Information Content of Order Flow and Cross-market Portfolio Rebalancing: Evidence for the Chinese Stock, Treasury and Corporate Bond Markets

This version: February 2009

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Abstract: This paper establishes within-market and cross-market information content of order flow for stocks, corporate bonds and Treasury bonds in China. With tick-by-tick data over three years on the Shanghai Security Exchange market, we show significant information content of order flow and its relationship with time-varying market conditions. Bi-directionally negative cross-market effects of order flow on returns both between stocks and bonds and between corporate and Treasury bonds are observed after the commonality and lead-lag relationship of the three markets are controlled. Our results provide evidence that cross-market portfolio rebalancing or flight produces cross-market effect of order flow. In particular, while Treasury bonds are the main choice as safe assets in stock-bond flight, corporate bonds are able to substitute Treasury bonds when either the stock or the bond market is more volatile. Due to the small size of the bond markets in China, stock-bond portfolio rebalancing will produce high price impact on the bond markets, which may incentives investors to search other substitute safe assets, such as the high-quality corporate bonds for Treasury bonds, or inversely.

Keywords: Order flow, Cross-market hedging, Market conditions, Chinese capital market

1 Introduction

Cross-market linkages involving both returns and order flow have become an active area of study. Previous studies have shown that cross-market portfolio rebalancing or flight, particularly flight-to-quality or flight-to-liquidity under stress market conditions, could be the main reason driving such linkages. However, these studies, which examine related issues jointly or in isolation, usually restrict themselves to the interactions between only two markets, typically stock and Treasury bond markets, and only focus on major OECD countries where microstructure data is more easily available.

This paper suggests enlarging the scope of this enquiry in these two directions. We take into account the corporate bond market in addition to the Treasury bond market to examine cross-market portfolio rebalancing or flight both between stock and bond markets and between corporate and Treasury bond markets[1]. We study these three markets in the largest emerging economy by far, China.

Our work thus first provides an important additional feature compared to related empirical studies which are only concerned with flight-to-quality between stocks and Treasury bonds that have a very different fundamental risk level (Underwood, 2008), flight-to-liquidity between Treasury and Refcorp bonds that have a similar fundamental risk level (Longstaff, 2004), or flight-to-liquidity accompanied by flight-to-quality (Goyenko and Ukhov, 2008; and Brunnermeier and Pedersen, 2007). By nature, cross-market asset allocation or risk management ranges over all available assets, and the safe assets (bonds) in the portfolio could include not only Treasury bonds but also possible (high-grade) corporate bonds; therefore, leaving out corporate bonds when examining cross-market portfolio rebalancing probably results in biased results.

Three features of the Chinese financial markets both distinguish them from OECD markets and lead us to expect specificities in cross-market portfolio rebalancing or flight. Firstly,

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[1] In this paper, we view flight-to-quality and flight-to-liquidity, which occurs particularly under extreme market conditions, as two types of portfolio rebalancing. The general portfolio rebalancing could also include investment adjustment due to reasons other than liquidity or quality problem of the assets themselves, such as the "liquidity trading" for reasons outside the stock market shown by Admati and Pfleiderer (1998). Connolly et al. (2005, 2007) and Underwood (2008) also refer to cross-market rebalancing as cross-market hedging, as return correlations between the stock and Treasury bond markets likely to be negative in crisis periods on the stock market.

individual investors predominate on the Chinese stock market, as opposed to the dominance of institutional investors in OECD markets. Previous theoretical studies about flight-to-quality or flight-to-liquidity behavior usually assume that market participants are fund managers or institutions who usually allocate investment between stocks and bonds (Vayanos, 2004, Brunnermeier and Pedersen, 2007), and previous empirical studies only focus on OECD markets that have more institutional than individual investors (Longstaff, 2004, Goyenko and Ukhov, 2008, Beber et al., 2008, Underwood, 2008). In China, individuals, who represent more than 90% of investors, held 51.29% of the total market value outstanding by the end of 2007[2]. Their ability to undertake cross-market asset allocation and hedging may be much weaker than that of institutional investors, and most individuals undertake little cross-market asset allocation between stocks and bonds, simply transferring funds between the stock market and bank accounts. Accordingly, the very existence of stock-bond market flight activities is questionable. Secondly, Chinese markets are characterized by a lack of international arbitrage due to the still-binding capital controls. Therefore, cross-market effects can only occur (officially) between domestic markets. Previous studies on OECD markets suffer from "missing" international cross-market effects, ignoring stocks-to-foreign-stocks and bonds-to-foreign-bonds effects. However, the empirical results of Connolly et al. (2007) etc. show that cross-country hedging should not be ignored. Our study on the Chinese market thus focuses on "pure" domestic cross-market effects. Thirdly, the Chinese bond market is a special case. The Treasury bond market is small and has no fixed time and no fixed term of bond issuing. The very strict conditions for the issuance of corporate bonds endow them with high quality, making them close to Treasury bonds. This makes the Chinese bond markets ideal for investigating the preference of institutional investors between Treasury and corporate bonds in the stock-bond flight and the stylized facts of flight between bond markets, which have not been granted much importance. We are particularly interested in the substitute effect between Treasury and corporate bonds in stock-bond market portfolio rebalancing. This sheds light on the possible role of each market and the extent to which investors bear credit risk in their flight.

The database we study for the Chinese financial markets covers tick-by-tick data over a

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[2] Related statistics here come from the Report of the Chinese Capital Market that is published by the China Securities Regulatory Commission (http://www.csrc.gov.cn/n575458/index.html).

three-year period starting in January 2004 for all stocks, Treasury bonds and corporate bonds. This enables us to examine cross-market effects not only among returns but also between and through order flow. Order flow here is defined as the excess of buying pressure, that is, the trading volume that buyers initiate over that initiated by sellers. Explanations for such a role stem from the information revealed by aggregate order flow on preferences, endowments and the projection of news by market participants (Lyons, 2001, Evans and Lyons, 2002, Underwood, 2008), and is supported by the empirical evidence of Hasbrouck and Seppi (2001), Chordia et al (2002), Evans and Lyons (2002), Brandt and Kavajecz (2004), and Harford and Kaul (2005) etc., who show that order flow present important information on variation of asset returns on the stock, bond and foreign exchange markets. There are two major public security exchange markets in China, the Shanghai Security Exchange (SHSE) and the Shenzhen Security Exchange (SZSE) market. This paper examines the information content of order flow for stocks, Treasury bonds and corporate bonds on SHSE, which has more stocks and bonds than in SZSE. By employing tick-by-tick data over a three-year sample for all stocks, Treasury bonds and corporate bonds on SHSE, we determine both the relative role of each market in cross-market flight and its precise features.

Firstly, we find that the Treasury bond market serves more for stock investor hedging than the corporate bond market, and, in addition to the stock-bond flight, flight between corporate and Treasury bond markets is also significant. Underwood (2008) provides evidence of a (unidirectional) negative correlation between Treasury bond market order flow and stock market returns, and attributes it to cross-market hedging. We find bi-directionally negatively cross-market effect of order flow on returns both between stocks and Treasury bonds and between corporate and Treasury bonds. Namely, a rise in order flow on one market means a fall in returns on another market. As aggregate order flow reveals information on preferences, endowments and the projection of news by market participants, the bi-directionally negative effect of order flow on returns between two markets imply widespread cross-market portfolio rebalancing or flight activities. Although both the Chinese Treasury and corporate bond markets are relative small and individual investor are predominant on the Chinese stock market, our results also provide evidence of cross-market portfolio rebalancing both between stocks and Treasury bonds and between corporate and Treasury bonds.

Secondly, when the stock market is more volatile and during extreme rising or falling, or when the Treasury bond market is more volatile or falling, corporate bond order flow also present significantly negative effect on stock returns. Furthermore, under extreme stock market conditions, order flow in both the corporate and Treasury bond markets has much stronger effect on stock market returns. This means that, with respect to portfolio rebalancing or flight-to-quality between the stock and bond markets in China, corporate bonds are able to substitute Treasury bonds as the "heaven" of stock investors, either when the demand of safe assets rises during stock market stress or when the cost of portfolio rebalancing during volatile Treasury bond market. Cross-market portfolio rebalancing or flight may have high price impact on the object market, even though such activities are "good news" for the object market due to more investment coming. This is particularly true in China since both the Treasury and corporate bond markets are relatively small compared with bond markets in other developed countries. Under this circumstance, the high price impact on the Treasury bonds during flight between the stock and Treasury bond markets should be an important reason that incentives investors to search other substitute safe assets, such as the high-quality corporate bonds for Treasury bonds, or inversely.

Finally, with respect to the within-market effect of order flow, in line with previous studies in relationship between liquidity and price discovery, e.g. Chordia and Swaminathan (2000) and Underwood (2008), we find that the information content of order flow differs significantly both between index and non-index stocks and between liquid and illiquid bonds. However, on the Chinese stock market, the order flow of non-index stocks has stronger effects on market returns than index stocks. Although this contrasts with the results of Harford and Kaul (2005) and Underwood (2008) that index stock order flow explains market movements more than non-index stock order flow, our results support the findings of Bailey et al. (2008) that the order flow of individual investors explains more fluctuation in stock returns than institutional investors in China, and are in line with the fact that the individual investor who are predominant on the Chinese stock market prefer small non-index stocks. Furthermore, we also find evidence of within-market portfolio rebalancing between index and non-index stocks when the stock market is more volatile or under extreme falling, which reduce the information of index stock order flow on stock market movements. On the bond markets, the order flow of actively traded bonds with high liquidity has

higher information content on market movements. In particular, off-the-run Treasury bonds in China are more liquid and have higher within-market information content of order flow than on-the-run Treasury bonds.

The rest of this paper is organized as follows. Section 2 offers a review of the related literature. Section 3 provides a briefly introduction to the Chinese capital markets and section 4 describes the data. In section 5 we present the empirical results and analyze the cross-market effects of order flow, the influence of market conditions on order flow information content. Section 6 concludes.

2 Literature Review

Our work is closely related to the previous studies on the information content of order flow, including both within-market and cross-market effects of order flow. For the within-market effects, there is evidence from stock, bond and foreign exchange markets.

On the stock market, Hasbrouck and Seppi (2001) find commonality of order flow between stocks. By means of principal component and canonical correlation analyses, the common information of order flow for the 30 Dow-Jones index stocks is extracted. The empirical results of Hasbrouck and Seppi show that the common movements of market order flow can explain more than two-thirds of the common movements of market returns, but returns of individual stocks are mostly affected by their own order flow. Similarly, Harford and Kaul (2005) suppose that the commonality of market order flow comes from the operation of index funds. They find that the commonality of order flow for S&P500 stocks is stronger than that for non-S&P500 stocks. In addition, Chordia et al. (2002) find a significant correlation between order flow and contemporaneous or lagged returns, and returns may reverse in the future when current order flow is too high (positive) or too low (negative)[3]. With a unique dataset of traders' accounts, Bailey et al. (2008) have examined commonality in order flow across individual, institutional, and proprietary investors on the Shanghai stock market. Their results show that the marginal explanatory power of order flow for individual investors on stock returns is higher than that for

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[3] In Chordia et al. (2002), the order flow is called order imbalance. Actually, both expressions have the same definition in this paper, as well as in other literature.

institutional and proprietary investors, and commonality of order flow for individual investors is also stronger.

Order flow on the bond and foreign exchange markets is also informative. Brandt and Kavajecz (2004) apply principal component and vector autoregressive (VAR) models to the U.S Treasury bond market and find that order flow affects bond yields due to liquidity premium but not inventory premium. Controlling for major macroeconomic news or policies, order flow can explain about 20% of variation in Treasury bond yields, and the information content of order flow is higher when market liquidity is lower. In the foreign exchange market, Evans and Lyons (2002) find that order flow explains more that 60% of the variation in exchange rates, which is much higher than the traditional macro-economic variables.

With respect to cross-market hedging or flight activities, our work is closely related to Underwood (2008), who studies the effect of order flow on cross-market returns between U.S stock and Treasury bond markets. His work shows that aggregate order flow plays a strong role in explaining the links between cross-market returns. The order flow of the Treasury bond market significantly negatively affects stock market returns. Moreover, the effect of Treasury bond market order flow is stronger when stock market volatility rises, and the effect of order flow for institutional investors or actively traded 5-year Treasury notes is also stronger than individual investors or Treasury bonds with other maturities. Underwood attributes such a cross-market effect of order flow to cross-market hedging. Chordia et al. (2005) also find that not only order flow affects its own-market returns, volatility and liquidity in both stock and bond markets, but order flow in one market may also affect returns, volatility and liquidity in another market.

Moreover, our work is also related to the literature which provides evidence about the effect of market uncertainty on market correlations and draws implications for cross-market hedging. Connolly et al. (2005, 2007) find that stock and bond market returns are positively correlated in the long run, but when uncertainty on the stock market rises, the attractiveness of the stock market is reduced and more investment will be transferred to the safer bond market, which leads to short-term negative stock-bond correlations. By using Chicago Board Options Exchange's Volatility Index (VIX) and the turnover of the stock market as the proxies of market uncertainty, Connolly et al. (2005) find that the higher stock market uncertainty, the higher probability of

future negative stock-Treasury bond correlations. Connolly et al. (2007) examine stock and bond market return correlations for the three countries, U.S, UK and Germany, and find that not only a rise, but a sharp change (rise or fall), in stock market uncertainty may also lead to negative stock-bond correlations. Connolly et al. (2005, 2007) show that cross-market hedging should be responsible for the short-term negative correlations between the stock and the Treasury bond markets.

This paper examines portfolio rebalancing or flight on the Chinese stock, Treasury and corporate bond markets by examining both within-market and cross-market information content of order flow. These previous studies shown above ensure that such an approach is effective as order flow provide direct on information on investors trading activities and explain asset returns very well. Departing from Chordia et al. (2005) and Underwood (2008), who also examine cross-market effects of order flow, this paper takes into account a third market, the corporate bond market, in order to extend investigations on investors portfolio rebalancing to include all possible assets. In line with Connolly et al. (2005), we also examine the information content of order flow on times of different market conditions to further test whether portfolio rebalancing or flight is the main source of cross-market effects of order flow.

3 Market background

General Situations and Market Segmentation

A well-running capital market is usually viewed as one of the most important requirements for a strong economy. China has the largest and fastest growing economy in the world. In US dollar term, the size of its economy stands at $3.4 trillion in 2007, ranked after US, Japan and Germany. In parallel with the fast-growing economy, its capital market also develops very fast. Right row, Stocks, Treasury bonds and corporate bonds are traded on the two public security exchange markets, the Shanghai Security Exchange (SHSE) and the Shenzhen Security Exchange (SZSE). However, as shown by Netftci et al. (2007), Fan and Zhang (2007), Qiao et al. (2008) and Wong et al. (2008), both the Chinese stock and bond markets are marked as being segmented.

Firstly, the Chinese stock market includes both an A-share market that is only available for

domestic investors (recently for some Qualified Foreign Institutional Investors, QFII) and a B-share market that is available only for foreign investors. The B-share market has been opening to domestic investors only after June 2001. By the end of 2005, 1240 companies had issued A-share, and 23 companies had issued B-share, and 86 companies were issuing both A and B shares[④]. The price of stocks on the A-share market is denominated in Renminbi (Chinese Yuan, CNY), but that on the B-share market is denominated in US dollars (for SHSE market) or Hongkong dollars (for SZSE market).

Secondly, because one of the main objectives to setup the stock market in China at the beginning of 1990's is to find a new source of financing for large state owned enterprises (SOEs), which were heavily dependent on bank loans. Before 2004, for the sake of socialist economic and political system, a large proportion of shares, about two-thirds, are held by these SOEs themselves and can not be traded publicly[⑤]. As a result, the A-share market was segmented as tradable and non-tradable shares. A new reform adopted by the China Security Regulatory Commission (CSRC) required all these non-publicly exchanged shares to be placed on the market after 2005, and most firms had complied with the reform by the end of 2007.

Thirdly, in addition to the exchange bond market, in the middle of 1997, an inter-bank bond market was established, and originally only commercial banks, latter other financial institutions, are allowed to trade in this market. Right now, three segmented markets, the inter-bank bond market, the exchange market (both on SHSE or SZSE) and the over-the-counter (OTC) market (for individuals to buy bonds on the counter of commercial banks), constitutes the secondary bond market. With respect to the four types of bonds on the Chinese domestic bond market, i.e. Treasury bonds, central bank notes, financial bonds and corporate bonds[⑥], all central bank notes and financial bonds are only traded on the inter-bank bond market. Treasury bonds and corporate bonds are traded on both on the inter-bank and exchange markets, but a larger proportion is only listed and traded on the inter-bank bond market. The 2007 Annual Report of the Chinese Bond Market show that the trading volume on the inter-bank market in 2007 is about 63.13 trillion

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[④] Related statistics here come from the Report of the Chinese Capital Market that is published by the China Securities Regulatory Commission (http://www.csrc.gov.cn/n575458/index.html).
[⑤] By the end of 2005, the total number of share of all these listed companies had reached 762.95 billion CNY, but the tradable shares were only 291.5 billion CNY, accounting for 38.2% of the total shares.
[⑥] More information of the four types of bonds will be provided latter this paper.

(CNY), but that on the exchange market and OTC market is respectively only 1.75 trillion and 3.5 billion. Moreover, with respect to the trading either on the inter-bank or exchange market, the volume of repo trading is more than spot trading. For instance, in 2007, the spot trading on the Shanghai and Shenzhen exchange markets is about 116.9 billion CNY, but that for the repo trading on the two markets is about 1629.3 billion CNY.

Security Issuing

Before the 1990's, bank loans were almost the only source of financing for all companies in China. This led to a large amount of non-performing loans from the banks and increased bank risk. At the beginning of the 1990's, with the further reform of the Chinese economy, the stock market was created to provide another source of company financing. By the end of 2007, the capitalization of the Chinese stock market had grown to 32.71 trillion CNY, the largest among the emerging markets, and the third largest in the world. In 2007, new issue of public equity reached about 459.59 billion CNY, the highest in the world. By the end of 2007, a total of 1,616 companies had been listed on SHSE and SZSE, ranging over almost every sector in the Chinese economy.

The value outstanding of the four types of bonds in Chinese domestic bond market, Treasury bonds, central bank notes, financial bonds and corporate bonds, is respectively 2,149 billion CNY (27.4% of total outstanding bonds), 2,931 billion (37.4%), 2,097 billion (26.8%) and 170 billion (2.2%) at the end of October, 2006 (Huang and Zhu, 2007). Treasury bonds are issued by the Ministry of Finance to the public and are mostly medium and long term bonds, but there is no fixed time and specified term for the issuance of Treasury bonds. Central bank notes are issued by the People's Bank of China for the implementation of monetary policies. Financial bonds are issued by Chinese policy banks (State Development bank, China Import and Export Bank, and China Agriculture Development Bank) to support the development projects in special economic sectors such as agriculture, import and export, and in special regions, especially rural and underdeveloped areas (Fan and Zhang, 2007).

In particular, the Chinese corporate bond market is composed of three parts. The first part includes all convertible bonds issued by public firms, most of which had eventually been

converted to equity[7]. The second part is corporate bonds that are issued by public firms without embedded options. However, the first bond of this type was issued on 24th September 2007, and there are only two on the market by the end of 2007. The third part ranges over all the bonds issued by large state-owned enterprises, which have no public equity. In this paper, we only focus on the third part, the corporate bonds without embedded option and issued by non-public state-owned firms. We don not consider the first or the second type of corporate bonds because of uncertainties option properties for convertible bonds or the limited data for corporate bonds issued by public firms. All corporate bonds issued by non-public firms have high credit quality due to state-ownership of these firms and strict issuing requirements. These requirements include a debt to asset ratio of less than 0.4, an average disposable profit in the past three years of higher than the one-year interest payment, a rating of higher than "A", a qualified guarantor etc. These requirements limit the size of the corporate bond market but greatly improve bond quality.

Secondary Market Participants

On the Chinese stock market, by the end of 2007, more than 90% investors are individual ones, who have hold 51.29% of the total stock shares. With a unique dataset of trader accounts on SHSE, Bailey et al (2008) find that for a typical stock on a typical trading day, 91.76% of all trades were initiated by individual investors. When it comes to institutional investors, there are no real investment banks because no Chinese financial institution is permitted to provide the full range of financial services currently provided by international investment banks. There were 133 security companies in China by the end of 2003 with total assets of only US$67.87 billion, merely 20.22% of the total assets of US$335.6 billion of one single US investment bank, Goldman Sachs (Zhang, 2004).

Except commercial banks and rural credit cooperatives, all types of investors (including institutional and individual investors) can participate in the exchange bond market. Though the trading volume on the inter-bank bond market, as mentioned above, is more than that on the exchange bond market, statistics show that trading is more frequently on the exchange bond

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[7] Some very strict limitations are regulated by the China Security Regulatory Commission (CSRC) for Seasoned Equity Offering (SEO), which is even stopped a long time around 2004, so it's more easily to issue convertible bonds than new shares for the public firms. However, because the original incentive is not for issuing equity but debt, so most of the convertible bonds are eventually transferred to shares.

market. For instance, in 2007, the number of trades on the exchange market is nearly 798,600, and that on the inter-bank market is only 188,600. That is, most of the trading on the inter-bank market is wholesale of big institutions such as the large state-owned commercial banks, insurance companies, but the participants in the exchange bond market are mainly the relative small institutions or individuals, who are also the main participants in the stock market[8]. Definitely, even individual investors on the exchange bond markets can not be neglected in terms of numbers, but in fact nonbank financial institutions play the dominant role (Neftci et al., 2007). Insurance companies, investment funds and other banks are the chief holders on the exchange bond market. The commercial banks, which are the chief participants on the inter-bank market, are not allowed to buy and sell stocks, and, at the same time, individuals or small institutional investors cannot participate in the inter-bank bond market.

This paper discusses the information content of order flow for A-share stocks, corporate bonds and Treasury bonds on SHSE. Only securities on SHSE are considered because both the capitalization and number of securities, particularly bonds, outstanding on SHSE is more than that on SZSE, and B-share stocks are excluded here to eliminate the effect of foreign exchange rate movements and because they accounts for only 2% of market shares. By the end of 2007, on SHSE, there are 850 A-share and 54 B-share firms are listed with total capitalization of 26.98 trillion CNY, 61 Treasury bonds with total issued value of 282.24 billion CNY, and 63 corporate bonds with total issued value of 39.68 billion CNY.

In examining cross-market flight activities, we do not directly consider the trading on the inter-bank bond market but only include inter-bank repo rates in our model, because 1) high-frequency trading data on the inter-bank market is not available; 2) the small institutional and individual investors who are the main participants on the stock market can not participate in the inter-bank market[9]. This naturally excludes the central bank notes and financial bonds that are

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[8] Statistics of the 2007 Annual Report of Chinese Bond Market (http://zsfx.chinabond.com.cn/chinabond/article/fj_content. jsp?sLmId=113&sFjId=18847&sType=2) show that the main participants in the inter-bank bond market are state-own commercial banks, insurance companies, mutual funds. Actually, these three types of institutions respectively hold 67.7%, 7.6% and 4.2% of the total value of all the bonds in the inter-bank market. The share for non-bank financial institutions and non-financial institutions is respectively 0.6% and 14.3%, and that for individuals (through the OTC market) is less than 1%. Thus, for these small institutional investors, exchange bond market should be an important choice even though the exchange bond market is smaller than the inter-bank bond market.
[9] To include the possible effect of inter-bank market trading on the exchange market trading, we also test the effect of inter-bank repo rate on the spot stock and bond market returns latter this paper.

only traded on the inter-bank market. Definitely, we do not discuss the OTC market because its trading volume is too small. In our sample, the corporate bond market is smaller than the Treasury bond market for lower value outstanding and lower turnover. However, there are more corporate bonds outstanding in the exchange market, and statistics show that while repo trading is much more than the spot trading on the Treasury bond market, spot trading dominates the corporate bond market because only a few of corporate bonds are related to repo trading (Neftci et al., 2007). This can, to some extent, reduce the low liquidity problem of the corporate bond market compared with the Treasury bond market.

4 Data

This paper uses intraday tick-by-tick data and daily data for all A-share stocks, Treasury bonds and corporate bonds from 2004 to 2006 on SHSE, with a total of 724 trading days. The data are provided by CSMAR Corporation, one of the chief database providers for the Chinese financial markets. The data are processed as follows.

With the tick-by-tick high frequency data, order flow for each stock, Treasury bond and corporate bond are aggregated every day. CSMAR database provides records that directly identify each trade as buyer- or seller-initiated after 2004. With these records, the total buyer-initiated trading volume in value over the total seller-initiated trading volume in value over one day is aggregated as daily order flow for each stock and bond[10]. The total number of observations of daily aggregated order flow for all bonds and stocks is 549597, including 509537 for stocks, 23429 and 16631 respectively for Treasury and corporate bonds.

Daily returns of stocks are computed as the first difference of the logarithm of daily close price. To dampen extreme price movements and provide a cool-off period in the events of overreaction in order to protect the public investors, SHSE currently sets the daily price limit at 10%. In addition to data errors, these data with daily absolute returns higher than 10% are chiefly connected to the stocks which were gotten rid of the special treat (ST) or particular transfer (PT)

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[10] Some literatures, such as Brandt and Kavajecz (2004), define the difference between buyer-initiated and seller-initiated trading volume in dollar as order imbalance, which, obviously, is the same as the order flow defined here.

classes[11]. Thus, data of ceiling or floor hit as well as with absolute return higher than 10% are excluded here. Daily returns of stocks are computed as the first difference of the logarithm of daily close invoice price, and data on the interest payment days are excluded.

Harford and Kaul (2005) and Underwood (2008) show that index and non-index stocks have different information content of order flow, or pricing discovery efficiency. Here we also split all stocks on the market into index and non-index stock portfolio. Shanghai Security 180 (SS180) index was created in Jul.2002 and composed of the typical 180 A-share stocks on SHSE. After that, the index is also adjusted with the change of the price and shares outstanding for all index stocks. We construct index and non-index portfolios with the sample and its change information about the SS180 index. Bonds are usually classified as on-the-run and off-the-run portfolio due to different liquidity. Here, we use this distinction since some studies pricing discovery efficiency between these two types of bond may also be different. For instance, Goyenko et al (2008) show that short-term off-the-run bonds reflect macro shocks first. The basic statistics for different stock and bond portfolios is shown in Table 1.

In Table 1, the daily average number of trades and trading volume in value for different stock and bond portfolios are provided. In addition to these two indirect proxies, we also provide statistics of another two direct proxies of liquidity. One is the relative spread computed from tick-by-tick trading data, and the other is the price impact coefficient, or illiquidity, of Amihud (2002) computed from daily data. The relative spread is defined as,

$$Pspread = \frac{Ask_1 - Bid_1}{(Ask_1 - Bid_1)/2}$$

Here, Ask_1 and Bid_1 are respectively the best ask and bid prices for each trade. The relative spread is computed for each trade and the daily relative spread is averaged over all trades every day for each stock and bond. In line with Amihud (2002), this paper define the price impact coefficients, or illiquidity, of the security i on day t as follows,

$$ILIQ_t^i = \frac{\left| R_t^i \right|}{M_t^i}$$

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[11] More information about the ST or PT can be achieved in the web http://www.csrc.gov.cn/.

Here, R_t^i is the return and M_t^i is the trading volume in value for security i on day t [12].

Liquidity for the market or a particular portfolio is equally weighted by individual $Pspread_t^i$ or $ILIQ_t^i$. The liquidity provided in Table 1 is the average daily liquidity over the total sample.

As shown in Table 1, the number of trades and trading volume in value for SS180-index stocks are much higher than non-SS180-index stocks. Moreover, spread (*Pspread*) and illiquidity (*ILIQ*) are lower for SS180-index stocks. Therefore, SS180-index stocks have higher liquidity. Similarly, on the corporate bond market, the number of trades and trading volume in value is higher, and *Pspread* and *ILIQ* are lower for on-the-run bonds than off-the-run bonds. Therefore, on-the-run bond liquidity is higher than off-the-run bond liquidity on the Chinese corporate bond market. However, on the Treasury bond market, we can observe that, while the number of trades for on-the-run bonds is higher than off-the-run bonds, trading volume in value is lower, and *Pspread* and *ILIQ* are higher than off-the-run bonds. This is contrast to the common facts that on-the-run bonds would be more liquid than off-the-run bonds. For instance, Sarig and Warga (1989), Houweling et al (2005) etc. find that off-the-run bonds are more likely to be included in the buy-and-hold portfolios of investors and may even have higher liquidity premium. Two reasons could be responsible for such a different result on the Chinese Treasury bond market. First, the small size of bond issuing in China is unable to satisfy investor demand, particularly for institutions. This easily leads to over-competition and biased price when a new bond is just issued (Schultz, 2001), and thus giving rise to high price impact and low liquidity for on-the-run bonds even they are traded more frequently (having higher number of trades as shown in Table 1). Secondly, in line with Goyenko et al (2008), off-the-run Treasury bonds may response macroeconomic shocks faster than on-the-run bonds. Therefore, off-the-run bonds may have higher information content of bond valuation and, thus, have higher liquidity than on-the-run bonds.

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[12] The logarithm of the trading volume in value is applied to reduce the data dimension problem.

Table 1 Basic Information of daily trading for the stock and bond portfolios

stock	Portfolios	Mean of daily trades	Mean of daily trading volume in value (Million Yuan)	Mean of daily illiquidity (Price impact)	Mean of daily relative Spread
Stock market	(1) SS180 index stock	768	45.46	1.14×10^{-3}	2.31×10^{-3}
	(2) Non-SS180 index stock	431	11.66	1.36×10^{-3}	3.33×10^{-3}
	Difference	337	33.80	-0.22×10^{-3}	-1.02×10^{-3}
	(1)-(2)	（0.00）	（0.00）	（0.00）	（0.00）
Corporate bond market	(3) On-the-run corporate bond	17	3.31	1.82×10^{-4}	4.87×10^{-3}
	(4) Off-the-run corporate bond	10	1.32	2.25×10^{-4}	6.61×10^{-3}
	Difference	7	1.99	-0.43×10^{-4}	-1.74×10^{-3}
	(3)-(4)	（0.00）	（0.00）	（0.00）	（0.00）
Treasury bond market	(5) On-the-run Treasury bond	102	32.36	1.13×10^{-4}	1.33×10^{-3}
	(6) Off-the-run Treasury bond	94	40.03	8.28×10^{-5}	8.16×10^{-4}
	Difference	8	-8.33	0.30×10^{-5}	0.51×10^{-3}
	(5)-(6)	（0.01）	（0.17）	（0.00）	（0.00）

Here, statistics about the trading activity and liquidity for different portfolios are provided, including the number of trades, trading volume in value, illiquidity (price impact of trading; Amihud, 2002) and relative spread. *Difference* is the difference test on mean and its p-value for specified variable of two specified portfolios in a market. Average trades, trading volume in value and liquidity for each portfolio are computed firstly, and then the mean of each variable for each portfolio and its difference statistics can be computed over the whole sample (724 days).

When comparing with trading activities between the stock and bond markets, results in Table 1 show that, while the number of trades on the stock market is much higher than that on the bond market, the average trading value of each trade is higher for bonds (both for Treasury and corporate bonds) than stocks. This is reasonable since more individual investors are participated in the stock market and have smaller trades, and more institutional investors are participated on the bond market and have larger trades. This is also the possible reason lead to much lower price impact or illiquidity on the bond market than on the stock market.

5 Empirical Results

Descriptive statistics of order flow and returns for the three markets are shown in Table 2, in which r^S and OF^S are the daily equally weighted returns and aggregated order flow for all A-share stocks on SHSE. r^T and r^C are respectively the daily equally weighted returns on the Treasury and corporate bond market, and OF^T and OF^C are respectively the aggregated order flow on the Treasury and corporate bond market.

As shown in Table 2, the stock market has the highest return and highest volatility (standard deviation of returns), and the Treasury bond market has the lowest returns and lowest volatility. However, the Sharp-ratio of mean returns divided by standard deviation is highest on the corporate bond market, and lowest on the stock market, which indicates that returns for bearing one unit of risk is much higher on the corporate bond market than on the Treasury bond market in spite of the close credit quality between the two bond markets. Mean and median of order flow for the stock market are negative, and that for the two bond markets are positive. Kurtosis of order flow on the corporate bond market is highest among the three markets, indicating that order flow in this market is more easily to have extreme values.

Correlations of order flow and returns among the three markets are provided in Table 3. As shown by Forbes and Rigobon (2002), return correlations between assets or markets are greatly affected by heteroskedasticity. Thus, to test the significance of correlations, we compute p-value for all correlations by the approach of bootstrapping[13].

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[13] This is particularly important, as results in Table 3 show that 0.0799 of the correlation between stock and

Table 2 Descriptive statistics of market returns and order flow

	Returns			Order flow (100 Million)		
	r^S	r^C	r^T	OF^S	OF^C	OF^T
Mean	0.019%	0.021%	0.011%	-1.6034	0.0033	0.0391
Median	0.120%	0.033%	0.019%	-1.7985	0.0003	0.0418
Maximum	7.528%	0.674%	0.905%	49.3227	0.1887	0.8639
Minimum	-7.778%	-1.052%	-1.176%	-66.4052	-0.3830	-1.0245
Std. Dev.	1.674%	0.155%	0.145%	10.4230	0.0267	0.2016
Skewness	-0.2784	-1.2135	-1.2547	-0.2513	-3.2468	-0.1558
Kurtosis	4.8407	10.6447	15.7876	8.0769	71.2155	4.6448
Sharp-ratio	0.0113	0.1364	0.0777	--	--	--

Here, r^S and OF^S are the daily average returns and aggregated order flow on the Shanghai stock market; r^T (r^C) and OF^T (OF^C) are the daily average returns and aggregated order flow, in 100 million, for all the Treasury (corporate) bonds on SHSE; Sharp-ratio are mean returns divided by their standard deviation.

Table 3 Correlation of order flow and returns among the stock, corporate and Treasury bond markets

	r^S	r^C	r^T	$\ln OF^S$	$\ln OF^C$	$\ln OF^T$
r^S	1.0000	0.0500 *	0.0399			
r^C		1.0000	0.5055***			
r^T			1.0000			
$\ln OF^S$	0.7869***	0.0419	0.0461*	1.0000	-0.0796	0.0779**
$\ln OF^C$	-0.0081	0.1351***	0.0144		1.0000	-0.0331
$\ln OF^T$	0.0372	0.2040***	0.4755***			1.0000

Here, r^S, r^C and r^T are respectively daily average returns on the stock, corporate and Treasury bond markets; $\ln OF^S$, $\ln OF^C$ and $\ln OF^T$ are respectively daily aggregated order flow on the stock, corporate and Treasury bond markets; the p-value of correlations are computed by bootstraps, *, ** and *** respectively represent significant at 10%, 5% and 1% level.

Treasury bond market order flow is significant but -0.0796 of the correlation between stock and corporate bond market order flow is insignificant. Thus, difference in heteroskedasticity on each market could have high effect on significance of correlation tests. The detail of bootstrapping could be get upon request.

In Table 3, regarding return or order flow correlations among the three markets (left-upper and right-lower parts of Table 3), results in Table 3 show that returns between the stock and corporate bond markets and order flow between the stock and Treasury bond markets are significantly positive. The correlation of returns between the two bond markets is relative high, about 0.5, but the correlation of their order flow is marginal. The correlations between return and order flow in each market (left-lower part of Table 3), i.e. within-market correlations between order flow and returns, are high on all three markets. In particular, it is highly positive for the correlation between order flow and returns on the stock market, about 0.79, and that on the Treasury bond market is also high, about 0.48. On the corporate bond market, however, the correlation between returns and order flow is lower, only 0.14, even less than the correlation between corporate bond returns and Treasury bonds order flow (about 0.20). Furthermore, stock market order flow is also significantly positively correlated with Treasury bond market returns. These cross-market correlations between order flow on one market and returns or order flow on another markets indicates that, on the whole, buying or selling of stocks could imply buying or selling of both stocks and Treasury bonds, and buying or selling of Treasury bonds could imply buying or selling of Treasury and corporate bonds as well as stocks. In line with Connolly et al (2005) and Underwood (2008), this indicates that there are long term positive correlations among the three markets since they are affected by many common economic factors.

5.1 Return correlations and market uncertainty

Though the stock, corporate and Treasury bond markets play its own role and have different fundamental factors of asset valuation, more and more studies find that return correlations among the three markets are varying with market conditions or uncertainties. Generally, at least two types of factors may affect correlations among the three markets. The first type includes common factors such as interest rate, inflation, macroeconomic conditions and polices, etc., and the second type is cross market portfolio rebalancing, including flight-to-quality, which transfers investment to market with lower risk, and the flight-to-liquidity, which transfers investment to market with higher liquidity.

With these factors, in the short term, the weak positive stock-bond correlations may become

negative[14], as shown by Connolly et al. (2005, 2007), and the highly positive Treasury-corporate bond correlations may become stronger or weaker. For instance, stock-bond market return correlations will fall when the stock market is under stress and more investment is transferred from the stock to the bond market, or when both markets are affected by macroeconomic common factors that have inversely effects on the two markets. By contrast, the correlations will rise when both markets are strongly affected by common factors that have similar effects on them.

Return correlations among the three markets on different market conditions are shown in Table 4. Here, we simply consider time-varying correlations conditional on the rise or fall of the market. Thus, for return correlations between market A and B, we split the whole sample into 5 subsamples respectively by returns on each market, and then correlations are computed and their significance are tested by bootstrapping in each subsample. For example, with respect to return correlations between the stock and corporate bond markets, $cor\left(r_t^S, r_t^C\right)$, we firstly split the whole sample respectively by the 20%, 40%, 60% and 80% quantile of stock market returns r_t^S and quantile of corporate bond market returns r_t^C, and then $cor\left(r_t^S, r_t^C\right)$ and its significance level (p-value) by bootstrapping in these subsamples are computed. There are about 145 observations in each subsample.

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[14] Without specified explain, the stock-bond correlations in this paper include the correlations between the stock and Treasury bond market, the correlations between the stock and corporate bond market, and the bond markets may denote both the corporate and Treasury bond market.

Conditional variables	Cor(r^S , r^T)		Cor(r^S , r^C)		Cor(r^C , r^T)	
	r^S	r^T	r^S	r^C	r^C	r^T
All	0.0404	0.0404	0.0500*	0.0500*	0.5055***	0.5055***
0-20th pctl	0.0479	0.1334**	0.0869	0.1110**	0.4462***	0.6823***
20-40th pctl	0.0557	0.1026**	0.1395**	0.0890	0.0809	0.2050***
40-60th pctl	0.1862***	0.0288	-0.0043	0.0814	-0.0632	-0.0048
60-80th pctl	0.0267	-0.0034	0.0213	0.0048	0.1457*	0.0596
80-100th pctl	-0.0316	-0.1726***	-0.1123**	0.0014	0.2102***	0.2597***

In Table 4, r^S , r^C and r^T are respectively the weighted average returns on the stock, corporate and Treasury bond markets; For correlations between market A and B returns, we split the whole sample into 5 subsamples by returns on each market, then correlations and their p-value in these subsamples are computed; For example, with respect to return correlations between the stock and corporate bond markets $cor(r_t^S, r_t^C)$, we firstly split the whole sample respectively by the 20%, 40%, 60% and 80% quantile of stock market returns r_t^S and corporate bond market returns r_t^C, and then we compute $cor(r_t^S, r_t^C)$ and its significance level (p-value) by bootstrapping in these subsamples. There are about 145 observations in each subsample; Pctl is the quantile of returns on each market; *, ** and *** respectively represent significant at 10%, 5% and 1% level.

Results in Table 4 show that both stock-bond and corporate-Treasury bond correlations are varied on different market conditions. In particular, we can observe that stock-bond correlations are significantly positive when returns on either bond market is low, but they are significantly negative when returns on the stock market are high or returns on the (corporate) bond market are high. In line with Connelly et al. (2005, 2007), our results may imply that portfolio rebalancing between stocks and bonds happens when stock market returns are high, and not only flight-to-quality or flight-to-liquidity but also flight-from-quality or flight-from-liquidity may reduce market correlations, as stock-bond market correlations follow an decreasing patter with bond returns. Due to the small size of the bond markets, such activities may have high impact on bond prices. That is, bond price may have a large rise during flight from stock to bond market since the small bond market should face a large hedging demand and coming investment. Furthermore, the different trend between stock-corporate bond correlations and stock-Treasury

bond correlations may indicate that the two bond markets may play a different role in stock-bond market hedging.

With respect to corporate-Treasury bond return correlations, it is interesting that, while they are highly positive in the whole sample, they largely varied in different subsamples. Generally, correlations between the two bond markets are high when either market has a fall, but become more weakly, but still significantly, correlated when either bond market has a rise. However, the correlations are insignificant, or negative, when both markets have neither a sharp rise nor a sharp fall. This means time-varying correlations between bond markets and the behind reasons also need to be examined more even though most of previous studies only examine correlations between stock and bond markets.

5.2 The cross-market information content of order flow

As above sections show evidence of time-varying correlations between markets conditional on market rising and falling that may be resulted from cross-market portfolio rebalancing or flight, here we examine such an issue by discussing the information content of order flow, because aggregated market order flow is able to reveal information on risk preferences, beliefs and endowments of investors that is relevant to pricing securities (Underwood, 2008), or reflect the different projection of public or macroeconomic information by investors even when there is no private information in the market (Lyons, 2001). Previous empirical studies have showed that order flow greatly explains variation in asset prices, such as the findings of Hasbrouck and Seppi (2001), Harford and Kaul (2005), Chordia et al. (2002) from the stock market, the findings of Brandt and Kavajecz (2004) from the Treasury bond market, and the findings of Evans and Lyons (2002) from the foreign exchange market.

In addition to within-market effects, order flow may also have cross-market effects due to investors' cross-market investing and hedging activities. The order flow on the stock market will rise when more is invested in stocks. Inversely, stock order flow may fall and bond order flow may rise when stock market risk rises and more investment is rebalanced to the bond market. For instance, because of cross-market hedging, Chordia et al. (2005) show that order flow in one market may be related to return, volatility or liquidity on its own market and on another market,

and Underwood (2008) finds significant cross-market effect of Treasury bond market order flow on stock market returns. Thus, in addition to the within-market effect of order flow on asset returns, the cross-market effect of order flow by nature provides direct evidence of asset allocation and portfolios rebalancing.

Here, to discuss cross-market portfolio rebalancing or flight both between stocks and bonds and between corporate and Treasury bonds, we examine the contemporaneous effect of order flow for one market on returns for another market by an SUR (System of Seemingly Unrelated Regression) model as follows,

$$r_t^S = a_0 + a_1 OF_t^{index} + a_2 OF_t^{non-index} + a_3 OF_t^{C,on} + a_4 OF_t^{C,off} + a_5 OF_t^{T,off} + a_6 OF_t^{T,on} \\ + a_7 Spread_t^S + a_8 r_t^{Common} + a_9 Repo_t + \varepsilon_t^S \tag{1}$$

$$r_t^C = b_0 + b_1 OF_t^{index} + b_2 OF_t^{non-index} + b_3 OF_t^{C,on} + b_4 OF_t^{C,off} + b_5 OF_t^{T,off} + b_6 OF_t^{T,on} \\ + b_7 Spread_t^C + b_8 r_t^{Common} + b_9 Repo_t + \varepsilon_t^C \tag{2}$$

$$r_t^T = c_0 + c_1 OF_t^{index} + c_2 OF_t^{non-index} + c_3 OF_t^{C,on} + c_4 OF_t^{C,off} + c_5 OF_t^{T,off} + c_6 OF_t^{T,on} \\ + c_7 Spread_t^T + c_8 r_t^{Common} + c_9 Repo_t + \varepsilon_t^T \tag{3}$$

$$E[\varepsilon_t^S] = 0, \ E[\varepsilon_t^C] = 0, \ E[\varepsilon_t^T] = 0 \ ;$$

$$E[\varepsilon_t^K \cdot \varepsilon_s^M] = \begin{cases} \sigma & \text{If } t = s \\ 0 & \text{Otherwise} \end{cases} \ , \ K, M = S, C, T$$

Here, r_t^S, r_t^C and r_t^T are respectively the equally weighted returns on the Shanghai stock, corporate and Treasury bond market on day t; OF_t^{index} and $OF_t^{non-Index}$ are respectively the aggregated order flow for the SS180-index and the non-SS180-index stock portfolio on day t; $OF_t^{C,on}$ and $OF_t^{C,Off}$ are respectively the aggregated order flow for the on-the-run and the off-the-run corporate bond portfolio on day t; $OF_t^{T,on}$ and $OF_t^{T,off}$ are respectively the aggregated order flow for the on-the-run and the off-the-run Treasury bond portfolio on day t. $Spread_t^S$, $Spread_t^C$ and $Spread_t^T$ are respectively liquidity variables (Relative Spread) on the stock, corporate and Treasury bond markets; r_t^{Common} is the return principal component decomposed by the sample correlation matrix for the vector of market return series (r_t^S, r_t^C, r_t^T); $Repo_t$ is the 7-day repo rates of the inter-bank Treasury bond market. Returns or liquidity is

equally weighted both for the three markets and for all stock and bond portfolios.

As shown in the three equations, we separate securities on each market into high and low-liquidity portfolios and discuss the difference in their information content of order flow. The reasoning behind such asset separation in examining both within-market and cross-market effect of order flow is following. First, assets with different liquidity would differ in efficiency of price discovery. For instance, Chordia and Swaminathan (2000) show that both daily and weekly returns on high volume stocks lead returns on low volume stocks, and Goyenko et al (2008) find that off-the-run Treasury bonds respond to macroeconomic shocks faster than on-the-run bonds. Here, we also expect that assets with high and low liquidity would provide different information on market movements[15]. Secondly, Harford and Kaul (2005) and Underwood (2008) show that the order flow of index stocks have a stronger effect on market returns. Here, the speculative individual investors, who are the chief participants on the Chinese stock market, prefer small non-index stocks to large index stocks, and index or investment funds on the stock market are very small (Zhang, 2004). Therefore, the difference in the information content of order flow between index and non-index stock needs to be tested further on the Chinese stock market.

Liquidity variables are also needed to be included in the three equations because of the pricing effect of liquidity in the financial markets shown in many previous studies, such as the findings of Amihud and Mendelson (1986), Amihud (2002), Acharya and Pedersen (2005) from the stock market, and the findings of Houweling et al (2005), Chen et al (2007) from the bond market. We thus include the market liquidity variables $Spread_t^K$ ($K = S, C, T$) in each equation to capture such a liquidity effect. Quote spread between ask and bid-price is a common variable to measure security liquidity. Using tick-by-tick data, we compute average relative spread for each stock every day, and the market liquidity is the averaged relative spread for all stocks or bonds on each market[16].

The common factor of return r_t^{Common} is also added to the three equations, as previous studies show that the effect of common factors should not be overlooked in analyzing

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[15] With a single OLS regression of market returns on the order flow of high and low-liquidity groups in each market, we also find that order flow for index and non-index stocks, or actively and non-actively traded bonds, present different information content.

[16] The results are qualitative the same if illiquidity variable of Amihud (2002), $ILIQ$, is used as asset liquidity.

cross-market relationship. For instance, Fleming et al (1998) show that common information may result in volatility linkage in the stock, bond and money markets, and Campbell and Aminer (1993) show that variation in real interest rates and inflation, or common movements in future expected returns, may affect both stock and bond market returns and lead to varying return correlations between the two markets. We get the common factor of the three market returns by Principal Component analysis, decomposing the sample correlation matrix for the vector of market return series (r_t^S, r_t^C, r_t^T). Our results show that the maximum Eigen-value of the sample second moment correlation matrix is respectively 1.51, and thus r_t^{Common} is able to explain more than 50% of their variance. This means the common variation of the three market returns can be properly captured by our principal component r_t^{Common}. We also run Granger tests on exogeneity of r_t^{Common} in our model, and results show that r_t^{Common} satisfy the exogenous property well and all causality relationship from the three market returns (r_t^S, r_t^C or r_t^T) to r_t^{Common} is rejected.

In addition to the common movements of returns among the three markets, we also add the Treasury bond repo rate on the inter-bank market, i.e. $Repo_t$, to the model as another common factor. As shown in section 3 this paper, bond trading volume is much higher on the repo market than on the spot market; therefore, we add the variable $Repo_t$ to the model to capture the effect from the repo market. The order flow on the inter-bank market is not used because its high-frequency data is not available. By using the repo rates on the interbank market, we hope to include extensive effect of capital flow in our analysis since inter-bank repo rates are highly linked to the asset-debt management of the commercial banks, which are both the main participants on the inter-bank repo market and the main holder of stock investor saving accounts. Fan and Zhang (2007) also show that the investment opportunity on the stock market has significant effect on the repo rates, and the repo markets in China are main place for borrowing or lending money. Short-selling is absolutely prohibited on the Chinese stock market, thus the variation in repo rates should provide information on stock investment demand and market movement. Thus, when the stock market rises, investment demand is high and the cost of financing on the repo market may rise. By contrast, when the stock market falls, more money leaves the stock market, and the

demand for and cost of financing in the repo market fall. Therefore, $Repo_t$ is expected to be positively correlated with stock market returns, i.e. a_7 is positive in Equation (1). Furthermore, b_7 and c_7 are also expected to be negative since repo rates are highly correlated with market risk-free rates and spot bond trading.

Before model estimation, to remove the lead-lag relationship of order flow or returns among the three markets, or some past information contained in the present order flow and returns, we firstly run a vector autoregressive model with 5 lags, i.e. VAR (5), on market return variables (r_t^S, r_t^C, r_t^T), a VAR (5) model on market liquidity variables $(Spread_t^S, Spread_t^C, Spread_t^T)$, and a VAR (5) model on order flow of all within-market asset portfolios respectively for the stock, corporate and Treasury bond market, i.e. an VAR (5) model respectively on exogenous variable vector of $(OF_t^{index}, OF_t^{non-index})$, $(OF_t^{C,on}, OF_t^{C,off})$ and $(OF_t^{T,on}, OF_t^{T,off})$ by turn. Then Equations (1) to (3) are estimated on residual series of these models. All these filtration is useful so as to ensure that the regression estimates of the order flow effects do not include any lagged effects but the true unanticipated component of trading suggested by Hasbrouck (1991), as well as Underwood (2008)[17].

After the autocorrelation or lead-lag relationship for all endogenous and exogenous variables are removed, we can estimated Equations (1) to (3) with SUR method. However, our results show that the order flow of all less liquid assets, i.e. non-index stock, off-the-run corporate bonds and on-the-run Treasury bonds, in the three equations present little cross-market effect[18]. By contrast, the order flow of all more liquid assets, i.e. index stock, on-the-run corporate bonds and off-the-run Treasury bonds present not only higher within-market effect on its own market returns but also significant cross-market effect on returns on another market. Thus, here we construct a more simply SUR model as follows,

$$
\begin{aligned}
r_t^S = a_0 &+ a_1 OF_t^{index} + a_2 OF_t^{C,on} + a_3 OF_t^{T,off} + a_4 OF_t^{non-Index} \\
&+ a_5 Spread_t^S + a_6 r_t^{Common} + + a_7 Repo_t + \varepsilon_t^S
\end{aligned}
\tag{4}
$$

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[17] In addition, liquidity may have cross-market on returns (Chordia et al, 2005), or order flow may be affected by past returns for the operation of technical traders. Therefore, we also use a VAR model in which the endogenous variables include returns, spread and order flow on all the three markets before estimation. However, the results will not be changed when such a "heavy" filtration is applied.

[18] These results are not reported here to save space but available upon request.

$$r_t^C = b_0 + b_1 OF_t^{index} + b_2 OF_t^{C,on} + b_3 OF_t^{T,off} + b_4 OF_t^{C,off}$$
$$+ b_5 Spread_t^C + b_6 r_t^{Common} + + b_7 Repo_t + \varepsilon_t^C \tag{5}$$

$$r_t^T = c_0 + c_1 OF_t^{index} + c_2 OF_t^{C,on} + c_3 OF_t^{T,off} + c_4 OF_t^{T,on}$$
$$+ c_5 Spread_t^T + c_6 r_t^{Common} + c_7 Repo_t + \varepsilon_t^T \tag{6}$$

$$E\left[\varepsilon_t^S\right] = 0, \ E\left[\varepsilon_t^C\right] = 0, \ E\left[\varepsilon_t^T\right] = 0;$$

$$E\left[\varepsilon_t^K \cdot \varepsilon_s^M\right] = \begin{cases} \sigma & \text{If } t = s \\ 0 & \text{Otherwise} \end{cases}, \ K, M = S, C, T$$

Here, all variables are defined as that in Equations (1) to (3), and only order flow for more liquid assets, i.e. index stock or more actively traded bonds, is assumed to exhibit cross-market effects. In particular, on the Treasury bond market, off-the-run bonds are more liquid than on-the-run bonds; therefore, the order flow of off-the-run Treasury bonds is included in Equations (4) and (5). After the lagged effect of all variables is removed, the estimation results of the three-market model, Equations (4) to (6), are shown in table 5.

Table 5 Estimation results of the three-market model

	C	OF_t^{index}	$OF_t^{C,on}$	$OF_t^{T,off}$	$OF_t^{K,Low-L}$	$Spread_t^k$	r_t^{Common}	$Repo_t$	$\overline{R}^2$
r_t^S	-1.06×10^{-4}	4.85×10^{-4}	-9.69×10^{-4}	-7.47×10^{-3}	2.01×10^{-3}	-6.3954	-5.57×10^{-4}	1.10×10^{-2}	0.6698
	(0.77)	(0.00)	(0.96)	(0.00)	(0.00)	(0.00)	(0.10)	(0.06)	
r_t^C	-7.28×10^{-6}	-8.48×10^{-6}	4.45×10^{-3}	-8.55×10^{-4}	1.65×10^{-3}	-1.18×10^{-2}	-8.83×10^{-4}	3.98×10^{-4}	0.5647
	(0.83)	(0.18)	(0.01)	(0.00)	(0.47)	(0.08)	(0.00)	(0.47)	
r_t^T	-3.35×10^{-6}	-1.77×10^{-5}	-2.41×10^{-3}	2.17×10^{-3}	8.41×10^{-4}	-1.72×10^{-3}	-7.07×10^{-4}	-3.21×10^{-4}	0.6228
	(0.91)	(0.00)	(0.09)	(0.00)	(0.01)	(0.91)	(0.00)	(0.50)	

Here, estimation results are shown in this table for the following model,

$$r_t^S = a_0 + a_1 OF_t^{index} + a_2 OF_t^{C,on} + a_3 OF_t^{T,off} + a_4 OF_t^{non-Index} + a_5 Spread_t^S + a_6 r_t^{Common} + + a_7 Repo_t + \varepsilon_t^S$$

$$r_t^C = b_0 + b_1 OF_t^{index} + b_2 OF_t^{C,on} + b_3 OF_t^{T,off} + b_4 OF_t^{C,off} + b_5 Spread_t^C + b_6 r_t^{Common} + + b_7 Repo_t + \varepsilon_t^C$$

$$r_t^T = c_0 + c_1 OF_t^{index} + c_2 OF_t^{C,on} + c_3 OF_t^{T,off} + c_4 OF_t^{T,on} + c_5 Spread_t^T + c_6 r_t^{Common} + c_7 Repo_t + \varepsilon_t^T$$

$$E\left[\varepsilon_t^S\right] = 0, \ E\left[\varepsilon_t^C\right] = 0, \ E\left[\varepsilon_t^T\right] = 0; \ E\left[\varepsilon_t^K \cdot \varepsilon_s^M\right] = \begin{cases} \sigma & \text{If } t = s \\ 0 & \text{Otherwise} \end{cases}, \ K, M = S, C, T$$

Here, r_t^K ($K = S, C, T$) are equally-weighted returns for the Shanghai stock, corporate and Treasury bond market on day t; OF_t^J ($J = index, C-on, T-off...$) are aggregated order flow (in 100 million) for high-liquidity

portfolios in each markets on day t; $OF_t^{K,Low-L}$ ($K=S,C,T$) are order flow (in 100 million) for low-liquidity portfolio in each market, i.e. non-index stock, off-the-run corporate bond, and on-the-run Treasury bond portfolios; $Spread_t^K$ ($K=S,C,T$) are equally-weighted liquidity (relative spread) for the three markets; r_t^{Common} is the principal component decomposed by the sample correlation matrix for market return series vector (r_t^S, r_t^C, r_t^T); $Repo_t$ is the 7-day repo rate of Treasury bonds. Returns, liquidity is equally-weighted, and order flow is aggregated for the three markets or all asset portfolios. Before model estimation, we run a vector autoregressive model of VAR (5) model respectively on endogenous variable vector (r_t^S, r_t^C, r_t^T), $(Spread_t^S, Spread_t^C, Spread_t^T)$, $(OF_t^{index}, OF_t^{non-index})$, $(OF_t^{C,on}, OF_t^{C,off})$ and $(OF_t^{T,on}, OF_t^{T,off})$ by turn to remove the strong autocorrelation and lead-lag relationship for all endogenous and exogenous variables.

Three series of results are presented in table 5. The first one refers to the within-market information content of order flow differs between high and low-liquidity assets. In the case of the stock market, both the order flow for SS180 index and non-SS180 index stocks significantly affect stock market returns, but the Wald test with null hypothesis of "$a_1 = a_4$" (not reported here) reveals that the effect of order flow for the non-SS180 index portfolio is stronger than the SS180 index portfolio. While this is different from the results of Harford and Kaul (2005) and Underwood (2008) on the mature markets that order flow for index stocks has stronger effect on market returns, our results are closely related to participant structure and preference on the Chinese stock market and in line with Bailey et al. (2008), who find that the marginal explanatory power of individual investor order flow on stock returns is higher than institutional or proprietary investor order flow in China. Indeed, as shown in section 3 this paper, individual investors predominate on the Chinese stock market, and the index funds or other institutions are also relative small. Compared with institutional investors, individual investors have lower ability to manage risk, and are more speculative and less conscious of risk. They prefer small-cap or non-index stocks with higher expected returns even though take higher risk. Thus, order flow for non-index stocks present higher information content of order flow here. On the corporate bond market, only order flow for the high-liquid on-the-run bonds significantly affect market returns, and that for off-the-run bonds is insignificant. On the Treasury bond market, while order flow for both on-the-run and off-the run bonds significantly affect market returns, Wald test with the null hypothesis of "$c_3 = c_4$" shows that order flow of off-the-run bonds dominates on-the-run bonds in driving Treasury bond market returns. Our results thus provide evidence that high-liquidity assets

have higher efficiency of price discovery, and thus higher information on preferences, endowments and the projection of news by market participants, which supports the results of Chordia and Swaminathan (2000), Harford and Kaul (2005), Goyenko et al. (2008), Underwood (2008) etc.

The second series of results refers to the cross-market effect of order flow between the stock and the two bond markets. The results of Equation (4) show that order flow of high-liquidity (off-the-run) Treasury bonds $OF_t^{T,off}$ is negatively correlated with stock market returns. At the same time, order flow of high-liquidity (index) stocks OF_t^{index} is also negatively correlated with Treasury bond market returns (Equation (6)). Such a result indicates that, between the stock and the Treasury bond market, a rise in order flow for one market means a fall in returns for another market. This contemporaneous negative cross-market effect of order flow is not from the lead-lag relationship of market returns or order flow, which has been removed before model estimation. In line with Underwood (2008), as aggregate order flow reveals information on preferences, endowments and the projection of news by market participants, the bi-directionally negative effect of order flow on returns shown in table 5 may imply cross-market portfolio rebalancing or flight between the stock and Treasury bond market. When the stock market is under stress, investors rebalance their portfolios and invest more in the safe Treasury bond market, and when the stock market is attractive, investors rebalance their portfolios and invest more in the profitable stock market[19].

Results in Table 5 provide evidence of cross-market portfolio rebalancing between the stock and Treasury bond market in China. However, the order flow of high-liquidity (on-the-run) corporate bonds does not have significant effect on stock market returns, nor does stock order flow on corporate bond returns. While all corporate bonds have high quality for being issued by large state-owned enterprises, our results show that the stock market is less linked with the corporate bond market than with the Treasury bond market.

The third series of results concern the cross-market effect of order flow between the corporate and Treasury bond markets. Similar with the stock-Treasury bond market relationship,

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[19] The latter instance is also named flight-from-quality or flight-from-liquidity as shown by Baur and Lucey (2008).

order flow and returns between the corporate and Treasury bond market also present significant cross-market effects. A rise in order flow for high-liquidity (off-the-run) Treasury bonds $OF_t^{T,off}$ means a fall in corporate bond market returns; at the same time, a rise in order flow of high-liquidity (on-the-run) corporate bonds $OF_t^{C,on}$ also means a fall in Treasury bond market returns. This indicates that the two bond markets are well linked, and in addition to portfolio rebalancing between stocks and Treasury bonds, portfolio rebalancing between the two bond markets is also important.

Results in Table 5 also provide information about the effect of liquidity on asset returns. Stock market liquidity $Spread_t^S$ and corporate bond market liquidity $Spread_t^C$ are significantly negatively correlated with their own market returns. Because the residual series of the VAR (5) model, with endogenous variables of liquidity on the three markets, are used to estimate the model, $Spread_t^K$ ($K = S, C, T$) should be taken as unexpected liquidity. In line with the findings of Amihud (2002) and Acharya and Pedersen (2005), our results that unexpected liquidity innovations are negatively correlated with asset returns indicate significant liquidity premium both on the stock and corporate bond markets. However, the effect of liquidity factor on the Chinese Treasury bond market is insignificant.

Moreover, owing to the results of principal components and negative loading in the Eigen-vector, the return common factors r_t^{Common} are negatively correlated with returns on all three markets. With respect to the effect of another common factor, i.e. inter-bank repo rates, results in Table 5 show that stock market returns are positively correlated with repo rates. This supports the findings of Fan and Zhang (2007) that a rise in investment demand on the stock market will produce a rise in repo rates because the repo markets in China are the main place for borrowing or lending money.

Over all, our empirical results show that, after the lead-lag relationship and the effect of market liquidity and common factors are controlled, order flow has significant bi-directionally negative cross-market effect on returns both between the stock and Treasury bond markets and between the corporate and Treasury bond markets. The fact that a rise in order flow on one market is accompanied by a fall in returns on another market provides evidence of cross-market portfolio

rebalancing or flight. However, according to Connolly et al. (2005), Underwood (2008) etc., cross-market hedging is closely related to market conditions. For instance, Connolly et al. (2005) show that higher stock market uncertainty may lead to higher probability of adjustment in portfolio rebalancing from stocks to Treasury bonds, thus higher probability of negative correlations between the stock and Treasury bond markets. Underwood (2008) also shows that signed order flows on the stock and bond markets are (more) negatively correlated in periods of high equity volatility, and increasing equity uncertainty should be associated with an increase in the cross-market effect of order flow. All these studies suggest order flow should have more negatively cross-market effect on returns during market crisis period if cross-market hedging or flight-to-quality is the real source for such an effect. Thus, in the following sections, we will discuss cross-market information content of order flow conditional on different market uncertainties. Departing from Connolly et al. (2005) or Underwood (2008), we define market uncertainties both from the stock and the bond markets, as Goyenko and Ukhov (2008) etc. find that Treasury bonds react to monetary shocks faster than stocks and act as a channel to transfer the effect of monetary policies to the stock market. Moreover, we also examine the cross-market effect of order flow conditional on extreme market conditions with large rises or falls on the stock market.

5.3 Market uncertainty and information content of order flow

To discuss the cross-market effect of order flow between the stock and bond markets or between the corporate and Treasury bond markets, we estimate Equation (4) to Equation (6) conditional on higher uncertainties on any of the three markets. This is useful to provide stronger evidence on whether cross-market hedging explains the cross-market effect of order flow. Furthermore, because the Treasury bond market in China is small, it should have higher impact on price if many investors rebalance their portfolios between the stock and Treasury bond markets. Thus, under extreme market conditions, corporate bonds may substitute Treasury bonds due to: 1) the rise of costs in Treasury bond trading; 2) the good quality of corporate bonds. Therefore, examining cross-market effect of order flow on different market conditions may also provide information on the role of the two bond markets in investor portfolio rebalancing.

To test this hypothesis, we estimate Equations (4) to (6) conditional on higher stock, corporate or Treasury bond market uncertainty. Here, market uncertainty is measured by conditional volatility of A VAR-MGARCH (Multi-variate GARCH) model that is estimated on the three market return series. By using a Vector Autoregressive (VAR) model on conditional mean, we use three types of models to capture the dynamic of conditional variance, i.e. the CCC model (Constant Conditional Correlation) model of Bollerslev (1990), the BKKK model (Engle and Kroner, 1995), and the VEC model (Bollerslev et al., 1988, Bali, 2008). Among these MGARCH models, we select the CCC model since it has higher likelihood than the others. However, the results are not altered qualitatively when we use different volatility models. The specification and estimation results of the MGARCH model are shown in the Appendix.

Using such market uncertainty proxies, we are also able to examine the influence of bond market uncertainty on cross-market effect of order flow, while most previous studies only consider stock market uncertainty when examining market correlations. Thus, we split the whole sample to two subsamples with high and low volatility with the median of conditional volatility on each market by turn. In line with Connolly et al. (2005, 2007), Underwood (2008) etc., we expect that the cross-market effect of order flow could be stronger under these stress market conditions if it is able to be explained by cross-market hedging activities. The estimation results of Equations (4) to (6) conditional on higher market volatility are shown in Table 6.

Results shown in Table 6 show many interesting results. In particular, when volatility on the stock market is high, the order flow for both corporate bonds and Treasury bonds exhibits significant (negative) cross-market effect on stock returns (Panel A table 6). Moreover, when the order flow for corporate bonds exhibit significant cross-market effect on stock returns, the effect of order flow for Treasury bond become less significant. This means that, with respect to portfolio rebalancing between stock and bond markets in China, corporate bonds may have substitute effect for Treasury bonds to be the heaven of stock investors, either when the demand of safe assets rises during volatile stock market or when the cost of portfolio rebalancing into Treasury bond market rises during volatile Treasury bond market.

Table 6 Estimation results of the three-market model

	C	OF_t^{index}	$OF_t^{C,on}$	$OF_t^{T,off}$	$OF_t^{K,Low-L}$	$Spread_t^k$	r_t^{Common}	$Repo_t$	$\bar{R}^2$
Panel A: Estimation results conditional on higher stock market volatility									
r_t^S	-3.38×10^{-4}	3.59×10^{-4}	-7.56×10^{-2}	-6.74×10^{-3}	2.28×10^{-3}	-5.2331	-1.11×10^{-3}	-6.49×10^{-3}	0.6915
	(0.54)	(0.08)	(0.09)	(0.10)	(0.00)	(0.00)	(0.04)	(0.58)	
r_t^C	-7.93×10^{-5}	3.75×10^{-6}	1.64×10^{-2}	-7.77×10^{-4}	1.37×10^{-3}	-9.18×10^{-3}	-9.28×10^{-4}	7.22×10^{-4}	0.6255
	(0.07)	(0.63)	(0.00)	(0.02)	(0.58)	(0.44)	(0.00)	(0.43)	
r_t^T	-2.64×10^{-5}	-1.75×10^{-5}	-3.14×10^{-3}	1.89×10^{-3}	6.20×10^{-4}	-4.80×10^{-3}	-7.96×10^{-4}	-1.55×10^{-3}	0.6523
	(0.49)	(0.01)	(0.31)	(0.00)	(0.17)	(0.73)	(0.00)	(0.06)	
Panel B: Estimation results conditional on higher Treasury bond market returns volatility									
r_t^S	-2.63×10^{-4}	5.50×10^{-4}	-7.36×10^{-2}	-7.15×10^{-3}	2.40×10^{-3}	-5.8794	-4.61×10^{-4}	9.98×10^{-3}	0.6655
	(0.60)	(0.01)	(0.02)	(0.06)	(0.00)	(0.00)	(0.27)	(0.35)	
r_t^C	6.06×10^{-5}	-3.67×10^{-6}	1.32×10^{-2}	-5.83×10^{-4}	2.17×10^{-4}	5.58×10^{-3}	-6.84×10^{-4}	-2.49×10^{-4}	0.5231
	(0.21)	(0.73)	(0.00)	(0.10)	(0.94)	(0.74)	(0.00)	(0.81)	
r_t^T	-1.25×10^{-5}	-2.21×10^{-5}	-5.05×10^{-3}	3.07×10^{-3}	1.36×10^{-3}	1.52×10^{-2}	-7.03×10^{-4}	8.59×10^{-4}	0.6465
	(0.80)	(0.04)	(0.11)	(0.00)	(0.00)	(0.62)	(0.00)	(0.41)	
Panel C: Estimation results conditional on higher corporate bond market returns volatility									
r_t^S	2.48×10^{-4}	4.91×10^{-4}	-7.20×10^{-2}	-2.59×10^{-3}	1.85×10^{-3}	-5.3229	-6.04×10^{-4}	1.85×10^{-2}	0.6822
	(0.62)	(0.00)	(0.03)	(0.49)	(0.00)	(0.00)	(0.16)	(0.01)	
r_t^C	-2.05×10^{-5}	-1.06×10^{-5}	5.27×10^{-3}	-7.68×10^{-4}	4.01×10^{-3}	-1.08×10^{-2}	-8.97×10^{-4}	-1.40×10^{-4}	0.5652
	(0.71)	(0.25)	(0.14)	(0.06)	(0.27)	(0.21)	(0.00)	(0.85)	
r_t^T	2.97×10^{-5}	-1.15×10^{-5}	-4.07×10^{-3}	2.16×10^{-3}	7.48×10^{-4}	-4.17×10^{-4}	-6.42×10^{-4}	4.36×10^{-4}	0.5570
	(0.52)	(0.14)	(0.17)	(0.00)	(0.14)	(0.98)	(0.00)	(0.50)	

Here, estimation results of Equations (4) to (6) conditional on higher stock, corporate or Treasury bond market volatility are shown in this table for the following model,

$$r_t^S = a_0 + a_1 OF_t^{index} + a_2 OF_t^{C,on} + a_3 OF_t^{T,off} + a_4 OF_t^{non-Index} + a_5 Spread_t^S + a_6 r_t^{Common} + + a_7 Repo_t + \varepsilon_t^S$$

$$r_t^C = b_0 + b_1 OF_t^{index} + b_2 OF_t^{C,on} + b_3 OF_t^{T,off} + b_4 OF_t^{C,off} + b_5 Spread_t^C + b_6 r_t^{Common} + + b_7 Repo_t + \varepsilon_t^C$$

$$r_t^T = c_0 + c_1 OF_t^{index} + c_2 OF_t^{C,on} + c_3 OF_t^{T,off} + c_4 OF_t^{T,on} + c_5 Spread_t^T + c_6 r_t^{Common} + c_7 Repo_t + \varepsilon_t^T$$

$$E\left[\varepsilon_t^S\right]=0, \quad E\left[\varepsilon_t^C\right]=0, \quad E\left[\varepsilon_t^T\right]=0; \quad E\left[\varepsilon_t^K \cdot \varepsilon_s^M\right]=\begin{cases}\sigma & \text{If } t=s \\ 0 & \text{Otherwise}\end{cases}, \quad K,M=S,C,T$$

Here, r_t^K ($K=S,C,T$) are returns for the three markets; OF_t^J ($J=index,C-on,T-off\ldots$) are aggregated order flow (in 100 million) for high-liquidity portfolios in each markets on day t; $OF_t^{K,Low-L}$ ($K=S,C,T$) are order flow (in 100 million) for low-liquidity portfolio in each market; $Spread_t^K$ ($K=S,C,T$) are liquidity for the three markets; r_t^{Common} is the principal component of the three market return vector (r_t^S, r_t^C, r_t^T); $Repo_t$ is 7-day repo rates of Treasury bonds on the inter-bank bond market. Returns, order flow or liquidity is equally-weighted for the three markets and all portfolios. Before model estimation, we run a vector autoregressive model of VAR (5) model respectively on endogenous variable vector (r_t^S, r_t^C, r_t^T), $(Spread_t^S, Spread_t^C, Spread_t^T)$, $(OF_t^{index}, OF_t^{non-index})$, $(OF_t^{C,on}, OF_t^{C,off})$ and $(OF_t^{T,on}, OF_t^{T,off})$ by turn

to remove the strong autocorrelation and lead-lag relationship for all endogenous and exogenous variables. We split the whole sample to two subsamples with high and low volatility based on the median of conditional volatility on each market. The market volatility is measured by a CCC type MGARCH model as shown in the appendix. Table 6 provides the estimation results of Equation (4) to (6) condition on higher volatility on each of the three markets by turn. P-values of coefficient estimation are shown in the parentheses.

The role of corporate and Treasury bond market could be reinforced by the results shown in Table 7, which provides the estimation results of Equations (4) to (6) conditional on stock market extreme falls and rises. The extreme falls and rises are defined as events with the highest and lowest 10% of stock market returns. The mean and maximum market returns in extreme stock falling are respectively -3.04% and -1.44%, and the mean and minimum returns during extreme rising are respectively 2.81% and 1.46%. Results in Table 7 show that when the stock market is in either extreme rises or falls, order flow for both corporate and Treasury bonds provide significant effect on stock returns. This means both the corporate and Treasury bond markets provide important information on stock market movements on these conditions. Furthermore, it is not surprising that, while the constant term, excess returns, in the stock equation (a_1) is insignificant for the unconditional results shown in Table 5, it is significantly negative under extreme stock market falls and significantly positive under extreme stock market rises. However, when the stock market is under extreme rises, the constant term in the Treasury bond equation (c_1) is significantly negative (b_1 is also weakly significantly negative), and when the stock market is under extreme falls, the c_1 is (weakly) significantly positive. This means that stock and bond markets depart from each other under extreme stock market conditions.

Results in Table 7 also confirm that cross-market hedging or flight-to-quality should be a real source for the cross-market effect of order flow in that order flow in both bond markets has much higher effect on stock market returns during extreme stock market conditions comparing with the unconditional results in Table 5. This supports the findings of Connolly et al (2005, 2007) and Underwood (2008) that cross-market portfolio rebalancing is more significant under more volatile market conditions. However, under extreme stock market conditions, stock order flow has insignificant effect on bond market returns. This is reasonable because individual investors are predominant on the stock market, thus investment may come from or leave for other places than the bond markets under extreme market conditions. Actually, most of individual investors in China

take asset allocation between the stock market and bank accounts but not between the stock and bond markets. Therefore, stock order flow may present weak effect on stock returns due to the "pull" or "push" effect of individual investors' funds.

Table 7 Estimation results of the three-market model conditional on EXTREME STOCK market rises or falls

	C	OF_t^{index}	$OF_t^{C,on}$	$OF_t^{T,off}$	$OF_t^{K,Low-L}$	$Spread_t^k$	r_t^{Common}	$Repo_t$	$\overline{R}^2$
Panel A: Estimation results conditional on EXTREME FALLS of stock market returns									
r_t^S	-2.29×10^{-2}	-3.66×10^{-6}	-1.39×10^{-1}	-1.43×10^{-2}	9.26×10^{-4}	-6.2732	-7.17×10^{-4}	1.85×10^{-2}	0.4004
	(0.00)	(0.99)	(0.06)	(0.04)	(0.01)	(0.04)	(0.45)	(0.29)	
r_t^C	-1.58×10^{-4}	-1.48×10^{-5}	1.32×10^{-2}	-6.43×10^{-4}	9.73×10^{-4}	-6.32×10^{-3}	-7.55×10^{-4}	-1.86×10^{-3}	0.6259
	(0.27)	(0.39)	(0.05)	(0.28)	(0.85)	(0.42)	(0.00)	(0.23)	
r_t^T	2.12×10^{-4}	-4.63×10^{-6}	-1.03×10^{-2}	1.24×10^{-3}	1.32×10^{-3}	4.55×10^{-1}	-9.05×10^{-4}	-3.90×10^{-5}	0.6770
	(0.17)	(0.80)	(0.14)	(0.06)	(0.10)	(0.02)	(0.00)	(0.98)	
Panel B: Estimation results conditional on EXTREME RISES of stock market returns									
r_t^S	1.95×10^{-2}	5.12×10^{-4}	-1.62×10^{-1}	-2.81×10^{-2}	6.16×10^{-4}	-1.5828	-1.25×10^{-3}	2.29×10^{-3}	0.4368
	(0.00)	(0.07)	(0.02)	(0.00)	(0.10)	(0.46)	(0.23)	(0.85)	
r_t^C	-2.92×10^{-4}	8.54×10^{-6}	7.70×10^{-3}	-7.30×10^{-4}	2.58×10^{-3}	-3.21×10^{-2}	-9.26×10^{-4}	2.08×10^{-4}	0.4575
	(0.13)	(0.69)	(0.40)	(0.46)	(0.60)	(0.46)	(0.00)	(0.89)	
r_t^T	-3.09×10^{-4}	6.05×10^{-6}	-1.81×10^{-3}	1.07×10^{-3}	1.36×10^{-3}	4.44×10^{-2}	-1.03×10^{-3}	-1.87×10^{-3}	0.6520
	(0.05)	(0.72)	(0.80)	(0.19)	(0.41)	(0.81)	(0.00)	(0.13)	

Here, estimation results of Equations (4) to (6) conditional higher stock, corporate or Treasury bond market volatility are shown in this table for the following model,

$$r_t^S = a_0 + a_1OF_t^{index} + a_2OF_t^{C,on} + a_3OF_t^{T,off} + a_4OF_t^{non-Index} + a_5Spread_t^S + a_6r_t^{Common} + +a_7Repo_t + \varepsilon_t^S$$

$$r_t^C = b_0 + b_1OF_t^{index} + b_2OF_t^{C,on} + b_3OF_t^{T,off} + b_4OF_t^{C,off} + b_5Spread_t^C + b_6r_t^{Common} + +b_7Repo_t + \varepsilon_t^C$$

$$r_t^T = c_0 + c_1OF_t^{index} + c_2OF_t^{C,on} + c_3OF_t^{T,off} + c_4OF_t^{T,on} + c_5Spread_t^T + c_6r_t^{Common} + c_7Repo_t + \varepsilon_t^T$$

$$E[\varepsilon_t^S]=0, \quad E[\varepsilon_t^C]=0, \quad E[\varepsilon_t^T]=0; \quad E[\varepsilon_t^K \cdot \varepsilon_s^M]=\begin{cases} \sigma & \text{If } t=s \\ 0 & \text{Otherwise} \end{cases}, \quad K,M=S,C,T$$

Here, r_t^K ($K=S,C,T$) are returns for the three markets; OF_t^J ($J=index, C-on, T-off\ldots$) are aggregated order flow (in 100 million) for high-liquidity portfolios in each markets on day t; $OF_t^{K,Low-L}$ are order flow (in 100 million)for low-liquidity portfolio in each market on day t; $Spread_t^K$ ($K=S,C,T$) are liquidity for the three markets; r_t^{Common} is the principal component of the three market return vector (r_t^S, r_t^C, r_t^T); $Repo_t$ is 7-day repo rate of Treasury bonds. Returns, order flow or liquidity is equally-weighted for the three markets and all portfolios. Before model estimation, we run a vector autoregressive model of VAR (5) model respectively on endogenous variable vector (r_t^S, r_t^C, r_t^T), $(Spread_t^S, Spread_t^C, Spread_t^T)$, $(OF_t^{index}, OF_t^{non-index})$, $(OF_t^{C,on}, OF_t^{C,off})$ and $(OF_t^{T,on}, OF_t^{T,off})$ by turn to remove the strong autocorrelation and lead-lag relationship for all endogenous and exogenous variables. Table 7 provides the estimation results of Equations (4) to (6) condition on extreme stock market rises or falls, which are respectively defined as events with the highest and lowest 10% of stock market returns. P-value of coefficient estimation is shown in the parentheses.

Furthermore, conditional on volatile times of the two bond markets, results in Table 6 show that the order flow of Treasury bonds exhibits significant cross-market effects when volatility on Treasury bond market is high (Panel B table 6), and the order flow of corporate bonds exhibit significant cross-market effects when volatility on the corporate bond market is high (Panel C table 6). This indicates that, cross-market portfolio rebalancing or flight activities may have high price impact on the object market even though such activities are "good news" for the object market due to more investment coming. This is particularly true in China as both the Treasury and corporate bond markets are relatively small compared with bonds markets in other developed countries. Under this circumstance, the rising of price impact on the safe assets, thus rising of hedging costs, should be an important reason that incentives investors to search other substitute assets, such as the high-quality corporate bonds for the Treasury bonds, or inversely.

With respect to the within-market effect of order flow, results in Table 6 and Table 7 show that the effect of order flow for SS180 index stocks on stock market returns becomes weaker or insignificant but that for non-SS180 index stocks become much stronger when the stock market is more volatile or under extreme falls. This may imply within-market flight-to-quality or flight-to-liquidity between index and non-index stocks. That is, if there is within-market flight-to-liquidity from non-index stock to index stocks during stock market falling, then the order flow of index stocks is affected by two opposite effects. On the one hand, a fall in the stock market results in a fall in order flow for both index and non-index stocks. On the other hand, the within-market flight from non-index to index stocks will produce a rise in order flow for index stocks, which reduce the influence of market falling on these index stocks. Therefore, due to these two opposite effects on index stocks, it is reasonable to anticipate that order flow for index stocks only has marginal information content on market returns during volatile or falling stock market.

In addition, we also test cross-market effect of order flow conditional on higher or lower returns on either the Treasury or corporate bond market, as shown in Table 8, in which Equations (4) to (6) are estimated in subsamples with higher or lower returns on either the Treasury or corporate bond market.

Table 8 Estimation results of the three-market model conditional on HIGH or LOW BOND market returns

	C	OF_t^{index}	$OF_t^{C,on}$	$OF_t^{T,off}$	$OF_t^{K,Low-L}$	$Spread_t^k$	r_t^{Common}	$Repo_t$	$\bar{R}^2$
Panel A: Estimation results conditional on LOW TREASURY bond market returns									
r_t^S	5.23×10^{-4}	5.97×10^{-4}	-7.18×10^{-2}	-4.00×10^{-3}	1.88×10^{-3}	-7.2762	-1.02×10^{-3}	1.08×10^{-2}	0.7109
	(0.39)	(0.00)	(0.03)	(0.28)	(0.00)	(0.00)	(0.03)	(0.14)	
r_t^C	2.18×10^{-5}	-1.43×10^{-5}	6.88×10^{-3}	-4.18×10^{-4}	-7.54×10^{-3}	-1.83×10^{-2}	-7.96×10^{-4}	-4.57×10^{-4}	0.5117
	(0.70)	(0.08)	(0.03)	(0.22)	(0.07)	(0.12)	(0.00)	(0.51)	
r_t^T	-4.62×10^{-4}	-1.47×10^{-5}	-9.52×10^{-4}	9.39×10^{-4}	3.61×10^{-4}	-4.03×10^{-3}	-6.43×10^{-4}	-3.54×10^{-5}	0.5809
	(0.00)	(0.01)	(0.67)	(0.00)	(0.31)	(0.77)	(0.00)	(0.94)	
Panel B: Estimation results conditional on HIGH TREASURY bond market returns									
r_t^S	4.34×10^{-4}	3.13×10^{-4}	2.70×10^{-2}	-1.11×10^{-2}	2.30×10^{-3}	-4.8308	-7.67×10^{-6}	8.21×10^{-3}	0.6287
	(0.48)	(0.10)	(0.20)	(0.01)	(0.00)	(0.00)	(0.99)	(0.40)	
r_t^C	-1.56×10^{-4}	5.40×10^{-7}	3.16×10^{-3}	-9.25×10^{-4}	5.20×10^{-3}	-9.05×10^{-3}	-1.05×10^{-3}	1.34×10^{-3}	0.5756
	(0.01)	(0.96)	(0.11)	(0.01)	(0.05)	(0.26)	(0.00)	(0.14)	
r_t^T	5.44×10^{-4}	-1.44×10^{-5}	-1.50×10^{-3}	1.50×10^{-3}	1.05×10^{-3}	1.42×10^{-2}	-4.13×10^{-4}	3.40×10^{-4}	0.3238
	(0.00)	(0.06)	(0.32)	(0.00)	(0.01)	(0.62)	(0.00)	(0.63)	
Panel C: Estimation results conditional on LOW CORPORATE bond market returns									
r_t^S	9.48×10^{-4}	7.12×10^{-4}	3.84×10^{-2}	-7.86×10^{-3}	1.71×10^{-3}	-6.0583	-1.39×10^{-3}	9.14×10^{-3}	0.6858
	(0.12)	(0.00)	(0.08)	(0.03)	(0.00)	(0.00)	(0.01)	(0.30)	
r_t^C	-6.28×10^{-4}	-7.99×10^{-6}	2.80×10^{-3}	-1.16×10^{-3}	3.16×10^{-4}	-8.60×10^{-3}	-6.02×10^{-4}	-6.62×10^{-4}	0.4443
	(0.00)	(0.25)	(0.08)	(0.00)	(0.92)	(0.16)	(0.00)	(0.31)	
r_t^T	8.84×10^{-5}	-2.40×10^{-5}	-2.42×10^{-3}	2.32×10^{-3}	-2.29×10^{-5}	-1.25×10^{-2}	-7.28×10^{-4}	-2.06×10^{-4}	0.5453
	(0.10)	(0.00)	(0.19)	(0.00)	(0.96)	(0.48)	(0.00)	(0.79)	
Panel D: Estimation results conditional on HIGH CORPORATE bond market returns									
r_t^S	-1.48×10^{-4}	2.99×10^{-4}	-1.17×10^{-1}	-4.36×10^{-3}	2.37×10^{-3}	-6.1748	-6.56×10^{-5}	1.09×10^{-2}	0.6753
	(0.81)	(0.07)	(0.00)	(0.23)	(0.00)	(0.00)	(0.91)	(0.16)	
r_t^C	6.78×10^{-4}	-2.89×10^{-7}	1.52×10^{-3}	-2.97×10^{-4}	1.16×10^{-3}	2.29×10^{-3}	-4.95×10^{-4}	1.72×10^{-3}	0.2651
	(0.00)	(0.97)	(0.59)	(0.30)	(0.63)	(0.85)	(0.00)	(0.01)	
r_t^T	-1.57×10^{-4}	-1.17×10^{-5}	-1.73×10^{-3}	1.99×10^{-3}	1.38×10^{-3}	3.64×10^{-2}	-8.26×10^{-4}	-5.24×10^{-4}	0.6205
	(0.00)	(0.10)	(0.51)	(0.00)	(0.00)	(0.21)	(0.00)	(0.38)	

Here, estimation results of Equations (4) to (6) conditional on higher stock, corporate or Treasury bond market volatility are shown in this table for the following model,

$$r_t^S = a_0 + a_1 OF_t^{index} + a_2 OF_t^{C,on} + a_3 OF_t^{T,off} + a_4 OF_t^{non-Index} + a_5 Spread_t^S + a_6 r_t^{Common} + +a_7 Repo_t + \varepsilon_t^S$$

$$r_t^C = b_0 + b_1 OF_t^{index} + b_2 OF_t^{C,on} + b_3 OF_t^{T,off} + b_4 OF_t^{C,off} + b_5 Spread_t^C + b_6 r_t^{Common} + +b_7 Repo_t + \varepsilon_t^C$$

$$r_t^T = c_0 + c_1 OF_t^{index} + c_2 OF_t^{C,on} + c_3 OF_t^{T,off} + c_4 OF_t^{T,on} + c_5 Spread_t^T + c_6 r_t^{Common} + c_7 Repo_t + \varepsilon_t^T$$

$$E\left[\varepsilon_t^S\right]=0, \ E\left[\varepsilon_t^C\right]=0, \ E\left[\varepsilon_t^T\right]=0; \ E\left[\varepsilon_t^K \cdot \varepsilon_s^M\right]=\begin{cases}\sigma & \text{If } t=s \\ 0 & \text{Otherwise}\end{cases}, \ K,M=S,C,T$$

Here, r_t^K ($K=S,C,T$) are returns for the three markets; OF_t^J ($J=index, C-on, T-off\dots$) are aggregated order flow (in 100 million) for high-liquidity portfolios in each markets on day t; $OF_t^{K,Low-L}$ are order flow

(in 100 million) for low-liquidity portfolio in each market; $Spread_t^K$ ($K = S,C,T$) are liquidity for the three markets; r_t^{Common} is the principal component of the three market return vector (r_t^S, r_t^C, r_t^T); $Repo_t$ is 7-day repo rate of Treasury bonds. Returns, order flow or liquidity is equally-weighted for the three markets and all portfolios. Before model estimation, we run a vector autoregressive model of VAR (5) model respectively on endogenous variable vector (r_t^S, r_t^C, r_t^T) , $(Spread_t^S, Spread_t^C, Spread_t^T)$, $(OF_t^{index}, OF_t^{non-index})$, $(OF_t^{C,on}, OF_t^{C,off})$ and $(OF_t^{T,on}, OF_t^{T,off})$ by turn to remove the strong autocorrelation and lead-lag relationship for all endogenous and exogenous variables. We split the whole sample to two subsamples with high and low returns either in the Treasury or corporate bond market based on the median of returns on each market. Table 8 provides the estimation results of Equation (4) to (6) respectively on these subsamples. P-value of coefficient estimation is shown in the parentheses.

Results in Table 8 show that corporate or Treasury bonds order flow is significantly negatively correlated with stock returns during their own market rising or during the other bond market falling. Moreover, with respect to the constant terms in the two bond market equations, i.e. b_0 and c_0 , when one is positive the other one is always negative, which is different from the unconditional results shown in Table 5. These results confirm the ideas that: 1) cross-market hedging is a strong factor producing cross-market effect of order flow, as a fall in stock market returns is not only accompanied by a rise in order flow in bond market but also a rise in bond market returns; 2) corporate and Treasury bonds are substitute each other for stock-bond market portfolio rebalancing, since when one market is under stress (or falling), order flow for the other market will exhibit significantly negative effect on stock returns, thus the other one takes the role as a safe heaven; 3) portfolio rebalancing or flight between bond markets are also significant and should not be ignored since returns in the two bond markets departs from each other when either bond market is rising or falling. However, stock order flow is always significantly negatively correlated with Treasury bond market returns even when Treasury bond order flow is not significantly correlated with stock returns. This means that, in line with Table 5, the Treasury bond market other than corporate bond market plays the dominating role in stock-bond market linkage in China and the corporate bond market only acts as a substitution in the sense of stock-bond portfolio rebalancing.

Overall, we have established both within-market and cross-market information content of order flow on the Chinese stock, Treasury and corporate bond markets by discussing how the information content of order flow is varied with asset liquidity and market conditions. With such

an approach, we provide evidence of cross-market hedging and portfolio rebalancing both between stocks and bonds and between corporate and Treasury bonds. However, it should be noted that, due to the special background of the financial markets in China, this does not means that investors act absolutely as what we have shown above, and we can not exclude some possible "indirect" cross-market effect of order flow. For instance, as mentioned above, most investors on the Chinese stock market are individuals, and they allocate assets more between the stock market and bank saving accounts than between the stock and bond markets. Therefore, there is a possible indirect channel of portfolio rebalancing between the stock and Treasury bond markets through the commercial banks, which hold most of the individual saving accounts, and the inter-bank bond market, which is the chief place permitting investment activities for state-owned commercial banks. For instance, when funds are transferred from the stock market to saving accounts in the commercial banks, the short-term surplus of bank funds could be invested in the inter-bank bond market, and finally affect the exchange bond market through the activities of some common participants, such as non-bank institutions or investment funds, who trade both on the inter-bank and exchange bond market.

Furthermore, with respect to the cross-market effect of corporate bond order flow on stock returns, it may not be resulted from the direct portfolio rebalancing between stocks and corporate bonds, but indirectly resulted from the portfolio rebalancing between stocks and Treasury bonds and between corporate and Treasury bonds. For example, owing to the portfolio rebalancing between the stock and Treasury bond markets, more investment will be invested in Treasury bonds when the stock market is under stress. This may resulted in a rise in Treasury bond prices but a fall in its yield to maturity. Then, owing to the portfolio rebalancing between the corporate and Treasury bond markets, investment will be rebalanced from Treasury to corporate bonds. This is possible since most of corporate bonds in China hold very high quality, close to Treasury bonds. Thus, a fall in stock market returns may be accompanied by a rise in corporate bond order flow even when there is no "direct" portfolio rebalancing between the two markets. Anyway, the substitute role of corporate bonds in such indirect portfolio rebalancing is true since they provide a choice to transfer investor position risk between the two bond markets, which may just come from the stock market.

6 Conclusions

This paper discusses within-market and cross-market information content of order flow on the Shanghai stock, corporate bond and Treasury bond markets. Three main messages can be drawn from the results.

Firstly, order flow has important within-market effects on returns both on the stock and bond markets. On the stock market, aggregate market order flow is highly correlated with market returns. However, by contrast with the stock markets in other developed countries, the impact of order flow for index (SS180) stocks is weaker than non-index stocks. On the bond market, the order flow for high-liquidity bonds has higher information to explain bond market returns.

Secondly, we find a bi-directionally negatively effect of order flow on returns both between the corporate and stock markets and between the corporate and Treasury bond markets. That is, a rise in order flow on one market means a fall in returns on another market. In line with Connolly et al. (2005, 2007), Underwood (2008) etc., our results provide evidence of cross-market portfolio rebalancing both between stocks and bonds and between corporate and Treasury bonds. The Treasury bond market serves more for hedging activities of stock market investors than the corporate bond market, and, in addition to the stock-bond flight, flight between corporate and Treasury bond markets is also vital.

Finally, with respect to portfolio rebalancing or flight-to-quality between the stock and bond markets in China, corporate bonds have substitute effect for Treasury bonds to be the heaven of stock investors, either when the demand of safe assets rises during stock market stress or when the cost of portfolio rebalancing into Treasury bond market rises during volatile or falling Treasury bond market.

Our results indicate that two points are vital. The first is that each market in the capital market system plays its own role for investors; therefore, each market should not be ignored in studying cross-market flight, and restricting analysis to only two markets (as shown in previous studies) may bias results. In the case of the Chinese market, corporate bonds are able to substitute Treasury bonds on particular market conditions. The second point is that asset characteristics (e.g. asset liquidity), market conditions (e.g. rise or fall), and even structure and preference of market

participants (e.g. individual or institutional investors predominant) have significant effect on the information content of order flow. Thus, the order flow of high-liquidity assets tends to have higher cross-market effects, but it is not surely to have higher within-market effects. For example, the less-liquid non-index stocks hold by most individual investors present much higher power to explain stock market returns than index stocks.

Appendix: MGARCH models and the estimation results

In section 5.3 of this paper, we estimate a VAR-MGARCH model to measure the market volatility. Among types of MGARCH model, the CCC (Constant Condition Correlation) model of Bollerslev (1990) is selected to get the proxies of market volatility. The definition of the CCC-type VAR-MGARCH is as follows.

CCC model

$$\mathbf{r}_t = \mathbf{A} + \mathbf{B}\mathbf{r}_{t-1} + \boldsymbol{\varepsilon}_t, \quad \mathbf{r}_t = \begin{pmatrix} r_t^S & r_t^T & r_t^C \end{pmatrix}', \quad \boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_t^S & \varepsilon_t^T & \varepsilon_t^C \end{pmatrix}'$$

$$\boldsymbol{\varepsilon}_t \sim \mathbf{N}(\mathbf{0}, \mathbf{H}_t)$$

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{ii,t-1}$$

$$h_{ij,t} = \rho_{i,j}(h_{ii,t} h_{jj,t})^{1/2}$$

$$i = S, T, C; j = S, T, C$$

Here, the coefficients vector $\mathbf{A}$, matrix $\mathbf{B}$ in conditional mean (a_i is the constant term and b_{ij} is the loading coefficient of lag return of the jth market on the ith market), the coefficients in conditional variance ω_i, α_i, β_i, and the correlation coefficients $\rho_{i,j}$ are estimated. To differentiate with other models, the CCC model shown above is named as VAR(1)-CCC model, in which VAR(1) is the specification of the conditional mean. The likelihood function of VAR(1)-CCC model is,

$$L(\Theta) = -\frac{1}{2}\sum_{t=1}^{N}\left[\ln(2\pi) + \ln|\mathbf{H}_t| + \boldsymbol{\varepsilon}_t'\mathbf{H}_t^{-1}\boldsymbol{\varepsilon}_t\right]$$

MLE results of our VAR (1)-CCC MGARCH model are shown in Appendix table 1. It can be found that $\alpha_i + \beta_i$ ($i = S, T, C$) is close to unit and the conditional variance is clustering for all three markets. The estimation results of correlation coefficients $\rho_{i,j}$ show that there is high positive correlation between Treasury and corporate bond market returns. However, both the stock-Treasury and stock-corporate bond market return correlations are insignificant. Particularly, the stock-corporate market returns correlation is very small with absolute value close to zero and

high p-value close to one. These results support the fact the corporate bond market is better and more-regarded place of hedging for the (institutional) investors in the stock market. Some diagnosis results of the VAR(1)-CCC model are shown in appendix Table 1. The autocorrelations of the standardized residuals $\varepsilon_t^i / \sqrt{h_{ii}}$, square of the standardized residuals $\left(\varepsilon_t^i / \sqrt{h_{ii}}\right)^2$ and cross products of standardized residuals $\varepsilon_t^i \varepsilon_t^j / \sqrt{h_{ii} h_{jj}}$ ($i = S, T, C$; $j = S, T, C$) indicate that VAR(1)-CCC model really does a good job to capture the dynamics of variance and covariance of the three markets. The Q-statistics with 10 lags for all the three squares and cross-products of standardized residuals are highly insignificant. Though one of the three standardized residuals has significant autocorrelations, we found that the chief reason responsible for it could be that there are higher autocorrelations for the bond market returns and more lags are needed to be included in the conditional mean, VAR, specifications. If VAR(3)-MGARCH is employed, all the standardized residuals have insignificant autocorrelations. However, in this case, too many redundant variables are included in the mean equations, particular for the stock market equation, and lead to the fall of the likelihood. Anyway, both VAR(1)-MGARCH and VAR(5)-MGARCH produce qualitative similar conditional variance for the three markets (as shown in Appendix figure 1, 2 and 3) and, what's more, qualitative similar empirical results in section 5 this paper (not reported here). The LR (Likelihood ratio) statistics in appendix Table 1 indicate that the Multivariate GARCH model is significant better than the three univariate counterparts. The LR statistic is constructed as follows.

$$LR = -2(L^S + L^T + L^C - L^{S,T,C})$$

Here, L^S , L^T and L^C are the likelihood value of the univariate GARCH model for stock, Treasury and corporate bond market returns, and $L^{S,T,C}$ is the likelihood value of the VAR(1)-MGARCH model.

As the robustness test of our results, we also apply two alternative MGARCH models, one is VEC type model (Bollerselv et al., 1988) and another is the BKKK model (Engle and Kroner, 1995). Our specifications of the conditional variance-covariance matrix of these two models are as follows.

VEC model

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{ii,t-1}$$

$$h_{ij,t} = \omega_{ij} + \alpha_{ij} \varepsilon_{i,t} \varepsilon_{j,t} + \beta_i h_{ij,t-1}$$

$$i = S,T,C \; ; \;\; j = S,T,C$$

BKKK model

$$\mathbf{H}_t = \boldsymbol{\omega}'\boldsymbol{\omega} + \boldsymbol{\alpha}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\,\boldsymbol{\alpha}' + \boldsymbol{\beta}\mathbf{H}_{t-1}\mathbf{H}'_{t-1}\,\boldsymbol{\beta}'$$

Here, $\boldsymbol{\omega}$ is a low triangular matrix, and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are dialog matrix.

The estimation results of these two models are not shown here. For the likelihood of the four MGARCH models, VAR(1)-CCC are better than all others. Thus VAR(1)-CCC is used to capture the variance dynamics of the three markets. In fact, as shown in Appendix Figure 1, 2, and 3, their conditional variances are not much different for the three models or with different conditional mean specification. Moreover, the empirical results in section 5 are qualitative the same when either model is used.

Appendix table 1 Estimation results of the VAR(1)-CCC model for the three markets

| Conditional Mean equation	Coefficients	Conditional variance equation	Coefficients	Correlations	Coefficients
a_s	4.38×10^{-5} (0.94)	ω_S	9.89×10^{-6} (0.00)	ρ_{SC}	0.0477 (0.25)
a_C	2.46×10^{-4} (0.00)	α_S	0.9181 (0.00)	ρ_{ST}	0.0326 (0.42)
a_T	1.11×10^{-4} (0.02)	β_S	0.0466 (0.00)	ρ_{TC}	0.4233 (0.00)×
b_{SS}	0.1309 (0.00)	ω_T	9.18×10^{-8} (0.00)		
b_{SC}	0.2521 (0.58)	α_T	0.8258 (0.00)		
b_{ST}	0.0733 (0.88)	β_T	0.1390 (0.00)		
b_{CS}	-0.0025 (0.38)	ω_C	9.55×10^{-8} (0.00)		
b_{CC}	0.1618 (0.00)	α_C	0.8117 (0.00)		
b_{CT}	0.2478 (0.00)	β_C	0.1285 (0.00)		
b_{TS}	0.0007 (0.76)	$\alpha_S + \beta_S$	0.9647		
b_{TC}	0.0849 (0.00)	$\alpha_C + \beta_C$	0.9648		
b_{TT}	0.2440 (0.00)	$\alpha_T + \beta_T$	0.9402		

In appendix table 1, a_i, b_{ij} ($i = S,T,C$; $j = S,T,C$) are the coefficients in the, VAR, conditional mean equations, and a_i is the constant term and b_{ij} is the loading coefficient of lag return of the jth market on the ith market; ω_i, α_i, β_i ($i = S,T,C$) are the coefficients in the conditional variance; $\rho_{i,j}$ ($i = S,T,C$; $j = S,T,C$) are the correlation coefficients; the value in the parentheses are the p-values of the coefficients.

Appendix Table 1 Model diagnosis

Panel A Statistics of the residuals

| Standardized residuals	Q(10)-statistics	Square of standardized residuals	Q(10)-statistics	Cross-products of standardized residuals	Q(10)-statistics
$\varepsilon_t^S / \sqrt{h_{SS}}$	12.29	$\left(\varepsilon_t^S / \sqrt{h_{SS}}\right)^2$	7.88	$\varepsilon_t^S \varepsilon_t^C / \sqrt{h_{SS} h_{CC}}$	9.31
	(0.27)		(0.64)		(0.50)
$\varepsilon_t^C / \sqrt{h_{CC}}$	45.10	$\left(\varepsilon_t^C / \sqrt{h_{CC}}\right)^2$	3.45	$\varepsilon_t^S \varepsilon_t^T / \sqrt{h_{SS} h_{TT}}$	14.03
	(0.00)		(0.97)		(0.17)
$\varepsilon_t^T / \sqrt{h_{TT}}$	17.76	$\left(\varepsilon_t^T / \sqrt{h_{TT}}\right)^2$	1.94	$\varepsilon_t^T \varepsilon_t^C / \sqrt{h_{TT} h_{CC}}$	6.26
	(0.06)		(0.99)		(0.79)

Panel B Comparison of multivariate GARCH and univariate GARCH

Model	Likelihood	LR	Model	Likelihood	LR
VAR(1)-CCC	9608.32	54.40	VAR(1)-VEC	9497.49	-167.27
		(0.00)			(----)
VAR(3)-CCC	9544.19	-62.82	VAR(1)-BKKK	9595.56	28.87
		(----)			(0.00)

Panel A provided the Q-statistics for the autocorrelations of square residuals of standardized residuals $\varepsilon_t^i / \sqrt{h_{ii}}$, square of standardized residuals $\left(\varepsilon_t^i / \sqrt{h_{ii}}\right)^2$, and cross-products of standardized residuals $\varepsilon_t^i \varepsilon_t^j / \sqrt{h_{ii} h_{jj}}$ ($i = S,T,C$; $j = S,T,C$) based on the estimation results of the VAR(1)-CCC model. In panel B, the LR ratio to compare the bi-variate GARCH and univariate GARHC model is computed as $LR = -2(L^S + L^T + L^C - L^{S,T,C})$. Here, L^S, L^T and L^C are the likelihood value of the univariate GARCH model for stock, Treasury and corporate bond market returns, and $L^{S,T,C}$ is the likelihood value of the VAR(1)-MGARCH model. Besides the VAR(1)-CCC model, likelihood and LR statistics for other three alternative models, VAR(3)-CCC, VAR(1)-BKKK, VAR(1)-VEC are also provided. VAR(1)-CCC is the MGARCH model with VAR(1) conditional mean and CCC-type conditional variance; VAR(3)-CCC is the MGARCH model with VAR(3) conditional mean and CCC-type conditional variance; VAR(1)-VEC is the MGARCH model with VAR(1) conditional mean and VEC-type conditional variance; VAR(1)-BKKK is the MGARCH model with VAR(1) conditional mean and BKKK-type conditional variance.
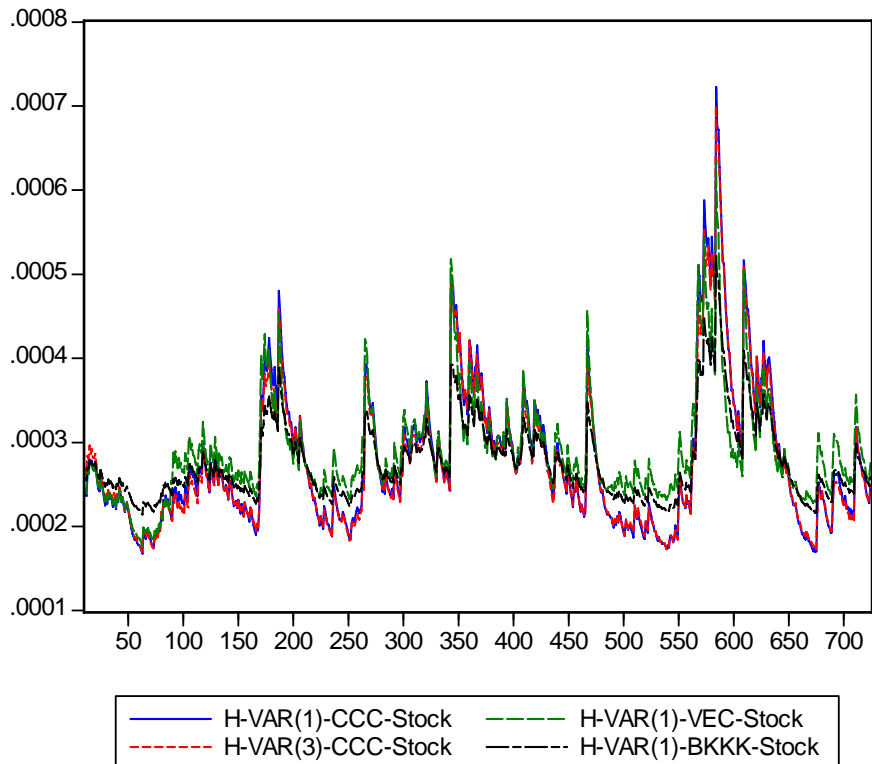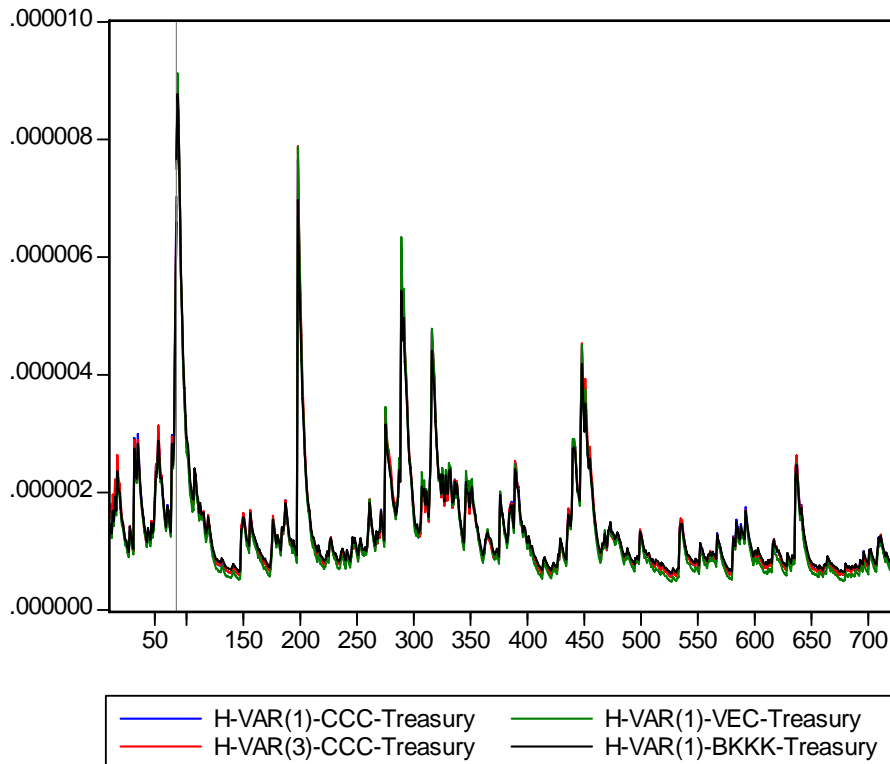
Here, the conditional volatility of the four MGARCH models for the stock market is shown in this figure. VAR(1)-CCC is the MGARCH model with VAR(1) conditional mean and CCC-type conditional variance; VAR(3)-CCC is the MGARCH model with VAR(3) conditional mean and CCC-type conditional variance; VAR(1)-VEC is the MGARCH model with VAR(1) conditional mean and VEC-type conditional variance; VAR(1)-BKKK is the MGARCH model with VAR(1) conditional mean and BKKK-type conditional variance.

Appendix figure 1 Conditional variance of stock market for four different models
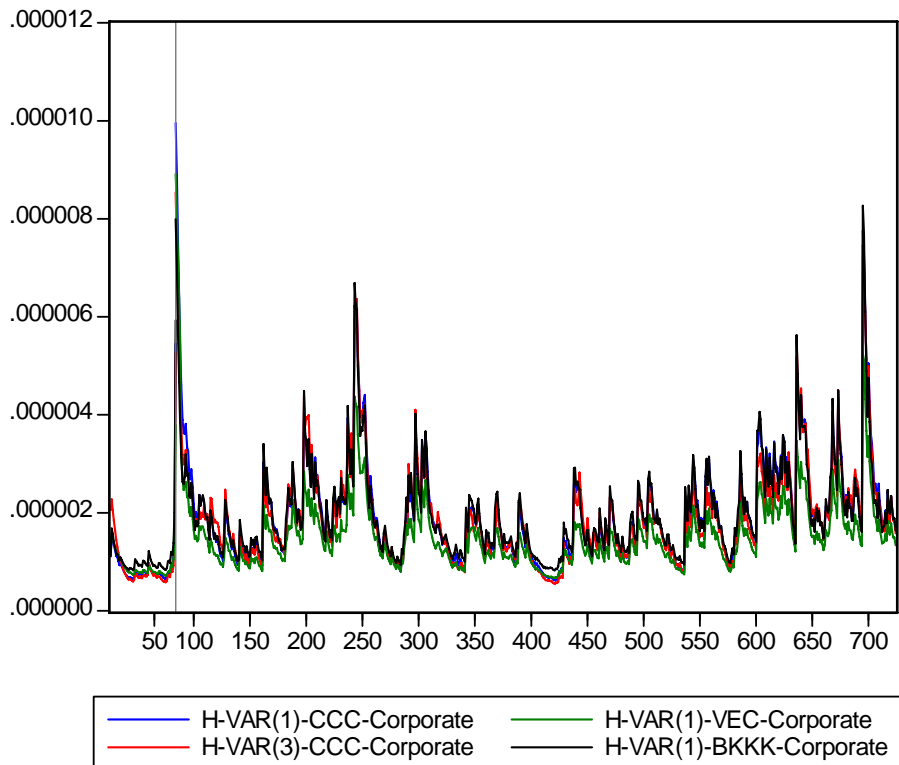
Here, the conditional volatility of the four MGARCH models for the Treasury bond market is shown. To differentiate the results of the four models clearly, 20 observations with highest volatility are removed around 25th, April, 2004 when the Centre Bank of China raised the deposit reserve ratio from 7% to 7.5% and adopted the policy of "Differential Ratio System" (different financial institutions take different deposit reserve ratio according to their risk level). More information is included in the website as follows:

http://www.pbc.gov.cn/detail.asp?col=443&ID=103).

Appendix figure 2 Conditional variance of corporate bond market for four different models

Here, the conditional volatility of the four MGARCH models for the corporate bond market is shown. To differentiate the results of the four models clearly, 20 observations with highest volatility are removed around 25th, April, 2004.

Appendix figure 3 Conditional variance of Treasury bond market for four different models

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