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Two Essays in Financial Economics

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Two Essays in Financial Economics

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by

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Dedication:

This dissertation is dedicated to my wife Yao, for whom I owe so much, and to my parents and in-laws. Thank you for all of your support.

Table of Contents

Abstract

This dissertation consists of two essays: the first investigates informed trading in the Chinese stock exchanges, and the second examines the persistency of correlation of currency future prices.

For the first essay, using a sample of Chinese firms dual-listed in both the China mainland stock exchange and the Hong Kong stock exchange, I investigate the two types of informed trading - insider trading and trading derived from better analysis in the A-and H-share markets. The results suggest that H-shares have relatively more informed trading based on better analysis. In addition, the results from the firm size regression can also be seen as indirect evidence that larger firms tend to have trading with better analysis and less insider trading. These patterns are also confirmed in the sub-period analysis. However, I find no significant relation between informed trading and the relative pricing of A- and H-shares.

For the second essay I examine the dynamic correlation between currency futures prices, focusing on the persistency of correlation of currency prices. Using the Dynamic Conditional Correlation model developed by Engle (2002), this study incorporates time-varying correlations into the analysis. The sample includes eight currency futures traded on the Chicago Mercantile Exchange from 1999 to 2008 and the U.S. dollar index future. The study finds that the Canadian dollar has the greater persistency while the Brazilian real has the weakest. No less important, the study finds that the time-varying conditional correlation between currency futures and the U.S. dollar futures is influenced by two types of liquidity: price impacts (Amihud illiquidity) and the logarithm of trading volume.

Keywords: informed trading, A- and H-shares, insider trading, currency futures, persistency, Amihud illiquidity

Chapter 1

Analyzing Informed Trading in Dually-Listed Chinese Stocks

1. Introduction

Informed trading can come from insider information or from better analysis, yet to my knowledge there is no study in the literature that empirically separates the two. This study attempts to do so by analyzing a large number of Chinese firms dual-listed in both the mainland Chinese exchanges (Shanghai and Shenzhen Stock Exchanges) and the Hong Kong Stock Exchange. This set of firms presents a natural experiment since, relative to the mainland markets, there is no doubt that the Hong Kong market is associated with less insider trading. So, in addition to understanding the extent of informed trading in China, China's unique setting has the potential to increase the understanding of two aspects of informed trading – insider trading and trading derived from better analysis. An added advantage of this analysis is that because the same set of firms is being analyzed, firm characteristics do not need to be controlled. Specifically, I investigate the two types of informed trading - insider trading and trading from better analysis in the A-and H-share markets, based on the methodology developed by Llorente, Michaely, Saar, and Wang (2002). The method primarily utilizes the relation between daily volume and first order return autocorrelation for individual stocks in order to infer the extent of informed trading. Intuitively, informed trading causes prices to change permanently and tends to be positively correlated with price changes; on the other hand, uninformed trading has only a temporary effect on prices and tends to be negatively associated with price changes. While Llorente, Michaely, Saar, and Wang (2002) analyze U.S. stocks, it does not empirically separate the two aspects of informed trading.

Given the assumptions that the A-shares market has more insider trading and that it has not increased over time, my results suggest that H-shares have relatively more informed trading based on better analysis. In other word, there is relatively more trading motivated by better analysis in the H-shares market. Together with results from a firm size regression, the implication is that larger firms tend to have more trading with better analysis and less insider trading. While this conclusion seems intuitive, to my knowledge this is the first study that explicitly analyzes the relation between firm size and aspects of informed trading.

I further examine the different aspects of informed trading by dividing the sample period into two sub-periods. More specifically, I examine the changes in coefficients of informed trading in the two subsequent sample periods. The sub-period results further confirm that H-shares have relatively more informed trading based on better analysis: since insider trading should not have increased, the substantial increase in the coefficients for informed trading of H-shares represents further evidence that trading based on better analysis dominates in the H-share market. This makes sense because the Hong Kong market has a long experience in analyzing stocks, but initially investors in Hong Kong might have difficulty evaluating Chinese firms with a host of transparency and political issues. The relatively small increase in the coefficients for informed trading of A-shares is indirect evidence that stock valuation has not substantially improved over time in A-shares. That is, it has implication for the changes in the Chinese investment environment.

One related question arising for cross-listed securities is whether informed trading in both the A- and H-share markets impacts the relative pricing of A-and H-shares. If H-shares have higher informed trading coefficients, suggesting that there is relative more trading motivated by better analysis in the H-shares market, than these better analyses will bring the stock price more in line to its intrinsic value. On the other hand, given the fact that the A-shares market tends to have excess speculative trading or insiders trading, the price might deviate more from its intrinsic value. Therefore, I expect that informed trading coefficients for H-shares are negatively correlated with the average H-share discount, while informed coefficients for A-shares are positively correlated with the H-share discount. However, the empirical results indicate no significant relation between informed trading on the relative pricing.

The remainder of the paper is organized as follows: Section 2 presents the literature review, Section 3 provides some background information concerning share structure in China, Section 4 describes data and methodology, Section 5 presents empirical results, and Section 6 gives the conclusion.

2. Literature Review

There are relatively few theoretical studies on trading volume, with few exceptions such as Wang (1994) and Campbell, Grossman, Wang (1993). Wang (1994) proposes a model of competitive stock trading. In this model, investors are heterogeneous in their information and private investment opportunities and rationally trade for both informational and non-informational motives. The author examines the link between the nature of heterogeneity among investors and the behavior of trading volume and its relation to price dynamics and finds that volume is positively correlated with absolute change in prices and dividends. He further shows that informational trading and non-informational trading lead to different dynamic relations between trading volume and stock returns. Campbell, Grossman, Wang (1993), on the other hand, investigate the relationship between aggregate stock market trading volume and the serial correlation of daily stock returns. For both stock indexes and individual large stocks they find the first order daily return autocorrelation tends to decline with volume. They explain this finding using a model in which risk-averse market makers accommodate buying or selling pressure from liquidity for non-informational traders and reward by changing expected stock returns. The other implication for the paper is that a stock price that declines on a high volume day is more likely than a stock price that declines on a low volume day to be associated with an increase in the expected stock return.

Gervais, Kaniel, and Mingelgrin (2001) and Bamber, Baron, and Stober (1999) investigate other aspects of trading. Gervais, Kaniel, and Mingelgrin (2001) investigate the idea that extreme trading activity contains information about future evolution of stock prices and find that stocks experiencing unusually high (low) trading volume over a week tend to appreciate (depreciated). Over the course of the following months, they argue that this high volume return premium is consistent with the idea that shocks in the trading activity of a stock affect its visibility and in turn the subsequent demand and price for that stock. Bamber, Baron, and Stober (1999) in contrast, provide evidence that differential interpretations are an important stimulus for speculative trading. They find two conditions under which differential interpretations play a significant role in explaining trading: 1) they present empirical evidence supporting Kandel and Pearson (1995) arguing that trading coincident with small price changes reflects investor's differential interpretations of information. This evidence is important because it is inconsistent with conventional models of trade that assume homogeneous interpretations and 2) they also find that differential interpretations explain a significant amount of the trading occurring in a sample where trading volume is higher than the firm specific announcement period average. This is consistent with informed traders acting on their differential interpretations when there is enough liquidity training to help camouflage their own information based trades.

Stickel and Verrecchia (1994) test the hypothesis that price changes are more likely to reverse following weak volume support than strong volume support. Since price changes reflect demand for a stock and therefore higher volume reflects a greater likelihood that demand originates from informed rather than uninformed trade. Consequently, as volume increases the probability that price change is informationally driven increases as well. There evidence suggests that a large price change on days with weak volume support tends to reverse the next day. They point out this volume effect is reinforced by, yet independent of, a bid-ask bounce effect. However, returns do not reverse following days of strong volume support. In fact, a large price increase with strong volume support tends to be followed by another price increase the next day. Kandel and Pearson (1995), present evidence on the volume return relationship around earnings announcement and argue that it is inconsistent with models that agents have identical interpretations of the public announcement. They also provided additional evidence on revisions on analyst forecasts which is also inconsistent with identical interpretations.

Chae (2005) and Lee and Rui (2002) provide further empirical evidence regarding stock volume. Chae (2005) investigates trading volume before scheduled and unscheduled corporate announcements to explore how traders respond to private information. The author shows that cumulative trading volume decreases by more than 15% prior to scheduled announcements. The decline in trading volume is largest when information asymmetry is high, while the opposite relation holds for volume after the announcement. In contrast, trading volume before unscheduled announcements increases dramatically and shows little relation to proxies for information asymmetry. The author argues all the results for scheduled announcements are consistent with asymmetric information series, where discretionary liquidity traders decrease volume when they know there is much adverse selection. However, discretionary liquidity traders do not seem to read information embedded in prices for before unscheduled announcements. In addition, market makers act appropriately by increasing price sensitivity before all announcements. This implies that market makers extract timing information from their order books. Lee and Rui (2002), however, examine the dynamic relations between stock market trading volume and returns (and volatility) for both domestic and cross-county markets by using the daily data of the three largest stock markets: New York, Tokyo, and London. Their major findings are as follows: 1) trading volume does not cause stock market returns on each of three stock markets 2) there exist a positive feedback relationship between trading volume and return volatility in all three markets 3) regarding the cross-country relationship U.S. financial market variables, in particular U.S. trading volume, contains an extensive predictive power for U.K. and Japanese market variables and 4) sub-sample analysis shows evidence of stronger spillover effects after the 1987 market crash and increased important of trading volume as an information variable after the introduction of options in the U.S. and Japan.

Also, there are several papers that deal with the dynamics of returns and volume. Gagnon and Karolyi (2009) investigate the joint dynamics of returns and trading volume of 556 stocks on the U.S. market. They use heterogeneous trading models rationalize how trading volume reflects trading quality of trader's information signals an how it helps to disentangle whether returns are associated with portfolio rebalancing trades or information motivated trades. Based on these models they hypothesize that returns in the home (U.S.) market on high volume days are more likely to continue to spill over into the U.S. (home) market for those cross-listed stocks subject to the risk of greater informed trading. Their empirical findings provided support for these predictions, which confirms the link between information trading volume and international stock return co-movements. Halling, Moulton and Panayides (2011) introduce a volume-based measure of multimarket trading to study the extent to which investors actively exploit multimarket environments. By analyzing a large set of cross-listed firms, they find higher multimarket trading among markets with similar designs and strong enforcement of insider trading laws and for firms with higher institutional ownership. These findings are important for firms evaluating the benefits of cross-listing and for markets competing for order flow. Menkveld (2008) studies British cross-listed stocks and finds evidence of multimarket trading even after controlling for the possibility of local traders in each market simultaneously receiving the same private signal and trading on it locally. Chen, Firth, and Rui (2001), in contrast, examine the dynamic relation between returns, volume, and volatility of stock indexes. Using the data from nine national markets spent over two decades they show that a positive correlation between trading volume and the absolute value of the stock price change. They also demonstrate that for some countries returns causes volume and volume causes returns. Their results indicate that trading volume contributes some information to the trading process.

Llorente, Michaely, Saar, and Wang (2002) also examine the dynamic relation between return and volume of individual stocks. Using a simple model in which investors trade in order to either share risk or speculate on private information, they show that returns generated by risk-sharing trades tend to reverse themselves while returns generated by speculative trades tend to continue onward. They test this theoretical prediction by analyzing the relation between daily volume and first-order return autocorrelation for individual stocks listed on the NYSE and AMEX. They conclude that the cross-sectional variation in the relation between volume and return autocorrelations are related to the extent of informed trading.

Jayaraman (2008) examines whether earnings that are smoother or more volatile than cash flows provide or garble information. Consistent with theories that predict more informed trading when public information is less informative, the author finds that bid-ask spreads and the probability of informed trading are higher both when earnings are smoother than cash flows and also when earnings are more volatile than cash flows. Additional tests suggest that managers' discretionary choices that lead to smoother or more volatile earnings than cash flows garble information, on average. Perottiand and Thadden (2003) argue that dominant investors can influence the publicly available information about firms by affecting the cost of information collection. They suggest that under strategic competition, transparency results in higher variability of profits and output. Thus, lenders prefer less transparency since this protects firms in a weak competitive position, while equity holders prefer more transparency. Market interaction creates strategic complementarity in gathering information on competing firms and thus entry by transparent competitors will improve price information. Moreover, as the return to information gathering increases with liquidity, increasing global trading may undermine the ability of bank control to keep firms opaque. Bardong, Bartram, and Yadav (2009) investigate and test hypotheses on how informed trading varies with market-wide factors and the structural and trading characteristics of a firm. They find strong evidence of commonality in informed trading, and a systematic dependence of informed trading on firm characteristics that is largely consistent with intuition and earlier theory and empirical evidence, wherever available. They then decompose informed trading into two components: one that reflects information asymmetry with respect to skilled information processors with potentially private information on systematic factors, who generate a private informational advantage using public data; and another unpredictable component that reflects truly private information, potentially of traditional insiders. They test the pricing relevance of both these components and find that it is only the predictable component reflecting truly private information that is priced, and is priced more strongly and in a manner more robust than total informed trading.

Lastly, there are several papers than examine information and stocks. Chen, Kim, Nofsinger, and Rui (2007) study investment decision making in an emerging market by examining single brokerage account data from China. Overall, they find that Chinese investors make poor trading decisions. The stocks they purchase tend to underperform those they sell. They also find that Chinese investors suffer from three behavioral biases: (i) they tend to sell stocks that have appreciated in price, but not those that have depreciated in price (consistent with a disposition effect - acknowledging gains but not losses), (ii) they seem overconfident, and (iii) they appear to believe that past returns are indicative of future returns (a representativeness bias). In comparisons to prior findings, Chinese investors appear more overconfident than U.S. investors (i.e., Chinese investors hold fewer stocks, yet trade more often) and seem to suffer from a stronger disposition effect. Finally, the authors categorize Chinese investors, based on proxy measures of experience, and find that ‘‘experienced’’ investors are not always less prone to behavioral biases than are ‘‘inexperienced’’ ones. In contrast, Karolyi and Li (2003) find that there is a negative relationship between firm size and information asymmetry and that there is also a statistically significant relationship between variations in B-share discount and firm size. Sun and Tong (2000) look at the relative volatility of B-share and A-share returns. They argue that since both A- and B-stocks represent the same claim to a firm’s assets, any excess A-share volatility (comparing to that of B-share) must be due to speculative trading and therefore associated with A-share premiums. Chen, Lee and Rui (2001) employ a variance ratio of returns to A- and B-shares in order to investigate changes in risk preferences. They do not find a statistically significant connection between levels of risk and B-share discounts.

3. Background Information

China began to open its economy in the late 1970's. After successfully liberalizing farm ownership and production China began to shift focus and start building stronger financial markets by opening the Shanghai Stock Exchange and the Shenzhen Stock Exchange.[1] Most of the original companies listed on the two exchanges were state-owned enterprises. The first shares traded on the exchanges were A-shares. A-shares are denominated in Renminbi (RMB) and issued to local citizens. By 1992 the two exchanges expanded trading by issuing B-shares, which were sold specifically to foreigners and denominated in U.S. dollars.

In contrast, the Hong Kong Stock Exchange had been operating for almost a century. China knew of Hong Kong's ability to raise large amount of capital within Asia and soon approached the exchange with an offer to have Chinese mainland businesses directly listed on the Hong Kong Exchange. The Hong Kong Exchange agreed, and since Hong Kong begins with the letter "H" the new shares were denoted as H-shares.

H-shares are stocks traded on the Hong Kong stock market and denominated in Hong Kong dollars. In order to sell H-shares companies must meet certain requirements: (1) the company must be incorporated in mainland China; (2) the company must have a market capitalization of HK $200 million; (3) the company must have earned, 3 years prior to application, a profit of HK $5 billion; this means a profit of HK $2 billion the year before the application and a total profit of HK $3 billion the two years prior to that; and (4) during the 3 year period prior to application management must have remained unchanged.

[1]Shenzhen was designated by the state as a special economic zone in 1980. Shenzhen was originally a part of the city of Guangdong.

A-shares generally trade at a premium to H-shares. This might be partially due to the fact that the Chinese government restricts mainland Chinese from investing abroad and foreigners, located in mainland China, from investing in the H-share market. For mainland Chinese, there are three ways for individual investors to invest in H-shares: (1) individual investors can travel to Hong Kong to set up an account in Hong Kong to buy H-shares; (2) individual investors can buy H-shares through Hong Kong brokerage companies that have offices in China; (3) in selected cities, individual investors can purchase H-shares using a special service called "H-share Express" provided by the Bank of China.

Table 1 Panel A shows the difference in stock exchange and investor types for A- and H-Share Markets. Table 1 Panel B reports the deceptive statistics for the two markets. In 2011, the GDP for China mainland is 6.989 trillion USD vs. for Hong Kong market 242.4 billion USD. For the Shanghai Stock Exchange the market capitalization is 2.357 trillion USD vs. Hong Kong stock exchange 2.258 trillion USD. As of 2011, there were 1,961companies listed on China's mainland stock exchange vs. 1,496 companies listed on the Hong Kong Stock Exchange. The value of shares traded for China mainland is 3,670,156 million USD vs. 1,444,712 million USD for Hong Kong. In addition, there are 1,273,276.900 trades happening in China mainland vs. 168,524,300 trades for Hong Kong. As for the number of shares traded, China mainland is 2,119,387 million vs. Hong Kong's 2,953,186 million. The average daily turnover dollar value for China mainland is 15,042 million USD while Hong Kong has 5.873 million USD. Further, the average value of trades for China mainland is 2,900 USD vs. 8600 USD for the Hong Kong market. In sum, relative to size of the economy, Hong Kong has a slightly larger stock market, more number of shares traded, lower turnover ratio, larger trade size, and greater trade value - all of which are characteristics of a more liquid market.

Table 1. A- and H-Share Markets Comparison

Panel A. Difference between A- and H-Share Markets

	A-share	H-share
Stock Exchange	Shanghai (SSE) Shenzhen (SZSE)	Hong Kong (HKEx)
Currency	RMB	HKD
Investor	Chinese mainland investor	HK residents, foreigners, some Chinese mainland investor

Panel B. Descriptive A- and H-Share Market

	China mainland Shanghai	Hong Kong
GDP	US$6.989 trillion	US$242.4 Billion
Market Capitalization	US$2.357 trillion	US$2.258 trillion
NO. Companies Listed	1691 (931)	1,496
Value of share trading (Total) ($millions)	3,670,155.70	1,444,711.70
Number of trades (thousands)	1,273,276.90	168,524.30
Number of shares traded (millions)	2,119,387.10	2,953,185.80
Average daily turnover value ($millions)	15,041.60	5,872.80
Average value of trades ($thousands)	2.9	8.6

4. Data and Methodology

The initial sample is constructed using all cross-listed A- and H-shares in both the Shanghai and Shenzhen Stock Exchanges for the period 2003 to 2011. For a firm to be included in the sample it must have daily price data, daily trading volume, and shares outstanding data available for both the A-and H-share market. The final sample covers 68 firms and spans from

January 1st, 2003 to December 31st, 2011. Table 2 reports the sample firms and their respective industries for the A- and H-shares markets.

Table 2. Sample of Companies

This table provides the basic information for the dual-listed A- and H-shares included in the sample. Column 1 provides the name of the company; column 2 provides the respective industry.

Company Name	Industry
ZTECorporation	Communications and Related Equipment Manufacturing
Zoomlion Heavy Industry Science And Technology Co., Ltd.	Special Equipment Manufacturing
Weichai Power Co., Ltd.	Transportation Equipment Manufacturing
Shandong Chenming Paper Holdings Ltd.	Paper and Allied Products
Northeast Electric Development Co., Ltd.	Electrical Machinery and Equipment Manufacturing
Jingwei Textile Machinery Co., Ltd.	Special Equipment Manufacturing
Shandong Xinhua Pharmaceutical Co., Ltd.	Medicine Manufacturing
Angang Steel Company Limited	Ferrous Metal Smelting and Extruding
HisenseKelon Electrical Holdings Company Limited	Electrical Machinery and Equipment Manufacturing
Xinjiang GoldwindScience&TechnologyCo.,Ltd	Electrical Machinery and Equipment Manufacturing
Shandong Molong Petroleum Machinery Co. Ltd.	Special Equipment Manufacturing
BYD Co., Ltd	Other Manufacturing
Huaneng Power International Co., Ltd	Electric Power, Steam and Hot Water Generation and Supply
Anhui Expressway Co., Ltd	Support Service for Transportation
China Minsheng Banking Co., Ltd.	Banking
China Shipping Development Co., Ltd	Water Transportation
Huadian Power International Co., Ltd.	Electric Power, Steam and Hot Water Generation and Supply
China Petroleum & Chemical Corporation	Oil and Gas Extraction
China Southern Airlines Co., Ltd	Air Transportation
China Merchants Bank Co., Ltd	Banking
China Eastern Airlines Co., Ltd.	Air Transportation
Yanzhou Coal Mining Co., Ltd.	Coal Mining and Quarrying
Guangzhou Pharmaceutical Co., Ltd.	Medicine Manufacturing
Jiangxi Copper Co., Ltd.	Non-Ferrous Metal Smelting, Rolling, Drawing, and Extruding
Jiangsu Expressway Co., Ltd	Support Service for Transportation
Shenzhen Expressway Co., Ltd	Support Service for Transportation
Anhui Conch Cement Co.,Ltd	Non-metallic Mineral Products
Tsingtao Brewery Co., Ltd.	Beverages
Guangzhou Shipyard International Co., Ltd.	Transportation Equipment Manufacturing
Sinopec Shanghai Petrochemical Co., Ltd.	Petroleum Processing & Coking
Nanjing Panda Electronics Co., Ltd.	Communications and Related Equipment Manufacturing
Shenji Group Kunming Machine Tool Co.,Ltd	Special Equipment Manufacturing

Maanshan Iron & Steel Co., Ltd.	Ferrous Metal Smelting and Extruding
Beiren Printing Machinery Holdings Ltd.	Special Equipment Manufacturing
Sinopec Yizheng Chemical Fibre Co., Ltd.	Chemical Fibre Manufacturing
Tianjin Capital Environmental Protectiongroup Co., Ltd.	Public Facilities Services
Dongfang Electric Corporation Limited	Electrical Machinery and Equipment Manufacturing
Luoyang Glass Co., Ltd.	Non-metallic Mineral Products
Chongqing Iron & Steel Company Limited	Ferrous Metal Smelting and Extruding
China Shenhua Energy Company Limited	Coal Mining and Quarrying
Sichuan Expressway Company Limited	Support Service for Transportation
Air China Limited	Air Transportation
China Railway Construction Corporation Limited	Civil Engineering Construction
Agricultural Bank Of China Limited	Banking
Ping An Insurance (Group) Company Of China, Ltd.	Insurance
Bank Of Communications Co., Ltd.	Banking
Guangshen Railway Company Limited	Railroad Transportation
China Railway Group Limited.	Civil Engineering Construction
Industrial And Commercial Bank Of China Limited	Banking
Beijing North Star Company Limited	Estate Development and Operation
Aluminum Corporation Of China Limited	Nonferrous Metal Mining
China Pacific Insurance (Group) Co., Ltd.	Insurance
Shanghai Pharmaceuticals Holding Co.,Ltd.	Medicine Manufacturing
Metallurgical Corporation Of China Ltd.	Civil Engineering Construction
China Life Insurance Company Limited	Insurance
Shanghai Electric Group Company Limited	Electrical Machinery and Equipment Manufacturing
China South Locomotive & Rolling Stock Co., Ltd.	Transportation Equipment Manufacturing
China Oilfield Services Limited	Oil and Gas Extraction
Petrochina Company Limited	Oil and Gas Extraction
China Shipping Container Lines Company Limited	Water Transportation
Dalian Port (Pda) Co., Ltd.	Port
China Coal Energy Company Limited	Coal Mining and Quarrying
Zijin Mining Group Co., Ltd.	Nonferrous Metal Mining
China Cosco Holdings Company Limited	Water Transportation
China Construction Bank Corporation	Banking
Bank Of China Limited	Banking
Datang International Power Generation Co., Ltd.	Electric Power, Steam and Hot Water Generation and Supply
China Citic Bank Corporation Limited	Banking

Table 3 provides summary statistics for the 68 firms in the sample. The average (median) total asset is 1,102,470.00 (76,912.96) millions of Renminbi, while the average (median) total liabilities is 991,832.00 (41,644.26) millions of Renminbi. The average (median) total shareholder's equity is 110,634.00 (28,087.92) millions of Renminbi. The average (median) net profit for the firms in the sample is 17,834.58 (2,446.03) millions of Renminbi. Also, the average (median) total number of shares outstanding is 29,356.67 (6,771.08) millions of shares. In addition, the average (median) market capitalization is 39,567.80 (14,316.90) millions of Renminbi. The mean of tradable A-share is 15,681.03 millions of shares, almost twice of the mean of tradable H-shares (8,745.80 millions of shares).

I use daily returns and trading volume to analyze the impact of information asymmetry on the dynamic volume/return relationship. The use of daily data follows that of previous literature (Campbell, Grossman, and Wang (1993), Stickel and Verrecchia (1994), Llorente, Michaely, Saar, and Wang (2002)). The return series I use for estimation is the daily return series for both A- and H-shares of individual stocks from Yahoo Finance.

Following Llorente, Michaely, Saar, and Wang (2002), I use daily turnover as a measure of trading volume for individual stocks. I define a stock's daily turnover as the total number of shares traded that day divided by the total number of shares outstanding. Since the daily time series of turnover is non-stationary, the turnover is measured in logs in order to detrend the resulting series. To avoid the problem of zero daily trading volume, small constant (0.00000255) is added to the turnover before taking the logs. The value of the constant is chosen to make the distribution of daily trading volume closer to a normal distribution.[2] The resulting series is then detrended by subtracting 200 trading day moving average:

[2] Richardson, Sefcik, and Thompson (1986); Ajinkya and Jain (1989); and Cready and Ramanan (1991)

$$V_t = \log turnover_t - \frac{1}{200}\sum_{s=-200}^{-1} \log turnover_{t+s}$$

where

$$\log turnover_t = \log(turnover_t + 0.00000255)$$

Table 3. Descriptive Statistics

Table 3 contains descriptive statistics of the 68 sample firms dual-listed in the A- and H-share market during the period 2003-2011. Total assets are obtained from the Hong Kong Stock Exchange. Cashflows are obtained from operating cash flows, generated from operating activities, and are measured as a ratio relative to the total assets of the firm. Operating revenue is Sales minus Cost of Goods Sold (and other expenses), before depreciation and amortization. Debt ratio is measured as the ratio of the short-term and long-term debt to the total assets of the firm. Items are in millions of RMBs. Tradable A-share size is the number of outstanding A-shares (in millions), while tradable H-share size is number of H-shares (in millions).

Variable	Maximum	Minimum	Mean	Median	Std Deviation
Total Asset	15476900	557.05	1102470	76912.96	3064500
Long Term Debt	180675	0	27504.46	9042.46	42053.88
Cash And Cash Equivalents	2762156	56.68	181576.38	7918.48	571080.97
Total Liabilities	14519000	295.05	991832	41644.26	2879280
Total Shareholders' Equity	1082570	78.71	110634	28087.92	227508
Total Liabilities and Shareholder's Equity	15476900	557.05	1102470	76912.96	3064500
Market Capitalization	1015780	139.47	39567.8	14316.9	124812
Total Profit	272311	-6805.55	23079.94	3035.1	54257.25
Total Operating Revenue	271000	-7807.39	22730.63	2873.73	54100.76
Net Profit	208445	-8838.83	17834.58	2446.03	41922.51
Basic Earnings per Share	3.36	-1.02	0.58	0.43	0.71
Net Cash Flow From Operating Activities	348123	-13480.35	33978.48	1872.31	77217.37
Total Number of Shares Outstanding	349083	398.92	29356.67	6771.08	72917.2
State Shares	268485	0	4421	0	32303.18
Tradable A Shares	262289	72.62	15681.03	3627.39	43233.64
Tradable H Shares	214837	100	8745.8	1431.03	29314.8

Table 4 provides summary statistics that describe the return ad volume series used in the estimation. The average return for A-shares is 0.03% vs. 0.09% for H-shares. The average size for A-shares is 44,196,036,115 RMB vs. 43,108,948,156 RMB. The average turnover for A-shares is 0.0204658 vs. 0.0088371 for H-shares. This implies that the trading is more active in the A-shares market than in H-share market. The variable of interest, volume, as defined previously is -0.1433377 for A-shares vs. -0.0331528 for H-shares. This also captures the much more active trading in the A-shares market. Next, I estimate the following relation for each individual stock:

$$Return_{i,t+1} = C0_i + C1_i*Return_t + C2_i*Volume_{i,t}*Return_t + error_{i,t+1}$$

where $Volume_{i,t}$ is the daily detrended log turnover of an individual stock and $Return_{i,t+1}$ is the daily return of an individual stock.

In principle, trading contains both hedging and speculative elements. The observed volume-return relation depends on the relative importance of one type of trade to another. Therefore, one should see a statistically significant positive C2 coefficient for stocks largely used for speculative trade, while stocks used predominantly for hedging should produce a clearly negative C2 coefficient. In addition, stocks for which neither speculative nor hedging trades dominate should produce a C2 coefficient that is insignificantly different from zero. In other words, the relation between C2 and the significance of a speculative trade, relative to a hedging trade, is monotonic.

Next, I examine the relation between the importance of informed trading, which includes both trading coming from better analysis and insider trading and firm size

$$C2_t = a + b*ORDCap_t + ERROR_t,$$

where ORDCap is a variable representing the ordinal scale of average firm size (market capitalization). I expect the coefficient b to be positive (negative) if C2 captures more of trading based on better analysis (insider trading).

Table 4. Summary Statistics

Variable	N	Mean	Median	StdDev	Minimum	Maximum
A Return	92254	0.0002698710	0.0000000000	0.0296557000	-0.5315488000	0.7361111000
H Return	92254	0.0008509780	0.0000000000	0.0403189000	-0.6666667000	2.0952381000
A Size	92254	44196036115	6666425864	152838011020	107020184	2063880000000
H Size	92254	43108948156	5714685525	127961935142	46497403	2056063000000
A Turnover	92254	0.0204658000	0.0118731000	0.0281283000	0.0000302930	1.4228630000
H Turnover	92254	0.0088371000	0.0057767000	0.0116996000	0.0000000000	0.4901600000
A Log(turnover)	92254	-4.5283590000	-4.4332658000	1.2457820000	-10.3236054000	0.3526728000
H Log(turnover)	92254	-5.4730336000	-5.1534757000	1.7921738000	-12.8774583000	-0.7130182000
A Volume	92254	-0.1433377000	-0.1692043000	0.8163219000	-5.1532660000	3.3824509000
H Volume	92254	-0.0331528000	0.0173589000	1.3874109000	-9.3021912000	11.7304722000

5. Empirical Results

In this section, I present the empirical results in testing the dynamic volume-return relation, especially in how it relates to the underlying informed trading. I first report the results on the C2 coefficient from the ordinary least squares (OLS) regression from the return equation, performed separately on A- and H-shares in order to analyze whether C2 captures more of trading based on better analysis (insider trading). I then separate my sample into 2 periods and examine the change in the C2 to further analyze the different components of informed trading - whether it captures increased transparency in the financial market or greater liquidity and trading from better analysis.

Table 5 presents the results from the above regression for individual stocks and how the regression coefficients change with the market capitalization. For each stock in the sample, I estimate the parameters C0, C1, and C2 of the above equation. In panel A, I present summary statistics for the time-series regressions for both A- and H- Share groups. The table shows that the mean value of C2 is 0.0883250 for A-shares and 0.1342797 for H-shares. I further perform a non-parametric Wilcoxon rank test to test whether the difference is statistically significant. The result indicates that the difference for C2 is indeed statistically significant across A- and H-shares. This indicates that H-share market is more affected by informed trading. The nonparametric analysis points in the same direction: seven out of 68 of the A-share stocks have negative coefficients, compared to 0 out of 68 of the H-share stocks. Both parametric and nonparametric results are consistent with the intuition that informed trading has a permanent effect on prices (positive correlation between volume and price changes) whereas non-informed trading tends to have temporary effect and results in price reversal (negative correlation).This indicates both A-and H-shares are associated with informed trading. Both C2 coefficients of A- and H-shares are positive and statistically different from zero, indicating the importance of speculative trading. More important is that the H-share market appears to be associated with a greater degree of informed trading. Arguably the H-share market should have less insider trading because the insider regulation for A-shares is looser and because the A-share market is the home market -- one would expect more insiders in the home market. To the extent this argument is true and that informed trading includes both insider trading and trading coming from better analysis, the results here present indirect evidence that, relative to the A-share market, in the H-share market substantially more informed trading can be attributed to trading based on better analysis. This inference is not a trivial contribution because, to my knowledge, no study evaluates the relative importance of insider trading and trading coming from better analysis.

In Table 5 Panel B I regress informed trading of A- and H-shares on firm size. The coefficient is -0.00035104 for A-shares and 0.00285 for H-shares. As mentioned earlier, I expect the coefficient to be positive (negative) if C2 captures more of trading based on better analysis (insider trading). The results represent indirect evidence that insider trading and firm size is negatively related. For H-shares, as argued above, informed trading is more from better analysis, and it is reasonable to argue larger firms have better analysis because large firms attract more attention, can offer greater compensation for analysts, and have greater liquidity and an investor base.

Next, I divide my sample period into two sub-periods. The first subsample covers the first half of the sample period, which spans from January 1, 2003 to June 30, 2007. The second subsample covers the second half of my sample periods from July 1, 2007 to December 31, 2011. Dividing the sample into two sub-periods allows me to examine the change in C2 in the two time periods. The transparency in China mainland financial market might have improved over the last decade. For example, China initiated a split-share reform in 2005. The reform allows investors with non-tradable shares to be able to convert them into tradable shares. This should enhance market liquidity and allows controlling shareholders to sell their shares at market prices. Before the Split-share Structure Reform, two-thirds of the A-shares outstanding were non-tradable shares owned mainly by the Chinese government and its affiliates and legal persons. The non-tradable shares were transacted on contract base and subject to the approval of regulatory authorities. The tradable shares were largely held by institutional and individual investors. The purpose of establishing such dual share structure was to enable the state-owned enterprises (SOE) to raise capital and the government to retain control. However, the structure fostered serious speculations and agency problems. Therefore, the Split-share Structure Reform was carried out in an effort to help the Chinese market to function as a more efficient entity. If this is true and if C2 decreases considerably, then C2 might capture more of insider trading since insider trading should also have declined with increased transparency. On the contrary if C2 increases, then it probably captures more of trading from better analysis, which is also another aspect of informed trading. By dividing the sample into 2 subsamples, one can better understand the nature of C2.

Table 5. The Influence of Volume on the Autocorrelation of Stock Returns in A- and H-Share Markets - Full Sample

This table shows the relation between information asymmetry and the influence of volume on the autocorrelation of stock returns. The average daily market capitalization of a stock over the sample period ($AvgCap_i$) is used as a proxy for information asymmetry. For each stock the parameter $C2_i$ from the following regression measures the influence of volume on the autocorrelation of stock returns: $Return_{i,t+1} = C0_i + C1_i*Return_t + C2_i*Volume_{i,t}*Return_t + error_{i,t+1}$ where $Volume_{i,t}$ is the daily detrended log turnover of an individual stock and $Return_{i,t}$ is the daily return of an individual stock. In Panel A, I report the mean value of each parameter for both A-and H-shares of the information asymmetry proxy (AvgCap), the number of negative parameters, and the number of statistically significant (at the 10% level) parameters. In panel B, I provide an analysis using the following cross-sectional regression: $C2_t = a + b*ORDCAP_t + ERROR_t$, where ORDCAP is a variable representing the ordinal scale of AvgCap. Standard errors appear in parentheses.

Panel A. Categorical Analysis

	C0 #<0	C1 #<0	C2 #<0	t-stat(C0) |#|>1.64	t-stat(C1) |#|>1.64	t-stat(C2) |#|>1.64	R-Square (%)
A Share	-0.0003853	0.0132361	0.0883250	-0.4635294	0.6816667	2.4434286	5.55
	(0.0008041)	(0.0631140)	(0.1081990)				
n=68	46	22	7	8	23	54	
H Share	0.0004036	-0.0066256	0.1342797	0.3222059	-0.4166176	3.1685294	5.70
	(0.0013601)	(0.0390351)	(0.0591813)				
n=68	26	39	0	8	28	57	
Wilcoxon Z	3.6173***	-3.2191***	1.8122**				

Panel B. Regression Analysis

	Dependent Variable	a	b	R-Square (%)	Observations
A Share	C2	0.10079***	-0.00035104***	1.4	68
		(0.04606)	(0.00113)		
H Share	C2	0.0343	0.00285***	4.87	68
		(0.06243)	(0.00153)		

Table 6 presents the results from the first half of the sample period. For the first subsample there are 43 cross-listed A/H stocks. For each stock in the sample I estimate the parameters C0, C1, and C2 similar to the regression used in Table 5. In Table 6 Panel A, I present summary statistics for the time series regression for both A- and H-share groups. The table shows that the mean value of C2 is 0.0868305 for A-shares and 0.0709947 for H-shares. The nonparametric analysis points in the same direction: 9 out of 43 of the A-share stocks have negative coefficients, compared to only 5 out of 43 of the H-share stocks. This indicates both A- and H-Shares are associated with information asymmetry. However, only C2 coefficients of H-shares are positive and statistically different from zero, indicating the importance of speculative trading. In Table 6 Panel B the firm size coefficient is -0.003466173 for A-share and 0.001823691 for H-Share. This result also suggests that A-shares have more informed trading that comes from insider trading, while H-shares have more informed trading based on better analysis.

Table 6. The Influence of Volume on the Autocorrelation of Stock Returns in A- and H-Share Markets (January 2003 – June 2007)

This table shows the relation between information asymmetry and the influence of volume on the autocorrelation of stock returns. The average daily market capitalization of a stock over the sample period ($AvgCap_i$) is used as a proxy for information asymmetry. For each stock the parameter $C2_i$ from the following regression measures the influence of volume on the autocorrelation of stock returns: $Return_{i,t+1} = C0_i + C1_i{*}Return_t + C2_i{*}Volume_{i,t}{*}Return_t + error_{i,t+1}$ where $Volume_{i,t}$ is the daily detrended log turnover of an individual stock and $Return_{i,t}$ is the daily return of an individual stock. In Panel A, I report the mean value of each parameter for both A-and H-shares of the information asymmetry proxy (AvgCap), the number of negative parameters and the number of statistically significant (at the 10% level) parameters. In panel B, I provide an analysis using the following cross-sectional regression: $C2_t = a + b{*}ORDCAP_t + ERROR_t$, where ORDCAP is a variable representing the ordinal scale of AvgCap. Standard errors appear in parentheses.

Panel A. Categorical Analysis

	C0 #<0	C1 #<0	C2 #<0	t-stat(C0) |#|>1.64	t-stat(C1) |#|>1.64	t-stat(C2) |#|>1.64	R-Square (%)
A Share	0.0017431	-0.0525420	0.0868305	0.9660000	-0.3822222	1.4937209	3.80
	(0.0018854)	(0.0720453)	(0.1280795)				
n=43	7	25	9	13	11	24	
H Share	0.0021729	-0.0331833	0.0709947	1.5453488	-0.5962791	2.1639535	7.80
	(0.001606)	(0.0678428)	(0.0963158)				
n=43	2	28	5	21	11	28	
Wilcoxon Z	2.5481**	-0.2381	-0.1396				

Panel B. Regression Analysis

	Dependent Variable	a	b	R-Square (%)	Observations
A Share	C2	0.163086279	-0.003466173*	2.86	43
		(0.079758205)	(0.003157658)		
H Share	C2	0.030873455	0.001823691*	1.31	43
		(0.062515493)	(0.002475012)		

Next, I analyze the second half of my sample period to see if there are changes in C2 coefficients. Table 7 presents the results from the second half of my sample period. For the second subsample there are 68 cross-listed A/H stocks. For each stock in the sample I estimate the parameters C0, C1, and C2 similar to the regression used in Table 5 and Table 6. In Table 7 Panel A, I present summary statistics for the time series regression for both A- and H-share groups. The table shows that the mean value of C2 is 0.0987509 for A-shares and 0.1428814 for H-shares. The nonparametric analysis points in the same direction: 4 out of 68 of the A-share stocks have negative coefficients, compared to 0 out of 68 of the H-share stocks. The non-parametric results shows that for both A-and H-Shares market, the numbers of firms have negative coefficients are smaller than the first half of my subsample. Both C2 coefficients of A- and H-shares are positive and statistically different from zero. In Table 7 Panel B I again use A- and H-share as proxies for information asymmetry and the coefficient is -0.001283962 for A-share and 0.002976575 for H-Share. This result is again consistent with my expectation that the coefficient b to be positive (negative) if C2 captures more of trading based on better analysis (insider trading). This implies that A-shares have more informed trading that comes from insider trading while H-shares have more of informed trading based on better analysis.

From the above analysis the C2 coefficients for both A- and H-shares increases in the second half of my sample period. As argued earlier, an increase in C2 suggests that C2 captures more of trading based on better analysis. The result here is consistent with this argument because the analysis and valuation of these firms should have improved over time. Stated differently, the result is inconsistent with C2 capturing more than insider trading because insider trading should not have increased with the increased transparency in the Chinese firms. The different degrees of C2 increase between the A- and H- markets are also noteworthy. In particular, for H-shares, C2 increased from 0.0709947 to 0.142881. The coefficient for the second half of the subsample almost doubles the coefficient in the first half for the H-shares. However, for the A share market, the increase in C2 is much lower. The much less pronounced change in A-share's C2 is consistent with the earlier conclusion that C2 captures more of insider trading in the A-share market. As argued above, informed trading derives more from better analysis and also from large firms since large firms tend to attract more attention, have greater compensation for analysts, and have greater liquidity and investor base.

Table 7.The Influence of Volume on the Autocorrelation of Stock Returns in A- and H- Share Markets-(July 2007 – December 2011)

This table shows the relation between information asymmetry and the influence of volume on the autocorrelation of stock returns. The average daily market capitalization of a stock over the sample period ($AvgCap_i$) is used as a proxy for information asymmetry. For each stock the parameter $C2_i$ from the following regression measures the influence of volume on the autocorrelation of stock returns: $Return_{i,t+1} = C0_i + C1_i*Return_t + C2_i*Volume_{i,t}*Return_t + error_{i,t+1}$ where $Volume_{i,t}$ is the daily detrended log turnover of an individual stock and $Return_{i,t}$ is the daily return of an individual stock. In Panel A, I report the mean value of each parameter for both A-and H-shares of the information asymmetry proxy (AvgCap), the number of negative parameters and the number of statistically significant (at the 10% level) parameters. In panel B, I provide an analysis using the following cross-sectional regression: $C2t = a + b*ORDCAP_t + ERROR_t$, where ORDCAP is a variable representing the ordinal scale of AvgCap. Standard errors appear in parentheses.

Panel A. Categorical Analysis

	C0 #<0	C1 #<0	C2 #<0	t-stat(C0) |#|>1.64	t-stat(C1) |#|>1.64	t-stat(C2) |#|>1.64	R-Square (%)
A Share	-0.0007802 (0.0011523)	0.0251611 (0.0672457)	0.0987509 (0.1146480)	-0.8262319	1.0491304	2.3272464	7.20
n=68	62	15	4	7	26	46	
H Share	-2.198E-05 (0.0015384)	-0.0088177 (0.0435726)	0.1428814 (0.0645906)	-0.1917391	-0.384058	2.7547826	5.60
n=68	40	43	0	4	21	53	
Wilcoxon Z	-4.1071***	4.5635***	1.9769**				

Panel B. Regression Analysis

	Dependent Variable	a	b	R-Square (%)	Observations
A Share	C2	0.14368954	-0.001283962*	1.8	68
		(0.046592368)	(0.001157002)		
H Share	C2	0.038701309	0.002976575**	5.17	68
		(0.062720092)	(0.001557492)		

As an additional test to confirm the above findings, I employ the variance ratio test in French and Roll (1986). Specifically, they analyze the ratio of the variance during trading period (weekday) to the variance of trading during non-trading period (weekend). If uninformed trading or noise represents a considerable part of trading, the weekday variance should be greater than that of weekend, adjusted for the number of days. In Table 8, I measure weekday and weekend volatility for both A- and H-stocks. Weekend variance is measured over 2+ days while weekday is daily. Volatility should increase proportionally with time, assuming other factors held constant. As the table shows, weekend variance measured over 2+ days is far less than 2+ times of weekday variance, suggesting a strong presence of noise trading. The average return weekday volatility for H-share is 0.0014922 and 0.000833701 for A-shares, almost double that of A-share return volatility, which further indicates that there is more informed trading in H-share markets that come from better analysis. The variance ratios for the A-shares and H-shares are 0.8774 and 0.8138 respectively. The greater the ratio, the greater the noise implied. The result indicates that H-share has less noise. This is consistent with the earlier conclusion that the H-share market has relatively more trading coming from informed analysis.

Given the assumptions that A-share has more insiders trading and that it has not increased over time, the results suggests that the H-share market has relatively more informed trading based on better analysis. With the assumption lower insider trading and the previous results of the C2 coefficients, the fact that H-shares have higher C2 coefficients suggests that there is relative more trading motivated by better analysis in H-shares market. I interpret the results as indirect evidence that larger firms tend to have trading with better analysis and less insider trading.

The sub-period results further confirm that H-shares have relatively more informed trading based on better analysis because insider trading should not have increased, and therefore the substantial C2 increase is further evidence that trading based on better analysis dominates in H-shares. This makes sense because Hong Kong shares market has a long experience n analyzing stocks. But initially, investors in Hong Kong might have difficulty evaluating Chinese firms with low degree of transparency and political factors. The relatively small C2 increase in A-shares is also indirect evidence that stock valuation has not substantially improved over time in A-shares. That is, it has implication on the changes in the Chinese investment environment. The results here also suggest the methodology developed by Llorente, Michaely, Saar, and Wang (2002), for established stocks, captures more of trading based on better analysis.

One related question arising for these cross-listed securities is whether informed trading in both the A- and H-shares market impacts the relative pricing of A-and H-shares. If H-shares have higher C2 coefficients, suggesting that there is relative more trading motivated by better analysis in H-shares market, these better analyses will bring the stock price more close to its intrinsic value. On the other hand, given the fact that the A-shares market tends to have excess speculative trading or insiders trading, the A-share price may deviate more from its intrinsic value. Given the assumption that the Hong Kong market has better transparency than the Chinese mainland stock market, the H-share price is more close to the stock's intrinsic value. Therefore, I expect that informed trading coefficients for H-shares to be negatively correlated with the average H-share discount, while informed coefficients for A-shares to be positively correlated with the H-share discount. To carry out this analysis, I first compute the discounts or premiums for H-shares as follow:

$$Discount\_H_{i,t} = \frac{P_{i,t}^{H} \times (RMB/_{HKD})}{P_{i,t}^{A}} - 1$$

where $Discount_{i,\,t}$ is the discount (premium) for H-shares i if it is negative (positive). $P_{i,t}^{H}$ is the H-share price from the Hong Kong Stock Exchange, $HKD/_{RMB}$ is the exchange rate for Hong Kong dollars to one Renminbi, and $P_{i,t}^{A}$ is the underlying A-share price from the Shanghai and Shenzhen Stock Exchange. I then average the discount over the entire sample period.

Table 8. Average Ratios of Weekdays and Weekends Variances for A- and H-Shares

Return	N	Mean	StdDev	Variance	Weekday /weekend variance Ratio
A Share					
Weekdays	56158	-0.000216525	0.0288739	0.000833701	0.8774
Weekends	36026	0.0010229	0.0308252	0.00095019	
H Share					
Weekdays	56158	0.000202364	0.0386291	0.0014922	0.8138
Weekends	36026	0.0018462	0.0428209	0.0018336	

Δ Return	N	Mean	StdDev	Variance	Weekday /weekend variance Ratio
A Share					
Weekdays	56157	0.0000001375	0.0409646000	0.0016781000	0.9649
Weekends	36025	0.0000009546	0.0417038000	0.0017392000	
H Share					
Weekdays	56157	-0.0000010279	0.0557001000	0.0031025000	0.8686
Weekends	36025	0.0000000521	0.0597648000	0.0035718000	

Next, I perform correlation and regression analysis to see how C2 coefficients for both A- and H-shares are related with the average H-share discount. The negative coefficients indicate that the variables in question have the effect of making the H-share discount bigger, i.e., more negative. Table 9 Panel A shows that C2 coefficients for A-share are positively correlated with the probability of discount, while that C2 coefficient for H-share is negatively correlated with the probability of discount. Although both C2 coefficients are correlated with the average discount, the correlation is insignificant. This positive/negative correlation is also confirmed in the regression analysis. In the regression analysis, I use the average discount as dependent viable while that C2 coefficient for A- and H-shares as independent variable:

$$\text{Average H} - Discount = Intercept + \text{C2 coefficients (A)} + \text{C2 coefficients (H)} + \text{Error}$$

Table 9 Panel B provides the regression results, and both coefficients are insignificant. Therefore, there is no conclusive evidence regarding the relation between informed trading and the relative pricing of A- and H-shares.

Table 9. H-Share Discount and Informed Trading

Panel A. Correlation Matrix for the Average Discount and Informed Trading

	Average discount	C2 (A-shares)	C2(H-shares)
Average discount	1.00000	0.09372	-0.13133
C2 (A-shares)		1.00000	0.02909
C2(H-shares)			1.00000

Panel B. Regression Analysis for the Average Discount and Informed Trading

Average discount	Parameter Estimate	Standard Error	t statistics
Intercept	-0.171975239	0.051303309	-3.35
C2 (A-shares)	0.181877289	0.224649176	0.81
C2 (H-shares)	-0.17999801	0.161764707	-1.11
R-Square (%)	2.68		

6. Conclusion

In this study, I adopt the methodology developed by Llorente, Michaely, Saar, and Wang (2002) to study a sample of Chinese firms dual-listed in both the China mainland stock exchange and the Hong Kong stock exchange. In particular, I investigate the two types of informed trading--insiders trading and better analysis in A-and H-shares market. With the unique two-market system one can better understand the nature of C2. That is, in addition to understanding the extent of informed trading in China, this unique setting helps one to understand the nature of C2. Llorente, Michaely, Saar, and Wang (2002) do not distinguish the two different aspect of informed trading – insider trading and trading comes from better analysis. However, the analysis in this paper provides new evidence on these two aspects of informed trading.

My results suggest that H-shares have relatively more informed trading based on better analysis. With an assumption of lower insider trading and the result that H-shares have higher C2 coefficients suggests that there is relative more trading motivated by better analysis in the H-shares market. Together with the firm size regression, the results can be interpreted as indirect evidence that larger firms tend to have trading with better analysis and less insider trading.

By dividing the sample into two sub-samples, I examine the changes in C2 in the two subsequent sample periods. The C2 coefficient for the second half of the subsample almost doubles the coefficient in the first half for the H-shares. The sub-period results further confirm that H-shares has relatively more informed trading based on better analysis because insider trading should not have increased, and therefore the substantial C2 increase is further evidence trading based on better analysis dominates in the H-shares market. This makes sense because the Hong Kong shares market has a long experience in analyzing stocks. The relatively small C2 increase in A-shares is also indirect evidence that stock valuation has not substantially improved over time in A-shares. That is, it has implication on the changes in the Chinese investment environment. Lastly, I also examine whether there is a relationship between informed trading and the relative pricing of A- and H-shares, but find no significant relation.

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Chapter 2

Dynamic Correlation of Currency Futures Prices and Liquidity

1. Introduction

A currency future is a standardized contract used to exchange, at some future date, one type of currency for another at a fixed exchange rate. Investors typically use currency future contracts for two distinct purposes: to hedge against foreign exchange risk and speculation and arbitrage. In regards to hedging, if an investor were to receive a cashflow denominated in a foreign currency, than that investor can lock in the current exchange rate by entering into an offsetting currency futures position that expires on the date of the cashflow. However, by incurring some amount of risk, investors can also speculate on currency futures and profit from the rising or falling of exchange rates.

As of late 2009 the IMM (International Monetary Market), a division of the Chicago Mercantile Exchange, estimated that the average daily notional value for the currency futures market was approximately $100 billion. Given the importance of currency futures this study investigates the dynamic correlation across currency futures prices to U.S. dollar index futures[3], with the focus on the persistency of correlation between eight currency futures prices traded on the Chicago Mercantile Exchange: Australian dollar, British pound, Brazilian real, Canadian dollar, Euro currency, Japanese yen, Russian ruble, and Swiss franc. Using the Dynamic Conditional Correlation (DCC) model developed by Engle (2002), I incorporate time-varying correlations into the analysis. This study differentiates from previous studies in that it is the first to analyze the persistency of relation between currencies future prices. Lyons (2002) shows

[3]U.S. dollar index futures are listed on the Financial Instruments Exchange (FINEX).

currency movement is heavily influenced by trading. Based on this study, liquidity also should be an important factor affecting dynamic correlation--that is, this study motivates the study of the relation between liquidity and dynamic correlation of currencies future prices. In regards to liquidity, there are numerous studies examining liquidity in the spots market; however, there is only a handful studies in regards to the futures market. Moreover, there is no previous study on how different aspects of liquidity impact the conditional correlation of currency futures. In this study, I analyze both price and trading aspects of liquidity of currency futures and how changing liquidity potentially affects time-varying conditional correlation. The data concerning liquidity is available daily, hence allowing for a more detailed analysis.

The sample spans from1999 to 2008. The study finds that the persistency of currency futures interactions varies substantially across different currencies. The Canadian dollar has the greater persistency while the Brazilian real has the weakest. Further, the time-varying conditional correlation between other currency futures and U.S. dollar futures are influenced by liquidity.

The rest of the paper is organized as follows: Section 2 is the literature review, Section 3 presents data, Section 4 describes the methodology used in the paper, Section 5 presents the empirical results, and Section 6 gives the conclusion.

2. Literature Review

This paper is most related to Lien and Yang (2006), who investigates the effects of spot-futures spread on the risk and return structure in currency markets. With the use of a bivariate GARCH framework, evidence is found that spreads on the risk and return structure of spot and futures markets produce asymmetric effects. The implications of these asymmetric effects are examined, with special consideration given to the performance of futures hedging strategies. A specific strategy, generated from a model incorporating asymmetric effects, is compared to several alternative models. The in-sample comparison results indicate that the asymmetric effect model provides the best hedging strategy for all currency markets examined, except for the Canadian dollar. Out-of-sample comparisons suggest that the asymmetric effect model provides the best strategy for the Australian dollar, the British pound, the Deutsche mark, and the Swiss franc markets, and that the symmetric effect model provides a better strategy (than the asymmetric effect model) for the Canadian dollar and Japanese yen. However, this study differentiates from Lien and Yang (2006) in that the DCC model is used instead of the bivariate GARCH. The DCC model is similar to a bivariate GARCH in spirit, but the DCC places some restrictions on how the correlation can change (in essence it is a special case of a bivariate GARCH).

There are also several important studies examining volatility and futures. Harvey and Huang (1991) examine the volatility implications of around-the-clock foreign exchange trading with transaction data on futures contracts from the Chicago Mercantile Exchange (CME) and the London International Financial Futures Exchange; whereas, Han, Kling and Sell (1999) use standard deviations and numbers of price changes calculated from tick data for currency futures. In Harvey and Huang's study the authors find higher U.S.-European and U.S.-Japanese exchange-rate volatilities during U.S. trading hours and higher European cross-rate volatilities during European trading hours. While the disclosure of private information through trading may partly explain these volatility patterns, they conclude that the increased volatility is more likely driven by macroeconomic news announcements. An analysis of inter- and intraday data also reveals that volatility increases at times that coincide with the release of U.S. macroeconomic news. In contrast, Han, Kling and Sell (1999) find strong day-of-the-week effects for the Deutsche mark and Japanese yen, mild day-of-the-week effects for the British pound, and no effects for the Canadian dollar after controlling for scheduled macroeconomic announcements and days to contract expiration. The day-of-the-week effects are found to be caused either by Mondays' low volatility, or by Thursdays' or Fridays' high volatility. This result suggests that the day-of-the-week effects in the currency futures market is not driven by the announcements of macroeconomic indicators as proposed in previous studies, but rather by other factors, such as private information-based trading or by market microstructure. The study also finds that the announcements are processed equally across the days of the week for all four currency futures.

In addition, Kho (1996) and Fung and Patterson also examine currencies from a volatility perspective. Kho (1996) re-examines the efficiency of foreign currency futures markets by evaluating the role of time-varying risk premia and volatility in explaining technical trading rule profits. The results show that large parts of the technical rule profits can be explained by time-varying risk premia estimated from a general model for the conditional CAPM. The bootstrap distributions for the profits under the null model average one-third to one-half of the actual profits and enclose the actual profits well within the 90% confidence intervals. Time-varying conditional volatility explains an additional 10% of the profits. In contrast, Fung and Patterson (1999) examine the dynamic interactions among return volatilities, volume, and market depth for five currency futures markets. They use vector autoregressive analysis (VAR) to identify not only the nature of these relations but also the direction and speed of the information flow between variables. They find that return volatility is subject to strong reversal effects from trading volume and market depth. The results also indicate that the volatility appears to have predictive power on volume, but not market depth. Furthermore, this study finds that volume and depth are not endogenously determined, as their lead–lag relationship is asymmetrical. In addition, they observe an increasing trend of integration between offshore and domestic information that affects the movement of currency futures prices.

More recent studies include Levich (2012), Röthig (2004), and Lien and Yang (2006). Levich (2012) studies both counterparty risk for financial institutions and currency futures. He finds that for the period 2005-2011 the market share for currency futures trading actually grew relative to the pre-crisis period of the 2007 Financial Crisis. He hypothesizes that this shift could be the result of one of several factors; namely, perceived increase in counterparty risk among banks, changes in relative trading costs, or changes in institutional factors. The framework Levich utilizes, which is mostly graphical analysis, is very different from Lien and Yang (2006) and Röthig (2004), who both utilize GARCH-type models.

Röthig (2004) examines the impact of currency futures trading on underlying exchange rates. Using a VAR-GARCH approach he examines the relationship between currency futures trading activity (as measured by number of contracts) and total amount of spot market turbulence for the exchange rates from 5 countries (i.e. Australia, Canada, Japan, Korea, and Switzerland) in terms of U.S. dollar. The author finds that there is a positive relationship between currency futures trading activity and spot volatility and, moreover, that futures trading activity adds significantly to spot volatility.

McCurdy and Morgan wrote several papers together concerning currency futures: McCurdy and Morgan (1987) and McCurdy and Morgan (1992). In their 1987 paper the authors test the martingale hypothesis for daily and weekly rates of change of futures prices for five currencies. Using daily data, they find some evidence against the null hypothesis for each currency. Although institutionally imposed limits on daily price changes were found to be frequently binding (often in the earlier years of the sample), the results are not substantially different when data affected by limit moves are removed. Trading day effects in foreign currency futures and spot prices introduce complicated day-of-the-week patterns in futures price. The study concludes with the retesting of the martingale hypothesis using weekly data. They reject the null hypothesis for only one currency. One interpretation regarding the evidence for this rejected currency is that a time-varying risk premium exists. This was followed by McCurdy and Morgan (1992), in which weekly data for foreign currency futures prices is examined for evidence of a risk premium. Covariance risks are measured with respect to the excess returns of benchmark portfolios for consumption and wealth. When the parameters representing the prices of the covariance risks are held constant, no risk premiums are detected. However, when these prices are allowed to vary with the conditional expected returns and the variances of the benchmark portfolios, possibly reflecting changing investment opportunities, strong evidence of risk premiums is obtained.

In the mid to late 1990s several studies examined currency futures from either option-like or statistical perspectives. In Bates (1996), Deutsche mark and yen futures options are examined for deviations from the lognormal assumption underlying standard option pricing models. Two methods are used: a theoretical skewness premium and daily estimates of moments using a model developed for pricing American foreign currency futures options under systematic exchange rate jump risk. Substantial variation over time is found in all moments, along with implicit skewness and kurtosis. These implicit abnormalities help predict future abnormalities for log-differenced U.S. dollar-Deutsche mark futures prices, but not U.S. dollar-Japanese Yen futures prices. Pan, Chan and Fok (1997), on the other hand, examines the random walk process for four currency futures prices for the period 1977–1987 by using a variance ratio test. The random walk hypothesis is tested through asymptotic standardized statistics as well as by computing the significance level, based on a bootstrap method. Both long time-series prices and individual contract prices for four currency futures (i.e. the British pound, the German mark, the Japanese yen, and the Swiss franc) are analyzed. The results provide little evidence against the random walk null hypothesis, though non-randomness is documented in the Japanese yen. Additionally, the currency futures markets apparently become more efficient as markets mature over time.

Bhar and Malliaris (1998) propose and test several hypotheses concerning time series properties of trading volume, price, short and long-term relationships between price and volume, and the determinants of trading volume in foreign currency futures. Contracts for the British pound, Canadian dollar, Japanese yen, German mark, and Swiss franc are analyzed in three frequencies: daily, weekly and monthly. They find supportive evidence for all five currencies that the price volatility is a determinant of the trading volume changes. Furthermore, the volatility of the price process is a determinant of the unexpected component of the changes in trading volume. They also find that there is a significant relationship between the volatility of price and the volatility of trading volume changes for three of the five currencies in the daily frequency and for one currency in the monthly frequency.

As for liquidity, it has been widely studied with stock markets. Amihud (2002) shows that over time, expected market illiquidity positively affects ex-ante stock excess return, suggesting that expected stock excess return partly represents an illiquidity premium. This complements the cross-sectional positive return–illiquidity relationship. In addition, stock returns are negatively related over time to contemporaneous unexpected illiquidity. The illiquidity measure here is the average across stocks of the daily ratio of absolute stock return to dollar volume, which is easily obtained from daily stock data for long time series in most stock markets. Illiquidity affects more strongly small firm stocks, thus explaining time series variations in their premiums over time. Further, liquidity is also studied in dual-listed markets. Chan et al (2008) study the liquidity effect in asset pricing by studying the liquidity- premium relationship of an American Depositary Receipt (ADR) and its underlying share. Using the Amihud (2002) measure, the turnover ratio and trading infrequency as proxies for liquidity, they show that a higher ADR premium is associated with higher ADR liquidity and lower home share liquidity, in terms of changes in these variables. They find that the liquidity effects remain strong and they control for firm size and a number of country characteristics, such as the expected change in the foreign exchange rate, the stock market performance, as well as several variables measuring the openness and transparency of the home market. Goss (2006) studies liquidity, volume and volatility in U.S. electricity futures. However, liquidity in futures is expected to behave differently to that of spot markets because of the unique asymmetries in futures markets. Liquidity in electricity markets is of interest in countries where markets are being deregulated. This study estimates these relationships for the Palo Verde electricity futures contract. The results show positive relations between all three pairs of key variables.

3. Data

The initial futures data consists of daily future prices for currency futures over the period January 1999 to June 2008. This data is collected from RC Research (www.Price-Data.com) and includes open, high, low, and close prices; as well as, volume and open interest. All daily future prices are in U.S. dollars. The currency futures included in this study are listed as follows: Australian dollar, British pound, Brazilian real, Canadian dollar, Euro currency, Japanese yen, Russian ruble, and Swiss franc. All eight currency futures are traded on the Chicago Mercantile

Exchange (CME) and all currencies prices are coded the same way—the US$ price of per unit of currency. Table 1 provides a summary of the contract size, approximate margin, and minimal fluctuation of the 8 currency futures. The weighted U.S. dollar futures are used as a basis for comparison. The U.S. dollar index (USDX)[4] is an index (or measure) of the value of the United States dollar relative to a basket of foreign currencies. The USDX futures contract has two features that influence its pricing and its use. First, the USDX index is a geometric average, rather than an arithmetic average,[5] of the constituent currencies. Second, the foreign exchange (FX) rates in the USDX index (in U.S. dollars per foreign exchange rate) are in the denominator of the index, implying that a dollar appreciation leads to a higher index level. Both the geometric averaging and the use of quoting convention have implication for the use of the USDX futures contract in hedging a foreign exchange exposure. Eytan, Harpaz, and Krull (1988) point out, the divergence between the geometric and arithmetic averages depend on both the volatilities of the individual currencies and their co-movements (sometimes referred to as their “correlations”).

Table 1. Sample Periods for Currency Futures Traded in U.S.

Symbol	Futures Contract	Sample Period	Contract Size	Approximate Margin	Minimum Fluctuation	Observation
AD	Australian Dollar	01/13/1987-06/02/2008	A$100,000	$1,688.00	0.01 c/A$ = $10	5378
BP	British Pound	02/13/1975-06/02/2008	62,500 pound	$1,890.00	0.01 c/pound = $6.25	8384
BR	Brazilian Real	11/08/1995-06/02/2008	BR100,000	$3,500.00	0.005 c/BR = $5	3122
CD	Canadian Dollar	1/17/1977-06/02/2008	C$100,000	$1,215.00	0.01 c/C$ = $10	7898
EC	Euro Currency	01/04/1999-06/02/2008	EUR $125,000	$2,700.00	0.01 c/EUR = $12.50	2355
JY	Japanese Yen	08/02/1976-06/02/2008	Yen 12,500,000	$2,430.00	0.0001 c/JY = $12.50	8014
RU	Russian Ruble	2/4/1993-06/02/2008	MRR 2,500,000	$3,000.00	0.001 c/RR = $25	3858
SF	Swiss Franc	02/13/1975-06/02/2008	SF 125,000	$1,958.00	0.01 c/SF = $12.50	8383

[4] The short-coming of using the U.S. Currency Futures Index is that it is an unequally weighted index - so, the currency that is weighted more heavily, such as Euro, will inherently move more closely with the index.
[5] This difference between arithmetic and geometric averaging is the source of the divergence between the index (and therefore futures contract) performance and the portfolio performance. (The portfolio is constructed as an investor is long $1 million in the six constituent currencies of the USDX index, in the proper weights (57.6% in euro, 13.5% in yen, etc.).The larger the divergence of performance of the different currencies, the larger the divergence between the geometric average and the arithmetic average.

The USDX futures contract began trading on November 20, 1985 on the Financial Instruments Exchange, a division of the New York Cotton Exchange, which is now part of the New York Board of Trade (NYBOT). The USDX index was originally a geometrically weighted average of ten different currencies, with each currency representing a country that was a major trading partner with the United States. With the introduction of the Euro, the USDX index became a geometrically weighted average of six currencies, which represent five major U.S. trading partners and the Euro. Appendix 2 describes the current contract specifications for the USDX futures contract.

Index Formula

The formula for the index level on date t is the product of the six currencies spot rates, each raised a power related to a currency-specific weight. The general formula for the index can be written as

$$USDX_t = K \prod_{i=1}^{N} \left(FX_{i,t}\right)^{-w_i}$$

where $USDX_t$ is the calculated level of the USDX index on date t, $FX_{i,t}$ is the foreign exchange rate (U.S. dollars per foreign currency unit) for currency i on date t, w_i is the weight associated with currency i (the weights are determined by the contract specs and sum to one, i.e.,$\sum_{i=1}^{N} w_i = 1$). N is the number of currencies in the index for the USDX index, (N is currently six and was formerly ten); and *K* is a constant. Under the current USDX futures contract specs, the USDX index is equal to

$$USDX_t = 50.14348112 \times (Euro_t)^{-0.576} \times (Yen_t)^{-0.136} \times (Sterling_t)^{-0.119} \times (Canadian\ Dollar_t)^{-0.091} \times (SwedishKroner_t)^{-0.042} \times (SwissFranc_t)^{-0.036}$$

In other words, it is a weighted geometric mean of the following:

Euro (EUR), 57.6% weight

Japanese yen (JPY) 13.6% weight

Pound sterling (GBP), 11.9% weight

Canadian dollar (CAD), 9.1% weight

Swedish krona (SEK), 4.2% weight and

Swiss franc (CHF) 3.6% weight

I first begin by checking for stationarity of the price series data and find that the price series are non-stationary (the null hypothesis of the unit root is not rejected), while their first differences are stationary. This implies that the use of a return series is appropriate, with the return being computed as the log of the current price over the previous price. Table 2 provides the summary statistics of the daily currency futures returns. The distribution of the daily futures returns is not normal, according to the Jarque-Bera test, and characterized by high kurtosis; especially, for the Brazilian real and Russian ruble. In addition, the Australian dollar, British pound, Brazilian real, Canadian dollar, and Euro currency futures returns are all negatively skewed. In contrast, the Japanese yen, Russian ruble, and Swiss franc are all positively skewed.

Table 2. Summary Statistics on Daily Currency Futures Returns

	Australian Dollar	British Pound	Brazilian Real	Canadian Dollar	Euro Currency	Japanese Yen	Russian Ruble	Swiss Franc
Mean	3.18E-05	-8.46E-06	-7.34E-05	1.13E-06	4.97E-05	5.62E-05	9.07E-05	4.43E-05
Median	0.000157581	0	0	0	6.87E-05	0	0.000430829	0
Maximum	0.022452484	0.019772928	0.277946112	0.009300023	0.011453081	0.035933091	0.154327806	0.021572106
Minimum	-0.019667895	-0.022873448	-0.320463148	-0.011405534	-0.011562519	-0.018272159	-0.155461735	-0.033270935
Variance	8.80676E-06	9.22146E-06	0.000323549	2.47396E-06	7.10789E-06	9.74863E-06	0.000455771	1.14048E-05
Std. Dev.	0.002967618	0.003036686	0.017987459	0.001572883	0.002666062	0.00312228	0.021348784	0.003377095
Skewness	-0.383453315	-0.077403656	-1.328845259	-0.098795122	-0.030307375	0.564362196	0.015603163	0.093215516
Kurtosis	5.886010598	7.149241707	172.7144473	6.350768181	3.829401019	8.376932798	34.1886891	5.910303671
Jarque-Bera	1997.825011	6021.848429	3746507.82	3707.210228	67.83249116	10078.1588	156326.6691	2970.239927
Probability	0	0	0	0	1.89E-15	0	0	0

Regarding liquidity, I measure liquidity in terms of the price impact of trading and trading activity/ trading volume. For this paper I adopt two liquidity measures, since previous literature suggests that liquidity cannot be measured by one metric alone (Sadka et al (2008)). The price impact of trading is computed using the Amihud (2002) illiquidity measure, which is the absolute percentage price change divided by trading volume. This impact is computed daily and averaged over the sample period. The larger the number the greater is the impact of trading on prices, indicating a more illiquid currency future. Amihud illiquidity measures the price impact aspect of liquidity and quantifies the price/return response to a given size of trade. Liquidity, also has another aspect – trading. To address this aspect, I use the logarithm of trading volume as an alternative liquidity measure and perform a similar analysis. Table 3 shows the Amihud illiquidity measure, trading volume, and logarithm of trading volume for the eight currency futures included in this study. From this table one can see that the Brazilian real is the most illiquid currency future contracts among the eight; also, that the Russian ruble[6] is much less liquid than other currency futures. Not surprisingly, the euro currency has the lowest number for the Amihud illiquidity measure. Most likely this is due to the fact that the euro is considered to be the most popularly traded currency futures contract. The Japanese yen also has a very low Amihud illiquidity measure number. This also makes sense since the Japanese yen is frequently used as a carry trade currency, due to the country's near zero interest rates. Finally, the trading volume data also tells the same story of the eight currency futures. That is, the Brazilian real is the least traded currency futures and the Euro currency and Japanese yen are the most common and popularly traded futures.

Table 3. Summary Statistics of Liquidity Measures

Liquidity Measures	Mean	Median	StdDev	Minimum	Maximum
Amihud Illiquidity Australian Dollar	0.000011	0.000002	0.000144	0.000000	0.005876
Amihud Illiquidity British Pound	0.000004	0.000001	0.000063	0.000000	0.002723
Amihud Illiquidity Brazilian Real	0.001849	0.000057	0.022539	0.000000	0.657169
Amihud Illiquidity Canadian Dollar	0.000003	0.000000	0.000031	0.000000	0.001110
Amihud Illiquidity Euro Currency	0.000002	0.000000	0.000024	0.000000	0.000998
Amihud Illiquidity Japanese Yen	0.000002	0.000000	0.000023	0.000000	0.000706
Amihud Illiquidity Russian Ruble	0.000005	0.000003	0.000008	0.000000	0.000131
Amihud Illiquidity Swiss Franc	0.000005	0.000001	0.000046	0.000000	0.001120
Volume Australian Dollar	3704.010000	2365.000000	4751.650000	0.000000	90210.000000
Volume British Pound	6289.750000	4316.000000	7280.260000	3.000000	116014.000000
Volume Brazilian Real	905.167022	1.000000	13039.380000	0.000000	343354.000000
Volume Canadian Dollar	7902.440000	6214.000000	6909.860000	0.000000	82970.000000
Volume Euro Currency	13468.880000	10391.000000	17259.540000	6.000000	351187.000000
Volume Japanese Yen	12856.850000	8563.000000	14709.740000	7.000000	226166.000000
Volume Russian Ruble	5018.870000	2796.000000	5225.780000	0.000000	47247.000000
Volume Swiss Franc	8168.680000	6105.000000	7665.540000	0.000000	98763.000000

[6] It should be noted that the Russian ruble had currency controls levied by the government until 2006.

Log(Volume)Australian Dollar	7.792657	7.769801	0.982771	0.000000	11.409896
Log(Volume) British Pound	8.348629	8.372165	0.996711	1.098612	11.661466
Log(Volume) Brazilian Real	4.356071	4.537947	2.061767	0.000000	12.746517
Log(Volume) Canadian Dollar	8.657030	8.734721	0.920326	1.945910	11.326234
Log(Volume) Euro Currency	9.139480	9.248647	0.941483	1.791760	12.769074
Log(Volume) Japanese Yen	9.010977	9.055673	1.057654	1.945910	12.329025
Log(Volume) Russian Ruble	8.007806	7.937018	1.066479	2.708050	10.763144
Log(Volume) Swiss Franc	8.582162	8.717355	1.098639	1.386294	11.500478

4. Methodology

For my analysis I chose to use both a GARCH (1,1) model (with a constant term in the mean equation) and a Dynamic Conditional Correlation (DCC) Model. The GARCH (1,1) model can be defined as follows:

$$y_t = \mu + \varepsilon_t \ , \varepsilon_t \left| I_{t-1} \sim N\left(0, h_t\right)\right.$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

The DCC model is merely an extension of the Constant Conditional Correlation (CCC) Model (Engle (2002)). The main difference between the DCC model and the CCC model is that the DCC model allows the correlation matrix to change over time. The DCC model is therefore unique in that it retains the parsimony of a univariate GARCH model while incorporating a GARCH-like, time varying correlation. Accordingly, the DCC can be written as:

$$H_t^{DCC} = D_t R_t D_t \ ,$$
$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2} \ ,$$

$$Q_t = S \circ (u' - A - B) + A \circ Z_{t-1} Z_{t-1}' + B \circ Q_{t-1} \ ,$$

where H_t^{DCC} is the covariance matrix for a vector of *k* asset returns, R is the possibly time-varying correlation matrix, and D_t is the $k \times k$ diagonal matrix of time-varying standard deviations from a univariate GARCH model with $\sqrt{h_{i,t}}$ on the i^{th} diagonal. $Q_t = \left[q_{ij,t}\right]$ denotes the conditional covariance matrix of the standardized residuals. In addition, *A* and *B* are parameter matrices and *o* denotes the Hadamard matrix product operator, i.e. element-wise multiplication. The symbol ι denotes a vector of ones and *S* denotes the unconditional covariance matrix of the standardized residuals. $Z_t = \left[z_{i,t}\right]$ is the standardized, but correlated, residual vector. Its conditional correlation matrix is given by the variable R_t. For the i^{th}element of R_t, the conditional correlation matrix is given by $q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$.

A simple DCC in a bivariate case would be

$$\begin{bmatrix} q_{11,t} & q_{12,t} \\ q_{12,t} & q_{22,t} \end{bmatrix} = (1-a-b)\begin{bmatrix} 1 & \bar{q}_{12,t} \\ \bar{q}_{12,t} & 1 \end{bmatrix} + a\begin{bmatrix} z_{1,t-1}^2 & z_{1,t-1}z_{2,t-1} \\ z_{1,t-1}z_{2,t-1} & z_{2,t-1}^2 \end{bmatrix} + b\begin{bmatrix} q_{11,t-1} & q_{12,t-1} \\ q_{12,t-1} & q_{22,t-1} \end{bmatrix}$$

where *a* and *b* stand for the DCC parameters alpha and beta. In most cases, *a* and *b* can substitute for more complicated matrices (e.g. A and B). Lastly, $\overline{\mathrm{q}_{12}}$ is the unconditional covariance of the two standardized residuals.

The DCC model is constructed to permit a two-stage estimation of the conditional covariance matrix H_t. During the first step, a univariate volatility model is fitted for each of the assets and the estimates of $h_{i,t}$ are obtained. In the second step, the asset returns are transformed by their estimated standard deviations and used to estimate the parameters of the conditional correlation.[7]

The log-likelihood function for the DCC model can be written as follows:

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_t \left(k\log(2\pi) + \log|H_t| + r_t' H_t^{-1} r_t\right) \\
&= -\frac{1}{2}\sum_t \left(k\log(2\pi) + \log|D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r\right) \\
&= -\frac{1}{2}\sum_t \left(k\log(2\pi) + 2\log|D_t| + \log|R_t| + Z_t' H_t^{-1} Z_t\right)
\end{aligned}
$$

One can perform the estimation by means of a quasi-maximum likelihood estimation (QMLE) to yield consistent parameter estimates. The log-likelihood function, which can be express as

$$L(\theta_1,\theta_2) = L_{Vol}(\theta_1) + L_{Corr}(\theta_1,\theta_2)$$

can be divided into two parts.

The volatility part:

$$L_{Vol}(\theta_1) = -\frac{1}{2}\sum_t \left(k\log(2\pi) + \log|D_t|^2 + r_t' D_t^{-2} r_t\right)$$

And the correlation component:

$$L_{Corr}(\theta_1,\theta_2) = -\frac{1}{2}\sum_t \left(\log|R_t| + Z_t' R_t^{-1} Z_t - Z_t' Z_t\right)$$

[7] The software used to estimation the DCC model is EViews.

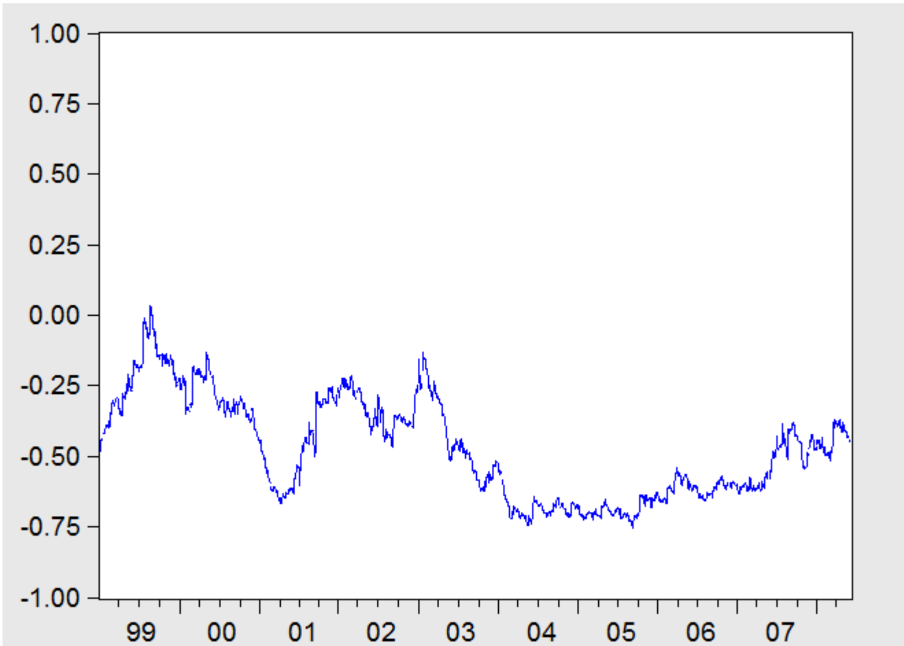
5. Empirical Results

A. Estimation of DCC Model

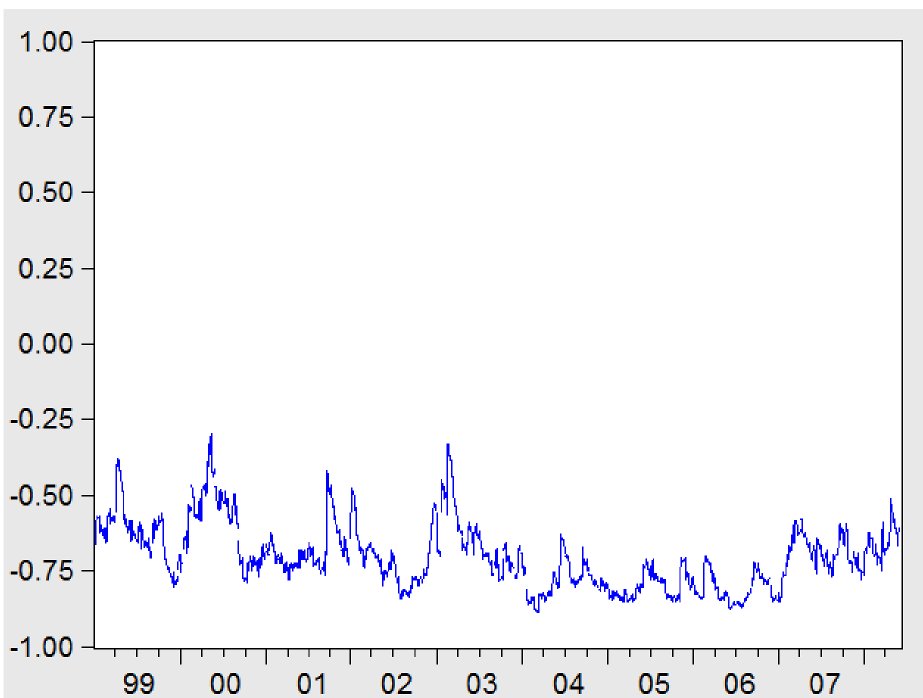
The estimate results for the DCC model are given in Table 4.The DCC beta parameter for the Brazilian real is -0.9079 and the Russian ruble is -0.5178. Both the real and rubble have a tendency to be near zero and often change signs—this may contribute to the negative betas for the two currencies. The rest of the eight currencies have a positive DCC beta parameter. The DCC beta parameter measures persistency of correlation and therefore better captures relative stability. For example, the DCC beta parameter for the Euro is only 0.6073. Recall that the Euro carries a 57.6% weight in the U.S. dollar index, which implies that a big currency like the Euro naturally is more closely related to the index. Therefore, the fact that the Euro comes out with a low persistency is even more clear evidence that its stability is low. On the other hand, the weight for the Japanese yen, British pound, and Canadian dollar are 13.6%, 11.9%, and 9.1% respectively; but the corresponding persistency of the correlation (the DCC beta parameter) is 0.9715, 0.9581, and 0.9837. This implies that the stability of the Japanese yen, British pound, and Canadian dollar are relatively high. Figure 1 shows the dynamic conditional correlation between each of the eight currencies with the U.S. dollar futures. Consistent with what has been estimated from the DCC model (namely the DCC beta parameter) the conditional correlation, noted as rho, between the Brazilian real and the U.S. dollar and the Russian ruble and the U.S. dollar have a tendency to be near zero and often change signs. Also, similar to the results of Table 4, the Australian dollar, British pound, Canadian dollar, and Japanese yen are the most positively correlated with U.S. dollar futures. One can observe that these relationships vary dramatically over the sample period.

Figure 1. Dynamic Conditional Correlation

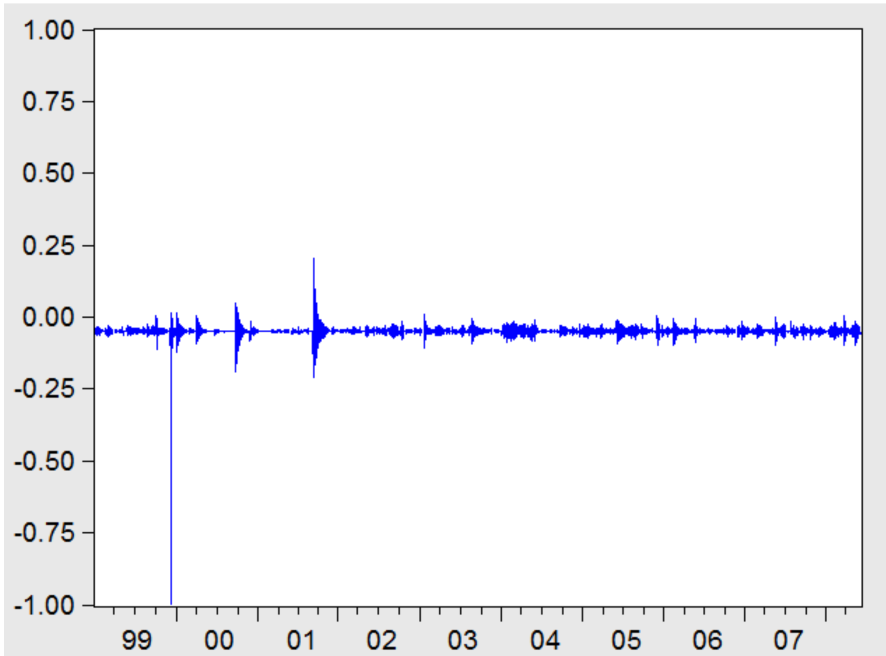
Panel A. Correlation between Australian Dollar and American Dollar Futures



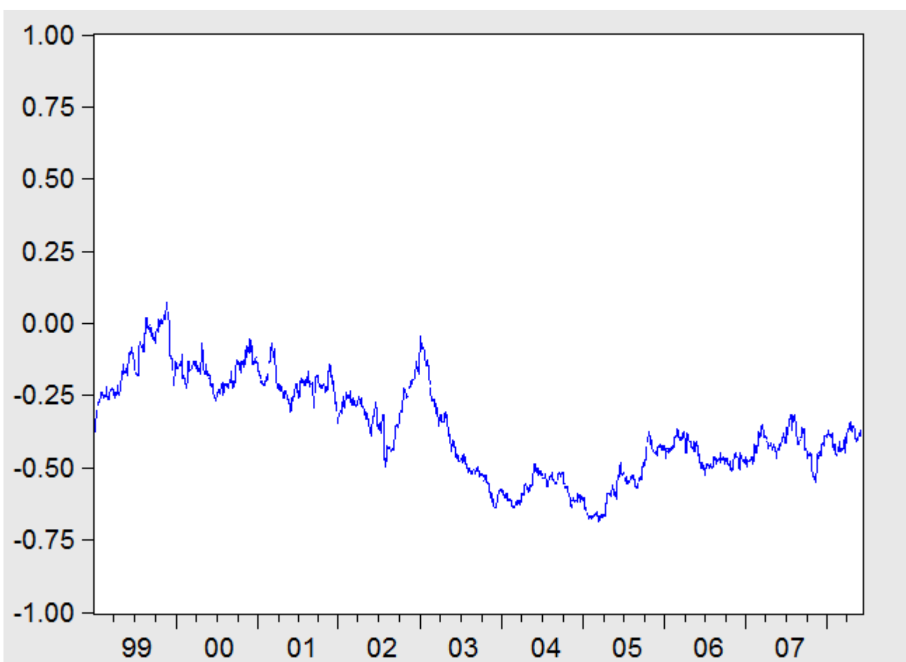
Panel B. Correlation between British Pound and American Dollar Futures



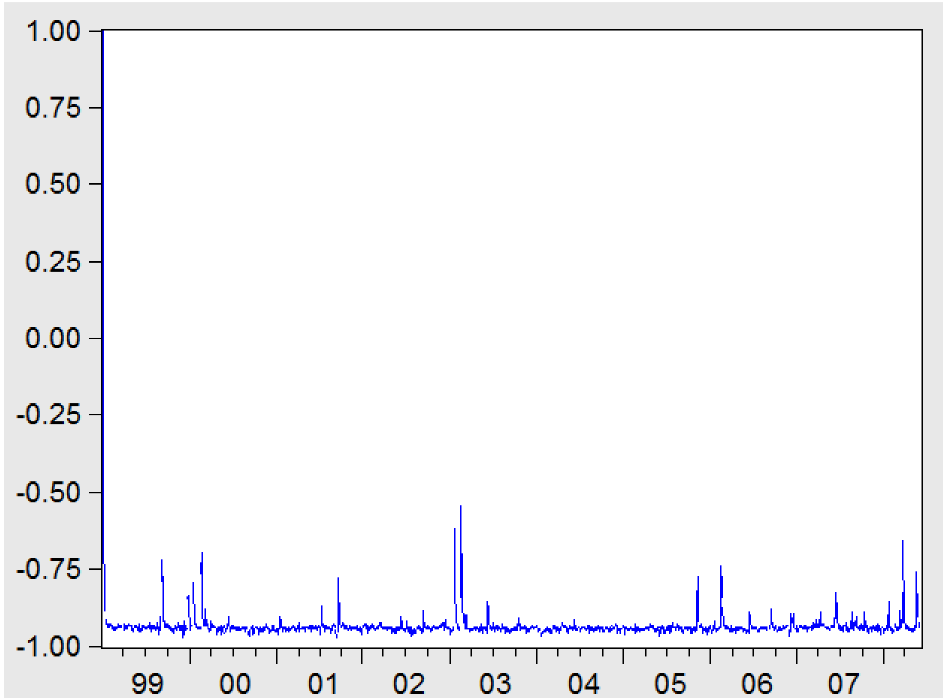
Panel C. Correlation between Brazilian Real and American Dollar Futures



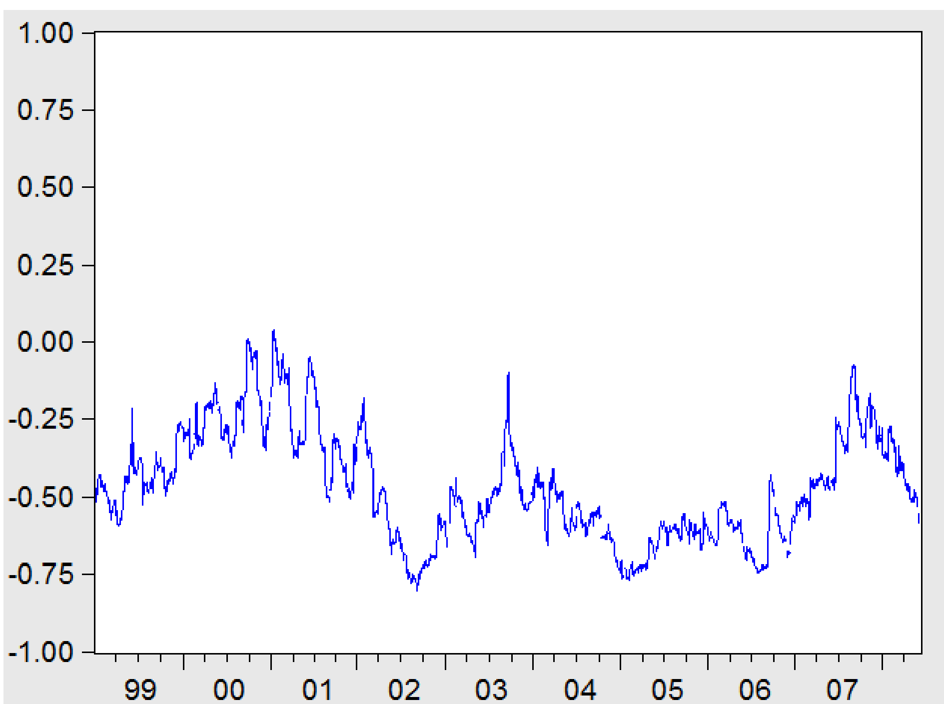
Panel D. Correlation between Canadian Dollar and American Dollar Futures



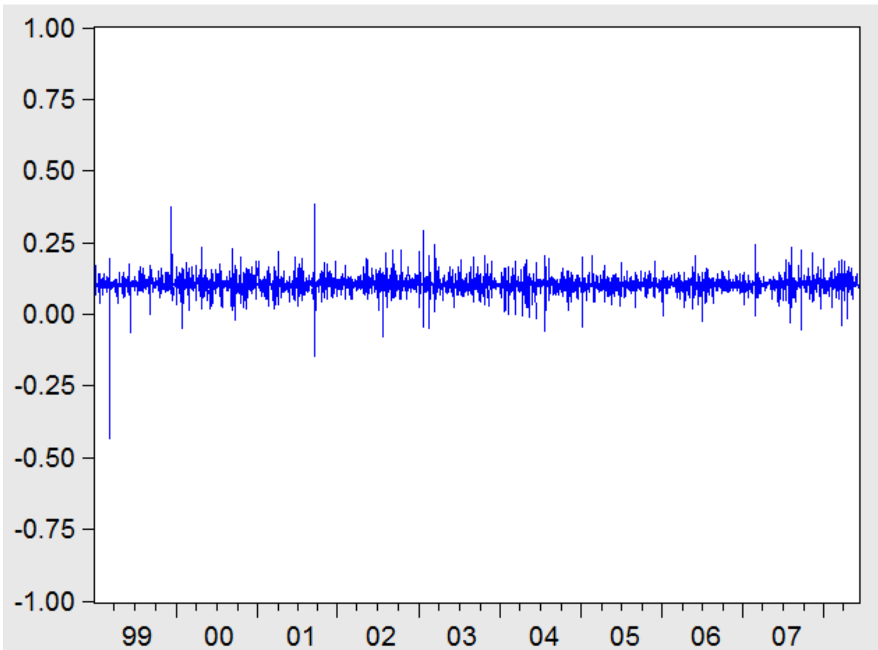
Panel E. Correlation between Euro Currency and American Dollar Futures



Panel F. Correlation between Japanese Yen and American Dollar Futures



Panel G. Correlation between Russia Ruble and American Dollar Futures



Panel H. Correlation between Swiss Franc and American Dollar Futures

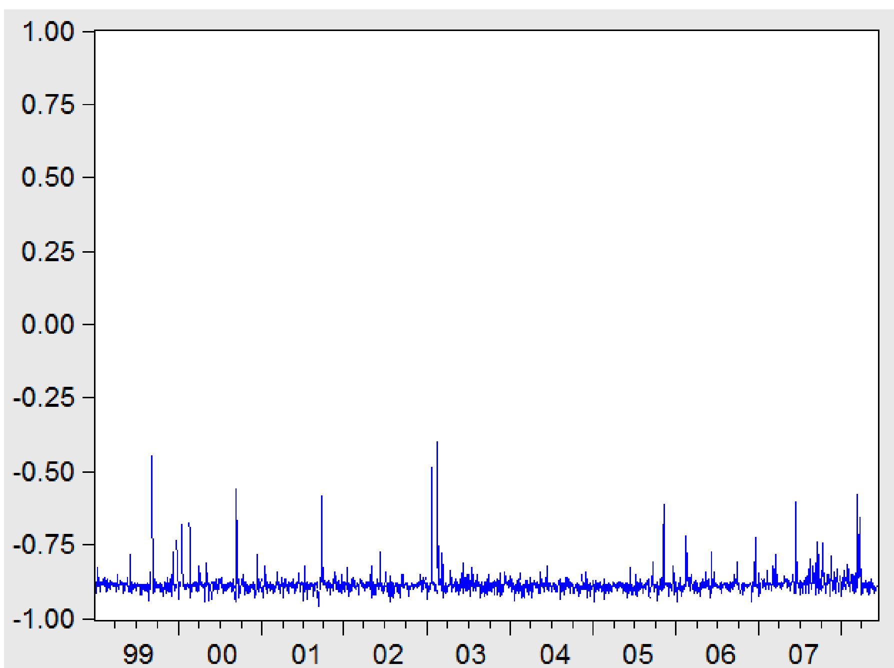


Table 4. DCC Model Results for Eight Currency Futures

Futures Contract	DCC α	Parameter	DCC β	Parameter	Correlation (Return)	Correlation (Volatility)	Log likelihood
Australian Dollar	0.0153***	(0.0026)	0.9832***	(0.0031)	-0.4766	-0.4710	-6279
British Pound	0.0331***	(0.0020)	0.9581***	(0.0029)	-0.7051	-0.7011	-5806
Brazilian Real	0.0069***	(0.0021)	-0.9079***	(0.2041)	0.0039	-0.0488	-6648
Canadian Dollar	0.0138***	(0.0031)	0.9837***	(0.0039)	-0.3767	-0.3641	-6433
Euro Currency	0.0728***	(0.0024)	0.6073***	(0.0079)	-0.9351	-0.9372	-4083
Japanese Yen	0.0253***	(0.0033)	0.9715***	(0.0041)	-0.4559	-0.4613	-6299
Russian Ruble	0.0304***	(0.0005)	-0.5178***	(0.0032)	0.0983	0.1043	-6638
Swiss Franc	0.0982***	(0.0073)	0.3075***	(0.0626)	-0.8860	-0.8834	-4791

B. The Role of Liquidity

Table 3, as previously stated, shows that liquidity varies across different currency futures. Table 5 provides further evidence using the correlation matrix coefficients regarding return, the time-varying correlation of currency futures and U.S. dollar index futures, and liquidity measures. For all the currency futures, the Amihud illiquidity measure is negatively correlated with the logarithm of trading volume.

Table 5. Correlation Matrix of Correlation and Liquidity Measures

	Return Australian Dollar	Correlation Australian Dollar	Amihud Australian Dollar	Log(Volume) Australian Dollar
Return Australian Dollar	1	0.00039	0.07506	-0.02918
Correlation Australian Dollar		1	0.08876	-0.18482
Amihud Australian Dollar			1	-0.48034
Log(Volume) Australian Dollar				1

	Return British Pound	Correlation British Pound	Amihud British Pound	Log(Volume) British Pound
Return British Pound	1	-0.01089	0.05073	-0.03872
Correlation British Pound		1	-0.17448	0.17887
Amihud British Pound			1	-0.43617
Log(Volume) British Pound				1

	Return Brazalia Ruble	Correlation Brazalia Ruble	Amihud Brazalia Ruble	Log(Volume) Brazalia Ruble
Return Brazalia Ruble	1	-0.02807	0.06981	-0.0321
Correlation Brazalia Ruble		1	-0.02921	0.02352
Amihud Brazalia Ruble			1	-0.73588
Log(Volume) Brazalia Ruble				1

	Return Canadian Dollar	Correlation Canadian Dollar	Amihud Canadian Dollar	Log(Volume) Canadian Dollar
Return Canadian Dollar	1	-0.01613	0.06774	-0.01738
Correlation Canadian Dollar		1	-0.31254	0.28138
Amihud Canadian Dollar			1	-0.44945
Log(Volume) Canadian Dollar				1

	Return Euro Currency	Correlation Euro Currency	Amihud Euro Currency	Log(Volume) Euro Currency
Return Euro Currency	1	0.00832	0.01982	0.00742
Correlation Euro Currency		1	0.00893	-0.00907
Amihud Euro Currency			1	-0.35878
Log(Volume) Euro Currency				1

	Return Japanese Yen	Correlation Japanese Yen	Amihud Japanese Yen	Log(Volume) Japanese Yen
Return Japanese Yen	1	-0.00362	-0.01726	0.00674
Correlation Japanese Yen		1	-0.07844	0.15545
Amihud Japanese Yen			1	-0.47326
Log(Volume) Japanese Yen				1

	Return Russian Ruble	Correlation Russian Ruble	Amihud Russian Ruble	Log(Volume) Russian Ruble
Return Russian Ruble	1	0.02585	0.06023	-0.04614
Correlation Russian Ruble		1	-0.01413	0.02745
Amihud Russian Ruble			1	-0.63667
Log(Volume) Russian Ruble				1

	Return Swiss Franc	Correlation Swiss Franc	Amihud Swiss Franc	Log(Volume) Swiss Franc
Return Swiss Franc	1	0.01132	0.01745	-0.00377
Correlation Swiss Franc		1	0.0107	0.01341
Amihud Swiss Franc			1	-0.49249
Log(Volume) Swiss Franc				1

For five out of eight currency futures, the correlation coefficient between the conditional correlations and Amihud measure is negative, which implies that higher illiquidity promotes a declining correlation between currency futures and U.S. dollar index futures. The exceptions are the Australian dollar, Brazilian real, and Swiss franc futures. For these futures, higher illiquidity actually promotes a closer conditional correlation between them and U.S. dollar index futures. For six out of eight currency futures the correlation coefficient between the conditional correlations and logarithm of trading volume is positive, which implies that more active trading promotes a higher correlation between currency futures and U.S. dollar Index futures. The exceptions are again the Australian dollar and the Brazilian real futures. For these futures, more active trading is related with declaiming conditional correlation between them and U.S. dollar index futures.

From the above analysis, it can be seen that liquidity does impacts the conditional correlations. In order to examine this further, a regression approach is used to examine the extent to which variations in the conditional correlations of currency futures and U.S. dollar index futures are related to the different aspects of liquidity. More specifically, I run the following regression:

$$rho = a + b_1 \times Amihud\ Illquidity + b_2 \times Log(trading\ volume) + \varepsilon$$

Table 6 shows how currency futures liquidity impacts the varied correlations between currency futures and U.S. dollar futures. The dependent variable is the correlation (i.e. rho) is estimated from the DCC model, while the independent variables are the Amihud illiquidity measure as well as the logarithms of the trading volumes for each future. One very striking result from Table 6 is that when the currency futures and U.S. dollar futures share a negative relationship, the independent variables (Amihud illiquidity and trading volume) do not have explanatory power in regards to the dynamic correlation. An example of this would include the results for the Brazilian real and the Russian ruble. However, the liquidity measure does have explanatory power for several positive correlations between currency futures and U.S. dollar, such as the results for the Australian dollar, British pound, and the Canadian dollar.

Table 6. The Varying Correlations and Currency Futures Liquidity

Futures Contract	a	b1	b2	t-stat(a)	t-stat(b1)	t-stat(b2)	R-Square
Australian Dollar	-0.3383	-20.7353	-0.0255	-9.42	-0.80	-5.65	0.30
	(0.0359)	(25.7881)	(0.0045)				
British Pound	-0.7805	152.9319	0.0061	-38.02	4.57	2.47	0.1810000
	(0.0205)	(33.4766)	(0.0025)				
Brazilian Real	-0.0494	0.0005	0.0001	-51.50	0.03	0.26	0.01
	(0.0010)	(0.0181)	(0.0002)				
Canadian Dollar	-0.5807	272.1610	0.0191	-16.03	2.57	4.48	0.172
	(0.0362)	(105.9979)	(0.0191)				
Euro Currency	-0.9182	311.7216	-0.0019	-43.08	1.13	-0.77	0.30
	(0.0213)	(275.1507)	(0.0024)				
Japanese Yen	-0.4531	-54.3483	-0.0063	-12.18	-0.33	-1.51	0.21
	(0.0372)	(166.2133)	(0.0042)				
Russian Ruble	0.1110	-201.2677	-0.0008	11.84	-1.65	-0.71	0.24
	(0.0094)	(121.6324)	(0.0012)				
Swiss Franc	-0.8919	2.5568	0.0011	-120.07	0.14	1.28	0.17
	(0.0074)	(17.7233)	(0.0009)				

6. Conclusion

This study investigates the dynamic correlation between currency futures prices, focusing on the persistency of correlation of currency prices. Using the Dynamic Conditional Correlation model developed by Engle (2002), this study incorporates time-varying correlations into the analysis. The sample includes eight currency futures traded on the Chicago Mercantile Exchange from 1999 to 2008 and the U.S. dollar index futures. The study finds that the Canadian dollar has the greater persistency while the Brazilian real has the weakest. No less important, the study finds that the time-varying conditional correlation between currency futures and the U.S. dollar futures is influenced by two types of liquidity: price impacts (Amihud illiquidity) and the logarithm of trading volume.

Appendix 1: Background Information of Each Currency

Australian Dollar

Beginning in 1966 the Australian dollar became the official currency of Australia. At that time, the global currency market was managed under the Bretton Woods system. This system operated throughcountries pegging their currency to the U.S. dollar (USD) by means of a fixed exchange rate. When the Bretton Woods system finally collapsed it forced many countries to adopt a floating rate of currency, including the Australian dollar in 1971. The Australian dollar's highest value relative to the USD was $0.881 in December of 1988. The lowest value was $0.4775 in April of 2001. The Australian dollar is heavily influenced by Australia's business cycle, due to the fact that the Australian economy is so heavily reliant upon commodities. The Australian dollar's exchange rate movement is often opposite the direction to reserve currencies, which tend to be stronger during downward turns of the business cycle.

British Pound

The British Pound has a long and distinguished history. In regards to its more recent history the pound officially adopted a floating rate in August of 1971 after the end of the Bretton Woods system. Later, in October of 1990 the British government joined the European Exchange Rate Mechanism (ERM). However, Britain was forced to quit that system on "Black Wednesday" (September 16, 1992) due to the fact that Britain's economic performance made the exchange rate unsustainable. As a member of the European Union, Britain retains the right to adopt the euro as the country's currency; however, the politics involved with such a decision are very divisive. In April 2007 the pound hit a 15-year high against the USD with an exchange rate of $2

USD to one British Pound. Since the global financial crisis of 2008 the pound has since depreciated considerably.

Brazilian Real

The modern real was introduced in July of 1994 where it was set equal to 1 USD. The new currency replaced the short-lived cruzeiro real (CR$). After its introduction, the real unexpectedly gained value against the USD. During the 1994-1995 periods it attained its maximum dollar value of $1.20. However, between 1996 and 1998 the Central Bank allowed the real to depreciate in a slow and smooth manner, so that by the end of 1998 the exchange rate had dropped from a 1:1 ratio to about a 1.2:1ratio. The currency's value continued a mostly downwards path for the next four years. By October 2002 the exchange rate had reached an historic low of almost 4 reals per 1 USD. In May 2007the real finally began to appreciate and became valued at more than $0.50 - even though the Central Bank was still trying to keep the exchange rate low. The Central Bank feared the effect that a rising exchange rate might have on the Brazilian economy due to its reliance on exports.

Canadian Dollar

Unlike most currencies in the Bretton Woods system the Canadian dollar actually had a floating exchange rate. This floating rate lasted from 1950 to 1962. In 1962 Canada decided to switch to a fixed exchange rate, which was set at $0.925. However, with the collapse of the Bretton Woods system it was forced to switch back to a floating rate in 1970. It has maintained a floating exchange rate ever since. During the 1990's the Canadian dollar fell in value against the USD, and was traded for as little as $0.6179 on January 21, 2002. In more recent years its value has appreciated due to the demand for commodities which Canada exports. By September 28, 2007, the Canadian dollar had actually closed above the USD for the first time in 30 years at a rate of $1.0052 to 1 Canadian dollar.

Euro Currency

The euro (€) is a currency currently used by 17 countries: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain. It is considered to be the second largest reserve currency in the world as well as the second most traded currency in the world. The euro was originally introduced as an accounting currency in January 1999. It was not until 2002 that actual paper money and coinage was issued. Since 2002 the euro has traded above the USD with a high of US$1.6038 on July 2008. While the euro has many strengths, a relative weakness has been the low interest rates tied to the currency. These low interest rates allowed governments that use the euro to borrow to excess, eventually causing public deficits to grow uncontrollable. Europe is still dealing with its public debt issues.

Japanese Yen

After World War II, Japan needed help in stabilizing its economy. To that end Japan joined the Bretton Wood System in 1949, whereupon it set the value of the yen at a fixed rate of ¥360 per 1 USD. This exchange rate remained in place until 1971, when the United States abandoned the gold standard (thus triggering the end of the Bretton Woods System).Although the yen has had a floating exchange rate since the early 1970's, the Japanese government has continuously interfered in the forex market by buying and selling USD in order to manipulate the country's exchange rate. In the 1990's the yen declined significantly against the dollar due to the bursting of the Japanese asset price bubble, reaching a low of ¥134 to $1 in February of 2002. In order to fight the downward pressure placed on the Japanese economy (from the bursting of the bubble) the Bank of Japan adopted a zero interest rate policy. This has caused the yen to become a major player in the carry trade market, since investors can borrow cheaply in yen and invest in other currencies with higher interest rates. The yen continued its decline from the 1990's all the way until 2007when the bursting of another bubble, the U.S. housing market bubble, finally caused the yen to appreciate.

Russian Ruble

Russia, over the years, has had many different rubles. The seventh version of the ruble was issued on January of 1998, with one new ruble equaling 1,000 old rubles. This seventh ruble was issued for purely psychological reasons. Regardless, the ruble was forced to depreciate significantly in August 1998 due to the Russian Financial Crisis. During this period the ruble lost almost 70% of its value against the USD. Since that time, the ruble has been doing better, although inflation in Russian still undermines much of the value of the currency.

Swiss Franc

In 1945, Switzerland joined the Bretton Woods system and pegged the Swiss franc to the USD at a rate of $1 = 4.30521 francs. Historically, the Swiss franc has been considered a safe currency especially because (since the 1920's) the Swiss franc was linked to gold. However, a referendum held in May 2000 delinked the Swiss franc from its gold peg. Nevertheless, this currency is still prized due to its extremely low inflation rates.

Appendix 2: USDX Futures Contract Specifications

U.S. Dollar Index (USDX) Futures Specifications (as of June 30, 2002):

Contract size: $1000 times the USDX index.

Trading hours: 3:00 a.m. to 8:00 a.m. and 8:05 a.m. to 3:00 p.m.

Contract months: March, June, September, December

Ticker symbol: DX

Price quotation: The U.S. dollar index is quoted as a percent of its value as of March 1973, calculated to two decimal places (e.g., on July 31, 2002, the USDX index officially closed at 107.41)

Minimum price fluctuation: The minimum price fluctuation, or "tick size" for the USDX index is 0.01 USDX point, which is equivalent to $10.00 per futures contract.

Limit on daily price move: 200 ticks above & below prior day's settlement, except during last 30 minutes of any trading session when no limit applies. Should the price reach the limit and remain within 100 ticks of the limit for 15 minutes, then new limits will be established 200 ticks above and below the previous price limit

Position limits: None

Last day of trading: 2nd business day prior to the 3rd Wednesday of the expiring month. On the last trading day, trading ceases at 10:16 a.m.

Settlement procedure: Contracts held to expiration are settled in cash, based on the value of the USDX index at 10am (New York time) on the last day of trading for an expiring contract. The USDX settlement value is computed by Reuters LTD, in accordance to New York Cotton Exchange regulations.

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