ESSAYS ON INTERNATIONAL MARKET EFFICIENCY AND MANIPULATION

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ABSTRACT

Three empirical studies in this dissertation all examine issues that important and related to the international market. Three essays share similar theme and try to address the common questions whether the institutional difference, such as exchange regulation, surveillance, national culture, economic and market condition, could explain the difference in market manipulation as well as market efficiency.

The first essay examines the impact of stock exchange regulation and surveillance around the world and seeks to understand whether or not exchange regulation and their enforcement facilitate more efficient markets with greater integrity. Using new indices for market manipulation, insider trading, and broker-agency conflict based on the trading rules of each stock exchange, along with surveillance to detect non-compliance with such rules, we show that more detailed exchange trading rules and surveillance over time and across markets significantly reduce the number of cases, but increase the profits per case.

The second essay examines the important role of high frequency traders (HFT) in the equity market. I 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. 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.

The third essay examines the institutional factor, national culture around the world and links this culture difference with overall stock market volatility. I find that Nations with lower value of individualistic culture are more likely to have a higher number of synchronized stock price movements. Further, the correlations between stock price movements apparently increase stock market volatility. The positive relationship between synchronized stock price movements and stock market volatility is stronger for emerging markets during the financial crisis from June 2007 to December 2008. Rather than due to the different levels of economic development, the empirical results here indicate that a portion of the difference in market level volatility is attributed to the investor bias of different cultures.

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CHAPTER 1

Introduction

Three empirical studies in this dissertation all examine issues that important and related to the international market. Three essays share similar theme and try to address the common questions whether the institutional difference, such as exchange regulation, surveillance, national culture, economic and market condition, could explain the difference in market manipulation activities as well as market efficiency.

The first essay examines the impact of stock exchange regulation and surveillance around the world and seeks to understand whether or not exchange regulation and their enforcement facilitate more efficient markets with greater integrity. The analysis in this paper involves monthly data from 22 exchanges in 17 countries around the world. One of the highlights of this paper is the use of the recent change required by European directives (MIFID II) to explore time series variation in the structure of exchange rules. These changes are not enacted in response to particular exchanges and provide a natural experiment for us to study the effectiveness of exchange regulations. Consistent with the Becker's economic model of crime, that is, crimes are committed if the expected benefits exceed the costs, this paper uncovers a non-trivial role for exchange trading rules and surveillance in mitigating the number of insider trading cases but exacerbating the profit per case. The data indicate exchange rules and surveillance, ceteris paribus, exacerbate the profits of insider trading since would-be manipulators are only likely to engage in insider trading if the expected profits outweigh the expected costs, and the greater the number of rules and the broader the scope of surveillance the greater the expected costs. Overall,

these findings highlight the importance of trading regulation and surveillance in comparing international differences in stock exchanges.

The second essay examines the important role of high frequency traders (HFT) in the equity market. Especially after the flash crash on May 6, 2010, HFT have gathered plenty of attention from media, fund managers and financial market regulators. One common view is that HFT, with its potential speed advantage, could increase the prevalence of market manipulations. Our study examines the relationship between HFT and one very important and specific form of manipulation: end-of-day (EOD) price dislocation. We empirically identify the HFT effective time and manually collect the co-location offer time in 22 exchanges in 17 countries. We show that in the presence of HFT, EOD manipulations are on average less frequent in terms of the number of EOD manipulation cases and less pronounced in terms of average EOD trading value surrounding suspected cases. In addition, our study finds that trading rules, surveillance and enforcement had less of an effect in mitigating EOD manipulations. Overall, our finding supports the view that the price discovery and liquidity function of HFT on average significantly dominates the role that HFT may play in facilitating market manipulations, at least with respect to the EOD manipulations.

The third essay examines the institutional factor, national culture around the world and links this culture difference with overall stock market volatility. In this paper, I show that synchronized stock price movements are more prominent for countries that have a lower value of individualistic culture than for countries that have a higher value of individualistic culture. Furthermore, the correlations between stock price movements apparently increase stock market volatility. Specifically, the positive relationship between synchronized stock price movements and stock market volatility is stronger for emerging markets during the financial crisis. This

paper provides new insights on why emerging markets tend to have higher synchronized stock price movements and have a higher level of stock market volatility. Rather than due to the different levels of economic development, the empirical results in the paper indicate that a portion of the difference in market level volatility is attributed to the investor bias of different cultures.

This dissertation is organized in the following manners: the first essay, *Exchange Trading Rules, Surveillance and Insider Trading*, is presented in Chapter 2. The second essay, *High Frequency Trading and End-of-Day Price Dislocation*, is presented in Chapter 3. Chapter 4 presents the third essay, *Individualism, Synchronized Stock Price Movements, and Stock Market Volatility*. Finally, concluding remarks follow in the last chapter.

CHAPTER 2

Exchange Trading Rules, Surveillance and Insider Trading[1]

2.1 Introduction

This paper addresses a central question at the intersection of law and finance: are rules and their enforcement effective at mitigating insider trading? Our approach differs from prior work in three important ways. First, for the first time, we examine exchange trading rules that govern market conduct and relate these rules to insider trading. Second, we use recent changes in such rules that resulted from European directives to explore time series variation in the structure of exchange trading rules pertinent to insider trading and market manipulation. These changes were mandated by the European Commission and were not enacted in response to market manipulation problems in any one country per se, thereby giving rise to a natural experiment with which to study the effectiveness of exchange trading rules. Third, we employ unique surveillance data in relation to insider trading and market manipulation. The surveillance data are based on alerts, or computer algorithms, used by surveillance authorities to detect instances or patterns of market manipulation. Our surveillance data cover a wide range of market manipulation and are used by sophisticated surveillance authorities to detect cross-product and cross-market manipulation. Unlike other studies on the impact of securities regulation, published and otherwise, we study the extent and timing of enforcement by considering surveillance.

[1] The current version of this paper is coauthored with Douglas Cumming and Michael Aitken.

We do not consider actual successful prosecutions of insider trading, but rather, suspected cases of insider trading. We distinguish between insider trading ahead of announcements from clear cases of market anticipation and thereby use data on suspected cases of insider trading applied by expert surveillance authorities in their ex post data analyses and assessment of market quality. Our analysis involves monthly data from 22 exchanges in 17 countries, including Australia, Canada, China, Germany, Hong Kong, India, Japan, Malaysia, New Zealand, Norway, Singapore, South Korea, Sweden, Switzerland, Taiwan, the United Kingdom (UK), and the United States (US) for the period January 2003 through June 2011. Insider trading data are compiled by the joint organizations Capital Market Cooperative Research Centre (CMCRC),[2] SIRCA,[3] and SMARTS Group Inc.[4] These organizations have both research and commercial interests in surveillance activities on many stock exchanges around the world.

An important aspect of this study involves the broad nature of insider trading and its detection. Insider trading can be facilitated by forms of market manipulation that are not, strictly speaking, by themselves insider trading. For example, spoofing, which involves giving up priority, switches, and layering of bids/asks, can be used to further illegal insider trades by creating other market distortions that would make insider trading more difficult to detect. Similarly, volume manipulation through churning and wash trades can likewise make the detection of insider trading more difficult. Therefore, the ability of an exchange to mitigate insider trading activity and profits from insider trading depend significantly on the overall rule structure of the exchange and the ability of the exchange to detect manipulation through domestic and cross-market surveillance.

An equally important aspect of this study is the difference between exchange trading rules and surveillance. Exchange trading rules are unambiguous and purposely made obvious to market participants,

[2] http://www.cmcrc.com/
[3] http://www.sirca.org.au/display/SBX/Home
[4] http://www.smartsgroup.com/

and they are very visible on each exchange's webpage. Surveillance activities, by contrast, are not made obvious, but can be estimated by market participants. If market participants knew exactly which computer algorithms were, or were not used, by surveillance authorities to alert them of breaches of trading rules, they could tailor their trades to avoid detection. Rules and surveillance together, therefore, have the potential to mitigate the perpetration of market manipulation or to exacerbate the profits from such manipulation according to the Becker (1968) economic model of crime (commit a crime if the expected benefits exceed the costs; see also Garfinkel and Nimalndran, 2003; Karpoff et al., 2008a,b, 2012; Brockman et al., 2009; Baker et al., 2010; Karpoff and Lou, 2010; Yu and Yu, 2011).

Based on the unique, and in some dimensions proprietary, data set in this study, we uncover a non-trivial role for exchange trading rules and surveillance in mitigating the number of insider trading cases, but exacerbating the profits per case. In our most conservative estimates, a 1-standard-deviation improvement in trading rule specificity gives rise to a 23.43% reduction in the number of insider trading cases and a 53.17% increase in profits per case. These findings are robust to numerous specifications, including but not limited to difference-in-differences regressions and two-stage instrumental variables regressions. Similarly, we conservatively estimate that a 1-standard-deviation improvement in surveillance gives rise to a 67.0% reduction in the number of cases and 26.3% increase in profits per case. Overall, the findings highlight complementarities across different trading rules and surveillance, and these complementarities are at least twice as important as stand-alone insider trading rules for predicting the frequency of insider trading cases; however, the complementarities are less economically important for predicting the trading value for surrounding the insider trading cases relative to stand-alone insider trading rules.

This paper is related to a substantial body of work in securities regulation that explores the question of whether securities laws and their enforcement facilitate more efficient markets with greater integrity. For instance, recent studies have shown a positive empirical link between securities regulation

and capital raising (La Porta et al., 2006; Roe, 2006; Jackson, 2007; Jackson and Roe, 2009), and liquidity (Cumming et al., 2011).[5] More specifically in the area of insider trading however, the evidence is more varied and generally shows that insider trading laws are relatively less effective (the Appendix provides an overview of related papers). Bris (2005) studies the adoption of insider trading laws across 54 countries from the 1960s through the 1990s and finds some evidence that such laws fail to mitigate the number of cases while increasing profits per case. Similarly, Beny (2005, 2007) and Bhattacharya and Daouk (2002, 2009) find evidence that insider trading laws do more harm than good when they are not properly enforced. The present paper complements this literature by examining, for the first time, whether surveillance (computer-based alerts based on algorithms) and exchange trading rules across countries and time mitigate insider trading activity. Our findings strongly support this prior work and extend the literature by highlighting the effect of different yet complementary market manipulation rules and specific direct policy mechanisms directly relevant to insider trading.

This paper proceeds as follows. Section 2.2 describes stock exchange trading rules and exchange surveillance. The data are introduced in Section 2.3. Section 2.4 presents multivariate analyses of the relation between the frequency and profitability of insider trading and exchange trading rules and surveillance. Concluding remarks are set forth in Section 5.

[5] See also, e.g., Aggarwal (2001), Aggarwal and Wu (2006), Allen and Gale (1992), Allen and Gorton (1992), Comerton-Forde and Rydge (2006), Daouk et al. (2006), DeMarzo et al. (2005), Gerard and Nanda (1993), Hillion and Suominen (2004), Jarrow (1992, 1994), La Porta et al. (1997, 1998, 1999, 2002, 2006), Mahoney (1999), Merrick et al. (2005), Ni et al. (2005), Peng and Röell (2009), O'Hara and Mendiola (2003), Pirrong (1993, 1995a,b, 1999, 2004), Pistor et al. (2003), Pistor and Xu (2003, 2005), Prichard (2003), Reiffen and Robe (2007), Romano (2001, 2002).

2.2 Expected impact of exchange trading rule complementarities on insider trading

Traditional studies of the impact of rules on insider trading have considered specific exchange trading rules pertaining to insider trading and governance (e.g., Bhattacharya and Daouk, 2002, 2009; Beny, 2005, 2007; Bris, 2005; see the Appendix). Our perspective is similar, but with three important differences. First, we conjecture that there are myriad exchange trading rules specific to insider trading that impact the frequency and severity of such trading. Second, we consider that non-insider trading exchange trading rules influence insider trading through rule complementarities. Finally, we believe that surveillance efforts directed towards these first two issues affect insider trading. We explain in this section each of these three points in turn prior to introducing the data and tests in the subsequent sections.

2.2.1. Insider trading rules

Insider trading, which generally refers to trading on material non-public information, is far from generic. Insider trading can be propagated through many different channels and brought about by different market participants. As a result, exchange trading rules regarding client precedence, front-running, trading ahead of research reports, separation of research and trading, broker ownership limits, restrictions on affiliation, restrictions on communications, investment company securities, influencing or rewarding the employees of others, and anti-intimidation/coordination could all potentially have an impact on the frequency and severity of insider trading.

Two types of rule affect the ability of brokers to impact trading on material non-public information: client precedence and front-running. Client precedence refers to brokers violating the time priority of client orders. A client precedence rule is violated during insider trading that the client's order

being executed at disadvantaged price, because the broker initiates a trade on his own account shortly before the execution of a known client's order. Similarly, brokers can front-run their client's order. Front-running by a broker refers to a broker trading their own or on the behalf of other clients shortly prior to the original client's order, with the expectation that the original client's large order will move the price up or down. Front-running can also refer to the situation when brokers take the exactly opposition position of their clients without acknowledging the clients first.

In addition, there are other forms of insider trading in which individuals trade by using non-public information about the company. By disallowing public trading before the release of any public information and information sharing between the broker's in-house research and trading department (such as "Chinese Walls"), exchange trading rules can eliminate the incidence of this type of insider trading. Also, rules could mitigate material and non-public information flow by limiting the affiliation between exchange members and member companies, and the connection between the member and their investment company. Rules can also set guidelines on how material and non-public information are released. Finally, detailed trading rules could limit brokerage ownership, thus reduce the broker's influence on the company decision, or ban intimidation and/or coordination activities (e.g., to stop people from reporting illegal activities). Therefore, detailed trading rules could have impact on the flow of non-public information.

2.2.2. Other exchange trading rules and insider trading

Insider trading can be facilitated by other forms of market manipulation, such as through price manipulation, volume manipulation, spoofing, disclosure manipulation, and broker–agency conduct.

Price manipulation can enable insider trading by distorting the market and prices prior to an announcement, thereby facilitating execution of insider trades while hindering detection of insider trading

by surveillance authorities. Price manipulation can be done in many different ways, can take many forms, and may be executed by multiple market participants. For example, one broker (or colluding brokers) could enter purchase orders at successively higher prices to create the appearance of active interests in a security with no intention of actually buying the stock at the given price. It also can be done in the form of pump and dump schemes. For example, exchange participants create a significant increase in price and volume for a security, then take a quick flip, and the securities are often sold to uninformed retail customers at the higher prices. Finally, another price manipulation can be done in the form of pre-arranged trading. In a pre-arranged trade, colluding parties simultaneously enter orders at an identical price and volume. The pre-arranged trades can influence the price of a security since these trades avoid the order queue. Additional forms of price manipulation include corners (which refers to taking control of bid or demand side of both the asset and its derivative in order to manipulate the price) and squeezes (which refers to the behavior of creating an artificial level of price by controlling the demand-side of the asset and abuse the market during the market congestion or asset shortage). Further, price manipulation could include mini-manipulations which manipulate the price of the underlying security of an option in order to make the options valuable (Merrick et al., 2005, Cumming et al, 2011). Price manipulation may be more pronounced at the market open or close, or on a particular date (end of month/quarter/year). Financial record keeping schedules among companies provide incentives, particularly for insider traders, to manipulate share prices around the end of the month/quarter/year.

Volume manipulation through churning and wash trades can likewise make the detection of insider trading more difficult for surveillance authorities. Churning refers to excessive trading of a particular stock with the purpose to inflate its volume, thereby creating a false impression that there is active interest in the stock. Wash trading, another form of volume manipulation, means having the same client on both sides of a trade. Similar to churning, wash trades also have the effect of creating a misleading appearance of active trading activities in a stock with no change of ownership.

Spoofing can be used to facilitate illegal insider trades by creating other market distortions that would make insider trading more difficult to detect. Spoofing, or "painting the tape", refers to the actions taken by market participants to give an improper impression of unusual activity either in price movement or volume movement in a security. Spoofing includes fictitious orders, giving up priority, layering of bids-asks, and switches. Spoofing may give rise to volume and price manipulations that make insider trading more profitable and easier to carry out, and more difficult to detect.

A market participant may also more effectively execute an insider trade by engaging in false disclosure, parking, and warehousing. Many exchanges stipulate rules prohibiting false disclosure of information. Market participants might otherwise actively distribute false or misleading information that has the effect of distorting the marketplace. On the other hand, there can be a failure to disclose required information to the public. For example, there may be a failure to disclose of ownership interests as required when they reach a threshold level.

Broker–agency conflicts can similarly facilitate insider trading transactions by misleading market participants who are not insiders. Brokers should act on behalf of clients and put their clients' interest first. Often, brokers may operate against their client's interest by failing to obtain the best execution price for the client (a breach of a trade through obligation [6]), charging excessive fees, or investing in securities/portfolios that do not follow the risk/return profile of the client (often called as breach of the "know-your-client rule"). The brokers might also use the exchange's brand/name unacceptably in marketing efforts and in selling their services.

[6] In the US, this obligation was released under Regulation NMS and published in the Federal Register in June 2005. Regulation NMS was phased in over many months in 2007; see http://www.nasdaqtrader.com/content/marketregulation/regnms/regnms_factsheet.pdf. Assigning the value 1 or 0 to trade through in the US during this period does not materially influence our results.

2.2.3. Surveillance and insider trading

As with most exchange trading platforms, surveillance systems within exchanges around the world are automated (Harris, 2002). Real time computer surveillance systems alert surveillance staff of unusual trading activity based on orders and executed trades. Such alerts are not usually based on single trades but are generated based on patterns of trading to detect potential manipulative practices. The different types of market manipulation identified in Table 1 can be subject to both single- and cross-market surveillance. Single-market manipulations can also be a cross-market manipulation (such as for a security that is listed on more than one exchange) or cross-product manipulation (such as a derivative and its associated stock). For example, wash trades may take place across markets (in fact, multiple transactions across markets could be used as a way to disguise wash trades). Front-running may also take place across markets, where brokers place orders ahead of client orders for the same security traded on a different exchange.

In our empirical tests below, we sum up the scope of domestic and cross-market surveillance to create an overall scope-of-surveillance index. As with the underlying logic pertaining to the scope of trading rules, we expect the scope of surveillance, and not merely surveillance of one type of manipulative activity, to be important with respect to insider trading. Other surveillance index specifications within the subset of domestic or the subset of cross-market surveillance alerts are expected to give rise to materially similar results; we also assess these specifications in our empirical tests. A greater scope of surveillance is expected to lower the profits to insider trading by making the market more efficient (Cumming and Johan, 2008). The scope of surveillance is not precisely known by market participants, but it may be estimated, and as such, surveillance by any one exchange is expected to mitigate the frequency of insider trading. Based on the economic model of crime (Becker, 1968; see also Karpoff et al., 2008a,b), when there is a greater chance of detection, risk taking insiders will be willing to engage only in the more profitable insider trades.

In sum, we conjecture that rules prohibiting insider trading alone may not necessarily influence insider trading, but rather, that the rules we have outlined above, along with the surveillance associated with these rules, operate together to jointly have greater influence on insider trading. More detailed rules mitigate the frequency of suspected insider trading. However, more detailed rules increase the expected costs of detection; based on the economic model of crime (Becker, 1968), insider traders will engage in insider trading only if the accompanying profits are larger. We test these propositions via a new, detailed panel data set, described in Section 3 below.

2.3. Sample and summary statistics

2.3.1 Sample

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 UK, and the US (NASDAQ and NYSE).

Table 2.1 describes the main variables in our data set. Our main dependent variables are the number of suspected information leakage cases and pre-announcement abnormal profits per suspected information leakage case. The dependent variable is based on identified suspected cases from surveillance authorities via SMARTS Group, Inc., and CMCRC. SMARTS surveillance staff constructed the dependent variable by first examining news releases from the exchanges themselves. SMARTS measures the return to the security in the six days prior to the announcement, up through two days following the announcement. SMARTS cross checked their findings with the Thompson Reuters News Network to ensure that no important news announcements were missed. SMARTS considers only news events that

have no companion news announcements that could alternatively explain as market anticipation price movements in the six days before and the two days after the relevant announcement.

For each news announcement, a price movement is abnormal if it is three standard deviations away from the mean abnormal return during the 250-day benchmarking period ending 10 days prior to the news release. SMARTS surveillance staff independently examined the data to distinguish between market anticipation and suspected insider trading;[7] since SMARTS includes as insider trading only large movements that are three-standard-deviation changes, the possibility that insider trades could be viewed as market anticipation is mitigated and not plausibly observed in the data. To be included in our sample, the stock must have at least 150 days of trading activity. A one-factor market model based on the market index from each particular exchange is used to calculate daily abnormal returns. To ensure that no temporary stock fluctuations are captured, nine-day cumulative abnormal returns (CARs[t-6, t-2]) are calculated as well . To be included in the final data set for suspected information leakage cases, the CAR around each event [t-6, t+2] must be three standard deviations away from the normal nine-day CAR during the benchmarking period for each individual stock. The abnormal profit per case is calculated as the total trading volume multiple abnormal returns from 6 days before to the day before the news announcement We standardize the number of suspected information leakage cases by the number of trades per month on the exchange (scaled by a million for the purpose of reporting the regression results). We standardize the pre-announcement abnormal profits per suspected information leakage case by the average monthly trade size on each exchange. Our results with these standardized dependent variables are consistent when we do not standardize and available in an earlier draft of this paper.

[Insert Table 2.1 about here]

[7] See, e.g., King (2009), for methods to distinguish between market anticipation and insider trading.

Trading rules for these stock exchanges are found on 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. We use the trading rule indices from Cumming et al. (2011). The trading rules for a stock exchange are drafted with varying degrees of specificity, as they outline exchange membership requirements, listing requirements, trading rules and regulations, and especially prohibited trading practices.

Surveillance data are taken 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 if precise information about surveillance activity were made available to a would-be manipulator, such entity might trade in ways that would obviously not be detected. The data are based on an equally weighted index that adds 1 each time a different type of single- and cross-market manipulation is monitored.

We also acquire a series of law and finance indices from La Porta et al. (1998, 2006) and Spamann (2010), which includes measures of 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 the 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. Otherwise, exchanges would not bother to carry out surveillance. We nevertheless proxy enforcement by using established indices of enforcement, such as efficiency of the judiciary. In other works, note that La Porta et al. (2006) find evidence that private enforcement facilitates the development of stock markets, while Jackson and Roe (2009) find stronger evidence of the value of liability standards and public enforcement (see also Roe, 2006; Jackson, 2007). The difference in Jackson and Roe (2009) is that these authors 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 considered all the indices in La Porta et al. (2006) and Jackson and Roe (2009); inclusion/exclusion of these indices does not materially affect our conclusions regarding the trading rule indices introduced herein. Similarly, in some countries, the probability of detection of insider trading is low, and even upon detection and prosecution, the ensuing fines are light (see, e.g., Bhattacharya and Daouk, 2002, 2009). We considered separate variables for insider trading laws around the world (e.g., Beny, 2005, 2007) among others, but these variables did not materially impact the results presented herein.

We use several exchange-level variables as controls from January 2003 through June 2011, the period considered in this study, using data from Capital Markets CRC and Reuters. To control for the influence of market-specific changes, we draw from an MSCI Global Standard Index series from Morgan Stanley Capital International's webpage. Also, we consider both exchange and year dummy variables in our multivariate analyses.

2.3.2 Summary statistics

Table 2.2 provides summary statistics of the trading rule variables used in this paper. 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. As discussed above, the indices are created by summing up the number of specific provisions in the exchange trading rules for each exchange. The Insider Trading Rules Index varies from a low value of 0 (for a number of exchanges listed in Table 2) to 10 (for NASDAQ). The Market Manipulation Rules Index varies from a low value of

2 (for Malaysia, Taiwan, and Tokyo) to 13 (for London and NYSE). The Broker-Agency Conflict Rules Index varies from a low value of 0 (for Australia, Hong Kong, Germany, Shanghai, Shenzhen, Taiwan, Tokyo, and OSLO) to 5 (for NASDAQ).

[Insert Table 2.2 about here]

Aside from differences in levels of rule detail across countries, few studies analyze a material change to trading rules across countries stemming from the Directive on Markets in Financial Instruments. In November 2007, MiFID, a Europe-wide harmonization directive, became effective. Because the timing, motivation, and content of MiFID were not instigated by a specific European exchange or European country, but were promulgated instead at the European Union level, this legislative change can be regarded as exogenous, thereby providing a useful test of causality between rules and liquidity. MiFID became effective November 1, 2007. While an earlier directive, the Market Abuse Directive (MAD), was introduced in 2004, appropriate measures were not in place in 2004 across member states, for a number of reasons. First, surveillance data from Cumming and Johan (2008) indicate that exchanges in 2004 and 2005 had not adopted/implemented the provisions in MAD in a meaningful way. Second, MiFID covers many aspects of MAD, and states that provisions are needed to ensure that MAD principles are in place by November 1, 2007 (see, for example, Article 25 in MiFID). The draft provisions in MiFID in 2004 already made this point, so investors in 2004 would expect adoption of MAD at the time of MiFID. Third, principles in MAD were added to / clarified in MiFID for the implementation and definition of conduct to ensure that MAD was legally effective. Hence, given that the legal situation in Europe is not perfectly delineated over time, we test for market adoption of these principles using the November 1, 2007 date, but also test for an earlier impact dating back to 2004. We expect that the substantial details provided in MAD/MiFID enhanced investor protection and mitigated insider trading, as discussed below.

Table 2.3 shows that the average (median) number of suspected information leakage cases in a month, divided by the number of trades on the exchange in that month (scaled by multiplying by 1 million) is 3.42 (0.17), with a range from a minimum of 0 to a maximum of 124.36.[8] Distribution across countries is shown graphically in Figure 1. One standard deviation in the monthly number of suspected information leakage cases is 9.40. The average (median) pre-announcement abnormal profit (in 2011 USD) per information leakage case per month divided by the ratio of the total dollar volume per month per number of trades per month is 3425.92 (248.83).[9] Table 2.3 also provides summary statistics for the Total Trading Rules Index, surveillance index, public enforcement, rule of law index, efficiency of the judiciary index, MSCI, and GDP per capita.

[Insert Table 2.3 about here]

Table 2.4 sets forth a comparison of means and medians tests of the number of suspected information leakage cases in relation to different cutoff values, which are the median value of the Total Trading Rule Index. Panel A reports differences in means and medians of the number of suspected information leakage cases for the full sample of all exchanges in the data. The data indicate that the number of suspected information leakage cases is significantly greater for higher values in the Total Trading Rules Index. The average (median) number of suspected information leakage cases for all exchanges is 1.29 (0.50) for exchanges with a value of more than 11 in the Total Trading Rules Index. The average (median) number of suspected information leakage cases is 5.21 (1.56) for exchanges with values of less than or equal to 18 in the Total Trading Rules Index. These differences in means and medians are statistically significant at the 1% level. Panel A also considers differences in the Total

[8] We scale by the number of trades to make the comparisons across markets and time more direct. Without scaling, we produce very similar results, which are available on request from an earlier draft of this paper. Note that without scaling, the average (median) number of cases per month is 10 (4) and the range is 0 to 287.

[9] As with the number of cases, the profits per case are scaled to make more direct comparisons across time and markets. Results without scaling produced nearly identical results and are available from an earlier draft of this paper. The raw data show the average (median) profit per case is $1.9 million ($0.8 million), with a range between $0 and $6.25 million profit per suspected case.

Trading Rules Index for the subset of European exchanges for which MiFID applies. The results are broadly consistent with those reported for the whole data set. We note, however, that in both MiFID and non-MiFID countries, there were fewer cases post-MiFID, which gives rise to the need to test for a difference-in-differences in our multivariate tests below. In Table 2.4, we also compare the difference in means and medians for the Surveillance Index in Panel A of Table 2.4, and the results are similarly significant for the whole sample and the subset of MiFID exchanges. For the MIFID countries, the change is 2.62 down to 1.46 for cases, and non-MIFID countries the change is 4.39 to 2.98. In other words, the percentage change is -44.3% for MIFID countries, and only -32.1% for non-MIFID countries. Clearly, the drop is bigger on a percentage basis for MIFID than non-MIFID countries.

[Insert Table 2.4 about here]

Table 2.4, Panel B presents a comparison of mean and median tests for pre-announcement abnormal profits. Both mean and median tests of the full sample show that pre-announcement abnormal profit is significantly higher for exchanges with higher Total Exchange Rules Index. The average (median) pre-announcement abnormal profit per suspected announcement (scaled by the average exchange-month trade size, as defined in Table 1) for all exchanges is 7854.22 (1333.73) for exchanges with a value of more than 11 in the Total Trading Rules Index. The average (median) pre-announcement abnormal profit per suspected announcement is 1201.998 (64.51) for exchanges with a value of less or equal to 11 in the Total Trading Rules Index. The difference in both means and medians are statistically significant at the 1% level. For a subset European exchanges, the pre-announcement abnormal profit per suspected announcement is 1154.44(225.75) for Total Trading Rules Index greater than 11, and 598.45 and 31.42 for Total Trading Rules Index less than or equal to 11, and these differences are significant at the 1% level. Similar differences in means and medians are observed for surveillance in Panel B. Finally, Panel B also shows that average and median pre-announcement abnormal profit is higher after November 2007 for MiFID exchanges and that these differences are significant at the 1% level; we observe similar results for

the non-MiFID exchanges. For the dollar value of trades surrounding insider trading, in MIFID countries the increase is 413.58 to 1676.22, or 305.3%, and in non-MIFID countries the increase is 4191.3 to 6288.2, or 50.0%.

Overall, the comparison of means and medians in the data highlight patterns that suggest that detailed exchange trading rules and a broader scope of surveillance are better in terms of being associated with fewer insider trading cases, but worse in terms of higher profits per insider trading case. But this type of univariate comparison is not fully informative for the following reasons. First, the data are highly skewed in terms of outlier observations on some exchanges and some months. Differences in case numbers are particularly right-skewed on some exchanges (see Figure 2.1). To address this skewness, we winsorize our dependent variables in the regression analyses in the next section, and consider robustness by removing some countries from the data set. Second, the comparison tests do not control for all other factors being equal, particularly economic conditions in terms of wealth and market depth, which differ across countries. In our empirical tests in the next section, we account for economic conditions to isolate the unique marginal impact of exchange trading rules and surveillance. We highlight the results in the regression tables and present partial regression plots to show the effects graphically. Moreover, we consider robustness checks with alternative explanatory variables, as well as difference-in-differences regressions and instrumental variable regressions, among others.

Table 2.5 presents a correlation matrix for the main variables used in the multivariate tests provided in section 4. The correlations highlight trends similar to those in the comparison tests. Further, 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 section 4.

[Insert Table 2.5 about here]

2.4. Multivariate analyses

2.4.1. Empirical methods

In this section, we empirically test whether exchange trading rules and surveillance have an impact on the frequency and profitability of insider trading, while controlling for other economic and institutional determinants of trading activity. We consider each exchange-month from January 2003 through June 2011 as a separate observation across 22 exchanges in 17 countries and cluster standard errors (as in Petersen, 2009). We use fixed effects by exchange and cluster by month (Model 1, difference-in-differences estimates), cluster by exchange and month (Models 2, and 3,), by country and month (model 4), cluster by exchange and year (Models 5, 6 and 7, robustness checks), and cluster by year alone (Models 8, further robustness checks). Also, we consider other approaches for treating standard errors for panel data sets (e.g., Bertrand et al., 2004), which we find to be quite robust.

Panels A and B of Table 2.6 examine the effect of exchange trading rules and surveillance on the frequency and profitability of insider trading, respectively. The dependent variable in Panel A is the number of suspected insider trading cases each month, excluding cases of clear market anticipation, divided by the number of trades in the month (scaled by 1 million, as defined in Table 1). The dependent variable in Panel B is the sum total of the profits from suspected insider trading in a market relative to the number of suspected cases, thereby giving a measure of profitability per case. Again, this variable is scaled by volume per trade, as defined in Table 2.1. In each of Panels A and B, we present eight identical regressions to show robustness to alternative specifications. Model 1 shows a difference-in-differences specification for the European regulatory change with trading rules with and without country fixed effect. Models 2 and 3 separately include the trading rules index and surveillance index, respectively. Model 4 shows the trading rule indices with a number of other legal and enforcement variables, including the public enforcement measures from Djankov et al. (2008) and the resource measure from Jackson and Roe (2009), in addition to creditors rights, investor protection, and disclosure index from La Porta et al. (1998,

2006). Model 5 shows the results without the US exchanges, and Model 6 excludes the US and Japan, since these countries are outliers (Figure 1). Model 7 presents the second step of the two-stage instrumental variable (IV) estimation, discussed further below. Finally, Model 8 presents the results with different dates for the implementation of the European changes dating back to 2004 under MAD (discussed above). For each regression, we control for economic factors, including market capitalization, market conditions (MSCI index), GDP, and exchange institutional features (Röell, 1992), as well as exchange and year dummy variables.

[Insert Table 6 about here]

As discussed above, the European rule changes came via a central directive, and were not prompted by any one country, thereby mitigating the effect of endogeneity. Nevertheless, in Model 7 we report two-step instrumental variable regressions for the possibility of endogeneity with respect to insider trading and trading rules, with legal origin variables as instruments, consistent with the La Porta et al. (2006) instrumental variable specifications. Diagnostic tests indicate that these instruments are suitably correlated with the potentially endogenous variables (correlation between common law and rules index=0.32), but not the left-hand-side variables for the number of insider trading cases (correlation=0.12) and profits per case (correlation=-0.10).

2.4.2. Regression results

Panel A of Table 2.6 presents regression results for the number of suspected information leakages in each market. The data consistently indicate (Models 1–8 in Panel A) that exchange trading rules are significantly negatively related to the number of suspected information leakages. The effect is significant at the 5% level in Models 2 and 3, , and at the 1% level in Models 5, 6, 7, and 8. The economic

significance in the difference-in-differences regression shows that the rule change in Europe gives rise to a 25.73% (=-0.88/3.42) reduction in the number of cases per trade relative to the average number of cases per trade. In the other specifications, the economic significance is such that a 1-standard-deviation change in rules gives rise to a reduction in the number of cases per trade from 23.43% (=-0.137*5.85/3.42) in the most conservative estimate (Model 2), to a 28.91% (=-0.169*-5.85/3.42) reduction in the number of cases per trade in the least conservative estimate. Even after controlling for potential endogeneity (Model 7), the statistical significance of this effect remains and the economic significance of this effect is consistent with other estimates. This finding pertaining to endogeneity not mitigating the results is not surprising; if there were an endogenous relationship, we would expect a positive association, since more trading rules would be adopted in response to insider trading, but instead we see a negative relationship. The findings are quite similar using the MAD start date (Model 8). Overall, the data provide very strong support for the notion that more detailed trading rules significantly reduce insider trading. To highlight the significance of this effect graphically, we generate a partial regression plot (Figure 2).

[Insert Figures 2–6 about here]

As a robustness check, we consider subsets of the trading rule indices described in Table 2.1 and Section 2, as well as combinations of different rule indices in the same regressions (and considering collinearity across indices). The index subsets are generally consistent with the Total Trading Rule Index. We report the Total Trading Rule Index results since, as discussed in Section 2, rules pertaining to market conduct, such as price and volume manipulation and the like, are all pertinent to the ability of an insider to effect insider trading.

Consistent with the Trading Rule Index, the data indicate that surveillance is negatively and significantly related to the number of suspected information leakages. The economic significance is

comparable to the effect of rules (a 1-standard-deviation increase gives rise to a reduction of 67.0% in Model 4 (-0.169*13.56/3.42)), as shown graphically in Figure 2.4.

Panel B of Table 2.6 reports regressions for the profitability of insider trading per suspected case. The same nine model specifications are reported as in Panel A. In Model 1, the difference-in-differences regression shows that average profits per case (scaled by volume per trade) are between 49.28% (1688.4/3425.92) higher after the legal change in Europe relative to average profit per case, and this effect is significant at the 10% level at a minimum. The economic significance of the results is much stronger in the other models, and the effect is significant at the 1% level in each of Models 2, 4, 7 and 8. The most conservative estimate is from Model 6 with outlier countries removed, which shows a 1-standard-deviation change increases profits per case by 53.17% (=311.398*5.85/3425.92), and in the least conservative case (Model 2) by 135.87% (=795.713*5.85/3425.92). To highlight the significance of this effect graphically, we generated a partial regression plot (Figure 3). This evidence is consistent with the Becker (1968) economic model of crime, such that the profits need to be worthwhile in view of the increased probability of expected detection in the presence of more rules.

Panel B of Table 2.6 further shows that a 1-standard-deviation improvement in surveillance gives rise to an increase in profits per case by 120.21% (Model 4) (303.70*13.56/3425.92), and this effect is significant at the 5% level in Model 4. The economic significance of this effect is lower at 26.3% when we exclude the US data from the sample (the equivalent of Model 7 with the surveillance variable added, not reported but available on request). In all specifications reported and otherwise, the data thus strongly support the view that like rules, surveillance increases profits per case, consistent with the Becker (1968) model of crime. See also Figure 2.5.

The control variable in Panel A for the regressions for the number of suspected insider trading cases shows that insider trading is less common in larger exchanges. This result is perhaps not surprising,

as insider trading is reputed to occur more in weaker markets. Some of the other legal indices included as control variables are significant, but the degree of significance depends in part on the exclusion or inclusion of other indices, due to collinearity across different indices; regardless, the inclusion or exclusion of these other indices does not alter the results pertaining to trading rules and/or surveillance. Finally, the control variables for the regressions with profits per case in Panel B show evidence in all models that market capitalization is positively related to profits per case, which is perhaps expected since smaller markets may have less profitable opportunities.

2.4.3. Additional robustness checks

In the course of our empirical analyses, we carry out a number of robustness checks. First, instead of using total trading rules, we use subsets of the trading rules indices. For these regressions, the results are as follows. A 1-standard-deviation increase in the price manipulation index, volume manipulation index, spoofing index, false disclosure index, market manipulation index, or insider trading index (each defined in Table 1 and summarized in Table 2) reduces the number of insider trading cases by 33.37%, 33.60%, 39.28%, 3.0%, 33.56% and 10.85%, respectively (regressions equivalent to Model 3 in Table 6, Panel A), and increases the profits per case by 47.24%, 84.47%, 128.5%, 71.72%, 150.0% and 169.5%, respectively (regressions equivalent to Model 3 in Table 2.6, Panel B). Relative to the economic magnitudes reported in Table 2.6 and discussed above, therefore, the findings highlight complementarities across different trading rules and surveillance, and these complementarities are at least twice as important as stand-alone insider trading rules for predicting the frequency of insider trading cases; however, the complementarities are less economically important for predicting the trading value for surrounding the insider trading cases relative to stand-alone insider trading rules. These and other specifications are available on request.

Second, we consider different specifications for the dependent variables, such as without the use of ratios and with different ratios (such as suspected cases/announcements), different time periods, etc. Third, we consider alternative dates for the timing of rule changes for European exchanges, as discussed in Section 2.2 above. Fourth, we consider other measures of law quality, such as anti-director rights (La Porta et al., 1998; Spamann, 2010), disclosure (La Porta et al., 2006), and other proxies for resources devoted to securities regulation (Jackson and Roe, 2009). Fifth, we consider other instrumental variable and difference-in-differences specifications, such as lagged dependent variables and other specifications. Sixth, we consider possible outlier time periods and outlier exchanges. These alternative models and checks, among others, do not suggest material differences in the array of results reported in the tables. Alternative specifications are available on request.

2.5. Conclusions

In this paper, we empirically examine the relationship between the frequency and profitability of insider trading and exchange trading rules and surveillance across 22 exchanges over the period January 2003 through June 2011. The ability of an exchange to mitigate insider trading activity and profits from insider trading depend significantly on the overall rule structure of the exchange and its domestic and cross-market surveillance. The scope of exchange trading rules is precisely known by market participants, since they are prominent on each exchange's webpage. The scope of surveillance, by contrast, is not precisely known,[10] but can only be estimated by market participants. Rules and surveillance, therefore, have the potential to exacerbate crime according to the Becker economic model of crime (commit a crime if the expected benefits exceed the costs).

[10] If market participants knew exactly what surveillance authorities did and did not have alerts (computer algorithms) for, then they could trade in precise ways to avoid detection.

The data examined herein are strongly consistent with the view that more detailed exchange trading rules and surveillance reduce the number of cases of market manipulation, as would-be manipulators are less likely to engage in insider trading where there are fewer ways to hide such trades. The data indicate that rules and surveillance, ceteris paribus, exacerbate the profits to insider trading, since would-be manipulators are likely to engage in insider trading only if the expected profits outweigh the expected costs, and the greater the number of rules and the broader the scope of surveillance the greater the expected costs. These findings are robust to many alternative specifications and highlight the importance of trading rules and surveillance in comparing international differences in stock exchanges.

Figures:

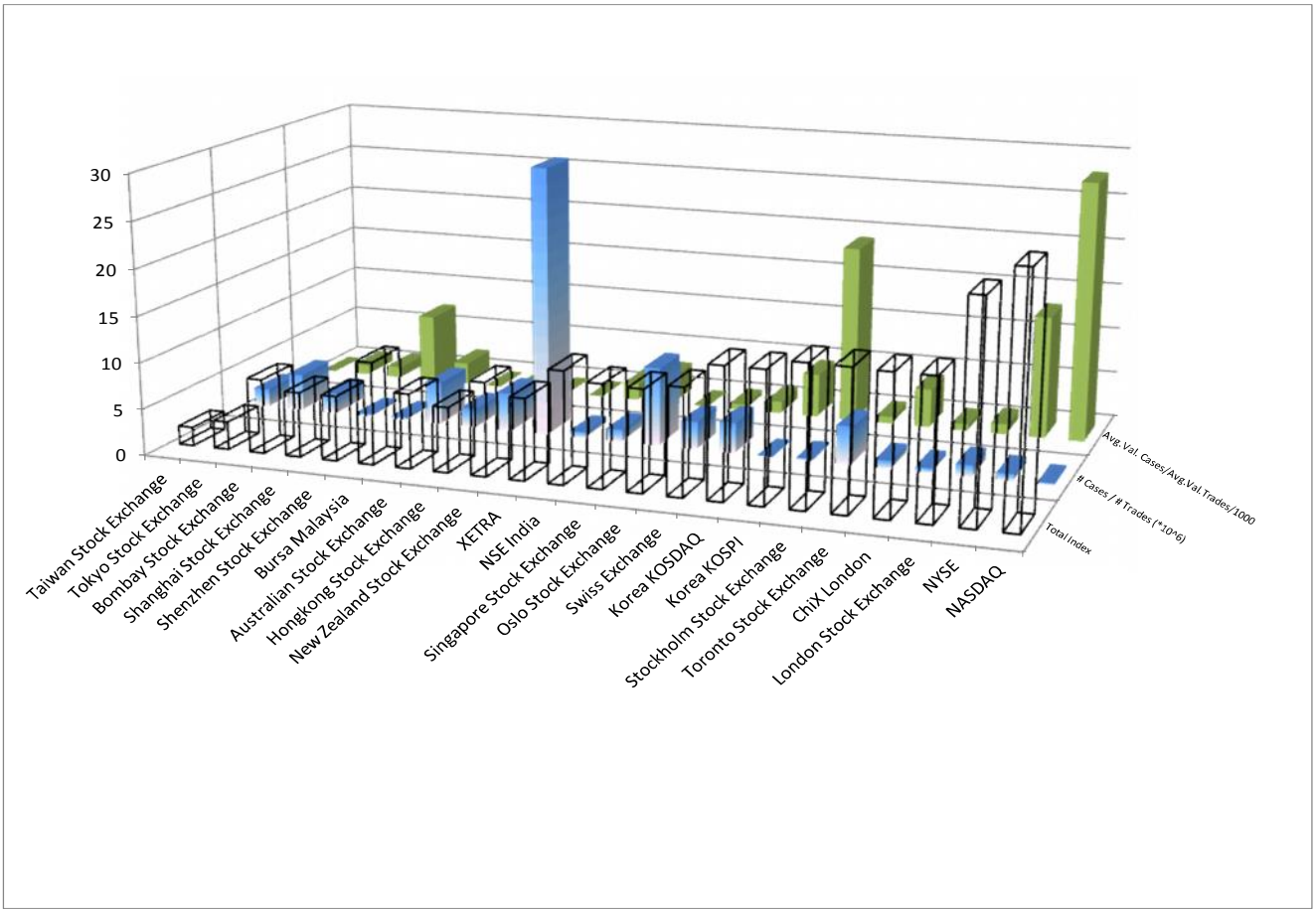

Figure 2.1. Three-dimensional graph comparison of Average Number of Suspected Information Leakage Cases, Average Pre-Announcement Abnormal Profit, and Total Trading Rules Index by exchange. Data involve monthly data from 22 exchanges in 17 countries, including Australia, Canada, China, Germany, Hong Kong, India, Japan, Malaysia, New Zealand, Norway, Singapore, South Korea, Sweden, Switzerland, Taiwan, the UK, and the US in the period January 2003–June 2011.

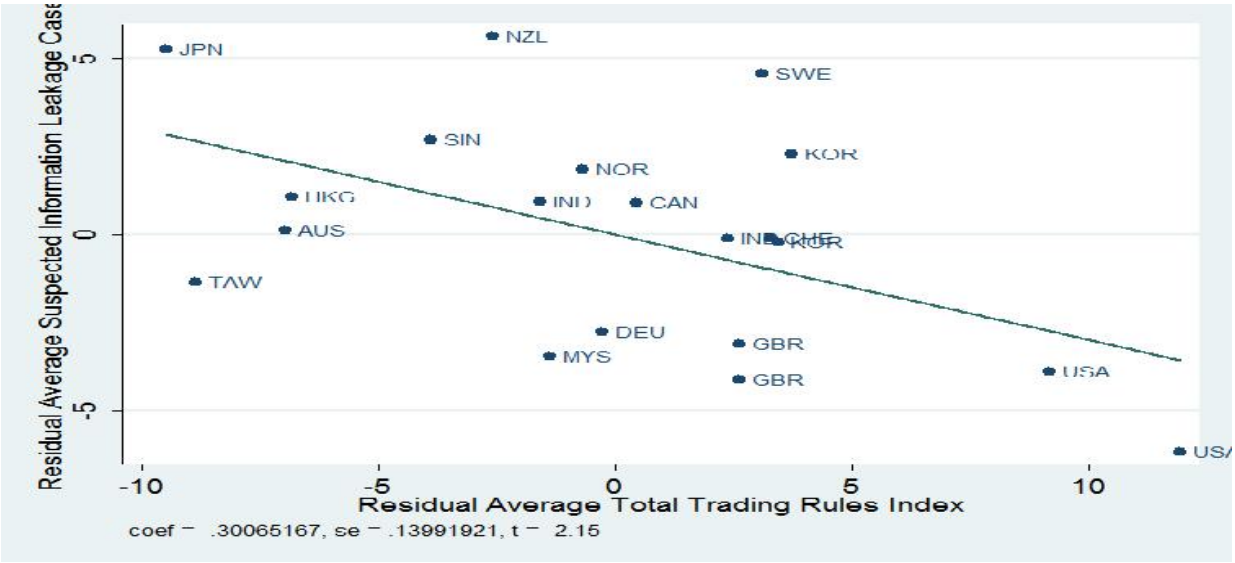

Figure 2.2. Partial regression plot of Average Suspected Information Leakage Case and Average Total Trading Rules Index. The dependent variable is winsorized at 95% before taking the average by exchange. Independent variables include rule of law index, efficiency of judiciary, log of lag GDP per capita, log of MSCI, and log of Market Capitalization. Variables are defined in Table 2.1.

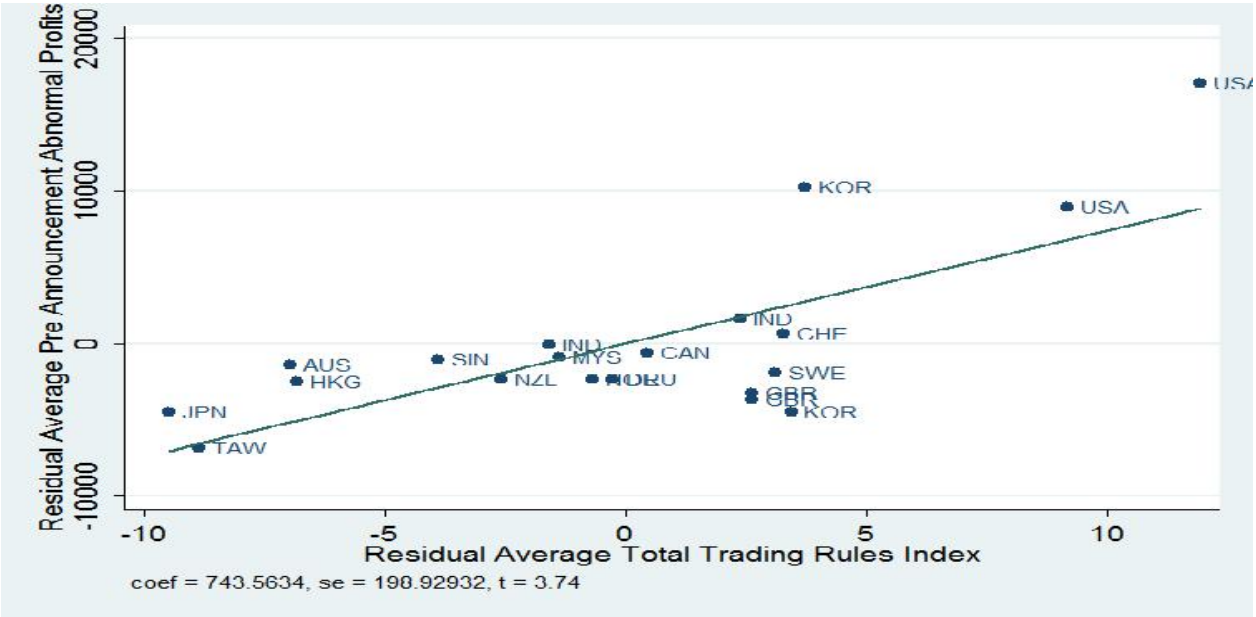

Figure 2.3. Partial regression plot of Average Pre-Announcement Abnormal Profits and Average Total Trading Rules Index. The dependent variable is winsorized at 95% before taking the average by exchange. Independent variables include rule of law index, efficiency of the judiciary, log of lag GDP per capita, log of MSCI, and log of Market Capitalization. Variables are defined in Table 2.1.

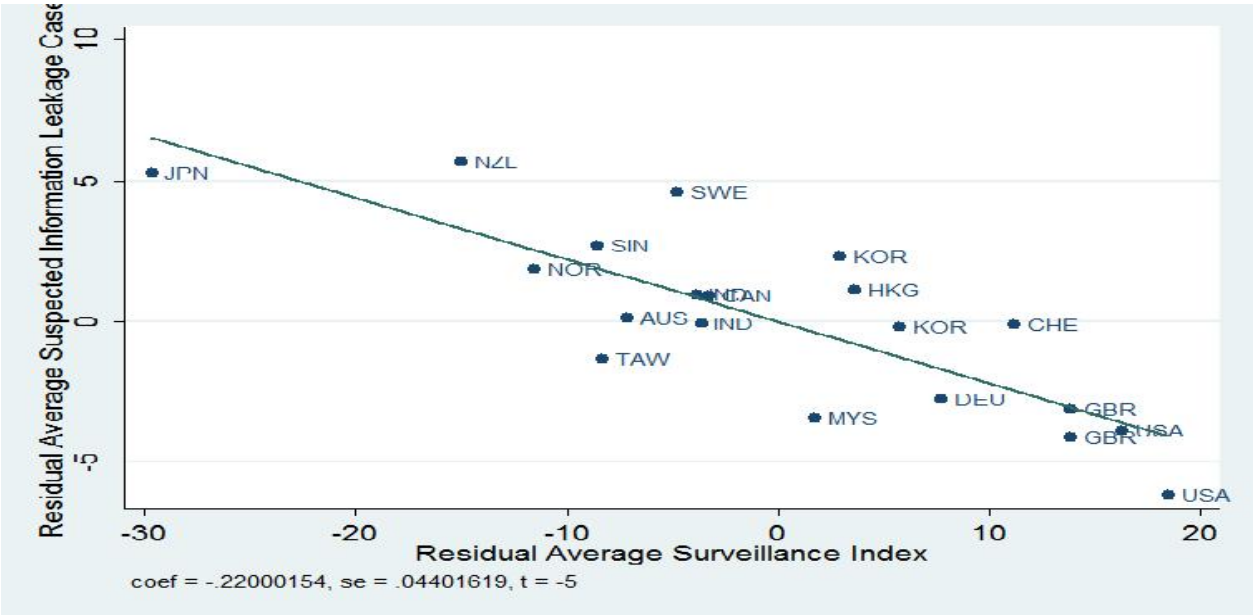

Figure 2.4. Partial regression plot of Average Suspected Information Leakage Case and Average Surveillance Index. The dependent variable is winsorized at 95% before taking the average by exchange. Independent variables include rule of law index, efficiency of judiciary, log of lag GDP per capita, log of MSCI and log of Market Capitalization. Variables are defined in Table 2.1.

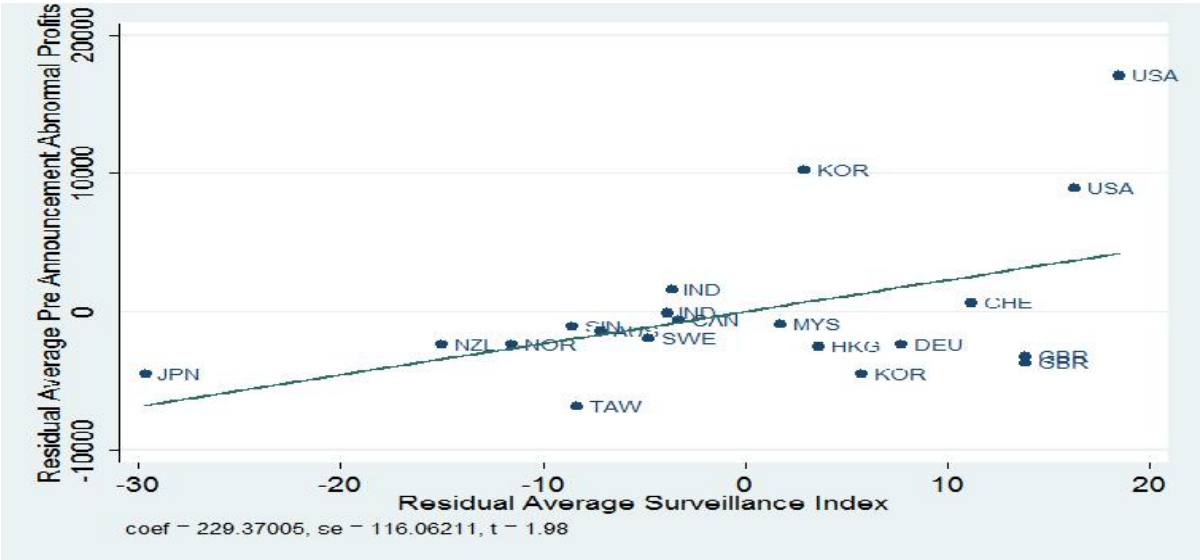

Figure 2.5. Partial regression plot of Average Pre-Announcement Abnormal Profits and Average Surveillance Index. The dependent variable is winsorized at 95% before taking the average by exchange. Independent variables include rule of law index, efficiency of judiciary, log of lag GDP per capita, log of MSCI, and log of market capitalization. Variables are defined in Table 2.1.

Table 2.1.

Definition of Variables.

This table defines our independent, dependent, and control variables.

Variable Name	Definition
Market Quality	
Average Number of Suspected Information Leakage Cases	Total number of announcements with suspected pre-announcement insider trading cases per month divided by the number of trades per month on the exchange (scaled by multiplying by 1 million). Source: Capital Markets Cooperative Research Centre (CMCRC) and SMARTS, Inc.*
Average Pre-Announcement Abnormal Profits	Pre-Announcement Abnormal Profit per Information Leakage Case divided by average monthly trade size on the exchange. Source: CMCRC and SMARTS Group Pty, Ltd.*
	* CMCRC and SMARTS surveillance staff constructed these two dependent variables. CMCRC and SMARTS first examined all news releases from the exchanges themselves. CMCRC and SMARTS measured the return to the security in the six days prior to the announcement up to the two days after the announcement. They double checked the Thompson Reuters News Network to ensure that they did not miss any important news announcements. They consider only news events that have no companion news announcements that could explain price movements in the six days before and the two days after the relevant announcement that could explain the price movement. For each news announcement, a price movement is abnormal if it is three standard deviations away from the mean abnormal return during the 250-day benchmarking period ending at 10 days before the news release. To be included in our sample, the stock must have at least 150 days' trading activities. A one-factor market model based on the market index for each exchange is used to calculate daily abnormal returns. To be included in the final data set as a suspected information leakage case, the CAR around each event over the period [t-6, t+2] must be three standard deviations away from the normal nine-day CAR for each individual stock. Once the suspected information leakage case is defined, abnormal profit per case is calculated as the trading-volume-multiple abnormal returns from six days before to the day before the news announcement. SMARTS surveillance staff independently examined the data to distinguish between market anticipation and suspected insider trading; since SMARTS includes as insider trading only large movements that are three-standard-deviation changes, the possibility that insider trades could be viewed as market anticipation is mitigated.
Trading Rule Index	
Insider Trading Rules Index	Sum of dummy variables for Front-running, Client precedence, Trading ahead of research reports, Separation of research and trading, Broker ownership limit, Restrictions on affiliation, Restrictions on communications, Investment company securities, Influencing or rewarding the Employees of Others, and Anti-intimidation / Coordination. Source: Cumming et al. (2011).
Price Manipulation Rules Index	Sum of dummy variables for marking the open, marking the close, misleading end of the month/quarter/year trades, intraday ramping/gouging, market setting, pre-arranged trades, and domination and control. Source: Cumming et al. (2011).
Volume Manipulation Rules Index	Sum of dummy variables for Churning and Wash trade. Source: Cumming et al. (2011).

Spoofing Rules Index	Sum of dummy variables for Giving up priority, Switch and Layering of bids/asks. Source: Cumming et al. (2011).
False Disclosure Rules Index	Sum of dummy variables for Dissemination of false and misleading information and Parking or warehousing. Source: Cumming et al. (2011).
Market Manipulation Rules Index	Sum of Price Manipulation Rules Index, Volume Manipulation Rules Index, Spoofing Rules Index, and False Disclosure Rules Index. Source: Cumming et al. (2011).
Broker-Agency Index	Sum of dummy variables for Trade through, Improper execution, and Restrictions on member use of exchange name, Restrictions on sales materials and telemarketing, and Fair dealing with customers. Source: Cumming et al. (2011).
Total Trading Rules Index	Sum of Insider Trading Rules Index, Market Manipulation Rules Index, and Broker-Agency Rules Index. Source: Cumming et al. (2011).
Surveillance, Enforcement, Efficiency of the Judiciary, Rule of Law Indices and Other Law and Finance Indices	
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 0 to 10, with lower scores for less tradition of law and order (we changed the scale from its original range from 0 to 6). Original data come from International Country Risk Guide. Source: La Porta et al. (1998).
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 et al. (2011).
Efficiency of the Judiciary	Assessment of the "efficiency and integrity of the legal environment as it affects business, particularly foreign firms" produced by the country risk rating agency International Country Risk (ICR).t "may be taken to represent investors' assessments of conditions in the country in question." Average between 1980 and 1983. Scale from 0 to 10; with lower scores, lower efficiency levels assessment of the efficiency and integrity of the legal environment. Scale from 0 to 10; with lower scores, lower efficiency levels. Original data come from International Country Risk Guide. Source: La Porta et al. (2006).
Staff per Million Population (extrapolated sample)	The 2005 size of the securities regulator's staff, divided by the country's population in millionsOrignial data come from regulators' annual report and nations' official document. Population data are from World Bank Data and Statistics Web site.. Source: Jackson and Roe (2009).
DLLS Public Enforcement Index	Public enforcement is an index aggregating whether certain suspect corporate transactions can lead to a fine or jail sentences for the approving body, or fine or jail sentence for the principal wrongdoer. Source: Jackson and Roe (2009); Original source: Djankov et al. (2008).
Creditor Rights	An index aggregating creditor rights. The index is formed by adding 1 when (1) the country imposes restrictions, such as creditor consent or minimum dividends to file for reorganization; (2) secured creditors are able to gain possession of their

	security once the reorganization petition has been approved (no automatic stay); (3) secured creditors are ranked first in the distribution of the proceeds that result from the disposition of the assets of a bankrupt firm; and (4) the debtor does not retain the administration of its property pending resolution of the reorganization. The index ranges from zero to four. Source: La Porta et al. (1998).
Corruption Index	ICR's assessment of corruption in government. Lower scores indicate that "high government officials are likely to demand special payments" and "illegal payments are generally expected throughout lower levels of government" in the form of "bribes connected with import and export licenses, exchange controls, tax assessment, policy protection, or loans." Average of the months of April and October of the monthly index between 1982 and 1995. Scale from 0 to 10, with lower scores for higher levels of corruption. The index ranges from zero to four. Original data come from International Country Risk Guide. Source: La Porta et al. (1998).
Risk of Expropriation	ICR's assessment of the risk of "outright confiscation" or "forced nationalization." Average of the months of April and October of the monthly index between 1982 and 1995. Scale from 0 to 10, with lower scores for higher risks. Original data come from International Country Risk Guide. Source: La Porta et al. (1998).
Accounting Standard	Index created by examining and rating companies' 1990 annual reports on their inclusion or omission of 90 items. These items fall into seven categories (general information, income statements, balance sheets, funds flow statement, accounting standards, stock data, and special items). A minimum of three companies in each country were studied. The companies represent a cross-section of various industry groups; industrial companies represented 70%, and financial companies represented the remaining 30%. Original data come from international accounting and auditing trends, Center for International Financial Analysis and Research. Source: La Porta et al. (1998).
Investor Protection	Principal components of the indices of disclosure requirements, liability standards, and anti-director right. Source: La Porta et al. (2006).
Disclosure	The Index of disclosure equals the arithmetic mean of (1) prospectus; (2) compensation; (3) shareholders; (4) inside ownership; (5) contracts irregular; and (6) transactions. Source: La Porta et al., Lopez-De-Silanes and Shleifer (2006).
Anti-director Rights	The updated Anti-director Rights index. Source: Spamann (2010).
<u>Market Statistics</u>	
Log (Market Capitalization)	Log of domestic market capitalization in USD millions. Source: Capital Markets Cooperative Research Centre (CMCRC).
Log (1+MSCI)	Log of 1one plus the MSCI index in the 1-month lagged period. Source: MSCI.COM (2003/01-2011/06).
Log (GDP)	Log of gross domestic product (GDP) per capita. Source: Global Insight. (2003/01-2011/06).

Table 2.2

Trading Rule Indices

This table summarizes the index values for the trading rules for each exchange, as defined in Table 2.1. 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 origins. Cochran and Cox (1950) t-statistics are shown in Panel B and *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A Indices by Exchange:

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 (LSE and ChiX 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)
New Zealand	2(2)	0 (0)	1(1)	1(1)	4(4)	3(3)	3(3)
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 (KOSPI and KOSDAQ)	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 (Sweden)	7 (2)	1 (1)	3 (2)	1 (1)	12 (6)	5 (4)	2 (2)
OSLO (Norway)	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 2.3.

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 2.2. The full number of exchange-months in the data is 2196, but some variables have missing values. Surveillance data are available for select countries from Cumming and Johan (2008) with updated information up to 2011, as indicated in Table 2.1. Index from La Porta (1998, 2006) is not available for China. Market Capitalization is from CMCRC with some missing data in the early portion of 2003.

		Mean	Median	Standard Deviation	Minimum	Maximum	Number of Observations
(1)	Average Number of Suspected Information Leakage Case	3.42	0.17	9.40	0.00	124.36	2196
(2)	Average Pre-Announcement Abnormal Profit	3425.92	248.83	8723.73	0.00	71504.02	2196
(3)	Total Trading Rules Index	11.48	11	5.85	2.00	26.00	2196
(4)	Surveillance Index	18.54	14.00	13.56	3.00	41.00	2196
(5)	Rule of Law (LLSV, 1998)	8.32	8.98	2.01	4.17	10.00	1992
(6)	Creditors' Rights (LLSV, 1998)	2.62	3.00	1.19	1.00	4.00	1992
(7)	Risk of Expropriation (LLSV, 1998)	9.17	9.40	0.79	7.75	9.98	1992
(6)	Accounting Standard (LLSV, 1998)	69.55	70.00	7.18	57.00	83.00	1992
(9)	Disclosure (LLS, 2006)	0.79	0.75	0.16	0.42	1.00	1992
(10)	Corruption Index (LLSV, 1998)	8.08	8.52	1.82	4.52	10.00	1992
(11)	Efficiency of the Judiciary (LLS, 2006)	9.08	10.00	1.37	6.00	10.00	1992
(12)	Investor Protection (LLS, 2006)	0.62	0.73	0.27	0.00	1.00	1992
(13)	Anti-director (Spamann, 2010)	4.18	4.00	1.03	2.00	6.00	1992
(14)	Public Enforcement (Jackson and Roe, 2009)	20.52	12.53	19.42	0.43	77.74	1992
(15)	Public Enforcement (DLLS, 2008)	0.47	0.50	0.42	0.00	1.00	1992
(16)	Log GDP	9.57	10.20	1.39	6.14	11.44	2196
(17)	Log MSCI	0.009	0.014	0.07	-0.41	0.31	2138
(18)	Log Market Capitalization	29.83	29.39	2.55	25.91	38.56	2178

Table 2.4

Comparison Tests

This table presents the comparison of mean and median tests for Average Number of Suspected Information Leakage Cases (Panel A) and Average Pre-Announcement Abnormal Profit (Panel B). Each Panel considers all exchanges in the data set, the subset of exchanges for which the Directive on Markets in Financial Instrument (MiFID) applies, and the last panel considers pre- versus post-MiFID for the subsample of MiFID and non-MiFID exchanges. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Average Number of Suspected Information Leakage Cases

	Total Trading Index		Total Trading Index	
	>11	≤11	>11	≤11
	All Countries		Subset of MiFID Exchange	
Group	**1**	**0**	**1**	**0**
Number of Observations	1002	1194	346	116
Mean	1.29	5.21	2.10	1.98
Standard Deviation	2.75	12.22	3.84	4.15
Median	0.50	1.56	1.13	0.58
Difference in Means (0-1)	10.75***		-0.27	
Difference in Medians (0-1)	*P*<0.01***		*P*=0.01***	

	Surveillance		Surveillance	
	>14	≤14	>14	≤14
	All Countries		Subset of MiFID Exchange	
Number of Observations	1074	1122	258	204
Mean	1.31	5.44	0.86	3.59
Standard Deviation	2.26	12.64	0.79	5.46
Median	0.50	1.63	0.62	2.00
Difference in Means (0-1)	10.76***		7.05***	
Difference in Medians (0-1)	*P*<0.01***		*P*<0.01***	

Pre-MiFID versus Post-MiFID	Non-MiFID Countries		MiFID Countries	
	Post-MiFID	Pre-MiFID	Post-MiFID	Pre-MiFID
Number of Observations	748	986	220	242
Mean	2.98	4.39	1.46	2.62
Standard Deviation	9.70	10.79	1.99	5.01
Median	0.52	1.17	0.83	1.27
Difference in	2.86***		3.33***	

Panel B: Average Pre-Announcement Abnormal Profits

	Total Trading Index		Total Trading Index	
	>11	≤11	>11	≤11
	All Countries		Subset of MiFID Exchange	
Group	**1**	**0**	**1**	**0**
Number of Observations	1002	1194	346	116
Mean	7854..22	1201.998	1154.44	598.45
Standard Deviation	23446.59	5487.16	4197.02	2245.30
Median	1333.73	64.51	225.75	31.42
Difference in Means (0-1)	-8.78***		-1.81*	
Difference in Medians (0-1)	*P*<0.01***		*P*<0.01***	

	Surveillance		Surveillance	
	>14	≤14	>14	≤14
	All Countries		Subset of MiFID Exchange	
Number of Observations	1074	1122	258	204
Mean	7000.32	1592.49	1295.19	660.28
Standard Deviation	22731.93	5959.32	3935.16	3618.56
Median	553.51	169.34	363.15	54.93
Difference in Means (0-1)	-7.55***		-1.80*	
Difference in Medians (0-1)	*P*<0.01***		*P*<0.01***	

Pre-MiFID versus Post-MiFID	Non-MiFID Countries		MiFID Countries	
	Post-MiFID	Pre-MiFID	Post-MiFID	Pre-MiFID
Number of Observations	748	986	220	290
Mean	6288.18	4191.38	1676.22	413.58
Standard Deviation	13444.8	21625.83	5187.16	1587.66
Median	919.10	145.98	367.72	62.37
Difference in	-2.49**		-3.47***	

Means (0-1) Difference in Medians (0-1)	*P*<0.01***	*P*=0.09*	Means (0-1) Difference in Medians (0-1)	*P*<0.01***	*P*<0.01***

Table 2.5

Correlation Matrix

This table presents Pearson correlation coefficients for the full sample of exchange-months in the data. * indicates correlations are statistically significant at least in the 5% levels.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)	Average Number of Suspected Information Leakage Cases	1																
(2)	Average Pre-Announcement Abnormal Profit	-0.0821*	1															
(3)	Total Trading Rules Index	-0.132*	0.301*	1														
(4)	Surveillance Index	-0.260*	0.254*	0.582*	1													
(5)	Rule of Law (LLSV, 1998)	0.106*	0.00152	0.164*	0.126*	1												
(6)	Efficiency of the Judiciary (LLS, 2006)	0.174*	-0.0675*	0.166*	-0.142*	0.725*	1											
(7)	Public Enforcement (Jackson and Roe, 2009)	0.118*	-0.027	0.0527*	-0.0689*	0.288*	0.362*	1										
(8)	Public Enforcement (DLLS, 2008)	0.01	-0.126*	-0.0533*	-0.415*	0.00987	0.0105	0.0917*	1									
(9)	Creditors' Rights (LLSV, 1998)	0.108*	-0.148*	-0.268*	-0.171*	-0.673*	-0.242*	0.0937*	0.0282	1								
(10)	Risk of Expropriation (LLSV, 1998)	0.0346	0.0582*	0.266*	0.280*	0.897*	0.602*	0.0810*	-0.0536*	-0.651*	1							
(11)	Corruption Index (LLSV, 1998)	0.147*	-0.0602*	0.145*	0.0658*	0.940*	0.795*	0.285*	0.141*	-0.490*	0.834*	1						
(12)	Investor Protection (LLS, 2006)	-0.0354	0.110*	0.387*	0.0687*	0.0274	0.291*	0.487*	-0.345*	-0.0301	-0.0991*	-0.0283	1					
(13)	Disclosure (LLS, 2006)	-0.0239	0.136*	0.340*	0.0700*	-0.244*	0.0603*	0.472*	-0.346*	0.159*	-0.300*	-0.291*	0.894*	1				
(14)	Anti-director (Spamann, 2010)	0.039	-0.135*	-0.481*	-0.105*	-0.460*	-0.613*	-0.180*	-0.0149	0.445*	-0.387*	-0.382*	-0.454*	-0.316*	1			
(15)	Log Market Capitalization	-0.195*	0.0890*	-0.127*	0.219*	-0.380*	-0.321*	-0.411*	-0.557*	0.136*	-0.183*	-0.384*	-0.108*	0.0546*	0.413*	1		
(16)	Log (1+MSCI)	-0.0570*	-0.0307	-0.0398	-0.0263	-0.0386	-0.0291	-0.000987	0.0425	0.0148	-0.0424	-0.0357	-0.00507	0.000507	0.00694	-0.0103	1	
(17)	Log GDP per Capita	0.0258	0.0808*	0.216*	0.306*	0.694*	0.357*	0.379*	-0.102*	-0.354*	0.644*	0.630*	-0.00804	-0.200*	0.0139	-0.110*	-0.0538*	1

Table 2.6.

Panel Regression

This table presents panel regression of determinants of market quality. Variables are as defined in Table 2.1. Panel A presents regression results for the Average Number of Suspected Information Leakage Cases and Panel B presents regression results for Average Pre-Announcement Abnormal Profits. Model 1 presents results of a difference-in-difference measure. Model 2 presents a regression results with Total Trading Rules Index. Model 3 presents the results with Surveillance Index. Model 4 presents the results with Total Trading Rules Index with various law and enforcement indexes. Models 5 and 6 present the regressions after removing the data from exchanges from the US and Japan, respectively. Model 7 presents the second-stage regression from a two-stage Least Square panel regression. In addition, we define the change of regulation in January 2004 after introduction of the Market Abuse Directive (MAD), and the results are shown in Model 8. *, **, and ***are statistically significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Average Number of Suspected Information Leakage Cases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Difference-in-Difference	Total Trading Rules Index	Surveillance	Total Trading Rules Index with Other Indices	Without Exchanges from US	Without Exchanges from US and Japan	Two-Stage IV Regression	Total Trading Rules Index (MAD)
Constant	7.976	6.292	25.134	19.917	-1.340	5.366	12.75***	12.75*
	[1.57]	[0.69]	[1.34]	1.04]	[-0.13]	[0.37]	[4.91]	[2.17]
Difference-in-Difference								
Treat	-6.284***							
	[-8.05]							
Treat*After	-0.880*							
	[-1.87]							
After	-0.235							
	[-0.63]							
Trading Rules and Surveillance								
Total Trading Rules Index		-0.137**		-0.153*	-0.147***	-0.117**	-0.177***	-0.247***
		[-2.10]		[-1.72]	[-3.29]	[-2.25]	[-5.72]	[-5.22]
Surveillance			-0.169**					
			[-2.42]					
Law and Enforcement Index								
Rule of Law (LLSV, 1998)		0.846	-0.224					-0.378
		[0.86]	[-0.40]					[-1.42]
Efficiency of the Judiciary (LLS, 2006)		0.266	0.32		1.196**	1.049	0.754***	1.107***
		[0.39]	[0.63]		[2.17]	[1.49]	[6.14]	[3.96]
Creditors Rights (LLSV, 1998)		1.439		0.605				
		[1.36]		[0.98]				
Public Enforcement (Jackson and Roe, 2009)			-0.013	-0.07				
			[-0.26]	[-01.13]				
Public Enforcement (DLLS, 2008)			-4.419	-4.563				
			[-1.26]	[-1.49]				
Corruption Index (LLSV, 1998)				2.072**	-0.031	-0.07		
				[2.34]	[-0.05]	[0.11]		
Investor Protection (LLS, 2006)				-15.38**	-12.009***	-11.075***		
				[-2.31]	[-4.63]	[-3.09]		
Disclosure (LLS, 2006)				32.57**	21.356***	19.951***		
				[2.34]	[6.08]	[4.78		
Risk of Expropriation (LLSV, 1998)				-1.391				
				[-0.81]				
Anti-director (Spamann, 2010)				1.260				
				[1.14]				
Exchange and Country Control Variables								
Log Market Capitalization		-0.367	0.751	-1.265*	-0.569**	-0.723**	-0.460***	-0.560***
		[-1.44	[-1.24]	[-1.81]	[-2.36]	[-2.15]	[-7.40]	[-3.49]
Log (1+MSCI)	-4.979*	-5.849	-5.149*	-4.886	-5.973*	-6.126	-2.292	-1.984
	[-1.82]	[-1.56	[-1.70]	[-1.67]	[-1.80]	[-1.85]	[-0.99]	[-0.78]
Log GDP per Capita	0.168	-0.359	0.534	-0.039	0.332	0.300	-0.0978	0.254
	[0.36]	[-0.86]	[0.63]	[-0.06]	[0.69	[0.64]	[-0.78]	[0.83]
Fixed Effect	Exchange	No	No	No	No	No	Exchange/Year	Year
Cluster	Month	Exchange/Month	Exchange/Month	Country/Month	Exchange/Year	Exchange/Year	Year	Year
Observations	2138	1916	1916	1916	1712	1610	1910	1916
R-squared	0.192	0.1107	0.142	0.181	0.108	0.114	0.100	0.125

Panel B: Average Pre-Announcement Abnormal Profits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Difference-in-Difference	Total Trading Rules Index	Surveillance	Total Trading Rules Index with All Indices	Without Exchanges from US	Without Exchanges from both US and Japan	Two-Stage IV Regression	Total Trading Rules Index (MAD)
Constant	-140501.3***	-10812.1	-4264.67	-5661.82	-10843.4	-23060.4	-25788.4***	-23025.2***
	[-12.22]	[0.95]	[-0.18]	[-0.35]	[-1.03]	[-1.02]	[-3.98]	[-5.72]
Difference-in-Difference								
Treat	-19246.9***							
	[-4.11]							
Treat*After	1688.4*							
	[1.88]							
After	-4400.4***							
	[-3.78]							
Trading Rules and Surveillance								
Total Trading Rules Index		795.713***		674.31***	379.80**	311.398**	1229.4***	890.6***
		[3.70]		[5.50]	[2.29]	[2.08]	[15.95]	[6.11]
Surveillance			303.70**					
			[2.29]					
Law and Enforcement Index								
Rule of Law (LLSV, 1998)		-1441.86*						393.7*
		[-1.94]						[2.19]
Efficiency of the Judiciary (LLS, 2006)		-548.92	-157.77		-1729.03*	-1377.26	-1505.5***	-1872.2***
		[-0.71]	[-0.09]		[-1.69	[-1.29]	[-4.92]	[-3.69]
Creditors Rights (LLSV, 1998)		-2498.66		-1947.07***				
		[-2.63]		[-6.28]				
Public Enforcement (Jackson and Roe, 2009)			-4.447	6.39				
			[-0.08]	[0.154]				
Public Enforcement (DLLS, 2008)			-429.37	-1800.87				
			[0.18]	[-0.80]				
Corruption Index (LLSV, 1998)				-2149.8***	80.0.821	78.447		
				[-4.463]	[0.14]	[0.12]		
Investor Protection (LLS, 2006)				-13132.8***	-3746.46	-6162.97		
				[-3.55]	[-0.80]	[-0.97]		
Disclosure (LLS, 2006)				16846.46*	5252.287	8592.34		
				[1.86]	[0.72	[0.96]		
Risk of Expropriation (LLSV, 1998)				-819.09				
				[-0.83]				
Anti-director (Spamann, 2010)				-2286.77***				
				[-3.18]				
Exchange and Country Control Variables								
Log Market Capitalization		541.964*	60.852	459.67	525.62*	772.291	704.5***	809.0***
		[1.92]	[0.08]	[0.74]	[1.95]	[1.50]	[4.55]	[8.71]
Log (1+MSCI)	-3653.9	-4607.27	-.5772.87	-4191.2***	-4137.1*	-4092.72	-2594.8	-3380.6
	[-1.12]	[-1.47]	[-1.42]	[-2.83]	[-1.69]	[-1.64]	[-0.45]	[-0.93]
Log GDP per Capita	15412.8***	1303.77**	602.26	2343.79***	675.262	808.799	607.7*	484.1
	[11.24]	[2.10]	[0.75]	[5.55]	[1.24	[1.31]	[1.95]	[1.64]
Fixed Effect	Exchange	No	No	No	No	No	Exchange/Year	Year
Cluster	Month	Exchange/Month	Exchange/Month	Country/Month	Exchange/Year	Exchange/Year	Year	Year
Observations	2138	1916	1916	1916	1712	1610	1916	1916
R-squared	0.164	0.128	0.07	0.146	0.167	0.170	0.09	0.112

Appendix: Overview of Related Studies on Insider Trading

Author(s)	Data Source(s)	Country Samples	Time Period	Dependent Variables	Insider Trading Law and Enforcement	Main Findings
Bhattacharya and Daouk (2009)	Morgan Stanley Capital Market International (MSCI), International Financial Corporation (IFC), International Monetary Fund (IMF), Datastream, etc.	55 countries	1969 to 1998	Cost of Equity	Insider Trading Law and Enforcement are from Bhattacharya and Daouk (2002).	This paper provides both theoretically and empirically arguments that sometimes no securities law may be better than a good securities law that is not enforced. The authors find that the cost of equity rises when some countries enact an insider trading law but do not enforce it.
Beny (2005, 2007)	La Porta et al. (1998, 2003), Morck et al. (2000), International Finance Corporation (IFC),Gaillard (1992), Stamp and Welsh (1996),	33 countries	cross section	Ownership Dispersion, Stock Market Turnover, Stock Price Synchronicity	**Insider Trading Law index** equals the sum of (1) Tipping, (2) Tippee, (3) Damages and (4) Criminal or , equivalently, the sum of Scope and Sanction. Insider Trading Law variables (Tipping, Tippee, Damages, Criminal, Scope and Sanction) are from Gaillard (1992) and Stamp and Welsh (1996). **Enforcement variables** are Enforced by 1994 (Bhattacharya and Daouk, 2002), Public Enforcement Power (La Porta et al., 2003), and Private Right (Gaillard, 1992; Stamp and Welsh, 1996).	Countries with more prohibitive formal insider trading laws are associated with more dispersed equity ownership, more informative stock prices and more liquidity stock markets. Both enforceability and formal insider trading laws have positive impact on stock market development.
Bris (2005)	SDC Mergers and Acquisitions Database	4,541 acquisitions across 52 countries	1990 to 1999	Insider Trading Profit	Insider Trading Law and their Enforcement: initial prosecution data are from Bhattacharya and Daouk (2002)	Insider trading enforcement increases both the incidence, and the profitability of insider trading. Harsher laws reduce the incidence of illegal insider trading.
Bhattacharya and Daouk (2002)	Morgan Stanley Capital Market International (MSCI), International Financial Corporation (IFC), International Monetary Fund (IMF), Datastream, etc.	103 countries	1969 to 1998	Cost of Equity	Survey Approach [Email, letter and Fax to 103 stock exchanges and their regulator on whether or not the stock market has insider trading laws and on whether or not there had been a prosecution under the insider trading laws]	Introduction of insider trading law has no impact on the cost of equity in a country, but the enforcement of insider trading laws is associated with a significant decrease in the cost of equity.
Seyhun (1992)	National Archives	19,571 firms (U.S.)	1975 to 1989	Insiders' abnormal profits and share traded	**Changes in Insider Trading Regulation**: (1) March 1980, when the Chiarella decision was announced; (2) August 1984, when ITSA was signed into Law, and (3) November 1988, when ITSFEA was signed into law.	The increased statutory sanctions in the 1980s on corporate insider-trading has no impact on corporate insider trading activities and profit. The enforcements by courts have negative impact on insider trading activities, especially around earning announcements and takeover information.

Appendix (Continued): Overview of Related Studies on Insider Trading

Author(s)	Data Source(s)	Country Samples	Time Period	Dependent Variables	Insider Trading Law and Enforcement	Main Findings
Our paper	SMARTS, Inc., Capital Markets CRC, Cumming and Johan (2008)'s survey data, Cumming, Johan and Li (2011) exchange trading rules indices, La Porta et al. (1998, 2006) law and finance indices, Jackson and Roe (2008) resource based enforcement indices; Thompson Reuters Datastream;	22 countries	01/2003 – 06/2011	Frequency of suspected insider trading and trading value surrounding insider trading from Capital Markets CRC and Smarts, Inc.	**Trading Rules:** Insider trading index: Sum of dummy variables for Front-running, Client precedence, Trading ahead of research reports, Separation of research and trading, Broker ownership limit, Restrictions on affiliation, Restrictions on communications, Investment company securities, Influencing or rewarding the Employees of Others, and Anti-intimidation / Coordination. Source: Cumming et al. (2011). Price Manipulation Rule Index: Sum of dummy variables for marking the open, marking the close, misleading end of the month/quarter/year trades, intraday ramping/gouging, market setting, pre-arranged trades, and domination and control. Source: Cumming et al. (2011). Volume Manipulation Rule Index: Sum of dummy variables for Churning and Wash trade. Source: Cumming et al. (2011). Spoofing Rules Index: Sum of dummy variables for Giving up priority, Switch and Layering of bids/asks. Source: Cumming et al. (2011). False Disclosure Rules Index: Sum of dummy variables for Dissemination of false and misleading information and Parking or warehousing. Source: Cumming et al. (2011). Market Manipulation Rules Index: Sum of Price Manipulation Rules Index, Volume Manipulation Rules Index, Spoofing Rules Index, and False Disclosure Rules Index. Source: Cumming et al. (2011). Broker Agency Rules Index: Sum of dummy variables for Trade through, Improper execution, and Restrictions on member use of exchange name, Restrictions on sales materials and telemarketing, and Fair dealing with customers. Source: Cumming et al. (2011). Total Trading Rules Index: Sum of Insider Trading Index, Market Manipulation Rules Index, and Broker-Agency Rules Index. Source: Cumming et al. (2011). **Enforcement:** 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 et al. (2011) Efficiency of the Judiciary: Assessment of the "efficiency and integrity of the legal environment as it affects business, particularly foreign firms" produced by the country risk rating agency International Country Risk (ICR).t "may be taken to represent investors' assessments of conditions in the country in question." Average between 1980 and 1983. Scale from 0 to 10; with lower scores, lower efficiency levels assessment of the efficiency and integrity of the legal environment. Scale from 0 to 10; with lower scores, lower efficiency levels. Original data come from International Country Risk Guide. Source: La Porta et al. (2006). Staff Per Million: The 2005 size of the securities regulator's staff, divided by the country's population in millions Original data come from regulators' annual report and nations' official document. Population data are from World Bank Data and Statistics Web site.. Source: Jackson and Roe (2009). DLLS Public Enforcement: Public enforcement is an index aggregating whether certain suspect corporate transactions can lead to a fine or jail sentences for the approving body, or fine or jail sentence for the princi*pal wrongdoer. Source: Jackson and Roe (2009); Original source: Djankov et al. (2008). Other LLSV Variables Used as summarized in Table 1 of our paper.	We show that more detailed exchange trading rules and surveillance over time and across markets significantly reduce the number of cases, but increase the profits per case. Overall, the findings highlight complementarities across different trading rules and surveillance, and these complementarities are at least twice as important as stand-alone insider trading rules for predicting the frequency of insider trading cases; however, the complementarities are less economically important for predicting the trading value for surrounding the insider trading cases relative to stand-alone insider trading rules.

CHAPTER 3

High Frequency Trading and End-of-Day Price Dislocation[11]

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

- *Johann Wolfgang von Goethe*

3.1. 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,[12] 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).

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11 The current version of this paper is coauthored with Douglas Cumming and Michael Aitken.

12 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

However, prior work has not empirically examined the impact of HFT on specific forms of price manipulation.

In this paper, we directly examine the link between HFT and one very important and specific form of manipulation: end-of-day price dislocation. 'Closing' or 'end-of-day' [hereafter EOD] prices are extremely important for a number of reasons, including the fact that they are often 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).[13] 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 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

[13] 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).

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 at the end of this chapter).

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 3.2 discusses EOD price dislocation in relation to HFT as well as various policy mechanisms designed to curb price dislocation. Section 3.3 introduces the data used in this paper and univariate tests results are presented in Section 3.4. Section 3.5 presents multivariate analyses of the relation between the end of day price dislocation and high frequency trading. Concluding remarks follow in the last section.

3.2. Market Manipulation

3.2.1. 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.

3.2.2. 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.

3.3. Data and Methodology

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 3.1. 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)[14] 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%.[15] 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 3.1 and 3.2 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 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.

[14] For securities exchanges that have closing auction, the close price at auction is used ($P_{auction}$).
[15] $(P_{auction\ or}\ P_t - P_{t+1})/(P_{auction\ or}\ P_t - P_{t-15}) \geq 50\%$

Exchange trading rule indices are obtained from Cumming et al. (2011), as summarized in Table 3.3. 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 3.2 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 3.2) 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 3.3 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 3.4 below.

3.4. Univariate Tests

Table 3.4 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 3.4 About Here]

Table 3.4 Panel A shows that the market-capitalization weighted median number of suspected dislocating the EOD price cases is 0.01 in 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 3.1 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 3.1 About Here]

Table 3.4 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 3.4 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.

Figure3.2 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 3.4 Panel B for comparing HFT and non-HFT countries discussed above. Figure 3.1 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 3.2 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 3.5 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 3.5 About Here]

3.5. Multivariate Tests

3.5.1. Primary Results

Table 3.6 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 3.6. 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.[16] 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 3.6 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.

The co-location variable is statistically insignificant in all of the models in Table 3.6 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., 2014).

The control variables in Table 3.6 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

[16] Our cancellation data (Table A3.3 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.

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 3.6 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 3.6 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.

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.

3.5.2. 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 3.7. The findings are very consistent with that reported in Table 3.6, with the exception that the economic significance or the size of the effects is slightly smaller as expected.

[Insert Table 3.7 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 3.6.

[Insert Table 3.8 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.

3.6. 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.

Figures:

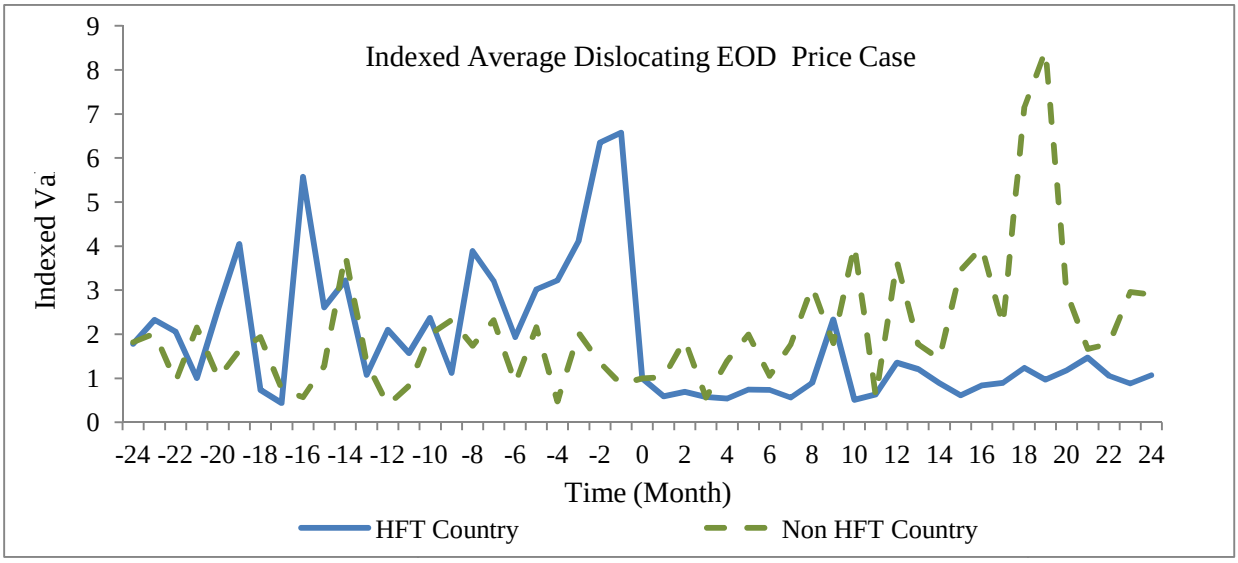

Figure 3.1: Plot of indexed of average (market capitalization weighted) EOD price case. Market Capitalization weighted average suspected EOD price dislocation cases of HFT countries and non-HFT countries are shown here. The values for HFT countries are presented surrounding the date 0, which is indexed 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.

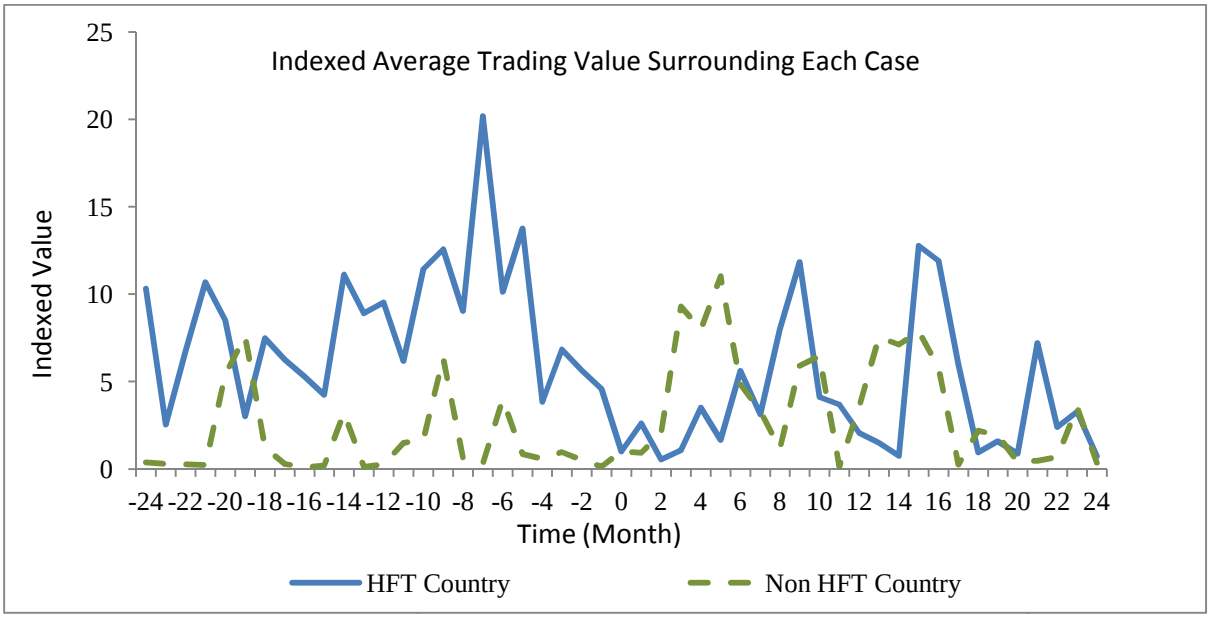

Figure 3.2: Plot of indexed of average (market capitalization weighted) total trading surrounding per EOD price case. Market capitalization weighted total trading value surrounding per suspected EOD dislocation case of HFT countries and non-HFT countries are shown here. The values for HFT countries are 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 3.1.

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 3.2.

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 3.2 (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 3.3.

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 3.4.

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	

Table3.5: 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 3.6: 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 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 3.7:

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					3972.1	6592.6	6195.7	12330.1	10507.0
(Jackson and Roe, 2009)					[0.44]	[0.75]	[0.76]	[1.09]	[0.99]
Public enforcement					1368410.9***	1062182.1*	1063450.0**	1121664.7**	1207577.8**
(DLLS, 2008)					[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 3.8

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		Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US		Public Enforcements	All Jointly	Without US	Without US
Constant	-649735937.5**	-1.00468e+09**	-613067324.0*	-647152079.8	Constant	-568734083.7*	-936833671.4**	-569487706.5*	-629199797.0
	[-2.22]	[-2.59]	[-1.85]	[-1.71]		[-1.93]	[-2.48]	[-1.72]	[-1.79]
HFT Dummy	**-37517189.7** [-2.46]**	**-37025586.3* [-2.25]**	**-41169193.1** [-2.54]**	**-40970064.5* [-2.11]**	**Co-Location Dummy**	**-23604183.6 [-1.08]**	**-23257616.4 [-0.87]**	**-25810104.5 [-1.17]**	**-25880687.9 [-1.12]**
Law/Legal Index					**Law/Legal Index**				
Total Trading Rule Index		624452.2 [0.25]		197302.3 [0.06]	Total Trading Rule Index		949929.9 [0.38]		932331.2 [0.31]
Surveillance		10734972.9** [2.47]		900137.2 [0.46]	Surveillance		10869318.7** [2.43]		1020043.4 [0.54]
Public enforcement	4734310.1** [2.02]	6874216.9* [2.09]	4856329.3** [2.00]	5041775.7 [1.79]	Public enforcement	4927703.5** [2.07]	7099827.1* [2.09]	5089612.5** [2.07]	5317667.8 [1.80]
Public enforcement	369610402.7** [2.50]	184446260.6* [2.26]	373159491.8** [2.42]	357904051.1** [2.77]	Public enforcement	379162166.7** [2.57]	191701533.4** [2.45]	387942196.3** [2.53]	371351653.6** [2.88]
Efficiency of the Judiciary	-147373465.3*** [-2.74]	-76792264.9 [-1.65]	-147111990.6*** [-2.67]	-141457110.5** [-2.43]	Efficiency of the Judiciary	-148422531.7*** [-2.74]	-77368654.6 [-1.65]	-150686222.8*** [-2.74]	-145403710.3** [-2.46]
Rule of Law	47731863.2 [0.79]	3410607.8 [0.07]	55407454.4 [0.81]	51962405.9 [0.78]	Rule of Law	67083411.9 [1.21]	22766903.4 [0.56]	68174534.8 [1.07]	65359804.0 [1.08]
Microstructure Control Variables					**Microstructure Control Variables**				
Log Market Capitalization	13683738.2 [1.62]	13797563.4 [1.14]	13100962.3 [1.50]	13134280.4 [1.09]	Log Market Capitalization	15474441.0* [1.83]	15609940.5 [1.26]	14945043.3* [1.69]	15046881.4 [1.17]
Log Trading Volume	-97553900.9** [-1.97]	-98597640.4** [-2.52]	-100088489.0* [-1.94]	-100455114.6** [-2.60]	Log Trading Volume	-100535832.5** [-2.01]	-102051755.7** [-2.57]	-104047378.5** [-2.01]	-105620687.7** [-2.67]
Log Number of Trades	107927948.2* [1.95]	108952846.6** [2.32]	110492953.7* [1.90]	110866361.9** [2.33]	Log Number of Trades	108128686.1* [1.94]	109672869.2** [2.31]	111976964.3* [1.93]	113661686.1** [2.36]
Log Average Market Trade Size	40473182.4 [1.54]	41360794.9 [1.56]	39674904.3 [1.47]	39980501.3 [1.41]	Log Average Market Trade Size	48665515.1** [2.02]	49840487.4** [2.33]	48884567.7** [1.99]	50043054.5* [2.22]
Log Market Volatility	6063559.9 [1.31]	6048336.3 [1.13]	6608081.1 [1.36]	6596162.9 [1.23]	Log Market Volatility	4949755.0 [0.97]	4942702.6 [0.74]	5112396.7 [0.95]	5054046.1 [0.75]
Country Control Variables					**Country Control Variables**				
Log GDP per capita	-3273155.8 [-0.04]	1972 0.062	-12295430.9 [-0.13]	1768 0.061	Log GDP per capita	-35504442.9 [-0.50]	-36933326.8 [-0.53]	-35789254.9 [-0.43]	-36000409.8 [-0.41]
Observations	1972	1972	1768	1768	Observations	1972	1972	1768	1768
R-squared	0.062	0.062	0.061	0.061	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		Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US		Public Enforcements	All Jointly	Without US	Without US
Constant	29.76**	28.08**	34.00***	34.95***	Constant	-10.52	-16.53	-8.184	-10.14
	[2.43]	[2.59]	[2.61]	[5.38]		[-0.61]	[-0.86]	[-0.49]	[-0.61]
HFT Dummy	**-1.951***	**-2.134****	**-2.671****	**-2.934*****	**Co-Location Dummy**	**0.574**	**0.608**	**0.608**	**0.602**
	[-1.81]	**[-2.84]**	**[-2.25]**	**[-4.78]**		**[0.85]**	**[0.91]**	**[0.98]**	**[0.99]**
Law/Legal Index					**Law/Legal Index**				
Total Trading Rule Index		-0.309***		-0.347***	Total Trading Rule Index		0.0927*		0.0832
		[-3.40]		[-4.25]			[1.95]		[1.70]
Surveillance		0.0865		0.0433	Surveillance		0.119		-0.0153
		[0.81]		[1.71]			[1.13]		[-0.74]
Public enforcement	-0.179*	-0.160**	-0.177*	-0.167**	Public enforcement	-0.0707	-0.0448	-0.0568	-0.0575
	[-1.86]	[-2.37]	[-1.81]	[-2.76]		[-1.34]	[-0.81]	[-1.05]	[-1.07]
Public enforcement	-10.98***	-11.27***	-11.92***	-11.44***	Public enforcement	0.0166	-1.988	0.0552	0.413
	[-2.77]	[-6.62]	[-2.78]	[-5.18]		[0.01]	[-0.85]	[0.02]	[0.13]
Efficiency of the Judiciary	2.515*	3.309**	2.828*	3.438**	Efficiency of the Judiciary	0.886	1.550*	0.991	0.755
	[1.80]	[3.24]	[1.91]	[3.34]		[1.21]	[2.16]	[1.26]	[0.92]
Rule of Law	-1.915	-2.988	-0.894	-1.608	Rule of Law	0.531	0.259	1.611	1.817
	[-1.20]	[-1.58]	[-0.54]	[-1.29]		[0.27]	[0.11]	[0.90]	[1.06]
Microstructure Control Variables					**Microstructure Control Variables**				
Log Market Capitalization	0.453**	0.350	0.375*	0.259	Log Market Capitalization	0.208	0.222	0.154	0.163
	[2.21]	[1.46]	[1.85]	[0.87]		[1.08]	[1.15]	[0.76]	[0.81]
Log Trading Volume	3.085*	3.367**	3.440**	3.791***	Log Trading Volume	1.112	0.964	1.218	1.078
	[1.96]	[3.16]	[2.06]	[3.72]		[1.17]	[1.00]	[1.25]	[1.09]
Log Number of Trades	-4.129**	-4.216***	-4.284**	-4.419***	Log Number of Trades	-0.945	-0.795	-0.847	-0.697
	[-2.47]	[-3.88]	[-2.44]	[-3.97]		[-0.98]	[-0.82]	[-0.83]	[-0.68]
Log Average Market Trade Size	-1.015	-1.327	-1.555	-1.933**	Log Average Market Trade Size	0.386	0.501	0.129	0.232
	[-1.04]	[-1.65]	[-1.53]	[-2.64]		[0.55]	[0.69]	[0.19]	[0.32]
Log Market Volatility	0.233	0.263	0.332	0.377	Log Market Volatility	0.421*	0.420*	0.508**	0.503**
	[1.15]	[0.89]	[1.62]	[1.19]		[2.06]	[1.99]	[2.57]	[2.63]
Country Control Variables					**Country Control Variables**				
Log GDP per capita	1.143	1.751	-0.0226	0.315	Log GDP per capita	-0.801	-0.941	-2.176	-2.194
	[0.53]	[0.97]	[-0.01]	[0.19]		[-0.30]	[-0.36]	[-0.89]	[-0.91]
Observations	1972	1972	1768	1768	Observations	1972	1972	1768	1768
R-squared	0.066	0.069	0.053	0.058	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		Model 1	Model 2	Model 3	Model 4
	Public Enforcements	All Jointly	Without US	Without US		Public Enforcements	All Jointly	Without US	Without US
Constant	-103172001.0***	-72595518.3***	-111253413.9***	-70441538.7***	Constant	-95655429.8***	-98045192.1*	-105967046.3***	-104129619.5**
	[-3.83]	[-3.45]	[-3.82]	[-3.44]		[-3.69]	[-2.30]	[-3.71]	[-2.41]
HFT Dummy	**-4188307.1****	**-3676615.0****	**-4074299.7****	**-3769506.1****	**Co-Location Dummy**	**184807.0**	**277601.4**	**-571114.6**	**-596132.5**
	[-2.53]	**[-2.25]**	**[-2.47]**	**[-2.20]**		**[0.35]**	**[0.49]**	**[-0.96]**	**[-0.79]**
Law/Legal Index					**Law/Legal Index**				
Total Trading Rule Index		134245.1*		137355.7*	Total Trading Rule Index		254346.5*		330460.7*
		[1.95]		[1.81]			[2.20]		[2.21]
Surveillance		-163682.4*		-255523.1***	Surveillance		-118395.8		-362857.3*
		[-1.72]		[-3.39]			[-0.79]		[-2.25]
Public enforcement	41891.2	-75562.2	47854.2	-92680.5	Public enforcement	84370.1*	67886.9	84176.4*	21960.8
	[0.90]	[-1.17]	[0.99]	[-1.47]		[1.93]	[1.03]	[1.88]	[0.43]
Public enforcement	2743201.5	3572288.5	3677889.6	5383160.3	Public enforcement	4260655.1	6436522.7	5364271.0	12009541.0*
	[0.59]	[1.09]	[0.75]	[1.37]		[0.92]	[1.56]	[1.12]	[1.94]
Efficiency of the Judiciary	-1198518.9	-154636.9	-1592649.9	-806634.5	Efficiency of the Judiciary	-1464032.6	-2595373.8**	-1941223.8	-4889863.8*
	[-0.86]	[-0.17]	[-1.09]	[-0.73]		[-1.03]	[-2.54]	[-1.32]	[-2.24]
Rule of Law	-4561445.3*	2024563.9	-5750568.0**	2415713.9*	Rule of Law	-2304614.6	-1139467.3	-4019356.2*	-1900241.1
	[-1.94]	[1.59]	[-2.14]	[1.79]		[-1.44]	[-0.35]	[-1.90]	[-0.53]
Microstructure Control Variables					**Microstructure Control Variables**				
Log Market Capitalization	1566533.3**	1933542.8**	1536220.6**	1940211.0**	Log Market Capitalization	1811021.6**	1847302.0	1759119.4**	1795215.5
	[2.18]	[2.39]	[2.14]	[2.37]		[2.42]	[1.40]	[2.38]	[1.41]
Log Trading Volume	236482.9	238392.5	138900.2	199753.4	Log Trading Volume	-378450.1	-784342.9	-459036.4	-1016688.9
	[0.37]	[0.37]	[0.22]	[0.29]		[-0.63]	[-1.08]	[-0.73]	[-1.32]
Log Number of Trades	948176.8	-179703.0	1209211.1	-131447.8	Log Number of Trades	1218873.1	1632332.7*	1493774.6*	2090916.8**
	[1.08]	[-0.21]	[1.31]	[-0.15]		[1.45]	[2.22]	[1.68]	[2.60]
Log Average Market Trade Size	-1540901.2***	73899.2	-1501727.6***	80006.8	Log Average Market Trade Size	-353686.5	-39084.3	-364850.9	45769.7
	[-2.87]	[0.20]	[-2.87]	[0.19]		[-1.23]	[-0.11]	[-1.18]	[0.14]
Log Market Volatility	669041.6	644072.6	642496.1	644628.2	Log Market Volatility	683389.0	681500.7	603221.5	582539.4
	[1.30]	[1.46]	[1.24]	[1.46]		[1.30]	[1.70]	[1.14]	[1.52]
Country Control Variables					**Country Control Variables**				
Log GDP per capita	9427670.2***	702789.0	11099040.5***	741621.4	Log GDP per capita	5575928.1**	5193340.3	8027994.0**	7953151.0
	[2.59]	[0.46]	[2.68]	[0.46]		[2.37]	[1.14]	[2.57]	[1.33]
Observations	1972	1972	1768	1768	Observations	1972	1972	1768	1768
R-squared	0.165	0.159	0.166	0.159	R-squared	0.157	0.159	0.159	0.162

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 A3.2, and shown graphically in Figures A3.1 and A3.2. 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 A3.2 and Figures A3.1 and A3.2 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 A3.3 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 A3.3 and A3.4 illustrate a similar story.

[Insert Tables A3.3 and Figures A3.3 and A3.4 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 A3.4 list the proximity hosting/co-location offer time for exchanges used in our study.

[Insert Table A3.4 About Here]

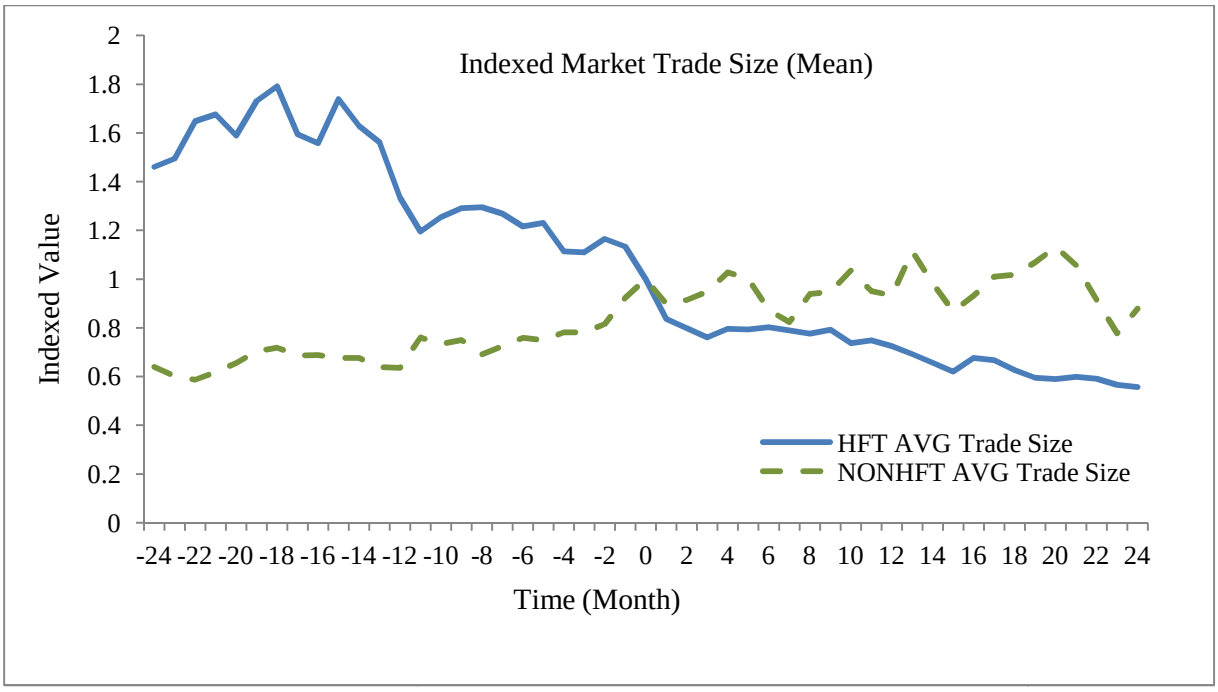

Figure A3.1: Plot of indexed of market average trading size. Mean of the market average trading size(AVG) of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare 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.

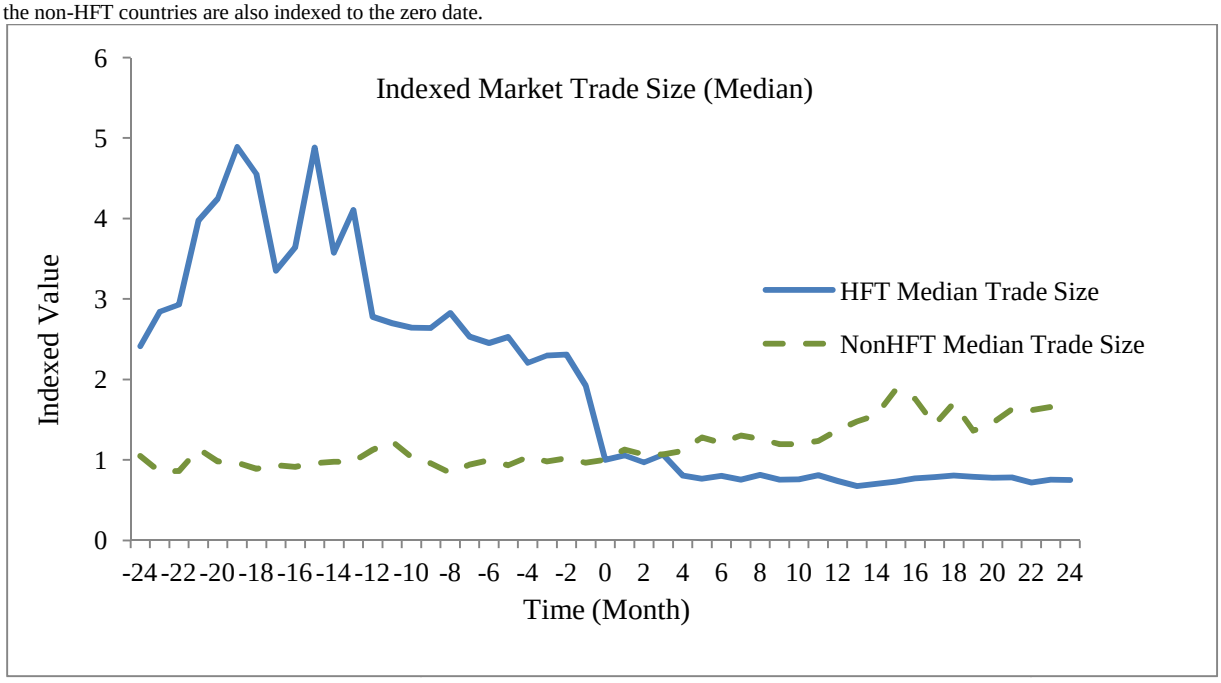

Figure A3.2: Plot of indexed of market average trading size. Median of the market average trading size of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of HFT in a particular country to compare 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.

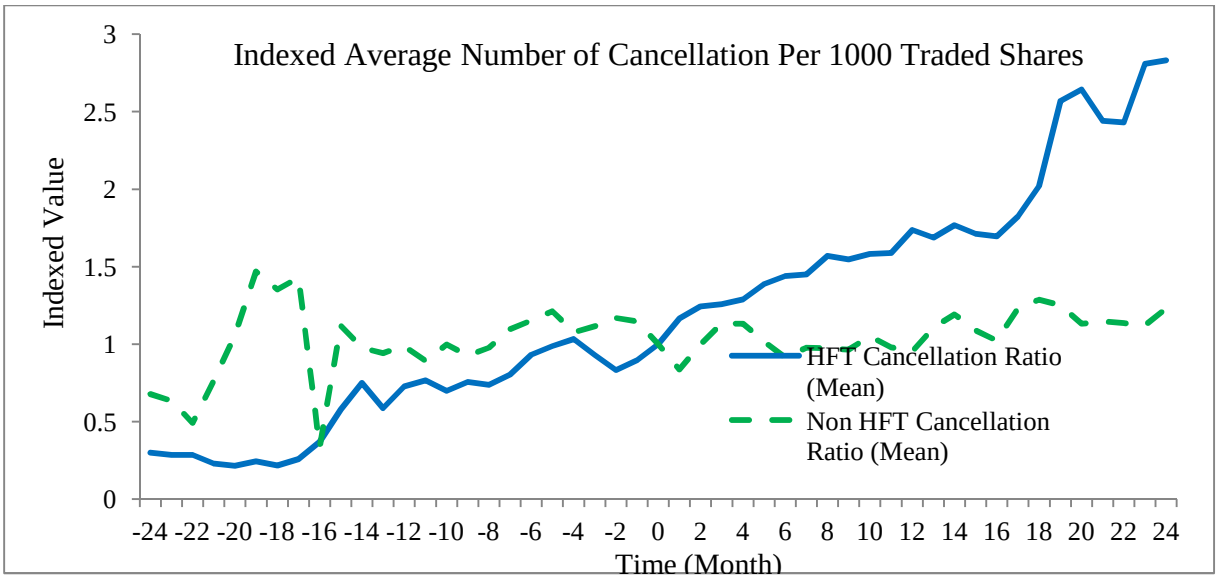

Figure A3.3: Plot of indexed value of number of cancellations per 1000 traded shares(cancellation ratio). Mean value of cancellation ratio of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time of 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.

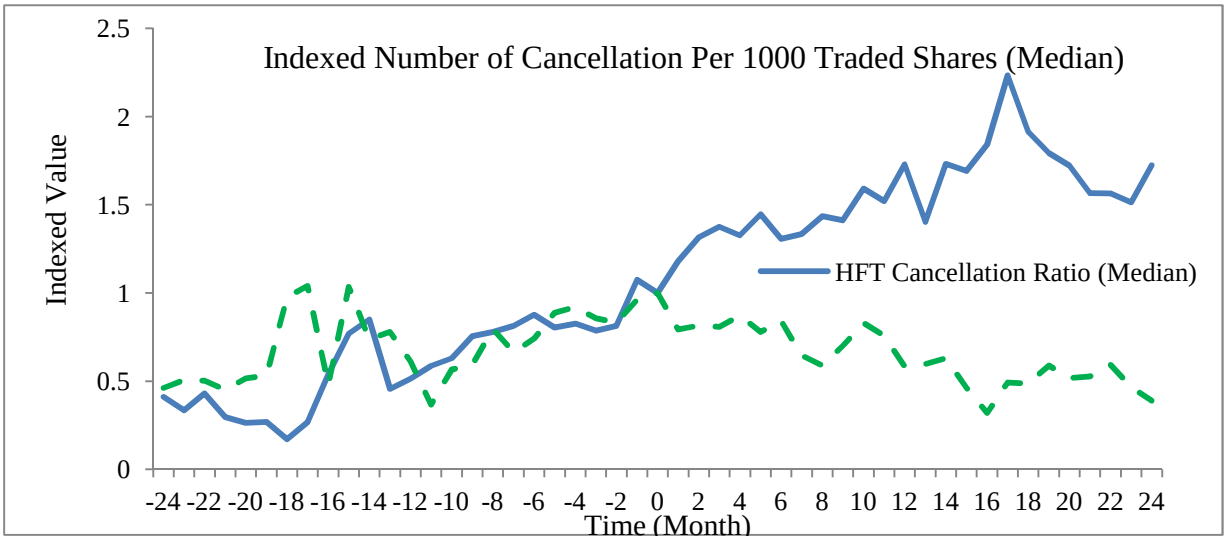

Figure A3.4:: Plot of indexed value of number of cancellations per 1000 traded shares(cancellation ratio). Median value of cancellation ratio of HFT countries and non-HFT countries are showing here. The values for HFT countries are presented surrounding the date 0, which is indexed to the start time 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 A3.1: 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 A3.2 : 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 A3.3 : 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 A3.4: : 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

CHAPTER 4

Individualism, Synchronized Stock Price Movements, and Stock Market Volatility

"If we learn anything from the history of economic development, it is that culture makes almost all the difference."
-David Landes (2000:2)[17]

4.1 Introduction

Financial markets in emerging countries can be characterised with both a high number of synchronized stock price movements and a high level of stock market volatility. Morck, et al. (2001) find highly synchronized stock price movements are more common in poor economies than that in rich economies. More importantly, they document that these synchronized stock price movements cannot be explained by the argument that firms in poor economies or emerging countries have more correlated fundamentals. Synchronized stock price movements, do not reflect firm-specific information, will have an effect on investors' diversification strategies and increase stock market volatility.

Some volatility is good for the economy and investors but excess volatility will affect the overall level of investments and increase the risk of individual investors (Du and Wei, 2004; Bartram, et al, 2012). This is an important issue for international investors. For example, synchronized stock price movements could increase the systematic risk of individual stocks and affect the diversification strategy of the portfolio. In general, emerging markets tend to have higher levels of overall stock market volatility compared to developed markets. Calculating the monthly stock market volatility as the standard deviation of daily returns within the month, the Chinese stock market is 127% as volatile as the Canadian stock

[17] Landes, D. (2000). Culture makes almost all the difference. In: Harrison, L. E., Huntington, S.P. (Eds.), Culture Matters. NewYork, NY.

market. The Hungarian stock market is 167% as volatile as the stock market in United Kingdom (UK). Nevertheless, there is also a notable difference in monthly stock market volatility within developed markets. For example, the monthly volatility in the UK stock market is 20% higher than that of the United States (US)[18].

The central objective of this paper is to measure the role of investor behavior bias in explaining the difference in synchronized stock price movement and in the overall stock market volatility across different nations. More specifically, I test the hypothesis of whether national culture has any influence on individual financial decisions and thus has an impact on the national stock market volatility. First, I seek to determine whether synchronized stock price movements are more common among countries that have lower values of individualistic culture compared to countries that have higher values of individualistic culture. Then, I test the hypothesis of whether synchronized stock price movements have an impact on stock market volatility.

Prior literatures (Trians, 1995; Bonetempo et al., 1990) have documented that national cultures have an influence on human behavior and investors in a collectivism culture are more likely to follow social pressures and conform to social norms. In this sense, synchronized stock price movements should be more prominent in nations with less individualistic culture.

The empirical results are in line with the previous predictions. Through the examination of synchronized stock price movements and stock market volatility in 47 countries around the world over the period of January 2003 to May 2012, I find that nations with lower values of individualistic culture (or higher value of collectivistic culture) are more likely to have a higher number of synchronized stock price movements. Furthermore, this highly correlated number of stock price movements increases the stock market volatility in the country. On the other hand, nations with high individualistic culture (or lower

[18] I compare the overall stock market volatility based on the summary statistics in Table 4.2 Panel B.

value of collectivistic culture) have a lower number of synchronized stock price movements, and thus have lower levels of stock market volatility.

More specifically, in the most conservative estimates, one standard deviation difference in individualistic value could lower the monthly average synchronized stock price movements by 8.20% (Table 4.5, Panel A, Model 5). For example, synchronized stock price movements are 17.16% lower in the United Kingdom, one of the countries with the high value of individualistic culture, in comparison to that of the Turkey, one of the countries with low value of individualistic culture. Similarly, the average monthly synchronized stock price movements are 4.62% lower in Poland than in Japan due to the difference in culture value.

In terms of stock market volatility, one standard deviation increase in the number of synchronized stock price movements will lead to an increase of average monthly stock market volatility by 28.15% in the simple measure (Table 4.6, Panel A, Model 5). The differences in the synchronized stock price movements between Turkey and United Kingdom leads to a 29.02% of higher average monthly volatility in Turkey than the average monthly volatility in United Kingdom. Similarly, the average monthly volatility is 4.53% lower in Poland than in Japan due to the difference in number of synchronized stock price movements.

This paper contributes to the existing literature in a variety of ways. First, this paper links the national culture with individual investor behaviours – herding– across country. (e.g. see Welch (1992), Banerjee (1992) and Bikhchandani et al. (1992) and Christie and Huang (1995) as these studies provide theoretical models on herding behavior, where rational individual investors observe the behavior of other investors and decide to imitate the behavior of others regardless of their own personal information.) Data used in this paper covers 47 nations encompassing a period of nine years.

Second this paper provides new insights on why emerging markets tend to have higher stock market volatility. The empirical results indicate that a portion of the difference in the overall market level

volatility across countries can be attributed to the investor bias in different cultures. After controlling for legal, economic and market differences, the results remain both economically and statistically significant. Investors in nations with lower individualistic culture are more likely to follow each other (Bontempo et al., 1990; Triandis, 1995). This conformity to unity reinforces one each other and has significant positive effect on the market level volatility. This effect is stronger in nations with lower individualistic culture rather than simply the result of the level of economic development of those countries.

The rest of the paper is organized in the following manner. Section 4.2 develops the hypotheses on national culture, synchronized stock price movements, and stock market volatility. The data and methodology are introduced in Section 4.3. Section 4.4 presents the univariate comparison and Section 4.5 provides the multivariate analyses of the relation between national culture and synchronized stock price movements, and between synchronized stock price movements and stock market volatility. Concluding remarks follow in the last section.

4.2. Literature Review and Hypotheses Development: Individualism, Synchronized Stock Price Movements, and Stock Market Volatility

Hofstede (1980, 2001, and 2005) introduces six dichotomous cultural dimensions: 1) individualism versus collectivism (IDV), 2) power distance (PDI), 3) uncertainty avoidance (UAI), 4) masculinity versus femininity (MAS), 5) long-term versus short-term orientation (LTO) and 6) indulgence versus restraint (IVR) as proxies for national culture[19]. Among these six dimensions, individualism versus collectivism (IDV) is one of the most widely used in finance and international studies. For example, Chui et al. (2010) find that investors in a nation with high values of individualistic culture trade more which lead to a lower returns. Eun et al. (2012) also show that national cultures have an impact on stock co-

[19] Hofstede (1980, 2001, 2005) first introduced four cultural dimensions in his 1980 publications: 1) individualism versus collectivism (IDV), 2) power distance (PDI), 3) uncertainty avoidance (UAI), 4) masculinity versus femininity (MAS). In the later publication, he included two additional culture dimension follow the research done by Michael Bond and his colleagues: 5) long-term versus short-term orientation (LTO) and 6) indulgence versus restraint (IVR). Detailed explanations and definitions as well as the value for each dimension can be found at Hofstede's website at: http://geert-hofstede.com/.

movements and increase individual stock return variations. This paper will mainly focus on this dimension of culture as well.

The difference between collectivism and individualism can be categorized in the following: first, collectivism focuses on interdependency with others while individualism emphasises independence from others (Markus and Kitayama, 1991; Reykowski, 1994; Triandis, 1995). Second, collectivism puts group goals ahead of personal desire whereas individualism behaves solely on personal needs (Miller, 1994; Triandis, 1994, 1995). In a collectivistic culture, people are more susceptible to pressures from social influences and enjoy doing what is expected of them to do (Hui and Triandis, 1986; Bontemop, Lobel and Triandis, 1990; Gudykunst, 1993; Triandis, 1995).

Many researchers have found that individualistic cultures value "autonomy, independence and self-reliance" and collectivistic cultures emphasise "conformity to others", "norm", "harmony" (Triandis, 1989, Triandis, Marin, Lisansky and Betancourt, 1984). In terms of financial markets, investors in a nation with lower value in individualistic culture are more likely to imitate the behavior of others therefore nation with lower value of individualistic culture tend to have higher numbers of synchronized stock price movements. The discussion above leads to my first hypothesis:

- **Hypothesis 4.1: Synchronized stock price movements are more prominent for countries that have lower value of individualistic culture than for countries that have higher value of individualistic culture.**

Early studies of synchronized stock price movements among different countries mainly focus on the differences in economic development between countries. Morck, et al. (2000) find that stock prices are more likely to move in the same direction in poor economies in comparison to rich economies. This synchronization of stock price movement is not thought to be because firms in poor economies or emerging countries have more highly correlated fundamentals but rather because property rights and investor protection are weaker in such emerging countries.

It is commonly believed that emerging countries have weaker law and legal protection compared with those of developed markets. La Porta, et al. (1998, 2006) compare the overall investor protection among different countries from a legal perspective and find the difference in investor protection could explain why emerging countries have less developed equity market.

National cultures influence the behavior of individuals. many studies have shown that people in a collectivistic culture are more vulnerable to social influences and have the tendency to follow social norms (Hui and Triandis, 1986; Bontempo, et al., 1990; Gudykunst, 1993; Triandis, 1995). In this case, a higher number of synchronized stock price movements in a nation with collectivistic culture may be expected as investors in these nations are more likely to follow the trend and are more likely to be influenced by social forces.

Several studies have found that various social forces such as news, media and past earnings announcements greatly influence investors' investment decisions (Odean, 1998, Barber and Odean 2008). Lou (2014) shows that there is a positive correlation between advertising spending and abnormal stock returns. Mao, et al. (2011) show that Twitter can be a leading indicator of investor sentiment for the financial market. In a study of the behavior of Dow Jones Industrial Average (DJIA) movement, Donaldson and Kim (1993) find that once the DJIA passes a key reference point, such as 3000, it moves up or down more than usual. Measuring investor behavior by the number of stock prices moving in the same direction, I find in this paper that investors in a nation with lower value of individualistic culture are more likely to imitate the behavior of other investors.

"Follow the trend" or herding behavior has also been widely studied in the finance literature. It is not the purpose of this paper to study how herding happens but several theoretical and empirical studies may reveal some insight on the mechanism of herding (see Welch (1992), Banerjee (1992) and Bikhchandani, et al. (1992) and Christie and Huang (1995)). Frott, et al. (1992) argue that bad portfolio managers intimate the behavior of good portfolio managers in order to avoid loss of reputation. Maug and

Naik (2011) show that some portfolio managers simply herd the benchmark in order to reduce the risk of deviating too far away from it.

Trueman (1994), Cooper, et al. (2001) and Welch (2000) illustrate with empirical evidence the herding behavior of security analysts. Other studies have also found the existence of herding behavior among mutual funds managers (Wermers, 1999; Brown et al, 2013), and institutional investors (Nofsinger and Sias, 1999; Sias, 2004). More recently, studies in non-US markets have revealed that herding activities are common in other markets as well. Walter and Weber (2006) provide evidence of herding activities and positive feedback behavior of German mutual funds managers. Wylie (2005) finds that UK funds managers herd both the largest and smallest stocks. Kim and Nofsinger (2005) argue that herding activities in Japan have a significant impact on the stock prices in the Japanese stock exchange. Although many studies on herding behavior have mainly focused on the developed markets, Chiang, et al. (2011) and Lao and Singh (2011) also find evidence of herding in emerging markets, particularly in the Chinese and Indian stock markets. Besides stock markets, herding behavior has also been observed in other areas as well. For example, studies have found herding in housing markets and in foreign exchange markets ((Frankel and Froot, 1986, Allen and Taylor, 1986).

Herding behavior could have an impact on the stock market volatility. Venezia, et al. (2011) find that both amateur and professional investors herd stocks and this herding behavior is positively related with stock market volatility. More importantly, they find that herding causes market volatility in a Granger causality test. Based on the above discussion, if investors in collectivistic culture have a tendency to intimate other investors' behavior, we should observe higher synchronized stock price movements. These synchronized stock price movements will enforce each other and thus, in turn, lead to higher stock market volatility. This discussion leads to my second hypothesis:

- **Hypothesis 4.2: Stock Market Volatility is higher for countries that have lower value of individualistic culture than for countries that have higher value of individualistic culture because the number of synchronized stock price movements are higher in countries with lower value of individualistic culture.**

Other studies have shown that various factors may be able to explain the difference in stock volatility between emerging markets and developed markets. Du and Wei (2004) find that insider trading activities in different countries can explain the differences in stock market volatility among different countries. Bae, et al. (2004) find that investability of the stock in emerging markets is positively correlated with stock market volatility. Chui, et al. (2010) reported investor bias measured by overconfidence is positively associated with stock market volatility. While controlling for the above mentioned factors, I find in this paper that synchronized stock price movements are positively and significantly related with the stock market volatility. Especially in emerging markets, highly synchronized stock price movements reinforce one another and thus increase the overall level of stock market volatility.

This research also builds upon existing literature on behavioural finance. Many studies have shown that stock market puzzles and anomalies cannot simply be explained by traditional finance theories. For example, French (1980) finds strong evidence that on Mondays, the average stock returns are negative. Cross (1973) finds that the stock price change from Friday to the following Monday is significantly different from the changes among the rest of the week. Others, Kamstra, et al (2000, 2003) find that depression and daylight savings have impact on the functioning of financial markets. This paper extends the literature and shows that national culture has an impact on investors' behavior. This behavior, in turn, affects the overall level stock market volatility.

4.3. Data and Methodology

The data used in the paper comprise 47 countries that are available through Thomson Reuters DataStream over the period from January 2003 to May 2012. The definitions and source of the variables used in the analysis are provided in Table 4.1. The main dependent variables are the number of synchronized stock price movements and stock market volatility.

Measure of synchronized stock price movements are from DataStream Global Equity Indices. DataStream Global Equity Indices provide equity indices for 53 countries in their local currency. The sample stocks in each country index covers around 80% of total market capitalization. One of the advantages of DataStream Global Equity Indices is it tracks the number of stock price moving up/down within the index on a daily basis. Following the methodology used by Morck, et al. (2000), I define the synchronized stock price movements as the fraction of stock price movement in the same direction. Number of falls/rises is defined as the number of the stocks whose closing price is lower/higher than the closing price on the previous day. I calculate both mean and median monthly synchronized stock price movements as the average and median daily fraction of stocks that move in the same direction within a given month.

$$\text{Synchronized Stock Price Movements (Mean)} = \frac{1}{T}\sum_t \frac{Max(n_{jt}^{Up}, n_{jt}^{Down})}{n_{jt}^{Up}+n_{jt}^{Down}}$$

$$\text{Synchronized Stock Price Movements (Median)} = \text{median}\left(\frac{Max(n_{jt}^{Up}, n_{jt}^{Down})}{n_{jt}^{Up}+n_{jt}^{Down}}\right)$$

Monthly stock market volatility in each country is defined as the standard deviation of daily return within the month. Stock market volatility is calculated based on the Morgan Stanley Capital International (MSCI). MSCI provides country indices for 23 developed countries and 27 emerging countries. The combined market capitalisation of companies in these indices represents around 85% of the market capitalisation in each country. After match the synchronized stock price movements and stock market volatility, final dataset used in this study contain a total of 47 countries in which 23 countries are defined as developed market and 24 countries are defined as emerging market by MSCI.

I also use Hofestede's (2001, 2005) cultural dimensions: individualism versus collectivism (IDV), power distance (PDI), uncertainty avoidance (UAI), masculinity versus femininity (MAS), long-term versus short-term orientation (LTO) and indulgence versus restraint (IVR) as a proxies for national culture. However, this study mainly focuses on one dimension of culture: individualism versus collectivism (IDV). Higher value in the individualism versus collectivism index means higher value of

individualistic culture (lower value of collectivistic culture). Nevertheless, I have tested other cultural dimensions in this study and the main results still hold.

[Insert Table 4.1 Here]

Several economic and market level variables for each country are also considered in this paper. The domestic market capitalizations at end of each year are measured as the market capitalization of listed companies. Stock traded is measured as the total trade value in current US$ for each country. Both stock market capitalization and stock traded as well as several economic indicators such as GDP per capita, import and export, foreign direct investment and current account balance are from World Bank's publication World Development Indicators 2012. Du and Wei (2004), and Chu, et al. (2010) find that exchange rate volatility is positively associated with stock market volatility. Similarly to the definition of stock market volatility, I define the monthly exchange rate volatility as the standard deviation of the nominal daily exchange rate with respect to US$ within the month. The exchange rate data is from MSCI on DataStream as well.

As additional control variables, I also obtain a series of exchange regulation, law and finance indices. I mainly focus on the Insider Trading index as Du and Wei (2004) indicates a strong influence of insider trading on stock market volatility. In addition, through the examination of suspected insider trading in 22 stock exchanges over 17 countries, Cumming, Zhan and Aitken (2012a) find that exchange regulations over time and across market have significantly reduced the number of suspected insider trading cases. The insider trading index used in this paper is from La Porta et al. (1998. 2006). Other legal indices were also considered but they did not impact the empirical tests reported in this paper such as updated anti-director index from Spamann (2010) as well as enforcement index from Jackson and Roe (2009) and exchange trading rule indices from Cumming, et al. (2012a). However, they did not impact the empirical tests reported in this paper and therefore excluded for conciseness.

I also obtain the property right index from Heritage foundation. Morck, et al. (2000) find that weaker property rights protection right is the reason for higher number of synchronized stock price movements in emerging economies. In their study however, the government index used is a sum of three different indices in La Porta, et al (1998): 1) government corruption index, 2) the risk of expropriation of private property by the government, and 3) the risk of the government repudiating contracts. Heritage Foundation's property rights index provides a more thorough continuous measure of property rights protection over 100 countries from 1995 to 2012. I believe this property rights index provides a more direct measure of property rights protections.

[Insert Table 4.2 Here]

Table 4.2 provides descriptive statistics for full sample (Panel A) as well as for country average on Individualism index, stock market volatility and synchronized stock price movements (Panel B). Panel A in Tables 4.2 indicates that the average (median) volatility is 1.58 (1.32) per month, with a range from minimum 0.31 to maximum of 10.92. On the national average (Panel B), the lowest volatility is 0.8979 in Malaysia and the highest volatility is 2.3556 in Turkey.

The average (median) synchronized stock price movements for the whole dataset is 0.6570 (0.6559) per month with a range from minimum 0.05 to maximum of 0.8649 when the synchronized stock price movements are defined as the average daily stocks that move in the same direction within a given month. For the median number of synchronized stock price movements, the average (median) is 0.6686 (0.6599) with a range from minimum 0 to maximum of 1. The national average (median) synchronized stock price movements range from minimum 0.6321 (Ireland) (0.6137 (New Zealand)) to maximum of 0.7248 (Turkey) (0.7196 (Sweden)). The average (median) individual index is 48.96 (48) with a range from minimum 12 (Venezuela) to maximum of 91 (United States) with missing values for South Africa and Sri Lanka.

4.4. Univariate Tests

Table 3 provides a comparison of means and medians tests of for synchronized stock price movements as well as for stock market volatility in relation to different cut off values, which are the median value of individualism index for comparison of synchronized stock price movements and the median value of synchronized stock price movements for the stock market volatility.

[Insert Table 4.3 Here]

Panel A of Table 4.3 reports difference in means and medians of two synchronized stock price movements measure for the full sample of all countries in the data. The mean (median) value of synchronized stock price movements (measured at the mean value) are 0.6457 (0.6430) for countries with higher individualistic culture and the mean (median) value are 0.6688 (0.6680) for countries with lower individualistic culture. The mean (median) value of synchronized stock price movements (measured at the median value) are 0.6538 (0.6435) for countries with higher value in individualism index and the mean (median) value are 0.6844 (0.6771) for countries with lower value in individualism index. The results show that the difference in both mean and medians are significant at the 1% level regardless of which measure of synchronized stock price movements used. The results indicate that countries with lower individualistic culture (high collectivistic culture) are more likely to have a higher number of synchronized stock price movements.

Table 4.3 Panel B shows that the average (median) value for volatility is 1.9066 (1.6125) for markets with higher number of synchronized stock price movements and the average (median) value for volatility is 1.2498 (1.09183) with lower number of synchronized stock price movements. Synchronized stock price movements used here is measured as the average value of number of stocks moving together. The results are similar when I use the median value of number of stocks moving together as the

measurement for synchronized stock price movements. The average (median) value for stock market volatility is 1.9226 (1.6297) with higher number of synchronized stock price movements and the average (median) value for stock market volatility is 1.2348 and 1.0832 with lower number of synchronized stock price movements. The difference in both mean and median for both measures are significant at 1%. This difference in values suggests that stock markets are more volatile when there are higher numbers of synchronized stock price moves in the same direction.

Overall, these comparison tests support the view that national culture has influence on individual trading behavior. Measuring individual trading behavior as number of synchronized stock price movement, nations with low individualistic culture/higher collectivistic cultures tend to have a higher number of stocks moving together and nations with higher individualistic culture/lower collectivistic culture tend to have a lower number of stock moving in the same direction.

The comparison results also support the view that the stock market is more volatile when we have higher fractions of stocks that move together. In other words, stock markets are more volatile when numbers of synchronized stock price movements are high. However, this type of univariate comparison is not fully informative since I have not yet controlled for other factors to be equal, particularly both economic and market condition in terms of wealth and market depth that differs across countries. In my empirical tests in the next section, I include variables in order to isolate the unique marginal impact of culture's influence on trading behavior and in turn on stock market volatility. Moreover, I also consider different robustness checks with alternative explanatory variables, with/without observations from the US, instrumental variables, as well as different time period, among other things discussed below.

Table 4.4 presents a correlation matrix for the main variables used in the multivariate tests provided in the next section. The correlation highlights similar trends as in the comparison tests. From table 4, I noticed that the correlations among several variables are high in which collinearity is potentially

problematic for regression analyses, and as such I present alternative specifications with and without collinear variables in the regression.

[Insert Table 4.4 Here]

4.5. Multivariate analyses

In this section, I conduct empirical tests showing that the national culture dimensions (mainly individualism) can explain stock market movement even by controlling for other legal, economic and market factors. More specifically, I run eight regression including three repeat models without the data from the US for synchronized stock price movements as the dependent variable. I run ten regressions including two repeat models on financial crisis period with emerging markets alone and non-emerging markets alone, and three repeat models without the data from the US for testing the stock market volatility. All regressions are controlled for both country and month clusters. I have also tested two-way clustering by country and year, and the results still hold.

4.5.1.Primary Results for Synchronized Stock Price Movements

Following the similar argument in Morck, et al. (2000), the basic stock price synchronicity measures are unsuitable as dependent variables in the regressions because they are bonded with the interval [0.5, 1]. To correct this, I have followed the standard econometric methodology and applied logistic transformation as the following:

$$\text{Logistic Transformation of Synchronized Stock Price Movements } (f) = \log\left(\frac{f-0.5}{1-f}\right)$$

To investigate the effect of national culture on two measures of synchronized stock price movement, I estimate the following regression

$$Sync_{i,t} = \beta_0 + \beta_1 Indv_i + \beta_2 Property_{i,t} + \beta_3 Corruption_{i,t} + \beta_4 X_{it} + e$$

where the subscripts i represent different country and t represent month. I cluster the residuals by both country and month (Petersen, 2009). The dependent variable here is the logistic transformation of synchronized stock price movements (Sync). The independent variables included the individualism index (Indv), Property right and corruption index, as well as economic and market control variables (X).

Panel A and B of table 4.5 illustrate the regression results. The dependent variable in Panel A is the logistic transformed synchronized stock price movement measured as the mean value of fraction of stock moving together within the month. The dependent variable in Panel B is synchronized stock price movements measured as the median value of fraction of stock moving together within the month. In each of Panels A and B, I present five identical regression plus three repeated models on subset of dataset without the value from the US to show the robustness to alternative specifications. Model 1 tests the overall synchronized stock price movement in relation with individualism index. Model 2 shows the results with controls on economic and market factors. Model 3 shows a result with an emerging market dummy. Model 4 shows the results of both property right index, corruption index with control of economic and market factors. Model 5, tests different dimensions of culture factors together to show that individualism is the dominant cultural dimension among the six dimensions in explaining stock market synchronicity. Finally, model 6, 7, 8 present a repeat test of model 1, 2, 5 without the data from the US, respectively.

The results in Table 4.5 Panel A consistently indicate that national culture with higher individualism value are significantly negatively related to the number of fraction stock moving together. The effect is significant at the 1% level for all models except model 4 at the 10% level with different legal indices. As mentioned before, all legal indices are highly correlated with the individualism index as well as among themselves. Similar results can be seen in the Panel B of Table 4.5. The effects of national culture with higher individualism value are negatively related to the number of the fraction stock moving together are at least at 5% on all models regardless the choice of control factors.

[Insert Table 4.5 Here]

Even in the most conservative estimates, one standard deviation difference in individualistic value could lower the monthly average synchronized stock price movements by 8.20[20]%. More specific, the number of synchronized stock price movements is 17.10[21]% lower in the United Kingdom, one of the countries with the high value of individualistic culture, in comparison to that of the Turkey, one of the countries with low value of individualistic culture. Similarly, the average monthly synchronized stock price movements are 4.62[22]% lower in Poland than in Japan due to the difference in culture.

Beside the main variable in interest, the individualism index, the results in Table 4.5 also indicate that countries with higher protection of property rights have significantly lower numbers of synchronized stock price movement. The result is not surprising since Morck, et al.(2001) find that the good government index is significantly negatively related to synchronized stock price movements even after control for economic and market factors. In their view, greater respect for private property rights has a negative impact on stock price synchronicity. High correlation between the good government index and individualism index may be expected. Several studies have shown that individualism cultures respect people's privacy, space and favours progress and technological innovation (Tridans, 1995). Schooler (1990a, 1990b) argues that individualism emerges when property right are attached to individual. Stulz and Williamson (2003) find that national culture influences the legal system as well.

Otherwise, I find that market with higher stock market capitalization has lower number of synchronized stock price movements. However, higher trading measured by the value of total stock traded, have positive impact on stock market synchronizations.

20 -0.00330*24.85=-0.0820

21 -0.00330*(89-37)=-0.1716

22 -0.00330*(60-46)=-0.0462

4.5.2. Primary Results for Stock Market Volatility

To investigate whether the synchronized stock price movements have an impact on the national stock market volatility, I estimate the following regression

$$Volatility_{i,t} = \beta_0 + \beta_1 Sync_{i,t} + \beta_2 Indv_i + \beta_3 X_{it} + e$$

where the subscripts i represent different country and t represent month. I also cluster the residuals by both country and month (Petersen, 2009). The dependent variable is the monthly volatility. Monthly volatility is defined as the standard deviation of daily stock returns within the month. The independent variables included two measures of synchronized stock price movements (Sync), the individualism index (Indv), as well as economic and market control variables (X).

Panel A and B in Table 4.6 report regression for the stock market volatility. Panel A examines the relationship between synchronized stock price movements measured as the average fraction of the stock price moving together and stock market volatility and Panel B examines the relationship between synchronized stock price movements measured as the median value of fraction of the stock price move together and stock market volatility. Similar to both Panels in Table 4.5, I present five identical regressions plus three repeated model on subset of dataset without the value from the US to show the robustness to alternative specifications. Model 1 tests the overall stock market volatility in relation with the stock market synchronicity. Model 2 shows the results with emerging market dummy. Model 3 shows a result with control of both economic and market factors. Model 4 shows the results of both insider trading index with control of economic and market factors. Since I use logistic transformed number of synchronized stock price movements' measurement from Model 1 to Model 4, in Model 5, tests this relationship between stock market volatility and synchronized stock price movements without the logistic transformation. Model 6 and 7, test the relationship between synchronized stock movements and stock market volatility for emerging market and for non-emerging market between June 2007 to December 2008,

respectively. Finally, model 8, 9, 10 present a repeat test of model 1, 2, 5 without the data from the US, respectively.

The results in Table 4.6 Panel A and Panel B consistently indicate that countries with a higher number of synchronized stock price movements have a significantly higher level of stock market volatility regardless the legal, economic and market factors included in the regression. The effect is significant at the 1% level for all models regardless of whether I use plain measure of synchronized stock price movements or logistic transformed synchronized stock price movements.

[Insert Table 4.6 Here]

In a more directly measure (Model 5 Table 4.6), one standard deviation increase in the number of synchronized stock price movements will lead to an increase of average monthly stock market volatility by 28.15[23]% in the simple measure. The differences in the synchronized stock price movement between Turkey and United Kingdom leads to a 29.02[24]% of higher average monthly volatility in Turkey than the average monthly volatility in United Kingdom. Similarly, the average monthly volatility is 4.53[25]% lower in Poland than in Japan due to the difference in number of synchronized stock price movements.

In Table 4.6, I test whether these synchronized stock price movements have a bigger impact on the stock volatility in emerging markets than or in non-emerging markets during the financial crisis in 2007 and 2008. The results (Model 6, 7 in Table 4.6 Panel A) show that this behaviour bias significantly causes a higher level of stock market volatility in emerging markets. On the contrary, synchronized stock

23 7.233*0.0615/1.58=0.2815

24 7.233*(0.7248-0.6614)/1.58=0.2902

25 7.233*(0.6566-0.6467)/1.58=0.0453

price movements have no impact on the stock market volatility in developed markets during the financial crisis.

Beside the main variable in interest, the synchronized stock price movements, the results in Table 6 also indicate that countries with higher insider trading regulation has significantly lower stock market volatility. In their paper, "Does Insider Trading Raise Market Volatility?" Du and Wei (2004) find that more prevalent insider trading is associated with more volatile stock markets. Cumming, Zhan and Aitken (2012a) find that detailed exchange trading regulations over time and across markets significantly reduced the number of cases. In this sense, my finding is not surprising that highly regulated financial markets will result in less insider trading activities thus negatively related to the stock market volatility. Similar to the results in Du and Wei (2004) paper, I find that the exchange rate is significantly positively related to the stock market volatility at the 1% level in all models. Also, larger stock markets, measured by the stock market capitalization, are significantly negatively related to the stock market volatility. However, highly liquid markets, measured by the stocks traded, are significantly positively related to the market volatility. These results are not surprising since higher markets are often highly regulated and more liquated, thus make insider trading more difficult. On the other hand, in highly liquid stock markets, it is relatively easy for buyers and sellers to transact, thus leading to more trading and more volatile stock markets. Other control variables are either not significant at all or has mixed results depend on other control factors as well as including/excluding data from the US.

4.6. Robustness Checks

4.6.1. Alternative Measure of Stock Market Volatility

I also test the results with average weighted and market capitalization weighted stock market volatility. However, the data used here are only cover 22 exchanges around 17 countries around the world, including Australia, Canada, China, Germany, Hong Kong, India, Japan, Malaysia, New Zealand,

Norway, Singapore, South Korea, Sweden, Switzerland, Taiwan, the U.K., and the U.S. and the years January 2003 – June 2011. Similar dataset is also used in Cumming, et al. (2012a, 2012b). The results in Table 4.6A are similar to the results in Table 4.6.

[Insert Table 4.6A Here]

4.6.2.Two-Stage IV regression

In Morck, et al. (2000), the authors argue that weaker property rights protection explains high stock market synchronization in emerging markets. To ensure that the results are not driven by the emerging markets, I have performed 2 stage instrumental variable regressions. The results in Table 4.7 show this is not the case. All results indicated that nations with lower individualism values have higher stock market synchronization thus leading to higher stock market volatility.

[Insert Table 4.7 Here]

4.6.3. Time period effects

The dataset in this paper covers the period from January 2003 to May 2012 includes the financial crisis during 2007 and 2008. To ensure that my results are not driven by the extreme volatility during the financial crisis period, I have tested all models in both Table 5 and Table 6 without data from year 2007 and year 2008. My results are robust to including and excluding the financial period. I also test the results without data after June 2007 and the results are still hold. To save space, the results are not present here but available on request.

4.6.4. Others

In both Table 4.5 and 6, I have tested the result without the data from the US, the country with the highest value in the individualism index. I have also tested the results without the data from Venezuela, the country with the lowest value in the individualism index. The results still hold. The results are robust even after removing data from both the US and Venezuela.

Besides removing data from both the US and Venezuela, I also test the results by removing outliers (Turkey and Sweden for Table 4.5, and Brazil, Turkey and Malaysia for Table 4.6) to ensure that the results are not driven by outliers. The results are still hold. As mentioned in an earlier section, clustering the standard error by country and year or by year/month individually does not affect the results as well.

4.7. Conclusions

This paper examines synchronized stock price movements and the stock market volatility of 47 nations around the world from January 2003 to May 2012. By constructing a monthly panel dataset, this paper tests the hypothesis of whether a nation's culture influences individuals' trading behaviours and how this, in turn, impacts the overall stock market volatility in the country. Certain volatility is good for the country since it can contribute to shareholder wealth and economic growth. However, excess volatility could also increase individual risk thus negatively impact stock markets and economic development (Bartram, et al, 2012).

The data examined in this paper show that nations with lower levels of individualistic culture are more likely to have higher number of synchronized stock price movements and have higher levels of stock market volatility over time. On the other hand, nations with higher levels of individualistic culture are less

likely to have synchronized stock price movements and thus have lower levels of stock market volatility. Overall, I find that investor behavior bias creates excess volatility that drives stock prices away from fundamentals. This impact is strong in nations with lower individualistic culture. More importantly, this investor behavior bias increases the stock market volatility significantly during the financial crisis in emerging markets.

The result from this research could have wider implications in the investment industry. For example, portfolio diversification through investments in different industries may be less effective in nations with lower levels of individualistic culture than that in nations with higher levels of individualistic culture since stocks in nation with lower levels of individualistic culture tend to move in the same direction regardless of firm-specific information.

Overall, the results support the view that the national culture has an impact on the behaviours of individual investors and thus impact the overall stock market volatility. This research use synchronized stock market movements as a proxy for herding behaviours. Future research could focus on whether institutional investors' investment strategy or even high-frequency trading strategy offset/re-enforce this individual behavior bias and has an impact on stock market volatility. In general, this paper supports the view that national culture should be taken into consideration for the international diversification strategy.

Figures

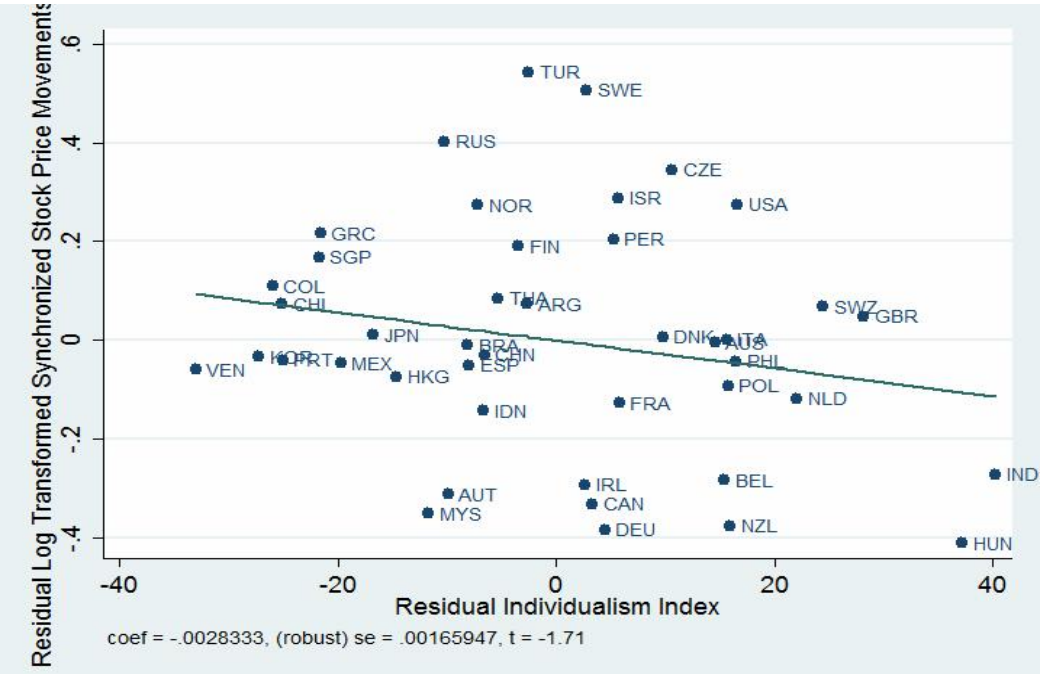

Figure 4.1.: Partial regression plot of Average logistic transformation of the fraction of synchronized stock price movements (mean) and Individualism index. The independent variables include log(GDP per Capita), log(Geographical size), log(Stock traded) and log(Market Capitalization). Both dependent variable and independent variables are averaged over the whole observation periods. Robust standard errors are clustered at country level. Country/Region name are displayed as the three letter of World Bank Country code, except Taiwan (TWN).

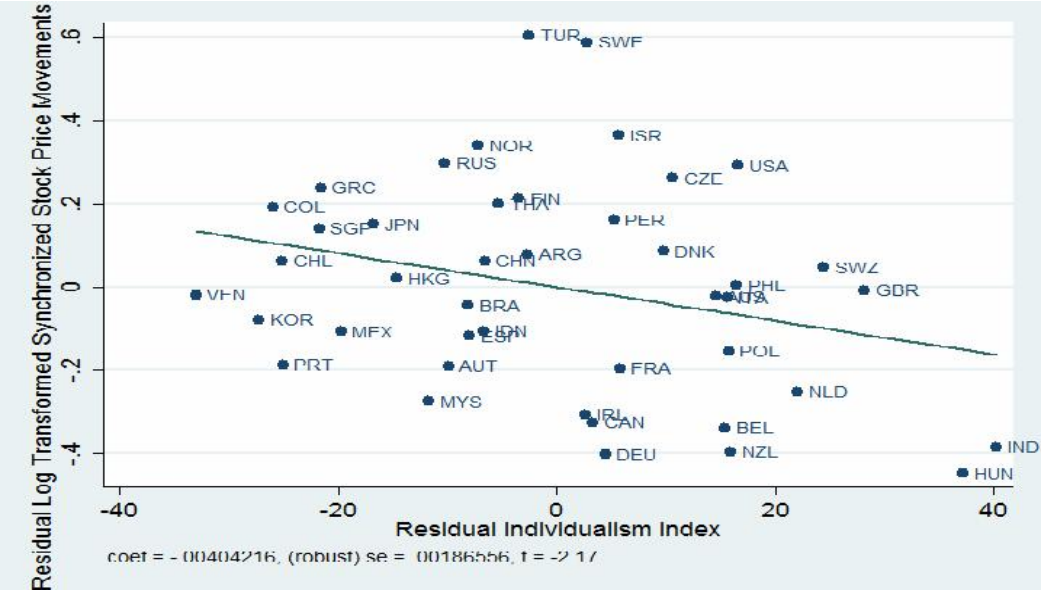

Figure 4.2.: Partial regression plot of Average logistic transformation of the fraction of synchronized stock price movements (median) and Individualism index. The independent variables include log(GDP per Capita), log(Geographical size), log(Stock traded) and log(Market Capitalization). Both dependent variable and independent variables are averaged over the whole observation periods. Robust standard errors are clustered at country level. Country/Region name are displayed as the three letter of World Bank Country code, except Taiwan (TWN).

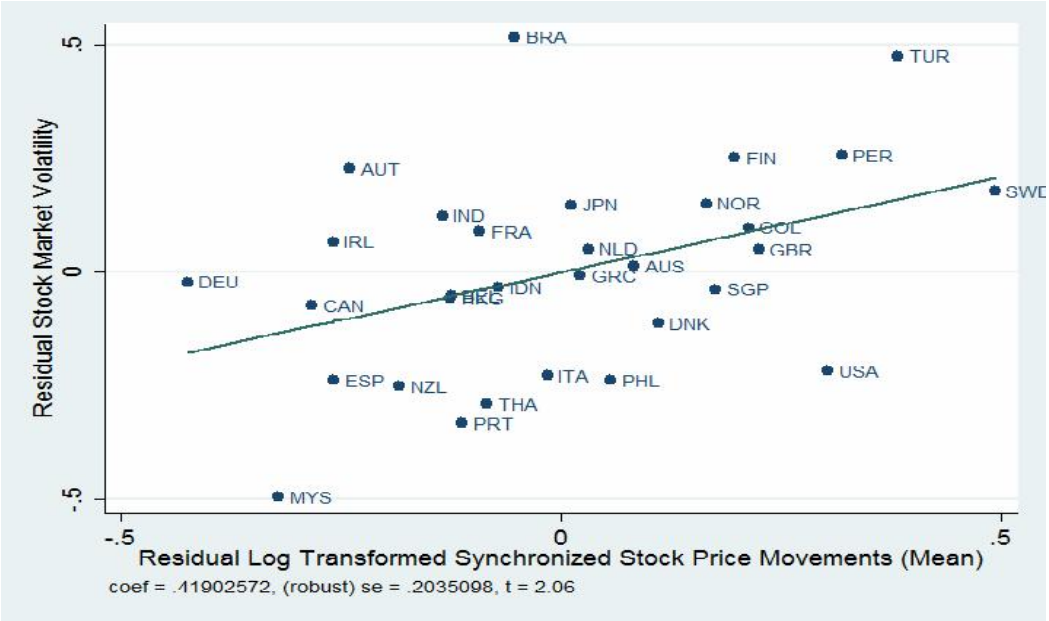

Figure 4.3.: Partial regression plot of Average of stock market volatility and Average logistic transformation of the fraction of synchronized stock price movements (mean). The independent variables include individualism index, insider trading index, exchange rate volatility, private credit flow, central government debt, log(GDP per Capita), log(Stock traded) and log(Market Capitalization). Both dependent variable and independent variables are averaged over the whole observation periods. Robust standard errors are clustered at country level. Country/Region name are displayed as the three letter of World Bank Country code, except Taiwan (TWN).

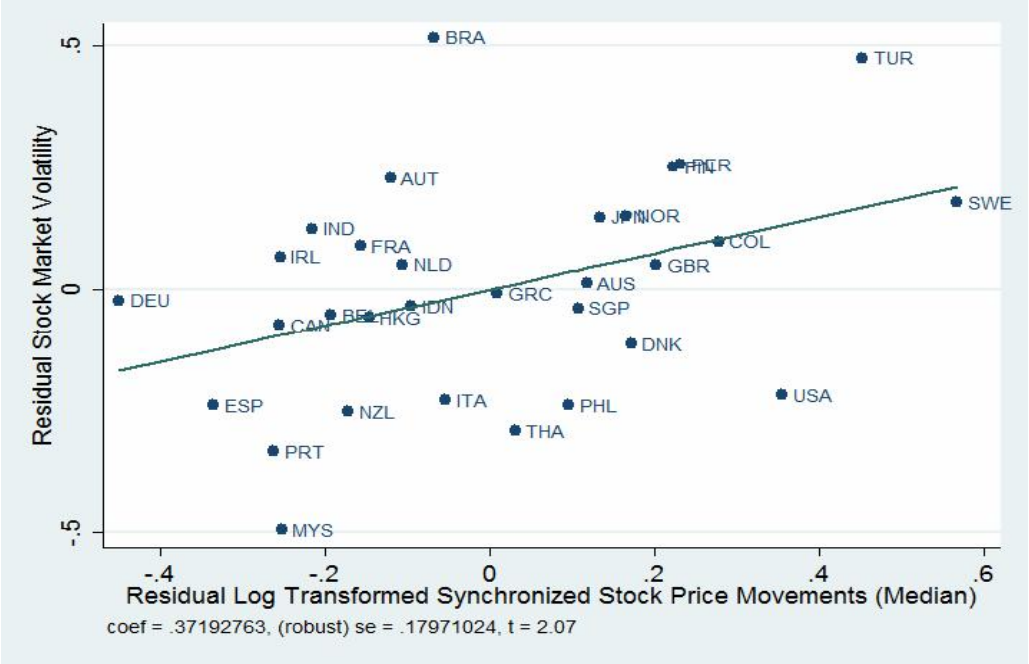

Figure 4.4.: Partial regression plot of Average of stock market volatility and Average logistic transformation of the fraction of synchronized stock price movements (median). The independent variables include individualism index, insider trading index, exchange rate volatility, private credit flow, central government debt, log(GDP per Capita), log(Stock traded) and log(Market Capitalization). Both dependent variable and independent variables are averaged over the whole observation periods. Robust standard errors are clustered at country level. Country/Region name are displayed as the three letter of World Bank Country code, except Taiwan (TWN).

Table 4.1.

Definition of Variables

This table defines our dependent, independent and control variables.

Variable Name	Definition
Stock Market Volatility	Monthly Stock Market Volatility is calculated as the standard deviation of daily return of the MSCI country index within the month for each country. Source: Morgan Stanley Capital International Index (MSCI) on DataStream.
Synchronized Stock Price Movement (Mean)	Monthly Synchronized Stock Price Movement (mean) is calculated as the average of daily fraction of stock that moves in the same direction within the month for each country. Source: DataStream Global Equity Indices.
Synchronized Stock Price Movement (Median)	Monthly Synchronized Stock Price Movement (median) is calculated as the median number of daily fraction of stock that moves in the same direction within the month for each country. Source: DataStream Global Equity Indices.
Hefstede Culture Dimensions	
Individualism Index	The high side of this dimension, called Individualism, can be defined as a preference for a loosely-knit social framework in which individuals are expected to take care of themselves and their immediate families only. Its opposite, Collectivism, represents a preference for a tightly-knit framework in society in which individuals can expect their relatives or members of a particular in-group to look after them in exchange for unquestioning loyalty. A society's position on this dimension is reflected in whether people's self-image is defined in terms of "I" or "we." Source: http://geert-hofstede.com/dimensions.html
Power Distance	This dimension expresses the degree to which the less powerful members of a society accept and expect that power is distributed unequally. The fundamental issue here is how a society handles inequalities among people. People in societies exhibiting a large degree of power distance accept a hierarchical order in which everybody has a place and which needs no further justification. In societies with low power distance, people strive to equalize the distribution of power and demand justification for inequalities of power. Source: http://geert-hofstede.com/dimensions.html
Masculinity	The masculinity side of this dimension represents a preference in society for achievement, heroism, assertiveness and material reward for success. Society at large is more competitive. Its opposite, femininity, stands for a preference for cooperation, modesty, caring for the weak and quality of life. Society at large is more consensus-oriented. Source: http://geert-hofstede.com/dimensions.html
Uncertainty Avoidance	The uncertainty avoidance dimension expresses the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity. The fundamental issue here is how a society deals with the fact that the future can never be known: should we try to control the future or just let it happen? Countries exhibiting strong UAI maintain rigid codes of belief and behavior and are intolerant of unorthodox behavior and ideas. Weak UAI societies maintain a more relaxed attitude in which practice counts more than principles. Source: http://geert-hofstede.com/dimensions.html
Long-term versus short-term orientation	The long-term orientation dimension can be interpreted as dealing with society's search for virtue. Societies with a short-term orientation generally have a strong concern with establishing the absolute Truth. They are normative in their thinking. They exhibit great respect for traditions, a relatively small propensity to save for the future, and a focus on achieving quick results. In societies with a long-term orientation, people believe that truth depends very much on situation, context and time. They show an ability to adapt traditions to changed conditions, a strong propensity to save and invest thriftiness, and perseverance in achieving results. Source: http://geert-hofstede.com/dimensions.html
Indulgence versus Restraint	Indulgence stands for a society that allows relatively free gratification of basic and natural human drives related to enjoying life and having fun. Restraint stands for a society that suppresses gratification of needs and regulates it by means of strict social norms. Source: http://geert-hofstede.com/dimensions.html
Legal and Regulation Index	
Insider Trading Index	Sum of dummy variables for Front-running, Client Precedence, Trading Ahead of Research Reports, Separation of Research and Trading, Broker Ownership Limit, Restrictions on Affiliation, Restrictions on Communications, Investment Company Securities, Influencing or Rewarding the Employees of Others, and Anti-Intimidation / Coordination. Source: La Porta, Lopez-de-Silanes, Shleifer and Vishny (1998).
Property Right Index	Measures the degree to which a country's laws protect private property right and the degree to which its government enforces those laws. It also assesses the likelihood that private property will be expropriated and analyzes the independence of the judiciary, the existence of corruption within the judiciary, and the ability of individuals and business to enforce contracts. The index rages from 0 to 100 with higher the index presents better property right protections. Source: Heritage Foundation http://www.heritage.org/index/visualize
Corruption Index	The score for corruption index is derived from Transparency International's Corruption Perception Index (CPI). The original CPI index is 10-point scale. The corruption index covert the CPI data to a scale of 0 to 100 by multiplying the CPI score by 10.

	The higher score represents lower level of corruption. Source: Heritage Foundation http://www.heritage.org/index/visualize
Economic and Market Control Variables	
Exchange Rate Volatility	The exchange rate volatility is measured as the standard deviation of the daily nominal exchange rate with respect to US$. The nominal exchange rate for US is zero. Source: Source: Morgan Stanley Capital International Index on DataStream.
Private Credit Flow	Private Credit Flow as % GDP. Source: World Bank: World Development Indicators 2012.
Central Government Debt %	Central Government Debt as % GDP. Source: World Bank: World Development Indicators 2012.
Log GDP per Capita	Log of GDP per capita (current US$) in the lagged period. Source: World Bank: World Development Indicators 2012.
Log Geographical Size	Log of geographical size. Source: CIA- The World FactBook, https://www.cia.gov/library/publications/the-world-factbook/geos
Log Market Capitalization	Log of market capitalization of listed companies (Current US$) in the same period. Source: World Bank: World Development Indicators 2012.
Log Stock Traded	Log of stock traded, total value (Current US$). Source: World Bank: World Development Indicators 2012.

Table 4.2

Descriptive Statistics

This table presents full sample of the country-year-month observations (Panel A) and summary statistics of Individualism Index, Synchronized stock price movements and Stock market volatility by country (Panel B). MSCI has incomplete data for Israel after July 2010 and for Venezuela after January 2008. Insider trading index is from La Porta (1998, 2005) and has missing value for China. Central Government Debt % is from WDI (2012) and missing for various countries for different years.

Panel A: Descriptive Statistics

	Mean	Median	Standard Deviation	Minimum	Maximum	Number of Observations
Stock Market Volatility	1.58	1.32	0.96	0.31	10.92	5235
Synchronized Stock Price Movement (Mean)	0.6569	0.6558	0.0615	0.05	0.86	5235
Synchronized Stock Price Movement (Median)	0.6685	0.6597	0.0666	0.00	1.00	5258
Individualism Index	48.96	48.00	24.85	12.00	91.00	5009
Power Distance	54.96	58.00	21.51	11.00	104.00	5009
Masculinity	51.26	54.00	19.25	5.00	95.00	5009
Uncertainty Avoidance	64.83	70.00	24.15	8.00	112.00	5009
Long-term versus short-term orientation	49.63	45.59	22.25	13.10	100.00	5122
Indulgence versus Restraint	51.20	49.55	20.26	0.00	100.00	5032
Insider Trading Index	4.55	4.40	0.87	2.80	6.20	4557
Property Right Index	65.89	70	22.90	20	95	5235
Corruption Index	59.10	57	23.99	19	99	5235
Exchange Rate Volatility	199.96	1.23	1030.55	0.00	21291.57	5235
Private Credit Flow	0.79	1.62	7.17	-37.66	67.59	4822
Central Government Debt %	55.80	47.81	29.30	6.50	174.37	2916
Log GDP per Capita	9.46	9.85	1.21	6.17	11.49	5004
Log Geographical Size	12.56	12.70	2.32	6.13	16.65	5235
Log Stock Traded	25.66	25.73	2.70	10.27	31.79	4932
Log Market Capitalization	0.50	0.23	0.48	0.00	1.00	4693

Panel B:

Descriptive Statistics by Country

Country	Individualism Index	Stock Market Volatility	Synchronized Stock Price Movement (Mean)	Synchronized Stock Price Movement (Median)
Argentina	46	1.9788	0.6607	0.6741
Australia	90	1.4750	0.6475	0.6545
Austria	55	1.6858	0.6177	0.6305
Belgium	75	1.4006	0.6218	0.6210
Brazil	38	2.0370	0.6623	0.6760
Canada	80	1.3222	0.6176	0.6255
Chile	23	1.2636	0.6624	0.6746
China	20	1.6746	0.6878	0.7159
Colombia	13	1.5376	0.6699	0.6950
Czech Republic	58	1.6197	0.6873	0.6936
Denmark	74	1.3536	0.6491	0.6596
Finland	63	1.7847	0.6685	0.6787
France	71	1.4856	0.6413	0.6422
Germany	67	1.5031	0.6200	0.6231
Greece	35	1.9431	0.6722	0.6822
Hong Kong	25	1.2216	0.6539	0.6688
Hungary	80	2.1607	0.6156	0.6227
India	48	1.6385	0.6596	0.6763
Indonesia	14	1.7688	0.6622	0.6870
Ireland	70	1.7816	0.6145	0.6157
Israel	54	1.1075	0.6783	0.7010
Italy	76	1.4842	0.6549	0.6607
Japan	46	1.3332	0.6566	0.6801
Malaysia	26	0.8979	0.6321	0.6484
Mexico	30	1.5296	0.6506	0.6580
Netherlands	80	1.4066	0.6402	0.6342
New Zealand	79	1.2980	0.6107	0.6137
Norway	69	1.8791	0.6699	0.6807
Pakistan	14	1.4875	0.6624	0.6796
Peru	16	1.8531	0.6901	0.6959
Philippines	32	1.4539	0.6712	0.6947
Poland	60	1.9417	0.6467	0.6527
Portugal	27	1.2613	0.6481	0.6436
Russia	39	2.1290	0.7064	0.7145
Singapore	20	1.2592	0.6747	0.6765
South Africa		1.7338	0.6404	0.6522
South Korea	18	1.7766	0.6566	0.6664
Spain	51	1.5444	0.6485	0.6549
Sri Lanka		1.2600	0.6269	0.6577
Sweden	71	1.7576	0.7018	0.7196
Switzerland	68	1.1511	0.6369	0.6363
Taiwan	17	1.4275	0.6842	0.7016
Thailand	20	1.5782	0.6820	0.7152
Turkey	37	2.3556	0.7248	0.7510
United Kingdom	89	1.2973	0.6614	0.6635
United States	91	1.0868	0.6858	0.6980

Venezuela	12	2.6640	0.6344	0.6473

Table 4.3.

Comparison Tests

This table presents the comparison of mean and median tests for Synchronized Stock Price Movement (Panel A) and Stock Market Volatility (Panel B). The *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Panel A: Stock Market Synchronization

	Synchronized Stock Price Movement (mean)		**Synchronized Stock Price Movement (median)**	
	Individualism Index > 48	Individualism Index<=48	Individualism Index > 48	Individualism Index<= 48
Group	1	0	1	0
Number of Observations	2689	2546	2689	2546
Mean	0.6457	0.6688	0.6535	0.6844
Standard Deviation	0.0580	0.0628	0.0611	0.0685
Median	0.6430	0.6680	0.6435	0.6771
Difference in Means (0-1)	13.7731***		17.1933***	
Difference in Medians (0-1)	p=0.0000***		p=0.0000***	

Panel B: Stock Market Volatility

	Stock Market Volatility		**Stock Market Volatility**	
	Synchronized Stock Price Movement (mean)>0.6558362	Synchronized Stock Price Movement (mean)<=0.6558362	Synchronized Stock Price Movement (median)>0.6597497	Synchronized Stock Price Movement (median)<=0.6597497
Group	1	0	1	0
Number of Observations	2618	2617	2617	2618
Mean	1.9066	1.2498	1.9216	1.2350
Standard Deviation	1.1001	0.6602	1.1138	0.6213
Median	1.6135	1.0918	1.6271	1.0840
Difference in Means (0-1)	-26.1937***		-27.5389***	
Difference in Medians (0-1)	p=0.0000***		p=0.0000***	

Table 4.4: Correlation Matrix

This Table presents Pearson Correlation Coefficients for the full sample of country-year-month data. The *, ** and *** indicate the correlations are statistically significant at the 10%, 5% and 1% level, respectively.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Stock Market Volatility	1																		
2	Synchronized Stock Price Movement (Mean)	0.500***	1																	
3	Synchronized Stock Price Movement (Median)	0.554***	0.865***	1																
4	Individualism Index	-0.0890***	-0.198***	-0.265***	1															
5	Power Distance	-0.000884	0.142***	0.179***	-0.694***	1														
6	Masculinity	-0.0509**	-0.121***	-0.100***	-0.0201	0.0970***	1													
7	Uncertainty Avoidance	0.0837***	0.011	0.00322	-0.150***	0.133***	0.173***	1												
8	Long-term versus short-term orientation	-0.0275	-0.102***	-0.128***	0.0555***	0.105***	0.148***	0.0345*	1											
9	Indulgence versus Restraint	-0.0147	-0.0429**	-0.0460**	0.435***	-0.492***	-0.129***	-0.162***	-0.410***	1										
10	Property Right Index	-0.136***	-0.221***	-0.299***	0.700***	-0.698***	-0.128***	-0.384***	0.176***	0.299***	1									
11	Corruption Index	-0.136***	-0.195***	-0.270***	0.638***	-0.676***	-0.206***	-0.376***	0.145***	0.387***	0.939***	1								
12	Insider Trading Index	-0.160***	-0.225***	-0.303***	0.682***	-0.596***	0.0490**	-0.318***	0.102***	0.506***	0.834***	0.859***	1							
13	Exchange Rate Volatility	0.148***	0.0598***	0.119***	-0.320***	0.216***	0.0249	-0.0227	0.0316	-0.0605***	-0.404***	-0.367***	-0.353***	1						
14	Private Credit Flow	0.0269	0.0519***	0.0581***	-0.0186	0.0775***	0.187***	0.286***	-0.137***	0.127***	-0.269***	-0.260***	-0.0835***	0.0544***	1					
15	Central Government Debt %	-0.0264	0.00807	-0.0182	-0.0512**	0.167***	0.363***	0.384***	0.455***	-0.201***	-0.0870***	-0.0552***	-0.00137	-0.103***	0.111***	1				
16	Log GDP per Capita	-0.0362*	-0.131***	-0.212***	0.660***	-0.664***	-0.0970***	-0.0520***	0.177***	0.322***	0.827***	0.854***	0.734***	-0.376***	-0.204***	0.157***	1			
17	Log Geographical Size	0.0347*	-0.0211	0.0276	0.318***	-0.0692***	0.111***	0.120***	-0.309***	0.276***	-0.178***	-0.225***	-0.111***	0.159***	0.262***	-0.150***	-0.192***	1		
18	Log Stock Traded	-0.0343*	0.0286	-0.00468	0.567***	-0.201***	0.0678***	-0.144***	0.314***	-0.0761***	0.428***	0.349***	0.369***	-0.201***	-0.0382*	0.0615***	0.424***	0.339***	1	
19	Log Market Capitalization	-0.122***	-0.00266	-0.0330*	0.498***	-0.0882***	0.197***	-0.122***	0.267***	-0.0446**	0.334***	0.260***	0.335***	-0.182***	0.00818	0.0627***	0.324***	0.337***	0.940***	1

Table 4.5.

Regression Results for Logistic Transformed Synchronized Stock Price Movements

This table presents Ordinary Lease Square regressions of determination of stock market synchronization. Variables are defined in Table 1. Standard errors are clustered by both countries and month. Panel A presents regression results of logistic transformed synchronized stock price movements (mean) and Panel B present regression results for logistic transformed synchronized stock price movements (median). Model 1 presents results of individualism index. Model 2 presents a regression with various economic and market control variables. Model 3 present results with emerging market dummy. Model 4 present results with property right index and free from corruption index from Heritage Foundation. Model 5 present regression results with all culture dimension index. Model 6, 7, and 8 present the results of Model 1, 2, and 5 without the data from the United States, respectively. T-statistics are in the parenthesis and the *,** and *** are statistically significant at the 10%, 5% and 1% level, respectively.

Panel A: Synchronized Stock Price Movements (Mean)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Individualism Index	Economic and Market Control	With Emerging Market Dummy	With Property Right Index	Culture Dimension Index	Model (1) Without US	Model (2) Without US	Model (5) Without US
Individualism Index	**-0.00422*** **	**-0.00486*** **	**-0.00389** **	**-0.00331***	**-0.00330** **	**-0.00560*** **	**-0.00464** **	**-0.00396** **
	[-2.66]	**[-3.17]**	**[-2.09]**	**[-1.91]**	**[-2.10]**	**[-3.61]**	**[-2.49]**	**[-2.32]**
Power Distance					0.00178			0.00194
					[0.63]			[0.69]
Masculinity					-0.00423***			-0.00464***
					[-2.96]			[-3.09]
Uncertainty Avoidance					0.000647			0.000725
					[0.42]			[0.48]
Long-term versus short-term orientation					-0.00124			-0.0000704
					[-0.64]			[-0.04]
Indulgence versus Restraint					-0.000548			-0.000304
					[-0.27]			[-0.15]
Property Right and Corruption								
Property Right Index				-0.00546*				
				[-1.73]				
Corruption Index				0.000495				
				[0.13]				
Economic and Market Control Variables								
Log (GDP per capita)		-0.0163	0.0406	0.0354	-0.0197	-0.0141	0.0406	-0.0173
		[-0.43]	[1.10]	[1.02]	[-0.38]	[-0.37]	[1.09]	[-0.33]
Log (Geographical size)		0.0110	0.00526	0.000347	0.00935	0.00871	0.00321	0.00897
		[0.62]	[0.30]	[0.02]	[0.44]	[0.51]	[0.19]	[0.43]
Log(Stock Traded)		0.0913**	0.0750*	0.0823*	0.0769*	0.103***	0.0870**	0.0865**
		[2.24]	[1.77]	[1.88]	[1.71]	[2.63]	[2.14]	[2.14]
Log(Market Capitalization)		-0.1000	-0.0731	-0.0869	-0.0764	-0.132*	-0.105	-0.112*
		[-1.39]	[-1.02]	[-1.18]	[-1.08]	[-1.91]	[-1.53]	[-1.69]

Emerging Market Dummy			0.205*				0.198*	
			[1.78]				[1.73]	
Constant	-0.628***	-0.301	-1.204	-0.513	-0.418	0.272	-0.616	0.203
	[-9.37]	[-0.32]	[-1.27]	[-0.54]	[-0.48]	[0.31]	[-0.69]	[0.25]
Observations	4987	4688	4688	4688	4601	4575	4575	4488
R-squared	0.027	0.050	0.059	0.061	0.072	0.058	0.066	0.081

Panel B: Synchronized Stock Price Movements (Median)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Individualism Index	Economic and Market Control	With Emerging Market Dummy	With Property Right Index	Culture Dimension Index	Model (1) Without US	Model (2) Without US	Model (5) Without US
Individualism Index	**-0.00582*** **	**-0.00627*** **	**-0.00530** **	**-0.00468** **	**-0.00591*** **	**-0.00708*** **	**-0.00612*** **	**-0.00658*** **
	[-3.35]	**[-3.38]**	**[-2.47]**	**[-2.39]**	**[-3.29]**	**[-3.75]**	**[-2.81]**	**[-3.43]**
Power Distance					0.000388			0.000551
					[0.15]			[0.22]
Masculinity					-0.00320*			-0.00363*
					[-1.69]			[-1.84]
Uncertainty Avoidance					-0.000578			-0.000496
					[-0.36]			[-0.31]
Long-term versus short-term orientation					-0.00148			-0.000279
					[-0.66]			[-0.13]
Indulgence versus Restraint					-0.000623			-0.000372
					[-0.25]			[-0.15]
Property Right and Corruption								
Property Right Index				-0.00764**				
				[-2.20]				
Corruption Index				0.00299				
				[0.71]				
Economic and Market Control Variables								
Log (GDP per capita)		-0.0378	0.0191	0.00457	-0.0400	-0.0355	0.0189	-0.0375
		[-0.90]	[0.42]	[0.13]	[-0.69]	[-0.86]	[0.43]	[-0.66]
Log (Geographical size)		0.0220	0.0162	0.0116	0.0252	0.0194	0.0140	0.0247
		[1.23]	[0.91]	[0.69]	[1.13]	[1.15]	[0.82]	[1.13]
Log(Stock Traded)		0.118***	0.102**	0.115**	0.106**	0.131***	0.115**	0.115**
		[2.70]	[2.21]	[2.43]	[2.12]	[3.09]	[2.57]	[2.53]
Log(Market Capitalization)		-0.135*	-0.108	-0.131*	-0.114	-0.170**	-0.143*	-0.151**
		[-1.82]	[-1.44]	[-1.67]	[-1.50]	[-2.36]	[-1.95]	[-2.05]
Emerging Market Dummy			0.206				0.197	
			[1.55]				[1.48]	
Constant	-0.435***	0.180	-0.724	0.117	0.198	0.810	-0.0748	0.837
	[-5.75]	[0.19]	[-0.70]	[0.12]	[0.22]	[0.90]	[-0.07]	[0.97]
Observations	5005	4699	4699	4699	4609	4586	4586	4496
R-squared	0.057	0.101	0.110	0.115	0.121	0.114	0.122	0.134

Table 4.6.

Regression Results for Stock Market Volatility

This table presents Ordinary Lease Square regressions of determination of stock market volatility. Variables are defined in Table 1. Standard errors are clustered by both country and month. Panel A presents regression results between the stock market volatility and stock market synchronization (mean) and Panel B present regression results between the stock market volatility and stock market synchronization (median). Model 1 presents results of stock market volatility and stock market synchronization. Model 2 presents a regression with Insider Trading Index, Price Manipulation Index, Volume and Market Manipulation Index (Cumming, et al., 2011), Rule of Law and Efficiency of the judiciary (LLSV, 1998 and 2006). Model 3 presents a regression results with Economic and Market control Variables. Model 4 presents a regression results with All variables. Model 6 and 7 run the regression during the financial crisis period (June 2007 to December 2008) on emerging market and non-emerging market alone, respectively. Model 8, 9, and 10 present the results of Model 1, 4, and 5 without the data from the United States, respectively. T-statistics are in the parenthesis and the *,** and *** are statistically significant at the 10%, 5% and 1% level, respectively.

Panel A: Market Volatility and Stock Market Synchronization (Mean)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Stock Market Synchronization	With Emerging Market Dummy	Economic and Market Variable	All Jointly	Average Fraction of Stocks Moving Together	Financial Crisis + Emerging Markets	Financial Crisis + non-Emerging Markets	Model (1) Without US	Model (2) Without US	Model(4) Without US
Logistic transformation of the average fraction of stocks moving together	**0.606*** **	**0.604*** **	**0.681*** **	**0.592*** **		**1.189** **	**0.764**	**0.611*** **	**0.618*** **	**0.600*** **
	[4.75]	**[4.61]**	**[4.48]**	**[4.20]**		**[2.38]**	**[1.50]**	**[4.75]**	**[4.69]**	**[4.15]**
Average Fraction of Stocks Moving Together					**7.233*** **					
					[5.14]					
Individualism										
Individualism Index		0.00338		0.00409	0.00449	-0.00149	0.00660		0.00469*	0.00453*
		[1.22]		[1.48]	[1.60]	[-0.40]	[1.10]		[1.80]	[1.69]
Legal, Economic and Market Control Variables										
Insider Trading Index			-0.151**	-0.0997	-0.0874					-0.101
			[-2.48]	[-1.34]	[-1.19]					[-1.35]
Exchange Rate Volatility			0.000118***	0.000129***	0.000130***	0.000169***	0.00858***			0.000134***
			[4.58]	[4.07]	[4.37]	[5.43]	[4.35]			[4.50]
Private Credit Flow			0.00475	0.00357	0.00320	0.0255**	-0.0139			0.00447
			[0.74]	[0.60]	[0.55]	[2.41]	[-1.42]			[0.73]
Central Government Debt			-0.00168	0.00143	0.00140	0.0158***	-0.00108			0.00130
			[-1.35]	[0.86]	[0.85]	[2.95]	[-0.43]			[0.81]
Log (GDP per Capita)			0.179**	0.400***	0.366***	0.264*	0.0525			0.408***
			[2.51]	[2.98]	[2.78]	[1.90]	[0.10]			[3.18]
Log (Market Capitalization)			-0.0885**	-0.474***	-0.451***	-0.426***	-0.719**			-0.416***
			[-2.16]	[-3.13]	[-3.10]	[-2.85]	[-2.18]			[-2.80]
Log (Stock Traded)				0.293**	0.274**	0.407***	0.400			0.272**
				[2.52]	[2.50]	[2.62]	[1.53]			[2.38]

Emerging Market Dummy		0.224*		1.153***	1.046***				0.228*	1.171***
		[1.76]		[3.10]	[2.86]				[1.86]	[3.23]
Constant	2.092***	1.813***	3.508***	2.869	-2.192	0.829	10.09	2.111***	1.777***	1.824
	[15.53]	[9.30]	[4.52]	[1.64]	[-1.19]	[0.24]	[1.49]	[15.58]	[9.56]	[1.12]
Observations	5211	4987	2574	2515	2520	228	405	5098	4874	2419
R-squared	0.161	0.168	0.252	0.322	0.354	0.280	0.233	0.164	0.173	0.319

Panel B: Market Volatility and Synchronized Stock Movements (Median)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Stock Market Synchronization	With Emerging Market Dummy	Economic and Market Variable	All Jointly	Average Fraction of Stocks Moving Together	Financial Crisis + Emerging Markets	Financial Crisis + non-Emerging Markets	Model (1) Without US	Model (2) Without US	Model(4) Without US
Logistic transformation of the average fraction of stocks moving together (median)	**0.765*** **	**0.773*** **	**0.870*** **	**0.779*** **		**1.351*** **	**1.062** **	**0.776*** **	**0.804*** **	**0.801*** **
	[6.66]	**[6.29]**	**[6.35]**	**[5.86]**		**[2.91]**	**[2.58]**	**[6.63]**	**[6.44]**	**[5.89]**
Average Fraction of Stocks Moving Together (median)					**7.735*** **					
					[5.94]					
Individualism										
Individualism Index		0.00456		0.00510*	0.00510*	0.00702	0.00873		0.00616**	0.00570**
		[1.47]		[1.91]	[1.92]	[1.16]	[1.45]		[2.12]	[2.21]
Legal, Economic and Market Control Variables										
Insider Trading Index			-0.0865	-0.0628	-0.0643					-0.0619
			[-1.49]	[-0.86]	[-0.91]					[-0.84]
Exchange Rate Volatility			0.000108***	0.000117***	0.000116***	0.000164***	0.00590***			0.000124***
			[3.74]	[3.79]	[3.80]	[6.49]	[3.61]			[4.35]
Private Credit Flow			0.00459	0.00304	0.00306	0.0177*	-0.0148			0.00408
			[0.77]	[0.55]	[0.55]	[1.66]	[-1.44]			[0.71]
Central Government Debt			-0.00134	0.00137	0.00135	0.0124**	-0.000834			0.00123
			[-1.23]	[0.87]	[0.86]	[2.13]	[-0.35]			[0.80]
Log (GDP per Capita)			0.193**	0.329**	0.324**	0.229	-0.134			0.335***
			[2.47]	[2.47]	[2.41]	[1.52]	[-0.25]			[2.66]
Log (Market Capitalization)			-0.0913*	-0.432***	-0.419***	-0.306**	-0.667**			-0.362**
			[-1.97]	[-2.92]	[-2.88]	[-2.32]	[-2.42]			[-2.53]
Log (Stock Traded)				0.250**	0.243**	0.330**	0.338			0.225**
				[2.27]	[2.26]	[2.27]	[1.60]			[2.09]
Emerging Market Dummy		0.159		0.873**	0.845**				0.160	0.886**
		[1.16]		[2.40]	[2.33]				[1.22]	[2.53]
Constant	2.133***	1.839***	3.201***	3.517*	-2.293	-0.302	12.32*	2.156***	1.802***	2.279
	[17.11]	[9.14]	[3.67]	[1.85]	[-1.29]	[-0.09]	[1.83]	[17.11]	[9.38]	[1.30]
Observations	5231	5005	2580	2520	2520	228	406	5118	4892	2424
R-squared	0.232	0.237	0.334	0.380	0.394	0.353	0.304	0.236	0.247	0.378

Table 4.6A: Alternative Measure of Market Volatility: Equal Weighted Market Volatility and Market Cap Weighted Market Volatility

This table presents Ordinary Lease Square regressions of determination of stock market volatility. The data used here are only cover 22 exchanges around 17 countries around the world, including Australia, Canada, China, Germany, Hong Kong, India, Japan, Malaysia, New Zealand, Norway, Singapore, South Korea, Sweden, Switzerland, Taiwan, the U.K., and the U.S. and the years January 2003 – June 2011. Standard errors are clustered by both country and month. Panel A presents regression results between the alternative measure of stock market volatility and synchronized stock price movements (mean) and Panel B present regression results between the alternative measure of stock market volatility and logistic transformed synchronized stock price movements (median). Model 1 presents a regression results with all variables. Model 2 presents a regression results with original measure of synchronized stock price movement. Model 3 repeat the regression model 1 without data from United States. Model 4, 5 and 6 present the results of Model 1, 2 and 3 with market cap weighted volatility as the dependent variables. T-statistics are in the parenthesis and the *,** and *** are statistically significant at the 10%, 5% and 1% level, respectively.

Panel A: Equal Weighted Monthly Stock Market Volatility/Market Cap Weighted Monthly Stock Market Volatility and Synchronized Stock Movements (Mean)

	(1)	(2)	(3)	(4)	(5)	(6)
	Equal Weighted Monthly Stock Volatility	Equal Weighted Monthly Stock Volatility	Model(1) Without US	Market Cap Weighted Monthly Stock Market Volatility	Market Cap Weighted Monthly Stock Market Volatility	Model(4) Without US
Logistic transformation of the average fraction of stocks moving together	**0.00302*** **		**0.00255*** **	**0.00368*** **		**0.00343*** **
	[3.62]		**[3.64]**	**[5.30]**		**[5.45]**
Average Fraction of Stocks Moving Together		**0.0320*** **			**0.0407*** **	
		[3.40]			**[4.95]**	
Individualism						
Individualism Index	0.0000147	0.0000146	0.000128	0.000121**	0.000121**	0.000163**
	[0.17]	[0.17]	[1.17]	[2.03]	[2.01]	[2.04]
Legal, Economic and Market Control Variables						
Insider Trading Index	-0.000201	-0.000190	-0.00267	-0.00331**	-0.00324**	-0.00424**
	[-0.09]	[-0.09]	[-1.24]	[-2.14]	[-2.06]	[-2.37]
Exchange Rate Volatility	0.000105	0.000103	0.0000138	0.000115***	0.000114***	0.0000823
	[0.92]	[0.89]	[0.14]	[2.69]	[2.68]	[1.53]
Private Credit Flow	-0.000168	-0.000167	-0.0000534	-0.000141	-0.000142	-0.000102
	[-0.83]	[-0.82]	[-0.28]	[-1.19]	[-1.22]	[-0.86]
Central Government Debt	-0.00000842	-0.00000861	0.0000495	0.0000869**	0.0000861**	0.000111**
	[-0.12]	[-0.12]	[0.65]	[2.51]	[2.46]	[2.20]
Log (GDP per Capita)	-0.00282**	-0.00283**	-0.00242**	-0.00230*	-0.00234*	-0.00217*
	[-2.22]	[-2.23]	[-2.01]	[-1.85]	[-1.89]	[-1.66]
Log (Market Capitalization)	-0.00234***	-0.00232***	-0.00246***	-0.00104	-0.00103	-0.00111
	[-3.11]	[-3.08]	[-3.18]	[-1.49]	[-1.48]	[-1.43]
Log (Stock Trading Volume)	0.00258**	0.00259**	0.00406***	0.00192**	0.00192**	0.00247**
	[2.08]	[2.07]	[3.01]	[2.16]	[2.15]	[2.20]
Constant	0.0764***	0.0525**	0.0455*	0.0391**	0.00908	0.0286
	[2.85]	[2.12]	[1.76]	[2.43]	[0.56]	[1.63]
Observations	1313	1314	1121	1313	1314	1121
R-squared	0.229	0.229	0.247	0.263	0.265	0.269

Panel B: Equal Weighted Monthly Stock Market Volatility/Market Cap Weighted Monthly Stock Market Volatility and Synchronized Stock Movements (Median)

	(4)	(5)	(8)	(4)	(5)	(8)
	Equal Weighted Monthly Stock Volatility	Equal Weighted Monthly Stock Volatility	Model(1) Without US	Market Cap Weighted Monthly Stock Market Volatility	Market Cap Weighted Monthly Stock Market Volatility	Model(4) Without US
Logistic transformation of the average fraction of stocks moving together	**0.00378*** **		**0.00331*** **	**0.00431*** **		**0.00415*** **
	[4.77]		**[4.60]**	**[5.05]**		**[4.83]**
Average Fraction of Stocks Moving Together		**0.0362*** **			**0.0414*** **	
		[4.62]			**[5.26]**	
Individualism						
Individualism Index	0.0000105	0.0000103	0.000129	0.000119**	0.000118**	0.000166**
	[0.12]	[0.12]	[1.15]	[1.98]	[1.98]	[2.07]
Legal, Economic and Market Control Variables						
Insider Trading Index	0.000138	0.0000937	-0.00244	-0.00299*	-0.00304*	-0.00401**
	[0.07]	[0.04]	[-1.15]	[-1.91]	[-1.94]	[-2.23]
Exchange Rate Volatility	0.0000907	0.0000872	-0.00000184	0.0000985**	0.0000944**	0.0000623
	[0.78]	[0.74]	[-0.02]	[2.32]	[2.22]	[1.17]
Private Credit Flow	-0.000171	-0.000169	-0.0000559	-0.000146	-0.000144	-0.000107
	[-0.85]	[-0.85]	[-0.29]	[-1.27]	[-1.27]	[-0.93]
Central Government Debt	-0.00000928	-0.00000846	0.0000519	0.0000881**	0.0000890**	0.000116**
	[-0.13]	[-0.12]	[0.66]	[2.49]	[2.51]	[2.25]
Log (GDP per Capita)	-0.00286**	-0.00285**	-0.00247**	-0.00235*	-0.00233*	-0.00224*
	[-2.29]	[-2.29]	[-2.09]	[-1.94]	[-1.92]	[-1.75]
Log (Market Capitalization)	-0.00228***	-0.00227***	-0.00244***	-0.000993	-0.000979	-0.00109
	[-3.00]	[-2.97]	[-3.10]	[-1.45]	[-1.42]	[-1.43]
Log (Stock Trading Volume)	0.00243*	0.00245*	0.00398***	0.00180**	0.00182**	0.00241**
	[1.95]	[1.96]	[2.99]	[2.09]	[2.10]	[2.19]
Constant	0.0778***	0.0500**	0.0464*	0.0397**	0.00799	0.0287*
	[2.91]	[2.01]	[1.81]	[2.52]	[0.49]	[1.67]
Observations	1314	1314	1122	1314	1314	1122
R-squared	0.209	0.210	0.225	0.272	0.274	0.277

Table 4.7:

Two Stage Least Square Regression

This table presents second stage results of two stage least square regressions of synchronized stock price movement and stock market volatility. The second stage results are showing in the table. T-statistics are in the parentheses and the *, ** and *** are statistically significant at the 10%, 5% and 1% level, respectively.

	(1) Stock Market Volatility	(2) Stock Market Volatility
Logistic Transformation of the average fraction of stocks moving fraction of stocks moving together (mean)	**1.080*** **	
	[2.93]	
Logistic Transformation of the average fraction of stocks moving fraction of stocks moving together (median)		**1.188*** **
		[2.94]
Individualism Index	**0.00633***	**0.00706***
	[1.76]	**[1.85]**
Legal, Economic and Market Control Variables		
Insider Trading Index	-0.0518	-0.0143
	[-0.61]	[-0.15]
Exchange Rate Volatility	0.000131***	0.000112***
	[4.64]	[3.69]
Private Cash Flow	0.00113	0.00119
	[0.18]	[0.19]
Central Government Debt	0.000975	0.00103
	[0.59]	[0.62]
Log (GDP per capita)	0.290*	0.221
	[1.72]	[1.15]
Log(Market Capitalization)	-0.400***	-0.361**
	[-3.24]	[-2.44]
Log(Stock Traded)	0.211**	0.174
	[2.08]	[1.38]
Emerging Market Dummy	0.813*	0.504
	[1.69]	[0.87]
Constant	4.359*	4.804*
	[1.95]	[1.96]
Observations	2515	2520
R-squared	0.235	0.328

Chapter 5.

Concluding remarks

The essay, 'Exchange Trading Rules, Surveillance, and Insider Trading', explores the relationship between institutional difference and market activities by examining the impact of stock exchange trading rules and surveillance on the frequency and severity of suspected insider trading cases. It documents that both exchange trading rules and surveillance mitigate the number of insider trading cases but exacerbating the profit per case. In the most conservative estimate, a 1-standard-deviation improvement in trading rules give rise to a 23.43% reduction in the number of insider trading cases and a 53.17% increase in the profits per case. Overall, the findings highlight complementarities across different trading rules and surveillance, and these complementarities are at least twice as important as stand-alone insider trading rules for prediction the frequency of trading cases; nevertheless, the complementarities are less economically important for predicting the trading value for surrounding the insider trading cases relative to stand-alone insider trading rules. The first essay is related to a substantial body of work in securities regulation that explores the question of whether securities laws and their enforcement facilitate more efficient markets with greater integrity. In addition, for the first time, the first essay in this thesis complements this literature by examining, whether surveillance (computer-based alerts based on algorithms) and exchange trading rules across countries and time mitigate insider trading activity. Our findings strongly support this prior work and extend the literature by highlighting the effect of different yet complementary market manipulation rules and specific direct policy mechanisms directly relevant to insider trading.

The essay, 'High Frequency Trading and End-of-Day Price Dislocation', complements the second chapter by investigating whether the presence of high frequency trading (HFT) has significantly exacerbate or mitigate the frequency and severity of end-of-day price dislocation - an issue has been generated many debate in the media. High frequency trading (HFT) involves implementing proprietary trading strategies through the use computerized algorithms. It is a new phenomenon but grow very fast. HFT has become commonplace in many exchanges around the world. The growth in HFT activities has generated plenty of attention from financial market regulators and commentators. Some commentators have likewise expressed concern that HFT might increase the prevalence of market manipulation (Biais and Woolley, 2011). Our study has shown that 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%. 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. Our findings imply HFT makes it more difficult for market manipulators to manipulate EOD closing prices. Our finding is consistent with the extant evidences and results in many studies that show the valuable role for HFT in facilitating price discovery.

The essay, ' Individualism, Synchronized Stock Price Movements, and Stock Market Volatility', examines the relation between national culture and investor behavior, and how it impacts overall market volatility is studied by examining synchronized stock price movements and stock market volatility. Financial markets in emerging countries can be characterized by both a high number of synchronized stock price movements and a high level of stock market volatility. I find that nations with lower values of individualistic culture are more likely to have a higher number of synchronized stock price movements.

Further, the correlation between stock price movements apparently increase stock market volatility. Nations with high individualistic culture have a lower number of synchronized stock price movements and thus have lower levels of stock market volatility. In the most conservative estimates, one standard deviation difference in individualistic value could lower the monthly average synchronized stock price movements by 8.20%. In terms of stock market volatility, one standard deviation increase in the number of synchronized stock price movements will lead to an increase of average monthly stock market volatility by 28.15% in the simple measure. The positive relationship between synchronized stock price movements and stock market volatility is stronger for emerging markets during the financial crisis from June 2007 to December 2008. This paper provides new insights on why emerging markets tend to have higher synchronized stock price movements and have a higher level of stock market volatility. The empirical results indicate that a portion of the difference in the overall market level volatility across countries can be attributed to the investor bias in different cultures.

Bibliography

Aggarwal, R., 2001. Regulatory infrastructure covering financial markets. Brookings-Wharton Papers on Financial Services, 55-76.

Aggarwal, R.K., Wu, G., 2006. Stock market manipulations. Journal of Business 79, 1915-1953.

Aitken, M., Cumming, D.J. and Zhan, F., 2014. Trade Size around the World. European Journal of Finance, forthcoming.

Aitken, M., Siow, A., 2003. Ranking equity markets on the basis of market efficiency and integrity. In: H. Skeete, Hewlett-Packard Handbook of World Stock, Derivative & Commodity Exchanges 2003. Dublin, pp. xliv-lv.

Allen, H., Taylor, M.P., 1990. Charts, noise and fundamentals in the London foreign exchange market. Economic Journal 100 (400), 49–59.

Allen, F., Gale, D., 1992. Stock-price manipulation. Review of Financial Studies 5, 503-529.

Allen, F., Gorton, G., 1992. Stock price manipulation, market microstructure and asymmetric information. European Economic Review 36, 624-630.

Bae, K., Chan, K., and Ng, A. 2004. Investibility and return volatility. Journal of Financial Economics, 71, 239-263.

Baker, M., L. Litov, J.A. Wachter, and J. Wurgler, 2010. Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements, Journal of Financial and Quantitative Analysis 45, 1111-1131.

Banerjee,A. 1992. A simple model of herd behavior. The Quarterly Journal of Economics. 107(3). 797-817.

Banerjee, A., and Eckard, E.W., 2001. Why Regulate Insider Trading? Evidence from the First Great Merger Wave (1897-1903). American Economic Review, 91(5): 1329-1349.

Bajgrowicz, P., and Scaillet, O., 2012. Technical Trading Revisited: False Discoveries, Persistence Tests, and Transaction Costs, Journal of Financial Economics, forthcoming

Barber, B. M., and Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21(2), 785-818.

Baron, M., Brogaard, J., and Kirilenko, A., 2012. "The Trading Profits of High Frequency Traders." Working Paper.

Bartram, S. M., Brown, G., and Stulz, R. M., 2012. Why are U.S. Stocks More Volatile? Journal of Finance, 67(4), 1329-1370.

Bebchuk, L.A., and C. Fershtman, 1994. Insider Trading and the Managerial Choice among Risky Projects, Journal of Financial and Quantitative Analysis 29, 1-14.

Becker, G., 1968. Crime and punishment: an economic approach. Journal of Political Economy 76, 169-217.

Beny, L.N., 2005. Do insider trading laws matter? Some preliminary comparative evidence. American Law and Economics Review 7, 144-183.

Beny, L.N., 2007. Insider trading laws and stock markets around the world: an empirical contribution to the theoretical law and economics debate. Journal of Corporation Law 32, 237-300.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust difference in difference estimates? Quarterly Journal of Economics 119, 249-275.

Bhattacharya, U., Daouk, H., 2002. The world price of insider trading. Journal of Finance 57, 75-108.

Bhattacharya, U., Daouk, H., 2009. When no law is better than a good law. Review of Finance 13, 577-627.

Biais, B., and Woolley, P., 2011. High Frequency Trading. Working Paper,

Bikhchandani, Sushil, David Hirshleifer and Ivo Welch, 1992, A theory of fads, fashion, custom, and cultural change as informational cascades, Journal of Political Economy 100(5), 992-1026.

Boehmer, E., Fong, K. Y. L., and Wu, J., 2012. Algorithmic Trading and Changes in Firms' Equity Capital, Working Paper.

Bontempo, R., Lobel, S. and Triandis, H., 1990. Compliance and Value Internalization in Brazil and the US. Journal of Cross-Cultural Psychology, 21, 200-213.

Branch, W.A., and Evans., G.W., 2011. Learning about Risk and Return: A Simple Model of Bubbles and Crashes. American Economic Journal: Macroeconomics, 3(3): 159-91.

Bris, A., 2005. Do insider trading laws work? European Financial Management 11, 267-312.

Brockman, P., D.Y. Chung, and X. Yan, 2009. Block Ownership, Trading Activity, and Market Liquidity, Journal of Financial and Quantitative Analysis 44, 1403-1426.

Brogaard, J., 2010. High Frequency Trading and its Impact on Market quality. Working Paper.

Brogaard, J., Hendershott, T., and Riordan, R., 2013. "High Frequency Trading and Price Discovery". Working Paper.

Brown, N., Wei, K. and Wermers, R., 2013, Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices, Management Science, forthcoming.

Carhart, M., R. Kaniel, D. Musto, and A. Reed, 2002. "Leaning for the Tape: Evidence of Gaming Behavior in Equity Mutual Funds," Journal of Finance 57, 661-693.

Carrion, A., 2013. Very fast money: High-Frequency trading on the NASDAQ. Working Paper.

Chaboud, A., E. Hjalmarsson, C. Vega, and Chiquoine, B., 2009. Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market. Federal Reserve Board International Finance Discussion Paper No. 980.

Chiang, T. C., Li, J., Tan, L., and Nelling, E. 2011. Dynamic herding behavior in Pacific-Basin markets: evidence and implications. Working paper.

Clayton, M.J., Jorgensen, B.N., Kavajecz, K.A., 2006. On the presence and market-structure of exchanges around the world. Journal of Financial Markets 9, 27-48.

Chlistalla, M., 2011. High-frequency trading: better than its reputation? In FOCUS. Retrieved from http://www.world-exchanges.org/focus/2011-09/m-2-2.php

Chui, A.C. W., Titman, S. and Wei, K.C. J., 2010. Individualism and Momentum around the World. The Journal of Finance, vol. LXV (1), 361-392.

Christie, W. G. and Huang, R. D., 1995. Following the Pied Piper: Do Individual Returns Herd around the Market? Financial Analysts Journal, 51, 31-37.

Comerton-Forde, C., and Putnins, T.J., 2011. Measuring Closing Price Manipulation. Journal of Financial Intermediation, vol.20:2, pp. 135-58

Comerton-Forde, C., Rydge, J., 2006. Market integrity and surveillance effort. Journal of Financial Services Research 29, 149-172.

Cross, F., 1973. The Behavior of Stock Prices on Fridays and Mondays. Financial Analysts Journal, 29 (Novemeber-December). 67-69.

Cumming, D., Johan, S.A., 2008. Global market surveillance. American Law and Economics Review 10, 454-506.

Cumming, D.J., Johan, S.A., Li, D., 2011. Exchange trading rules and stock market liquidity. Journal of Financial Economics 99(3), 651-671.

Cumming, D., Zhan, F. and Aitken, M., 2012a. Exchange Trading Rules, Surveillance and Insider Trading. Working Paper.

Cumming, D., Zhan, F. and Aitken, M., 2012b. High Frequency Trading and End-of-Day Price Dislocation. Working Paper.

Cooper, R.A., T.E. Day, and C. M. Lewis, 2001, Following the leader: a study of individual analysts' earnings forecasts. Journal of Financial Economics, 61, 383-416.

Daouk, H., Lee, C.M.C., Ng, D.T., 2006. Capital market governance: how do security laws affect market performance? Journal of Corporate Finance 12, 560-593.

DeMarzo, P.M., Fishman, M.J., Hagerty, K.M., 2005. Self-regulation and government oversight. Review of Economic Studies 72, 3, 687-706.

Djankov, S., La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2008. The law and economics of self-dealing. Journal of Financial Economics 88, 430-465.

Donaldson, R. G. and Kim, Harold, Y., 1993. Price Barriers in the Dow Jones Industrial Average. Journal of Financial and Quantitative Analysis, vol 28, no 3, 313-330.

Du, J. and Wei, S. J., 2004. Does Insider Trading Raise Market Volatility? The Economic Journal, 114, 916-942.

Easley, D., M.M. Lopez de Prado, and O'Hara, M., 2011. The Microstructure of the 'Flash Crash': Flow Toxicity, Liquidity Crashes and the Probability of Informed Trading, The Journal of Portfolio Management, 37, 118-128.

Edelen, R. M., and Kadlec, G. B., 2012. Delegated Trading and the Speed of Adjustment in Security Prices. Journal of Financial Economics, 103(2), 294-307.

Eun, C. S., Wang, L, and Xiao, S., 2012. Culture and Stock Price Synchronicity: The Effects of Tightness and Individualism. Working Paper.

European Commission, 2010. Review of the Markets in Financial Instruments Directive (MiFID), Retrieved from http://ec.europa.eu/internal_market/consultations/docs/2010/mifid/consultation_paper_en.pdf

Feng, L., and Seashole, M. S.. 2002. Herding and Information Flows in Emerging Markets. Working Paper, Harvard Business School.

Frott, K. A., Scharfsteinm, D. and Stein, J. C., 1992. Herd on the Street: Informational Inefficiencies in a Market with Short-term Speculation. Jounral of Finance, 47, 1461-1484.

Franke, R. H., Hofstede, G. and Bond, M. H., 1991. Cultural Roots of Economic Performance: A Research Note. Strategic Management Journal, vol l2. 165-173.

Frankel, J. A. and Froot, K. A., 1986. Understanding the US dollar in the Eighties: The expectations of chartists and fundamentalists. The Economic Record, S62, 24-38.

French, K. R. (1980). Stock Returns and The Weekend Effect. Journal of Financial Economics, 8, 55-69.

Garfinkel, J. A., and Nimalendran, M., 2003. Market structure and trader anonymity: An analysis of insider trading, Journal of Financial and Quantitative Analysis 38, 591-610.

Gerard, B., Nanda, V., 1993. Trading and manipulation around seasoned equity offerings. Journal of Finance 48, 213-245.

Grant, J. (2011, April 12th). High-frequency boom time hits slowdown. Financial Times.

Gomber, P., Arndt, B., Lutat, M., and Uhle, T., 2011. High-Frequency Trading. Working Paper.

Gudykunst, W. B. (ed.)., 1993. Communication in Japan and the United States. Albany: State University of New York Press.

Hagstomer, B., and Norden, L., 2012. The Diversity of High Frequency Traders. Working Paper.

Harris, L., 2002. Trading and Exchanges: Market Microstructure for Practitioners. Oxford University Press, Ocford, UK.

Harris, F.H. de B., Aitken, M.A., Cook, R.M., McInish, T.H., 2008. Market design and execution costs for matched securities worldwide. Institutional Investor's Guide to Global Liquidity, Vol 2, Goldman Sachs, New York.

Hendershott, T., Jones, C.M. and Menkveld, A.J., 2011. “Does Algorithmic Trading Improve Liquidity” Journal of Finance 66, 1-33.

Hendershott, T., and Riordan, R., 2010. High Frequency Trading and Price Discovery Working Paper,

Henrikson, F., 2011. Characteristics of High-Frequency Trading. Royal Institute of Technology, Sweden, Working Thesis, October, 2011.

Hillion, P., Suominen, M., 2004. The manipulation of closing prices. Journal of Financial Markets 7, 351-375.

Hofstede, G., 1980. Culture's Consequences: International Differences in Work-Related Values. Beverly Hills CA: Sage Publications.

Hofstede, G., 1995. Multilevel Research of Human Systems: Flowers, Bouquets and Gardens. Human Systems Management, 14, 207-217.

Hofstede, G., 2001. Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations Across Nations. 2nd Edition, Thousand Oaks CA: Sage Publications.

Hofstede, G. and Bond, M. H,. 1988. The Confucius Connection: From Cultural Roots to Economic Growth. Organizational Dynamics, 16 (4), 4-21.

Hofstede, G and Hofstede, G. J. 2005. Cultures and Organizations: Software of the Mind. 2nd Edition, McGraw-Hill USA, 2005.

Ho, D. Y. F. and Chiu, C-Y., 1994. Complement Ideas of Individualism, Collectivism and Social Organization: An Application in the Study of Chinese Culture. In U. Kim, H.C. Triandis, C. Kagitcibasi, S-C Choi and G. Yoon. Individualism and Collectivism: Theory, Method and Applications. Newbury Park, Calif: Sage Press.

Hui, C. H. and Triandis, H. C., 1986. Individualism and Collectivism: A Study of Cross-Cultural Researchers. Journal of Cross-Cultural Psychology, 17, 255-248.

Jackson, H.E., 2007. Variation in the intensity of financial regulation: preliminary evidence and potential implications. Yale Journal on Regulation 24, 253-291.

Jackson, H.E., Roe, M.J., 2009. Public and private enforcement of securities laws: resource-based evidence. Journal of Financial Economics 93, 207-238.

Jarrow, R.A., 1992. Market manipulation, bubbles, corners and short squeezes. Journal of Financial and Quantitative Analysis 27, 311-336.

Jarrow, R.A., 1994. Derivative security markets, market manipulation and option pricing theory. Journal of Financial and Quantitative Analysis 29, 241-261.

Karpoff, J., Koester, A., Lee, D.S., Martin, G.S., 2012. A critical analysis of databases used in financial misconduct research. Mays Business School Research Paper No. 2012-73.

Karpoff, J., Lee, D.S., Martin, G.S., 2008a. The consequences to managers for cooking the books. Journal of Financial Economics 88, 193-215.

Karpoff, J.M., Lee, D.S., Martin, G.S., 2008b. The consequences to managers for financial misrepresentation. Journal of Financial Economics 85, 66-101.

Karpoff, J.M., Lou, X., 2010. Short sellers and financial misconduct. Journal of Finance 65, 1879-1913.

Kezdi, G. (2003). Robust Standard Error Estimation in Fixed-Effects Panel Models. Hungarian Statistical Review, 9, 95-116.

Kim, K.A., and Nofsinger, J. R. 2005. Institutional herding, business groups, and economic regimes: evidence from Japan. The Journal of Business, 78(1), 213-242.

King, M., 2009. Pre-bid run-ups ahead of Canadian takeovers: how big is the problem? Financial Management 38, 699-726.

Kirilenko, A., Kyle, A., Samadi, M., and Tuzun, T., 2011. "The Flash Crash: The Impact of High Frequency Trading on an Electronic Market." Working Paper.

Kramstra, M. J., Kramer, L. A. and Levi, M., 2000. Losing Sleep at the Market: The Daylight Saving Anomaly. American Economic Review, 1005-1011.

Kramstra, M. J., Kramer, L. A. and Levi, M., 2003. Winter Blues: A SAD Stock Market Cycle. American Economic Review, 324-343.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 1999. Corporate ownership around the world. Journal of Finance 54, 471-517.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2006. What works in securities laws? Journal of Finance 61, 1-32.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Legal determinants of external finance. Journal of Finance 52, 1131-1150.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance. Journal of Political Economy 106, 1113-1155.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 2002. Investor protection and corporate valuation. Journal of Finance 57, 1147-1170.

Landes, D., 2000. Culture makes almost all the difference. In: Harrison, L. E., Huntington, S.P. (Eds.), Culture Matters. NewYork, NY.

Lao, P., and Singh, H. 2011. Herding behaviour in the Chinese and Indian stock markets. Working paper. http://ssrn.com/abstract=1937956

Lou, D. 2014. Attracting investor attention through advertising. Working Paper.

MacIntosh, J. G, 2013. High Frequency Traders: Angels or Devils?, CD Howe Institute Commentary, forthcoming.

Mahoney, P.G., 1999. The stock pools and the Securities Exchange Act. Journal of Financial Economics 51, 343-369.

Malinova, K., Park, A., and Riodan, R., 2012. Do Retail Traders Suffer from High Frequency Traders? Working Paper.

Mao, H., Counts, S., and Bollen, J., 2011. Predicting financial markets: comparing survey, news, twitter and search engine data. Working Paper.

Markus, H. R., and Kitayama, S., 1991. Culture and the Self: Implications for Cognition, Emotion, and Motivation. Psychological Review, 1991, vol. 98 (2), 224-253.

Maug, E., and Naik, N., 2011. Herding and Delegated Portfolio Management: The Impact of Relative Performance Evaluation on Asset Allocation. . Quarterly Journal of Finance, 01, 265.

Menkveld, A., 2012. High Frequency Trading and the New-Market Makers. Working Paper.

Merrick, J.J. Jr., Naik, N.Y., Yadav P.K., 2005. Strategic trading behavior and price distortion in a manipulated market: anatomy of a squeeze. Journal of Financial Economics 77, 171-218.

Morck, R. Yeung, B. and Yu, W., 2000. The Information Content of Stock Markets: Why do Emerging Markets Have Synchronous Stock Price Movements? Journal of Financial Economics, 58, 215-260.

Ni, S.X., Pearson, N.D., Poteshman, A.M., 2005. Stock price clustering on option expiration dates. Journal of Financial Economics 78, 49-87.

Nofsinger, J.R., and Sias, R. W. 1999. Herding and feedback trading by institutional and individual investors. The Journal of Finance, 54(6), 2263-2295.

Odean, Terrance, 1998, Volume, Volatility, Price and Profit When All Traders are Above Average. Journal of Finance, 53, 1887-1934.

O'Hara, M., 2001. Overview: market structure issues in market liquidity. Market Liquidity: Proceedings of a Workshop Held at the BIS, BIS Papers, No. 2, April, Basel, 1-8.

O'Hara, M., Mendiola, A.M., 2003. Taking stock in stock markets: the changing governance of exchanges. Unpublished working paper, Cornell University, New York.

O'Reilly, R., 2012. High Frequency Trading: Are Our Vital Capital Markets at Risk from a Rampant Form of Trading that Ignored Business Fundamentals? The Analyst (March 2012).

Peng, L., Röell, A., 2009. Managerial incentives and stock price manipulation, CEPR Discussion Paper No. DP7442.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Review of Financial Studies 22, 435-480.

Pirrong, S.C., 1993. Manipulation of the commodity futures market delivery process. Journal of Business 15, 335-370.

Pirrong, S.C., 1995a. The self-regulation of commodity exchanges: the case of market manipulation. Journal of Law and Economics 38, 141-206.

Pirrong, S.C., 1995b. Mixed manipulation strategies in commodity futures markets. Journal of Futures Markets 15, 13-38.

Pirrong, C., 1999. The organization of financial exchange markets: theory and evidence. Journal of Financial Markets 2, 329-357.

Pirrong, S.C., 2004. Detecting manipulation in futures markets: the Ferruzi soybean episode. American Law and Economics Review 6, 28-71.

Pistor, K., Keinan, Y., Kleinheisterkamp, J., West, M., 2003. The evolution of corporate law: a cross-country comparison. Journal of International Economic Law 23, 791-871.

Pistor, K., Xu, C., 2003. Incomplete law – a conceptual and analytical framework and its application to the evolution of financial market regulation. Journal of International Law and Politics 35, 931-1013.

Pistor, K., Xu, C., 2005. Governing stock markets in transition economies: lessons from China. American Law and Economics Review 7, 184-210.

Pritchard, A.C., 2003. Self-regulation and securities markets. Regulation 26 (1), 32-39.

Reiffen, D., Robe, M.A., 2007. Ownership structure and enforcement incentives at self-regulatory financial exchanges. Unpublished working paper, American University, Washington DC.

Reykowski, J., 1994. Collectivism and individualism as dimensions of social change. In U. Kim, H. C. Triandis, Ç. Ka itçiba i, S. C. Choi, and G. Yoon (Eds.), Individualism and Collectivism: Theory, Method, and Applications. London: Sage.

Roe, M.J., 2006. Legal origins, politics, and modern stock markets. Harvard Law Review 120, 460-527.

Röell, A., 1992. Comparing the performance of stock exchange trading systems. In: J. Fingleton and D. Schoenmaker (Eds.), The Internationalisation of Capital Markets and the Regulatory Response. Kluwer, Amsterdam.

Romano, R., 2001. The need for competition in international securities regulation. Theoretical Inquiries in Law 2, 1-179.

Romano, R., 2002. The Advantage of Competitive Federalism for Securities Regulation. AEI Press, Washington DC.

Scheinkman, J. A. and Xiong, W., 2003. Overconfidence and Speculative Bubbles. Journal of Political Economics, 111(6), 1183-1220.

Schooler, C., 1990a. Individualism and Historical and Social Structural Determinants of People's Concerns Over Self-directedness and Efficiency. In J. Rudin, C. Schooler and K. W.Schaie (eds.). Self-directedness. Hillsdale, N.J., Erlbaum.

Schooler, C., 1990b. The Individual in Japanese history: Parallels to an Divergences from the European Experience. Sociological Forum 5, December.

Schwartz, S. H., 1990. Individualism-Collectivism: Critique and Proposed Refinements. Journal of Cross-Cultural Psychology, vol, 12 (2), 139-157.

Sias, R. W., 2004. Institutional herding. The Review of Financial Studies, 17(1), 165-206.

Spamann, H., 2010. The "antidirector rights index" revisited. Review of Financial Studies 23, 467-486.

Stulz, R. M. and Williamson, R., 2003. Culture, Openness, and Finance. Journal of Financial Economics, 70, 313-349.

Triandis, H. C., 1989. The Self and Social Behavior in Differing Cultural Contexts. Psychological Review, 1989, vol. 96 (3), 506-520.

Triandis, H. C., 1995. Individualism and Collectivism. Westview Press, Inc.

Triandis, H. C., Marin, G., Lisansky, J., and Betancourt, H., 1984. Simpatia as a Cultural Script of Hispanics. Journal of Personality and Social Psychology, 47, 1363-2375.

Trueman, B., 1994. Analyst forecasts and herding behaviour. Review of Financial Studies 7, 97–124.

Venezia, I, Nashikkar, A. and Shapira, Z., 2011. Firm Specific and Macro Herding by Professional and Amateur Investors and Their Effects on Market Volatility. Journal of Banking and Finance, 35, 1599-1609.

Walter, A., and Weber, F.M., 2006. Herding in the German Mutual Fund Industry. European Financial Management 12, 375-406.

Welch, I., 1992. Sequential sales, learning and cascades, Journal of Finance, 47 (2), 695-732.

Welch, I., 2000. Herding among security analysts. Journal of Financial Economics 58, 369–396.

Wermers, R., 1999. Mutual Fund Herding and the Impact on Stock Prices. Journal of Finance, 54, 581-622.

Wylie, S., 2005. Fund Manager Herding: a Test of the Accuracy of Empirical Results Using UK Data. Journal of Business, 78, 381-403.

Yu, Frank, and Xiaoyun Yu, 2011, Corporate lobbying and fraud detection, Journal of Financial and Quantitative Analysis 46, 1865-1891.

Zhang, F, X., 2010. High-Frequency Trading, Stock Volatility, and Price Discovery. Working Paper.