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High Frequency Trading and End-of-Day Price Dislocation

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HIGH FREQUENCY TRADING AND END-OF-DAY PRICE DISLOCATION*

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HIGH FREQUENCY TRADING AND END-OF-DAY PRICE DISLOCATION

Abstract

We show that the presence of high frequency trading (HFT) has significantly *mitigated* the frequency and severity of end-of-day price dislocation, counter to recent concerns expressed in the media. The effect of HFT is more pronounced on days when end of day price dislocation is more likely to be the result of market manipulation on days of option expiry dates and end of month. Moreover, 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 price dislocation. We show our findings are robust to different proxies of the start of HFT by trade size, cancellation of orders, and co-location.

Keywords: High frequency trading, End-of-day Price dislocation, 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,[1] 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 (Biais and Woolley, 2011). However, prior work has not empirically examined the impact of HFT on specific forms of price manipulation.

[1] 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). Commentators indicated recently that "[l]eading fund managers are calling for greater regulation of high frequency trading which they warn is resulting in market manipulation"; see Financial Review, August 15 2102, http://afr.com/p/business/companies/crack_down_on_high_frequency_trading_CSA9PgK9WGQJp9sgngTF7K. 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

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 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).[2] 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 dislocation 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 price dislocation cases. Suspected cases on EOD price dislocation 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; Branch and Evans, 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 price dislocation 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

[2] For related work on market manipulation and exchange governance, see Aggarwal and Wu (2006), Allen and Gale, (1992), Allen and Gorton (1992), Carhart et al. (2002), Merrick et al. (2005), O'Hara (2001), O'Hara and Mendiola (2003), Peng and Röell (2009), Pirrong (1999, 2004), and Röell (1993).

characterized by large number of orders with smaller order quantities, speedy cancellations, and tending to have short position-holding periods with almost no overnight position (Aldridge, 2009; Brogaard, 2010; Gomber, et al., 2011; Henrikson, 2011). 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, including trade size, cancellation of orders, and co-location (see the Appendix).

The data examined in this paper show that marketplaces with a significant presence of HFT are substantially less likely to experience EOD price dislocation and more severe EOD price dislocation. In particular, the number of suspected EOD price dislocation cases decrease by 7.64 cases per month due to HFT in the most conservative estimate; given the average number of cases per month in the data is 36.56, this means that HFT decreases the probability of EOD dislocation by 20.90%. 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 41.09% relative to the average size of the total trading value surrounding per suspected dislocating the EOD price case; the least conservative estimate is 64.71%.

Interestingly, on days when end of day dislocation is more likely to be attributable to manipulation, the effect of HFT is even more pronounced. At the end of month and on days when options expire, HFT reduces the number of cases by 72-80%, (while the economic significance of HFT on the reduction on average trading values is analogous to the other days).

It is noteworthy that policy mechanisms, including trading rules, surveillance and enforcement, appear to have had less of an effect in mitigating EOD price dislocation. 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; 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 price dislocation.

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 75% 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.

Biais 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 than HFT trades, thereby leading to a reduced market participation among 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 (HFTs) 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 price dislocation.

This paper is organized as follows. Section 2 discusses EOD price dislocation in relation to HFT as well as various policy mechanisms designed to curb price dislocation. Section 3 introduces the data used in this paper and univariate tests results are presented in Section 4. Section 5 presents multivariate analyses of the relation between the end of day price dislocation 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 (Biais 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; for related work see also Bajgrowicz and Scaillet, 2012; Edelen and Kadlec, 2012). 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; Banerjee and Eckard, 2001), 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.

International start dates of algorithmic trading (AT) and HFT are not well delineated or even known by most exchanges themselves (Aitken et al., 2012). One approach is to identify news announcements on the timing of co-location (Boehmer et al., 2012). Co-location involves an exchange renting a space to the trading firm next to the trading facility, which provides added speed for the flow of time-sensitive information. When one asks the directors of the exchange themselves, it becomes quite clear that the precise start date is not always known due to the differential timing and ambiguous presence of AT and HFT orders in the market. AT and HFT orders in all most countries began years in advance of co-location (this fact is documented in Aitken et al., 2012). High frequency traders themselves are widely known to have physically located themselves next to the exchange in order to obtain time advantages, and established such proximate location long before co-location started. Co-location is not a pre-requisite for algorithmic or high-frequency trading. Therefore, even with proxies for co-location start dates, where defined, such start dates do not measure "effective" dates. "Effective" refers to the impact on the marketplace. Impact in this case is most commonly studied by exchange participants through unusual and permanent drops in trading size. Additional proxies for HFT effective dates include quote updates to trade ratio and the order entry/amendment/cancellation to trade ratio; these alternative methods do not materially affect our inferences drawn herein, unlike the differences observed with the co-location dates. As explained further in the Appendix, we focus on the effective date based on trade size and cancellations to identify HFT start dates, not co-location dates. In our multivariate empirical tests below, we nevertheless include the co-location date as well as the effective HFT date in case there is an added marginal effect of co-location services offered by the exchange.

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. The SMARTS surveillance staff constructed the dislocation of EOD price case by looking at the price change between the last trade price (P_t)[3] and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). A price movement is abnormal if it is four standard deviations away from the mean abnormal price change during the past 100 trading days benchmarking period. To be considered as dislocation of EOD price case, the price movement between the last trade price (P_t) and the next day opening price (P_{t+1}), and between last trade price (P_t) and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}) has to be equal or bigger than 50%.[4] Table 2 indicates that the average (median) number of suspected dislocating the EOD price cases 36.56 (15) 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$685,637.80 ($142,727).

[Tables 1 and 2 About Here]

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

[3] For securities exchanges that have closing auction, the close price at auction is used ($P_{auction}$).

[4] $(P_{auction\ or}\ P_t - P_{t+1})/(P_{auction\ or}\ P_t - P_{t-15}) \geq 50\%$

stock exchange are obtained from Capital Markets Cooperative Research Centre (CMCRC). Some observations are missing, such as index values from La Porta et al. (1998) and Jackson and Roe (2009).

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.

[Insert Table 3 About Here]

We use 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 include control variables for volatility. 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.

[Insert Table 4 About Here]

Table 4 Panel A shows that the market-capitalization weighted median number of suspected dislocating the EOD price cases is 0.01in HFT exchange time periods, which is lower than the 0.13 weighted median number of cases in non HFT-exchange time periods; however, due to a few outliers, the market-capitalization weighted average for the number of EOD cases is higher at 3.54 for HFT than the 0.64 for non-HFT countries. These differences in means and medians are significant at the 1%. Moreover, considering the impact of introducing HFT in a market, Table 4 Panel A shows that post-HFT exchanges had on average (median) 1.05 (0.004) cases, which is lower than the average (median) of 6.70 (0.04) in pre-HFT time periods. Again, these differences in means and medians are significant at the 1% level.

Figure 1 plots the indexed average number of EOD price dislocation 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 price dislocation cases are less frequently associated with HFT both in terms of comparing pre- and post-HFT time periods and HFT and non-HFT exchanges.

[Insert Figure 1 About Here]

Table 4 Panel B shows that the market-capitalization weighted average (median) trading value surrounding suspected the EOD price dislocation cases is 40586.67 (27.82) in HFT exchange time periods, which is lower than the 118325.60 (269.01) average (median) trading value surrounding cases in non HFT-exchange time periods. These differences are significant at the 1% level. 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 a market capitalization weighted average (median) 22465.07 (35.45) trading value surrounding cases, which is lower (higher) than the average (median) of 63554.75 (18.75) in pre-HFT time periods. This difference in means is significant at the 1% level, but the difference in median is not statistically significant.

Figure 2 plots the indexed total trading value surrounding EOD price dislocation 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 1 clearly shows that EOD price dislocation cases are less frequently associated with HFT both in terms of comparing pre- and post-HFT time periods and HFT and non-HFT exchanges.

[Insert Figure 2 About Here]

Overall, these comparison tests support the view that HFT is associated with a lower frequency of EOD price dislocation. Further, the pre- versus post-HFT tests support the view that there is less trading value surrounding EOD price dislocation 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.

[Insert Table 5 About Here]

5. Multivariate Tests

5.1. Primary Results

Table 6 presents panel data regression results with 9 alternative econometric models for the two dependent variables for the number of EOD price dislocation cases and the average trading value surrounding such cases. All dependent variables are winsorized at 99% in Table 6. The nine models include different sets of explanatory variables to highlight robustness. Model 1 and model 2 present difference-in-difference (DID) tests. Models 3-6, and 8 include the HFT variable along with microstructure control variables in terms of exchange characteristics such as market capitalization, dollar volume, and the number of trades. Models 5 include different sets of trading rule and enforcement variables, which is useful to show explicitly since many of these variables are highly correlated. Models 6-9 include a complete set of variables all at once, with model 7 and 9 using HFT effective date defined by cancellation ratio.[5] Models 8 and 9 exclude the US observations. We do not use two-way clustering in some of the models due to estimation problems with the time-invariant legal/country variables. Models 5-9 use one-way clustering of errors by year, model 1 and 2 use one way clustering by month, while Models 3 and 4 use two-way clustering by month and exchange. We also control fixed effect at the exchange level on model 1.

[Insert Table 6 About Here]

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 this effect is significant at the 10% level for model 1 and 2, at 5% level for model 5, 6, 7, and 9, and at 1% level for model 3, 4, and 8. In terms of the economic significance, the data indicate that HFT gives rise to an average of 7.64 fewer cases in the most conservative estimate in Model 2, and up to a reduction in cases by 40.07. Given that the average number of cases per month per exchange is 36.56, this is equivalent to a conservative estimate of a reduction by 20.90% in the number of cases with HFT.[6]

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[5] Our cancellation data (Table A3 in the Appendix) does not comprise data from OMX, SWX and NZX. As such, we use the dates defined by trade size for those countries in these regressions. We considered dropping those countries from these 2 models but the inferences were not materially different.

[6] Also, we considered a difference-in-differences estimator using the average start date for HFT across exchanges. We do not explicitly report this estimator because the average start date is an imperfect choice since the start dates vary widely across exchanges (see the Appendix). This estimator showed a reduction in the number of cases by 16.56 (significant at the 1% level), which is a reduction by 45.2% relative to the average number of cases of 36.56.

The co-location variable is statistically insignificant in all of the models in Table 6 Panel A. This finding is consistent with the fact that HFT started long in advance of co-location (see the Appendix; see also Aitken et al., 2012).

The control variables in Table 6 Panel A show some consistent statistical significance in ways that are expected. EOD price dislocation is less common with public enforcement (Models 5, 8 and 9), less common among higher rule of law countries (Models3, 5-9), and more common when volatility is higher (Models 2-9). These effects are significant at least at the 10% level. The other controls are either insignificant or not robust across different specifications.

Table 6 Panel B presents the regression results for the number of suspected EOD price cases. 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 10% level in Models 1, 2 and 9, at the 5% level in Models,5, 7 and 8, and the 1% level in Model 3, 4 and 6. The economic significance shows that HFT curtails extreme events with EOD price dislocation cases. The most conservative estimate is from Model 1 in Panel B, which shows a reduction by 281720.3. Given the average trading value surrounding EOD cases is 685637.8, this reduction is economically significant at 41.09% of the average value. The least conservative estimate is from Model 4 in Panel B which shows a reduction by 443645.7, or 64.71%.

The co-location variable in Table 6 Panel B is insignificant in all specifications. Hence, that latter timing of co-location relative to the start of HFT (Appendix; see also Aitken et al., 2012) has on average had no material effect on trading values surrounding suspected cases.

Likewise, we considered other specifications all of which yielded consistent results that the number of cases goes down.

The control variables show some consistent significance. Trading value surrounding suspected cases is higher with public enforcement (Models 5-9) and lower with average market trade size (Models 3-8). Log of trading volume is significant in Models 3, 4, 6 and 7, but not robust in the other models. Similarly some of the surveillance and enforcement estimates are significant but the effects are not robust.

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. Results with winsozing at the 95th percentile appear in Table 7. The findings are very consistent with that reported in Table 6, with the exception that the economic significance or the size of the effects is slightly smaller as expected.

[Insert Table 7 About Here]

Second, we report findings with other measures of end-of-day price dislocation by examining only end-of-month cases and only cases of end-of-day price dislocation that match with option expiry dates. We examine these dates in particular since they are at times when dislocation is more likely to be attributable to manipulation (Comerton-Forde and Putnins, 2011). These findings are reported in Table 8. The statistical significance of the results are consistent with those reported in Table 6 for the dependent variables in the other tables with all possible end-of-day price dislocation cases. Interestingly, however, the economic significance of the results is more pronounced. At the end of month and on days when options expire, HFT reduces the number of cases by 72-80% depending on the specification (relative to the average number of cases on those days). However, the economic significance of HFT on the reduction on average trading values is analogous to the other days as reported in Table 6.

[Insert Table 8 About Here]

Third, instead of using total trading rules, we used subsets of the trading rules indices. Fourth, 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). Fifth, we considered other instrumental variable and difference-in-differences specifications (see footnote 5), such as with lagged dependent variables and other specifications. Sixth, we considered possible outlier time periods and outlier exchanges. Seventh, we considered other proxies for HFT, such as trending variables instead of a binary variable, to account for increases in HFT over time. Eighth, we have considered other explanatory variables, including but not limited to other measures of volatility other than that reported in the tables. 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 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. The results are extremely similar for each of Panels A and B in Table 6 when we re-run the regressions with the full sample. We note that Model 1 in Table 6 uses the full set of observations and the findings are very consistent with the regressions which include variables with some missing observations. Again, additional specifications and full details are available on request.

6. Conclusions

This paper examined the relationship between HFT and EOD price dislocation in 22 exchanges around the world spanning the period January 2003 – June 2011. EOD price dislocation is one of the most common and important forms of price dislocation 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 price dislocation cases in a way that is consistent across exchanges. We related the frequency and trading value surrounding suspected EOD price dislocation 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 price dislocation are on average less frequent in terms of the number of EOD price dislocation 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 price dislocation.

The data also indicate that EOD price dislocation 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 price dislocation.

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 price dislocation, at least with respect to the very important EOD price dislocation. 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. When Did HFT Start?

In this Appendix we explain our three empirical strategies to identify the start of high-frequency trading (HFT): trade size, order cancellations, and co-location. Herein we refer to HFT and not algorithmic trading (AT). Some prior studies have indicated that HFT is a subset of AT (Chlistalla, 2011; Gomber et al., 2011), while other studies have indicated that HFT is an instrument of AT (e.g., MacIntosh, 2013, European Commission Report, 2010). Regardless, AT is by itself not likely to be associated with manipulation, while HFT is potentially associated (Biais and Wolley, 2012). While our start dates analyzed herein may pick up the start of both AT and HFT, we reference HFT herein due to our focus on manipulation.

HFT is usually characterized by large number of orders with smaller order quantities, speedy order cancellations, and tending to have short position-holding periods with almost no overnight position (Aldridge, 2009; Brogaard, 2010; Gomber, et al., 2011; Henrikson, 2011). Many studies on HFT activities use data at trades and quotes level with detailed identification code to identify HFTs vs. non-HFTs. Those studies often focus on single exchange or a group of highly liquid stocks over a short period (Brogaard, 2010; Kirilenko, et al., 2011; Baron, et al., 2012; Malinova, et al., 2012; Menkveld, 2012; Brogaard, et al., 2013; Carrion, 2013; Hirschey, 2013). Table A1 provide a brief summary in term of size of HFT trading in various market and various methods academics use to identify HFTs. An optimal proxy to define the HFTs' influence in our study would be a percentage of trading volume/value by HFT 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 two proxies to identify the impact of activities by HTF 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 HFT have flourished and have significant market influence.

Defining HFT Effective Dates Using Average Trade Size

In order to identify the start time of HFTs' 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 HFT 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. Three exchanges NASDAQ, 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. 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, 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 A2, 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).

[Insert Tables A2 and Figures A1 and A2 About Here]

Defining HFT Effective Dates Using Order Cancellations

Similar to the methods used for trade size, we collected the daily number of order cancellations and total trading volumes for each individual stock for each exchange. We calculate the cancellation ratio for each stock as follows:

$$CR_{i,j} = \frac{\#\ COrder_j}{TV_j/1000}$$

where $CR_{i,j}$ represents the Cancellation Ratio with the subscripts i inidcates the day of the month and j indicates the individual stock. $\#\ COrder_j$ represent the total number of cancellation orders at the end of day for stock j and TV_j represent the total daily trading volume for stock j. Finally, we get the monthly cancellation ratio by taking the median of daily cancellation ratio within the month. We define the HFT effective month as the first of five or more months of continuously increasing cancellation ratios. For three exchanges, XET, BSE and NSE, we use the first of three months of continuously increase in the cancellation ratio since the cancellation ratio goes up and down more frequently, and the smallest increase in the cancellation ratio is more than 70% for three months among these three exchanges. In order to collect the completed number of orders cancellation for each individual stocks, we need data for both sides of order book. Several stock exchanges such as OMX, SWX, NZX, NASDAQ and CHI-X London have incomplete data or missing data. In the empirical test, we use the HFT effective date from the average trade size. For NASDAQ and Chi-X London, we continue to define the HFT effective date as the beginning of data sample.

Table A3 lists the HFT effective date and comparison of means and medians tests of cancellations on each exchange. In general, on market average trading size drops significantly after the HFT start date, and the average cancellation ratio increases dramatically after the HFT start date in all exchanges. Compare with the HFT effective date defined using average trade size, we notice that several exchanges have the same date using two different methods such as National Stock Exchange in India (NSE), Australia Stock Exchange (ASX) and a few of them have date very close to each other. For example, using average trade size, HFT effective date for Bombay stock Exchange (BSE) is May, 2009 and using cancellation ratio, the HFT effective date for BSE is June, 2009. Similarly, HFT effective date for New York Stock Exchange (NYSE)is May 2003 and July 2003 using average trade size and cancellation ratio, respectively. In three exchanges, TMX, TSE and

LSE, the HFT effective date defined using cancellation ratio is early than the date defined using average trade size. We also perform a comparison test on both mean and median of cancellation ratio for each exchange, and all comparison t-statistics are significant at the one percent level. Graphically, figure A3 and A4 illustrate a similar story.

[Insert Tables A3 and Figures A3 and A4 About Here]

Defining HFT Effective Dates Using Co-location Dates

Finally, note that co-location involves an exchange renting a space to the trading firm next to the trading facility, which provides added speed for the flow of time-sensitive information. Co-location is not a pre-requisite for AT or HFT. AT and HFT orders in all most countries began years in advance of co-location (Aitken et al., 2012). High frequency traders themselves are widely known to have physically located themselves next to the exchange in order to obtain time advantages, and established such proximate location long before co-location started. Nevertheless, we manually collect all known co-location offer date and Table A4 list the proximity hosting/co-location offer time for exchanges used in our study.

[Insert Table A4 About Here]

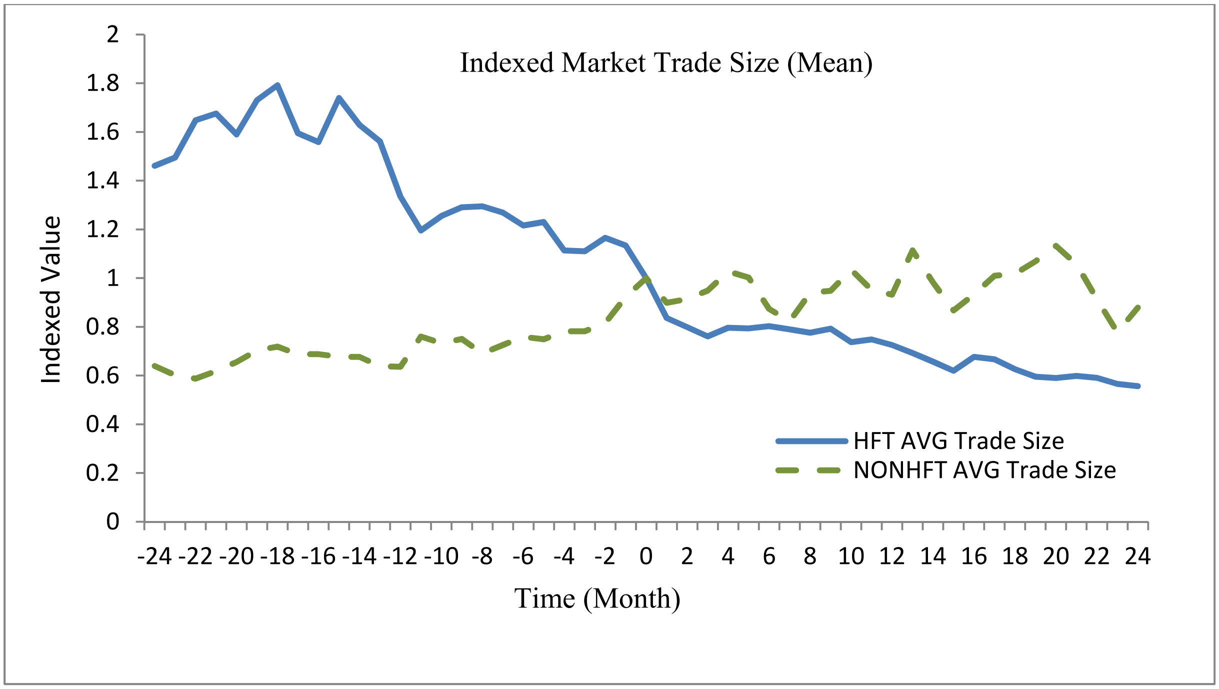

Figure A1: Plot of indexed of market average trading size. Mean of the market average trading size(AVG) of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare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

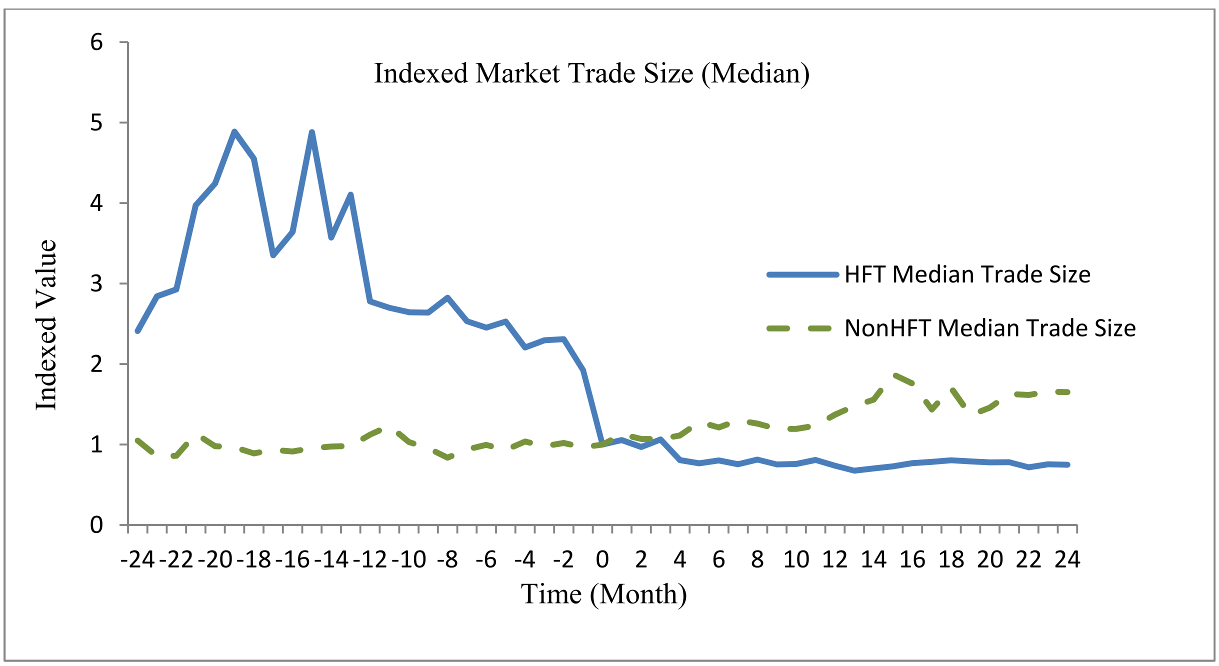

Figure A2: Plot of indexed of market average trading size. Median of the market average trading size of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare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

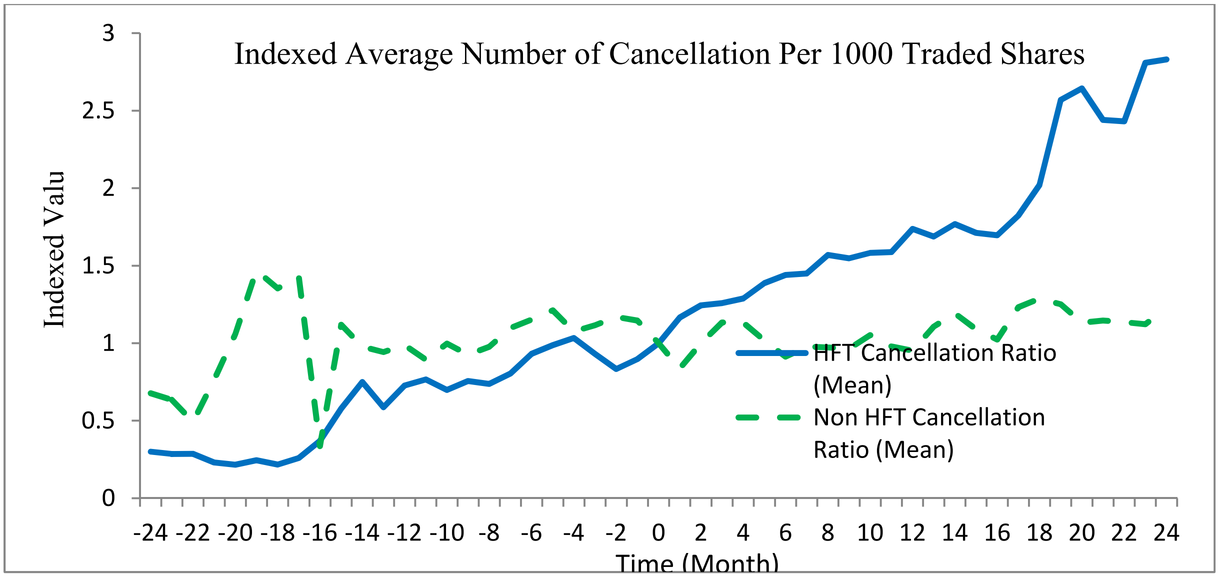

Figure A3: Plot of indexed value of number of cancellations per 1000 traded shares(cancellation ratio). Mean value of cancellation ratio of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. For non-HFT countries, the zero month is January 2005. The values for the non-HFT countries are also indexed to the zero date.

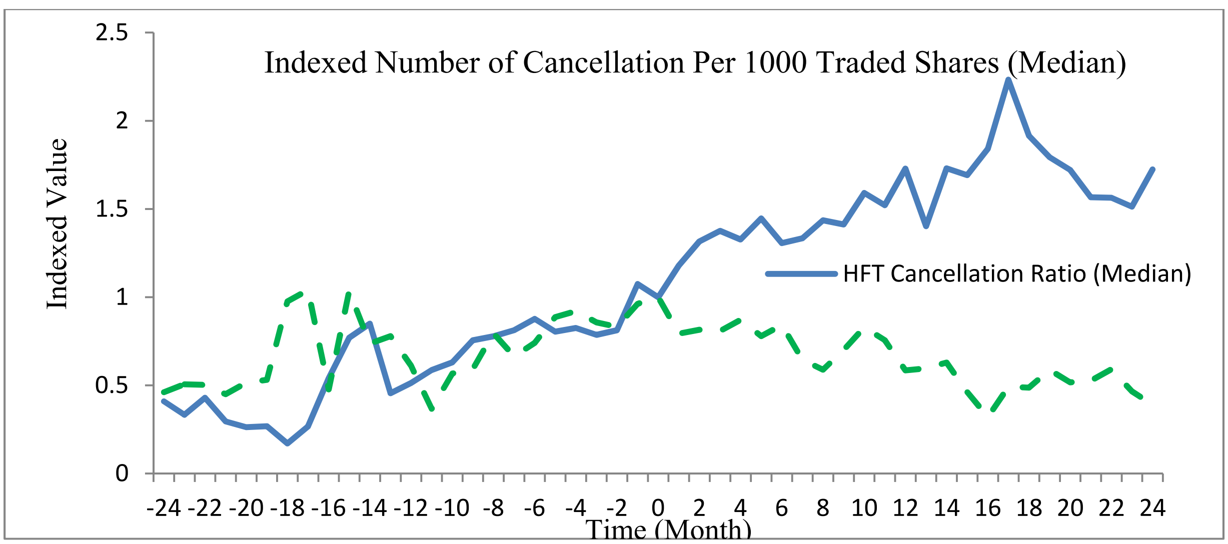

Figure A4:: Plot of indexed value of number of cancellations per 1000 traded shares(cancellation ratio). Median value of cancellation ratio of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. For non-HFT countries, the zero month is January 2005. The values for the non-HFT countries are also indexed to the zero date.

Table A1: Empirical Studies of High Frequency Trading (HFT)

Authors	Title of the Working Paper	Markets	HFT Trading Activities	Identifying HFT
Baron, Brogaard and Kirilenko (2012)	The Trading Profits of High Frequency Traders	E-mini S&P 500 equity index futures markets (US)	46.8% of double-counted trading volume or 1.49 million contact daily	HFTs are defined as firms with high volume, low intraday inventory and low overnight inventory.
Brogaard (2010)	High Frequency Trading and Its Impact on Market Quality	NASDAQ (US)	60.4% to 75.9% of all dollar-volume traded daily	NASDAQ indicator
Brogaard, Hendershott and Riordan (2013)	High Frequency Trading and Price Discovery	NASDAQ and NYSE (US)	42% of trading volume in large stocks and 18% trading volumes in small stocks.	NASDAQ identify HFT firms based on the net trading day, order duration and order to trade ratio
Carrion (2013)	Very fast money: High-Frequency trading on the NASDAQ.	NASDAQ (US)	68.3% of all dollar trading volume	NASDAQ indicator
Hagstomer and Norden (2012)	The Diversity of High Frequency Traders	NASDAQ-OMX Stockholm (Sweden)	26% to 29% of total trading volume	NASDAQ OMX in-house expertise identifies HFT firms based on their member activities.
Hirschey (2013)	Do High-Frequency Traders Anticipate Buying and Selling Pressure	NASDAQ (US)	40% of trading volume	NASDAQ indicator
Kirilenko, Kyle, Samadi and Tuzun (2010)	The Flash Crash: The Impact of High Frequency Trading on an Electronic Market	E-mini S&P 500 equity index futures markets (US)	34% Total Trading Volume on May 3-5 and 29% Total Trading Volume on May 6, 2010.	HFTs are defined as traders with high volume and low inventory.
Malinova, Park and Riordan (2012)	Do Retail Traders Suffer from High Frequency Traders?	TMX (Canada)	82.1% of messages (March 1, 2012)	HFTs are defined based on the total number of messages and the message-to-trade ratios for each unique identifier in Canadian market
Menkveld (2013)	High Frequency Trading and the New-Market Makers	Dutch local index stocks for both Chi-X and Euronext	14.4% of all trades	Broker ID that fits all HFT characteristics
Zhang (2010)	High-Frequency Trading, Stock Volatility, and Price Discovery	US	78% of dollar volume in 2009	HFTs are defined as all short-term trading activities by hedge funds and other institutional traders not captured in the 13f database

Table A2 : HFT Effective Dates as Defined by changes in Average Trade Size

This table lists the Exchange name, HFT Effective date and Comparison test on both Mean and Median of average trading size for each exchange. HFT identified prior to the start date of our sample for CHI-X, NASDAQ, and XET and hence are not listed here.

Exchange Name	HFT Effective 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	2009/05	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	2005/05	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***
NYSE	2003/05	1072.75	517.74	14.98***	1067.5	378.5	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***

Table A3 : HFT Effective Dates as Defined by number of Cancellation orders per 1000 traded shares

This table lists the Exchange name, HFT start date and Comparison test on both Mean and Median of cancellation ratio for each exchange. HFT identified prior to the start date of our sample for CHI-X, London, and NASDAQ, and hence are not listed here. For XET, the HFT effective date starts 2003/02.

Exchange Name	HFT Effective Date	Mean			Median		
		Pre-HFT	Post-HFT	t-statistics	Pre-HFT	Post-HFT	P-value
TMX	2004/01	1.0051	6.9058	-10.0394***	0.9944	4.8666	p<0.00***
NSE	2009/05	1.3018	4.3661	-11.262***	1.5337	4.0662	p<0.00***
BSE	2009/06	0.9446	6.0677	-10.577***	0.6759	6.4829	p<0.00***
TSE	2004/04	0.4772	1.4154	-7.5344***	0.4816	0.8118	p<0.00***
ASX	2006/06	0.1370	0.3142	-22.9202***	0.1388	0.3135	p<0.00***
NYSE	2003/07	3.2300	7.4315	-14.8225***	3.2685	7.2748	p<0.00***
LSE	2004/02	0.3260	5.2619	-9.8659***	0.3196	3.2237	p<0.00***
OSLO	2005/02	0.7422	4.9244	-9.5636***	0.7303	2.3037	p<0.00***

Table A4: : HFT Effective Dates as Defined by Co-Location

Exchange Name	Co-Location Offer Month	Note/Link
Stockholm Stock Exchange	2011/03	https://www.alipesnews.com/App.aspx#id=3474436580000000&languageId=4000
Swiss Stock Exchange	2012/04	http://www.six-swiss-exchange.com/news/overview_en.html?id=inet_colo
Toronto Stock Exchange	2008/04	Information provided by TMX Datalinx
NASDAQ	2007/03	http://ir.nasdaqomx.com/common/mobile/iphone/releasedetail.cfm?releaseid=352163&CompanyID=NDAQ&mobileid=
Bursa Malaysia	N/A	
NSE India	2010/01	http://www.nseindia.com/technology/content/tech_intro.htm
Bombay Stock Exchange	2010/02	http://www.world-exchanges.org/news-views/co-location-services-bombay-stock-exchange-premises
Tokyo Stock Exchange	2010/01	http://www.tse.or.jp/english/rules/co-location/index.html
Australia Stock Exchange	2008/Fourth Quarter	http://www.asxgroup.com.au/media/PDFs/mr030708_co-location_hosting.pdf
XETRA Germany	2006/08	Information provided by XETRA Support
NYSE	2008/04	https://europeanequities.nyx.com/sites/europeanequities.nyx.com/files/327777.pdf
London Stock Exchange	2009/09	http://www.londonstockexchange.com/about-the-exchange/media-relations/press-releases/2010/lsegmakescolocationdirectlyavailabletovendorsandserviceproviders.htm
Chi-X London	2008/11	Information provided by ChiX Support
Hongkong Stock Exchange	2012/Fourth Quarter	http://www.hkex.com.hk/eng/newsconsul/hkexnews/2011/documents/115_e_stone%20laying%20fact%20sheet.pdf
KOSDAQ	N/A	
Korea Stock Exchange	N/A	
Singapore Stock Exchange	2011/07	http://www.sgx.com/wps/wcm/connect/sgx_en/home/higlights/news_releases/sgx+offers+fastest+connection+to+its+markets
Shanghai Stock Exchange	N/A	
Shenzhen Stock Exchange	N/A	
Taiwan Stock Exchange	2010/Fourth Quarter	http://www.world-exchanges.org/news-views/taiwan-stock-exchange-launch-co-location-services
New Zealand Stock Exchange	N/A	
OLSO Norway	2010/04	http://www.oslobors.no/ob_eng/Oslo-Boers/Trade/Delta/The-strategic-partnership-with-the-London-Stock-Exchange-Group

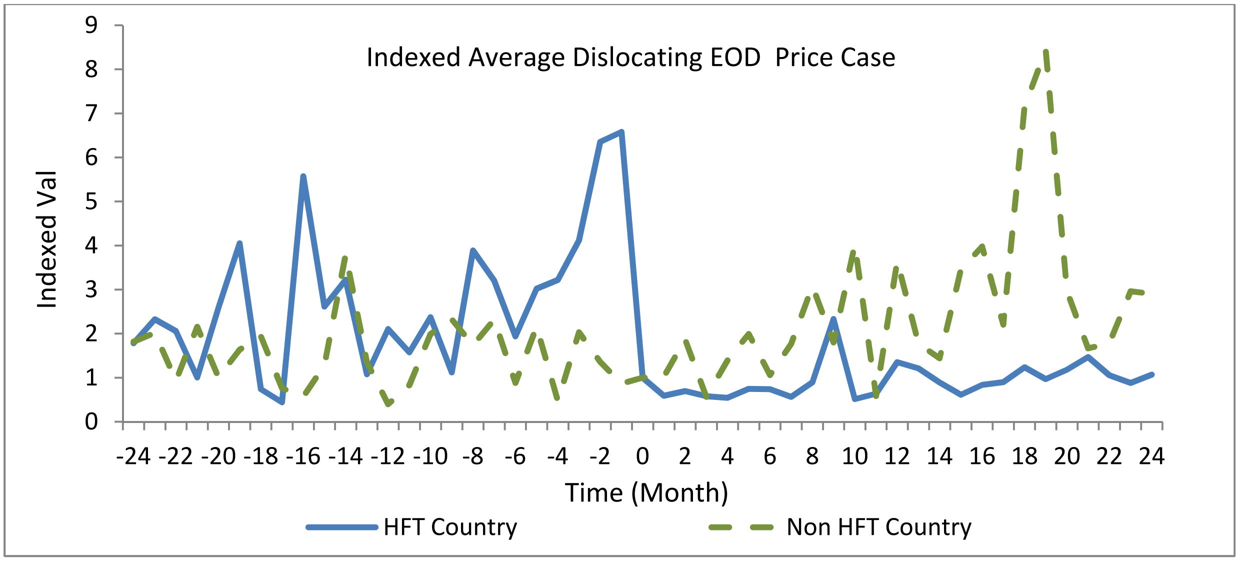

Figure 1: Plot of indexed of average (market capitalization weighted) EOD price case. Market Capitalization weighted average suspected EOD price dislocation cases of HFT countries and non-HFT countries are shown here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare pre- and post-HFT in a given country. . For non-HFT countries, the zero month is March 2007 (Mid-point). The values for the non-HFT countries are also indexed to the zero date.

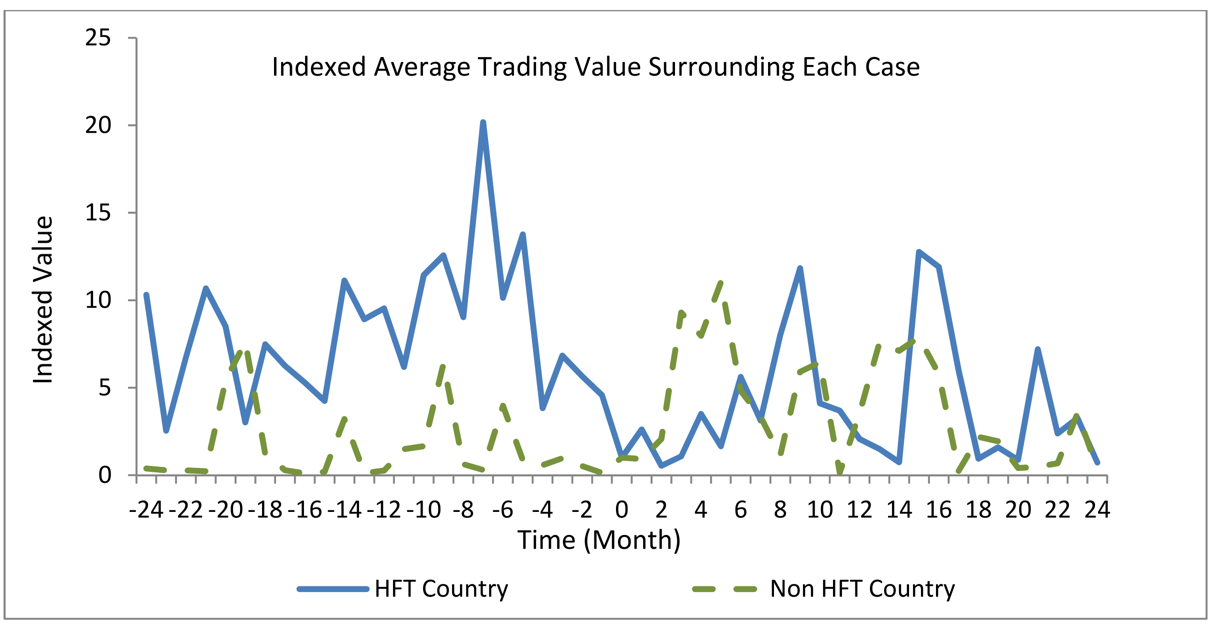

Figure 2: Plot of indexed of average (market capitalization weighted) total trading surrounding per EOD price case. Market capitalization weighted total trading value surrounding per suspected EOD dislocation case of HFT countries and non-HFT countries are shown here. The values for HFT countries are 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 non-HFT countries, the zero month is March 2007 (Mid-point). The values for the non-HFT countries are also indexed to the zero date.

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

Variable Name	Definition
HFT (Average Trade Size)	Dummy variable indicates when HFT starts in the market, as listed in Table A2 in the Appendix.
HFT (Cancellation Ratio)	Dummy variable indicates when HFT starts in the market, as listed in Table A3 in the Appendix.
Co-Location	Dummy variable indicates when the exchange starts to offer the co-location services, as listed in Table A2 in the Appendix.
Law/Legal Index	
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. Source: Djankov, La Porta, Lopez-de-Silanes, and Shleifer (2008a).
Efficiency of the Judiciary Index	Assessment of the ''efficiency and integrity of the legal environment as it affects business, particularly foreign firms'' produced by the country risk rating agency Business International Corp. It ''may be taken to represent investors' assessments of conditions in the country in question.'' Average between 1980 and 1983. Scale from zero to 10; with lower scores, lower efficiency levels 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).
Rule of Law Indices	Assessment of the law and order tradition in the country produced by the country risk rating agency International Country Risk (ICR). Average of the months of April and October of the monthly index between 1982 and 1995. Scale from zero to 10, with lower scores for less tradition for law and order (we changed the scale from its original range going from zero to six). Original data comes from International Country Risk guide. 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).
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).
Exchange Trading Rule Index	Sum of insider trading rules index, market manipulation rules index, and broker-agency rules index. Source: Cumming, Johan, and Li (2011).
Market Statistics	
Log (Market Capitalization)	Log of domestic market capitalization in USD millions. Source: Capital Markets Cooperative Research Centre (CMCRC).
Log (Volume)	Log of total value of shares trading in USD millions. Source: Capital Markets Cooperative Research Centre (CMCRC).
Log (Number of Trades)	Log of total number of trades in thousands in the same period. Source: Capital Markets Cooperative Research Centre (CMCRC).
Log (Market Volatility)	Log of market volatility. Market volatility is calculated as stock market capitalization weighted volatility for each exchange. Source: Source: Capital Markets Cooperative Research Centre (CMCRC).
Log (GDP Per Capita)	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 the EOD Price Dislocation Cases	Total number of suspected dislocating of the end of day price cases. The SMARTS surveillance staff constructed the dislocation of EOD price case by looking at the price change between the last trade price (P_t) and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). For securities exchanges that have closing auction, the close price at auction is used ($P_{auction}$). A price movement is abnormal if it is four standard deviations away from the mean abnormal price change during the past 100 trading days benchmarking period. To be considered as dislocation of EOD price case, the price movement between the last trade price (P_t) and the next day opening price (P_{t+1}), and between last trade price (P_t) and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}) has to be bigger than 50%. $(P_{auction\ or}\ P_t - P_{t+1})/(P_{auction\ or} P_t - P_{t-15}) \geq 50\%$. Source: Capital Markets Cooperative Research Centre (CMCRC).
Average Trading Value Surrounding Per Suspected the EOD Price Dislocation Case	Average trading value surrounding each suspected dislocating EOD price case. Source: Capital Markets Cooperative Research Centre (CMCRC).

Table 2.
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)
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)
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 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)

Table 2 (Continued)

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***)
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**)

Table 3.
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. Index from La Porta (1998, 2006), Jackson and Roe (2009) and DLLS (2008) are not available for China.

	Mean	Median	Standard Deviation	Minimum	Maximum	Number of Observations
Suspected Dislocating the EOD Price Cases	36.56	15	86.03	0	1645	2196
Total Trading Value Surrounding Per Suspected Dislocating the EOD Price Case	685637.8	142727	2408576	0	5.72e+07	2196
HFT Dummy(Average Trade Size)	0.46	0	0.50	0	1	2196
Co-Location Dummy	0.16	0	0.40	0	1	2196
Total Trading Rule Index	11.48	11	5.85	2	26	2196
Surveillance	18.54	14	13.93	3	41	2196
Resource-based measures of public enforcement (Jackson and Roe, 2009)	20.52	12.53	19.42	.43	77.74	1992
Public enforcement index (DLLS, 2008)	0.47	0.5	0.42	0	1	1992
Rule of Law	8.32	8.98	1.98	4.17	10	1992
Efficiency of the Judiciary	9.08	10	1.36	6	10	1992
log(Market Capitalization)	29.83	29.39	2.55	25.91	38.56	2178
log(Volume)	23.12	23.27	1.81	15.60	27.10	2196
log(Number of Trades)	26.75	26.77	2.90	19.37	32.81	2196
log(Average Market Trade Size)	7.96	7.87	1.62	5.16	12.88	2196
log (Market Volatility)	-3.82	-3.79	0.69	-9.45	-1.61	2174
log(GDP per capita)	9.57	1.39	10.20	6.14	11.44	2196

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) for the period January 2003 to December 2007. Market capitalization weighted mean and median are used for the test. The *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Panel A: Suspected Dislocating the EOD Price Cases

	All Countries		HFT Countries	
	HFT Countries	Non-HFT Countries	Post -HFT	Pre-HFT
Group	1	0	1	0
Number of Observations	780	480	436	344
Mean	3.541	0.635	1.052	6.697
Standard Deviation	18.046	1.327	4.716	26.325
Median	0.006	0.129	0.004	0.035
Difference in means (0-1)	-4.478***		3.927***	
Difference in medians (0-1)	11.638***		6.012***	

Panel B: Total Trading Value Surrounding Per Suspected Dislocating the EOD Price Case

	All Countries		HFT Countries	
	HFT Countries	Non-HFT Countries	Post -HFT	Pre-HFT
Group	1	0	1	0
Number of Observations	780	480	436	344
Mean	40586.67	118325.6	22465.07	63554.75
Standard Deviation	183767.8	607398.7	122898.5	237899
Median	27.82	269.01	35.45	18.75
Difference in means (0-1)	2.728***		2.912***	
Difference in medians (0-1)	2.728***		-1.247	

Table 5: Correlation Matrix

This Table presents Pearson Correlation coefficients for the full sample of exchange-months in the data. The * indicate the correlations are statistically significant at least in the 5% .

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	Suspected EOD Price Dislocation Case	1															
(2)	Total Trading Value Surrounding Per EOD Price Dislocating Case	-0.033	1														
(3)	HFT Dummy (Average Trade Size)	-0.0476*	0.0856*	1													
(4)	Co-Location Dummy	0.0101	0.0101	0.396*	1												
(5)	Exchange Trading Rule Index	0.0486*	0.0847*	0.336*	0.205*	1											
(6)	Surveillance	-0.106*	0.109*	0.163*	0.148*	0.582*	1										
(7)	Public Enforcement(Jackson and Roe, 2009)	-0.115*	-0.0402	-0.214*	-0.0471*	0.0583*	-0.0486*	1									
(8)	Public Enforcement (DLLS, 2008)	-0.0785*	0.0611*	-0.0490*	-0.00332	-0.0411	-0.365*	0.110*	1								
(9)	Efficiency of the Judiciary (LLSV, 2006)	-0.0493*	0.0508*	0.484*	0.121*	0.159*	-0.158*	0.345*	-0.0131	1							
(10)	Rule of Law (LLSV, 1998)	-0.262*	0.0879*	0.532*	0.119*	0.155*	0.0987*	0.268*	-0.0193	0.729*	1						
(11)	Log (Market Capitalization	0.0995*	0.0262	-0.0793*	-0.0293	-0.111*	0.250*	-0.371*	-0.483*	-0.335*	-0.399*	1					
(12)	Log (Volume)	0.0317	0.00966	-0.230*	0.0800*	-0.0197	0.219*	0.398*	-0.374*	-0.0701*	-0.0806*	0.328*	1				
(13)	Log (Number of Trades)	0.0584*	0.0582*	-0.165*	0.0147	0.0435	0.419*	-0.242*	-0.370*	-0.515*	-0.431*	0.840*	0.580*	1			
(14)	Log (Average Market Trade Size)	-0.210*	-0.0527*	-0.428*	-0.263*	-0.527*	-0.355*	0.570*	-0.0398	0.215*	0.187*	-0.258*	0.390*	-0.216*	1		
(15)	Log (Market Volatility)	0.126*	-0.0663*	-0.228*	-0.173*	0.0877*	-0.0811*	0.0630*	-0.152*	-0.210*	-0.300*	0.203*	0.134*	0.234*	-0.0328	1	
(16)	Log (GDP per Capita)	-0.332*	0.114*	0.327*	0.168*	0.214*	0.295*	0.374*	-0.106*	0.359*	0.692*	-0.114*	0.323*	0.0709*	0.262*	-0.173*	1

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 each cases. Variables are as defined in Table 1. Standard Standard errors are clustered by exchange and month for models 3 and 4, clustered by month for model 1 and 2, and clustered by year for Models 5-9. 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. Model 1 and 2 present difference-in-difference (DID) tests: Treat is defined as HFT countries. After is defined as date after the May 2006 (Average effective date of HFT in table A2, Appendix). Model 1 is also controlled for fixed effect on the exchange level. Model 3 presents a regression result with market control variables as well as law index from LLSV (1998, 2006). Model 4 presents a regression result with the Total Trading Rule Index from Cumming, et al. (2010). Model 5 presents the results with Public Enforcement Index from Jackson and Roe, (2009) and from Djankov, et al. (2008), Total Trading Rule Index from Cumming, et al. (2010), surveillance index from Cumming and Johan (2008) and with Efficiency of the judiciary index and rule of law index from LLSV (1998, 2006). Model 6 and Model 8 present the results with all index and control variables including and excluding data from the United States, respectively. Model 7 and Model 9 replicates the Model6 and Model 8, respectively with alternative HFT dummy. The *, ** and *** are statistically significant at the 10%, 5% and 1% level, respectively. All dependent variables are winsorized at 99% and t-statistics are in square brackets.

Panel A: Suspected Dislocating the EOD Price Case (Winsorized at 99%)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	DID with Fixed Effect	DID with Market Control Variables	Market Control Variables	Trading Rules and Surveillance Index	Public Enforcements	All Jointly	All Jointly (Alternative)	Without US	Without US (Alternative)
Constant	7.167***	13.78	-221.7	-252.0**	-51.19	-152.1	-232.0	14.14	-71.16
	[8.24]	[0.37]	[-0.57]	[-2.24]	[-0.30]	[-0.70]	[-1.07]	[0.09]	[-0.44]
Treat	-5.392*	59.02***							
	[-2.14]	[4.69]							
After	8.450***	5.725***							
	[10.74]	[3.12]							
Treat x After	**-8.403***	**-7.638***							
	[-2.16]	**[-2.00]**							
HFT Dummy (Trade Size)			**-33.34*****	**-28.25*****	**-34.62****	**-34.16****		**-40.07*****	
			[-3.71]	**[-3.37]**	**[-2.98]**	**[-2.92]**		**[-3.78]**	
HFT Dummy (Cancellation Ratio)							**-33.96****		**-36.31****
							[-2.78]		**[-3.15]**
Co-Location Dummy			**-4.681**	**-4.504**	**-4.783**	**-4.590**	**-6.099**	**-1.712**	**-4.157**
			[-1.41]	**[-1.33]**	**[-0.55]**	**[-0.54]**	**[-0.73]**	**[-0.22]**	**[-0.55]**
Law/Legal Index									
Total Trading Rule Index				1.007**		0.595	0.368	0.338	0.238
				[2.13]		[1.09]	[0.59]	[0.73]	[0.43]
Surveillance				0.0705		2.750	3.425*	-0.347	-0.137
				[0.11]		[1.70]	[2.18]	[-0.74]	[-0.27]
Public enforcement					-0.961***	-0.397	-0.560	-1.020***	-1.265***
(Jackson and Roe, 2009)					[-3.49]	[-0.78]	[-1.08]	[-4.01]	[-5.61]
Public enforcement					19.49	-27.59	-30.07	18.80	29.31
(DLLS, 2008)					[0.42]	[-1.16]	[-1.27]	[0.38]	[0.60]
Efficiency of the Judiciary			54.39**		7.722	25.19***	32.51***	7.519	10.62
			[1.99]		[0.91]	[5.38]	[5.99]	[0.73]	[0.98]
Rule of Law			-51.54***		-46.77*	-56.82*	-61.56*	-36.95	-40.80*
			[-4.14]		[-2.01]	[-1.94]	[-2.27]	[-1.55]	[-1.87]
Microstructure Control Variables									
Log Market Capitalization		1.099	1.110	1.806	0.864	0.975	2.448	0.579	2.349
		[1.42]	[0.72]	[1.48]	[0.34]	[0.38]	[0.90]	[0.19]	[0.78]
Log Trading Volume		13.48***	9.137	-0.840	9.643	8.631	8.975	8.626	7.692
		[24.74]	[0.80]	[-0.10]	[0.94]	[0.83]	[0.92]	[0.75]	[0.70]
Log Number of Trades		-2.681**	-9.612	-2.012	-4.594	-3.601	-5.207	-4.599	-5.213
		[-2.94]	[-0.80]	[-0.26]	[-0.37]	[-0.29]	[-0.42]	[-0.34]	[-0.40]
Log Average Market Trade Size		-5.403***	-4.465	2.843	-6.651	-5.790	-0.608	-7.449	-0.233
		[-4.11]	[-0.47]	[0.33]	[-0.93]	[-0.79]	[-0.10]	[-0.95]	[-0.03]
Log Market Volatility		10.83***	5.501***	6.145***	6.411***	6.406***	5.809***	6.838***	6.105***
		[4.64]	[2.69]	[3.76]	[4.45]	[4.45]	[3.60]	[4.16]	[3.38]
Country Control Variables									
Log GDP per capita		-21.31***	39.82**	35.70***	39.04	37.72	37.42	29.07	29.83
		[-3.44]	[2.17]	[4.59]	[1.23]	[1.18]	[1.26]	[0.82]	[0.93]
Observations	2196	2174	1972	2174	1972	1972	1972	1768	1768
R-squared	0.320	0.203	0.343	0.349	0.326	0.326	0.326	0.319	0.317

Panel B: Total Trading Value Surrounding Per Suspected Cases (Winsorized at 99%)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	DID with Fixed Effect	DID with Market Control Variables	Market Control Variables	Trading Rules and Surveillance Index	Public Enforcements	All Jointly	All Jointly (Alternative)	Without US	Without US (Alternative)
Constant	-267496.1***	-1866321.0***	-15522393.3***	-10614410.8***	-11131917.2***	-11265671.5***	-12186841.4***	-14155347.7***	-15176162.3***
	[-8.65]	[-3.19]	[-5.07]	[-5.34]	[-5.87]	[-3.75]	[-4.37]	[-4.75]	[-5.38]
Treat	219443.1**	449742.9***							
	[2.33]	[4.15]							
After	456468.9***	373654.6***							
	[10.09]	[6.93]							
Treat x After	**-281720.3***	**-308068.6***							
	[-1.90]	**[-2.09]**							
HFT Dummy (Trade Size)			**-422078.6*****	**-443645.7*****	**-370406.4****	**-396880.6*****		**-364674.0****	
			[-2.87]	**[-3.20]**	**[-2.56]**	**[-3.48]**		**[-2.70]**	
HFT Dummy (Cancellation Ratio)							**-392476.7****		**-409268.9***
							[-2.32]		**[-1.90]**
Co-Location Dummy			**161279.2**	**82889.6**	**170329.6**	**159097.4**	**141555.1**	**108006.4**	**88129.3**
			[0.84]	**[0.45]**	**[0.88]**	**[0.60]**	**[0.54]**	**[0.40]**	**[0.33]**
Law/Legal Index									
Total Trading Rule Index				-38065.2		-34528.3	-37124.3	-22780.1	-25401.9
				[-0.77]		[-0.76]	[-0.84]	[-0.51]	[-0.58]
Surveillance				-59680.8**		28962.3	36778.4	47852.0***	49840.7***
				[-2.05]		[1.27]	[1.60]	[6.82]	[6.75]
Public enforcement					-8722.0	-4188.7	-6047.4	2112.2	-1576.3
(Jackson and Roe, 2009)					[-0.63]	[-0.26]	[-0.37]	[0.13]	[-0.10]
Public enforcement					2718959.5***	2191516.1*	2163375.9*	2264895.6**	2351807.5**
(DLLS, 2008)					[3.25]	[1.95]	[1.94]	[2.56]	[2.75]
Efficiency of the Judiciary			896705.1***		-245064.8	-4154.4	80387.1	5622.0	47900.7
			[3.78]		[-1.51]	[-0.01]	[0.27]	[0.03]	[0.22]
Rule of Law			-53184.3		76954.9	-150854.4	-204475.6	-415830.2	-498205.4
			[-0.36]		[0.27]	[-0.32]	[-0.44]	[-0.96]	[-1.16]
Microstructure Control Variables									
Log Market Capitalization		-84852.7*	34753.4	60092.3	45583.5	39153.0	56304.3	24294.6	39230.4
		[-2.16]	[0.61]	[1.25]	[0.85]	[0.59]	[0.91]	[0.34]	[0.59]
Log Trading Volume		-16854.9	314733.9*	415304.5***	250079.1	308813.8*	312467.1*	222740.0	227998.8
		[-0.73]	[1.81]	[2.99]	[1.54]	[1.87]	[1.89]	[1.18]	[1.22]
Log Number of Trades		131158.7***	-11029.0	-91051.8	154791.1	97174.7	78767.9	231920.2	215889.8
		[3.46]	[-0.08]	[-0.72]	[1.17]	[0.67]	[0.55]	[1.38]	[1.31]
Log Average Market Trade Size		-33466.4	-233356.8**	-333283.6***	-249051.9***	-299019.5*	-238540.0	-251755.3	-197075.6
		[-0.95]	[-2.47]	[-4.21]	[-2.78]	[-2.04]	[-1.37]	[-1.83]	[-1.16]
Log Market Volatility		-172241.1	159050.8	109653.7	162541.1	162831.4	155920.2	163720.2	156128.7
		[-1.59]	[1.00]	[0.75]	[1.10]	[0.94]	[0.90]	[0.91]	[0.86]
Country Control Variables									
Log GDP per capita		119313.9***	439456.3	738888.5**	338863.3	414919.7	409512.9	710042.3	786361.5
		[8.37]	[1.29]	[2.06]	[0.96]	[0.89]	[0.86]	[1.46]	[1.59]
Observations	2196	2174	1972	2174	1972	1972	1972	1768	1768
R-squared	0.096	0.033	0.101	0.109	0.099	0.100	0.100	0.100	0.100

Table 7:

Robustness Check.

This table presents Ordinary Least Square panel regressions of determinates of the number of suspected EOD price cases and the trading value surrounding each cases. Variables are as defined in Table 1 and regression model definitions are described in Table 6. The *, ** and *** are statistically significant at the 10%, 5% and 1% level, respectively. Dependent variables are winsorized at 95% and t-statistics are in square brackets.

Panel A: Suspected Dislocating the EOD Price Case (Winsorized at 95%)									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	DID with Fixed Effect	DID with Market Control Variables	Market Control Variables	Trading Rules and Surveillance Index	Public Enforcements	All Jointly	All Jointly (Alternative)	Without US	Without US (Alternative)
Constant	7.260***	16.63	-206.2	-250.6**	-35.02	-137.4	-205.3	27.14	-44.88
	[9.54]	[0.49]	[-0.62]	[-2.52]	[-0.23]	[-0.74]	[-1.14]	[0.19]	[-0.33]
Treat	-5.270**	56.50***							
	[-2.53]	[5.16]							
After	7.944***	5.409***							
	[11.46]	[3.29]							
Treat x After	**-8.378****	**-7.805****							
	[-2.58]	**[-2.45]**							
HFT Dummy (Trade Size)			**-27.66*****	**-23.23*****	**-28.47****	**-27.96****		**-33.48*****	
			[-3.69]	**[-3.32]**	**[-2.84]**	**[-2.78]**		**[-3.64]**	
HFT Dummy (Cancellation Ratio)							**-28.46****		**-30.57****
							[-2.77]		**[-3.15]**
Co-Location Dummy			**-3.650**	**-3.482**	**-3.611**	**-3.391**	**-4.625**	**-0.825**	**-2.860**
			[-1.25]	**[-1.15]**	**[-0.48]**	**[-0.45]**	**[-0.63]**	**[-0.12]**	**[-0.41]**
Law/Legal Index									
Total Trading Rule Index				1.034**		0.677	0.477	0.375	0.286
				[2.46]		[1.56]	[0.95]	[0.96]	[0.63]
Surveillance				0.124		2.740*	3.302**	-0.290	-0.114
				[0.22]		[2.15]	[2.72]	[-0.70]	[-0.26]
Public enforcement					-0.749**	-0.185	-0.329	-0.807***	-1.016***
(Jackson and Roe, 2009)					[-2.89]	[-0.42]	[-0.73]	[-3.52]	[-4.80]
Public enforcement					21.19	-25.67	-27.92	18.36	27.12
(DLLS, 2008)					[0.56]	[-1.25]	[-1.36]	[0.47]	[0.70]
Efficiency of the Judiciary			49.04**		5.505	22.80***	28.96***	5.918	8.553
			[2.11]		[0.77]	[5.85]	[6.60]	[0.69]	[0.95]
Rule of Law			-46.91***		-42.73*	-52.50*	-56.83**	-32.54	-35.91*
			[-4.50]		[-2.15]	[-2.16]	[-2.58]	[-1.63]	[-2.02]
Microstructure Control Variables									
Log Market Capitalization		0.701	1.115	1.700	0.888	1.014	2.210	0.694	2.169
		[1.13]	[0.82]	[1.54]	[0.41]	[0.47]	[0.99]	[0.28]	[0.85]
Log Trading Volume		12.93***	7.204	-2.337	7.453	6.302	6.697	7.137	6.399
		[22.43]	[0.72]	[-0.31]	[0.86]	[0.71]	[0.80]	[0.76]	[0.72]
Log Number of Trades		-2.388**	-7.223	0.194	-2.779	-1.650	-3.048	-3.296	-3.841
		[-2.72]	[-0.69]	[0.03]	[-0.26]	[-0.15]	[-0.29]	[-0.30]	[-0.35]
Log Average Market Trade Size		-5.147***	-3.861	3.104	-5.704	-4.725	-0.578	-6.752	-0.757
		[-3.92]	[-0.48]	[0.42]	[-0.89]	[-0.72]	[-0.10]	[-1.02]	[-0.13]
Log Market Volatility		10.20***	4.849***	5.568***	5.794***	5.788***	5.288***	6.165***	5.550***
		[5.03]	[2.89]	[3.94]	[4.66]	[5.26]	[4.17]	[4.81]	[3.86]
Country Control Variables									
Log GDP per capita		-20.30***	34.87**	32.35***	34.03	32.54	32.91	23.16	24.02
		[-3.77]	[2.22]	[4.79]	[1.23]	[1.17]	[1.30]	[0.77]	[0.89]
Observations	2196	2174	1972	2174	1972	1972	1972	1768	1768
R-squared	0.368	0.233	0.389	0.396	0.372	0.372	0.373	0.361	0.360

Panel B: Total Trading Value Surrounding Per Suspected Cases (Winsorized at 95%)									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	DID with Fixed Effect	DID with Market Control Variables	Market Control Variables	Trading Rules and Surveillance Index	Public Enforcements	All Jointly	All Jointly (Alternative)	Without US	Without US (Alternative)
Constant	-234682.3***	-2057566.1***	-13350474.9***	-9681790.6***	-8017022.5***	-8088260.5***	-8622212.7***	-10690427.5***	-11353120.0***
	[-8.15]	[-7.95]	[-5.57]	[-6.76]	[-5.64]	[-5.13]	[-6.30]	[-7.23]	[-8.58]
Treat	180201.7***	365651.6***							
	[4.07]	[4.07]							
After	396740.1***	298843.6***							
	[8.61]	[5.84]							
Treat x After	**-254002.8*****	**-254449.9*****							
	[-3.54]	**[-3.58]**							
HFT Dummy (Trade Size)			**-371319.2*****	**-397191.8*****	**-344925.3*****	**-360499.5*****		**-323712.6*****	
			[-3.33]	**[-3.58]**	**[-3.80]**	**[-3.82]**		**[-3.39]**	
HFT Dummy (Cancellation Ratio)							**-274742.9****		**-284776.8***
							[-2.50]		**[-2.15]**
Co-Location Dummy			**171832.9****	**102457.3**	**174711.8**	**168104.2**	**151962.5**	**137293.9**	**117289.6**
			[2.05]	**[1.27]**	**[1.14]**	**[1.12]**	**[1.03]**	**[1.08]**	**[0.95]**
Law/Legal Index									
Total Trading Rule Index				-22150.6		-20312.3	-21030.7	-8869.2	-9489.6
				[-1.03]		[-0.93]	[-1.01]	[-0.39]	[-0.44]
Surveillance				-81854.2***		16803.4	22753.5	34386.4***	36076.3***
				[-4.02]		[1.34]	[1.82]	[5.53]	[5.65]
Public enforcement (Jackson and Roe, 2009)					3972.1	6592.6	6195.7	12330.1	10507.0
					[0.44]	[0.75]	[0.76]	[1.09]	[0.99]
Public enforcement (DLLS, 2008)					1368410.9***	1062182.1*	1063450.0**	1121664.7**	1207577.8**
					[3.60]	[2.28]	[2.34]	[2.40]	[2.68]
Efficiency of the Judiciary			770408.9***		-210215.7	-70053.9	-13995.4	-61693.6	-38158.9
			[3.98]		[-1.58]	[-0.33]	[-0.07]	[-0.34]	[-0.21]
Rule of Law			-108388.6		-179231.7	-312238.1	-304723.7	-567518.3*	-593513.3*
			[-1.07]		[-0.70]	[-1.02]	[-1.03]	[-2.20]	[-2.29]
Microstructure Control Variables									
Log Market Capitalization		-42208.8*	37332.7	56024.3**	44261.6	40478.7	57342.7	29936.8	44364.5
		[-2.10]	[1.30]	[2.25]	[0.93]	[0.83]	[1.24]	[0.56]	[0.87]
Log Trading Volume		6833.7	202783.0**	286487.8***	161261.3	195813.7	185270.5	103569.3	94541.6
		[0.34]	[2.05]	[2.84]	[1.82]	[1.77]	[1.67]	[0.72]	[0.67]
Log Number of Trades		91271.6***	-492.5	-55519.9	118204.2	84309.7	77857.5	208563.1	204729.5
		[3.84]	[-0.01]	[-0.58]	[1.27]	[0.72]	[0.68]	[1.41]	[1.42]
Log Average Market Trade Size		-21598.2	-235854.7***	-304461.7***	-246471.1*	-275866.0**	-209500.0	-216484.0*	-156994.5
		[-0.77]	[-3.04]	[-5.13]	[-2.00]	[-2.41]	[-1.52]	[-2.16]	[-1.23]
Log Market Volatility		-55158.1	86077.6*	43871.8	84136.5	84307.3	79355.2	80574.3	74746.5
		[-1.68]	[1.69]	[0.90]	[1.71]	[1.64]	[1.53]	[1.50]	[1.39]
Country Control Variables									
Log GDP per capita		93992.2***	576177.6***	861854.9***	510729.7	555472.1	474715.5	835791.9*	834484.9*
		[8.09]	[2.65]	[4.15]	[1.35]	[1.45]	[1.21]	[2.30]	[2.23]
Observations	2196	2174	1972	2174	1972	1972	1972	1768	1768
R-squared	0.172	0.049	0.185	0.197	0.181	0.182	0.180	0.184	0.183

Table 8

Robustness Checks with Alternative Dependent Variables

This table presents Ordinary Least Square panel regressions of determinates of the number of suspected EOD price cases and the trading value surrounding each cases. Both dependent variables are either measured at the end of each month or measured with matching option expire dates. Variables are as defined in Table 1). Model 1 presents the results with Public Enforcement Index from Jackson and Roe, (2009) and from Djankov, et al. (2008), Total Trading Rule Index from Cumming, et al. (2010), surveillance index from Cumming and Johan (2008) and with Efficiency of the judiciary index and rule of law index from LLSV (1998, 2006). Model 2 and Model 4 present the results with all index and control variables including and excluding data from the United States, respectively. Model 3 repeats Model 1 without data from the United States. Standard errors are clustered by year. The *, ** and *** are statistically significant at the 10%, 5% and 1% level, respectively. T-statistics are in parentheses.

Panel A1: Suspected Dislocating the EOD Price Case (at the end of Month)

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	-38.95**	-51.75**	-34.39**	-33.00**
	[-2.32]	[-2.88]	[-1.97]	[-2.42]
HFT Dummy	**-3.815*** **	**-3.778*** **	**-4.244*** **	**-4.230*** **
	[-3.54]	**[-4.21]**	**[-3.82]**	**[-4.97]**
Law/Legal Index				
Total Trading Rule Index		0.0466		0.0141
		[0.82]		[0.30]
Surveillance		0.370**		-0.0563
		[3.11]		[-0.97]
Public enforcement (Jackson and Roe, 2009)	-0.0640	0.0106	-0.0649	-0.0754
	[-1.24]	[0.16]	[-1.26]	[-1.59]
Public enforcement (DLLS, 2008)	3.838	-2.526	3.326	4.322
	[0.91]	[-1.03]	[0.76]	[1.14]
Efficiency of the Judiciary	0.164	2.562***	0.376	-0.0229
	[0.18]	[3.88]	[0.40]	[-0.02]
Rule of Law	-5.578***	-7.031**	-5.023***	-4.750*
	[-3.25]	[-2.66]	[-2.79]	[-2.20]
Microstructure Control Variables				
Log Market Capitalization	0.500**	0.508	0.435*	0.437
	[2.03]	[1.19]	[1.73]	[0.94]
Log Trading Volume	0.859	0.781	0.840	0.814
	[0.70]	[0.78]	[0.66]	[0.86]
Log Number of Trades	-0.188	-0.112	-0.194	-0.167
	[-0.14]	[-0.09]	[-0.14]	[-0.13]
Log Average Market Trade Size	-0.549	-0.483	-0.688	-0.666
	[-0.64]	[-0.79]	[-0.79]	[-1.05]
Log Market Volatility	0.473**	0.472**	0.519**	0.518**
	[2.36]	[2.47]	[2.54]	[2.48]
Country Control Variables				
Log GDP per capita	6.516***	6.413*	5.843**	5.828
	[2.60]	[2.07]	[2.21]	[1.82]
Observations	1972	1972	1768	1768
R-squared	0.140	0.140	0.117	0.117

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	-31.89**	-46.67**	-28.53*	-29.90
	[-2.01]	[-2.35]	[-1.69]	[-1.85]
Co-Location Dummy	**-0.227**	**-0.192**	**0.120**	**0.113**
	[-0.52]	**[-0.22]**	**[0.30]**	**[0.13]**
Law/Legal Index				
Total Trading Rule Index		0.0967		0.0862
		[1.58]		[1.50]
Surveillance		0.392**		-0.0365
		[2.81]		[-0.68]
Public enforcement (Jackson and Roe, 2009)	-0.0283	0.0517	-0.0223	-0.0270
	[-0.57]	[0.67]	[-0.45]	[-0.44]
Public enforcement (DLLS, 2008)	5.157	-1.569	5.163	5.892
	[1.17]	[-0.64]	[1.12]	[1.43]
Efficiency of the Judiciary	-0.0570	2.420***	0.0148	-0.368
	[-0.06]	[3.45]	[0.02]	[-0.32]
Rule of Law	-3.536**	-4.972	-3.051*	-2.748
	[-2.31]	[-1.69]	[-1.81]	[-1.09]
Microstructure Control Variables				
Log Market Capitalization	0.716***	0.730	0.681***	0.691
	[2.95]	[1.84]	[2.76]	[1.71]
Log Trading Volume	0.338	0.184	0.143	-0.00228
	[0.27]	[0.17]	[0.11]	[-0.00]
Log Number of Trades	0.0234	0.181	0.152	0.308
	[0.02]	[0.14]	[0.11]	[0.24]
Log Average Market Trade Size	0.494	0.614	0.577	0.684
	[0.52]	[1.28]	[0.60]	[1.43]
Log Market Volatility	0.467**	0.466**	0.517**	0.511**
	[2.27]	[2.33]	[2.52]	[2.35]
Country Control Variables				
Log GDP per capita	3.043	2.897	2.375	2.356
	[1.40]	[0.89]	[0.99]	[0.68]
Observations	1972	1972	1768	1768
R-squared	0.132	0.132	0.106	0.106

Panel B1: Total Trading Value Surrounding Per Suspected Case (at the end of Month)

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	-649735937.5**	-1.00468e+09**	-613067324.0*	-647152079.8
	[-2.22]	[-2.59]	[-1.85]	[-1.71]
HFT Dummy	**-37517189.7** [-2.46]**	**-37025586.3* [-2.25]**	**-41169193.1** [-2.54]**	**-40970064.5* [-2.11]**
Law/Legal Index				
Total Trading Rule Index		624452.2		197302.3
		[0.25]		[0.06]
Surveillance		10734972.9**		900137.2
		[2.47]		[0.46]
Public enforcement	4734310.1**	6874216.9*	4856329.3**	5041775.7
	[2.02]	[2.09]	[2.00]	[1.79]
Public enforcement	369610402.7**	184446260.6*	373159491.8**	357904051.1**
	[2.50]	[2.26]	[2.42]	[2.77]
Efficiency of the Judiciary	-147373465.3***	-76792264.9	-147111990.6***	-141457110.5**
	[-2.74]	[-1.65]	[-2.67]	[-2.43]
Rule of Law	47731863.2	3410607.8	55407454.4	51962405.9
	[0.79]	[0.07]	[0.81]	[0.78]
Microstructure Control Variables				
Log Market Capitalization	13683738.2	13797563.4	13100962.3	13134280.4
	[1.62]	[1.14]	[1.50]	[1.09]
Log Trading Volume	-97553900.9**	-98597640.4**	-100088489.0*	-100455114.6**
	[-1.97]	[-2.52]	[-1.94]	[-2.60]
Log Number of Trades	107927948.2*	108952846.6**	110492953.7*	110866361.9**
	[1.95]	[2.32]	[1.90]	[2.33]
Log Average Market Trade Size	40473182.4	41360794.9	39674904.3	39980501.3
	[1.54]	[1.56]	[1.47]	[1.41]
Log Market Volatility	6063559.9	6048336.3	6608081.1	6596162.9
	[1.31]	[1.13]	[1.36]	[1.23]
Country Control Variables				-
Log GDP per capita	-3273155.8	1972	-12295430.9	1768
	[-0.04]	0.062	[-0.13]	0.061
Observations	1972	1972	1768	1768
R-squared	0.062	0.062	0.061	0.061

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	-568734083.7*	-936833671.4**	-569487706.5*	-629199797.0
	[-1.93]	[-2.48]	[-1.72]	[-1.79]
Co-Location Dummy	**-23604183.6 [-1.08]**	**-23257616.4 [-0.87]**	**-25810104.5 [-1.17]**	**-25880687.9 [-1.12]**
Law/Legal Index				
Total Trading Rule Index		949929.9		932331.2
		[0.38]		[0.31]
Surveillance		10869318.7**		1020043.4
		[2.43]		[0.54]
Public enforcement	4927703.5**	7099827.1*	5089612.5**	5317667.8
	[2.07]	[2.09]	[2.07]	[1.80]
Public enforcement	379162166.7**	191701533.4**	387942196.3**	371351653.6**
	[2.57]	[2.45]	[2.53]	[2.88]
Efficiency of the Judiciary	-148422531.7***	-77368654.6	-150686222.8***	-145403710.3**
	[-2.74]	[-1.65]	[-2.74]	[-2.46]
Rule of Law	67083411.9	22766903.4	68174534.8	65359804.0
	[1.21]	[0.56]	[1.07]	[1.08]
Microstructure Control Variables				
Log Market Capitalization	15474441.0*	15609940.5	14945043.3*	15046881.4
	[1.83]	[1.26]	[1.69]	[1.17]
Log Trading Volume	-100535832.5**	-102051755.7**	-104047378.5**	-105620687.7**
	[-2.01]	[-2.57]	[-2.01]	[-2.67]
Log Number of Trades	108128686.1*	109672869.2**	111976964.3*	113661686.1**
	[1.94]	[2.31]	[1.93]	[2.36]
Log Average Market Trade Size	48665515.1**	49840487.4**	48884567.7**	50043054.5*
	[2.02]	[2.33]	[1.99]	[2.22]
Log Market Volatility	4949755.0	4942702.6	5112396.7	5054046.1
	[0.97]	[0.74]	[0.95]	[0.75]
Country Control Variables				
Log GDP per capita	-35504442.9	-36933326.8	-35789254.9	-36000409.8
	[-0.50]	[-0.53]	[-0.43]	[-0.41]
Observations	1972	1972	1768	1768
R-squared	0.062	0.062	0.060	0.060

Panel A2: Suspected Dislocating the EOD Price Case (Matched with option expiry date)

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	29.76** [2.43]	28.08** [2.59]	34.00*** [2.61]	34.95*** [5.38]
HFT Dummy	**-1.951* [-1.81]**	**-2.134** [-2.84]**	**-2.671** [-2.25]**	**-2.934*** [-4.78]**
Law/Legal Index				
Total Trading Rule Index		-0.309*** [-3.40]		-0.347*** [-4.25]
Surveillance		0.0865 [0.81]		0.0433 [1.71]
Public enforcement	-0.179* [-1.86]	-0.160** [-2.37]	-0.177* [-1.81]	-0.167** [-2.76]
Public enforcement	-10.98*** [-2.77]	-11.27*** [-6.62]	-11.92*** [-2.78]	-11.44*** [-5.18]
Efficiency of the Judiciary	2.515* [1.80]	3.309** [3.24]	2.828* [1.91]	3.438** [3.34]
Rule of Law	-1.915 [-1.20]	-2.988 [-1.58]	-0.894 [-0.54]	-1.608 [-1.29]
Microstructure Control Variables				
Log Market Capitalization	0.453** [2.21]	0.350 [1.46]	0.375* [1.85]	0.259 [0.87]
Log Trading Volume	3.085* [1.96]	3.367** [3.16]	3.440** [2.06]	3.791*** [3.72]
Log Number of Trades	-4.129** [-2.47]	-4.216*** [-3.88]	-4.284** [-2.44]	-4.419*** [-3.97]
Log Average Market Trade Size	-1.015 [-1.04]	-1.327 [-1.65]	-1.555 [-1.53]	-1.933** [-2.64]
Log Market Volatility	0.233 [1.15]	0.263 [0.89]	0.332 [1.62]	0.377 [1.19]
Country Control Variables				
Log GDP per capita	1.143 [0.53]	1.751 [0.97]	-0.0226 [-0.01]	0.315 [0.19]
Observations	1972	1972	1768	1768
R-squared	0.066	0.069	0.053	0.058

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	-10.52 [-0.61]	-16.53 [-0.86]	-8.184 [-0.49]	-10.14 [-0.61]
Co-Location Dummy	**0.574 [0.85]**	**0.608 [0.91]**	**0.608 [0.98]**	**0.602 [0.99]**
Law/Legal Index				
Total Trading Rule Index		0.0927* [1.95]		0.0832 [1.70]
Surveillance		0.119 [1.13]		-0.0153 [-0.74]
Public enforcement	-0.0707 [-1.34]	-0.0448 [-0.81]	-0.0568 [-1.05]	-0.0575 [-1.07]
Public enforcement	0.0166 [0.01]	-1.988 [-0.85]	0.0552 [0.02]	0.413 [0.13]
Efficiency of the Judiciary	0.886 [1.21]	1.550* [2.16]	0.991 [1.26]	0.755 [0.92]
Rule of Law	0.531 [0.27]	0.259 [0.11]	1.611 [0.90]	1.817 [1.06]
Microstructure Control Variables				
Log Market Capitalization	0.208 [1.08]	0.222 [1.15]	0.154 [0.76]	0.163 [0.81]
Log Trading Volume	1.112 [1.17]	0.964 [1.00]	1.218 [1.25]	1.078 [1.09]
Log Number of Trades	-0.945 [-0.98]	-0.795 [-0.82]	-0.847 [-0.83]	-0.697 [-0.68]
Log Average Market Trade Size	0.386 [0.55]	0.501 [0.69]	0.129 [0.19]	0.232 [0.32]
Log Market Volatility	0.421* [2.06]	0.420* [1.99]	0.508** [2.57]	0.503** [2.63]
Country Control Variables				
Log GDP per capita	-0.801 [-0.30]	-0.941 [-0.36]	-2.176 [-0.89]	-2.194 [-0.91]
Observations	1972	1972	1768	1768
R-squared	0.093	0.094	0.081	0.081

Panel B2: Total Trading Value Surrounding Per Suspected Case (Matched with option expiry date)

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	-103172001.0***	-72595518.3***	-111253413.9***	-70441538.7***
	[-3.83]	[-3.45]	[-3.82]	[-3.44]
HFT Dummy	**-4188307.1****	**-3676615.0****	**-4074299.7****	**-3769506.1****
	[-2.53]	**[-2.25]**	**[-2.47]**	**[-2.20]**
Law/Legal Index				
Total Trading Rule Index		134245.1*		137355.7*
		[1.95]		[1.81]
Surveillance		-163682.4*		-255523.1***
		[-1.72]		[-3.39]
Public enforcement	41891.2	-75562.2	47854.2	-92680.5
	[0.90]	[-1.17]	[0.99]	[-1.47]
Public enforcement	2743201.5	3572288.5	3677889.6	5383160.3
	[0.59]	[1.09]	[0.75]	[1.37]
Efficiency of the Judiciary	-1198518.9	-154636.9	-1592649.9	-806634.5
	[-0.86]	[-0.17]	[-1.09]	[-0.73]
Rule of Law	-4561445.3*	2024563.9	-5750568.0**	2415713.9*
	[-1.94]	[1.59]	[-2.14]	[1.79]
Microstructure Control Variables				
Log Market Capitalization	1566533.3**	1933542.8**	1536220.6**	1940211.0**
	[2.18]	[2.39]	[2.14]	[2.37]
Log Trading Volume	236482.9	238392.5	138900.2	199753.4
	[0.37]	[0.37]	[0.22]	[0.29]
Log Number of Trades	948176.8	-179703.0	1209211.1	-131447.8
	[1.08]	[-0.21]	[1.31]	[-0.15]
Log Average Market Trade Size	-1540901.2***	73899.2	-1501727.6***	80006.8
	[-2.87]	[0.20]	[-2.87]	[0.19]
Log Market Volatility	669041.6	644072.6	642496.1	644628.2
	[1.30]	[1.46]	[1.24]	[1.46]
Country Control Variables				
Log GDP per capita	9427670.2***	702789.0	11099040.5***	741621.4
	[2.59]	[0.46]	[2.68]	[0.46]
Observations	1972	1972	1768	1768
R-squared	0.165	0.159	0.166	0.159

	Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US
Constant	-95655429.8***	-98045192.1*	-105967046.3***	-104129619.5**
	[-3.69]	[-2.30]	[-3.71]	[-2.41]
Co-Location Dummy	**184807.0**	**277601.4**	**-571114.6**	**-596132.5**
	[0.35]	**[0.49]**	**[-0.96]**	**[-0.79]**
Law/Legal Index				
Total Trading Rule Index		254346.5*		330460.7*
		[2.20]		[2.21]
Surveillance		-118395.8		-362857.3*
		[-0.79]		[-2.25]
Public enforcement	84370.1*	67886.9	84176.4*	21960.8
	[1.93]	[1.03]	[1.88]	[0.43]
Public enforcement	4260655.1	6436522.7	5364271.0	12009541.0*
	[0.92]	[1.56]	[1.12]	[1.94]
Efficiency of the Judiciary	-1464032.6	-2595373.8**	-1941223.8	-4889863.8*
	[-1.03]	[-2.54]	[-1.32]	[-2.24]
Rule of Law	-2304614.6	-1139467.3	-4019356.2*	-1900241.1
	[-1.44]	[-0.35]	[-1.90]	[-0.53]
Microstructure Control Variables				
Log Market Capitalization	1811021.6**	1847302.0	1759119.4**	1795215.5
	[2.42]	[1.40]	[2.38]	[1.41]
Log Trading Volume	-378450.1	-784342.9	-459036.4	-1016688.9
	[-0.63]	[-1.08]	[-0.73]	[-1.32]
Log Number of Trades	1218873.1	1632332.7*	1493774.6*	2090916.8**
	[1.45]	[2.22]	[1.68]	[2.60]
Log Average Market Trade Size	-353686.5	-39084.3	-364850.9	45769.7
	[-1.23]	[-0.11]	[-1.18]	[0.14]
Log Market Volatility	683389.0	681500.7	603221.5	582539.4
	[1.30]	[1.70]	[1.14]	[1.52]
Country Control Variables				
Log GDP per capita	5575928.1**	5193340.3	8027994.0**	7953151.0
	[2.37]	[1.14]	[2.57]	[1.33]
Observations	1972	1972	1768	1768
R-squared	0.157	0.159	0.159	0.162

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