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# Margin trading and spillover effects: Evidence from the Chinese stock markets

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ABSTRACT

Using a sample of Chinese stocks, we demonstrate that liquidity and return in stocks with margin trading can spread to other stocks causing spillover effects. Furthermore, the level of margin interest has a positive relation with the degree of spillover effects from relevant stocks. In addition to the deleverage mechanism which has received support from recent studies, we propose the cross-asset learning behavior in stock markets as a new mechanism to explain such relation. The mediation models suggest that the cross-asset learning mechanism can explain a large proportion of the relation between margin trading and spillover effects in stock markets.

## 1. Introduction

Margin trading has been a pervasive feature for most of the stock markets in the world. Despite the recent finding that margin trading improves the market quality (e.g., Chang et al., 2014; Chen et al., 2016; Kahraman and Tookes, 2017; Ye et al., 2020), it is also commonly accepted that it contributes to the contagion and spillover of negative shocks and therefore the commonalities and systematic risk in stock markets. For instance, margin trading has been frequently blamed as the fuel for stock market bubbles as well as the crucial reason for subsequent price crash and liquidity dry up. Therefore, it is important to understand why it may lead to contagion and spillover effects in stock markets.

Existing theoretical literature mainly explains such impacts of margin trading with the deleverage mechanism: margin traders must deleverage facing negative shocks in order to release the funding constraints induced by their leveraged position and such deleverage action often involves selling other stocks they hold, and hence the negative shocks spill out to the rest of the market (e.g., Schinasi and Smith, 2000; Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2009; Caccioli et al., 2014). The prediction of these theoretical work has been confirmed by several recent empirical studies in different countries (e.g., Hu et al., 2019; Kahraman and Tookes, 2020; Bian et al., 2021) which demonstrate that margin trading is a causal factor for the stock market contagion and comovement during the crisis period.

In addition to the deleverage mechanism suggested above, cross-asset learning behavior of market participants has recently received increasing attention in the literature as a source of spillover effect and comovement in stock markets (e.g., Boulatov et al., 2013; Cespa and Foucault, 2014; Pasquariello and Vega, 2015; Asriyan et al., 2017; Honkanen and Schmidt, 2022). In the cross-asset learning theory, new information and the stock price and liquidity changes caused by such new information in one asset will spill out to

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the other assets because market participants watch and learn from the price signal of the former asset to guide their trading of the latter.

In this paper, building on the literature on the cross-asset learning theory as well as the literature on the impacts of trader leverage on liquidity, volatility, and information efficiency of relevant stocks (e.g., Chang et al., 2014; Chen et al., 2016; Kahraman and Tookes, 2017; Ye et al., 2020), we argue that margin trading may also induce the stock market spillover effects through market participants' cross-asset learning behavior. In particular, margin trading decreases the volatility and improves the price discovery and liquidity of margin eligible stocks, and this will improve the price signal provided by them. Greater quality of price signal by the margin eligible stocks promotes the market participants' learning from these price signals when trading other stocks. This therefore promotes the spillover from margin eligible stocks. Theoretically, unlike the deleverage mechanism which only plays its role at market downturns, cross-asset learning mechanism can work at both market upturns and downturns. Hence, it is an important complementary mechanism to explain the relation between margin trading and stock market spillover effects.

Empirically, we make use of the unique setting in the Chinese stock markets, where margin eligible stocks and ineligible stocks co-exist, to investigate the propagation of both price and liquidity spillover from the margin eligible stocks. The proxy of spillover effects in this study is the lead-lag effects, which are estimated with the vector autoregressive (VAR) models, between return and liquidity of margin eligible stocks and margin ineligible stocks. If there exists spillover from the margin eligible stocks to the ineligible ones, then past movements (e.g., in price or liquidity) of the margin eligible stocks will lead those of the ineligible stocks and this will be captured by the differential cross-autocorrelation coefficients (i.e., lead-lag effect) from the VAR models.

Using the lead-lag coefficients as the proxy for spillover effects, we firstly establish that there indeed exist spillover effects from the margin eligible stocks. Stocks with margin trading have significant spillover effects to those without margin trading in terms of both intraday price movements and liquidity. These results hold for both portfolios and individual stocks, and they are robust to different lags of the VAR models. The spillover effects of the margin eligible stocks are found to be significantly stronger in days with low funding liquidity and in crisis period, which are consistent with the deleverage mechanism. However, in days with high funding liquidity and in non-crisis period, margin eligible stocks still have significant spillover effects to the ineligible stocks suggesting the existence of additional mechanisms.

Secondly, since margin eligible stocks are also short eligible, we use the multivariate regression analysis to control the influence of the short selling activity as well as other share characteristics on margin eligible stocks' spillover effects. We find that margin interest of the relevant stocks, which measures the extent of leverage used by the margin traders, is still significantly positively associated with both return and liquidity spillover effects from the margin eligible stocks while the other influential factors are controlled.

Finally, building on the multivariate regressions mentioned above, we conduct mediation analysis to investigate whether the various channels (i.e., price discovery channel, liquidity channel and volatility channel) of the cross-asset learning mechanism can explain the relation between margin interest and relevant stocks' spillover effects. We find that the total explanatory power from the cross-asset learning mechanism is as large as that of the deleverage mechanism.

Our research makes several important contributions to relevant literature. To start with, similar to several recent studies (e.g., Hu et al., 2019; Kahraman and Tookes, 2020; Bian et al., 2021), our empirical evidence supports the theoretical work which implies that trader leverage may cause the contagion of negative shocks across the stock market (e.g., Schinasi and Smith, 2000; Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2009; Caccioli et al., 2014). In fact, the intraday spillover effects from the margin eligible stocks documented in our study suggest that liquidity shocks and price changes of relevant stocks can transmit to other stocks at a very short horizon. And this explains the formation of liquidity and return commonality at a lower frequency (i.e., daily or weekly).

In addition, this paper sheds light on the mechanisms through which investor leverage may lead to spillover and contagion in stock markets. We highlight a new mechanism which is caused by the cross-asset learning behavior of market participants. The cross-asset learning mechanism provides a significant amount of explanatory power for the impacts of margin trading on stock market spillover effects. This not only lends support to the cross-asset learning theory which has received increasing attention in literature (e.g., Boulatov et al., 2013; Cespa and Foucault, 2014; Pasquariello and Vega, 2015; Asriyan et al., 2017; Honkanen and Schmidt, 2022), but also extends our knowledge of why margin trading may cause contagion and spillover in stock market.

Furthermore, this paper adds to the strand of literature on the lead-lag relations in stock markets (e.g., Brennan et al., 1993; Badrinath et al.,1995; Chordia and Swaminathan, 2000). Our paper suggests a new influential factor, namely the investors' leverage in margin trading, that determines the lead-lag effects. In addition, most of the existing literature on the lead-lag relations focuses on stock price movements. Our paper is one of the first papers that directly document the lead-lag relations in liquidity which further increases our understanding of the liquidity dynamics in the stock market.

Last but not least, the results of the paper contribute to the debate on the costs and benefits of margin trading. Financial market regulators are generally interested in understanding what impacts margin trading may have on the stock markets. Although various studies have suggested that margin trading may improve the market quality on liquidity, volatility, and price discovery of relevant stocks, our paper shows that the downside of the margin trading in increasing the spillover, hence commonalities and systematic risk, of the stock markets also needs to be taken into consideration.

The rest of this paper is organized as follows: we review some of the relevant literature and establish our hypothesis in Section 2. Section 3 is mostly about the sample stocks and the proxy for spillover effects used in this study. In Section 4, we report the empirical evidence on the spillover effects of the margin eligible stocks in both portfolios and individual stocks. We also demonstrate that the degree of the spillover effects in margin eligible stocks is positively associated with the level of the margin interest in this section. The importance of cross-asset learning mechanism in explaining the relation between margin interest and spillover effects is explored in Section 5. Finally, we conclude in Section 6.

## 2. Mechanisms of stock market spillover effects

There are two major strands of research that deals with the causes of the contagion and spillover in financial markets: one focuses on the impacts that losses in some assets have on the funding ability of traders and therefore their trading of other assets; the other focuses on how the new information represented by the negative shocks in some assets may spread out to other assets with linked cash flows (Haß et al., 2014).

Following this thinking, margin trading may cause the contagion and spillover effects through two potential mechanisms. Firstly, negative shocks in margin eligible stocks may propagate to other stocks with shared owners that are financially constrained (e.g., Schinasi and Smith, 2000; Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2009; Caccioli et al., 2014). Trade with borrowed funds (i.e., margin trading) introduces a scenario where, when negative shocks occur, funding constraints begin to bind and influence traders' trading decision. For example, Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2009) predict that destabilizing margin and losses on existing positions cause leveraged investors to de-lever which increases the liquidity commonality among various securities and intensify the liquidity crash during the crisis period. More specifically, when a severe drop in stock market occurs, margin traders who are facing greater funding constraints at this moment may be forced to liquidate their holding of margin eligible stocks if they fail to meet the margin calls. This will cause a significant increase in the demand of liquidity for relevant stocks. When such liquidity demand cannot be fully met, margin traders may turn to other stocks for liquidity. They may decide to sell other stocks in their portfolios to raise the necessary capital in order to reduce the probability of forced liquidation by the brokers. The negative shocks in the margin eligible stocks hence spread to other stocks. Furthermore, even when there are no margin calls, margin traders may still choose to unwind their positions in other stocks voluntarily in order to reduce their investment risk when negative shocks occur (Schinasi and Smith, 2000).

The deleverage mechanism of the spillover effect has been documented by several recent empirical studies. In a sample of Chinese stocks, Hu et al. (2019) show that, at the intraday level, the deleverage need of margin traders during Chinese stock market's recent crash period (i.e., between June and August of 2015) may lead to the illiquidity transmission across stocks. In particular, they show that sudden price drops in the margin eligible stocks will lead to negative order imbalances of other stocks within the same industry and across different industries. Also using China's data at a similar period, Bian et al. (2021) find that common margin investor ownership is positively correlated with the pairwise return comovements between two margin eligible stocks. At the India market where margin trading eligibility also pertains to only part of the stocks, Kahraman and Tookes (2020) are able to identify a causal link between margin trading and increased return co-movement during the crisis period.

Secondly, spillover effect and comovement in stock markets could also arise due to cross-asset information flows. Several recent studies suggest that cross-asset learning behavior causes trading and price movements in one asset to spill out to peer assets (e.g., Boulatov et al., 2013; Cespa and Foucault, 2014; Pasquariello and Vega, 2015; Asriyan et al., 2017; Honkanen and Schmidt, 2022). For example, as the uninformed market makers learn from the trading of other assets, the multi-period model of Boulatov et al. (2013) predict the lead-lag relation between the informed order flow of one asset and the future returns of other assets with correlated fundamentals. Similarly, Asriyan et al. (2017) argue that when asset values are correlated and traders are privately informed, a trade of one asset can provide information about the value of the other asset. Therefore, both trading and prices of the two assets will be correlated. The correlation in fundamentals, however, is not essential in the return and liquidity spillover. In Pasquariello and Vega's (2015) model with both informed speculator's cross-trading and subsequent market maker's learning from such trading, the cross-price impact could also exist among fundamentally unrelated assets. Furthermore, in a setting with two assets, Cespa and Foucault (2014) suggest that when the reference asset becomes illiquid, the quality of its price signal will decline which will cause traders of the other asset to scale back their liquidity provision. Hence, the liquidity shortage in the reference asset will propagate to the other asset causing liquidity spillover. At last, more recently, Honkanen and Schmidt (2022), using mutual fund fire sales to identify cases where the stock movements are not caused by fundamental signals, demonstrate that the return and liquidity spillover induced by such cross-asset learning behavior still exist even if the changes of the reference asset are purely "noise". In general, we can see that the role of cross-asset learning behavior as an important driver of stock market commonalities in return and liquidity has received continuous attention in the literature in the past decade.

Margin trading may amplify the degree of such cross-asset learning behavior discussed above, hence the return and liquidity spillover, from the margin eligible stocks to other stocks through various channels. To begin with, margin trading can increase the speed with which relevant stocks incorporate new information in prices. Chang et al. (2014) find that lifting bans on margin-trading and short-selling improves the price efficiency of the leverage eligible stocks in the Chinese markets. Chen et al. (2016) further demonstrate that the degree of the information efficiency of relevant stocks increases with the intensity of the margin trading and short selling. The greater price efficiency and price discovery speed of the margin eligible stocks may induce traders to rely more on their price signals when trading other assets. This hence may strength the information spillover from the leveraged stocks. We call this channel the "price discovery channel" of the cross-asset learning mechanism.

Furthermore, studies have found that allowing margin trading may reduce the illiquidity and volatility of relevant stocks in China (e.g., Chang et al., 2014; Ye et al., 2020). When illiquidity of a stock decreases, the quality of its price signal increases as it is less influenced by the transmit demand shocks. Also, for stocks with smaller volatility, their prices provide clearer signals in their valuation. Therefore, when margin trading reduces illiquidity and volatility of margin eligible stocks, it increases the quality of the price signals provided by them. Logically, this will promote the cross-asset learning from the price signals of margin eligible stocks and enhance the spillover effect that they demonstrate. In addition, the beneficial impacts of margin trading on margin eligible stocks'

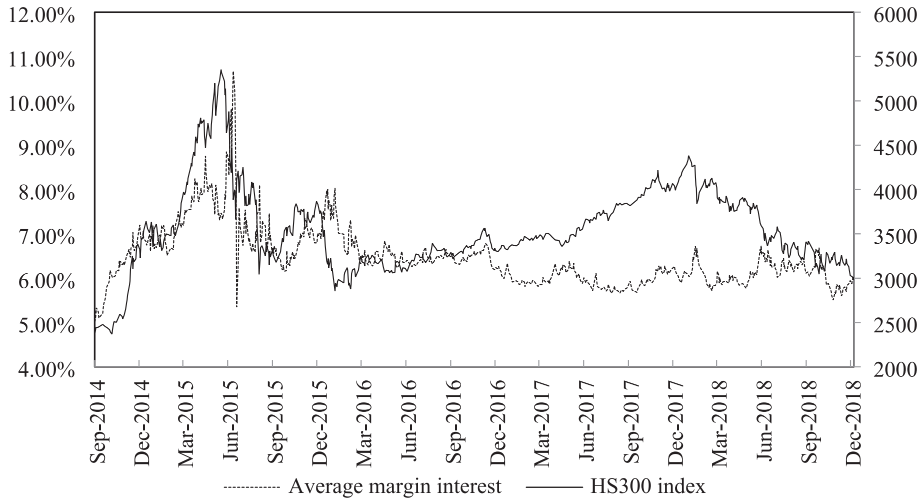


**Fig. 1.** HS300 index and margin interest. Fig. 1 reports the movements of HS300 index and average margin interest in the Chinese stock markets between Sep 2014 and Dec 2018.

liquidity and volatility may also make these stocks to become more popular as the reference stocks in the cross-asset learning scenarios.[1] We call the impact of margin trading on the margin eligible stocks' spillover effect through its influence on their liquidity and volatility as the "liquidity channel" and "volatility channel" of the cross-asset learning mechanism respectively. Similar to the price discovery channel, the liquidity and volatility channels promote the information spillover from the margin eligible stocks to the ineligible ones. Therefore, the three channels of cross-asset learning mechanism are fundamentally different from the deleverage mechanism in which spillover and contagion occur due to impaired funding ability of the traders.

In summary, based on the deleverage mechanism and the channels in the cross-asset learning mechanism, we hypothesize that the liquidity and price movements of margin eligible stocks will spill out to those of the ineligible stocks. In the following empirical analysis, we will provide evidence supporting this hypothesis. More importantly, employing the mediation models, we will investigate how much of the spillover induced by the margin trading is caused by the channels from the cross-asset learning mechanism.

## 3. Sample stocks and the measurement of spillover effects

### *3.1. Sample stocks*

Our study is conducted using A shares listed in the Shanghai and Shenzhen stock exchanges. Although using leverage in trading (e.g., margin trading and short selling), has long become pervasive in many countries, it is a recent innovation in the Chinese stock market. Only since March 2010, margin trading (as well as short selling) was gradually allowed for certain stocks, starting from a list of 90 pilot stocks in 2010 to 950 stocks by the end of our sample period. The choice of stocks for this list is based on an indicator which is a weighted average of the relative market capitalization and relative trading volume of the stock.[2] The higher this indicator of a stock, the more likely it is to be included in the list of marginable stocks.[3]

The sample period of this study starts from 22nd Sep 2014 to 31st Dec 2018. At the start of our sample period, the list of margin eligible stocks was just expanded from 700 stocks to 900 stocks, and it was not until 12th Dec 2016 when another 50 stocks were added to the list. We focus our empirical analysis between Sep 2014 and Dec 2018 because the compositions of the margin eligible stocks in this period are both adequate and relatively invariant. In addition, as can be seen from Fig. 1 which displays the movements of HS300 index, the stock markets in China have experienced boom, crash and comparatively stable days in our sample period which allows us to examine the spillover effects in different market conditions.

Fig. 1 also plots the average margin interest, which is the dollar balance of the margin debt of a stock divided by the market value of the stock's floating shares, across all margin eligible stocks on each day in our sample period. We can see that the movements of margin interest mostly follow a similar pattern with those of the HS300 index with some lags. When stock market index changes, the margin

[1] Consistent with this conjecture, Isshaq and Faff (2016) find that volatility of a firm's profitability is negatively associated with its liquidity commonality as lower volatility increases the likelihood that the firm serves as the reference stock in the setting of the cross-asset learning of fundamentals.

[2] The market value (trading volume) is scaled by the average market value (trading volume) of A shares in the exchange in which the stock is listed.

[3] Furthermore, the eligible stocks also need to have listed for more than 3 months and have met a minimum requirement on the number of shares outstanding, the number of existing shareholders, volatility, and turnover.

interest tends to change in the same direction later. The most apparent observation is between June 2015 and August 2015, when the collapse of the stock market index has caused the collapse of margin interest, which suggests a large scale deleverage behavior by the investors. This is also the period when Hu et al. (2019) and Bian et al. (2021) studied the deleverage mechanism in the Chinese stock markets.

In Table 1, we report the summary statistics for margin trading activities in our sample. As a comparison, we also report those for the short selling activities. We can see that margin trading is the primary form of leverage trading in the Chinese markets. On average, the margin trading volume consists of 18.88% of the total trading volume on each day. The margin interest averages to 6.42% in our sample period. Furthermore, on a particular day, the average dollar balance of the margin debt across leveraged stocks is as high as 900 million RMB. By contrast, short selling is much less active with average short turnover being less than 0.5% on an average day and average short interest being only 0.01%.

While more and more stocks were included to the list of marginable stocks over time, many stocks with margin trading constraints co-exist in the market. During our sample period, the number of margin eligible stocks is around half of the number of the ineligible stocks. By nature, the margin eligible stocks tend to be much larger in market capitalization and trading volume than the ineligible stocks since historical size and trading volumes are two important criteria that determine whether a stock can be included in the list of margin eligible stocks. To reduce the difference in share characteristics between eligible and ineligible stocks to have a more meaningful analysis of their spillover effects, for each eligible stock on each day, we match it with an ineligible stock with similar share characteristics in the same industry. The margin eligible stocks and their matched stocks on each day form our sample of the following empirical analysis.

We obtain most of the data for our sample of stocks such as daily values of market capitalization, price, return, trading volume, quarterly institutional ownership, and daily data on margin trading and short selling of the leverage eligible stocks from the China Stock Market and Accounting Research (CSMAR) database. The matching between the margin eligible stocks and the ineligible stocks follows the method used in Huang and Stoll (1996) and Bacidore and Sofianos (2002). We calculate the sum of squared relative differences (i.e., SSRD) between each margin eligible stock and each ineligible stock within the same industry in three characteristics including stock price, market capitalization and trading volume using equation:

$$SSRD = \left[\frac{Price_E - Price_I}{(Price_E + Price_I)/2}\right]^2 + \left[\frac{Size_E - Size_I}{(Size_E + Size_I)/2}\right]^2 + \left[\frac{Volume_E - Volume_I}{(Volume_E + Volume_I)/2}\right]^2 \tag{1}$$

where the subscript $E$ and $I$ represents eligible and ineligible stocks respectively. We select the ineligible stock within the same industry that minimizes this SSRD as the matching stock for the corresponding margin eligible stock.[4]

This effort of matching, although cannot eliminate, largely reduces the differences between the margin eligible stocks and ineligible stocks in terms of the market capitalization, trading volume and price. Table 2 reports the summary statistics of relevant share characteristics for the margin eligible stocks, all ineligible stocks and matched ineligible stocks. We can see that restricting the sample of ineligible stocks to the matched ones increases their average market capitalization from 4585 million RMB to 6739 million RMB. The average trading volume in the sample of margin ineligible stocks increases from 132 million RMB to 189 million RMB when focusing on the matched ones. The matching has been much more successful in terms of stock prices. The average price for all ineligible stocks is 19.81 while that for matched ineligible stocks is 16.01 which is almost the same with that of the eligible ones. As explained previously, the selection of stocks for margin eligibility is based on the historical market capitalization and trading volume, the setting of the market does not allow us to produce a perfectly matched sample. Unavoidably, there are still significant differences in market capitalization and trading volumes between the margin eligible stocks and matched ineligible stocks even after the matching process. We therefore include market capitalization and trading volume as control variables in the following empirical analysis. We also conduct some robustness checks in Section 4 to eliminate the concern that these differential share characteristics are the sole reason behind the observed spillover effects.

### 3.2. The measurement of spillover effects

In this study, the spillover effects of the margin eligible stocks at each day are proxied by the intraday relative leading effects (i.e., lead-lag effect) of the margin eligible stocks over the ineligible stocks estimated using the vector autoregressive regressions (VAR). This is a variation of the Granger causality approach that is popularly used in the literature on spillover effects and network connections in the financial system (e.g., Goyenko and Ukhov, 2009; Chordia et al., 2011; Smimou and Khallouli, 2016; Farzami et al., 2021). The

[4] The matching was conducted with two options: with replacement and without replacement. Using the without-replacement approach, the matching quality is slightly worse than that in the with-replacement approach. In addition, as there is insufficient number of leverage ineligible stocks in the finance industry, matching cannot be done for the 47 leverage eligible financial stocks. They, therefore, are excluded from our sample for most of the following empirical analysis with the exception of the industry portfolio VAR analysis (i.e., Table 3). The benefit of the with-replacement option is that slightly better matches on relevant share characteristics can be made. However, due to the limited number of ineligible stocks in existence, this method often needs to reuse the same ineligible stocks more than once on each day during the matching process. For example, on each day, on average, there are only around 346 stocks that were selected as the matching ineligible stocks for all the eligible stocks in the with-replacement approach. In order to include more ineligible stocks in our sample, this study reports the empirical evidence from sample formed in the without-replacement approach. Fortunately, most of our conclusions still hold if we use sample formed in the with-replacement approach.

**Table 1**
Short selling and margin trading activities for leverage eligible stocks.

| | Mean | Stdev | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|
| Margin volume (In million RMBs) | 65 | 118 | 0 | 12 | 29 | 71 | 5557 |
| Margin turnover (%) | 18.88 | 7.02 | 0 | 14.09 | 18.57 | 23.16 | 72.30 |
| Margin balance (In million RMBs) | 900 | 858 | 0 | 434 | 670 | 1069 | 19,456 |
| Margin interest (%) | 6.42 | 4.10 | 0 | 3.24 | 5.69 | 8.96 | 29.98 |
| Short volume (In 000 shares) | 182 | 1870 | 0 | 0 | 2 | 42 | 218,618 |
| Short turnover (%) | 0.32 | 0.85 | 0 | 0 | 0.02 | 0.27 | 42.21 |
| Short balance (In 000 shares) | 187 | 615 | 0 | 4 | 38 | 157 | 51,314 |
| Short interest (%) | 0.01 | 0.02 | 0 | 0.0004 | 0.0037 | 0.01 | 0.99 |

Table 1 reports the summary statistics for margin trading and short selling activities among the leverage eligible stocks during our sample period. Margin volume is the dollar amount of stocks purchased on margin at day $n$. Short volume is the number of shares shorted at day $n$. Margin (short) turnover is the margin (short) volume divided by the total trading volume in the day. Margin balance is the dollar balance of margin debt of a stock at day $n$. Short balance is the number of stocks that have been sold short but have not yet been covered at day $n$. Margin interest is margin balance divided by the market value of the stock's floating shares. Short interest is short balance divided by the number of outstanding floating shares of the stock.

**Table 2**
Share characteristics for leverage eligible and ineligible stocks.

| | Mean | Stdev | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|
| *Market capitalization (in million RMBs)* | | | | | | | |
| Margin eligible stocks | 24,063 | 63,726 | 1298 | 7332 | 12,229 | 22,652 | 2,372,158 |
| All ineligible stocks | 4585 | 4620 | 113 | 2090 | 3568 | 5700 | 345,299 |
| Matched ineligible stocks | 6739 | 5628 | 256 | 3937 | 5593 | 8058 | 345,299 |
| *Trading volume (in million RMBs)* | | | | | | | |
| Margin eligible stocks | 343 | 637 | 2 | 71 | 160 | 370 | 49,693 |
| All ineligible stocks | 132 | 217 | 0.0005 | 31 | 68 | 151 | 24,113 |
| Matched ineligible stocks | 189 | 251 | 1 | 55 | 110 | 228 | 24,113 |
| *Price* | | | | | | | |
| Margin eligible stocks | 16.01 | 20.20 | 1.27 | 7.36 | 11.58 | 19.27 | 799.19 |
| All ineligible stocks | 19.81 | 18.66 | 0.21 | 8.71 | 14.27 | 24.27 | 467.57 |
| Matched ineligible stocks | 16.01 | 14.75 | 1.11 | 7.42 | 11.81 | 19.54 | 359.01 |

This table reports the summary statistics of the market capitalization, trading volume and stock price for margin eligible stocks, all ineligible stocks as well as the matched ineligible stocks listed in the Chinese stock markets during our sample period.

Granger causality between two variables indicates a predictive relation between past values of one variable and future values of another. In the traditional Granger causality approach to assess spillover effect, one focuses on testing whether the predictive relation is statistically significant or not. The statistically significant predictive relation between relevant financial time series is often used as evidence to indicate the presence of spillover effect across assets/markets (e.g., Goyenko and Ukhov, 2009; Billio et al., 2012).

However, only paying attention to the statistical significance in the Granger causality test after the VAR estimation suffers from the problem of arbitrary significance level and ignorance of the magnitude of the VAR coefficients (Diebold and Yılmaz, 2014). Alternatively, one can draw on the cross-serial coefficients of the Granger causality regressions to gauge the magnitude of the predictive relation between the dynamic movements of relevant time series data (e.g., Brennan et al., 1993; Chordia and Swaminathan, 2000; Hou, 2007). For example, if past values of one variable have greater predicting power of the future values of another variable than vice versa, it suggests a relative leading effect of, hence spillover effect from, the former variable. The greater the differential predictive coefficients between the two variables, the greater the spillover effects. In this study, we are interested in how the degree of spillover from the margin eligible stocks to ineligible stocks is influenced by margin trading, simply identifying whether there exists a Granger causality relation, that is whether there exists a spillover effect, between the eligible stocks and ineligible stocks isn't sufficient. Therefore, we use the differential predictive coefficients from the Granger causality regression system (i.e., VARs) to construct a measure that can reflect both the direction and the size of the spillover effect between the eligible and matched ineligible stocks.

Specially, we estimate the lead-lag relation (hence spillover effect) between each pair of margin eligible and ineligible stocks/portfolios at each day in order to associate it to the level of margin which changes every day. The lead-lag effect at day $n$ is obtained from the following VARs:

$$S_{E,t} = a_E + \sum_{j=1}^{k} b_j \times S_{E,t-j} + \sum_{j=1}^{k} c_j \times S_{I,t-j} + \varepsilon_{E,t} \tag{2}$$

$$S_{I,t} = a_I + \sum_{j=1}^{k} d_j \times S_{E,t-j} + \sum_{j=1}^{k} e_j \times S_{I,t-j} + \varepsilon_{I,t} \tag{3}$$

where $S_{E,\ t}$ is the liquidity/return of a particular margin eligible stock/portfolio at minute $t$ of day $n$, and $S_{I,\ t}$ is the liquidity/return for this stock's matched non-margin stock/portfolio at minute $t$ of day $n$. We use activity during the regular trading time, that is, the 240 minutes between 9:30 am and 11:30 am and between 1:00 pm and 3:00 pm, to estimate the VAR models for each day. The stock return at minute $t$ is calculated using the stock prices at the end of minute $t$ and minute $t$-$1$. The liquidity is measured by either the percentage effective spread or the Amihud's (2002) price impact measure at minute $t$. In particular, the percentage effective spread is calculated the following way:

$$Effective\ Spread_t = 2|ln(P_t) - ln(M_t)| \tag{4}$$

where $P_t$ is the transaction price at the end of minute $t$, and $M_t$ is the average of best bid and best ask price at the end of minute $t$. The Amihud's (2002) price impact measure at minute $t$ is the absolute value of the stock return in minute $t$ divided by the trading volume within the same minute.

On each day, we run Eqs. (2) and (3) with $k = 1$ or $5$.[5] We then record the coefficients $\sum_{j=1}^{k} b_j$, $\sum_{j=1}^{k} c_j$, $\sum_{j=1}^{k} d_j$, and $\sum_{j=1}^{k} e_j$ for each day and calculate their mean and t-values during our sample period. Among these four coefficients, $\sum_{j=1}^{k} b_j$ and $\sum_{j=1}^{k} e_j$ are autoregressive coefficients while $\sum_{j=1}^{k} d_j$ and $\sum_{j=1}^{k} c_j$ are cross-autoregressive coefficients. The cross-autoregressive coefficients are the ones that capture the predicting power of margin eligible stocks over ineligible stocks and of margin ineligible stocks over eligible stocks. If the sum of coefficients on lagged values for the margin eligible stock/portfolio in Eq. (3) exceeds the sum of coefficients on lagged values for the ineligible stock/portfolio in Eq. (2) (i.e., $\sum_{j=1}^{k} d_j > \sum_{j=1}^{k} c_j$), it suggests that the liquidity/return of the eligible stocks/portfolios lead those of the ineligible ones, and the direction of spillover is from the eligible stocks to ineligible stocks. In addition, the higher the differential coefficients between $\sum_{j=1}^{k} d_j$ and $\sum_{j=1}^{k} c_j$, the stronger the spillover effects from the margin eligible stocks.

In order to evaluate whether the proxy of spillover effect explained above indeed captures what it tends to, we cross check it using some stock market events in which we know, *ex ante*, the direction of spillover among stocks. We identified three stocks (i.e., China Evergrande Group, Evergrande Property Services Group and China Evergrande New Energy Vehicle Group) in HongKong stock markets which have shareholding relations among them and major negative events occurred for two of the three stocks in recent years. Among the three firms, China Evergrande Group is the shareholding company for both Evergrande Property Services Group and China Evergrande New Energy Vehicle Group while there is no shareholding relation between the latter two firms.

The first negative event was on China Evergrande Group.[6] On the 19th July 2021, the stock price of China Evergrande Group declined by 16.22%. The problem with China Evergrande also spread to its two listed subsidiaries (i.e., Evergrande Property and Evergrande Vehicle) at the same day causing their stock prices to decline by 13.38% and 19.10% respectively. We take the minute level data of the three stocks on the 19th July 2021 and calculate the differential cross-serial coefficients between stock returns of China Evergrande and Evergrande Property, and between stock returns of China Evergrande and Evergrande Vehicle. The differential cross-serial coefficients indeed indicate that China Evergrande leads both Evergrande Property and Evergrande Vehicle in terms of price movements. For example, the differential cross-serial coefficients in the five-lag VARs ($\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$) is 0.580 between China Evergrande and Evergrande Property, and it is 0.399 between China Evergrande and Evergrande Vehicle. They are both positive and economically significant which is consistent with our expectation.[7]

The second negative event was on Evergrande Property Services Group.[8] On the 14th March 2022, the stock price of Evergrande Property declined by 11.52%. It was expected that the problem with Evergrande Property should spread to China Evergrande, its controlling shareholder, but not to Evergrande Vehicle who has no direct shareholding relation with Evergrande Property. Our proxy of spillover indeed suggests so. We find that the price movements of the China Evergrande were indeed led by those of the Evergrande Property with the differential cross-serial coefficient from the five-lag VARs being as substantial as −0.883. However, the price movements of Evergrande Vehicle had little lead-lag relation with those of the Evergrande Property as the differential cross-serial

[5] We also tried VARs with $k = 3$ and $k = 10$. Conclusions are qualitatively similar. For the sake of brevity, we only report results with $k = 1$ and $k = 5$.

[6] On 19th July 2021, China Evergrande Group announced its intention to prosecute one Chinese bank, who applied for freezing 0.132 billon RMB of Evergrande's assets, for abusive usage of the procedural preservation before the litigation. Such announcement had made stock market investors to be even more concerned with Evergrande's financial distress which emerged itself at the beginning of 2021. Please see https://xueqiu.com/1593596824/191002473 for more information about the event.

[7] As a reference to determine whether 0.399 and 0.580 are economically significant, we can see in Table 4 that the average lead-lag effect in five-lag VARs between price movements of eligible stock and matched ineligible stock in A-share markets is only 0.077.

[8] On 21st March 2022, all three Evergrande Group firms announced the suspension of trading of their stocks. On the following day, the reason of trading halts became clear: Evergrande Property Services lost 13.4 billion RMB of deposit as the pledge guarantor for a third-party company. Although it was only announced on the 22nd March 2022, the stock market had scented the problem in Evergrande Property Services as early as a week ago and the stock price of Evergrande Property Services declined by 11.52% on the 14th March 2022. Please see more information for this event on https://iqidian.com/news/intellect/2022_03_14-55268982_0.html and https://new.qq.com/rain/a/20220322A0292400.

coefficient was only 0.09. Overall, we find that our proxy of spillover effect provides results that are consistent with expectation in the above discussed scenarios where the existence and direction of spillover effect can be identified *ex ante*.

## 4. Methodology and empirical results on spillover effects

### 4.1. The spillover effects between margin eligible and ineligible industry portfolios

In this section, we demonstrate empirical evidence showing that spillover effects exist between margin eligible and ineligible industry portfolios. On each day during our sample period, we assign all A-shares listed in Shenzhen and Shanghai stock exchanges to one of six industries according to their 2001 CSRC (i.e., China's Securities Regulatory Commission) classifications. The six industries are: (1) Finance; (2) Utilities; (3) Real Estates; (4) Industrials; (5) Commerce; (6) Conglomerate.[9] We then divide stocks in each industry into margin eligible portfolio and ineligible portfolio.

On each day, we firstly calculate return and liquidity for each stock at each minute of the trading time and then average each stock's return and liquidity across the portfolio to get portfolio return and liquidity at each minute. To estimate the spillover effects between margin eligible and ineligible industry portfolios, we run panel vector autoregressions (VARs) stated in Eqs. (2) and (3) using 240 minutes of data on portfolio return and liquidity at each day. The coefficients estimation for both one-lag and five-lag VARs (i.e., $\sum_{j=1}^{k} b_j$, $\sum_{j=1}^{k} c_j$, $\sum_{j=1}^{k} d_j$, and $\sum_{j=1}^{k} e_j$) for each day are averaged across the sample period. The mean values and t-statistics of relevant coefficients are in Table 3.

Results for the one-lag regressions in Panel A of Table 3 show that, in all regressions, $d_1s$ are positive and statistically significant at 1% level. Thus, the lagged liquidity/return of margin eligible portfolios at minute $t-1$ do predict liquidity/return of ineligible portfolios at minute $t$ even when we control the autocorrelation in the liquidity/return of the ineligible portfolios. Similarly, for both liquidity VARs and return VAR, $c_1s$ are positive and statistically significantly different from zero suggesting the predicting power of ineligible portfolios over the eligible ones. However, the last column in Panel A of Table 3 shows that the differences between $d_1s$ and $c_1s$ are significantly positive indicating the spillover from the margin eligible portfolios to the ineligible portfolios. The results in panel B of Table 3 for the five-lag VARs are qualitatively similar to those in Panel A. Table 3 therefore provides strong evidence indicating the leading role of the eligible portfolios and hence the existence of spillover effects from them.

### 4.2. The spillover effect between margin eligible and ineligible stocks

In this section, we aim to verify that the spillover effects of margin eligible portfolios also exist at individual stock level. To this end, we conduct the VARs between return/liquidity of each pair of margin eligible and matched ineligible stocks. In Table 4, we report the mean values and t-statistics for $\sum_{j=1}^{k} b_j$, $\sum_{j=1}^{k} c_j$, $\sum_{j=1}^{k} d_j$, $\sum_{j=1}^{k} e_j$ across all pairs of matched stocks and days during our sample period. We can see that, the leading effects of the margin eligible portfolios over the ineligible portfolios still hold when it comes to individual stocks. For both one-lag VARs and five-lag VARs, the differential cross-autoregressive coefficients between eligible stocks and ineligible stocks are significantly positive at 1% level in both price movements and liquidity.

To demonstrate that the spillover effects from margin eligible stocks reported in Table 4 are not purely because large size stocks with greater volume are more likely to become margin eligible, we conduct an event study to investigate whether the spillover effects in these stocks have increased after they become margin eligible. During our sample period, the list of margin eligible stocks was expanded twice, with the first one on 22nd September 2014 when constitution stocks in the list increased from 700 to 900, and the second one on 12nd December 2016 when it was further increased to 950. There were close to 300 stocks that turned from the status of margin ineligible to margin eligible in these two events.[10] We match these stocks to the best ineligible stocks in the same industry using the method described in Section 3.1, and then compare the spillover effects from the margin eligible stocks in 200 days before and after the event dates.

The results are reported in Table 5. We can see that, even prior becoming margin eligible, relevant stocks still lead the matched ones with significantly positive $d-c$. This is consistent with the fact that these stocks that later became margin eligible tend to be larger in size and higher in trading volume. However, after becoming margin eligible, the $t$-tests of the difference in means in Table 5 indicate that their leading effects increased significantly, especially those in stock return and in the price impact measure of liquidity. For the leading effect in the effective spread measure of liquidity, although the mean values are not significantly different post the events, the Wilcoxon z-statistics suggest that the median values of the leading effects have increased significantly after the relevant stocks become margin eligible. Overall, statistics reported in Table 5 provide support for the claim that being margin eligible contributes to the spillover effects of relevant stocks and the differential share characteristics between margin eligible and ineligible stocks are not the

[9] We use the six industry classifications instead of further divided classification systems as we want to ensure that there are sufficient stocks in each industry when we further split each industry portfolio to margin eligible and ineligible portfolios.

[10] The list of leverage eligible stocks increased from 700 to 900 on 22nd September 2014. However, as 17 stocks have exited from the list due to various reasons before 22nd September 2014, 217 new stocks were added to the list so that the new list can contain 900 stocks. Similarly, on 12nd December 2016, 77 stocks were added to the list so that the new list can contain 950 stocks. Therefore, there are altogether 294 non-leveraged stocks that became leverage eligible in these two events. The number of relevant stocks decreased to 285 when we use the without replacement approach in the matching process.

**Table 3**
Spillover effects between margin eligible and ineligible industry portfolios.

| Panel A: One-lag VARs | | | | | |
|---|---|---|---|---|---|
| | $b_1$ | $c_1$ | $d_1$ | $e_1$ | $d_1 - c_1$ |
| Effective spread | 0.382 | 0.118 | 0.217 | 0.541 | 0.099 |
| | (150.95)*** | (90.94)*** | (85.96)*** | (180.86)*** | (42.66)*** |
| Stock return | 0.408 | 0.089 | 0.517 | 0.130 | 0.428 |
| | (49.56)*** | (15.74)*** | (85.64)*** | (28.87)*** | (39.09)*** |
| Price impact | 0.082 | 0.032 | 0.188 | 0.056 | 0.156 |
| | (28.49)*** | (7.44)*** | (11.22)*** | (24.60)*** | (8.99)*** |

| Panel B: Five-lag VARs | | | | | |
|---|---|---|---|---|---|
| | $\sum_{j=1}^{5} b_j$ | $\sum_{j=1}^{5} c_j$ | $\sum_{j=1}^{5} d_j$ | $\sum_{j=1}^{5} e_j$ | $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$ |
| Effective spread | 0.53 | 0.092 | 0.200 | 0.629 | 0.108 |
| | (178.39)*** | (48.93)*** | (58.70)*** | (191.61)*** | (32.89)*** |
| Stock return | 0.238 | 0.171 | 0.551 | 0.036 | 0.379 |
| | (39.62)*** | (39.59)*** | (94.00)*** | (6.23)*** | (45.27)*** |
| Price impact | 0.197 | 0.079 | 0.445 | 0.145 | 0.366 |
| | (15.65)*** | (17.42)*** | (11.71)*** | (27.89)*** | (9.69)*** |
| Obs. | 1043 | 1043 | 1043 | 1043 | 1043 |

On each day, we form margin eligible and ineligible portfolio for each industry and run VARs in Eqs. (2) and (3) with the minute level effective spread, stock return and price impact measure for these portfolios. This table reports the average spillover effects between margin eligible and ineligible industry portfolios across the 1043 days during our sample period. Obs. is the number of observations that are used in calculating the mean and t-statistics in this table. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

**Table 4**
Stock level spillover effects between margin eligible and ineligible stocks.

| Panel A: One-lag VARs | | | | | |
|---|---|---|---|---|---|
| | $b_1$ | $c_1$ | $d_1$ | $e_1$ | $d_1 - c_1$ |
| Effective spread | 0.184 | 0.010 | 0.018 | 0.209 | 0.009 |
| | (848.64)*** | (100.96)*** | (88.92)*** | (1032.69)*** | (39.26)*** |
| Stock return | −0.096 | 0.045 | 0.075 | −0.069 | 0.030 |
| | (−448.44)*** | (480.49)*** | (558.75)*** | (−337.29)*** | (187.18)*** |
| Price impact | 0.081 | 0.018 | 0.113 | 0.074 | 0.095 |
| | (746.70)*** | (104.83)*** | (78.67)*** | (674.63)*** | (65.46)*** |
| Obs. | 829,551 | 829,551 | 829,551 | 829,551 | 829,551 |

| Panel B: Five-lag VARs | | | | | |
|---|---|---|---|---|---|
| | $\sum_{j=1}^{5} b_j$ | $\sum_{j=1}^{5} c_j$ | $\sum_{j=1}^{5} d_j$ | $\sum_{j=1}^{5} e_j$ | $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$ |
| Effective spread | 0.25 | 0.02 | 0.043 | 0.284 | 0.023 |
| | (906.37)*** | (101.90)*** | (92.88)*** | (1086.52)*** | (46.86)*** |
| Stock return | −0.396 | 0.116 | 0.193 | −0.343 | 0.077 |
| | (−898.04)*** | (477.58)*** | (574.15)*** | (−858.09)*** | (187.97)*** |
| Price impact | 0.189 | 0.073 | 0.433 | 0.176 | 0.361 |
| | (828.97)*** | (151.03)*** | (124.28)*** | (756.53)*** | (102.26)*** |
| Obs. | 826,941 | 826,941 | 826,941 | 826,941 | 826,941 |

On each day, we run VARs in Eqs. (2) and (3) with minute level spread, return and price impact measure of the margin eligible stock against those of the matched ineligible stock. This table reports the mean, and t-statistics, of the relevant coefficients averaged across all pairs of matched stocks and all days during our sample period. Obs. is the number of observations that are used in calculating the mean and t-statistics in this table. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

sole reason behind their spillover effects.

### *4.3. The spillover effects at sub-periods with varying market conditions*

To further improve our understanding of the observed spillover effects in Table 4, we compare the strength of the spillover effects from margin eligible stocks under different market conditions. In Panel A of Table 6, we report the average spillover effects in days with various funding liquidity. We proxy the funding liquidity with the 6-month SHIBOR rate which represents the cost of funding for

**Table 5**
Comparison of spillover effects before and after relevant stocks become margin eligible.

| | One-lag VARs $d_1 - c_1$ | | | Five-lag VARs $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$ | | |
|---|---|---|---|---|---|---|
| Event window | Stock Return | Effective Spread | Price Impact | Stock Return | Effective Spread | Price Impact |
| (−200,−1) | 0.008 | 0.009 | 0.009 | 0.024 | 0.016 | 0.090 |
| | (7.45)*** | (6.65)*** | (2.55)*** | (6.86)*** | (5.84)*** | (6.92)*** |
| (+1,+200) | 0.017 | 0.010 | 0.047 | 0.037 | 0.017 | 0.202 |
| | (12.43)*** | (9.51)*** | (7.66)*** | (12.08)*** | (8.22)*** | (9.03)*** |
| *Difference in mean* | 0.008 | 0.000 | 0.038 | 0.013 | 0.001 | 0.113 |
| *t-statistic* | (4.87)*** | (0.21) | (5.28)*** | (2.73)*** | (0.27) | (4.35)*** |
| *Wilcoxon z-statistic* | (4.96)*** | (1.81)* | (3.68)*** | (3.18)*** | (2.04)** | (2.56)** |

This table reports the pre-event and post-event spillover for the stocks that became leverage eligible on 22nd September 2014 or 31st December 2018. *t-statistic* line tests whether the mean spillover effects are equal between pre-event days and post-event days. *Wilcoxon z-statistic* line tests whether the median values of the spillover effects are equal between pre-event days and post-event days. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

financial intermediaries, and rank all days in our sample period based on the 6-month SHIBOR. We take days in the bottom 20% as the days with low funding liquidity and those in the top 20% as days with high funding liquidity. In high funding liquidity days, the average 6-month SHBIOR rate is 2.94% and it is 4.74% in low funding liquidity days. We then test whether the mean and medium values of the spillover effects are the same in days with different funding liquidity.

Brunnermeier and Pedersen (2009) argue that funding liquidity and stock market liquidity are mutually reinforcing which leads to liquidity spirals. In periods with lower funding liquidity (i.e., greater cost of borrowing), margin constraints of the leveraged traders become tighter. Logically, the deleverage mechanism discussed previously should suggest a stronger liquidity spillover effect from the margin eligible stocks in low funding liquidity days. The results of the liquidity spillover effects reported in Panel A of Table 6 are consistent with this conjecture. For both liquidity measures in both one-lag and five-lag VARs, we find that the leading effects of the margin eligible stocks are much stronger (i.e., with larger mean and median) in days with low funding liquidity than days with high funding liquidity.

In Panel B, we report the spillover effects between margin eligible and ineligible stocks in crisis days and non-crisis days. Based on the historical movements of the HS300 index, we define the crisis period to be days between 16th Jun 2015 and 26th Aug 2015, and days between 31st Dec 2015 and 28th Jan 2016. As displayed in Panel B, we can see that the spillover effects in both return and liquidity are indeed much stronger in crisis days. For example, in the one-lag VAR of effective spread spillover, the $d_1 - c_1$ is 0.012 in crisis days which is almost 40% higher than that in the non-crisis period (i.e., 0.008). Similar patterns can be found in one-lag VARs of stock return and price impact liquidity measure, as well as five-lag VARs. These results are consistent with the deleverage mechanism in which the margin trading induced spillover mostly happen when severe negative shocks occur. However, as we can see in Panel B, the lead-lag relation between margin eligible and ineligible stocks are still significantly positive in non-crisis days, which suggests that there exist other mechanisms that drive the spillover effects from the margin eligible stocks.

### *4.4. The impacts of margin interest on the spillover effects of relevant stocks*

Although we have established that there exist spillover effects from the margin eligible stocks, one could argue that margin eligible stocks are also short eligible and therefore the spillover effects may be caused by the short eligibility of relevant stocks. In this section, we aim to demonstrate that margin interest has significant impacts on relevant stocks' spillover effects even when we control the impacts (if there is any) from the short interest of the same stock, as well as other influential share characteristics.

To this end, we run the following panel regressions using the stock-day (*i, n*) observations:

$$Spillover_{i,n} = \alpha + c_m Margin_{i,n} + c_s Short_{i,n} + \sum_{j=1}^{k} \gamma_j Share\ characteristics_{j,i,n} + \varepsilon_{i,n} \tag{5}$$

To keep the brevity, we focus the following analysis on spillover effects estimated in the five-lag regressions. Therefore $Spillover_{i,n}$ in Eq. (5) is the lead-lag effects estimated in the five-lag VARs for stock $i$ at day $n$. $Margin_{i,n}$ and $Short_{i,n}$ are the margin interest and short interest for stock $i$ at day $n$. We also include a range of control variables that may influence both the spillover effects and the level of margin and short interests. They are the log values of market capitalization, price, and trading volume of the margin (short) eligible and ineligible stocks at day $n$. In addition, we control the institutional ownership of the eligible and ineligible stocks as previous studies have found that institutional ownership is an important determinant of the lead-lag relation in stock markets (e.g., Brennan et al., 1993; Badrinath et al., 1995; Chordia and Swaminathan, 2000).

Several statistical tests ensure that we estimate the regression model in Eq. (5) appropriately. Firstly, the Fisher type unit root test (Choi, 2001) rejects the null hypothesis that all the panels contain a unit root. Secondly, the mean value of variance inflation factors (VIFs) for the explanatory variables of Eq. (5) is 1.97 which eliminates the concern of collinearity. Thirdly, we run the Hausman test (Hausman, 1978) to determine whether fixed effect model or random effect model should be selected. For both return lead-lag and liquidity lead-lags, the null hypothesis of Hausman test is rejected and this suggests that fixed effect models should be used. We

**Table 6**
Stock level spillover effects between margin eligible and ineligible stocks in sub-periods.

Panel A: Spillover effects in periods with different funding liquidity

| | One-lag VARs $d_1 - c_1$ | | Five-lag VARs $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$ | |
|---|---|---|---|---|
| | Effective Spread | Price Impact | Effective Spread | Price Impact |
| High funding liquidity period | 0.008 | 0.060 | 0.022 | 0.227 |
| | (16.21)*** | (26.43)*** | (19.86)*** | (38.48)*** |
| Low funding liquidity period | 0.010 | 0.107 | 0.025 | 0.500 |
| | (20.94)*** | (25.48)*** | (23.10)*** | (49.28)*** |
| *Difference in mean* | 0.002 | 0.043 | 0.003 | 0.274 |
| *t-statistic* | (3.54)*** | (8.92)*** | (2.14)** | (23.32)*** |
| *Wilcoxon z-statistic* | (2.70)*** | (5.14)*** | (2.61)*** | (8.92)*** |

Panel B: Spillover effects in crisis and non-crisis periods

| | One-lag VARs $d_1 - c_1$ | | | Five-lag VARs $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$ | | |
|---|---|---|---|---|---|---|
| | Effective Spread | Stock Return | Price Impact | Effective Spread | Stock Return | Price Impact |
| Non-crisis period | 0.008 | 0.026 | 0.088 | 0.023 | 0.071 | 0.350 |
| | (36.88)*** | (164.69)*** | (58.72)*** | (44.56)*** | (170.31)*** | (95.62)*** |
| Crisis period | 0.012 | 0.089 | 0.207 | 0.027 | 0.177 | 0.543 |
| | (15.86)*** | (99.81)*** | (37.40)*** | (16.74)*** | (90.13)*** | (42.38)*** |
| *Difference in mean* | 0.003 | 0.063 | 0.119 | 0.004 | 0.106 | 0.193 |
| *t-statistic* | (4.38)*** | (69.51)*** | (20.71)*** | (2.24)*** | (52.94)*** | (14.50)*** |
| *Wilcoxon z-statistic* | (7.28)*** | (74.06)*** | (35.53)*** | (8.00)*** | (53.28)*** | (32.17)*** |

In Panel A, we calculate the margin eligible stocks' spillover effects in periods with low and high funding liquidity. Low (high) funding liquidity period includes days with the highest (lowest) 20% of 6-month SHIBOR rate in our sample period. In Panel B, we compare the margin eligible stocks' spillover effects in crisis days (16th Jun 2015 to 26th Aug 2015 and 31st Dec 2015 to 28th Jan 2016) and non-crisis days. For each sub-period specified in Panel A and Panel B, we report the mean spillover effects (i.e., $d_1 - c_1$ and $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$), and the t-statistics, across all pairs of matched stocks and days in the relevant sub-periods. *t-statistic* line tests whether the mean lead-lag relations are equal in different sub periods. *Wilcoxon z-statistic* line tests whether the median values of the spillover effects are equal in different sub periods. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

therefore include both the firm fixed effect and the time fixed effect in the model.[11]

In Panel A of Table 7, we report the correlation matrix for the dependent and explanatory variables in Eq. (5). We can see that prices of the margin eligible stocks and ineligible stocks are highly correlated, we therefore only include one of them in the regression. Panel B of Table 7 reports the regression results for the liquidity spillover and return spillover. We can see that margin interests are significantly positively associated with the spillover effects in return. For example, for return spillover, the coefficient on margin interest is 0.011 with a t-value of 15.46. This suggests that the return spillover effect (i.e., $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$) would increase by 0.011 when the margin interest increases by 1%. Similar results can be found for spillover effects in liquidity. For both liquidity measures, margin interest is positively associated with the liquidity spillover effects.

Although it is not the focus of the paper, the results on the impacts of short interest on spillover effects are a bit mixed. The coefficients on short interest are significantly positive in the regressions of return spillover. But the impacts of short interests on the liquidity spillovers have mixed evidence. The coefficient on the short interest is 10% significant when liquidity is proxied by the price impact measure and it is not statistically significantly different from zero when liquidity is proxied by the effective spread. Overall, the results in Table 7 strongly suggest that, margin trading contributes to the spillover effect from the leverage eligible stocks when all the other influential characteristics and short selling activities of the investors are controlled.

## 5. Mediation models and the mechanism analysis

The increase in the return and liquidity spillover effects due to margin trading is consistent with several possible mechanisms. We argue that, in addition to the deleverage mechanism that has been verified in the literature, the cross-asset learning mechanism is also an important complementary mechanism. In particular, there are three potential channels through which the margin trading could give rise to the spillover effects of relevant stocks in the cross-asset learning mechanism: namely the price discovery channel, the liquidity channel and the volatility channel. To confirm this, we follow Malceniece et al. (2019) and estimate multiple mediation models to investigate how much of the spillover effects are contributed by these channels.

[11] To reduce the influences from outliers, we winsorize the top and bottom 1% for all variables in Eq. (5).

**Table 7**
The impacts of margin interest on spillover effects from the margin eligible stocks.

Panel A: Correlation matrix for the dependent and explanatory variables in Eq. (4)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Stock return spillover | 1 | | | | | | | | | | | | |
| (2) Price impact spillover | 0.034 | 1 | | | | | | | | | | | |
| (3) Effective spread spillover | 0.005 | 0.005 | 1.000 | | | | | | | | | | |
| (4) Short interest | 0.032 | 0.050 | 0.001 | 1.00 | | | | | | | | | |
| (5) Margin interest | 0.007 | −0.031 | −0.004 | 0.067 | 1 | | | | | | | | |
| (6) $Size_E$ | 0.085 | 0.121 | 0.010 | 0.131 | −0.580 | 1 | | | | | | | |
| (7) $Size_I$ | −0.035 | −0.069 | −0.005 | −0.090 | −0.129 | 0.154 | 1 | | | | | | |
| (8) $Volume_E$ | 0.071 | 0.117 | 0.003 | 0.249 | 0.030 | 0.507 | 0.043 | 1 | | | | | |
| (9) $Volume_I$ | 0.023 | −0.050 | −0.003 | 0.110 | 0.127 | 0.202 | 0.303 | 0.706 | 1 | | | | |
| (10) $Price_E$ | 0.036 | −0.006 | −0.008 | 0.130 | −0.052 | 0.240 | 0.162 | 0.401 | 0.410 | 1 | | | |
| (11) $Price_I$ | 0.035 | −0.006 | −0.007 | 0.131 | −0.057 | 0.254 | 0.171 | 0.412 | 0.419 | 0.991 | 1 | | |
| (12) $IO_E$ | −0.016 | −0.001 | −0.001 | 0.042 | −0.241 | 0.148 | 0.067 | −0.105 | −0.124 | 0.091 | 0.093 | 1 | |
| (13) $IO_I$ | −0.027 | −0.020 | −0.002 | 0.062 | −0.116 | 0.055 | 0.176 | −0.143 | −0.111 | 0.120 | 0.123 | 0.429 | 1 |

Panel B: Regression results on the impacts of margin interest on spillover effects

| | Margin interest | Short interest | $Size_E$ | $Volume_E$ | $Price_E$ | $IO_E$ | $Size_I$ | $Volume_I$ | $IO_I$ | Constant | Obs. | $Adj\_R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock return spillover | 0.011 | 0.437 | 0.056 | −0.014 | 0.010 | 0.044 | −0.025 | −0.008 | −0.022 | −0.341 | 671,550 | 3.94% |
| | (15.46)*** | (4.22)*** | (10.28)*** | (−8.90)*** | (1.89)* | (1.91)* | (−15.48)*** | (−6.34)*** | (−2.18)** | (−3.02)*** | | |
| | 0.031 | 1.269 | 0.277 | 0.685 | −0.075 | −0.023 | −0.005 | −0.708 | −0.372 | −5.842 | | |
| Price impact spillover | (7.71)*** | (1.74)* | (6.38)*** | (32.34)*** | (−2.28)** | (−0.16) | (−0.42) | (−33.70)*** | (−5.24)*** | (−6.42)*** | 671,550 | 5.27% |
| Effective spread spillover | 0.002 | −0.038 | 0.012 | −0.004 | −0.007 | −0.026 | −0.010 | −0.002 | 0.009 | 0.090 | | |
| | (3.87)*** | (−0.47) | (2.34)** | (−2.48)** | (−1.59) | (−1.69)* | (−5.54)*** | (−1.46) | (0.89) | (0.85) | 671,550 | 0.66% |

We regress the spillover effects between each pair of margin eligible and ineligible stocks against the margin interest of the margin eligible stock in the pair. Dependent variables are spillover effects in stock return, effective spread and price impact and they are calculated from the coefficients in the five-lag VARs in Eq. (5). Margin interest is margin balance divided by the market value of the stock's floating shares. Short interest is short balance divided by the number of outstanding floating shares of the stock. Size, volume and price for relevant stocks are taken as the logged values. IO represents the institutional ownership of the stock. The coefficients on IO have been multiplied by 100. The subscripts *E* and *I* represent leveraged and non-leveraged stocks respectively. Obs. is the number of observations used in the regression. $Adj\_R^2$ is the adjusted $R^2$ of the regression. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels.

### 5.1. Mediation models and mechanism analysis

Mediation is the process in which some variables exert influences on other variables through mediator variables (Preacher and Hayes, 2008). Mediator models have been widely adopted in research of psychology and social science. They allow researchers to assess the effect of a proposed cause ($X$) on some outcome ($Y$) through proposed mediators (e.g., $M_1 \ldots M_j$). According to Baron and Kenny (1986), a particular mediation channel $M_j$ can be verified if the following requirements can be met: 1) $X$ significantly affects $Y$; 2) $X$ significantly affects $M_j$; 3) $M_j$ significantly affects $Y$ when $X$ is controlled. 4) $X$'s effect on $Y$ decreases substantially when $M_j$ is controlled. These requirements can be evaluated through a series of regressions that involve the dependent variable $X$, the independent variable $Y$, the proposed mediator variables ($M_1$, $M_2 \ldots M_j$ etc) as well as the control variables which may confound the relationships among $X$, $Y$ and $M_j$s.

In our study, the outcome variable $Y$ is the spillover effect in liquidity or return between margin eligible and ineligible stocks. The key independent variable $X$ is the margin interest which captures the level of leverage in long position in each stock. We have three mediators of interest. Firstly, the liquidity and volatility channels of the cross-asset learning theory implies that the margin trading contributes to the leading effects of relevant stocks through its impacts on the liquidity and volatility, hence the quality of the price signals, of the margin eligible stocks. Therefore, we use the liquidity and volatility of the margin eligible stocks as the mediators for these two channels. We calculate the volume-weighted average of the percentage effective spread across the 240 min of trading time on each day as the liquidity (i.e., *Illiquidity*) of the eligible stock during day $n$, and the standard deviation of the minute level stock returns across the 240 min of trading time as the volatility of eligible stock $i$ at day $n$ (i.e., *Volatility*).

To construct the mediator for the price discovery channel, we calculate a *Delay* variable which is designed to reflect the speed of information adjustment of a particular stock using a similar method developed by Hou and Moskowitz (2005) and used in Malceniece et al. (2019). Our *Delay* variable at day $n$ is estimated from the $R^2$s in the following two regressions that use minute level data in a day:

$$r_{i,t} = \alpha_i + \sum_{j=0}^{4} \beta_{i,j} r_{m,t-j} + \varepsilon_{i,t} \# \tag{6}$$

$$r_{i,t} = \alpha_i + \sum_{j=0}^{9} \beta_{i,j} r_{m,t-j} + \varepsilon^{r}_{i,t} \tag{7}$$

where $r_{i,t}$ is the return for stock $i$ at minute $t$ and $r_{m,t-j}$ is the market return at minute $t$-$j$. The $R^2$ from Eq. (6), which reflects how much $r_{i,t}$ can be explained by the contemporaneous and four lagged market returns (i.e., recent five minutes of market returns), is saved as $R^{2,\ four\ lags}_{i,\ n}$. The $R^2$ from Eq. (7), which reflects how much $r_{i,t}$ can be explained by the contemporaneous and nine lagged market returns (i.e., recent ten minutes of market return), is saved as $R^{2,\ nine\ lags}_{i,\ n}$. The *Delay* at day $n$ is calculated the following way:

$$Delay = \frac{R^{2,nine\ lags}_{i,n} - R^{2,four\ lags}_{i,n}}{R^{2,nine\ lags}_{i,n}} \tag{8}$$

It is essentially the proportion of return variations that is explained by the five additional lags of market returns (i.e., $r_{m,t-5}$ to $r_{m,t-9}$) in Eq. (7). The greater the *Delay,* the less that $r_{i,t}$ has responded to the more recent five minutes of market returns (i.e., $r_{m,t}$ to $r_{m,t-4}$), hence, the slower the speed of information adjustment in stock $i$.[12]

Once the mediators for the cross-asset learning channels are determined, we run the following regressions to test the impacts of the margin interest on the three mediators:

$$Illiquidity_{i,n} = \alpha_1 + a_{m1} Margin_{i,n} + a_{s1} Short_{i,n} + \sum_{j=1}^{k} \rho_j Share\ characteristics_{j,i,n} + \varepsilon_{i,n} \tag{9}$$

$$Volatility_{i,n} = \alpha_2 + a_{m2} Margin_{i,n} + a_{s2} Short_{i,n} + \sum_{j=1}^{k} \theta_j Share\ characteristics_{j,i,n} + \varepsilon_{i,n} \tag{10}$$

$$Delay_{i,n} = \alpha_3 + a_{m3} Margin_{i,n} + a_{s3} Short_{i,n} + \sum_{j=1}^{k} \delta_j Share\ characteristics_{j,i,n} + \varepsilon_{i,n} \tag{11}$$

The share characteristics variables in the above set of regressions are the same with those in Eq. (5). Firm fixed effect and time fixed effect are also controlled in Eqs. (9), (10), and (11).

Finally, we include the three mediators in Eq. (5), and re-estimate the impacts of margin interest on the return or liquidity spillover effects:

[12] As a robustness check, we also calculate an industry delay variable that reflects the speed of price adjustment to industry level information. The industry delay variable is highly correlated ($\rho = 0.85$) with *Delay* which reflects the speed of price adjustment to market wide information. All of our conclusions still hold if we replace *Delay* with this industry delay variable in the following empirical analysis.

**Table 8**
The impacts of margin interest on mediators and the direct effect of margin interest on spillover effects.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Illiquidity | Volatility | Delay | Price impact spillover | Effective spread spillover | Stock return spillover |
| Margin interest | −0.030 | −0.037 | −0.047 | 0.020 | 0.001 | 0.005 |
| | (−18.32)*** | (−21.72)*** | (−18.68)*** | (5.12)*** | (1.67)* | (8.05)*** |
| Short interest | −0.378 | 0.505 | −1.805 | 1.305 | −0.030 | 0.482 |
| | (−1.73)* | (2.02)** | (−5.36)*** | (1.80)* | (−0.37) | (4.80)*** |
| $Delay_E$ | | | | −0.016 | 0.001 | −0.007 |
| | | | | (−3.39)*** | (1.21) | (−12.16)*** |
| $Volatility_E$ | | | | −0.200 | −0.020 | −0.130 |
| | | | | (−6.70)*** | (−4.52)*** | (−27.39)*** |
| $Illiquidity_E$ | | | | −0.100 | −0.011 | −0.022 |
| | | | | (−5.15)*** | (−4.51)*** | (−8.72)*** |
| $Size_E$ | −0.171 | −0.278 | −0.184 | 0.202 | 0.005 | 0.014 |
| | (−11.88)*** | (−16.81)*** | (−8.32)*** | (4.88)*** | (0.90) | (2.80)*** |
| $Volume_E$ | 0.001 | 0.270 | −0.081 | 0.738 | 0.001 | 0.021 |
| | (0.35) | (62.49)*** | (−12.87)*** | (30.59)*** | (0.52) | (10.64)*** |
| $Price_E$ | −0.405 | −0.098 | 0.039 | −0.134 | −0.013 | −0.012 |
| | (−23.22)*** | (−6.73)*** | (1.86)* | (−4.08)*** | (−3.01)*** | (−2.57)** |
| $IO_E$ | −0.187 | −0.205 | −0.450 | −0.090 | −0.032 | 0.010 |
| | (−3.47)*** | (−3.46)*** | (−5.36)*** | (−0.62) | (−2.07)** | (0.46) |
| $Size_I$ | −0.008 | −0.015 | −0.037 | −0.010 | −0.010 | −0.027 |
| | (−3.96)*** | (−6.71)*** | (−10.23)*** | (−0.78) | (−5.75)*** | (−17.07)*** |
| $Volume_I$ | −0.007 | −0.018 | −0.016 | −0.713 | −0.003 | −0.011 |
| | (−5.05)*** | (−9.85)*** | (−4.76)*** | (−33.74)*** | (−1.73)* | (−8.33)*** |
| $IO_I$ | −0.135 | −0.138 | −0.248 | −0.417 | 0.005 | −0.044 |
| | (−8.95)*** | (−9.07)*** | (−9.12)*** | (−5.81)*** | (0.50) | (−4.47)*** |
| Constant | −1.116 | −3.882 | 5.453 | −6.645 | −0.003 | −0.832 |
| | (−3.50)*** | (−11.15)*** | (11.33)*** | (−7.17)*** | (−0.03) | (−7.68)*** |
| Obs. | 70.50% | 73.04% | 26.64% | 5.30% | 0.67% | 4.73% |
| Adj_R2 | 671,550 | 671,550 | 671,550 | 671,550 | 671,550 | 671,550 |

In columns (1) to (3), we regress the three mediators for the cross-asset learning mechanism against the margin interest as well as the control variables. In columns (4) and (5), we regress the return and liquidity spillover effects against the margin interest, the three mediators and the other control variables. *Illiquidity* is the volume weighted average of the percentage effective spread across the 240 minutes of trading time for stock *i* at day *n*. *Volatility* is the standard deviation of the minute level stock returns across the 240 minutes of trading time for stock *i* at day *n*. *Delay* is calculated using Eq. (8). Liquidity and return spillover effects are calculated from the coefficients in the five-lag VARs in Eq. (5) (i.e., $\sum_{j=1}^{5} d_j - \sum_{j=1}^{5} c_j$). Margin interest is margin balance divided by the market value of the stock's floating shares. Short interest is short balance divided by the number of outstanding floating shares of the stock. Size, volume and price for relevant stocks are taken as the logged values. *IO* represents the institutional ownership of the stock. The coefficients on *IO* have been multiplied by 100. The subscripts *E* and *I* represent leveraged and non-leveraged stocks respectively. Obs. is the number of observations used in the regression. Adj_R$^2$ is the adjusted R$^2$ of the regression. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

$$Spillover_{i,n} = \alpha' + c_m' Margin_{i,n} + c_s' Short_{i,n} + b_1 Illiquidity_{i,n} + b_2 Volatility_{i,n} + b_3 Delay_{i,n} + \sum_{j=1}^{k} \varphi_j Share\ characteristics_{j,i,n} + \varepsilon_{i,n} \tag{12}$$

This allows us to estimate the impacts of mediators on the return/liquidity spillover effects, as well as the remaining influence of margin interest on spillover effects when the channels represented by the mediators are taken into consideration. If margin interest has significant impacts on a particular mediator, this mediator also has significant impacts on the return and liquidity spillover, and the two impacts have the same signs, we can conclude that the channel represented by that mediator indeed plays its role in bridging the margin interests and the spillover effects. In addition, after all the mediators are controlled, the coefficients on margin interest in Eq. (12) give us the direct and remaining effect of margin trading on return/liquidity spillover without go through the mediators. As previously discussed, this direct effect is most likely to be caused by the deleverage mechanism. If there are any other mechanisms that we did not identify, it should also be reflected in this remaining effect.

### 5.2. Empirical results for the mechanism analysis

The results for the regressions of mediators are reported in columns (1) to (3) in Table 8. In columns (1) and (2), we can see that margin interest could reduce both *Illiquidity* and *Volatility* of the margin eligible stocks. This is consistent with many existing work (e.g., Chang et al., 2014; Kahraman and Tookes, 2017; Ye et al., 2020) which find that illiquidity and volatility generally reduces after the ban of the margin trading was lifted. Column (3) of Table 8 shows that, margin interest also reduces the *Delay* of the margin eligible stocks. This is consistent with Chang et al. (2014) and Chen et al. (2016) who find that the price efficiency of the margin eligible stocks improves after the leverage constraint is lifted. In summary, columns (1), (2) and (3) in Table 8 indicate that margin trading have significant impacts on the three mediators for the cross-asset learning mechanism.

We then add all three mediators in the regressions of spillover effects on margin interest. Columns (4) and (5) of Table 8 report the regression results for the two liquidity spillover effects, one in effective spread measure and another one in price impact measure. Firstly, we find that, for both measures, both *Illiquidity* and *Volatility* are significantly negatively associated with the liquidity spillover effects suggesting that lower *Illiquidity* and *Volatility* will increase the liquidity spillover. This is consistent with our arguments of the liquidity and volatility channels of the cross-asset learning mechanism. The impacts of *Delay* on the liquidity spillover are mixed, with significantly negative coefficient in column (4), but not significant coefficient in column (5). Therefore, the price discovery channel seems to be a contributing factor to the liquidity spillover when liquidity is proxied by the price impact measure, but not when the liquidity is proxied by the effective spread measure.

Secondly, in Table 8, the coefficients on margin interest in the regressions of price impact spillover (column 4) and effective spread spillover (column 5) are 0.020 and 0.001 respectively. They are reduced significantly compared with those reported in Panel B of Table 7. This suggests that, the cross-asset learning channels have contributed substantially to the liquidity spillover. However, since the coefficients on margin interest in the regressions of both liquidity spillover in Table 8 are still significantly positive after we control the cross-asset learning mediators, this suggests that cross-asset learning mechanism cannot explain all the relation between margin interest and liquidity spillover effects. Other mechanism, such as the deleverage mechanism, may exist.

In column (6) of Table 8, we report the regression results for the return spillover when the mediators for the cross-asset learning channels are controlled. Similar to that in the liquidity spillover, both *Illiquidity* and *Volatility* are significantly negatively associated with the return spillover. For the price discovery channel, the coefficient on *Delay* in column (6) is also significantly negative. Therefore, these results confirm the usefulness in all three cross-section learning channels in causing the return spillover effects from the margin eligible stocks. The coefficient on margin interest reduced significantly from 0.011 in panel B of Table 7 to 0.005 in column (6) of Table 8 indicating that these three channels can explain away more than 50% of the relation between margin trading and return spillover. Furthermore, despite the reduction in magnitude, the coefficient on margin interest is still significantly positive suggesting that deleverage channel also plays its role in causing the return spillover between margin eligible stocks and ineligible stocks.

In Fig. 2, we graphically illustrate the results of column (4) of Table 8 and demonstrate the percentage explanatory power of each cross-asset learning channel in explaining the relation between margin interest and the price impact spillover. We can see that the mediators in the cross-asset learning channels (including *Delay, Illiquidity* and *Volatility*) contribute 36.15% to the relation between margin interest and price impact spillover.[13] Among them, the price discovery channel contributes 2.38% and the liquidity and volatility channels contribute 9.87% and 23.90% respectively.[14] In Fig. 3, we illustrate the results for the effective spread spillover effect. We can see that the three mediators in the cross-asset learning channels can explain away 56.74% of the relation between margin interest and effective spread spillover effect. In addition, most of the explanatory power (i.e., 39.54%) still comes from the *Volatility* channel. In Fig. 4, we illustrate the mediation process for the return spillover effect. The volatility channel in the cross-asset learning mechanism, which explains 45.32% of the total effect of margin interest, is again the most important driving force. The liquidity channel and price discovery channel provide 6.45% and 3.20% of the explanatory power of the effect of margin interest on return spillover respectively. Adding together, the cross-asset learning channels explain 54.98% of the impact of margin interest on the return spillover effect. In summary, Figs. 2, 3 and 4 indicate that the cross-asset learning mechanism is a very important driving force that gives rise to the spillover effects of the margin eligible stocks. In cases of return spillover and spread spillover, it even explains more than 50% of the impacts of margin interest.

## 6. Conclusions

The impact of margin trading on stock markets has been a continuous topic in the literature. Existing empirical studies mostly suggest that margin trading improves stock market quality. Despite the theoretical work which predicts that margin trader's deleverage behavior may lead to contagion effects and increased systematic risk, direct empirical support to such prediction is relatively scare. In this paper, we document the significant spillover effects in price movements and liquidity from the margin eligible stocks to ineligible stocks. In addition, we show that the level of margin interest is significantly positively associated with the degree of margin stocks' spillover effects. Our paper, therefore, complements several recent work which discovers that margin trading causes illiquidity contagion and co-movements in crisis period (e.g., Hu et al., 2019; Kahraman and Tookes, 2020; Bian et al., 2021).

Beyond that, we extend the analysis of spillover effects from crisis periods to non-crisis periods. We discover that the spillover effects from the margin eligible stocks are still significant, both economically and statistically, in tranquil periods. We suggest that the deleverage process of traders is unlikely to be the only mechanism behind the margin induced spillover effects.

To provide a new mechanism, we build on the cross-asset learning theory and propose several channels within its framework to explain why margin trading may lead to spillover effects. The empirical results largely support our hypothesis. We find that margin trading could reduce the volatility, and increase the liquidity and price discovery of margin eligible stocks. All these influences improve the price signals of the margin eligible stocks and thus promote the information spillover from them. Such findings provide empirical supports to the cross-asset learning theory and highlight the information spillover as an important rationale behind the stock market

[13] The explanatory power for all three mediators is calculated the following way: $\left(1-\frac{c_m'}{c_m}\right)\times 100\% = 36.15\%$

[14] The explanatory power for each channel is calculated the following way: 1) Delay channel: $\left(1-\frac{c_m'}{c_m}\right)*\left(\frac{a_{m3}*b_3}{a_{m1}*b_1+a_{m2}*b_2+a_{m3}*b_3}\right)\times 100\% = 2.38\%$; 2) Liquidity channel: $\left(1-\frac{c_m'}{c_m}\right)*\left(\frac{a_{m1}*b_1}{a_{m1}*b_1+a_{m2}*b_2+a_{m3}*b_3}\right)\times 100\%=9.87\%$; 3) Volatility channel: $\left(1-\frac{c_m'}{c_m}\right)*\left(\frac{a_{m2}*b_2}{a_{m1}*b_1+a_{m2}*b_2+a_{m3}*b_3}\right)\times 100\% = 23.90\%$

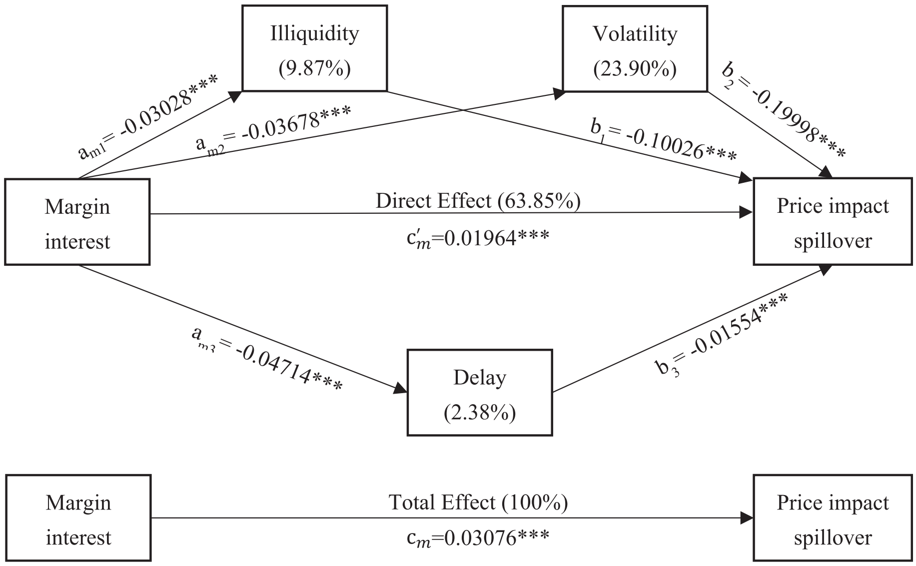


**Fig. 2.** Total effect, direct effect and mediation effects of the margin interest on the price impact spillover.

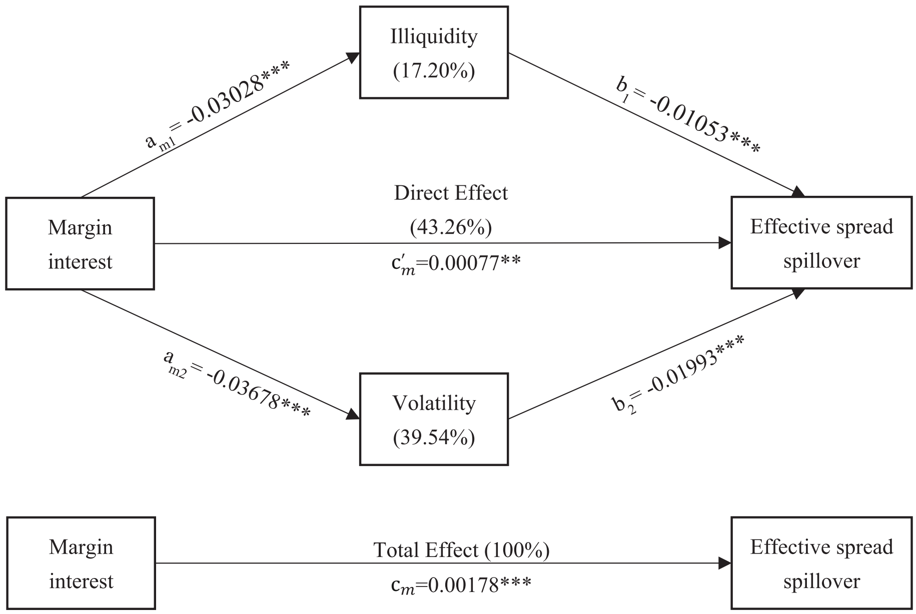


**Fig. 3.** Total effect, direct effect and mediation effects of the margin interest on the effective spread spillover.

commonalities.

Overall, the empirical results in this study help us to understand whether and why margin trading promotes the stock market spillover effects. It also provides useful insights to stock market regulators to design policy that aims to prevent the contagion and spillover of negative shocks across stocks.

## CRediT authorship contribution statement

**Shengjie Zhou:** Data curation, Formal analysis. **Qing Ye:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing, Supervision.

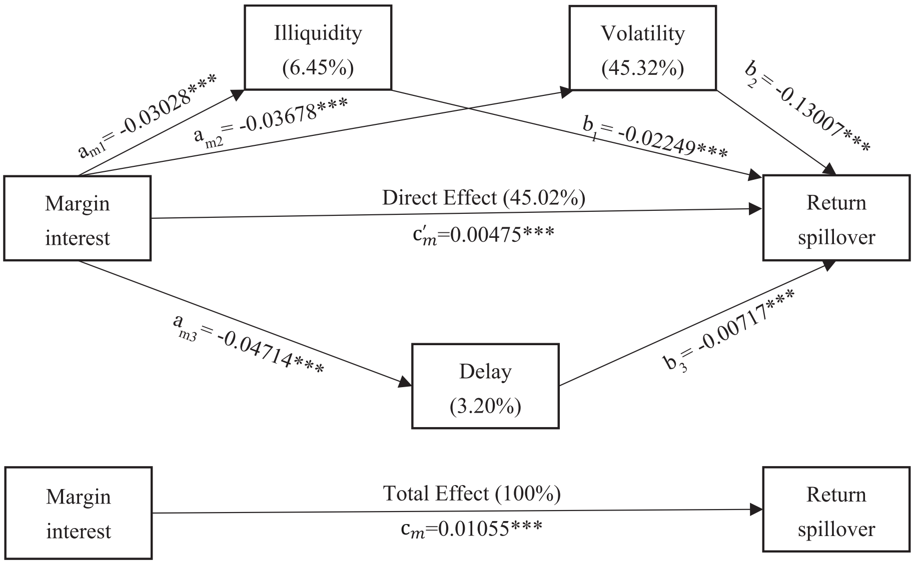


**Fig. 4.** Total effect, direct effect and mediation effects of margin interest on the return spillover.

## Data availability

The authors do not have permission to share data.


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