including but not limited to measured of volatility. These alternative models and checks, among others, did not suggest material differences to the array of results reported in the tables. Alternative specifications are available on request.

Finally, recall in section 3 above we noted that some observations are missing, such as data from the WFE and index values from La Porta et al. (1998) and Jackson and Roe (2009). We assessed robustness to excluding these legal observations by filling in missing values for the indices based on taking the median and mean values of the indices for the missing countries based on the countries of the same legal origin. Further, we obtained missing WFE values using Reuters exchange data from Capital Markets CRC for WFE. The results are extremely similar for each of Panels A, B and C in Table 6 when we re-run the regressions with the full sample. For Panel A, the HFT coefficient with the full sample is -28.6 and significant at the 1% level. For Panels B and C, the coefficient is -2.54E+05 and significant at the 1% level. Similarly, the other results were not materially different. Again, additional specifications and full details are available on request.

6. Conclusions

This paper examined the relationship between HFT and EOD manipulation in 22 exchanges around the world spanning the period January 2003 – June 2011. EOD manipulation is one of the most common and important forms of manipulation in view of the many important functions of EOD prices, such as computing index values, prices for related securities, compensation, and computing fund net asset values. We examined data used by actual surveillance systems to ascertain suspected EOD manipulation cases in a way that is consistent across exchanges. We related the frequency and trading value surrounding suspected EOD manipulation cases. We controlled for a variety of market conditions, legal conditions, trading rules, surveillance and other differences across exchanges.

The data examined unambiguously indicate that in the presence of HFT, EOD manipulation are on average less frequent in terms of the number of EOD manipulation cases in the presence, and on less pronounced in terms of the average EOD trading value surrounding suspected cases. In fact, HFT is the most robust and statistically significant factor that affects EOD manipulation.

The data also indicate that EOD manipulation varies frequently with market conditions. As well, the data indicate somewhat related to surveillance and regulatory standards in a country. But the importance of HFT is much more consistently pronounced and effective in terms of mitigating the frequency and magnitude of manipulation.

Overall, the data support the view that the price discovery and liquidity function of HFT on average significantly dominates and role that HFT may play facilitating market manipulation, at least with respect to the very important EOD manipulation. Future research could explore the effect of HFT on other types of manipulation. As well, future research could explore differences in manipulation across different HFT firms pursuing different strategies. It is possible that there are some HFT manipulators present in the market, and if so, it would be important to know the context in which their trades are executed to enable surveillance authorities and regulators to detect such forms of manipulation. But overall the data considered herein show that the presence of HFT has done more good than harm and that manipulation, at least EOD manipulation, is not as pronounced under HFT as current regulatory concerns might suggest.

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Appendix: High Frequency Trading influential dates

High-frequency trading (HFT) is usually characterized by large number of orders with smaller order quantities and tending to have short position-holding periods with almost no overnight position (Aldridge, 2009; Henrikson, 2011; Brogaard, 2010).

Many studies on HFT activities use data at trades and quotes level with detailed identification code to identify HFTrs vs. non-HFTrs. Those studies often focus on single exchange or a group of highly liquid stocks over a short period (Brogaard, 2010; Kirilendo, et al., 2011; Menkveld, 2012). An optimal proxy to define the HFTr influence in our study would be a percentage of trading volume/value by HFTr over the total market trading volume/value. Our study covers twenty-two exchanges in seventeen countries over a period nine years. Obtaining detailed trade and quote data over the whole period for all exchanges in our study was nearly impossible. As such, we have developed a proxy to identify the impact of activities by HTFrs in each exchange and used this proxy to demonstrate whether or not HFT have significant impact on market quality. In other words, we are not trying to pin point the start date of HFT activities in each exchange rather we are trying to identify the period of time that HFTrs have flourished and have significant influence in the market.

In order to identify the start time of HFTrs' influence on a market, we first check whether the exchange in our sample offers direct market access (DMA). Eighteen out of twenty-two exchanges either have DMA access earlier compared to the start period of our data sample or have just began to offer DMA during the period of sample coverage. Second, we obtained the monthly on market trading volume and number of trade for each exchange from January 2003 to December 2011 and calculate the average monthly market trading size as the monthly total on market trading volume over the monthly total number of trades. We define the start month of HFTr influence on the market as the first of four continuously declining months in average market trading size or the biggest single drop from previous month. We also exclude significant declines during the financial crisis period between 2007 and 2008. For example, the maximum four months decline for the Australian Stock Exchange (ASE) is 42 percent which started on April, 2006 and the biggest single decline in trade size for OSLO Stock Exchange (OLSO) is 48 percent which occurred on May 2005. Therefore, we define the HFT start date for ASE and OSE as April 2006 and May 2005, respectively. We also looked at both the three-month and five-month continuous declines in average market trading size and found the results to be similar. Few exchanges have continuously declines in trading size over five months. Among eighteen exchanges, we were unable to observe any pattern of significant change for Singapore Stock Exchange (SGX), Hong Kong Stock Exchange (HKX), or the two Korean stock exchanges (KOE and KSC) except during financial crisis period. In these cases, we were unable to define a HFT start date. Four exchanges NASDAQ, the New York Stock Exchange (NYSE), CHI-X London (CHIX) and XETRA German (XET) have a HFT start date at the beginning of the data period.

Our final list contains fourteen exchanges from eleven different countries. We acknowledge that our definition of HFT activities may exclude HFT activities in certain exchanges. However, such bias will work against our study and make a consistent finding more difficult to obtain. Nevertheless, our findings in Table 6 show that HFT activities have a significant impact on both price dislocating cases and total trading surrounding each case. To confirm that there are changes in trading behaviours between pre-HFT and post-HFT period, we performed a comparison test on both the mean and median of average trading size. Since by our definition, exchanges such as CHIX, NASDAQ, NYSE, and XET have a start date at the beginning of our study period, they are excluded from the comparison test. The results of the comparison test for all other exchanges as well as the HFT start date for each exchange are listed in Table A1, and shown graphically in Figures A1 and A2. In general, on market average trading size drops significantly after the HFT date. The average trading size dropped more than fifty percent after the HFT start date in six out of ten exchanges in the table. All comparison t-statistics are significant at the one percent level except the Bombay Stock Exchange (BSE) in India, which is significant at the five percent level. The median test tells a similar story with the sole exception of the BSE which it is not significant at any level (although our findings in the paper are invariant to different treatment of the HFT variable for BSE).

Table 1A. HFT start date. This table lists the Exchange name, HFT start date and Comparison test on both Mean and Median of average trading size for each exchange. HFT started prior to the start date of our sample (2003/01) for CHIX, NASDAQ, NYSE and XET and hence are not listed here.

Exchange Name	HFT Start Date	Mean			Median		
		Pre-HFT	Post-HFT	t-statistics	Pre-HFT	Post-HFT	P-value
OMX	2005/04	10333.11	3520.41	16.73***	10342.00	2951.00	p<0.00***
SWX	2004/01	1816.58	372.08	21.22***	1746.50	340.50	p<0.00***
TMX	2005/05	2618.71	1245.60	20.04***	2586.50	1097.00	p<0.00***
NSE	2011/01	1002.61	441.08	15.29***	988.00	402.50	p<0.00***
BSE	2009/05	559.21	428.69	2.34**	514.50	376.50	p=0.4895
TSE	2009/05	4409.64	3230.08	10.99***	4476.50	3150.00	p<0.00***
ASX	2006/04	11358.67	5122.21	15.32***	10772.00	4574.00	p<0.00***
LSE	2006/02	9793.97	3284.28	23.09***	9905.00	2487.00	p<0.00***
NZX	2004/11	8973.96	7046.03	4.26***	7774.50	6957.50	p<0.00***
OSLO	2005/04	7376.22	4368.37	6.11***	6736.00	3818.00	p<0.00***

Figure A1. Plot of indexed of market average trading size. Mean of the market average trading size of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. For nonHFT countries, the zero month is January 2005. The values for the nonHFT countries are also indexed to the zero date.

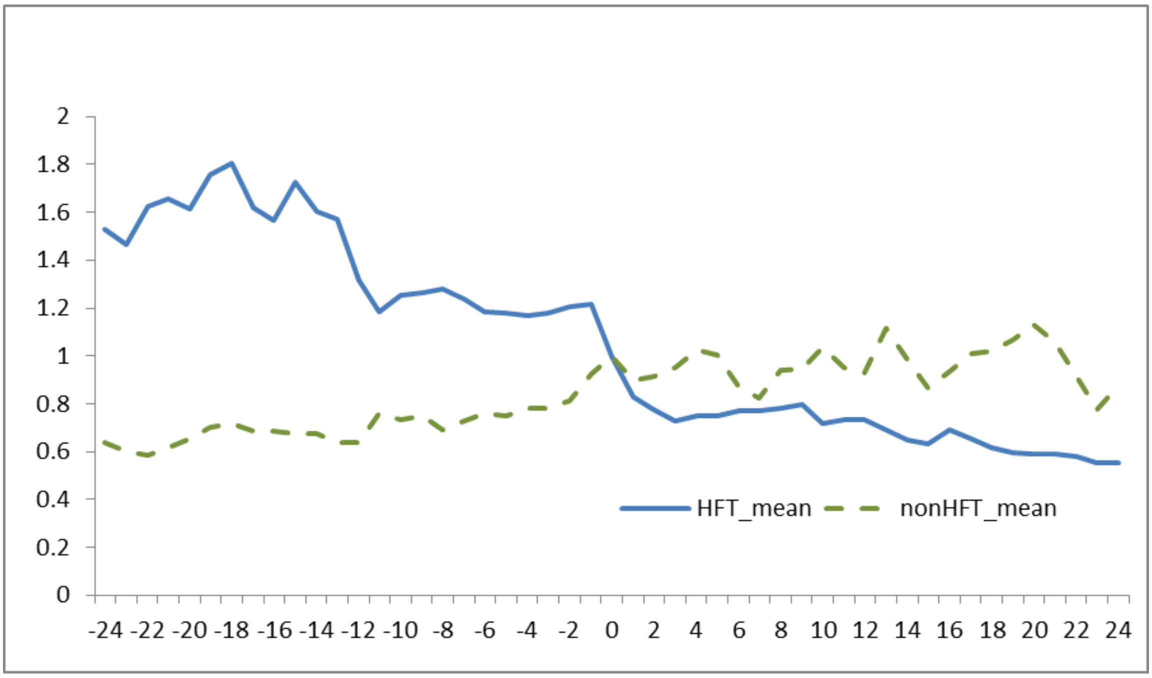
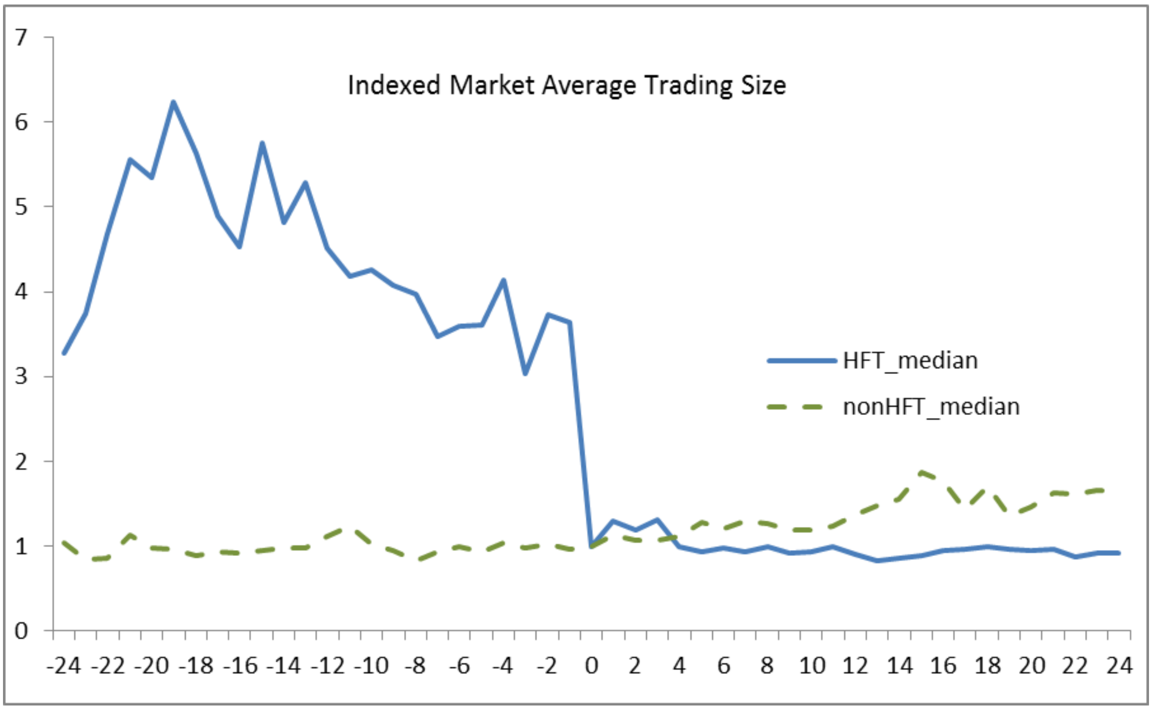


Figure A2. Plot of indexed of market average trading size. Median of the market average trading size of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. . For nonHFT countries, the zero month is January 2005. The values for the nonHFT countries are also indexed to the zero date.



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