FACULTY OF ECONOMICS AND
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Essays on Empirical Asset Pricing

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To my parents

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"Let's withdraw and meet the time as it seeks us."

"让我们泰然若素，与自己的时代狭路相逢"

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[1] My preferred translation of "resilience" in Chinese is "士不可以不弘毅", which I find to be the most inspiring trait that I have learnt from you.

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Nederlandstalige samenvatting

De hoofdstukken in dit proefschrift bestuderen verschillende aspecten van empirische activaprijsstelling. De eerste twee artikelen gaan over de voorspelbaarheid van seizoensgebonden rendementen in dwarsdoorsneden op de aandelenmarkt. Het laatste werk richt zich op het thema van eigendomsconcentratie en marktkwaliteit. Dit proefschrift bestaat uit vijf hoofdstukken. **Hoofdstuk 1** biedt een algemene inleiding. **Hoofdstukken 2-4** presenteren respectievelijk de onderzoeksstudie**. Hoofdstuk 5** trekt de conclusie en bespreekt de implicaties. Hieronder volgt een korte samenvatting van **Hoofdstukken 2-4**.

Hoofdstuk 2 onderzoekt of het proces van private geldcreatie (ook bekend als "cash investing") andere financiële activa en instrumenten buiten de geldmarkt kan beïnvloeden, d.w.z. de aandelenmarkt. We vinden een uniek patroon van dagelijkse rendementsseizoensgebondenheid op de Chinese aandelenmarkt: long-short anomalie strategieën die niet-speculatieve aandelen kopen en speculatieve aandelen verkopen ervaren lage rendementen van maandag tot woensdag en hoge rendementen van donderdag tot vrijdag. We stellen voor dat de kenmerkende eigenschap van rendementsaccumulatie op de geldmarkt en de weekdaghandelsinstelling speculatieve aandeelhouders stimuleert om op een specifieke dag veiligheid te zoeken, en dit "veiligheidsvraagmechanisme" drijft de dagelijkse seizoensgebondenheid in dwarsdoorsneden op de aandelenmarkt. De causaliteitsinference van het veiligheidsvraagmechanisme wordt aangepakt met het verschil-in-verschillen model door de FinTech-revolutie van 2013 op de geldmarkt als natuurlijk experiment te nemen. Bovendien tonen de resultaten aan dat de vergrote seizoensgebondenheid voornamelijk afkomstig is van speculatieve aandelen, en dit effect is meer uitgesproken in perioden van hoge volatiliteit.

Hoofdstuk 3 presenteert een opvallend puzzel van het rendement aan het einde van de dag in de dwarsdoorsnede van de aandelenrendementen in China: een lang-minus-kort mispricing factor vertoont significant positieve rendementen in het laatste halfuur handelsinterval, maar presteert slecht tijdens de andere daghandelsperiode. Dit patroon is omgekeerd vergeleken met dat in de VS (Bogousslavsky 2021), dus de institutionele beperkingen en nachtelijke risicoverklaringen voorgesteld door Bogousslavsky (2021) zijn niet van toepassing in ons geval. We schrijven deze puzzel van het rendement aan het einde van de dag toe aan het dispositie-effect. Beleggers, vooral speculatieve aandelenbeleggers, hebben een sterkere neiging om aandelen met eerdere kapitaalwinsten (hoge CGO) aan het einde van de dag te verkopen. We testen onze hypothese met behulp van de dubbele sorteermethodologie en Fama-MacBeth regressie. Bovendien is de markt aan het einde van de dag (laatste halfuur) liquider met minder transactiekosten en een kleinere prijsimpact, wat beleggers een optimale periode biedt om hun portefeuille te herbalanceren.

Hoofdstuk 4 onderzoekt de relatie tussen eigendomsconcentratie en marktprestaties aan de hand van het geval van het economische stimuleringspakket na de wereldwijde financiële crisis van 2008 in China. De aan de overheid gerelateerde eigendomsconcentratie in staatsbedrijven (SOE's) wordt na de implementatie van het stimuleringspakket na de crisis van 2008 prominenter vanwege hun rol als efficiënt fiscaal instrument voor de overheid. Deze meer uitgesproken controleconcentratie leidt tot zorgen over ineffectief ondernemingsbestuur en kan verder de marktkwaliteit verslechteren. Empirisch gebruiken we de panelgegevens OLS-regressie om het effect van eigendomscontrole op de marktprestaties te testen door het economische stimuleringspakket als de schok op de eigendomsstructuur van de SOE's te nemen. We vinden dat SOE's minder liquiditeit, volatiliteit en efficiëntie vertonen dan andere entiteiten, vergeleken met de periode voor de stimulans op lange termijn. Ook leidt het beleid van het stimuleringspakket tot een afname van de winstgevendheid voor SOE's op de aandelenmarkt.

Summary

The chapters in this dissertation study different aspects of empirical asset pricing. The first two papers work on cross-sectional return seasonality predictability in the stock market. The last work focuses on the topic of ownership concentration and market quality. This dissertation comprises five chapters. **Chapter 1** provides a general introduction. **Chapters 2-4** present the research study respectively. **Chapter 5** draws the conclusion and discusses the implications. A brief summary of **Chapters 2-4** is given below.

Chapter 2 examines whether the process of private money creation (aka “cash investing) could affect other financial assets and instruments beyond the money market, i.e., the stock market. we find the unique pattern of the daily return seasonality in the Chinese stock market: Long-short anomaly strategies that buy nonspeculative stocks and sell speculative stocks experience low Monday-through-Wednesday returns and high Thursday-through-Friday returns. We propose that the distinctive feature of yield accrual on the money market and the weekday trading institution incentivizes speculative stockholders to seek safety on a specific day and this “demand-for-safety mechanism” drives the cross-sectional daily seasonality in the stock market. Causality inference of the demand-for-safety mechanism is addressed using the Difference-in-differences model by taking the 2013 FinTech revolution on the money market as the natural experiment. Moreover, the results show that the enlarged seasonality comes mainly from speculative stocks, and this effect is more pronounced in high volatility periods.

Chapter 3 presents a distinctive end-of-day return puzzle in the cross-sectional stock returns in China: Long-minus-short mispricing factor exhibits significantly positive returns at the last half-hour trading interval but performs poorly during the other daytime trading period. This pattern is reversed compared to it in the US (Bogousslavsky 2021), thus the institutional constraints and overnight risk explanations proposed by Bogousslavsky (2021) are not applicable in our case. We attribute this end-of-day return puzzle to the disposition effect. Investors, especially speculative stock investors, have a stronger tendency to sell out stock with prior capital gains (high CGO) at the end of the day. We test our hypothesis using the double-sorting methodology and Fama-MacBeth regression. Moreover, at the end of the day (last half-hour) the market is more liquid with less transaction cost and smaller price impact, offering investors an optimal period to rebalance their portfolio.

Chapter 4 examines the relationship between ownership concentration and market performance using the case of the economic stimulus package after the 2008 global financial crisis in China. The government-related ownership concentration in state-owned enterprises (SOEs) becomes more salient after the implementation of the stimulus package after the 2008 crisis due to their role as an efficient fiscal instrument for the government. This more pronounced control concentration leads to ineffective corporate governance concerns and further can deteriorate the market quality. Empirically, we use the panel data OLS regression to test the effect of ownership control on the market performance by taking the economic stimulus package as the shock on the SOEs' ownership structure. We find that SOEs exhibit less liquidity, volatility, and efficiency than other entities, relative to the pre-stimulus period in the long-term period. Also, the stimulus package policy leads to decreased profitability for SOEs in the stock market.

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Chapter 1

Introduction

The chapters in this dissertation cover different aspects of empirical asset pricing. The first two Chapters work on return seasonality. One of the most striking anomalies challenging the efficient market hypothesis (EMH) is the return seasonality, which has attracted much attention not only in academic journals but also in the financial press. Asset price seasonalities could be driven by investors' predictable trading. In other words, systematic variation in investors' demand for specific types of assets, e.g., risky assets, from one period to the next could dislocate asset prices from fundamental values (Heston, Korajczyk, and Sadka 2010; Keloharju, Linnainmaa, and Nyberg 2021).

Over the past several decades, one of the most popular seasonality effects is the day-of-the-week effect documented by Cross (1973) firstly in academic literature. Cross (1973) finds that in the U.S. stock market, stock prices have risen on Fridays more often than on any other day of the week and have the tendency to decrease on Mondays. Recently, using the new testing approach, Alt, Fortin, and Weinberger (2011) revisited the Monday effect in the US, UK, and German stock markets. Their finding supports previous findings of a Monday effect for the 1970s and 1980s, while also documenting that the Monday effect has vanished after the 1990s in three markets. Various competing explanations have been proposed regarding this generalized weekday effect (Monday and Friday effect), including short sellers having a tendency to close positions over non-trading periods such as weekends (Chen and Singal 2003), the timing of corporate news releases, e.g., earning and dividend announcements (Damodaran 1989), and the comparative advantage of informed investors when market first open after the weekend (Foster and Viswanathan 1990).

All the research above focuses on the market-level returns. Birru (2018) firstly examines the day-of-the-week effect of the U.S. stock market using the cross-sectional returns. He finds that long-minus-short anomalies which the speculative leg is the short leg and the unspeculative leg is the long leg can experience the highest returns on Monday and lowest returns on Friday. Birru (2018) states that the day-of-the-week seasonality predictability can emanate from investor's sentiment. Investors' mood elevates on Friday and decreases on Monday, thus, investors tend to evaluate future markets more optimistically on Friday than any other day. Following the study of Birru (2018), Chiah and Zhong (2021) evaluate the impact of investor mood on the cross-sectional returns of the Austrian stock market. They document that Australian stock returns on Tuesday are significantly lower than the other days. The 'Tuesday effect' is more pronounced for speculative stocks, which are more difficult to value and arbitrage and are more likely to be influenced by the mood. They attribute this day-of-the-week effect to the same-day domestic mood and the spill-over effect of the U.S. market. However, we did not find research on the day-of-the-week effect of cross-sectional stock returns on the Chinese market, the second-largest market in the world. Overall, our research questions for ***Chapter 2*** are: *What's the day-of-the-week cross-sectional return pattern in the Chinese market? What's the most plausible explanation for this pattern?*

The research working on the return seasonality over the trading day is limited. Wood, McINISH, and Ord (1985) examine the minute-by-minute market return series using the short sample data for 6 months. They document the unusually high returns and standard deviations of returns at the beginning and the end of the trading day. Smirlock and Starks (1986) use 21 years of hourly returns to test the weekend effect but are restricted to the Dow Jones Industrial. They only focus on each hour trading behavior on Monday and Friday and find that Monday average hourly returns after noon are all positive. None of these studies examine return seasonality from the perspective of intraday trading.

Regarding to the overnight and intraday cross-sectional seasonality predictability, Bogousslavsky (2021) firstly documents that the mispricing factor earns positive returns throughout the day but performs poorly at the end of the day, i.e., the last half-hour trading period. He proposes that the overnight risk and institutional constraints incentivize arbitrageurs to systematically trade on mispricing before the market closes. In ***Chapter 3***, I try to examine the cross-sectional intraday seasonality in the Chinese stock market and also answer the question, why it is different from the U.S. market.

Overall, ***Chapters 2*** and ***3*** show that the cross-sectional daily and intraday seasonality in China is different from the pattern in the U.S. and other developed countries. Our findings point to that the external factor, i.e., Money Market Funds market, and the behavioral factor, i.e., disposition effect can be the potential explanations for the asset pricing seasonality predictability. Theoretically, our results are consistent with Bogousslavsky (2016)'s infrequent rebalancing theory and Keloharju et al. (2021)'s mispricing-induced explanation for seasonality.

This dissertation focuses the stories on the Chinese stock market. Over the last ten years, China's GDP has tripled for the third consecutive decade. In 2018, China became the world's largest investor, with investments totaling \$5.9 trillion, surpassing the United States at \$4.3 trillion and Japan at \$1.2 trillion. Additionally, China has emerged as the leading contributor to global economic growth, highlighting the global significance of its market efficiency. Liu, Stambaugh, and Yuan (2019) and Carpenter, Lu, and Whitelaw (2020) state that it is crucial to explore the unique features in China to deepen our understanding of global resource allocation and asset pricing. ***Chapter 4*** focuses on the topic of ownership concentration and market quality also through the view of the Chinese stock market.

Chapter 4 focuses on the topic of ownership concentration and market quality through the view of the Chinese stock market. Corporate ownership concentration plays a vital role in corporate governance research studies. However, the net effect of corporate concentrated ownership on the market dynamics is still controversial. Chung, Elder, and Kim (2010) and Gul, Kim, and Qiu (2010) argue that the disproportional ownership structure can impair the market quality and increase the stock price synchronicity. On the contrary, Grossman and Stiglitz (1980) find that ownership concentration can serve as a credible commitment, thus reducing the information asymmetry and improving market liquidity. The research question for ***Chapter 4*** is what's the relationship between ownership structure and market dynamics in the context of economic stimulus package implementation.

The Chinese stock market differs significantly from the U.S. and other developed markets in several key aspects of market structure and participants, stock trading and settlement regulations, and regulatory environments. Next, I would compare the differences between the

Chinese and U.S. stock markets in detail.

Firstly, the market structure between those two markets is significantly different. These are the two main stock exchanges in China, Shanghai and Shenzhen stock exchange. The market is segmented into the Main Board, SME (Small and Medium Enterprise) Board, and ChiNext (similar to NASDAQ, focusing on technology and growth enterprises). The shares in the Chinese stock market are divided into A-shares and B-shares. A-shares are denominated in local RMB currency and are mainly available to domestic investors. B-shares are denominated in foreign currencies (USD in Shanghai, HKD in Shenzhen), and aimed at foreign investors. While in the U.S. stock market, these are the two largest exchanges, New York Stock Exchange and NASDAQ, with no major distinctions in classes of stocks like in China regarding foreign accessibility. Also, there are no separate classes of stocks based on investor origin.

Secondly, regarding the investing participants, the Chinese stock market is quite unique compared to the U.S. market. Individual investors are the major participants in the Chinese stock market. Based on the Shanghai Exchange report, at the end of 2016, over 101 million individuals had trading accounts, and these individuals held 88% of all free-floating shares. As a result, the Chinese market is heavily influenced by retail investors, contributing to high turnover and speculative trading (Liu et al. 2019). The U.S. market has a balanced mix of retail and institutional investors, leading to greater market stability and liquidity.

Thirdly, from the perspective of the trading mechanisms, the Chinese stock market has special characteristics. The Chinese stock exchanges have a mid-day break, specifically, trading hours are 9:30-11:30 AM and 1:00-3:00 PM China Standard Time. While for the U.S. stock exchange, trading occurs from 9:30 AM to 4:00 PM Eastern Time without a break. This feature makes our technical analysis in Chapter 3 a bit different from the literature. Besides, stocks in China have daily price limits. The price of a stock can't rise or fall beyond a specified percentage (typically ±10% for most stocks, and ±20% for newer listings) from the previous day's close. In the U.S. market, while there are circuit breakers that halt trading market-wide under extreme conditions, individual stocks do not have daily price limits.

Fourthly, regarding to the settlement cycle, China primarily operates on a T+1 settlement cycle, meaning transactions are settled one business day after the trade is executed. This cycle restricts the ability to sell newly purchased shares on the same day (day trading). The U.S. moved from T+3 to T+2 in 2017, where trades are settled two business days after the transaction. Just after May 28, 2024, the U.S. changed its T+2 to T+1, which allows more flexibility compared to the

Chinese system.

In the following paragraphs, I will give a brief introduction to each chapter.

Chapter 2 examines the interconnection between the stock market and the money market through the view of the daily seasonal return of the stocks. Our research question is whether the process of private money creation in the form of money market funds could affect other financial assets and instruments beyond the money market, e.g., the stock market.

Private money creation refers to the broad economic phenomenon that investors seek money market funds or other similar money-likeness assets issued by the private sector for liquidity and safety. Private money creation in the form of money market funds caters to the increasing demand for safety, and addresses the global shortage of public safe assets such as Treasury bills and short-term corporate bonds (Gorton and Ordoñez 2022; Krishnamurthy and Vissing-Jorgensen 2012; Nagel 2016). Moreover, money market funds become the centerpiece in the recent wave of the FinTech revolution in China's deposit market (Buchak, Hu, and Wei 2021).

We argue that private money creation exerts a hidden yet disproportionate impact on stock returns in the cross-section in China. We propose that the distinctive feature of yield accrual on market money funds, that the yields are accrued on a calendar day basis and the trading is only allowed on business days, incentivizes investors of speculative stocks to display an uneven demand for safety across days within a week. This demand-for-safety mechanism has the power to explain the stylized cross-sectional return pattern in the Chinese stock market: Long-short anomaly strategies that buy nonspeculative stocks and sell speculative stocks experience low Monday-through-Wednesday returns and high Thursday-through-Friday returns.

However, our demand-for-safety mechanism for the daily seasonality pattern of cross-sectional stock returns has some identification concerns, such as omitted variable concern and reverse-causality concern. To overcome those concerns and make our causal inference more convincing, we exploit a natural experiment—the event of China's FinTech revolution, including the launch of FinTech-customized Money Market Funds (MMFs) and Money Market Exchange-traded Funds (MMETFs), which triggers a significant exogenous shock to the demand for safety and eventually imposes enormous stresses on the cross-sectional stock returns.

We construct a difference-in-differences regression framework to validate the demand-based explanation. The regression results show that the benchmark-adjusted return of the Thursday-through-Friday long-short anomaly strategy (treatment) increases by a further 1.15% per month, equivalent to 13% per year, more than its Monday-through-Wednesday counterpart (control) following the 2013 FinTech revolution. Therefore, the day-of-the-week seasonality is amplified by over 100% after the 2013 FinTech revolution. Moreover, the increase in the daily seasonality comes mainly from the short-leg portfolio of speculative stocks. Overall, our difference-in-differences results indicate that the positive demand shock to money market funds has a causal effect on the daily cross-sectional return seasonality.

Furthermore, we find that the daily cross-sectional return seasonality is more pronounced on Thursdays and Fridays with unusually strong demand for safety (i.e., abnormal order imbalance of MMETFs). Also, this correlation between the stock market and the money market is more salient in periods of high market volatility and/or uncertainty.

Chapter 3 explores the distinctive end-of-day pattern in the cross-sectional returns in China, which is reversed compared to that of the U.S. (Bogousslavsky 2021). We find that in China Long-minus-short mispricing factor exhibits significantly positive returns at the last half-hour trading interval but performs poorly during the other daytime trading periods. In other words, mispricing worsens over the daytime and gets corrected at the end of the day. Therefore, the explanation of institutional constraints and overnight risk used by Bogousslavsky (2021) for the U.S. intraday cross-sectional return pattern is not applicable in our case. We argue that the disposition effect is the most plausible explanation for the cross-sectional end-of-day return pattern in the Chinese stock market.

The disposition effect refers to the phenomenon that investors have a greater propensity to sell stocks with prices that have increased since purchase rather than those with prices that have dropped. The prospect theory proposed by Kahneman and Tversky (1992), together with Thaler (1980, 1985)'s mental accounting framework (MA/PT), is perhaps the mainstream explanation for the disposition effect. Based on the disposition effect explanation, at the end of the day, when infrequent rebalancing investors face lower transaction costs and price impact, they are more likely to sell their portfolios with prior capital gain overhang to achieve gains on paper. Then, we would expect that stocks with capital gains, especially risky stocks have selling pressure at the end of the day, specifically during the last half hour, thus inducing the end-of-day seasonality.

Empirically, we first construct the measure of capital gains overhang (CGO), following the method of Grinblatt and Han (2005), for individual stock each day. We find that intraday returns decrease monotonically within their CGO quintile, which is consistent with the literature. Strikingly, the intraday disposition effect predominantly stems from the last half-hour's trading. Then, we test to what extent the predictability of mispricing factors at the end of the day depends on the stocks' capital gain overhang status. We conduct a double-sorting portfolio analysis by sorting the stocks into quintiles first by Score then CGO (and first by CGO then Score). We then calculate the portfolio returns for each individual group and each half-hour trading interval. We find that during the last half-hour trading, risky stocks within extreme capital gains (CGO5-Score5) experience considerably negative returns, which is about –5.36 basis points (*t*-statistic equal to –5.84).

This result is consistent with our prediction that when speculative stockholders face prior gains, they have a strong tendency to sell out their holdings to get the positive realization utility. However, for other intraday half-hour intervals, the disposition effect fades or even disappears. Moreover, our results still hold in the regression of Fama and MacBeth (1973) after controlling a battery of additional variables.

Next, following Bogousslavsky (2016, 2021), we also examine the market quality, trading order imbalance, and infrequent rebalancing for each half-hour interval. We find that the relative quoted spread and price impact (Amihuld ratio) are lower, and the turnover and volume are higher at the last half-hour trading interval. The results are consistent with the literature (Bogousslavsky and Muravyev 2021; Lou, Polk, and Skouras 2019), that the last half-hour interval is the optimal time for investors to reshuffle their portfolios. From the perspective of trading behavior, we find that speculative stocks experience larger selling pressure relative to others at the end of the day. Besides, following Jegadeesh (1990) and Heston et al. (2010), we run the cross-sectional regressions for the returns in each half-hour trading horizon. The results show that the coefficients of autocorrelation are only positive for the last half-hour trading interval, indicating the short-term reversal.

Chapter 4 investigates the effect of corporate ownership concentration on the market performance. The examination of the relationship between concentrated ownership and market dynamics poses several empirical challenges. For example, many characteristics between firms with different ownership structures are unobservable to researchers. Thus, in this chapter, we introduce the 2008 Chinese stimulus package policy as the exogenous shock to the ownership concentration of state-owned enterprises (SOEs). We test whether and to what extent the shock of stimulus package exacerbates the ownership discrimination effect on the market quality and stock returns.

In China, corporate ownership is highly concentrated. Large controlling shareholders, especially government-related entities, are actively involved in the managerial process and typically possess full control over major corporate decisions (Gul et al. 2010). Given this unique institutional environment, we try to explore whether the ownership concentration in China induces market quality and performance deterioration by increasing the information asymmetry. Moreover, the government-related ownership concentration in SOEs (State-Owned Enterprises) become more pronounced after the implementation of the 2008 stimulus package, which may lead to ineffective corporate governance concerns and further deteriorate market quality.

Empirically, first, we examine the relationship between liquidity measures and ownership discrimination. We adopt an OLS panel data regression model following Bertrand, Schoar, and Thesmar (2007) to exploit the dynamic change in liquidity for firms within different ownership structure groups, SOEs and POEs, after the implementation of the stimulus package in 2008. We find that compared to other firms, SOEs exhibit lower market liquidity after the rollout of the stimulus policy, indicating that the enhanced state control in SOEs can decrease market liquidity. Second, we observe that intraday volatility has decreased for SOEs in the post-stimulus period than before, reflecting the information withholding by SOEs. In this case, the lowered volatility is considered undesirable.

Then, we test the impact of the enlarged state control for SOEs after the rollout of the stimulus policy on price efficiency. We first use the updated data to re-test the finding of Gul et al. (2010) that the synchronicity is higher when the largest shareholder is government-related based on the analysis using the data from 1996 to 2003. We find that this managerial entrenchment effect of ownership concentration on the stock price synchronicity has been persistent over the last two decades. Moreover, we find that compared to the other firms, the market efficiency has deteriorated following the stimulus policy implementation.

Next, we investigate the impact of firms' ownership structure change on equity performance. We find that the SOEs underperform the other firms by about 91 basis points per month during the post-stimulus period, relative to the pre-stimulus period. However, POEs experience higher returns after the stimulus policy rollout. Moreover, we find that compared to the benchmark firms, the mispricing characteristic is more pronounced for SOEs after the exit of the stimulus policy, and there is no marked pattern for POEs.

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Chapter 2

FinTech Revolution

The Hidden Impact of Private Money Creation on the Cross Section of Stock Returns

Abstract:

Private money creation in the form of money market funds exerts a disproportionate impact on stock returns in the cross section. We argue that the distinctive feature of yield accrual (as opposed to stock investing) incentivizes investors of speculative stocks to seek safety on specific days, which has the power to explain the stylized cross-sectional pattern: Long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks experience *low* Monday-through-Wednesday returns and *high* Thursday-through-Friday returns. Causality is addressed using the FinTech revolution on money market funds: Difference-in-differences evidence indicates that the cross-sectional seasonality is amplified by more than 100 percent after the FinTech-led exogenous shock. The enlarged seasonality comes predominantly from the short-leg speculative stocks, and is stronger in high volatility periods.

JEL Classification: G11, G12, G23

Keywords: Money market funds, FinTech, Cross-sectional predictability, Demand for safety, Seasonality

An important aspect of the FinTech phenomenon that we are observing right now is that a big part of it is taking place outside the United States. China is clearly at the front of financial technology […]. Things are very different in China and other emerging economies; with less developed financial sectors, they are more prone to innovation, stage-skipping, and disruption […]. For many years, research in finance has been US-focused, and now with the interest in FinTech there is a natural path to expand the target of research more globally.

— Goldstein, Jiang, Karolyi (2019, To FinTech and Beyond)

2.1. Introduction

Private money creation in the form of money market funds caters to the increasing demand of safety, and addresses the global shortage of public safe assets such as Treasury bills (Krishnamurthy and Vissing-Jorgensen, 2012; Nagel, 2016; Gordon and Ordonez, 2022). It also massively reduces the cost of financial intermediation, and contributes to interest rate liberation in the emerging markets (Kacperczyk, Perignon, and Vuillemey, 2021; Cipriani and La Spada, 2021). More crucially, money market funds become the centerpiece in the recent wave of FinTech revolution in China's deposit market (Buchak, Hu, and Wei, 2021). During this massive-scale FinTech revolution, BigTech-BigData platforms engage investment companies to re-design money market funds with a number of innovative money-likeness features: One prime example is that shares of money market mutual funds (MMMFs hereafter) become a widely accepted method of payments supported by FinTech platforms' extensive digital payment network (such as Alipay and Wechat Pay). In short, FinTech applications facilitate the process of private money creation, and provide BigTech-BigData platforms a huge competitive advantage, through which they bring significant disruptions to the incumbent commercial banks in the deposit market (Goldstein et al., 2019; Buchak et al., 2021). Yet, little do we know how the process of private money creation could affect other financial assets and instruments beyond the money market.

In this paper, we address the hidden impact of private money creation on the stock market. We argue that private money creation in the form of money market funds (aka "cash investing") exerts a disproportionate impact on daily stock returns in the cross section. On the one hand, money market funds, as an investment alternative, provide stock investors with safety benefits (i.e., yields) when they convert their stock holdings into cash holdings. The yields of money market funds are accrued on a calendar day basis, which guarantees a positive return on weekends, when the stock market "sleeps". Nevertheless, to reap these over-the-weekend yields is not without conditions, because there exists an obvious misalignment between interest accrual on calendar days and trading (i.e., clearance and settlement) on business days. For example, if a discerning short-term investor were to seek safety by earning the guaranteed yield over the weekend, she must factor in this distinctive feature by either subscribing the MMMF shares on Thursday (due to the next business day rule for subscription) or buying the shares of money market exchange-traded funds (MMETFs hereafter) on Friday, so that the yield would start to accrue on the Friday, Saturday, and Sunday of the same week (We have more to say about the detailed trading rules on MMMFs and MMETFs in **Section 2.2**). In short, the demand for money market funds does not spread evenly across days within a week, but heightens on Thursday and Friday. On the other hand, the anticipated demand for safety, accommodated by money market funds, will vary across stocks. In particular, speculative stocks are more likely to incur selling pressure than non-speculative stocks before a weekend when their holders seek safety. First, investors are reluctant to hold speculative stocks for long due to relatively high holding costs and inventory risk concerns (Liu, Wang, Yu, and Zhao, 2020). Second, speculative stocks are more susceptible to overvaluation and (potential) price crashes and have a less liquid (or perhaps no) derivative market to hedge these risks. Taken together, our central prediction is that, *ceteris paribus*, the price of speculative stocks drops more than that of the non-speculative stocks on Thursday through Friday rather than on Monday through Wednesday (**Hypothesis 1**).

Empirically, this is exactly what we find. The long-short anomaly portfolios that bet against speculative stocks—those of high idiosyncratic risk, lottery demand, turnover, beta, and return volatility—and bet on stocks with opposed characteristics tend to earn *low* returns on Monday through Wednesday, but deliver *high* returns on Thursday through Friday in China (see **Figure 2**). The magnitude of this daily seasonality is also large, as the Thursday-through-Friday return accounts for one hundred percent or more of the total monthly return of the anomaly strategies.

Note our documented daily cross-sectional pattern is in sharp contrast to the predictions implied by the investor psychology theory (Birru, 2018; Hirshleifer, Jiang, and DiGiovanni, 2020). Under the conventional investor psychology explanation, these long-short anomaly strategies should deliver *high* returns at the start of the week (i.e., Monday), but *low* returns at the end of the week (i.e., Friday), because investor mood increases cyclically on Friday and decreases on Monday. Instead, our demand-based mechanism is consistent with the Bogousslavsky (2016) infrequent rebalancing theory in which the anticipated seasonality in the cross section arises when a subset of investors self-select to infrequently adjust their holdings. It also strongly supports the temporary mispricing view of Keloharju, Linnainmaa, and Nyberg (2016, 2021) that the recurring in- and out-flows, as opposed to investor sentiment, could dislocate stock prices from fundamental values on specific days of the week.

However, our safety demand-based explanation of the daily seasonality pattern is confronted with identification concerns. Firstly, the incentive to seek safety in the money market and seasonal return patterns in the stock market could be driven by common factors that may not be observable to researchers, which causes the omitted variable concern. For example, investor mood on a particular weekday is unobservable and likely to affect both stock returns and the incentive to seek safe assets (e.g., Hirshleifer et al., 2020). Secondly, the presence of seasonality in returns can drive traders to seek safe assets, representing the typical reverse-causality concern. To overcome the identification difficulties, we require an empirical setting where a plausibly exogenous shock to the demand for safety affects the cross-sectional stock returns. Thus, we exploit a natural experiment—the event of China's 2013 FinTech revolution of cash investing, which originates from the tug of war between FinTech firms and traditional banks competing for household deposits on the deposit market (Buchak, et al., 2021). In 2013, Alipay—a well-trusted, dominant FinTech platform in China—launches YEB, the first-ever FinTech-customized MMMF, which marks the onset of China's FinTech revolution on cash investing.[2] This landmark event set new industry standards and brought revolutionary changes to money market funds, including using MMMF shares as a method of payments supported by FinTech platforms' extensive digital payment network, lowering the minimum investment amount to one Chinese yuan, and offering real-time redemption at par. Although these enhanced money-likeness features, designed by FinTech platforms, are mainly targeting household depositors, they "unintentionally" provide strong economic incentives for all types of MMMF investors—depositors as well as stock investors—to pull out their money from

[2] YEB, the abbreviation of YuE Bao, or Yu'E Bao, or Yu Ebao (in Chinese: 余额宝), refers to the Tianhong YuE Bao Money Market Fund (ticker: 000198). It was launched in mid-June 2013 as the first-ever FinTech-customized MMMF. Given that the money market is an extremely competitive industry, the success of YEB and its innovative money-likeness features (as we explain later in **Section 2.2**) immediately set the new industry standards for other existing and newly issued money market funds. Other money market funds quickly followed suit by incorporating these innovative features. Therefore, throughout the article, we use the term **FinTech-customized MMMFs** to refer to all MMMFs that adopt the FinTech-related characteristics (i.e., serving as a method of payments, one-dollar minimum investment amount, and real-time on-demand redemption at par) in the FinTech era.

elsewhere to the money market funds. In short, the FinTech revolution greatly boosts the demand for money market funds. This exogenous increase in demand for safety is expected to have a causal impact on the stock market. We expect an increase in the day-of-the-week seasonality of speculative stocks relative to their non-speculative counterparts following the 2013 FinTech revolution (**Hypothesis 2**). We also postulate that the *increased* day-of-the-week seasonality in the long-short anomaly returns after the 2013 FinTech revolution stems primarily from the short-leg speculative stocks—the source of temporary mispricing (**Hypothesis 3**).

We employ a difference-in-differences (DiD) framework to validate the demand-for-safety mechanism (**Hypotheses 2** and **3)**: For each anomaly variable, we assess the change in the return spread between two non-overlapping long-short anomaly strategies—one that invests solely on Thursday and Friday, and the other that invests on Monday, Tuesday, and Wednesday—after the 2013 FinTech revolution. When using the aggregated analysis, in which all anomaly strategies are pooled together, we find that the benchmark-adjusted return of the Thursday-through-Friday long-short anomaly strategy (treatment) increases by a further 1.15% per month more than its Monday-through-Wednesday counterpart (control) following the 2013 FinTech revolution. That is, the day-of-the-week seasonality is amplified after the 2013 FinTech revolution, supporting **Hypothesis 2**. Moreover, the increase in the daily seasonality stems mainly from the short-leg portfolio of speculative stocks: Their Thursday-through-Friday return drops more than the Monday-through-Wednesday counterpart, rendering strong support for **Hypothesis 3.** Overall, our difference-in-differences results indicate that the positive demand shock to money market funds has a causal effect on the daily cross-sectional return seasonality.

To substantiate the creditability of the difference-in-differences results, we proceed with a set of validation tests. First, we perform the placebo difference-in-differences regressions by replacing the actual anomaly strategies with "placebo" strategies sorted on randomly generated stock attributes. The placebo regression is repeated 500 times to generate the empirical distributions of the DiD coefficients and the corresponding t-statistics. We find that the mean of placebo DiD estimates and associated t-statistics are close to zero, suggesting that an exogenous increase in demand for safety has no material impact on "placebo" long-short strategies formed by randomly generated stock attributes. In contrast, our "true" DiD estimate of 1.15% (the change in return spread between the Thursday-through-Friday long-short portfolio and its Monday-through-Wednesday counterpart) and its t-statistic of 3.78 are located far to the right of the 95th percentile of the empirical distribution, indicating a significant difference from the placebo mean. The sizeable departure from the placebo mean underscores that the 2013 FinTech-led exogenous shock has a real effect on the daily cross-sectional return seasonality. Second, we perform the “pre-trend” test. The validity of the difference-in-differences model rests on the parallel trends assumption that, in the absence of treatment, the average outcomes for the treated and control groups should follow parallel trends over time. Using a dynamic DiD regression, we find that our DiD coefficients on the long-short anomaly portfolio are all insignificantly different from zero during the pre-event period (i.e., prior to the FinTech revolution), but they become significantly positive in the post-event period (i.e., after the FinTech revolution). The results indicate that the parallel trends assumption is satisfied in the pre-event period and the event of FinTech revolution in 2013 does have a material impact on the daily seasonality. Third, our causal relationship between the demand of money market funds and the daily return seasonality pattern may be challenged by using a long estimation window (1996-2019). Such a long period increases the likelihood that other confounding factors drive our results other than the demand shock for money market funds in 2013. To alleviate this concern and strengthen our casual interpretation, we instead focus on a short period over nine weeks centered on the week of the roll-out of YEB. The result shows that speculative stocks indeed experience a sharp increase in both the return spread (i.e., return difference between the Thursday long-short anomaly portfolio and its Monday-through-Friday counterpart) and the order imbalance (i.e., additional selling pressure on Thursday relative to Monday-through-Wednesday) over the four weeks *after* the launch of YEB. Taken together, our three validation tests largely mitigate the concern that our DiD results are spurious and driven by unobserved time-varying confounders (e.g., sentiment, unobservable risk exposure). It also establishes that the FinTech-led demand shock to money market funds has a first-order impact on the seasonal cross-sectional return predictability.

Next, we carry out three additional tests to shed light on the interrelation between the demand for safety and the daily cross-sectional return predictability. Firstly, we propose that there should be a stronger day-of-the-week seasonality (in magnitude) for the long-short anomaly strategy in the presence of an unexpected surge in demand of safety on Thursday and Friday (**Hypothesis 4**). Moreover, the stronger day-of-the-week seasonality should stem mainly from the short leg, as we expect greater underperformance of speculative stocks precisely when money market funds incur unusually high buying pressure. Empirically, we adopt the daily order imbalance of MMETFs as a valid proxy of the demand for safety, and construct a time dummy that identifies the unusual Thursdays and Fridays when there is an unexpected surge in demand for safety. Consistent with our prediction (**Hypothesis 4**), there exists a significantly positive loading on the time dummy, indicating that the day-of-the-week seasonality indeed gets larger for the long-short anomaly strategy. Moreover, the stronger seasonality on these “abnormal” Thursdays and Fridays stems purely from the short-leg speculative stocks, confirming that speculative stocks experience strong selling pressure precisely when money market funds are in high demand.

Secondly, we conjecture that the interrelation between the abnormal demand for money market funds and the magnitude of the daily seasonality should hold stronger in times of high volatility (uncertainty) than in times of low volatility (uncertainty) (**Hypothesis 5**). This is because the value of holding money market funds would vary across the market states. For example, if the stock market is in turbulent or uncertain states in which the marginal utility of wealth is high, it is plausible that investors become more inclined to hold money market funds rather than speculative stocks. By splitting the whole sample into high- and low-volatility (low-uncertainty) subsamples, we find consistent evidence in support of **Hypothesis 5** that the magnitude of the daily seasonality on Thursdays and Fridays with an unexpectedly large buying pressure of money market funds is fairly large in periods of high market volatility (uncertainty), but it becomes almost negligible in those low-volatility (low-uncertainty) periods. Again, this incremental increase in the daily seasonality during the high-volatility (high-uncertainty) periods stems entirely from the short-leg speculative stocks, highlighting the disproportionate impact in the cross section.

Thirdly, we examine the “holiday effect”. We argue that investors tend to convert their stock positions into cash positions prior to long holidays, because the safety yields of money market funds continue to accrue over the prolonged holidays when the stock market “sleeps”. Again, we expect this demand-based effect matters more for speculative stocks than non-speculative stocks. Taken together, we predict a strong holiday seasonality in the cross section over the two business days prior to long holidays (due to the rigid cut-off dates for the entitlement to the over-the-holiday yields). Consistent with this notion, we document that the long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks indeed deliver *high* returns over the two business days prior to long holidays, confirming the holiday effect.

Finally, we consider several alternative explanations and conduct a battery of robustness checks on our main results. Firstly, one may argue that the cross-sectional seasonal pattern could arise from short selling activity. For example, short sellers might systematically sell speculative stocks on Thursday and Friday. We show that this is not the case, because short-sellers tend to reduce, rather than increase, their overall short positions on Thursday through Friday. Moreover, given that only a subset of stocks are eligible for short selling in China, we find that the day-of-the-week effect is more pronounced for the subset of non-eligible stocks (i.e., those cannot be short-sold) than the subset of eligible stocks. Therefore, short selling activity, as an alternative explanation, is not compatible with our documented daily seasonality of the cross-sectional returns. Secondly, we test whether the daily seasonality is due to the timing of macroeconomic and firm-specific news releases. By excluding days with central bank announcements and macroeconomic news releases, we find that the day-of-the-week pattern of the anomaly returns remains virtually intact. Similarly, when we exclude days with earnings announcements from the sample, we document that the long-short anomaly returns over different days of the week also remain virtually unchanged. Collectively, these analyses indicate that our primary results are unlikely to be driven by news announcements. Thirdly, we carefully check whether the daily seasonality is induced by the systematic selling pressure due to the settlement of derivative contracts on the third Friday of the month (Cao, Chordia, and Zhan, 2021). Again, we find that this is unlikely the main driver of our documented cross-sectional pattern, because the economic magnitude of the long-short anomaly returns is nearly identical for the settlement week and the non-settlement week. Last but not least, we perform a battery of robustness checks to ensure that our key findings are robust to various empirical twists. The robustness checks include testing on other anomalies (e.g., size, illiquidity, profitability), and using alternative weighting scheme (i.e., equally weighted), daily risk factors, and alternative factor model. Overall, we can rule out the alternative explanations of the documented cross-sectional seasonality, and the key empirical results remain stable in the robustness tests.

In summary, our contribution is threefold. First, our paper complements the evolving literature on private money creation, which addresses the key question of how privately produced safe assets can substitute publicly produced safe assets to cater to the increasing demand for safety (Brunnermeier and Niepelt, 2019; Krishnamurthy and Vissing-Jorgensen, 2012; Nagel, 2016; Kacperczyk et. al., 2021; Cipriani and La Spada, 2021; Gorton and Ordonez, 2022). We extend this line of research to the stock market by exploring the related issue of how private money creation ultimately exerts its hidden and disproportionate impact on stock prices. To the best of our knowledge, we are the first to explore the broad implications of cash investing outside the money market.

Second, our paper contributes to the growing literature on cross-sectional return seasonality and the explanation of asset pricing anomalies (Birru, 2018; Bogousslavsky, 2016; Keloharju et al., 2016, 2021).[3] We uncover a novel mechanism that rationalizes the stylized daily seasonality in China. The safety demand-based explanation—investors who hold speculative stocks engage in correlated trading to demand safety on specific days of the week by shifting between stock investing and cash investing—provides an economic channel and direct evidence to support the perspective that daily cross-sectional seasonality could arise from predictable in- and out-flows (i.e., correlated trading) unrelated to seasonal swing of mood (Keloharju et al., 2021). Our study also enriches the Bogousslavsky (2016) infrequent rebalancing theory by providing direct empirical evidence to help understand the economic motive (i.e., demand of safety) why a subset of investors infrequently rebalance their portfolios over certain time horizon.

Third, we provide novel evidence that contributes to the emerging literature on FinTech and its implications in the modern financial markets (Goldstein et al., 2019; Buchak et al., 2021). Contrary to the wide belief that FinTech revolution and technology advances would enhance the market efficiency (i.e., reduce cross-sectional return predictability) by reducing costs and frictions in the financial system, our empirical evidence presents somewhat a challenge to this belief and documents the exact opposite: The recent FinTech revolution on money market funds in China unexpectedly exerts *adverse* externalities on the stock market by worsening price efficiency in general and amplifying the cross-sectional stock return predictability in particular.

The rest of the paper is organized as follows: Section 2.2 provides background on money market funds and the FinTech revolution in China, and develops the testable predictions. Section 2.3 describes the data and the anomaly variables. Section 2.4 provides the motivating evidence on the seasonal return patterns. Section 2.5 presents the difference-in-differences analysis and the validation tests. Section 2.6 performs a bunch of further analyses. Section 2.7 examines alternative explanations and performs robustness checks. Section 2.8 concludes.

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[3] Studies on daily return seasonality date back to the 1970s. Early works on the non-random price behavior focus mostly on individual stocks or the overall market (see Abraham and Ikenberry, 1994; Chen and Singal, 2003; Cross, 1973; Connolly, 1989; Draper and Paudyal, 2002; Fishe, Gosnell, and Lasser, 1993; French, 1980; among others), while recent attention shifts towards exploring the cross-sectional patterns (see Birru, 2018; Bogousslavsky, 2016; Keloharju et al., 2021; among others).

2.2 Background on money market funds and China's FinTech revolution

The increasing demand for safety, coupled with the shortage of Treasure bills, leads to the global trend of private money creation—issuance of high-quality safe assets by the private sector (Brunnermeier and Niepelt, 2019; Kacperczyk et. al., 2021; Cipriani and La Spada, 2021). Money market funds are the major player in this process: They seek to preserve the principal of an investment at $1.00 per share, while offering a return higher than that in the bank deposit accounts (Kacperczyk and Schnabl, 2010).

China introduced the money market funds in the early 2000s, as an investment alternative that complements the existing fund family such as equity and bond funds. As a highly popular financial instrument, money market funds possess a number of competitive features: First, money market funds offer a *market-based* yield, which is better than the *regulated* deposit rates offered by commercial banks. For instance, as of June 2019, the annualized after-fee yield of the top 10 largest MMMFs ranges between 2.305% and 2.915% per annum (p.a.), whereas the 1-year bank deposit rate remains low at 1.5% p.a. (due to the interest rate ceiling imposed by central banks on depository institutions). **Figure 2.A 4** shows the dual-track interest rates under ceiling regulation in China. The yield of the YEB MMF traces the market rate well and is substantially higher than the regulated deposit rate. The considerable interest rate wedge between the MMMFs (YEB 7-days annualized yield) and banks' deposit rates creates incentives for households to transfer money from their bank accounts to YEB accounts (Buchak et al., 2021). FinTech revolution in 2013 through MMMFs with deposit-like features serves as a financial liberator.

Second, money market funds are featured for its on-demand redemption at par. In comparison, other competing interest-bearing instruments such as term deposits and wealth management products (WMPs) normally impose a fixed term over which the investors either cannot withdraw their money early, or alternatively, they would incur a financial penalty for early withdrawals. Third, money market funds usually adopt a "user-friendly" pro-rata fee structure. There are no (front-end and back-end) load fees: Subscribing and redeeming the MMMF shares are cost-free, making it more comparable to deposit money into and withdraw money from a current bank account.[4]

[4] Strictly speaking, there exists a so-called mandatory redemption fee of 1% which is required by law in exceptional cases. A mandatory redemption fee of 1% is charged (and added to the fund's AUM), if a single investor requests to redeem a total amount exceeding 1% of the fund's AUM when the fund's market value is 5% below its net asset value (see Article 17 of CSRC Decree No. 120: Measures for the Supervision and

2.2.1. Interest accrual and the uneven demand for money market funds across days

Although money market funds seem to be the "safe haven" where investors could park their money outside the stock market to earn a market-based yield, the demand for cash investing (i.e., money market funds) does not spread evenly across days within a week. Per nature of money market instruments, interest incomes are accrued on a calendar day basis, including Saturday and Sunday. This means that the yields to money market funds can continue to accumulate over the weekend when the stock market "sleeps". However, the entitlement to the over-the-weekend safety yields is not without conditions: Trading (i.e., clearance and settlement) of money market funds is strictly operated on a business day basis. This misalignment between the interest income that accrues on calendar days and the clearance and settlement that operates on business days motives the short-term stock investors—those who demand for safety by temporarily parking their money outside the stock market—to display a strong tendency to convert their stock holdings into cash holdings at the end of the week (such as Thursday and Friday) rather than at the start of the week.

Note the clearance and settlement for the subscription (and redemption) of MMMFs take one *business* day (i.e., the next business day rule). Therefore, if a discerning short-term stock investor were to seek safety and earn the guaranteed yield *over the weekend*, she must liquidate the stock holdings first and use the proceeds to submit the order to subscribe the MMMF shares before the market closes on Thursday *at the latest*, so that the subscription can be confirmed on Friday and the yield would start to accrue on the same Friday, and the Saturday and Sunday that follows (see **Panel A** of **Figure 2.A1** in the appendix for the timeline of the subscription and interest accrual). Instead, if the same investor submits the order to subscribe the MMMF shares *after* the market closes on Thursday, this is treated (equivalently) as an order submitted on Friday, and the subscription will be confirmed only on Monday of the next week (due to the next business day rule), thus forfeiting the Friday-Saturday-Sunday interest over the weekend (see **Panel B** of **Figure 2.A1** in the appendix). Alternatively, if she prefers to trade MMETFs, which offer a last-minute solution to earn the safety yields over the same weekend, she would need to liquidate the stock holdings first and use the proceeds to buy MMETF shares on Friday rather than on Thursday (see **Figure 2.A2** in the appendix for the timeline of the purchase and

Administration of Money Market Mutual Funds). For a median-sized MMMFs, even the holdings of their top investors never reach 1% of the AUM. Therefore, the mandatory redemption fee is rarely seen in reality. In fact, large investors will self-select to put money in larger-sized money market funds to avoid the mandatory redemption fee.

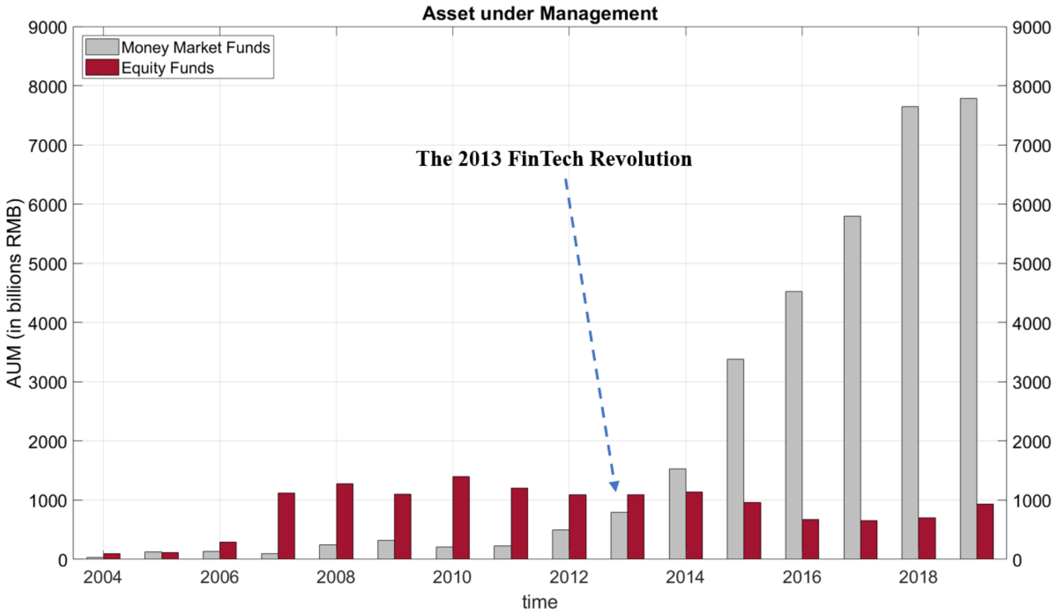
interest accrual of MMETFs).

In short, irrespective of the investor preference of MMMFs or MMETFs, the rigid cut-off date to earn the over-the-weekend safety yields dictates that the demand for money market funds does not spread evenly across days within a week, but heightens on Thursday and Friday.

2.2.2. The 2013 FinTech revolution

China’s money market funds experience moderate growth in the 2000s. The landscape, however, changes dramatically over the recent years: 2013–present (see **Figure 2.1**). FinTech revolution and innovations—that originate from the deposit market due to the tug of war between the BigTech-BigData platforms (such as Alipay and Wechat Pay) and the traditional banks—are the key drivers behind China’s unprecedented growth of money market funds from 2013 onwards. In particular, the launch of YEB—the first **FinTech-customized MMMF**—on the Alipay platform in 2013 marks the onset of the FinTech revolution in China (Chen, 2016; Buchak et al., 2021; Hua and Huang, 2021). The overwhelming growth of cash investing since the 2013 FinTech revolution enables money market funds to quickly become the dominant investment funds in China’s asset management sector: As of June 2019, they hold a combined NAV exceeding 7.7 trillion Chinese yuan (equivalent to 1.2 trillion USD), representing approximately 60 percent of total AUM in China’s investment funds and surpassing the total AUM of equity, bond, balanced, and other investment funds combined (see **Table 2.A1** in the appendix).

Figure 2. 1 Asset under management of money market funds and equity mutual funds



Note: The figure plots the total assets under management (AUM) of money market funds (the grey bar) and equity mutual funds (the dark red bar) over time. The annual AUM is defined as the simple average of the beginning value and the ending value of AUM of a year. All figures are measured in billions of RMBs.

FinTech-customized MMMFs. Goldstein et al., (2019) emphasize that China is at the forefront of the global wave of FinTech development and has been experiencing unprecedented financial development in recent years. Money market funds are the centerpiece of this massive-scale FinTech revolution in China. The re-design of money market funds with innovative money-likeness features, which cater to the increasing demand for safety and fast-paced liquidity service, is vital to BigTech-BigData platforms in their competition with traditional banks.[5] Moreover, the tug of war in the deposit market between the BigTech-BigData platforms and traditional banks "unintendedly" sets the new industrial standards for money market funds:

First and foremost, FinTech application empowers the MMMF shares to become the *de facto* money in the digital era. BigTech-BigData platforms such as Alipay and Wechat Pay set the new industry standards by adopting shares of these tailored MMMFs as one widely-accepted method of payments supported by their extensive digital-based payment system. To the best of our knowledge, this is by far the biggest technological advance that greatly enhances the money-likeness feature of money market funds: It transforms shares of money market funds into real money (i.e., some sort of e-currency) that can be used in every-day life (e.g., for online and offline purchase). As China quickly evolves into a "cashless" society with digital payment as the dominant payment option (i.e., with a QR code), both FinTech firms and traditional banks are increasingly competing for their client base. Thus, it becomes strategic and crucial for these BigTech-BigData firms to team up with investment companies to issue these tailored money market funds as the "e-currency" that offers the market-based yields (i.e., better than bank deposit rates) and also serves as the method of payments for online and offline transactions. This specific FinTech application on money market funds turns out to be an immediate success: Taking YEB as an example, more than a third of Chinese invest in this fund, and it quickly becomes the world's largest money market fund in 2017.[6] In fact, the growing popularity of YEB and dozens of other FinTech-customized MMMFs provides FinTech firms a huge competitive advantage, through which they bring significant challenges

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[5] The re-design of money market funds ensures that the funds could adapt to the evolving financial infrastructure, and cater to the increasing liquidity and safety demand of the investors. Arguably, the re-design of money market funds is also influenced the mandate from the regulatory body, as it provides legislations that could facilitate the growth of the industry (i.e., favourable tax treatments). We would like to thank Mengna Zhu of Fullgoal Fund Management for helping us improve our understanding of the legal aspects of the money market funds.

[6] Yan, S. (2019, March 28). More Than a Third of China Is Now Invested in One Giant Mutual Fund. *Wall Street Journal*. Retrieved from: https://www.wsj.com/articles/more-than-a-third-of-china-is-now-invested-in-one-giant-mutual-fund-11553682785

Lucas, L. (2017, April 17). Chinese money market fund becomes world's biggest. *FT.Com*. Retrieved from: https://www.ft.com/content/28d4e100-2a6d-11e7-bc4b-5528796fe35c and disruptions to commercial banks (Buchak et al., 2021).

Second, the 2013 FinTech revolution leads MMMFs to adopt the "one-dollar" minimum investment amount. That is, the minimum investment amount has been significantly reduced to one Chinese yuan (equivalent to 100 Chinese cents) or even one Chinese cent. Note prior to the FinTech revolution, MMMFs usually have a much higher investment hurdle, as their minimum investment amount are 5,000 Chinese yuan or above. The reduction in minimum investment amount is crucial for FinTech-customized MMMFs because they are designed as the interest-bearing e-currency to "replace" the small notes or coins that were stored in real wallets.

Third, the FinTech revolution leads MMMFs to offer *real-time* on-demand redemption at par. This innovative feature that the MMMF shares can be converted into cash in real time effectively removes the conventional one-business-day redemption requirement. Again, the shortened time in redemption significantly enhances the money-likeness features of money market funds in the FinTech era.

MMETFs. Silber (1983) posits that financial innovation is always related to fulfilling the new investment demand and/or the circumvention of the regulation constraints. The launch of MMETFs in China in January 2013 is no exception. Unlike MMMFs, MMETFs allow investors to trade their MMETF shares among each other in the security exchange just like trading stocks. This increases the marketability of these money market funds (i.e., liquidity enhancement), making them a popular cash investing tool over time. As of June 2019, MMETFs hold a total AUM worth RMB 236.8 billion.

MMETFs offer a last-minute solution for short-term stock investors to seek safety and earn the yields over the (first) weekend by trading on Friday, rather than on Thursday. In that sense, the emergence of MMETFs redistributes partially the concentrated demand for safety from Thursday to Friday (i.e., the redistribution effect). In the absence of MMETFs, we should expect a much concentrated demand for MMMFs on Thursday.

We are aware that the launches of YEB (i.e., FinTech-customized MMMFs) and MMETFs can be argued as two separate events. However, these two salient events coincide with each other in time (i.e., both in the first half of 2013), and more importantly, they have homogenous implications: First, they are both designed to offer investors the legitimate and innovative ways to circumvent the interest rate ceiling imposed by the central bank (i.e., regulatory arbitrage).

Second, they both exploit the combination of financial and technical advances to increase the money-likeness attributes of money market funds, and lower the investment hurdles and costs for holding money-like assets. In that sense, they complement each other in boosting the demand for safety from 2013 onwards. Therefore, for ease of exposition, we treat them as one joint event under the grand theme of China's FinTech revolution in our baseline analysis in **Section 2.5**. However, we do disentangle their respective impacts in later analysis (see **Section 2.7.4**).

2.2.3. Testable predictions

The discussion in the prior subsections leads to a number of testable predictions on the hidden impact of private money creation on the stock market, which are summarized as follows:

First, private money creation in the form of money market funds exerts a disproportionate impact on stock returns in the cross section. On the one hand, we expect the demand for money market funds varies across days within a week, and heightens on Thursday and Friday. This is driven by the distinctive feature of cash investing as opposed to stock investing: The safety yields are accrued on calendar days (including Saturday and Sundays) while trading of MMMFs and MMETFs is settled on business days. Irrespective of the investor preference of MMMFs or MMETFs, the rigid cut-off dates to earn the safety yields over the weekend dictates that short-term investors tend to leave the stock market on Thursday and Friday rather than on Monday, Tuesday, and Wednesday. On the other hand, the demand-based channel (i.e., demand for safety) matters more for speculative stocks than non-speculative stocks. As is explained in Liu, Wang, Yu, and Zhao, (2020), the positions to hold speculative stocks are short-lived due to holding costs and inventory risk concerns. Cash investing offers easy access to safety which is more valuable for speculative stocks precisely when it comes to the end of the week (i.e., to unload the stock inventory before the weekend). Taken together, this leads to our central prediction in the cross section:

Hypothesis 1 (Day-of-the-week effect): *Everything else equal, the price of speculative stocks drops more than that of the non-speculative stocks on Thursday through Friday (rather than on Monday through Wednesday).*

Second, we should stress here that the 2013 FinTech revolution offers us a natural experiment to validate the causal effect of the (increased) demand for safety on the daily seasonality of cross-sectional returns. Note the FinTech revolution originates from the deposit market, in which the BigTech-BigData platforms mainly target household depositors to pull out their money from traditional banks to money market funds. During this process, FinTech applications (i.e., these revolutionary changes in **Section 2.2**) significantly increased the money-likeness feature and lowered the investment hurdles for all types of investors, including stock investors. Thus, the 2013 FinTech revolution can ultimately boost stock investors' demand for safety as well. Again, for the same reasoning as in **Hypothesis 1**, the safety benefits offered by money market funds are more valuable to speculative stocks (than non-speculative stocks) precisely when it comes to Thursday and Friday, as holders of speculative stocks tend to unload their stock inventory and to reap the over-the-weekend yields. Therefore, we expect that the 2013 FinTech revolution amplifies the seasonal stock returns in the cross section.

Hypothesis 2: *For the long-short anomaly portfolios that buy non-speculative and sell speculative stocks, the day-of-the-week seasonality—the high Thursday-through-Friday return relative to the Monday-through-Wednesday counterpart—becomes more pronounced subsequent to the 2013 FinTech revolution.*

Hypothesis 3: *The increased day-of-the-week seasonality following the 2013 FinTech revolution comes predominantly from the short-leg anomaly portfolios. That is, the Thursday-through-Friday return of the short legs of speculative stocks drops more than their Monday-through-Wednesday counterpart subsequent to the 2013 FinTech revolution.*

2.3. Data and variables

2.3.1. Data and data sources

We construct a comprehensive dataset from multiple sources. The equity data include all available A-shares listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange. Daily and monthly market data are retrieved from Thomson Reuters Datastream. Following Liu, Stambaugh, and Yuan(2019), we adopt similar filtering rules to compile the dataset: First, we exclude stocks that have just become public within the past three months. Second, we filter out stocks which have consecutive zero returns over the past three months, which prevents our results from being influenced by stocks that are experiencing trading suspensions. Third, we also exclude the bottom 30% of stocks ranked by market capitalization at the end of the previous month. This ensures that our results are not driven by the smallest-cap stocks that are considered to have unique characteristics (Liu et al. 2019). After applying these filtering rules, we end up with a total of 3,371 sample stocks over the sample period from July 1996 to June

2019.

The data of money market funds, including the daily order imbalance of MMETFs, are retrieved from Wind information Inc. (WIND). Following the prior literature (Han and Li 2017; Liu et al. 2019), we use the monthly rate of the one-year bank time-deposit (retrieved from WIND) as the proxy for the risk-free rate in China. The Fama and French (1993) risk factors in China are constructed similarly by using the 2×3 double-sorted portfolios, which are formed in July each year and holds for 12 months.

2.3.2. Anomaly variables

We use a number of prominent anomalies to capture the speculative nature of stocks in the cross section (Kumar 2009; Kumar, Page, and Spalt, 2016). These anomaly measures include idiosyncratic volatility (Ivol), lottery demand (Max), turnover ratio (Turnover), return volatility (Sigma), and market beta (Beta). As all of these anomaly measures capture a certain dimension of the speculative nature of the stocks, and are highly positively correlated in the cross section, we also construct an average score measure in the spirit of Stambaugh and Yuan (2017). This subsection describes how these variables are defined.

Idiosyncratic volatility (Ivol): Idiosyncratic volatility is defined as the standard deviation of the residuals obtained from regressing the daily excess returns of a stock on the Fama-French (1993) three-factors over the prior month. Ang, Hodrick, Xing, and Zhang (2006) find that stocks with low idiosyncratic volatility earn relatively high average returns compared to those with high idiosyncratic volatility.

Lottery demand (Max): The lottery demand measure is computed as the average of the largest five daily returns in the prior month. Bali et al. (2011) document a negative relation between the lottery demand measure and the subsequent stock returns. They attribute the negative relation to the lottery demand of gambling investors, who are willing to overpay the positive-skewed stocks.

Turnover ratio (Turnover): Turnover ratio is defined as the average of daily turnover ratios over the past month. Liu et al. (2019) suggest that turnover is a stock-level sentiment measure in China, and document that stocks with low turnover ratio outperform counterparts with high turnover ratio.

Return volatility (Sigma): Return volatility is measured as the standard deviation of daily returns over the prior month. Blitz, Hanauer, and van Vliet (2021) interpret return volatility as a firm-level speculative measure, and they document that the low-volatility effect is stronger and more persistent than the low-beta effect in China.

Market beta (Beta): Market beta is constructed as the product of the return correlation (with the market portfolio) and the market-adjusted volatility, using the approach in Frazzini and Pedersen (2014). Han, Li, and Li (2020) document that the low-beta anomaly is strong in China, and the magnitude of the low-beta anomaly varies with investor overconfidence over time.

Average score (Score): The score measure captures the overall speculative feature of a stock by averaging across five prominent anomaly measures (Ivol, Max, Turnover, Sigma, and Beta). It is computed in two steps. In the first step, we compute the five individual anomaly scores for each stock. To be specific, each month we assign a score (ranging from 1 to 10) to a stock based on its decile ranking of a specific anomaly variable in the cross section. For example, a stock that is in the 6th decile group sorted by Max receives an individual Max score of 6. In the second step, we equally weigh a stock's rankings across the individual scores. We require a stock to have at least three individual anomaly scores to compute the average score (for that stock-month observation). The rationale for averaging is that, through diversification, a stock's average score yields a less noisy measure of its speculative feature than it does with any single anomaly. Given that all five individual anomaly variables are highly positively correlated and negatively predict returns in the cross section, we expect stocks with a high average score to have a lower expected return than those with a low average score.

2.3.3. Descriptive statistics

In this section, we show that the portfolios of interest have the return patterns that are consistent with the empirical literature: Speculative stocks earn lower average returns than non-speculative stocks (Bali, Cakici, Whitelaw, 2011; Kumar, 2009). Each month we sort stocks (in ascending order) into decile portfolios based on one of the anomaly variables (in **subsections 2.3.2**) measured at the end of the prior month. The portfolios are value-weighted and rebalanced on a monthly basis. For each anomaly variable, we also form the zero-cost long-short portfolios. **Panel A of Table 2.1** lists the sorting variables and the composite stocks held in the long and short legs, respectively. The long-short portfolios are formed by buying non-speculative stocks and selling speculative stocks. The long-short portfolio is designed to ensure that it produces a positive expected return as predicted by the empirical literature—non-speculative stocks outperform speculative stocks. In addition to each anomaly strategy, we also construct a combination strategy (denoted as combo), which is the equal-weighted average of the returns of the individual anomaly strategy. That is, it makes a bet in each of the anomaly strategies with equal weights.

Panel B of the table reports the portfolio statistics over the full sample period from July 1996 to June 2019. As expected, all of the anomaly strategies deliver positive expected returns. The annualized mean excess returns range from 5.64% to 14.02% for the anomaly strategies. The standard deviations of these anomaly strategies range between 21.39% and 26.88% per annum. The Sharpe ratios of these strategies, ranging from 0.23 to 0.59, reinforces that betting against speculative stocks results in impressive gains for the mean-variance investors over the full sample period. Overall, the descriptive statistics in this section corroborate with prior literature that speculative stocks earn lower average returns than non-speculative stocks.

Table 2. 1 Description of the long-short strategies

Panel A: Formation of the long-short anomaly portfolios

Variable	Notation	Long leg	Short leg	Speculative leg
Idiosyncratic volatility	Ivol	Decile 1	Decile 10	Short
Lottery demand	Max	Decile 1	Decile 10	Short
Turnover	Turnover	Decile 1	Decile 10	Short
Return volatility	Sigma	Decile 1	Decile 10	Short
CAPM Beta	Beta	Decile 1	Decile 10	Short
Average Score	Score	Decile 1	Decile 10	Short
Combination	Combo	Decile 1	Decile 10	Short

Panel B: Descriptive statistics of the anomaly portfolios

	Ivol	Max	Turnover	Sigma	Beta	Score	Combo
Mean	13.68	7.42	14.02	10.50	5.64	13.79	10.25
Sharpe	0.59	0.30	0.52	0.41	0.23	0.51	0.48
STD	23.15	24.41	26.97	25.76	24.37	26.88	21.39
Skew	–0.21	–0.25	–0.54	–0.56	–0.25	–0.38	–0.32
Kurt	3.76	5.30	5.51	4.19	4.59	4.83	4.29
Min	–21.34	–27.94	–31.98	–23.86	–25.83	–28.09	–20.67
Max	23.11	23.95	28.92	21.63	28.03	28.61	19.47
Rho	0.06	–0.01	0.05	–0.02	–0.10	–0.02	0.00
Obs.	276	276	276	276	276	276	276

Note: Panel A of the table describes the constructions of the value-weighted long-short anomaly strategies. It lists the anomaly variables used to sort stocks in ascending orders to the decile portfolios. It also lists the decile portfolios used to compose the long and short legs, and also the speculative leg. Panel B reports the portfolio statistics over the sample period from July 1996 to June 2019. It reports the annualized mean, standard deviation, and Sharpe ratio of the monthly excess returns of the strategies.

2.4. Evidence at first glance

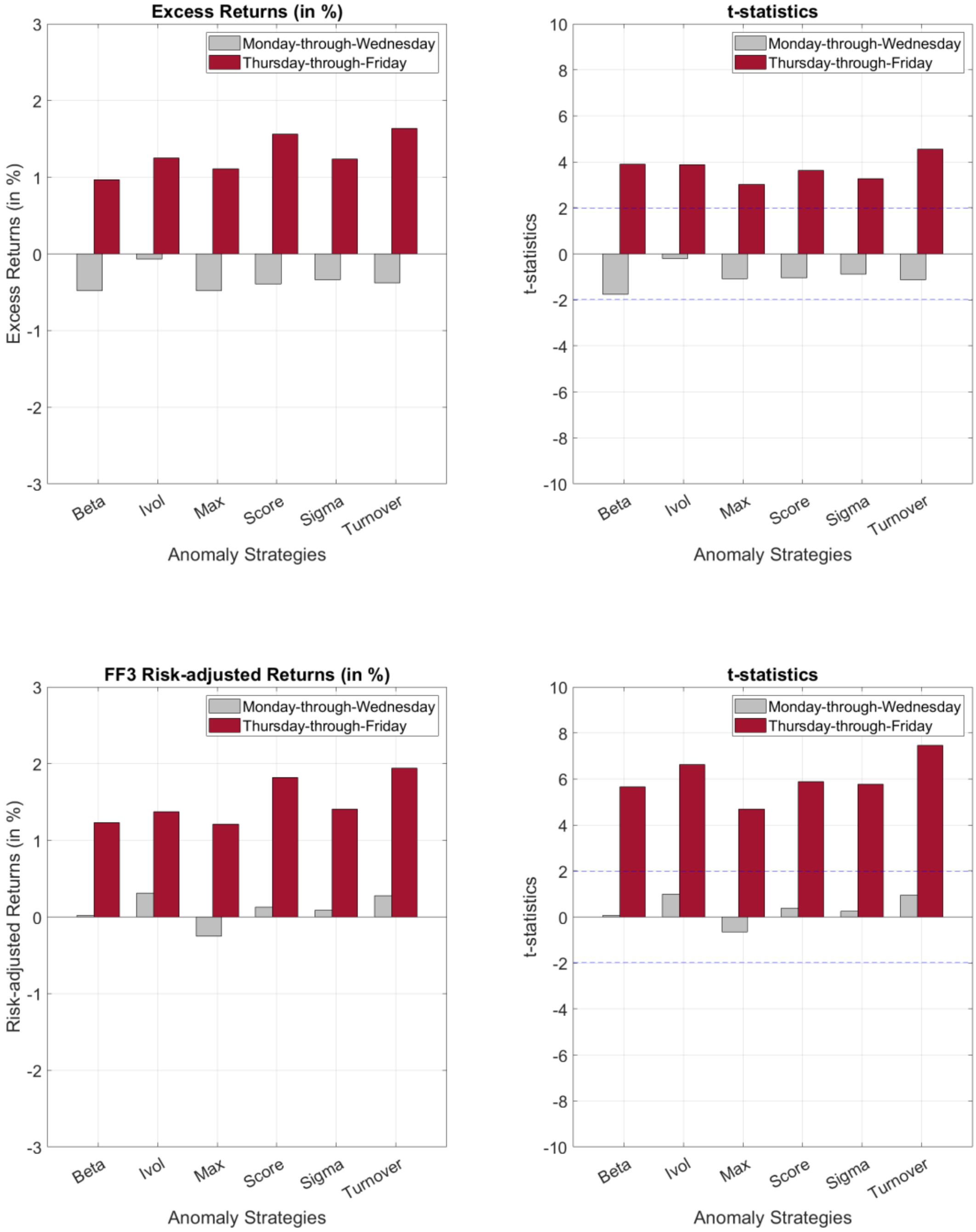
In this section, we examine the day-of-the-week effect of the long-short anomaly strategies over the full sample period. As stated in **Section 2.2.3**, our central prediction lies in the cross section (**Hypothesis 1**): Everything else equal, the price of speculative stocks drops more than that of non-speculative stocks on Thursday through Friday (rather than on Monday through Wednesday). To validate this notion, we evaluate the performance of the anomaly strategies over different days of the week. To be specific, we first compute the daily returns of the value-weighted anomaly portfolios (as described in **Section 2.3.3**). Next, we cumulate the daily returns on Mondays, Tuesdays, and Wednesdays (on Thursdays and Fridays) within each month to get the monthly Monday-through-Wednesday (Thursday-through-Friday) return series.

Table 2. 2 Monday through Wednesday and Thursday through Friday

	Monday to Wednesday			**Thursday to Friday**		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	–0.07	0.10	0.31	1.25	1.39	1.37
	[–0.21]	[0.31]	[1.00]	[3.87]	[7.24]	[6.63]
Max	–0.48	–0.30	–0.25	1.11	1.22	1.21
	[–1.08]	[–0.87]	[–0.65]	[3.03]	[5.11]	[4.69]
Turnover	–0.38	–0.12	0.28	1.64	1.82	1.94
	[–1.13]	[–0.37]	[0.95]	[4.56]	[8.05]	[7.46]
Sigma	–0.34	–0.13	0.09	1.24	1.37	1.41
	[–0.88]	[–0.40]	[0.24]	[3.26]	[6.08]	[5.77]
Beta	–0.48	–0.26	0.02	0.97	1.10	1.23
	[–1.77]	[–1.01]	[0.07]	[3.90]	[5.49]	[5.66]
Score	–0.39	–0.14	0.13	1.56	1.71	1.82
	[–1.04]	[–0.41]	[0.39]	[3.62]	[6.68]	[5.88]
Combo	–0.35	–0.14	0.09	1.25	1.38	1.44
	[–1.17]	[–0.53]	[0.32]	[3.97]	[7.49]	[6.89]

Note: The table reports the monthly average excess return (Excess), the CAPM alpha (CAPM), and the Fama-French three-factor alpha (FF3) of each of the value-weighted long-short strategies. The Newey-West adjusted *t*-statistics are reported in brackets. It presents the results for the anomaly strategies over Monday through Wednesday and Thursday through Friday, respectively. The sample period spans from July 1996 to June 2019.

Figure 2. 2 Performance of the long-short anomaly strategies on Monday through Wednesday and Thursday through Friday



Note: The upper (lower) left panel reports the monthly excess return (FF3 alpha) of the value-weighted long-short anomaly strategies on specific days of the week, and the upper (lower) right panel visualizes the Newey-West adjusted t-statistics. Each anomaly strategy goes long (short) the non-speculative (speculative) stocks to ensure an unconditional positive premium over the sample period. The anomaly variables are idiosyncratic volatility (Ivol), lottery demand (Max), turnover (Turnover), return volatility (Sigma), CAPM beta (Beta) and average anomaly score (Score). The sample period spans from July 1996 to June 2019.

Figure 2.2 visualizes the performance of the anomaly strategies on Monday-through-Wednesday versus that on Thursday-through-Friday. It depicts a striking seasonal pattern in the cross section: Long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks tend to experience *low* (or even negative) returns on Monday through Wednesday and *highly positive* returns on Thursday through Friday. In **Table 2.2**, we show that the average excess returns of the Monday-through-Wednesday long-short anomaly strategies are small and uniformly negative, ranging from –48 basis points (bps) to –7 bps per month over the full sample period. In comparison, the Thursday-through-Friday average excess returns are positive and economically sizeable, ranging from 97 bps to 164 bps per month (i.e., equivalent to an annualized return between 11.64% and 19.68% per annum which are larger than their all-weekday counterparts in **Table 2.1**). When interpreting the evidence from **Tables 2.1** and **2.2** collectively, it becomes clear that the Thursday-through-Friday return accounts for one hundred percent or more of the total monthly return of these long-short anomaly strategies.

The salient seasonal pattern remains intact when we evaluate the risk-adjusted performance under alternative factor models. For example, the long-short anomaly strategies deliver fairly low Fama-French three-factor (FF3) alphas (ranging from –25 bps to 31 bps per month) on Monday-through-Wednesday, but offer strong and sizeable FF3 alphas (ranging from 1.21% to 1.94% per month) on Thursday-through-Friday.

Table 2. 3 Short leg portfolios versus long leg portfolios

Panel A: Monday to Wednesday

	Short leg			Long leg		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	0.80	0.19	0.16	0.73	0.29	0.47
	[1.33]	[0.68]	[0.50]	[1.26]	[1.09]	[1.61]
Max	0.92	0.31	0.38	0.44	0.01	0.13
	[1.42]	[1.02]	[1.15]	[0.73]	[0.02]	[0.42]
Turnover	0.96	0.26	0.12	0.58	0.14	0.40
	[1.53]	[0.96]	[0.41]	[1.21]	[0.54]	[1.47]
Sigma	1.02	0.37	0.32	0.67	0.23	0.41
	[1.55]	[1.22]	[0.98]	[1.20]	[0.96]	[1.46]
Beta	0.97	0.30	0.29	0.49	0.04	0.31
	[1.58]	[1.19]	[1.05]	[0.81]	[0.19]	[1.20]
Score	1.06	0.38	0.30	0.67	0.24	0.43
	[1.57]	[1.29]	[0.97]	[1.19]	[0.97]	[1.52]
Combo	0.93	0.28	0.25	0.58	0.14	0.34
	[1.52]	[1.08]	[0.86]	[1.06]	[0.61]	[1.33]

Panel B: Thursday to Friday

	Short leg			Long leg		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	–1.31	–1.64	–1.55	–0.06	–0.25	–0.18
	[–3.68]	[–6.56]	[–5.90]	[–0.26]	[–1.36]	[–0.90]
Max	–1.26	–1.58	–1.49	–0.14	–0.36	–0.28
	[–3.27]	[–5.96]	[–4.98]	[–0.52]	[–1.96]	[–1.39]
Turnover	–1.59	–1.98	–2.01	0.05	–0.15	–0.07
	[–4.34]	[–6.92]	[–6.12]	[0.23]	[–0.85]	[–0.38]
Sigma	–1.12	–1.46	–1.43	0.12	–0.10	–0.02
	[–3.23]	[–5.39]	[–4.81]	[0.48]	[–0.57]	[–0.09]
Beta	–0.94	–1.29	–1.26	0.03	–0.19	–0.02
	[–3.14]	[–5.25]	[–4.62]	[0.15]	[–1.27]	[–0.14]
Score	–1.38	–1.75	–1.74	0.17	–0.04	0.09
	[–3.77]	[–6.14]	[–5.10]	[0.65]	[–0.23]	[0.45]
Combo	–1.25	–1.59	–1.55	0.00	–0.21	–0.11
	[–3.67]	[–6.33]	[–5.53]	[0.02]	[–1.29]	[–0.64]

Note: The table reports the monthly average excess return (Excess), the CAPM alpha (CAPM), and the Fama-French three-factor alpha (FF3) to each portfolio that invests in the short leg and long leg of the anomaly-based strategies. Panel A and B report the results based the portfolios investing on Thursday through Friday and on Monday through Wednesday. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to June 2019.

Next, we also examine the performance for the long-leg and short-leg portfolios separately over different days of the week (see **Table 2.3**). We find that the short-leg speculative stocks experience large price drops on Thursday and Friday (see **Panel B** of **Table 2.3**): Their raw Thursday-through-Friday returns are highly negative and large in magnitude, ranging from –0.94% (*t*-statistics = –3.14) to –1.59% (*t*-statistics = –4.34) per month. Their risk-adjusted returns are more prominent, as the FF3 alphas range from –1.26% (*t*-statistics = –4.62) to –2.01% (*t*-statistics = –6.12) per month. These sizeable negative returns indicate that speculative stocks indeed experience large selling pressure at the end of the week (i.e., Thursday and Friday). In comparison, there seem no material price changes for the long-leg non-speculative stocks on Thursday and Friday, because both the excess returns and the risk-adjusted returns for the long-leg portfolio are indistinguishable from zero on these two days. On Monday through Wednesday, however, we do not find much difference in the performance between the long-leg non-speculative stocks and short-leg speculative stocks (see **Panel A** of **Table 2.3**): It appears that average Monday-through-Wednesday returns are relatively small for both the short-leg speculative stocks and long-leg non-speculative stocks, as none of these returns are statistically significant.

Overall, we find consistent evidence in support of **Hypothesis 1**, as the long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks experience *low* returns on Monday through Wednesday and *high* returns on Thursday through Friday. Moreover, the striking cross-sectional seasonal pattern is largely driven by speculative stocks, suggesting that these stocks experience large price drops on the last two business days of the week (i.e., Thursday and Friday).[7]

[7] We also find that the Thursday-through-Friday price drop of speculative stocks (relative to non-speculative stocks) is concurrent with the recurring day-of-the-week pattern in the money market: There exhibits a concurrent unbalanced buying pressure of MMETFs at the end of the week (see **Panel A** of **Figure 2.8**), suggesting the strong interconnection between stock investing and cash investing. We formally test their interconnection in **Section 2.7**.

2.5. Empirical analysis

2.5.1. The difference-in-differences framework

In this subsection, we validate the two main hypotheses, **Hypotheses 2** and **3**. As discussed in **Section 2.2**, the 2013 FinTech revolution brings favourable changes, which includes, but not limited to, (i) shares of MMMFs as a new method of payments supported by FinTech platforms' extensive digital payment network, (ii) one-dollar minimum investment amount, and (iii) real-time on-demand redemption at par. These new features empower money market funds to better cater to the increasing demand for safety and fast-paced liquidity consumption. In other words, the 2013 FinTech revolution greatly expands the client base for money market funds, and ultimately boosts the demand for safety. Therefore, we would expect this plausibly exogenous shock to the demand for money market funds to exert a causal impact on the daily seasonality of asset pricing anomalies. To validate this notion, we employ the difference-in-differences (DiD) framework with the following model specification:

$$R_{i,t} = \alpha_t + \lambda_0 Treat_i + \lambda_1 Treat_i \times Post_t + \lambda_2 Interest_t + \varepsilon_{i,t}, \qquad [1]$$

where α_t is the time fixed effects, and $R_{i,t}$ denotes the monthly excess returns or benchmark-adjusted returns (CAPM-adjusted and FF3-adjusted returns) of the anomaly strategy i, which only invests in certain days within a week (i.e., Monday through Wednesday versus Thursday through Friday). $Treat_i$ is the treatment dummy that equals 1, if it is the portfolio that invests only on Thursday through Friday, and zero otherwise. The coefficient on the treatment dummy captures the difference in returns between the Thursday-through-Friday strategy and the Monday-through-Wednesday counterpart (i.e., the day-of-the-week effect), and is expected to have a positive sign. $Post_t$ is the post-event dummy that equals 1 if it is in 2013 and beyond (i.e., following the 2013 FinTech revolution), and zero otherwise. $Interest_t$ is the 3-month interest rate, which is included to mitigate the concerns of the safety-demand influence from the deposit market. Following Chu, Hirshleifer, and Ma (2020), we do not include the individual term $Post_t$, because it is subsumed by the time fixed effect in the regression.

Our key focus lies on the slope coefficient (λ_1) on the DiD term (*i.e.*, the interaction term between Treat and Post), which captures the differential impact on the portfolio returns between the Thursday-through-Friday strategy and the Monday-through-Wednesday strategy after the 2013 FinTech revolution. The coefficient λ_1 is expected to be positive, as we expect the FinTech revolution to amplify the daily seasonality of the asset pricing anomalies from 2013 onwards.

We perform the DiD test for the long leg, the short leg, and the long-short portfolio, respectively. **Table 2.4** presents the estimation results for the slope coefficients on the DiD term. The empirical results lend strong support to **Hypotheses 2** and **3**. The DiD coefficients are uniformly positive for the long-short portfolios, which holds for the raw returns as well as the benchmark-adjusted returns. Taking the FF3-adjusted returns as an example, the DiD coefficients are statistically significant in five out of the seven anomaly strategies. Moreover, for the aggregated analysis on the FF3-adjusted returns (when the seven anomaly strategies are combined), the DiD coefficient amounts to 1.14% with a t-statistics of 3.78. This confirms **Hypothesis 2** that the cross-sectional return seasonality is *amplified* after the FinTech shock in 2013. In particular, the average Thursday-through-Friday long-short return has an *additional* increase of 1.14% per month relative to the Monday-through-Wednesday counterpart following the 2013 FinTech revolution. Note prior to 2013, the FF3-adjusted return spread between the Thursday-through-Friday long-short anomaly portfolios (i.e., treatment group) and their Monday-through-Wednesday counterparts (i.e., control group) amounts to an average of 1.08% per month (unreported for brevity purpose). This indicates that the daily seasonality increases more than 100 percent after the 2013 FinTech revolution.

Consistent with the mispricing interpretation and our conjecture that the demand-for-safety channel matters more for speculative stocks than non-speculative stocks, we find that the amplified day-of-the-week seasonality comes predominantly from the short-leg portfolios (i.e., speculative stocks), which supports **Hypothesis 3**. That is, the DiD coefficients for the short-leg portfolios are uniformly negative, and are statistically significant in four out of seven cases for the FF3-adjusted returns. In the aggregated analysis on the FF3-adjusted returns, the DiD coefficient amounts to –1.75% with a t-statistic of –5.20, indicating the Thursday-through-Friday return of the short legs of speculative stocks has a further drop of –1.75% per month (relative to their Monday-through-Wednesday returns), subsequent to the 2013 FinTech revolution. Similar patterns also hold for the raw and CAPM-adjusted returns. Overall, consistent with our testable predictions, we find strong supporting evidence that a positive exogenous shock to the demand of money market funds (i.e., the FinTech revolution) leads to an increase in the daily cross-sectional stock return seasonality.

Table 2. 4 Difference-in-differences results

	Excess Returns			CAPM-Adjusted Returns			FF3-Adjusted Returns		
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
Ivol	-0.17	-1.13	0.95	0.07	-0.92	0.88	0.07	-0.91	0.99
	[-0.32]	[-1.44]	[1.60]	[0.16]	[-1.52]	[1.60]	[0.17]	[-1.52]	[1.97]
Max	-0.43	-1.08	0.65	-0.34	-0.87	0.58	-0.20	-0.81	0.61
	[-0.87]	[-1.32]	[1.03]	[-0.89]	[-1.32]	[0.97]	[-0.54]	[-1.24]	[1.04]
Turnover	-0.53	-1.22	0.69	-0.18	-0.98	0.58	-0.24	-1.03	0.78
	[-1.03]	[-1.48]	[1.09]	[-0.43]	[-1.52]	[1.01]	[-0.60]	[-1.59]	[1.47]
Sigma	-0.23	-1.29	1.06	-0.09	-1.08	0.98	0.020	-1.08	1.10
	[-0.46]	[-1.58]	[1.76]	[-0.24]	[-1.66]	[1.74]	[0.05]	[-1.67]	[2.05]
Beta	-0.25	-1.21	0.96	0.007	-0.99	0.88	0.074	-0.98	1.05
	[-0.51]	[-1.57]	[1.77]	[0.02]	[-1.65]	[1.75]	[0.20]	[-1.64]	[2.18]
Score	-0.45	-1.24	0.79	-0.21	-1.01	0.70	-0.16	-1.03	0.86
	[-0.89]	[-1.44]	[1.19]	[-0.57]	[-1.48]	[1.12]	[-0.46]	[-1.51]	[1.42]
Combo	-0.32	-1.19	0.86	-0.10	-0.97	0.78	-0.05	-0.96	0.91
	[-0.65]	[-1.52]	[1.58]	[-0.27]	[-1.60]	[1.56]	[-0.15]	[-1.60]	[1.92]
Aggregate	-0.57	-1.70	1.13	-0.63	-1.78	1.15	-0.60	-1.75	1.14
	[-1.90]	[-3.58]	[3.23]	[-2.71]	[-5.22]	[3.59]	[-2.68]	[-5.20]	[3.78]

Note: The table reports the DiD coefficient λ_1 from the regression $R_{i,t} = \alpha_t + \lambda_0 Treat_i + \lambda_1 Treat_i \times Post_t + \lambda_2 Interest_t + \varepsilon_{i,t}$ for the individual anomalies and for all of them in aggregate. The dependent variable $R_{i,t}$ is the monthly excess returns, the CAPM-adjusted returns, and the Fama-French three-factor adjusted returns of the anomaly strategy i in month t, which either invests on Monday through Wednesday or on Thursday through Friday. $Treat_i$ is the treatment dummy that equals 1 if portfolio i invests only on Thursday through Friday, and zero otherwise. $Post_t$ is the post-event dummy that equals 1 following the FinTech revolution (i.e., from 2013 onwards), and zero otherwise. α_t denotes time fixed effects. $Interest_t$ is the 3-month interest rate. The results for the long-leg (Long) portfolios, short-leg (Short) portfolios, and long-short (Long-Short) anomaly portfolios are tabulated respectively. Robust t-statistics are reported in brackets below the coefficient estimates. The sample period spans from July 1996 to June 2019.

2.5.2. Placebo regressions

In this section, we perform placebo regressions to substantiate the creditability of our difference-in-differences results in the prior subsection (**Section 2.5.1**). One concern about the main results is that our estimated treatment effect may be an outcome of chance, rather than the real impact of the safety demand on the cross-sectional return predictability. Another concern is that the standard errors in a typical difference-in-differences regression may be biased if firm characteristics are persistent (Bertrand, Duflo, and Mullainathan, 2004). To address both concerns, we conduct placebo regressions, and examine the empirical distributions of the DiD coefficient and *t*-statistics.

The placebo regressions proceed in six steps as follows: Step 1: We set the stock universe as the actual sample by applying the same data filtering rules as mentioned in **Section 2.3.1**. Step 2: We randomly generate the stock attributes, and sort stocks into decile portfolios based on the "placebo" stock attributes at the beginning of each month. Step 3: We take the bottom and top deciles (D1 and D10) to generate the long-short placebo anomaly strategy. The long and short legs are determined *ex post* to ensure that the long-short portfolio has a positive unconditional value-weighted excess return over the full sample period. Step 4: We compute the monthly Thursday-through-Friday (treatment) and Monday-through-Wednesday (control) strategy returns based on the "placebo" anomaly portfolios. Step 5: We randomly combine six individual placebo anomaly strategies as the panel sample, re-run the panel regression of Equation [1] as in **Section 2.5.1** (i.e., the DiD analysis), and save the DiD coefficient and the *t*-statistics. Step 6: We repeat the above steps (i.e., steps 1 to 5) 500 times to generate the empirical distribution of the DiD coefficients and associated *t*-statistics.

Table 2.5 summarizes the distributions of the coefficients and *t*-statistics on our variable of interest. Importantly, in all specifications, both the actual estimates of DiD coefficients and the *t*-statistics are significantly different from the averages from the placebo regressions. Taking the case of the FF3-adjusted returns of the long-short portfolio as an example, the placebo mean of the DiD coefficient is only 0.02. The 5th and 95th percentiles of the DiD coefficient are −0.20 and 0.26, respectively. The zero mean, together with the fairly small sample dispersion (between the 5th and 95th percentile), is expected to a large extent, because those randomly assigned placebo anomalies are unlikely to display a similarly large increase in the daily cross-sectional return seasonality. In comparison, our "true" estimate of 1.15 in **Table 2.4** lies clearly to the right of the 95th percentile, indicating a significant difference from the placebo mean.

We also obtain similar results comparing the *t*-statistics of the DiD term in **Table 2.4** to the distribution of t-statistics from the placebo regressions.

Similarly, the sample estimate of –1.75 (–0.61) for the short-leg (long-leg) portfolio in **Table 2.4** lies clearly to the left (right) of the 5th (95th) percentile. These anticipated, sizeable deviations from the placebo mean indicate that the FinTech-driven exogenous shock to the demand of money market funds indeed generates a disproportional impact on the daily return seasonality in the cross section: Speculative stocks (non-speculative stocks) are the most (least) impacted after the 2013 FinTech reform.

Overall, the sizeable departures from the placebo mean for the long-short portfolio as well as the long and short legs reinstate our confidence that our DiD results (in **Section 2.5.1**) are not due to random chance or pure luck. Instead, it captures the real economic channel that a boost in the demand for safety disproportionately impacts speculatively stocks more than non-speculative stocks on specific days of the week.

Table 2. 5 Placebo regressions

	Excess returns			CAPM-adjusted returns			FF3-adjusted returns		
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
Coefficient on $Treat \times Post$									
mean	–0.88	–0.90	0.02	–0.96	–0.98	0.02	–0.93	–0.95	0.02
5th percentile	–1.03	–1.05	–0.21	–1.11	–1.12	–0.20	–1.08	–1.09	–0.20
95th percentile	–0.72	–0.76	0.26	–0.80	–0.83	0.25	–0.77	–0.81	0.26
Actual estimate from Table 4	–0.57	–1.70	1.13	–0.63	–1.78	1.15	–0.61	–1.75	1.15
Percentile of actual estimate	<1%	<1%	<1%	<1%	<1%	<1%	<1%	<1%	<1%
t-statistic on $Treat \times Post$									
mean	–2.47	–2.55	0.16	–3.91	–4.00	0.16	–3.82	–3.91	0.16
5th percentile	–2.91	–2.94	–1.50	–4.58	–4.60	–1.49	–4.49	–4.49	–1.48
95th percentile	–2.03	–2.12	1.97	–3.24	–3.39	1.88	–3.14	–3.29	1.93
Actual estimate from Table 4	–1.90	–3.58	3.23	–2.71	–5.22	3.59	–2.68	–5.21	3.78
Percentile of actual estimate	<1%	<1%	<1%	<1%	<1%	<1%	<5%	<1%	<1%

Note: The table reports the empirical distribution of the DiD coefficient λ_1 and the associated t-statistics from the panel regression $R_{i,t} = \alpha_t + \lambda_0 Treat_i + \lambda_1 Treat_i \times Post_t + \lambda_2 Interest_t + \varepsilon_{i,t}$ based on the placebo anomaly portfolios. The dependent variable $R_{i,t}$ is the monthly excess returns, the CAPM-adjusted returns, and the Fama-French three-factor adjusted returns of the placebo anomaly strategy i in month t, which either invests on Monday through Wednesday or on Thursday through Friday. $Treat_i$ is the treatment dummy that equals 1 if portfolio i invests only on Thursday through Friday, and zero otherwise. $Post_t$ is the post-event dummy that equals 1 following the FinTech revolution (i.e., from 2013 onward), and zero otherwise. α_t denotes time fixed effects. The placebo anomaly portfolios are constructed using randomly generate the stock attributes. The long-leg (Long) and the short-leg (Short) are defined by ensuring the value-weighted long-short (Long-Short) placebo portfolio has a positive average monthly return over the full sample period. Each time, we randomly select six placebo anomaly strategies and run the difference-in-differences panel regression. This procedure is repeated 500 times to generate the empirical distribution.

2.5.3. Dynamic difference-in-differences test

In this section, we perform the "pre-trends" test on the plausibility of the parallel trends assumption. One key identifying assumption in the difference-in-differences framework is the "parallel trends" assumption that the observed trend in the control group can mimic the trend in the treated group in the absence of the treatment. Based on this assumption, the counterfactual outcomes of the treatment group can be established by using outcomes of the control group.

In order to test the parallel trends and study the dynamics of the treatment effects, we estimate a dynamic difference-in-differences model with time indicators for distances to/from the 2013 FinTech revolution. Specifically, we run the following panel regression:

$$R_{it} = \alpha_t + \beta_1 Treat_i + \sum_{k=-7,k\neq 0}^{+4} \lambda_k \times Treat_i \times I_{t,k} + \mu_1 Interest_t + \varepsilon_{it}, \qquad [2]$$

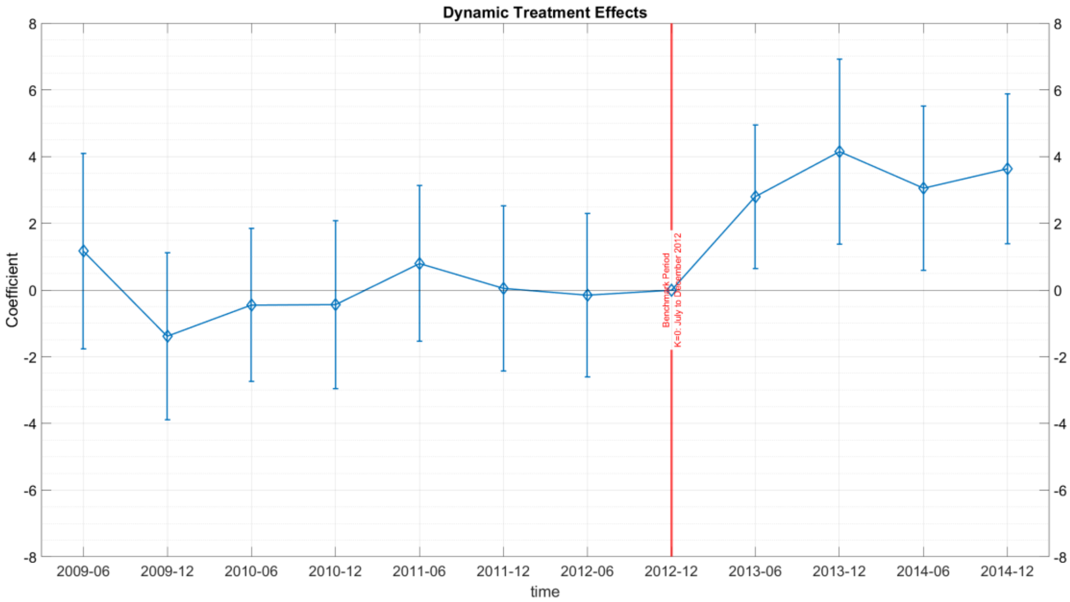
where $I_{t,k}$ is the set of time indicators that take the value of one in a specific non-overlapping six-month time period, and zero otherwise. k is the event index number. For example, $k = 0$ indicates that it is the first six-month period (i.e., from July 2012 to December 2012) prior to the 2013 FinTech revolution. All other variables are defined the same as in equation [1]. The sample period is from January 2009 to December 2014. Note we set the second half-year in 2012 as the benchmark period (i.e., $k = 0$), and thus, it is omitted in the regression as the reference group.

Our key variable of interest, λ_k, captures the difference in the return spread between each leading/lagging six-month period and the benchmark period (from July 2012 to December 2012). If the 2013 FinTech revolution, as an exogenous shock to the demand for safety, indeed amplifies the day-of-week seasonality, we would expect the coefficients λ_k to be constant over time for the time periods before the benchmark period. We also expect the coefficients λ_k to be significantly larger than zero for the time periods after the FinTech revolution.

Figure 2.3 visualizes the λ_k estimates and their 95% confidence intervals. It shows that the dynamic treatment effects are consistent with the parallel trends assumption: The estimated λ_k coefficients are statistically insignificantly different from zero, and exhibit no discernible pre-trends before the 2013 FinTech revolution (see k ranges from -7 to -1). Strikingly, the four post-FinTech λ_k coefficients across the two years from 2013 to 2014 range from 2.79% to 4.15% per month, and are all significantly larger than that of the benchmark period (see k ranges from $+1$ to $+4$), indicating the FinTech revolution indeed amplifies the daily cross-sectional stock return predictability substantially, as compared to the benchmark period (i.e., from July 2012 to December 2012).

Overall, the results of the dynamic treatment effects confirm that the parallel trends assumption is satisfied in the pre-event period. Besides, it also reinforces the material impact of the 2013 FinTech revolution, as an exogenous shock to demand of money market funds, on the daily cross-sectional return seasonality in the post-event period.

Figure 2. 3 Dynamic treatment effects



Note: The figure plots the difference-in-differences coefficients λ_k and the associated 95% confidence interval from the panel regression: $R_{it} = \alpha_t + \beta_1 Treat_i + \sum_{k=-7,k\neq 0}^{+4} \lambda_k \times Treat_i \times I_{t,k} + \varepsilon_{it}$, where the dependent variable $R_{i,t}$ is the monthly excess returns of the long-short anomaly strategy i in month t, which could be Thursday-through-Friday or Monday-through-Wednesday strategies. $Treat_i$ is the treatment dummy that equals 1, if it is the strategy that invests only on Thursday through Friday, and zero otherwise. $I_{t,k}$ is the set of time indicators that take the value of one in a specific six-month time period, and zero otherwise. k is the event index number. For example, $k = 0$ indicates that it is the six-month period from July to December 2012, which is set as our benchmark period (i.e., the first six-month period prior to the 2013 FinTech revolution).

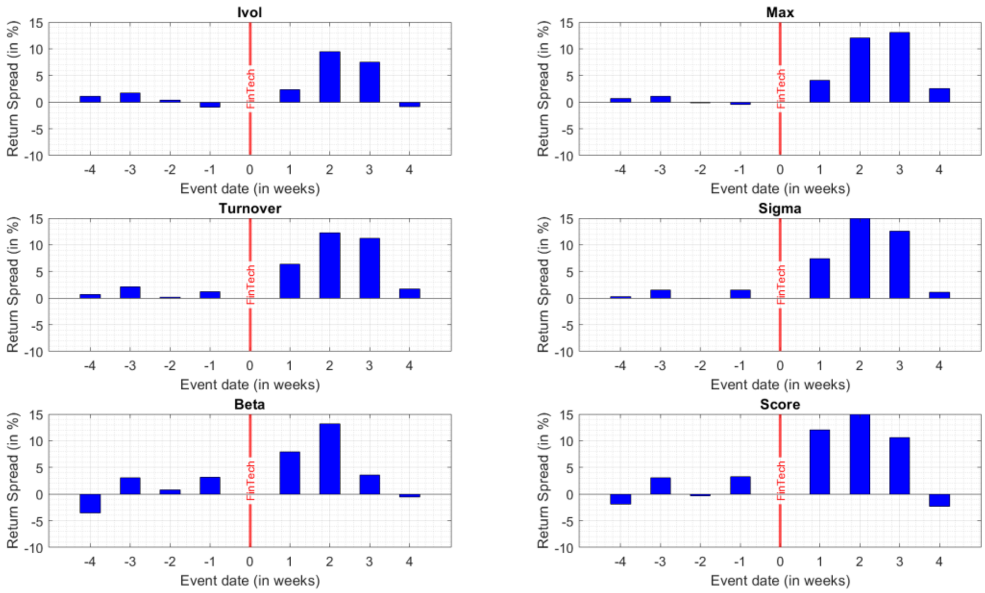
2.5.4. Event study around the launch of YEB

In prior subsections, we use the full sample period from 1996 to 2019 to estimate the treatment effect arising from the 2013 FinTech revolution and obtain consistent evidence supporting the casual relationship that the daily cross-sectional seasonality increases in the presence of a positive shock to the demand for money market funds. However, using a long sample period increases the likelihood that unobserved time-varying confounders may change returns differentially between the treatment and the control groups, thus invalidating our causal inference. For example, time-varying risk exposure, sentiment, and other unobservable factors can also cause similar changes in the seasonal cross-sectional return predictability over the long sample period. To mitigate this concern, it may be plausible to isolate a causal effect over a relatively short event window.

We zoom in a narrow window around the launch of YEB, the first-ever FinTech-customized MMMF, to provide direct evidence that the FinTech revolution in private money creation has a first-order impact on the seasonal return patterns. To be specific, we track the portfolio performance of the long-short anomaly strategies over a nine-week event window centered on the event week when YEB was launched (week 0). Our interest is to contrast the portfolio performance in the four full weeks *before* the introduction of YEB with that *after* the introduction of YEB. Over this short period, changes in seasonal return predictability and trading activities are predominantly caused by the FinTech shock—the inception of YEB. Moreover, we could reduce the chances that the shifts in daily seasonality are induced by other plausible factors or events, because none of them fall within our event window.

Empirically, we find consistent evidence to support our predictions from the event study. **Figure 2.4** visualizes the *change* in the return difference between the excess return of the Thursday long-short anomaly portfolio (treatment) and that of its Monday-through-Wednesday counterpart (control) *before* and *after* the launch of the YEB. Note here we focus on the Thursday long-short anomaly portfolio rather than the Thursday-through-Friday long-short anomaly portfolio, because the inception of YEB, as a MMMF (rather than a MMETF), should have a sharp impact on Thursday rather than on Friday (see **Section 2.2.1**). Over the four weeks prior to the event, the weekly return spreads are quite moderate, indicating that there exists little difference in returns between Thursday and Monday-through-Wednesday. Consistent with our prediction, the launch of YEB drastically *amplifies* the cross-sectional return seasonality, as there exhibits a salient increase in the return spread between the Thursday and the Monday-through-Wednesday long-short anomaly portfolio in the four weeks *after* the inception of YEB. Graphically, the weekly return spreads jump to above 5% (or even above 10%) multiple times within the four weeks following the launch of YEB. This applies to all six individual anomaly strategies.

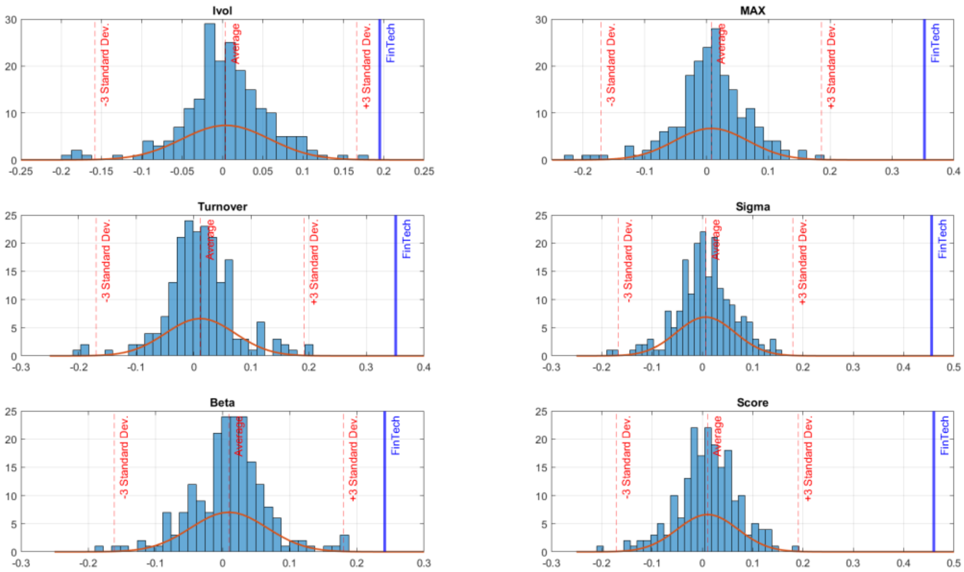
Figure 2. 4 Event window of the return spread



Note: The figure plots the return spread over the nine-week event window centered on the event week when YEB was launched (week 0). The weekly return spread is defined as the excess return of the Thursday long-short anomaly strategy minus that of its Monday-through-Wednesday counterpart. All long-short anomaly strategies are value-weighted, and the anomaly variables are idiosyncratic volatility (Ivol), lottery demand (Max), turnover (Turnover), return volatility (Sigma), CAPM beta (Beta) and average anomaly score (Score). The return spreads are measured in percentage.

In fact, the sheer magnitude of the salient increase in the return spreads shortly after the launch of YEB is unlikely to be driven by a random event or due to chances. To understand this, we cumulate the weekly return spreads over the four weeks after the event to form the event-month return spread, and compare it to the pre-2013 sample (i.e., prior to the FinTech revolution). **Figure 2.5** plots the empirical distribution of the monthly return spreads between the Thursday long-short anomaly strategy and its Monday-through-Wednesday counterpart based on the pre-2013 sample. The location of the event-month return spread is more than three standard deviations to the right of the sample mean, indicating that the FinTech shock to the cross-sectional return seasonality is unlikely to be a purely random event from a statistical perspective.

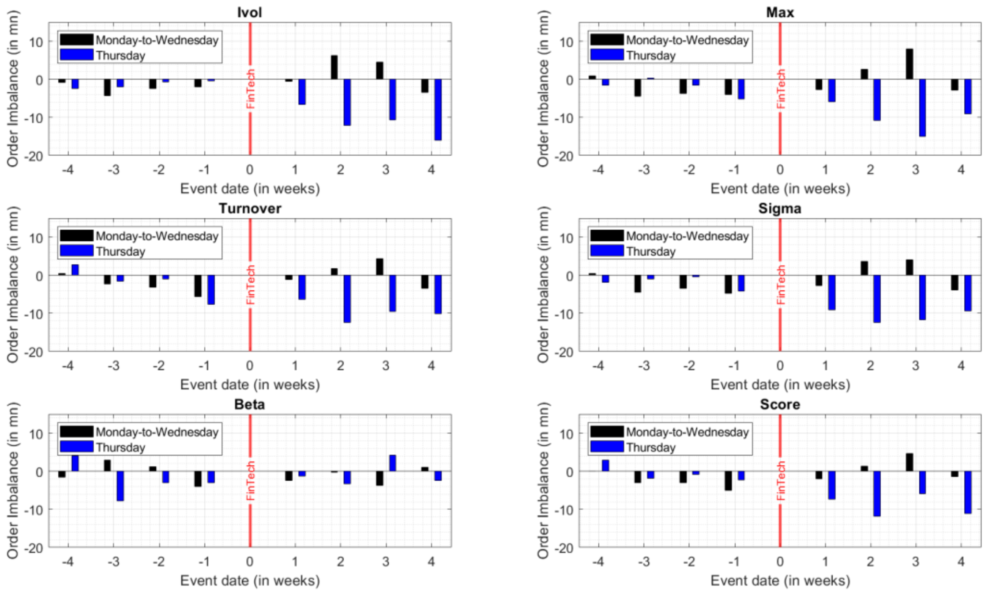
Figure 2. 5 Histogram of the monthly return spread



Note: The histogram depicts the empirical distribution of the monthly return spread based on the pre-2013 sample (i.e., prior to the FinTech revolution). The monthly return spread is defined as the excess return of the Thursday long-short anomaly strategy minus that of its Monday-through-Wednesday counterpart. The three dashed vertical lines (in red) indicate the locations of three standard deviations to the left of the mean (left), the mean (center), and three standard deviations to the right of the mean (right), respectively. The solid vertical line (in blue) indicates the location of the return spread of the FinTech month (spanning the first four full-week after the launch of YEB). All long-short anomaly strategies are value-weighted, and the anomaly variables are idiosyncratic volatility (Ivol), lottery demand (Max), turnover (Turnover), return volatility (Sigma), CAPM beta (Beta) and average anomaly score (Score). The return spreads are measured in decimals.

Next, we also investigate the stock trading activities measured by the order imbalance around the launch of the YEB. **Figure 2.6** plots the order imbalances for the Thursday long-short anomaly strategy and the counterpart for the Monday-through-Wednesday long-short anomaly strategy, respectively. The order imbalance of the long-short portfolio is computed as the difference between the equal-weighted average of order imbalances across all stocks in the short leg (i.e., speculative stocks) and that of all stocks in the long leg (i.e., non-speculative leg), and it is measured in millions of the local currency. Thus, a negative (positive) order imbalance indicates that speculative stocks experiences stronger selling (buying) pressure than non-speculative stocks.

Figure 2. 6 Event window of the portfolio-level order imbalance



Note: The figure plots the order imbalance of the Thursday long-short anomaly strategy (in blue) versus that of the Monday-through-Wednesday long-short anomaly strategy (in black) over the nine-week event window centered on the event week when YEB was launched (week 0). The portfolio-level order imbalance is computed as the difference between the equal-weighted average of all stocks in the short leg (i.e., speculative stocks) and that of all stocks in the long leg (i.e., non-speculative leg), and it is measured in millions of the local currency. The anomaly variables are idiosyncratic volatility (Ivol), lottery demand (Max), turnover (Turnover), return volatility (Sigma), CAPM beta (Beta) and average anomaly score (Score).

As expected, the launch of YEB also has a first-order impact on stock trading activities: First, selling pressure heightened drastically for speculative stocks (relative to non-speculative stocks) on Thursday as compared to Monday-through-Wednesday. In the four weeks prior to YEB, a typical speculative stock experiences moderately more selling pressure with an average order imbalance of –2 million Chinese yuan than a typical non-speculative stock on Thursday. Besides, there seems no obvious difference in the *additional* order imbalance on Thursday versus that on Monday-through-Wednesday in the pre-event periods. This, however, changes drastically following the onset of YEB, as the *additional* selling pressure on speculative stocks (relative to a typical non-speculative stock) more than quadrupled over the post-event four weeks on Thursday. Moreover, there exists a sharp contrast between the order imbalances on Thursday and those on Monday-through-Wednesday, as the Monday-through-Wednesday counterparts remain fairly small in magnitude and even turn into positive values in some weeks. The salient change in order imbalance around the event window is consistent with the implications of the FinTech shock generated by YEB, as it attracts holders of speculative stocks to more strongly pull money out of stock market (to seek safety) that causes stronger selling pressure on speculative stocks (relative to non-speculative stocks) on certain days of the week which cannot be absorbed by the rest of the market. Except for beta, the salient pattern on order imbalance applies to all individual anomaly strategies.

Overall, the sheer magnitude of the salient change in return spreads and order imbalance around the event window confirms two predictions: First, the launch of YEB substantially changed the daily cross-sectional return predictability, which demonstrates the “unintended” consequence of the FinTech revolution on the stock market. Second, holders of speculative stocks are more exposed to the sudden increase in the demand for money market funds, because the benefits of seeking safety via money market funds are more precious and valuable for these stocks than non-speculative stocks.

2.6. Further analysis

2.6.1. Evidence based on money market measures

In this subsection, we use measures derived directly from the money market to shed more light on the interconnection between the demand for safety and the daily cross-sectional return seasonality. To be specific, we validate the following testable predictions:

Hypothesis 4a: *The return of the long-short anomaly portfolio exhibits a stronger day-of-the-week seasonality on the specific Thursday and Friday with an unusually large demand for money market funds. That is, the daily Thursday-through-Friday return relative to their Monday-through-Wednesday counterpart becomes larger on the specific Thursday and Friday with an unusually large abnormal demand of money market funds (than that on the normal Thursday and/or Friday).*

Hypothesis 4b: *The high daily Thursday-through-Friday return relative to the Monday-through-Wednesday counterpart on the specific Thursday and Friday with an unusually large abnormal order imbalance of money market funds stems mainly from the short-leg anomaly portfolios.*

Testing **Hypotheses 4a** and **4b** is straightforward, but subjects to two minor caveats. First, **Hypotheses 4a** and **4b** are merely correlation statements rather than causal inferences. That is, we are validating the intuition that a stronger day-of-the week seasonality (in magnitude) for the long-short anomaly strategy is associated with an unexpected surge in the demand for safety on Thursday and Friday. Second, we use the MMETF's daily order imbalance as the proxy of the demand of money market funds. Ideally, one should leverage the MMMF's net inflows (i.e., subscription minus redemption), as a valid gauge of the demand for safety, to test the above predictions. Unfortunately, subscription and redemption data of MMMFs are not publicly available at the daily frequency. Despite the unavailability of MMMF data, the daily order imbalance of MMETFs still captures, to a large extent, the aggregated demand for safety, because both MMMFs and MMETFs are homogenous money market products and are popular alternatives when investors seek safety.

For ease of interpretation on the market outcome (i.e., return seasonality) associated with an unusual demand of safety, we construct a time dummy that captures the specific Thursday and Friday when there exists a salient, positive demand shock to money market funds: Specifically, we first compute the daily *abnormal* order imbalance based on the daily order imbalance of

MMETFs (measured in dollar terms). To account for the daily seasonality and the time trend of the order imbalance, abnormal order imbalance is defined as the difference between the daily order imbalance and the sample mean on the same day of the week over the prior 12-month rolling window. Finally, based on the daily abnormal order imbalance, we construct the time dummy, denoted as IMB, that equals one if the daily abnormal order imbalance on the specific Thursday and Friday is in the top quartile over the prior 30-day rolling window, and zero otherwise. The employment of a rolling window (rather than based on the full sample) ensures that our IMB measure is free of look-ahead bias.

To validate **Hypotheses 4a** and **4b**, we perform the following time-series regression:

$$y_t = \alpha + \beta_1 DOW_t + \beta_2 IMB_t + Controls_t + \varepsilon_t, \quad [3]$$

where y_t is the daily excess return of the anomaly portfolio (which is the long-leg portfolio, the short-leg portfolio, and the long-short portfolio, respectively). DOW_t is the day-of-the-week dummy that equals one if it is on Thursday and Friday, and zero otherwise. IMB_t is the time dummy related to abnormal order imbalance described above. The control variables are the daily market, size, and value factors in the Fama-French three-factor model. The sample period spans from January 2013 to June 2019 due to the availability of MMETF data. The intercept term captures the average daily return on Monday, Tuesday, and Wednesday (i.e., the benchmark days). The slope coefficient on the DOW_t dummy captures the incremental return earned on "normal" Thursday and Friday (i.e., the return spread of anomaly strategies on Thursday and Friday over the counterpart on Monday, Tuesday, and Wednesday under normal conditions). In comparison, our key variable of interest is the slope coefficient on the IMB_t dummy, which estimates the *additional* return spread on the specific Thursday and Friday under *unusual* conditions—when there is a salient increase in the demand for safety.

Table 2.6 presents the estimation results for the slope coefficient on the IMB_t dummy. As expected, the coefficients for the long-short anomaly portfolios are uniformly positive and statistically significant, providing strong support to **Hypothesis 4a**. That is, the daily seasonality in the long-short anomaly returns is more pronounced on the Thursday and Friday with an unusually large abnormal buying pressure of MMETFs than the normal Thursday and Friday. The magnitude of the increased daily seasonality on these unusual Thursday and Friday amounts to at least 20 bps per day, which is three or four times of its usual level (i.e., 4 to 6 bps per day).

Table 2. 6 Impact of abnormal order imbalance

	Long leg	Short leg	Long-Short
Ivol	0.00	–0.22	0.23
	[0.04]	[–2.74]	[2.35]
Max	–0.04	–0.24	0.20
	[–0.72]	[–2.54]	[1.79]
Turnover	0.00	–0.26	0.25
	[0.05]	[–2.85]	[2.81]
Sigma	0.02	–0.19	0.21
	[0.30]	[–2.00]	[1.84]
Beta	0.04	–0.18	0.22
	[0.74]	[–2.78]	[2.45]
Score	0.02	–0.26	0.28
	[0.38]	[–2.40]	[2.28]
Combo	0.00	–0.22	0.22
	[0.05]	[–2.90]	[2.57]

Note: The table reports the estimated slope coefficients of β_2 in the daily regression: $y_t = \alpha + \beta_1 DOW_t + \beta_2 IMB_t + Controls + \varepsilon_t$, where the variable y_t is the daily excess return of the anomaly portfolio, DOW_t is the dummy variable that equal one if it is Thursday and Friday, and zero otherwise. IMB_t is the dummy variable that equals one if the daily abnormal order imbalance of the Money Market ETFs on Thursday or Friday is in the top quartile over the prior 30-day rolling window, and zero otherwise. The control variables are the daily market, size, and value factors in the Fama-French three-factor model. It presents the results for the long-leg portfolios, the short-leg portfolios, and the long-short portfolios, respectively. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from January 2013 to June 2019.

When comparing the coefficients on the IMB_t dummy for the long-leg and short-leg portfolios, we also find consistent evidence in support of **Hypothesis 4b**. The coefficients for the short-leg portfolios (i.e., speculative stocks) are all negative and statistically significant, while the coefficients for the long-leg portfolios (i.e., non-speculative stocks) are indistinguishable from zero. In other words, the additional daily seasonality of the anomaly returns on these unusual Thursday and Friday (with a sudden, unexpected increase in the demand for safety) stems mainly from the short-leg anomaly portfolios. Overall, we confirm the prediction that an *unusually* large demand for safety on Thursday and Friday is *positively* associated with stronger daily seasonality of the long-short anomaly portfolios.

2.6.2. Time variation in the demand of safety

In this subsection, we provide further evidence on the time variation in the interrelation between the demand for safety and the seasonal anomaly returns. Kacperczyk and Schnabl

(2010) argue that investors regard money market funds as a safe haven (i.e., an investment that is anticipated to preserve or increase value in times of economic downturns). Baele et al. (2020) identify the episode of the movements in bond and equity markets in periods of financial stress as flights to safety. The safety benefits offered by money market funds become more precious to holders of speculative stocks, precisely when the market is in high volatility or uncertainty states, because holding costs and inventory risk of speculative stocks escalate in these extreme market states. As a result, we should observe that the association between abnormal demand of money market funds and the seasonal anomaly returns gets stronger in high market volatility (uncertainty) state than in low market volatility (uncertainty) state.

The above discussion leads to the following testable predictions:

Hypothesis 5a: *The interrelation between the abnormal demand of money market funds and the day-of-the-week seasonality in the long-short anomaly returns holds more strongly in high market volatility (uncertainty) periods than in low market volatility (uncertainty) periods.*

Hypothesis 5b: *The stronger interrelation between the abnormal demand of money market funds and the day-of-the-week seasonality in the long-short anomaly returns stems mainly from the short-leg anomaly portfolios.*

To test the above predictions, we divide the sample into high and low volatility (uncertainty) periods and re-estimate **Equation 3** for the two subsamples. For each daily return observation, it is classified as in high/low volatility (uncertainty) periods if the prior month-end market volatility (uncertainty) is above/below average.

Table 2.7 presents the estimation results for the slope coefficient on the IMB_t dummy. For the long-short anomaly returns, the slope coefficients on the IMB_t dummy are positive and statistically significant only in the high volatility periods, while the coefficients are small in magnitude and insignificant in the low volatility periods. This confirms **Hypothesis 5a** that the interrelation between the magnitude of the day-of-the-week seasonality in long-short anomaly returns and the unusual demand of safety on abnormal Thursday and Friday is more pronounced in high market volatility periods than in low market volatility periods. We also find consistent evidence to support **Hypothesis 5b** after comparing the coefficients on the IMB_t dummy for the long-leg and short-leg portfolios, respectively. The amplified daily seasonality of the anomaly returns on Thursdays and Fridays with a sudden increase in the demand for safety concentrates only in the high market volatility periods, and stems purely from the short-leg anomaly portfolios (i.e., speculative stocks).

We also repeat the exercise with the Baker, Bloom, and Davis (2016) China-specific economic policy uncertainty (EPU) index constructed by Davis, Liu, and Sheng (2019). We divide the sample into high and low uncertainty periods and re-estimate **Equation 3** for the two subsamples. Each daily return observation is classified as in high/low uncertainty periods, if the prior month-end demeaned EPU value is above/below average.[8] For the long-short anomaly returns, the slope coefficients on the IMB_t dummy are highly positive and statistically significant only in the high uncertainty subsample, while they tend to be small in magnitude and insignificant in the low uncertainty subsample (see **Table 2.A3** in the appendix).

Table 2. 7 Impact of abnormal order imbalance in high and low volatility periods

Panel A: High volatility periods			
	Long leg	Short leg	Long-Short
Ivol	–0.13	–0.61	0.48
	[–0.80]	[–3.03]	[1.90]
Max	–0.26	–0.77	0.51
	[–1.26]	[–2.88]	[1.47]
Turnover	–0.06	–0.64	0.57
	[–0.46]	[–2.50]	[2.43]
Sigma	–0.04	–0.58	0.54
	[–0.25]	[–2.02]	[1.49]
Beta	0.12	–0.57	0.69
	[0.68]	[–3.47]	[2.82]
Score	0.02	–0.86	0.88
	[0.12]	[–2.52]	[2.19]
Combo	–0.08	–0.64	0.56
	[–0.49]	[–3.03]	[2.24]

[8] The EPU index exhibits a strong time trend. Therefore, we demean the monthly EPU value by a six-month rolling window average that has no forward-looking bias. Days within a month is classified as in a high (low) EPU state, if the prior month-end demeaned EPU value is above (below) zero.
In unreported analysis, we also use investor sentiment as an alternative state variable to validate the state-dependent interrelation between the demand for safety and the seasonal anomaly returns, and find very similar results. Using the Han and Li (2017) China investor sentiment index, we divide the sample into high and low sentiment periods and re-estimate **Equation 3** for the two subsamples. For each day-return observation, it is classified as in high (low) sentiment periods if the prior month-end market sentiment is above (below) average. For the long-short anomaly returns, the slope coefficients on the IMB_t dummy are highly positive and statistically significant only in the low sentiment subsample, while the coefficients are small in magnitude and insignificant in the high sentiment subsample (see **Internet appendix** for details).

Panel B: Low volatility periods			
	Long leg	Short leg	Long-Short
Ivol	0.03	–0.07	0.10
	[0.58]	[–0.97]	[1.14]
Max	0.03	–0.04	0.07
	[0.70]	[–0.51]	[0.75]
Turnover	0.01	–0.10	0.11
	[0.18]	[–1.41]	[1.32]
Sigma	0.03	–0.04	0.06
	[0.57]	[–0.49]	[0.70]
Beta	0.01	–0.04	0.05
	[0.19]	[–0.66]	[0.57]
Score	0.02	–0.03	0.05
	[0.40]	[–0.40]	[0.52]
Combo	0.02	–0.06	0.08
	[0.50]	[–0.97]	[1.06]

Note: The table reports the estimated slope coefficients of β_2 in the daily regression: $y_t = \alpha + \beta_1 DOW_t + \beta_2 IMB_t + Controls + \varepsilon_t$, where the variable y_t is the daily excess return of the anomaly portfolio, DOW_t is the dummy variable that equal one if it is Thursday and Friday, and zero otherwise. IMB_t is the dummy variable that equals one if the daily abnormal order imbalance of the Money Market ETFs on Thursday or Friday is in the top quartile over the prior 30-day rolling window, and zero otherwise. The control variables are the daily market, size, and value factors in the Fama-French three-factor model. Panel A (B) presents the results for the long-leg portfolios, the short-leg portfolios, and the long-short portfolios in high (low) volatility periods. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from January 2013 to June 2019.

We also re-examine our main specification in **Section 2.5.1**, the DiD regression for the aggregated analysis, under the low and high volatility periods. To mitigate the contamination of the extreme market period, we use data varying from July 2009 to December 2014. [9] Similar to the analysis before, we divide our time sample into high/low volatility periods if the prior month-end market volatility is above/below average. **Table 2.A4** in the appendix presents the DiD coefficient results for low and high periods. For the aggregated analysis on the FF3-adjusted returns, the DiD coefficient amounts to 4.72% with a t-statistics of 3.19 under high volatility periods, which is around 30% higher than that under low volatility periods, amounting to 3.45 with a t-statistics of 6.25. Overall, our findings confirm our safe-haven prediction that the demand-for-safety phenomenon is more pronounced during the high volatility period.

[9] In this way we can exclude the 2008 financial crisis period (January 2008 to October 2008) and the 2015 market turbulence periods (June 2015 to January 2016).

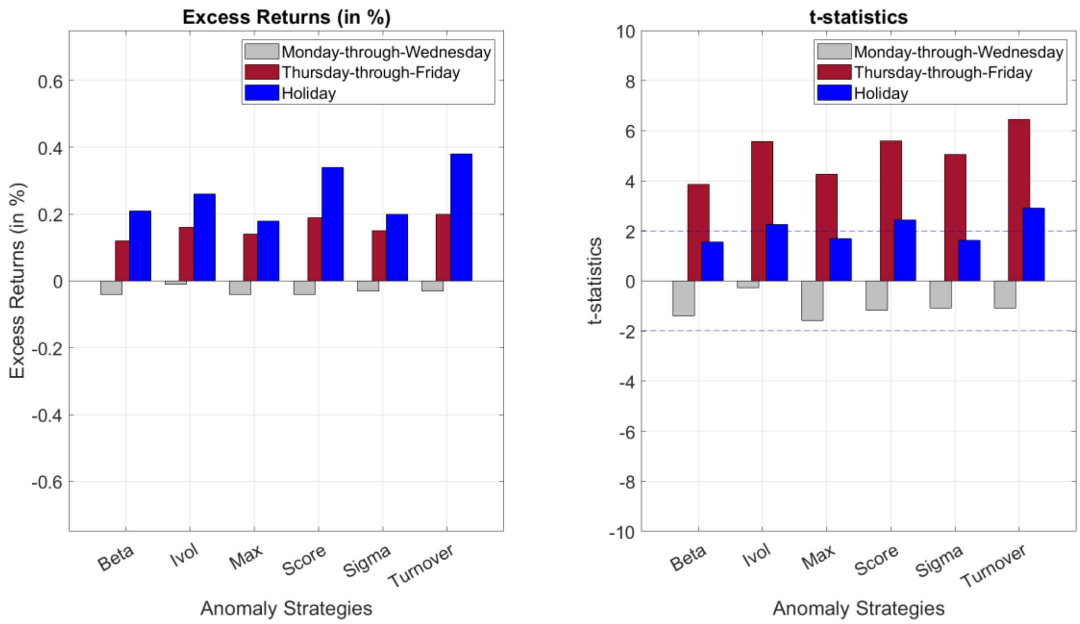
2.6.3. Holiday effect

In this subsection, we provide further evidence on the demand-for-safety channel by exploring the holiday effect. Over a prolonged period when the stock market closes due to national holidays, the guaranteed yield (accrued over holidays days) in money market funds may become attractive to short-term stock investors, in particular, holders of speculative stocks. Thus, the tendency for these investors to demand safety (i.e., by shifting away from the stock market to the money market) should also occur on days preceding holidays. This holiday effect would imply that the long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks tend to deliver *high* returns over the two business days prior to long holidays.

Empirically, we define a long holiday as the one that is associated with the stock market closure for at least three consecutive days. These holidays involve New Year (in January), Chinese New Year (in late January or February), Qingming Festival (in April), International Workers' Day (in May), Dragon Boat Festival (in late May or June), Mid-autumn Festival (in September), National Day (in October), among others. Based on the criteria, we identify 122 long holidays over the full sample period from July 1996 to June 2019.

As expected, we document a strong holiday effect, as the long-short anomaly strategies earn relatively high returns over the two working days prior to the long holidays. As is shown in **Figure 2.7**, the average daily excess return of the long-short anomaly strategies over the two days prior to holidays are nearly two times larger than their Thursday-through-Friday counterparts. Overall, the documented holiday effect provides "out-of-sample" evidence to support the demand-for-safety channel.

Figure 2. 7 Holiday Effect



Note: The left panel reports the average daily excess return of the value-weighted long-short anomaly strategies that invest only on Monday-through-Wednesday, Thursday-through-Friday, and the two business days prior to holidays, respectively. The right panel visualizes their respective Newey-West adjusted *t*-statistics. Each anomaly strategy goes long (short) the non-speculative (speculative) stocks to ensure an unconditional positive premium over the sample period. The anomaly variables are idiosyncratic volatility (Ivol), lottery demand (Max), turnover (Turnover), return volatility (Sigma), CAPM beta (Beta) and average anomaly score (Score). The sample period spans from July 1996 to June 2019.

2.7. Alternative explanations and robustness checks

In this subsection, we carefully check a number of alternative mechanisms which may explain our main results.

2.7.1. Short-selling activities

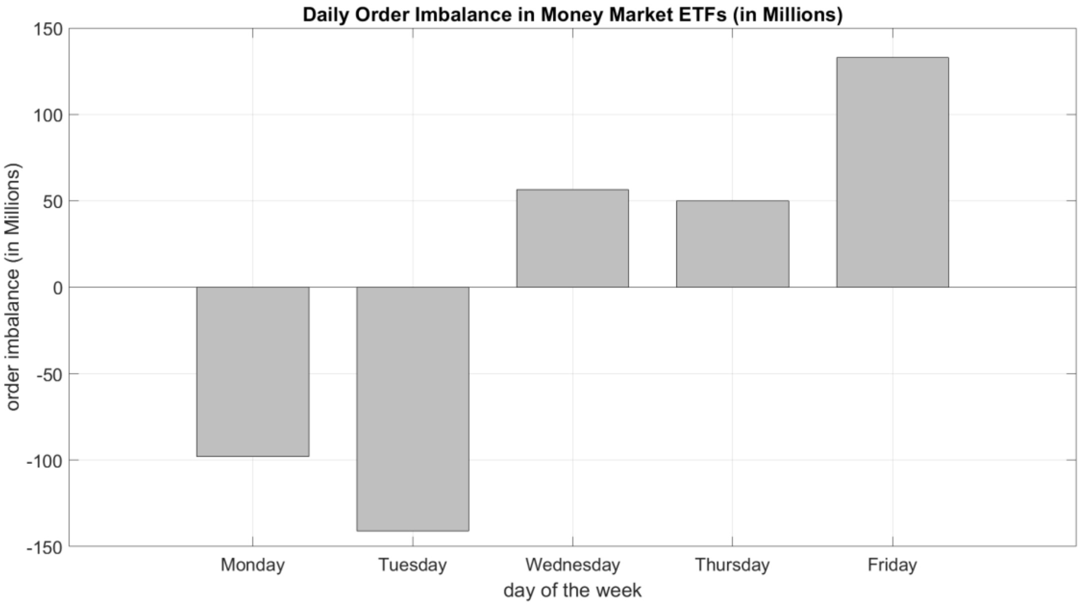
We are aware that one might argue that the seasonal pattern in the cross section could be induced by arbitrageurs (i.e., short-sellers), who can systematically short-sell stocks on Thursday and Friday, generating excessive selling pressure on speculative stocks (relative to non-speculative stocks) at the end of the week. Consistent with this argument, Blau, Van Ness, and Van Ness (2009) find some evidence that short selling activity on Friday is higher than that on Monday. Besides, speculative stocks tend to have high volatility and are the attractive target of short sellers (Diether, Lee, and Werner, 2009). However, we believe that short selling is unlikely to be the main driver of our documented cross-sectional daily seasonality for the following reasons:

First, short-sellers are informed investors, whose trades are information-motivated (Engelberg, Reed, and Ringgenberg, 2012; Boehmer, Jones, Wu, and Zhang, 2020). Given that value-relevant information flows are disseminated to the market in a random fashion, it is unlikely that arbitrageurs short-sell speculative stocks only on specific days of the week such as Thursday and Friday.

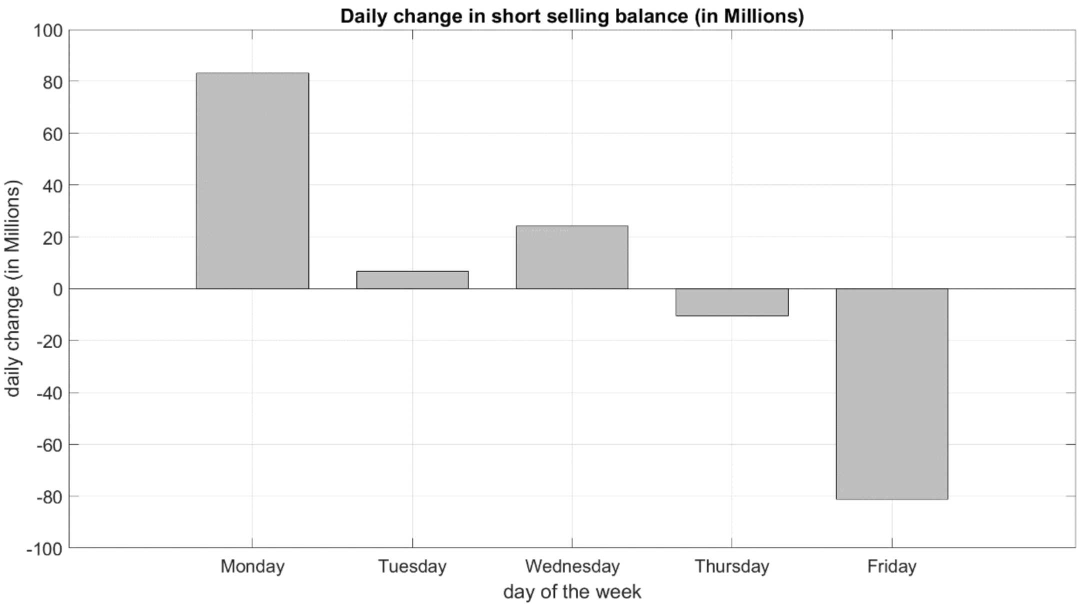
Second, short-selling is highly risky and costly. The positions are held only for a limited time to reduce holding costs and inventory risk (Shleifer and Vishny, 1997; Engelberg, Reed, and Ringgenberg, 2018). Given that stock lending fees are charged on a *calendar* day basis, short-sellers have a strong motivation to close out, rather than open, their position at the end of the week (i.e., Thursday and Friday). By examining the aggregated short-selling balance across days of the week, we find the empirical pattern that is consistent with the inventory cost concern: Short-sellers tend to buy back stocks to close out the short positions, rather than short sell stocks at the end of the week (see **Panel B** of **Figure 2.8**). The empirical pattern on short selling, is also consistent with the prior US evidence in Chen and Singal (2003) that short-sellers tend to close out their short position on Friday (due to inventory concern and the inability to trade over the weekend) and re-establish new short positions on Monday.

Figure 2. 8 Daily order imbalance of MMETFs and daily change in short-selling balance

Panel A: Order imbalance of MMETFs



Panel B: Short selling balance



Note: Panel A plots the demeaned order imbalance of the Money Market ETFs (measured in millions of RMB) on specific day of the week. The sample period spans from January 2013 to June 2019. Daily order imbalance is aggregated over the top 5 largest MMETFs, which represents more than 99% of the AUMs among all MMETFs. Panel B plots the daily change in short-selling balance (measured in millions of RMB) on specific days of the week. The sample period spans from January 2013 to June 2019. Note a positive (negative) change in short-selling balance represents an increase (decrease) of short-selling activities as more short position are opened (closed).

Third, short-selling is only allowed in China from 2010 onwards and is still in a limited scope: Only the stocks in the short-selling list approved by the China Securities Regulatory Commission (CSRC) are eligible for short-selling (Chang, Luo, and Ren, 2014). If short-selling is the main driver of the cross-sectional daily seasonality, we should at least observe that the day-of-the-week effect is stronger in the subsample of eligible stocks for short-selling than in the subsample of non-eligible stocks. However, as is shown in **Table 2.8**, we find exactly the opposite pattern that the long-short anomaly returns on Thursday-through-Friday seem stronger (in magnitude) in the subsample of non-eligible stocks than in the subsample of eligible stocks for short-selling.

Table 2. 8 Subsample analysis of the stocks eligible for short selling versus those non-eligible for short selling

	Panel A: Eligible for short selling					
	Monday to Wednesday			Thursday to Friday		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	–0.36	–0.29	–0.44	0.84	0.88	0.70
	[–0.74]	[–0.60]	[–0.95]	[2.89]	[2.76]	[2.44]
Max	–0.16	–0.09	–0.28	0.61	0.65	0.49
	[–0.39]	[–0.21]	[–0.63]	[2.00]	[1.89]	[1.61]
Turnover	–0.38	–0.30	–0.32	1.33	1.37	1.31
	[–0.74]	[–0.62]	[–0.74]	[3.33]	[3.24]	[3.57]
Sigma	–0.53	–0.46	–0.57	0.74	0.78	0.61
	[–1.44]	[–1.14]	[–1.39]	[1.95]	[1.95]	[1.66]
Beta	–0.01	0.07	0.10	1.11	1.16	1.08
	[–0.02]	[0.19]	[0.22]	[3.70]	[3.56]	[3.24]
Score	–0.27	–0.19	–0.28	1.08	1.13	0.95
	[–0.59]	[–0.40]	[–0.58]	[2.71]	[2.63]	[2.22]
Combo	–0.29	–0.21	–0.30	0.93	0.97	0.84
	[–0.73]	[–0.53]	[–0.77]	[2.90]	[2.78]	[2.63]

	Panel B: Non-eligible for short selling					
	Monday to Wednesday			Thursday to Friday		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	0.35	0.38	0.33	1.40	1.42	1.34
	[1.20]	[1.26]	[1.11]	[7.83]	[7.53]	[6.90]
Max	–0.24	–0.20	–0.32	0.87	0.89	0.76
	[–0.72]	[–0.53]	[–0.89]	[3.07]	[3.05]	[2.69]
Turnover	–0.02	0.02	0.15	1.53	1.55	1.53
	[–0.07]	[0.11]	[0.74]	[6.40]	[6.34]	[6.54]
Sigma	–0.27	–0.23	–0.26	1.17	1.19	1.08
	[–1.04]	[–0.85]	[–1.01]	[4.40]	[4.42]	[4.10]
Beta	–0.39	–0.35	–0.36	0.60	0.62	0.55
	[–1.48]	[–1.12]	[–1.17]	[2.12]	[2.10]	[1.80]
Score	–0.14	–0.10	–0.14	1.37	1.39	1.25
	[–0.49]	[–0.28]	[–0.41]	[4.98]	[4.76]	[4.51]
Combo	–0.11	–0.08	–0.09	1.11	1.13	1.05
	[–0.50]	[–0.30]	[–0.39]	[5.21]	[5.11]	[4.88]

Note: The table reports the monthly average excess return (Excess), the CAPM alpha (CAPM), and the Fama-French three-factor alpha (FF3) of each of the value-weighted long-short strategies for the subsamples of stocks in the short-selling list (in Panel A) and non-short-selling stocks (in Panel B), respectively. The Newey-West adjusted *t*-statistics are reported in parenthesis. It presents the results the Monday-through-Wednesday and Thursday-through-Friday strategy, respectively. The sample period spans from April 2010 to June 2019.

2.7.2. News announcements

One possible alternative explanation of the daily seasonality is that economic news systematically released on specific days of the week, which leads to the day-of-the-week effect in the cross section. That is, the regularity of information flows induces the cyclical asset price changes on certain days of the week (Abraham and Ikenberry 1994; Fishe et al., 1993).

Following Savor and Wilson (2013), we gather the announcement dates on Gross Domestic Product (GDP), Consumer Price Index (CPI), and Producer Price Index (PPI) that are sourced from the National Bureau of Statistics. We also retrieve the dates on open market operations announcements by the central bank. Few events in China are as closely watched by investors as open market operations, which are the main indicator of the central bank's monetary policies. Bernanke and Kuttner (2005) point out that macroeconomic announcements, especially those pertaining monetary policies, can have a major influence on the security market. We define the announcement date as the first trading day that the market participants could trade on the information. That is, if the announcements are released during the off-market period of a trading day (i.e., after 15:00 PM) or on weekends or holidays, we code it to the next trading day in our sample.

Following Birru (2018), we exclude all the announcement dates from the sample, and re-estimate the anomaly portfolios on Monday through Wednesday and on Thursday through Friday, respectively. The results presented in **Panel A** of **Table 2.9** show that the day-of-the-week patterns remain robust to the exclusion of these news announcement dates. Therefore, the daily seasonality is unlikely to be driven by the regularity of information flows.

In a similar vein, the announcements of firm-specific earnings news on Fridays may also play a role in explaining the daily seasonality. Prior studies (e.g., DellaVigna and Pollet, 2009; Doyle and Magilke, 2009) find that managers opportunistically time their announcements of bad news to take advantage of reduced media coverage and investor attention on Fridays or after the market closes. To the extent that certain firms (i.e., those with speculative stocks) choose Friday to announce bad earnings news, it is not surprising that speculative stocks underperform their non-speculative counterparts on Fridays.

To gauge this possible alternative explanation, we obtain all firm-specific earnings announcement dates from WIND. Following Birru (2018), we exclude all the earnings announcement dates from the sample, and re-estimate the anomaly portfolios on Monday through Wednesday and on Thursday through Friday, respectively. The results in **Panel B** of **Table 2.9** indicate that the day-of-the-week patterns remain robust to the exclusion of these firm-specific earnings announcement dates. Therefore, the daily seasonality is unlikely to be driven by the regularity of firm-specific information flows.

Table 2. 9 Excluding the announcement days

	Panel A: Excluding macro announcement days					
	Monday to Wednesday			Thursday to Friday		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	0.03	0.19	0.40	1.48	1.66	1.77
	[0.02]	[0.43]	[0.88]	[3.10]	[5.33]	[6.75]
Max	–0.33	–0.14	–0.09	1.09	1.22	1.39
	[–0.51]	[–0.26]	[–0.16]	[2.20]	[3.26]	[4.03]
Turnover	–0.69	–0.45	0.12	1.78	2.01	2.28
	[–1.78]	[–1.18]	[0.34]	[3.84]	[5.20]	[6.07]
Sigma	–0.25	–0.05	0.16	1.42	1.55	1.68
	[–0.46]	[–0.09]	[0.32]	[2.95]	[4.22]	[5.42]
Beta	–0.40	–0.14	–0.04	1.10	1.29	1.37
	[–1.17]	[–0.51]	[–0.14]	[3.07]	[4.41]	[4.33]
Score	–0.36	–0.10	0.13	1.53	1.72	1.85
	[–0.71]	[–0.22]	[0.30]	[2.75]	[4.55]	[4.85]
Combo	–0.33	–0.11	0.11	1.38	1.55	1.70
	[–0.80]	[–0.29]	[0.30]	[3.05]	[4.91]	[5.81]

	Panel B: Excluding earnings announcement days					
	Monday to Wednesday			Thursday to Friday		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	–0.08	0.03	0.28	1.25	1.36	1.36
	[–0.24]	[0.11]	[0.82]	[5.26]	[5.83]	[6.39]
Max	–0.52	–0.38	–0.28	1.11	1.21	1.20
	[–1.37]	[–1.01]	[–0.69]	[4.31]	[4.64]	[4.89]
Turnover	–0.45	–0.28	0.20	1.61	1.75	1.94
	[–1.35]	[–0.99]	[0.70]	[6.56]	[6.72]	[7.19]
Sigma	–0.38	–0.22	0.02	1.24	1.34	1.39
	[–1.02]	[–0.63]	[0.04]	[4.96]	[5.04]	[5.83]
Beta	–0.50	–0.32	–0.07	0.96	1.06	1.19
	[–1.93]	[–1.22]	[–0.24]	[4.82]	[5.15]	[5.59]
Score	–0.45	–0.27	0.06	1.55	1.66	1.83
	[–1.24]	[–0.78]	[0.18]	[5.82]	[5.84]	[6.08]
Combo	–0.39	–0.23	0.03	1.24	1.34	1.42
	[–1.32]	[–0.85]	[0.10]	[5.76]	[6.05]	[6.77]

Note: The table reports the monthly average excess return (Excess), the CAPM alpha (CAPM), and the Fama-French three-factor alpha (FF3) of each of the value-weighted long-short strategies over Monday through Wednesday and Thursday through Friday, respectively. Panel A reports the monthly return series excluding macro announcement days with open market operations announcements by the central bank, and Gross Domestic Product (GDP), Consumer Price Index (CPI) and Producer Price Index (PPI) announcements by the National Bureau of Statistics. The sample period spans from January 2007 to June 2019. Panel B reports the monthly return series excluding the firm-specific earnings announcement days. The sample period spans from July 1996 to June 2019. The Newey-West adjusted *t*-statistics are reported in brackets.

2.7.3. Mitigating microstructure concerns

Another legitimate concern is that certain market microstructure features could lead to the daily seasonality in the cross section. Note option and futures contracts expire regularly on the third Friday of the month. It is possible that selling pressure induced by option and futures expirations has a disproportional impact in the cross section, which leads to increased seasonality on specific dates. For example, Cao et al. (2021) find that after removing the equity option's expiration day (i.e., the third Friday of a month), the seasonal premium of the long-short strategy based on idiosyncratic volatility is reduced by around 40%.

Following Cao et al. (2021), we investigate whether the expiration day effect is the (main) source of the daily seasonality in China. The sample is confined to 2010 onwards, as derivative contracts on financial assets are launched in China only post-2010. Each month we form two long-short anomaly portfolios. One that invests only on the Thursday and Friday in the third week of the month, covering the expiration date of derivative contracts (denoted as the expiration strategy). The other invests on all remaining non-expiration Thursdays and Fridays of the month (denoted as the non-expiration strategy). We rescale the returns series of the two value-weighted strategies (to monthly level) to ensure they have the same number of days. We then validate whether there exists a systematic difference between the expiration and non-expiration strategies.

Table 2.10 presents the Fama-French three-factor alphas of the expiration strategy and the non-expiration strategy, respectively. For both strategies, the portfolio alphas are highly positive, and are mostly statistically significant. Moreover, the difference in the alphas of the two strategies is indistinguishable from zero across all anomalies. The evidence indicates that the seasonal (Thursday-through-Friday) phenomenon is robust whether it is in the expiration week of the month or in the non-expiration weeks of the month. Therefore, the expiration day of derivative contracts is unlikely to be the main driver of the day-of-the-week effect in China.

Table 2. 10 Expiration and non-expiration dates

	Expiration	Non-Expiration	Difference
Ivol	1.65	1.65	–0.00
	[3.04]	[6.79]	[–0.03]
Max	1.26	1.13	0.13
	[2.64]	[3.13]	[0.20]
Turnover	1.86	1.99	–0.13
	[4.66]	[7.89]	[–0.21]
Sigma	1.56	1.47	0.09
	[2.87]	[5.22]	[0.16]
Beta	0.87	1.08	–0.26
	[1.91]	[4.04]	[–0.44]
Score	0.39	0.78	–0.39
	[1.04]	[4.08]	[–0.97]
Combo	1.17	1.08	0.09
	[2.53]	[5.63]	[0.18]

Note: The table reports the Fama-French three-factor alpha of the two long-short strategies: One that only invest on the third-week's Thursday through Friday in each month (the index future expiration dates), and the other that invest on the remaining Thursdays through Fridays of the month (the non-expiration dates). Both return series are rescaled to ensure comparability. It also tests the return difference between the two non-overlapping monthly strategies. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from April 2010 to June 2019.

2.7.4. Robustness checks

We also perform a battery of robustness checks to validate that our main results are robust to alternative measures and specifications.

Disentangling the increased Thursday-through-Friday seasonality. In our main analysis, we treat the launches of FinTech-customized MMMFs (i.e., YEB) and MMETFs as one joint event under the grand theme of China's FinTech revolution (see **Section 2.2.2**). This is because these two salient events coincide with each other in time (i.e., both in the first half of 2013), and they complement each other in boosting the demand for safety from 2013 onwards. Nevertheless, MMETFs offer investors a last-minute solution to seek safety and earn the yields over the weekend by trading on Friday, rather than on Thursday. In that sense, the emergence of MMETFs redistributes partially the "otherwise" concentrated demand for safety from Thursday to Friday (i.e., the redistribution effect).

Empirically, we assess the redistribution effect by disentangling the increased Thursday-through-Friday seasonality. Specifically, we modify the difference-in-differences analysis in **Section 2.5.1** by replacing the treatment dummy with a Thursday dummy and a Friday dummy. Moreover, the post dummy interacts with the Thursday dummy and the Friday dummy separately, which generates two DiD terms capturing the increased Thursday seasonality and the increased Friday seasonality, respectively. **Table 2.A5** in the appendix presents the slope coefficients on the two DiD terms. As expected, both DiD coefficients are positive and fairly large in magnitude, indicating that the launches of FinTech-customized MMMFs and innovative MMETFs complement each other in amplifying the cross-sectional return seasonality, albeit on different days (i.e., Thursday versus Friday). It also confirms the redistribution effect related to the emergence of MMETFs. Without MMETFs, we might expect the salient increase in return seasonality after the FinTech shock to be more concentrated on Thursday alone.

Other anomalies. We also validate whether our documented day-of-the-week pattern also holds for other well-known cross-sectional anomalies in China. To be specific, we explore the long-short strategies based on size (Size), value (E/P ratio), profitability (Prof), short-term return reversal (Strev), and illiquidity (Illiq). Note, except for size and illiquidity, the speculative leg of the long-short anomaly is the short leg. Following Liu et al. (2019), we do not include investment and momentum strategies as they are not priced in China.

Similar to **Section 2.4.1**, we calculate the monthly value-weighted excess returns for the Monday-through-Wednesday and Thursday-through-Friday long-short portfolios, respectively. **Table 2.A6** in the appendix reports the (monthly) excess returns, CAPM, and FF3 risk-adjusted returns for these strategies. In general, the day-of-the-week patterns also hold for these well-known firm characteristics. That is, for these long-short strategies (in which the short leg is the speculative leg), their raw and risk-adjusted returns are relatively low on Monday through Wednesday, and relatively high on Thursday and Friday. Conversely, for the two anomalies (i.e., size and illiquidity) of which the speculative leg is the long leg, they experience more negative returns at the later part of the week (i.e., Thursday and Friday), which again confirms the daily seasonality that speculative stocks experience large price drops on Thursday and Friday relative to non-speculative stocks.

Alternative weighting scheme. The daily seasonality that the long-short anomaly strategies earn their premium entirely on Thursday through Friday remains robust when we analyze the equal-weighted portfolios. The magnitude of the excess returns and the risk-adjusted returns of the equal-weighted long-and-short anomaly strategies are sizeable for Thursday through Fridays (results are available in the internet appendix).

Daily risk factors. One legitimate concern in our baseline analysis in **Section 2.2.4** is that the risk factors could also vary over different days of the week. Therefore, we re-evaluate the risk-adjusted performance of the monthly long-short strategies on specific days using the alternative risk factors based on their corresponding daily components. It remains robust that the long-short anomaly strategies earn their profits mostly on Thursday and Friday (results are available in the internet appendix).

Alternative factor model. We also test the robustness of our baseline results by evaluating the portfolio performance using the Liu et al. (2019) China three-factor model (CH3). Similar to the baseline results in **Section 2.2.4**, prominent anomalies tend to earn significantly negative risk-adjusted returns Monday through Wednesday. In comparison, these anomaly strategies earn sizeable and positive alphas Thursday through Friday (results are available in the internet appendix).

Overall, the result in this subsection reinforces the robustness of the daily seasonality of the cross-sectional stock returns.

2.8. Conclusion

This paper provides a novel perspective on how private money creation in the form of money market funds exerts its hidden yet disproportionate impact on stock returns in the cross section. The distinctive feature of yield accrual on money market funds incentivizes investors of speculative stocks to display an uneven demand for safety across days within a week. This demand-for-safety channel has the power to explain the stylized cross-sectional pattern in China: Long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks experience low Monday-through-Wednesday returns and high Thursday-through-Friday returns.

FinTech applications and innovations in China's money market funds offer us a unique laboratory to address the causality issue related to the proposed demand-for-safety mechanism. Using the 2013 FinTech revolution as a plausibly exogenous shock that boosts the demand for money market funds, we provide difference-in-differences evidence that the daily cross-sectional seasonality increases by more than 100 percent after the demand shock, and the enlarged daily seasonality comes entirely from the short leg of speculative stocks.

Our novel evidence indicates that the recent FinTech revolution and technological advances, which boost the demand for money market funds, lead to a more dramatic temporary mispricing in the cross section—an unintended consequence on the stock market. In addition, the daily seasonality is more pronounced on the Thursdays and Fridays with unusually strong demand of safety (i.e., abnormal order imbalance of MMETFs) and in periods of high market volatility and/or uncertainty, confirming the interconnection between the money market and the stock market.

Our work is the first to address the economic consequence of FinTech revolution stemming from the money market on the stock market. Arguably, one might believe that any financial development, innovation, and technology advances should enhance the price efficiency by reducing the overall costs and frictions in the financial system. Interestingly, our empirical evidence presents somewhat a challenge to this belief, and speaks to the exact opposite: Recent financial development and FinTech revolutions in money market funds that significantly reduce the cost of financial intermediation (i.e., interest rate liberation) unexpectedly worsen price efficiency with the symptom of *amplified* cross-sectional return predictability and temporary mispricing.

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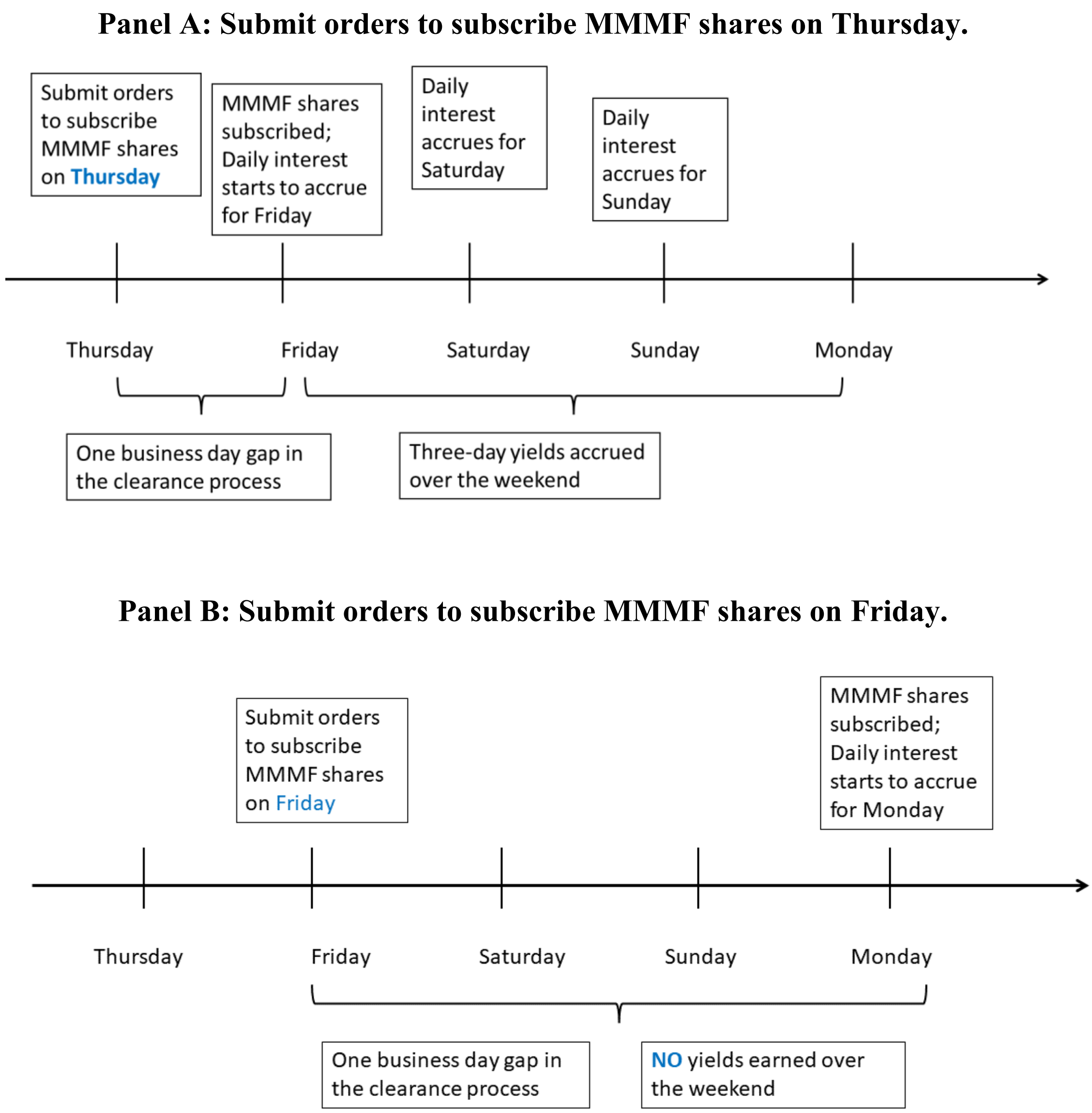
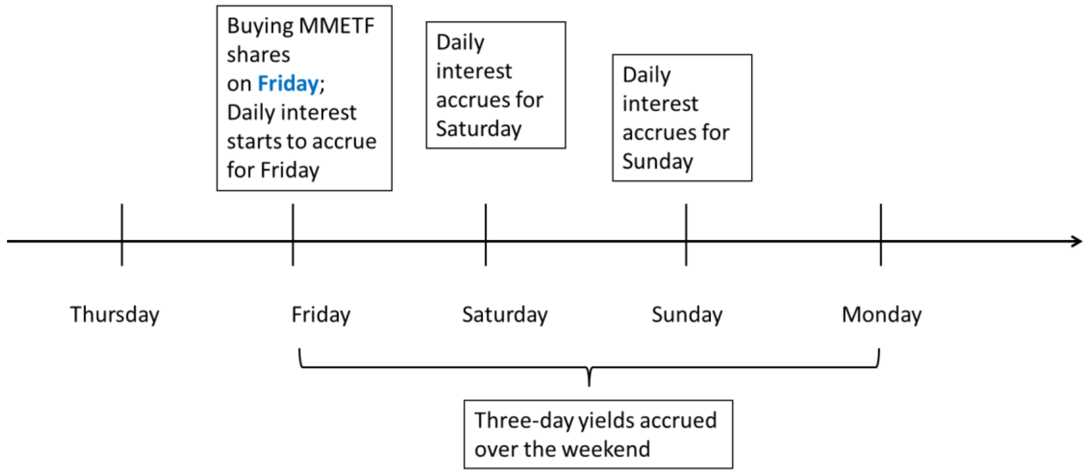
Appendix

Figure 2.A 1 Illustration of the subscription of the shares of a money market mutual fund on Thursday



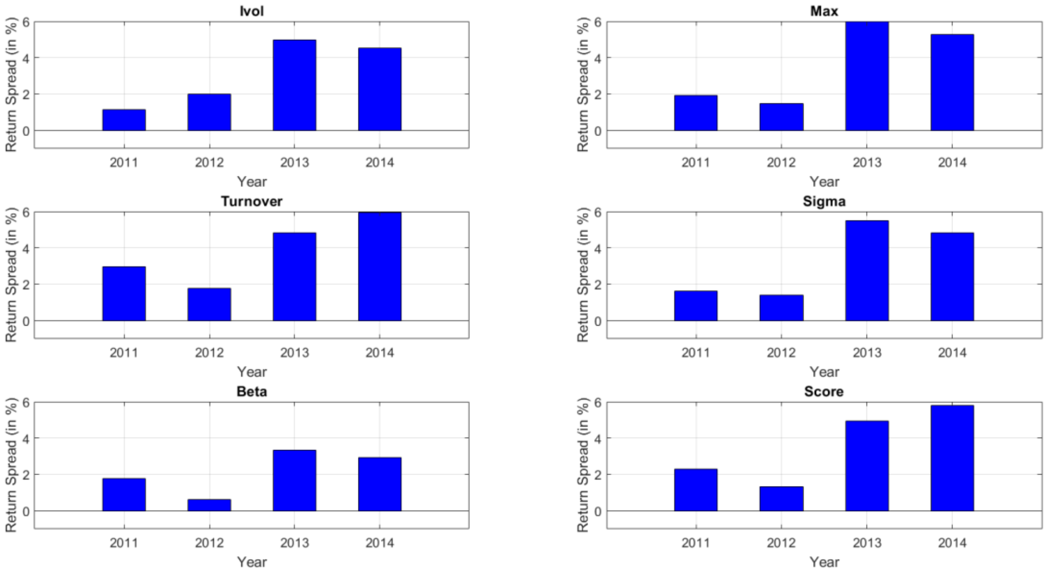
Note: The figure illustrates the clearance and settlement process for an investor who submits the order to subscribe the MMMF shares on Thursday in order to earn the guaranteed three-day yields over the Friday, Saturday, and Sunday. The investor submits the order on Thursday, and the subscription is confirmed on Friday (due to the one business day gap in the clearance process), and the daily interest starts to accrued on the day when subscription is confirmed.

Figure 2.A 2 Illustration of the purchase of the shares of a money market exchange-traded fund on Friday



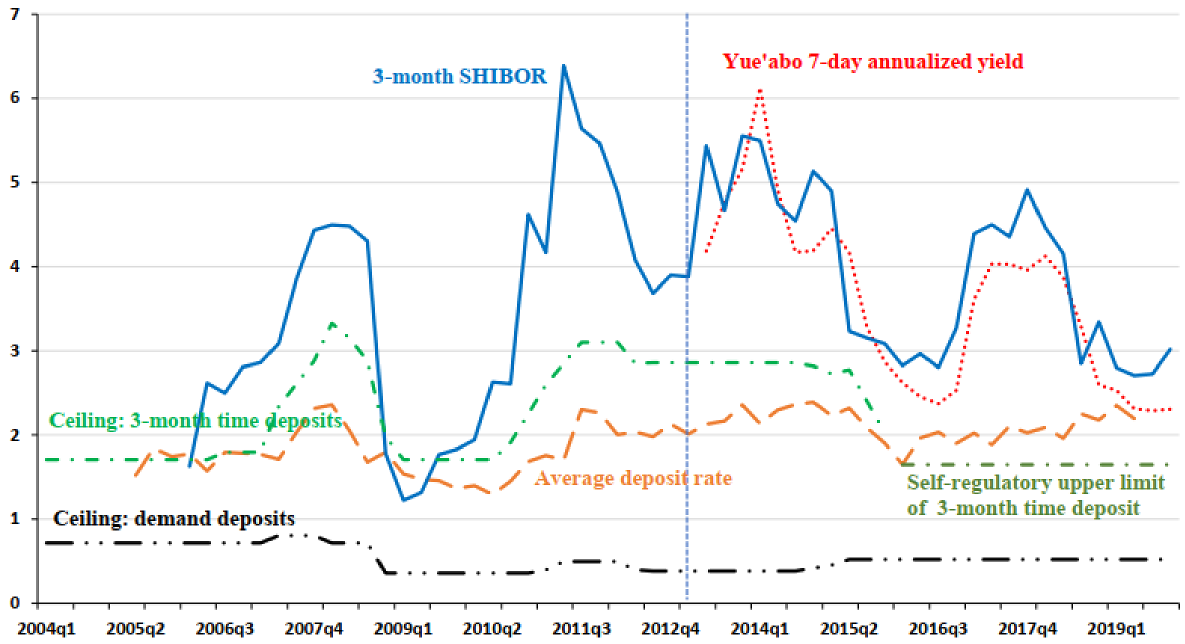
Note: The figure illustrates the clearance and settlement process for an investor who submits the order to buy the MMETF shares on Friday in order to earn the guaranteed three-day yields over the Friday, Saturday, and Sunday. The investor submits the buy order on Friday, and the purchase is immediately confirmed on Friday, and the daily interest starts to accrued on the same day when trade is settled.

Figure 2.A 3 Difference in average returns between the Thursday-through-Friday and Monday-through-Wednesday lone-short anomaly strategies, 2011 till 2014



Note: The figure visualizes the difference in average (monthly) returns between the Thursday-through-Friday and Monday-through-Wednesday long-short anomaly strategies in each of the four years from 2011 to 2014. The years 2011 and 2012 correspond to the two-year pre-event period (i.e., immediately before the 2013 FinTech-led real boom of cash investing), while the latter two years 2013 and 2014 correspond to the post-event period. The anomaly variables are idiosyncratic volatility (Ivol), lottery demand (Max), turnover (Turnover), return volatility (Sigma), CAPM beta (Beta) and average anomaly score (Score).

Figure 2.A 4 Dual-track Interest Rates under Deposit Rate Ceiling Regulation



Note: The blue dashed vertical line represents the introduction of Yu'ebao in Jun 2013. The blue solid line is the 3-month Shanghai Interbank Offered Rate (SHIBOR). The red dotted line is Yu'ebao's seven-day annualized yield. The green dash-dotted line indicates the deposit rate ceiling for 3-month time deposits, while the black dash-dotted line is the interest rate cap on demand deposits (both were lifted in Oct. 2015). The dark green and black dash-dotted lines after 2015 October represent the implicit deposit rate cap imposed by the self-discipline mechanism. The orange dashed line is the average deposit rate across all banks in the sample.

Table 2.A 1 Mutual funds by investment classification as of 30 June 2019

Panel A: Mutual funds by investment classification in China

By Classification	Assets (in billions RMB)	Percentage of Total Assets	Number of Funds
Money Market Funds	7,706.48	58.02	379
Bond Funds	2,785.20	20.97	1,623
Equity Funds	937.71	7.06	949
Hybrid (Bond/Stock) Funds	1,756.99	13.23	2,426
Alternative Investments Funds	17.37	0.13	26
QDII Funds	74.58	0.56	151
Total	**13,281.52**	**100.00**	**5,555**

Source: WIND Financial Terminal

Panel B: Mutual funds by investment classification in the US

By Classification	Assets (in billions USD)	Percentage of Total Assets	Number of Funds
Money Market Funds	3,334.52	17.10	366
Bond Funds	4,382.68	22.47	2,166
Equity Funds	10,301.97	52.83	4,709
Hybrid (Bond/Stock) Funds	1,481.47	7.60	779
Total	**19,500.63**	**100.00**	**8,020**

Source: Investment Company Institute 2019, 2020

Note: The table reports the dollar value and the proportion of assets under management, and the number of funds for each type of mutual funds.

Table 2.A 2 Day of the week

	Monday			Tuesday			Wednesday			Thursday			Friday		
	Excess	CAPM	FF3	Excess	CAPM	FF3	Excess	CAPM	FF3	Excess	CAPM	FF3	Excess	CAPM	FF3
Ivol	0.38	0.45	0.54	–0.34	–0.25	–0.23	–0.12	–0.11	–0.02	0.56	0.62	0.63	0.70	0.78	0.76
	[1.56]	[1.99]	[2.25]	[–2.08]	[–1.63]	[–1.43]	[–0.73]	[–0.65]	[–0.12]	[2.60]	[4.08]	[4.00]	[3.58]	[5.77]	[5.36]
Max	–0.05	0.05	0.04	–0.29	–0.23	–0.26	–0.17	–0.16	–0.08	0.57	0.63	0.62	0.55	0.60	0.60
	[–0.17]	[0.17]	[0.15]	[–1.83]	[–1.38]	[–1.59]	[–0.89]	[–0.91]	[–0.41]	[2.57]	[3.44]	[3.50]	[2.73]	[3.86]	[3.61]
Turnover	0.10	0.22	0.43	–0.46	–0.37	–0.27	–0.03	0.01	0.10	0.86	0.95	1.02	0.80	0.90	0.95
	[0.66]	[1.14]	[2.13]	[–2.97]	[–2.35]	[–1.73]	[–0.08]	[0.07]	[0.54]	[3.62]	[5.36]	[5.35]	[3.77]	[6.34]	[5.82]
Sigma	0.24	0.35	0.44	–0.43	–0.36	–0.36	–0.18	–0.15	–0.03	0.57	0.64	0.65	0.67	0.73	0.77
	[0.93]	[1.43]	[1.70]	[–2.36]	[–2.13]	[–2.01]	[–1.22]	[–0.94]	[–0.13]	[2.75]	[3.87]	[3.83]	[2.71]	[4.52]	[4.31]
Beta	–0.00	0.12	0.21	–0.47	–0.40	–0.35	–0.02	0.02	0.14	0.49	0.57	0.61	0.47	0.53	0.62
	[–0.01]	[0.77]	[1.36]	[–2.99]	[–2.52]	[–2.06]	[–0.10]	[0.14]	[0.72]	[3.02]	[3.78]	[3.75]	[2.73]	[3.84]	[4.07]
Score	0.01	0.14	0.26	–0.36	–0.27	–0.25	–0.08	–0.05	0.06	0.78	0.85	0.90	0.78	0.87	0.93
	[0.08]	[0.63]	[1.09]	[–1.86]	[–1.50]	[–1.30]	[–0.43]	[–0.28]	[0.31]	[2.92]	[4.28]	[4.06]	[3.07]	[5.40]	[5.16]
Combo	0.14	0.24	0.33	–0.40	–0.32	–0.30	–0.10	–0.08	0.02	0.61	0.68	0.71	0.64	0.71	0.74
	[0.74]	[1.23]	[1.60]	[–2.79]	[–2.25]	[–1.99]	[–0.78]	[–0.52]	[0.15]	[3.13]	[4.69]	[4.58]	[3.41]	[5.65]	[5.34]

Note: The table reports the monthly average excess return (Excess), the CAPM alpha (CAPM), and the Fama-French three-factor alpha (FF3) of each of the value-weighted long-short strategies on different day of the week. The Newey-West adjusted *t*-statistics are reported in brackets below the respective coefficients. The sample period spans from July 1996 to June 2019.

Table 2.A 3 Impact of abnormal order imbalance in high and low EPU periods

	Panel A: High EPU periods			**Panel B: Low EPU periods**		
	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Ivol	0.03	–0.11	0.14	–0.05	–0.08	0.02
	[0.43]	[–1.21]	[1.07]	[–1.14]	[–1.36]	[0.28]
Max	0.04	–0.24	0.28	–0.04	–0.07	0.03
	[0.64]	[–2.45]	[2.47]	[–0.73]	[–0.93]	[0.3)]
Turnover	0.09	–0.19	0.28	0.00	–0.14	0.14
	[1.37]	[–2.15]	[2.42]	[–0.06]	[–2.03]	[1.68]
Sigma	0.06	–0.18	0.24	–0.05	–0.12	0.07
	[0.81]	[–1.63]	[1.79]	[–1.13]	[–1.76]	[0.75]
Beta	–0.02	–0.13	0.12	–0.01	–0.09	0.08
	[–0.33]	[–1.50]	[0.95]	[–0.19]	[–1.79]	[1.03]
Score	0.05	–0.22	0.27	–0.04	–0.14	0.10
	[0.68]	[–2.13]	[2.13]	[–0.88]	[–1.65]	[0.86]
Combo	0.04	–0.17	0.21	–0.03	–0.10	0.07
	[0.73]	[–2.06]	[2.03]	[–0.76]	[–1.76]	[0.88]

Note: The table reports the estimated slope coefficients of β_2 in the daily regression: $y_t = \alpha + \beta_1 DOW_t + \beta_2 IMB_t + Controls + \varepsilon_t$, where the variable y_t is the daily excess return of the anomaly portfolio, DOW_t is the dummy variable that equal one if it is Thursday and Friday, and zero otherwise. IMB_t is the dummy variable that equals one if the daily abnormal order imbalance of the Money Market ETFs on Thursday or Friday is in the top quartile over the prior 30-day rolling window, and zero otherwise. The control variables are the daily market, size, and value factors in the Fama-French three-factor model. Panel A (B) presents the results for the long-leg portfolios, the short-leg portfolios, and the long-short portfolios in high (low) EPU periods. The Newey-West adjusted t-statistics are reported in brackets. The sample period spans from January 2013 to June 2019.

Table 2. A 4 Difference-in-differences results in high and low volatility periods

	High Volatility			Low Volatility		
	Long	Short	Long-Short	Long	Short	Long-Short
Excess Returns	0.04	-4.60	4.63	-0.88	-4.80	3.93
	[0.03]	[-2.19]	[2.85]	[-2.30]	[-5.61]	[5.76]
CAPM-adjusted Returns	-0.17	-4.88	4.70	-0.37	-4.13	3.76
	[-0.17]	[-2.62]	[3.03]	[-1.26]	[-6.94]	[6.21]
FF3-adjusted Returns	-0.62	-5.34	4.72	-0.49	-3.94	3.45
	[0.62]	[-3.08]	[3.19]	[-1.79]	[-6.87]	[6.25]

Note: The table reports the DiD coefficient λ_1 from the regression $R_{i,t} = \alpha_t + \lambda_0 Treat_i + \lambda_1 Treat_i \times Post_t + \lambda_2 Interest_t + \varepsilon_{i,t}$ for aggregate panel data including all the individual anomalies. The dependent variable $R_{i,t}$ is the monthly excess returns, the CAPM-adjusted returns, and the Fama-French three-factor adjusted returns of the anomaly strategy i in month t, which either invests on Monday through Wednesday or on Thursday through Friday. $Treat_i$ is the treatment dummy that equals 1 if portfolio i invests only on Thursday through Friday, and zero otherwise. $Post_t$ is the post-event dummy that equals 1 following the FinTech revolution (i.e., from 2013 onwards), and zero otherwise. α_t denotes time fixed effects. $Interest_t$ is the 3-month interest rate. The results for the long-leg (Long) portfolios, short-leg (Short) portfolios, and long-short (Long-Short) anomaly portfolios in high (low) volatility periods are tabulated respectively. Robust *t*-statistics are reported in brackets below the coefficient estimates. The sample period spans from July 2009 to December 2014.

Table 2.A 5 Disentangling the Thursday-through-Friday effects

Panel A: The Thursday DiD coefficient, $\lambda_{\mathbf{Thur}}$

	Excess Returns			CAPM-Adjusted Returns			FF3-Adjusted Returns		
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
Ivol	–0.05	–0.80	0.75	–0.02	–0.75	0.73	0.01	–0.78	0.79
	[–0.15]	[–1.45]	[1.89]	[–0.06]	[–1.56]	[1.94]	[0.03]	[–1.64]	[2.22]
Max	–0.20	–0.81	0.61	–0.16	–0.75	0.59	–0.14	–0.77	0.63
	[–0.60]	[–1.45]	[1.37]	[–0.55]	[–1.55]	[1.38]	[–0.49]	[–1.59]	[1.49]
Turnover	–0.26	–0.60	0.34	–0.22	–0.54	0.31	–0.19	–0.55	0.36
	[–0.72]	[–1.01]	[0.77]	[–0.68]	[–1.05]	[0.76]	[–0.60]	[–1.07]	[0.90]
Sigma	–0.10	–0.85	0.75	–0.07	–0.80	0.73	–0.04	–0.81	0.77
	[–0.30]	[–1.50]	[1.75]	[–0.23]	[–1.62]	[1.80]	[–0.14]	[–1.65]	[1.95]
Beta	–0.07	–0.50	0.43	–0.04	–0.45	0.41	–0.02	–0.45	0.44
	[–0.23]	[–0.91]	[1.14]	[–0.13]	[–0.92]	[1.14]	[–0.06]	[–0.95]	[1.24]
Score	–0.18	–0.85	0.66	–0.15	–0.79	0.64	–0.12	–0.80	0.68
	[–0.56]	[–1.43]	[1.43]	[–0.50]	[–1.51]	[1.44]	[–0.43]	[–1.54]	[1.57]
Combo	–0.14	–0.71	0.58	–0.10	–0.66	0.55	–0.08	–0.67	0.60
	[–0.41]	[–1.30]	[1.49]	[–0.34]	[–1.38]	[1.53]	[–0.26]	[–1.43]	[1.70]
Aggregate	–0.53	–1.32	0.79	–0.62	–1.45	0.83	–0.62	–1.42	0.80
	[–1.92]	[–3.01]	[2.48]	[–2.91]	[–4.68]	[2.86]	[–2.97]	[–4.65]	[2.90]

Panel B: The Friday DiD coefficient, λ_{Fri}

	Excess Returns			CAPM-Adjusted Returns			FF3-Adjusted Returns		
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
Ivol	0.05	–0.28	0.33	0.07	–0.24	0.31	0.10	–0.26	0.35
	[0.15]	[–0.59]	[0.88]	[0.23]	[–0.53]	[0.84]	[0.32]	[–0.58]	[0.99]
Max	–0.22	–0.28	0.05	–0.19	–0.23	0.04	–0.17	–0.23	0.06
	[–0.75]	[–0.55]	[0.14]	[–0.71]	[–0.49]	[0.10]	[–0.65]	[–0.49]	[0.14]
Turnover	–0.00	–0.65	0.65	0.02	–0.60	0.62	0.06	–0.60	0.66
	[–0.01]	[–1.31]	[1.68]	[0.07]	[–1.28]	[1.63]	[0.20)]	[–1.29]	[1.77]
Sigma	–0.07	–0.43	0.35	–0.04	–0.38	0.34	–0.02	–0.39	0.37
	[–0.25]	[–0.83]	[0.86]	[–0.16]	[–0.78]	[0.82]	[–0.07]	[–0.81]	[0.93]
Beta	0.00	–0.43	0.43	0.03	–0.39	0.42	0.05	–0.39	0.45
	[0.01)]	[–0.92]	[1.28]	[0.12]	[–0.88]	[1.24]	[0.20]	[–0.89]	[1.36]
Score	–0.11	–0.37	0.26	–0.08	–0.32	0.23	–0.06	–0.31	0.25
	[–0.37]	[–0.68]	[0.59]	[–0.31]	[–0.62]	[0.54]	[–0.21]	[–0.61]	[0.59]
Combo	–0.05	–0.41	0.36	–0.02	–0.37	0.34	0.00	–0.37	0.38
	[–0.17]	[–0.87]	[1.04]	[–0.08]	[–0.82]	[1.00]	[0.01]	[–0.84]	[1.12]
Aggregate	–0.44	–0.99	0.55	–0.54	–1.13	0.59	–0.54	–1.09	0.55
	[–1.64]	[–2.36]	[1.78]	[–2.60]	[–3.75]	[2.06]	[–2.63]	[–3.67]	[2.01]

Note: The table reports the two DiD coefficients λ_{Thur} and λ_{Fri} from the DiD regression: $R_{i,t} = \alpha_t + \lambda_0 Thur_i + \lambda_1 Fri_i + \lambda_{\text{Thur}} Thur_i \times Post_t + \lambda_{\text{Fri}} Fri_i \times Post_t + \varepsilon_{i,t}$, where the dependent variable $R_{i,t}$ is the monthly excess returns, the CAPM-adjusted returns, and the Fama-French three-factor adjusted returns of the anomaly strategy i in month t, which only invests in specific day(s) within a week (i.e., Monday through Wednesday, Thursday, and Friday, respectively). $Thur_i$ is the Thursday dummy that equals 1 if the portfolio invests only on Thursday, and zero otherwise. Fri_i is the Friday dummy that equals 1 if the portfolio invests only on Friday, and zero otherwise. $Post_t$ is the post-event dummy that equals 1 following the FinTech revolution (i.e., from 2013 onwards), and zero otherwise. α_t denotes time fixed effects. The results for the long-leg (Long) portfolios, short-leg (Short) portfolios, and long-short (Long-Short) anomaly portfolios are tabulated respectively. Robust t-statistics are reported in brackets below the coefficient estimates. The sample period spans from July 1996 to June 2019.

Table 2.A 6 Other anomalies: Monday through Wednesday and Thursday through Friday

	Monday to Wednesday			Thursday to Friday		
	Excess	CAPM	FF3	Excess	CAPM	FF3
Size	0.86	0.73	0.11	–0.49	–0.62	–0.94
	[2.85]	[2.36]	[0.52]	[–2.45]	[–3.33]	[–5.86]
ILLIQ	0.46	0.41	–0.09	–0.56	–0.63	–0.95
	[1.47]	[1.31]	[–0.40]	[–2.67]	[–3.23]	[–5.64]
E/P	0.22	0.30	0.78	0.92	1.03	1.40
	[0.75]	[0.97]	[2.48]	[4.16]	[5.12]	[7.91]
Prof	–0.43	–0.33	0.30	0.83	0.90	1.34
	[–1.73]	[–1.26]	[1.31]	[4.78]	[6.14]	[7.47]
Strev	0.11	0.10	–0.03	0.68	0.68	0.50
	[0.33]	[0.33]	[–0.09]	[2.94]	[3.18]	[2.41]

Note: The table reports the monthly average excess return (Excess), the CAPM alpha (CAPM), and the Fama-French three-factor alpha (FF3) of the value-weighted long-short strategies sorted on one specific firm characteristic. The firm characteristics includes firm size (Size), earnings-to-price ratio (E/P), profitability (Prof), short-term return reversal (Strev), and Amihud illiquidity ratio (ILLIQ). The Newey-West adjusted *t*-statistics are reported in parenthesis. It presents the results the Monday-through-Wednesday and Thursday-through-Friday strategy, respectively. The sample period spans from July 1996 to June 2019.

Chapter 3

Cross-sectional End-of-day Return Puzzle and Disposition Effect

Abstract:

This paper presents a distinctive end-of-day pattern in the cross-sectional stock returns in China: Long-minus-short mispricing factor exhibits significantly positive returns at the last half-hour trading interval but performs poorly during the other daytime trading period. This cross-sectional intraday seasonality pattern of China is reversed compared to that of the US (Bogousslavsky 2021). We attribute this end-of-day return puzzle to the disposition effect, specifically, investors have a strong tendency to sell out stocks with prior capital gains at the end of the day, when the market is most liquid. We validate the consistency of this end-of-day pattern over different time-series samples and prominent anomalies.

JEL Classification: G11, G12, G23

Keywords: End-of-day returns, Disposition effect, Capital gain overhang (CGO), Seasonality, Mispricing

3.1. Introduction

An extensive literature exists on seasonality in stock market returns[10]. Yet only a few papers investigate intraday seasonality in cross-sectional stock returns: Bogousslavsky (2021) documents that due to institutional constraints and overnight risk, a mispricing factor earns positive returns throughout the day but performs poorly at the end of the day. In contrast to the findings of the US, this paper presents a reversed seasonality pattern in China: Mispricing anomaly portfolios that go long the unspeculative stocks and go short the speculative stocks experience negative returns over the daytime but have significantly sizable positive returns in the last half-hour of trading. In other words, mispricing worsens over the daytime and gets corrected at the end of the day. Thus, we argue that the explanation based on the institutional constraints and arbitrageurs' fear of overnight risk proposed by Bogousslavsky (2021) is not applicable in this case. Liu, Stambaugh, and Yuan (2019) and Carpenter, Lu, and Whitelaw (2020) state that it is crucial to explore the unique features in China to deepen our understanding of global resource allocation and asset pricing. In this paper, our goal is to find out the possible intuition for this distinctive feature of the end-of-day puzzle of the asset pricing anomalies in China.

After the whole day's gambling in the stock market, the last half-hour interval is the optimal time for investors to reshuffle their portfolio, during which the market experiences higher liquidity, lower transaction costs, and higher turnover (Bogousslavsky and Muravyev 2021; Lou, Polk, and Skouras 2019). This is consistent with Bogousslavsky (2016)'s infrequent rebalancing theory, that a bunch of traders choose to rebalance their portfolio at a certain horizon and this effect generates seasonality in the cross-section of stock returns. Besides, we propose that the disposition effect is the most plausible explanation for the cross-sectional end-of-day return pattern. The disposition effect refers to the phenomenon that investors have a greater propensity to sell stocks with prices that have increased since purchase rather than those with prices that have dropped. [11] An et al. (2020) document that the performance of anomalies associated with lottery features are state-dependent and vary substantially across different levels of capital losses or gains, supporting the view of reference-dependent preference mechanism. Barberis, Jin, and Wang (2021) take all the elements of prospect theory into consideration and then construct a prospect theory model as a possible factor for

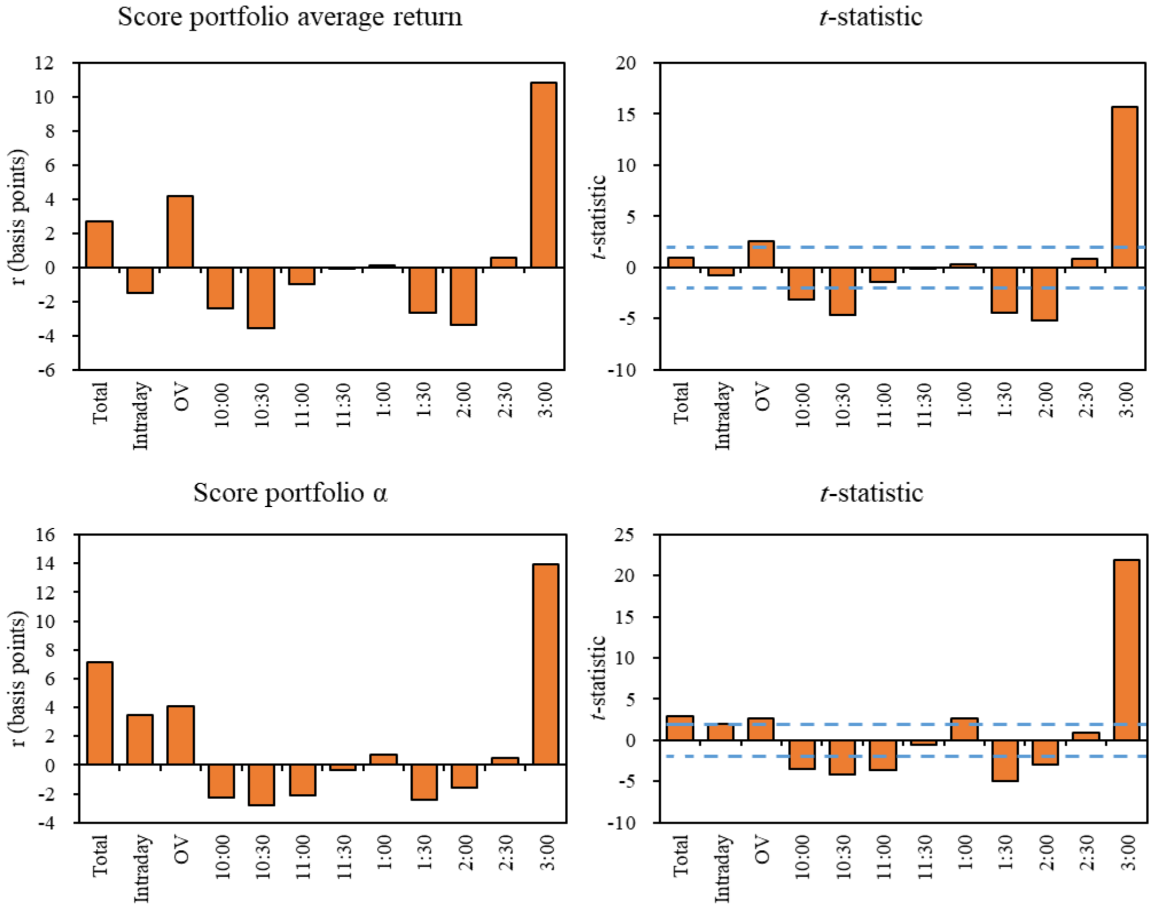
[10] For example, the January effect uncovered by Rozeff and Kinney (1976); the day of the week effect shown by French (1980) and the recent Birru (2018); the holiday effect tested by Lakonishok and Smidt (1988).
[11] The disposition effect has attracted big attention and developed competing alternative theories, both rational and behavioral (Barberis and Xiong 2012; Kaustia 2010; Odean 1998; Shefrin and Statman 1985).

the anomaly predictability explanation. In our case, at the end of the day, when infrequent rebalancing investors face lower transaction costs and price impact, they are more likely to sell their portfolios with prior capital gain overhang to achieve gains on paper. Overall, under the scenario of the disposition effect, stocks with capital gains, especially risky (speculative) stocks experience selling pressure at the end of the day, thus inducing the end-of-day cross-sectional seasonality.

We first construct a Score measure, following the methodology of Stambaugh and Yuan (2017), as the mispricing factor to capture the speculative characteristics (i.e. Idiosyncratic volatility, lottery demand, turnover ratio, return volatility, and, market beta) of a stock. We then compute the value-weighted returns in different trading intervals for the Score strategy that bets against speculative stocks (top-quintile) and bets on unspeculative stocks (bottom-quintile) over the period from July 1999 to June 2019. **Figure 3.1** graphically displays this result, which shows that the Score strategy portfolio earns a negative return every half-hour of the trading day except for the last half-hour interval. Strikingly, between 2:30 and 3:00 pm, the long-minus-short Score portfolio earns sizable positive returns, with an alpha of 14.57 basis points (bps) with a *t*-statistic of 20.74. The magnitude of this end-of-day mispricing return is nontrivial, as the return is twice as large as it is for the total return. However, for the other intraday periods, the returns are close to zero or negative. Therefore, the mispricing tends to worsen over the day and gets corrected at the end of the day.

To shed more light on the mechanism of cross-sectional end-of-day return puzzle, we display the critical role of the disposition effect. The prospect theory proposed by Kahneman and Tversky (1992), together with Thaler (1980, 1985)'s mental accounting framework (MA/PT), is perhaps the mainstream explanation for the disposition effect. PT states that the utility value function is S-shaped that is concave over gains and convex over losses relative to a reference point, capturing risk aversion over gains and risk-seeking over losses. MA means that decision-makers set a reference point for the accounts that determine gains and losses. As explained above, we postulate that the disposition effect may be the most plausible explanation for the cross-sectional end-of-day return puzzle of mispricing factors.

Figure 3. 1 Score portfolio average return and alpha



Note: The upper (lower) left panel reports the total, intraday, and overnight average returns (alphas) in basis points of the value-weighted long-short Score portfolio. Score is the mispricing measure calculated with the average score of mispricing anomalies (idiosyncratic volatility, lottery demand, turnover, return volatility, and CAPM beta). Portfolios are value-weighted and are re-adjusted for one month. Stock returns are computed using quote midpoints. The first intraday interval 10:00 starts at 9:45 am and ends before 10:00 am; 10:30 indicates the half-hour interval that starts at 10:30 am and ends before 11:00 am. Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am. The upper (lower) right panel visualizes the Newey-West adjusted *t*-statistics with a lag length of 12. The dashed horizontal line denotes the 5% significant level. The sample period is from July 1999 to June 2019.

First, following the method of Grinblatt and Han (2005), we construct the measure of capital gains overhang (CGO) for individual stock each day. CGO is defined as stock returns relative to a reference price, with positive CGO referring to capital gains relative to the reference price, and vice versa. Empirically, using the one-way sorting method for CGO, we find that intraday returns decrease monotonically with their CGO quintile, indicating the selling pressure of stocks with prior gains relative to others. Moreover, the intraday disposition effect predominantly comes from the last half-hour's trading.

We next examine to what extent the predictability of mispricing factors at the end-of-day depends on stocks' capital gain overhang status. To test our prediction, we conduct a double-sorting portfolio analysis by sorting the stocks into quintiles first by Score then CGO (and first by CGO then Score). We next calculate the value-weighted portfolio returns for each group and each trading interval. We find that referring to the total returns, the mispricing correction (positive returns of long-minus-short mispricing strategy) comes mostly from the stocks with higher prior gains (high-CGO). Our key focus is the result over the trading interval from 2:30 to 3:00 pm. We find that the predictability of the Score strategy for end-of-day returns exists in each CGO portfolio, that is, the long-minus-short anomaly returns decrease monotonically with their CGO quintile. It is worth noting that the speculative stocks within extreme capital gains (CGO5-Score5) experience considerably negative returns, which is about –5.36 basis points (*t*-statistic equal to –5.84). This supports the prediction of the disposition effect on end-of-day cross-sectional seasonality that when speculative investors face prior gains for risky assets, they have a strong tendency to sell out their holdings to get the positive realization utility. That is, due to the disposition effect, the selling pressure for speculative stocks at the end of the day is more likely to be driven by stocks with prior capital gains. However, for other intraday half-hour intervals, the disposition effect fades or even disappears. Then, our results still hold in the regressions of Fama and MacBeth (1973) after controlling a battery of additional variables, such as firm size, book-to-market ratio, profitability ratio, investment ratio, return momentum, short-time return reversal, and share turnover.

In addition, we provide additional evidence from the perspective of market quality, trading order imbalance, and infrequent rebalancing. First, we construct the half-hour interval market quality measures. We find that relative quoted spread and price impact (Amihuld ratio) are lower, and the turnover and volume are higher at the last half-hour trading interval, indicating that it would be easier for investors to execute their large orders at the end of the day. This provides a partial explanation for the rebalancing trading happening at the end of the day rather than the other periods over the daytime. We also consider the potential impact of the end-of-day effect on market efficiency. We find statistically significant evidence that the price efficiency deteriorates for both the long- and short-leg portfolios at the end of the day, which is consistent with the more pronounced mispricing anomaly predictability at the end of the day. We then provide support for the end-of-day capital reshuffling from the perspective of order imbalance. Order imbalance is defined as the buyer-initiated volume minus seller-initiated volume divided by their sum. Consistent with our main results, speculative (unspeculative) stocks tend to experience lower (higher) order imbalance at the end of the day relative to other stocks. That is, speculative stocks do experience selling pressure relative to others at the end of the day. Besides, cross-sectional regression tests also provide support for the infrequent asset rebalancing behavior of end-of-day investors. Bogousslavsky (2016) states that the return autocorrelation can switch signs from negative to positive during trading horizons only with the infrequent rebalancing behavior of investors. Thus, we would expect to see positive predictability for cross-sectional returns at the end of the day. To test this notion, in the spirit of Jegadeesh (1990) and Heston et al. (2010), we run the cross-sectional regressions for the returns in each half-hour trading horizon. Consistent with our prediction, we find that only in the last half-hour trading interval, the coefficients of autocorrelation are positive, while for other times during the daytime, the coefficients are negative, indicating the short-term return reversal.

Finally, we also perform a battery of robustness checks. We first apply the above insights to individual anomaly portfolios to check the robustness of the end-of-day effect. We test the intraday pattern of the five prominent anomalies respectively used to construct the Score strategy. All those anomalies are highly correlated and capture different aspects of the nature of mispricing. We find that all these anomalies earn uniformly positive returns in the last half-hour of trading and perform poorly over the other times of the day. This result supports our intraday seasonality of cross-sectional returns. Second, following Bogousslavsky (2021), we test the day-of-the-week effect. The yields on the weekend in the shadow banking market would be more attractive for the short-term investors (Han, Liu, and Wu 2023) and investors are more likely to leave the stock market at the end of the week. We find that the end-of-day effect is more pronounced during Thursday-through-Friday compared to Monday-through-Tuesday. We also re-calculate the equal-weighted portfolio returns and the results are consistent with before.

This paper is more closely related to the empirical literature on cross-sectional return seasonality. The seasonal pattern of stock returns has long been a fertile area of finance research. One strand of this literature is working on the seasonality in the stock market index returns, not considering the cross-sectional differences (Ariel 1987; Bouman and Jacobsen 2002; Rozeff and Kinney 1976). Another strand of this literature does focus on the cross-sectional seasonality patterns but does not decompose open-to-close returns (Birru 2018; Heston and Sadka 2008). Overall, our results complement their findings: Intraday half-hour interval cross-sectional returns provide valuable information to evaluate asset pricing intuitions. We show that in China the asset pricing anomalies achieve mispricing correction mainly at the end of the day, which is contradict with the pattern in the US and other developed markets. Besides, our disposition effect mechanism provides an economic channel and direct evidence to support the statement that cross-sectional seasonality could arise from the predictable in- and out-flows (Keloharju, Linnainmaa, and Nyberg 2021).

In doing so, our paper also adds to the literature that studies the disposition effect. To the best of my knowledge, we are the first to explore the disposition effect on the asset pricing intraday seasonality. The disposition effect has the potential to shed light on asset prices and investor behavior. We provide new evidence that, consistent with the analysis of An et al. (2020), the disposition effect influences the performance of lottery anomalies. Recently, Barberis, Jin, and Wang (2021) build a new model of asset prices incorporating prospect theory. They show that the behavioral model of either beliefs or preferences can be used to predict a wide range of anomalies. Our paper provides support that prospect theory and the associated disposition effect can be the potential "behavioral" explanations for the asset pricing anomalies. Our findings also support the notion that realized gains and losses may play a vital role in forming the disposition effect (Barberis and Xiong 2012; Ingersoll and Jin 2013).

The rest of the paper is organized as follows. **Section 3.2** describes the data sources and methodology of key variables' construction. **Section 3.3** presents the pattern of the cross-sectional intraday returns. **Section 3.4** discusses the impact of disposition effect on the end-of-day pattern. **Section 3.5** performs further analysis and **Section 3.6** does the robustness checks. **Section 3.7** concludes.

3.2. Data and variables

3.2.1. Data sources

The intraday and daily data used in this paper are sourced from multiple databases. Specifically, the intraday 5-min frequency trading data are retrieved from Thomson Reuters Datastream, which include all available A-shares listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange. We construct the half-hour interval returns using this 5-min dataset. The intraday 1-min frequency trading data are obtained from the Resset dataset, used for calculating the half-hour market quality measures. The daily and monthly equity data are obtained from Wind Information Inc. (WIND) and Thomson Reuters Datastream.

To compile the dataset, following Liu et al.(2019) we adopt several filtering rules: First, we exclude stocks that have just become public within the past three months. Second, we filter out stocks that have consecutive zero returns over the past three months to ensure that our results are not influenced by stocks that are experiencing trading suspension. Third, to prevent our results from being driven by the smallest-cap stocks that are considered to have unique characteristics (Liu et al. 2019), we exclude the bottom 30% of stocks ranked by market capitalization at the end of the previous month. After applying these filtering rules, we end up with a total of 3,371 sample stocks covering the sample period from July 1999 to June 2019.

Following prior literature (Han and Li 2017; Liu et al. 2019), we use the monthly rate of the one-year bank time deposit (retrieved from WIND) as the proxy for the risk-free rate in China. The CH-3 risk factors of China are obtained from Liu et al. (2019).

3.2.2. Key variables

3.2.2.1. Intraday and overnight returns

First, in order to capture a rich set of market dynamics in the Chinese stock market, we compute intraday half-hour interval returns for each stock during regular trading hours. Specifically, we separate the trading hours (9:45 am to 3:00 pm) into 9 half-hour intervals including the lunch break interval from 11:30 am to 1:00 pm. To assuage concerns about microstructure noises, we calculate returns using the quote midpoints.[12] Due to the occurrence of inaccurate quotes at the opening, which may generate spurious reversal in the first half-hour returns, following

[12] The results are robust to use trade-based price for the return calculation. To be more precise, the results in the paper only with the midquote returns.

Bogousslavsky (2021) we set the first interval to start from 9:45 am to 10:00 am.[13] The last half-hour interval return (2:30 to 3:00 pm) is calculated using the last quote available during trading hours.[14]

Then, we follow Lou et at. (2019) in constructing the intraday (open-to-close) returns and overnight (close-to-open) returns. For daily intraday return for stock i, we compute as the simple return from market open to market close over the same day s:

$$r_{i,s}^{\text{intraday}} = \frac{P_{i,s}^{\text{close}}}{P_{i,s}^{\text{open}}} - 1, \qquad (1)$$

where $P_{i,s}^{\text{open}}$ is the mid-quote at 9:45 am, $P_{i,s}^{\text{close}}$ is the last quote available during trading hours. Hence, the first 15 minutes of trading is excluded from the intraday return and included in the overnight return.

The daily overnight return component is computed based on the intraday return and the standard daily return:

$$r_{i,s}^{\text{overnight}} = \frac{1+r_{i,s}}{1+r_{i,s}^{\text{intaday}}} - 1, \qquad (2)$$

where $r_{i,s}$ is the daily return for stock i on day s. The above definition ensures that all corporate events, such as dividend adjustments and share splits, accrue over the night. As a result, to compute average excess returns, the daily risk-free returns are subtracted from overnight returns because risk-free rate should not be earned intraday and transactions are settled at the end of the trading day (Heston et al. 2010; Lou et al. 2019).

3.2.2.2. Mispricing anomaly

In the spirit of Stambaugh and Yuan (2017), we first construct the mispricing measure ***Score*** which captures the speculative features of a stock by averaging across the five prominent

[13] Similar to many markets, the Chinese A-share market adopts a 10-minute pre-open call auction (from 9:15 to 9:25 am to determine the opening prices at 9:30 am on each trading day). Hence, the overnight return includes the first 15 minutes of trading. We discuss robustness tests with earlier sampling of the opening price at 9:30 am in Section 3.6.

[14] Due to the time slippage, the data contain some trading that happens several seconds after 3:00 pm. Under this scenario, for all the results we report in this paper, we use the mid-quote price of the last trade recorded as the close price for the last half-hour interval. For the robustness check, we have another close price version that uses the last mid-quote price before 3:00 pm as the close price. There is no significant difference for results with those two data versions.

anomaly measures: idiosyncratic volatility (Ivol), lottery demand (Max), Turnover ratio (Turnover), return volatility (Sigma), and Market beta (Beta)[15]. It is computed in two steps. In the first step, we compute the five individual anomaly scores for each stock. To be specific, each month we assign a score (ranging from 1 to 10) to a stock based on its decile ranking of a specific anomaly variable in the cross-section. For example, a stock that is in the 6th decile group sorted by Max receives an individual Max score of 6. In the second step, we equally weight a stock's rankings across the individual scores. We require a stock to have at least three individual anomaly scores to compute the average score (for that stock-month observation). The rationale for averaging is that, through diversification, a stock's average score yields a less noisy measure of its speculative feature than it does with any single anomaly. Given that all five individual anomaly variables are highly positively correlated and predict negative returns in the cross-section, we expect stocks with high average scores to have lower expected returns than those with low average score.

The anomaly measures (Ivol, Max, Turnover, Sigma, and Beta) we use for ***Score*** construction have been shown to be effective in capturing relative mispricing in the cross-section of stocks of the Chinese stock market (Qiao 2019). Note that although we need to calculate the half-hour portfolio return, the portfolio itself is constructed for a buy-and-hold strategy that is rebalanced at the beginning of each month, instead of intraday rebalancing.

Then, we construct anomaly portfolios based on the ***Score*** index. Specifically, we sort all stocks into deciles according to the ***Score*** ranking at the beginning of each month and calculate the returns of the highest-performing decile (decile 1, long leg), the returns of the lowest-performing decile (decile 10, short leg), and the differences between the two (long-short leg). Following Bogousslavsky (2021), we calculate value-weighted average returns and market-risk adjusted alphas of the mispricing strategy portfolio for each half-hour interval over the day. Specifically, the average returns are calculated for a portfolio in each interval t. Similarly, we estimate alphas of the anomaly strategies for each decile portfolio over the day:

$$r_t = \alpha_t + r_t^m \beta_t + \varepsilon_t, \qquad (3)$$

where r_t denotes the return of a portfolio in the interval t (for instance, between 10:00 and 10:30 am), r_t^m is the market (excess) return in interval t. The market return equals the value-weighted return of all stocks in the sample. As mentioned above, we exclude the smallest 30%

[15] More details on the definition of these anomaly measures are provided in Appendix.

stocks in our sample. The risk-free rate is subtracted from the overnight returns and total returns. Alpha in a given hour is estimated using returns in the same half-hour. Beta in this methodology varies across the day but is consistent over time. As Bogousslavsky (2016) states, the intraday variation of the beta can occur if the proportion of traders active in the market is not consistent over the day. For all of the portfolio returns calculation, we adjust standard errors for heteroskedasticity and autocorrelation using a Newey and West (1986) correction with 12 lags.

3.2.2.3. Capital gain overhang

The Capital Gain Overhang (CGO) is proposed by Grinblatt and Han (2005). By definition, CGO is the return of a stock relative to a reference price, with positive CGO referring to capital gains relative to the reference price and vice versa. The reference price is proposed in the prospect theory (Tversky and Kahneman 1992), and is calculated based on the past turnover and price information. CGO is calculated as the deviation between the final price (P) and the reference price (RP), divided by the final price. Our proxy for CGO at day t is shown below:

$$g_t = \frac{P_{t-1} - RP_{t-1}}{P_{t-1}}, \quad (4)$$

We use the prior 5-day data to construct reference price in our main analysis, instead of using the methodology of Grinblatt and Han (2005), which uses past five-days (one-week) price and turnover data. Under this specification, reference prices get reset every day. This assumption is particularly well suited for Chinese market where the turnover is extreme high and investors reshuffle their portfolios almost once every month (Liu et al. 2022) [16].

The reference price of day $t-1$ is the average cost basis based on past 5-day trading calculated from the formula:

$$\begin{gathered} RP_{t-5} = P_{t-5} \\ RP_{t-4} = V_{t-5}P_{t-5} + (1 - V_{t-5})RP_{t-5} \\ RP_{t-3} = V_{t-4}P_{t-4} + (1 - V_{t-4})RP_{t-4} \\ \dots \\ RP_{t-1} = V_{t-2}P_{t-2} + (1 - V_{t-2})RP_{t-2}, \quad (5) \end{gathered}$$

where V_t is day t's turnover which is equal to the daily trading volume over shares outstanding. P_t is day t's close price.

[16] We also construct reference price using the prior one-month (20-day) data, the results are consistent with our main results. We also use the reference price constructed by Grinblatt and Han (2005) for the robustness check, the results are also consistent with our main results. See online appendix.

3.3. Cross-sectional return pattern

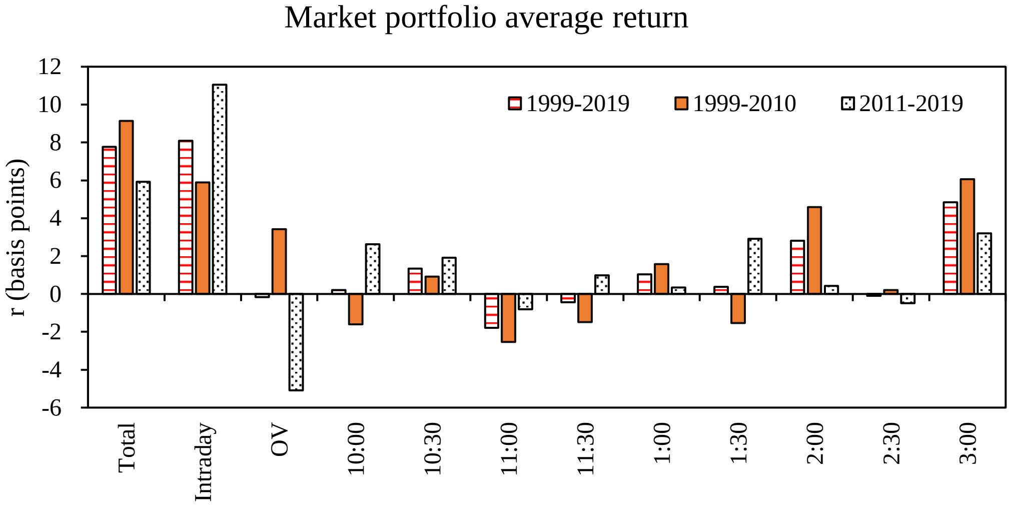
This section reports the striking pattern of the overnight and intraday returns for the market and mispricing portfolios in China. Then, we show that the overnight risk effect proposed by Bogousslavsky (2021) cannot explain the last half-hour cross-sectional return puzzle in China.

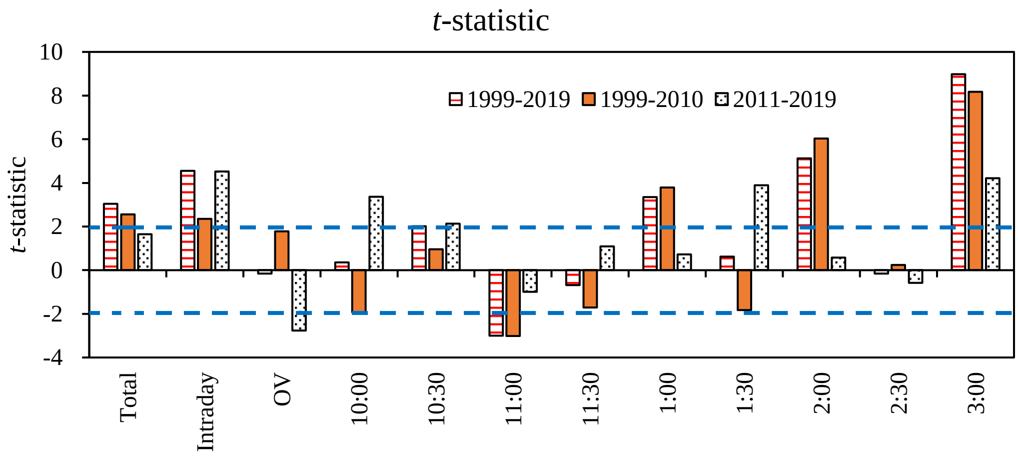
3.3.1. Intraday returns

We first estimate the average returns of different trading intervals of the market portfolio. **Figure 3.2** visualizes the market portfolio's value-weighted average returns for total, overnight, intraday, and each half-hour interval across subsamples. It depicts a striking intraday seasonality at the market level. In vast contrast to the US, in which the market portfolio shows positive overnight returns and no marked pattern over the trading day (Berkman et al. 2012; Bogousslavsky 2021; Lou et al. 2019), the Chinese market portfolio experiences positive day returns and insignificant overnight returns.

Moreover, during the trading daytime, the market portfolio does not display any consistent market pattern for each half-hour interval in average returns except for the last half-hour (2:30-3:00 pm). The market portfolio earns a striking positive average return of 4.84 bps, with a *t*-statistics of 8.97, in the last 30 minutes of trading (2:30-3:00 pm) over the full sample. Also, the last half-hour pattern is robust across sub-samples, 1999-2010 and 2011-2019. This indicates that from the whole market view, the prevalent buying pressure happens at the end of the day. Bogousslavsky and Muravyev (2021) also find that the closing auction price in the US has an increase deviation due to the massive trading of passive mutual fund ownership and ETF ownership, who seek to trade at the close to minimize tracking error as they are benchmarked against closing prices for indices they track.

Figure 3. 2 Market portfolio average return





Note: The figure visualizes the market portfolio's total, intraday, and overnight average returns (in basis points) and *t*-statistics across different time-series subsamples. The market return equals the value-weighted return of all stocks in the sample. The sample excludes the bottom 30% smallest firms. Stock returns are computed using quote midpoints. The first intraday interval 10:00 starts at 9:45 am and ends before 10:00 am; 10:30 indicates the half-hour interval that starts at 10:30 am and ends before 11:00 am. Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am. The upper panel reports the total, intraday and overnight average returns (in basis points). The lower panel plots the associated Newey-West adjusted *t*-statistics with a lag length of 12. The dashed horizontal line denotes the 5% significant level. The sample period is from July 1999 to June 2019.

Figure 3.1 depicts the average returns and alphas for specific trading intervals of the long-short Score strategy that buys non-speculative stocks and sells speculative stocks over the full sample period, July 1999 to June 2019. The upper-left panel of the figure plots the average (excess) returns for the specific intervals. The Score strategy experiences positive average returns over the total day, which mainly comes from the overnight period compared to the intraday time. Moreover, the mispricing strategy Score performs extremely poor over the day: its average half-hour interval returns are negative and statistically significant in several intervals of the daytime trading, e.g., 10:00 am to 10:30 am interval earns –3.53 bps (t-statistic equal to –4.62), and the average return of 1:00 pm to 1:30 pm interval is –2.67 bps (t-statistic equal to –4.48). However, the Score portfolio experiences a strikingly massive positive return of 10.85 bps in the last half-hour of trading, from 2:30 pm to 3:00 pm. Also, the returns at the end of the day are statistically significant at the 1% or finer levels (see the lower-right panel for the Newey-West t-statistics). The magnitude of the last half-hour returns for the long-short Score portfolio is twice as large as it is for the market portfolio.

The same salient intraday pattern emerges when we examine the risk-adjusted returns of the Score portfolio. The lower-left panel of **Figure 3.1** shows that the long-short Score strategy experiences significantly positive alphas for the whole day (Total), with 7.12 bps (*t*-statistic equal to 2.93) and offers strong and sizeable alphas at the end of the day (2:00 to 2:30 pm), with 13.94 bps (*t*-statistic equal to 21.91). Hence, in China, the mispricing worsens over the day and mispricing correction happens mainly at the end of the trading day. This end-of-day seasonality contradicts the cross-sectional intraday pattern in the US and other developed markets, where the mispricing factor earns positive returns over the day but performs poorly at the end of the day (Bogousslavsky 2021). We also show the consistency of this end-of-day seasonality for mispricing factors. **Figure 3.A2** shows the average sub-sample alphas for the Score portfolio within different time intervals, which indicates that the last half-hour pattern is robust across sub-samples, 1999-2010 and 2011-2019.

Next, we examine the intraday seasonality for the long-leg and short-leg portfolios of the Score strategy, respectively. **Panel B and C** of **Table 3.1** compare the performance of the unspeculative (underpriced) stocks in the long-leg portfolio with that of the speculative (overpriced) stocks in the short-leg portfolio. We show that, for the total close-to-close returns, the patterns of our portfolios are consistent with the empirical literature: Unspeculative stocks earn higher returns than speculative stocks (Bali, Cakici, and Whitelaw 2011; Kumar 2009). As it stands, both the average excess returns and the alphas for the long-leg portfolio are significantly positive at the end of the trading day (2:30 to 3:00 pm): The average return is highly positive and sizable with 7.32 bps (*t*-statistic equal to 15); the alpha is smaller than the average return with 3.76 bps but still significantly positive with *t*-statistic of 13.30. This positive last half-hour long-leg portfolio return is consistent with the striking end-of-day pattern of the market portfolio, indicating that the non-speculative stocks experience large buying pressure at the end of the day. Overall, the mispricing of the underpriced stocks is corrected at the end of the day and this may be induced by the trading of passive investors (Bogousslavsky and Muravyev 2021). In comparison, the short-leg portfolio earns striking negative returns at the last half-hour trading interval. The average return is –3.53 bps (*t*-statistic equal to –4.34), and the alpha is more prominent with –10.17 bps (*t*-statistic equal to –22.59). This indicates that at the end of the day, stocks in the short-leg portfolio have an extremely large price drop tendency relative to the market trend with positive price deviation.

To provide additional insights, we examine whether various subsamples are driving the intraday return pattern results. **Panel D** of **Table 3.1** shows that the end-of-day return pattern is robust across sub-samples (1999 to 2010 and 2011 to 2019). Both sub-samples have positive alphas: The last half-hour alpha is 14.07 bps (*t*-statistic equal to 17.9) over the first part of the period (1999 to 2010) with a similar alpha of 13.63 bps (*t*-statistic equal to 12.92) over the second part of the period (2011 to 2019). Hence, the end-of-day effect is consistent over the decades.

When interpreting the evidence of **Figure 1** and **Table 3.1** collectively, it becomes clear that both the speculative stocks and non-speculative stocks experience the mispricing correction at the end-of-day. That is, non-speculative stocks earn sizable positive returns while speculative stocks earn large negative returns during the last half-hour interval, from 2:30 to 3:00 pm. Overall, the mispricing anomaly Score strategy has consistent negative returns over the day whereas earns sizable positive returns at the end of the day. The goal then is to explore the mechanism of this cross-sectional last half-hour return pattern.

Table 3. 1 Total, Intraday, and Overnight properties of Score portfolio

	Total	Intraday	OV	10:00	10:30	11:00	11:30	1:00	1:30	2:00	2:30	3:00
Panel A: Long-short portfolio												
AveRet	2.72	–1.50	4.20	–2.40	–3.53	–0.99	–0.08	0.11	–2.67	–3.37	0.54	10.85
	[0.98]	[–0.80]	[2.60]	[–3.14]	[–4.62]	[–1.47]	[–0.13]	[0.32]	[–4.48]	[–5.22]	[0.86]	[15.73]
Alpha	7.12	3.43	4.09	–2.28	–2.83	–2.09	–0.34	0.72	–2.45	–1.57	0.49	13.94
	[2.93]	[2.04]	[2.71]	[–3.54]	[–4.19]	[–3.60]	[–0.61]	[2.67]	[–4.96]	[–3.01]	[0.96]	[21.91]
Panel B: Long and short legs (AveRet)												
Long leg	8.28	8.60	–0.19	–0.44	0.90	–1.72	0.05	0.94	–0.23	1.97	0.10	7.32
	[3.57]	[5.29]	[–0.14]	[–0.87]	[1.53]	[–3.33]	[0.09]	[3.39]	[–0.44]	[4.24]	[0.22]	[15.00]
Short leg	5.56	10.10	–4.40	1.97	4.43	–0.73	0.13	0.82	2.44	5.34	–0.44	–3.53
	[1.50]	[3.99]	[–2.24]	[2.08]	[4.60]	[–0.81]	[0.15]	[1.73]	[2.86]	[6.22]	[–0.49]	[–4.34]
Panel C: Long and short legs (Alpha)												
Long leg	2.55	2.74	–0.03	–0.59	–0.12	–0.42	0.37	0.20	–0.51	–0.09	0.17	3.76
	[2.18]	[3.28]	[–0.04]	[–2.13]	[–0.39]	[–1.56]	[1.42]	[1.49]	[–2.14]	[–0.4]	[0.83]	[13.30]
Short leg	–4.58	–0.69	–4.12	1.69	2.71	1.67	0.70	–0.53	1.94	1.48	–0.31	–10.17
	[–2.93]	[–0.64]	[–4.26]	[3.73]	[5.72]	[4.13]	[1.86]	[–2.66]	[5.99]	[4.01]	[–0.86]	[–22.59]
Panel D: Subsamples (1999-2010, 2011-2019) (Alpha)												
Pre2011	5.00	1.82	3.21	–1.07	–0.84	–2.90	–0.93	1.11	–3.16	–2.94	–0.79	14.07
	[1.60]	[0.83]	[1.85]	[–1.23]	[–0.92]	[–3.79]	[–1.30]	[3.32]	[–5.55]	[–4.73]	[–1.23]	[17.90]
Post2011	9.74	6.84	2.40	–2.75	–5.23	–0.78	0.71	–0.01	–0.68	–0.45	2.10	13.63
	[2.68]	[2.69]	[0.90]	[–3.18]	[–5.35]	[–0.92]	[0.83]	[–0.01]	[–0.89]	[–0.55]	[2.63]	[12.92]

Note: This table reports the total, intraday, and overnight average returns (AveRet) and alphas in basis points of Score portfolio. Portfolios are value-weighted and are re-adjusted for one month. Stock returns are computed using quote midpoints. The first intraday interval 10:00 starts at 9:45 am and ends before 10:00 am; 10:30 indicates the half-hour interval that starts at 10:30 am and ends before 11:00 am. Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am. The *t*-statistics shown in brackets are based on Newey-West standard errors with 12 legs. The sample spans from July 1999 to June 2019.

3.3.2. Overnight risk effect

Bogousslavsky (2021) documents an impressive pattern of the cross-sectional intraday and overnight returns of the US stock market. He uncovers that the correction of mispricing anomalies accrues over the night and every half hour on the trading day except the last one. Due to institutional constraints and overnight risk, arbitrageurs who trade on mispricing choose to close their position at the end of the trading day. Obviously, the pattern and its associated mechanism of the cross-sectional return end-of-day seasonality are different between China and US.

First, the short-selling and margin-trading program is only allowed in China since March 2010 and is still in a limited scope: Only the stocks on the designated list that is approved by China Securities Regulatory Commission (CSRC) are eligible for the short-selling and margin-trading (Chang, Luo, and Ren 2014). Also, the end-of-day effect is consistent over the decades in China, not starting from 2010. Thus, the influence of the institutional constraints channel, referring to overnight lending fees and margin interest, on the mispricing anomalies' end-of-day pattern may be limited in the Chinese stock market. Second, the Chinese stock market is generally considered a speculative market (Chui, Subrahmanyam, and Titman 2022; Jones et al. 2020). According to the annual report of the Shanghai Stock Exchange in 2017, retail investors are the major participants who contribute about 82% of the daily trading volume on the exchange. As a result, the pronounced effect of overnight risk aversion of rational arbitrageurs on the seasonality may be not applicable in China. However, we expect that the overnight risk effect on mispricing anomaly returns would be reversed to be positive in China, while in US the overnight risk has negative relation with last half-hour mispricing returns (Bogousslavsky 2021). That is, with the fear of high overnight risk, investors in China may be reluctant to hold speculative stocks and are more likely to leave the stock market at the end of the day, which would drive the positive long minus short mispricing factor returns. We test the effect of the overnight risk channel on the intraday seasonality in China as follows.

Following Bogousslavsky (2021), we replicate the overnight variance regressions in China. First, we compute each day the logarithm of the overnight variance of the Score strategy return over the past 100 trading days. Then we estimate the time-series regression of the value-weighted strategy half-hour returns around the end of the day on lagged changes in its log overnight variance. To attenuate the influence of market factor, we also include the market portfolio return as the control variable in the regression [17]. **Column 1** and **2** of **Table 3.2** report the results of the regression of long-minus-short mispricing returns on overnight risk for different intraday intervals. For the 2:30 to 3:00 pm interval, the effect on returns is positive for the current day, one- and two-day lagged overnight risk shocks, but not statistically significant. Shown in **Column 3** to **6** of **Table 3.2**, there is no marked pattern for 2:00 to 2:30 pm and 1:30 to 2:00 pm intervals. The effect of overnight risk on the end-of-day abnormal returns is not salient, which contradicts the situation in the US.

Overall, we state that the overnight risk effect and institutional constraints proposed by Bogousslavsky (2021) cannot explain the end-of-day effect of the mispricing long-short strategy in China. We will try other possible explanations in the following sections.

Table 3. 2 Overnight risk effect

	2:30-3:00 pm		2:00-2:30 pm		1:30-2:00 pm	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α	14.23	21.53	0.50	0.85	–1.70	–3.06
$\Delta\sigma_{i,t}^2$	2.62	0.13	–37.06	–1.58	–15.60	–0.83
$\Delta\sigma_{i,t-1}^2$	49.87	1.55	–3.42	–0.17	10.16	0.56
$\Delta\sigma_{i,t-2}^2$	38.84	1.59	6.35	0.42	28.02	1.47
$\Delta\sigma_{i,t-3}^2$	–5.75	–0.34	1.73	0.10	6.69	0.38
Mkt	–0.66	–25.51	–0.63	–21.38	–0.65	–18.03

Note: This table reports estimates of time-series regressions of a value-weighted long-short Score strategy half-hour returns on the several explanatory variables:

$$Ret_{i,\tau,t} = \alpha + \sum_{s=0}^{3} \beta_s \Delta\sigma_{i,t-s}^2 + \beta_4 Mkt_{\tau,t} + \epsilon,$$

where $\Delta\sigma_{i,t-s}^2$ is the lagged changes in the overnight variance for long-short Score portfolio returns. Following Bogousslavsky (2021), overnight variance is the logarithm of the overnight return variance over the past 100 days. $Ret_{i,\tau,t}$ is the portfolio $i's$ return in each day t and each half-hour interval τ. $Mkt_{\tau,t}$ is the value-weighted market level portfolio return of all stocks in the sample in each day t and each half-hour interval τ. 2:30-3:00 pm (2:00-2:30 pm and 1:30-2:00 pm) indicates the regression results of taking the return of half-hour interval that starts at 2:30 (2:00 and 1:30) pm and ends at 3:00 (2:30 and 2:00) pm as the dependent variable. The sample spans from July 1999 to June 2019. The *t*-statistics shown in parentheses are based on Newey-West standard errors with 5 legs.

[17] The results still hold if we exclude the market factor.

3.4. End-of-day pattern and disposition effect

The previous section documents a striking cross-sectional intraday return pattern in China that the mispricing factor performs poorly throughout the day but earns massive positive returns at the end of the day. In this section, we present the empirical findings of the role of disposition effect in cross-sectional last half-hour return predictability (2:30 pm to 3:00 pm).

The disposition effect is the robust empirical fact referring to that investors have a stronger tendency to sell stocks holding at a gain position relative to purchase price than stocks holding at a loss position (Barberis and Xiong 2009, 2012; Shefrin and Statman 1985). It is presumed that the disposition effect is combined by Kahneman and Tversky (1992)'s prospect theory and Thaler (1980, 1985)'s mental accounting framework (MA/PT). More explicitly, prospect theory has an S-shaped value function that is concave in the domain of capital gains and convex in the domain of capital losses, both measured relative to a reference point. The theory further indicates that investors weight outcomes not by objective probabilities but by transformed subjective probabilities that may overweight the tails of the distribution that they think. Mental accounting states that investors tend to mentally frame different types of gambles as belonging to independent accounts, and then apply prospect theory to each account by ignoring possible interactions among those gambles. Therefore, investors subject to realization utility have a strong propensity to exhibit a disposition effect[18].

Recently, numerous studies have attempted to explore the mechanism of asset pricing anomalies through the intuition of PT/MA: An et al. (2020) argue that the performance of mispricing anomalies varies substantially across different levels of capital losses or gains; Barberis et al. (2021) treat the prospect theory as a possible factor for the anomaly predictability explanation. As demonstrated in the previous section, in China, the correction of the intraday mispricing anomaly primarily occurs at the end of the trading day. Hence, we can ask whether the disposition effect serves as a potential explanation for the end-of-day puzzle observed in cross-sectional returns in China's stock market, in which the market experiences prevalent speculative trading and a remarkable turnover rate.

We first calculate the measure of capital gains overhang (CGO) for each firm each day

[18] Starting from Shefrin and Statman (1985), the development of the literature on the disposition effect is far-reaching. They propose a general disposition framework of selling winners too early and holding losers too long. Besides this, Barberis and Xiong (2009, 2012) and Ingersoll and Jin (2013) construct realization utility models to show that realized gains and losses may play a pivotal role in forming the disposition effect. Empirically, Odean (1998) and Frydman et al. (2014) provide support for the realization utility model.

following the instructions in **Section 3.2.2.3** and report the summary statistics of single-sorted portfolios by CGO. CGO essentially proxies the stock returns relative to a reference price, with negative CGO meaning capital losses relative to the reference price and vice versa. Next, we examine the effect of CGO on Score portfolio returns using the double-sorting analysis and Fama-MacBeth regressions (Fama and MacBeth 1973).

3.4.1. One-way sorts

This subsection reports the results for one-way CGO sorted portfolios. For each day, we sort all the stocks in our sample into quintiles by the ranked value of CGO calculated following **Section 3.2.2.3**. Then, the portfolio value-weighted average return is calculated for the specific intervals in each quintile. All *t*-statistics (in parentheses) are based on the adjusted standard errors of Newey and West (1986) with a lag equal to 12.

Table 3.3 presents the results of value-weighted average returns for different trading intervals based on CGO sorting. Stocks with capital gains (high CGO) tend to underperform stocks with capital losses (low GCO) for the current intraday trading period (9:45 am to 3:00 pm). Intraday returns decrease monotonically with their CGO quintile, ranging from 16.26 bps for the CGO1 portfolio to 6.63 bps for the CGO5 portfolio. The result is consistent with the PT/MA framework which states that investors are risk aversion (risk loving) over gambling for stocks with high capital gains (losses). In contrast, for the overnight returns, the relationship between CGO and returns is reversed to be positive, that is, the OV returns increase monotonically from the bottom to the top CGO quintiles. In other words, the overnight traders aren't influenced by the disposition effect and they even trade on the CGO direction, specifically, buying stocks with capital gains and selling stocks with capital losses. Taken together, there is no distinguishable pattern for the relationship between total return and CGO.

Table 3. 3 One-way sorts by CGO

	3:00 pm	2:30 pm	2:00 pm	Total	OV	Intraday	CGO	Turnover	lnME
CGO1	9.18	1.16	4.08	8.63	–7.49	16.26	–0.07	1.15	15.51
CGO2	6.59	0.50	3.00	6.27	–2.89	9.16	–0.02	0.97	15.49
CGO3	5.44	–0.15	2.74	5.43	–1.58	7.00	0.00	1.00	15.50
CGO4	3.82	–0.36	2.27	6.25	0.36	5.94	0.02	1.15	15.54
CGO5	1.19	–1.08	2.67	10.28	3.96	6.63	0.06	1.77	15.60
C5–C1	–7.99	–2.24	–1.41	1.65	11.45	–9.63	0.13	0.62	0.10
t-stat	[–13.42]	[–5.31]	[–3.14]	[0.82]	[7.13]	[–6.95]	[62.66]	[28.12]	[8.03]

Note: The table reports the time-series average of the value-weighted returns and equal-weighted other characteristics for five portfolios sorted by CGO. For each day t, we sort all the A share stocks (excluding the smallest 30%) into five groups based on the quintile of the ranked value of CGO. CGO5 refers to the highest CGO index group, and CGO1 refers to the lowest CGO index group. The last row shows the return and firm characteristics' difference of portfolio CGO5 and CGO1. CGO at day t is computed as one less the ratio of the day $t-1$ reference price to the day $t-1$ close price. The day $t-1$ reference price is the average cost basis calculated from the formula:

$$RP_{t-5} = P_{t-5}$$
$$RP_{t-4} = V_{t-5}P_{t-5} + (1 - V_{t-5})RP_{t-5} = P_{t-5}$$
$$RP_{t-3} = V_{t-4}P_{t-4} + (1 - V_{t-4})RP_{t-4}$$
$$\dots$$
$$RP_{t-1} = V_{t-2}P_{t-2} + (1 - V_{t-2})RP_{t-2},$$

where V_t is day t's turnover in the stock, P_t is day t's close price. 3:00 (2:30 and 2:00) pm indicates the return of half-hour interval that starts at 2:30 (2:00 and 1:30) pm and ends at 3:00 (2:30 and 2:00) pm. Total is the daily total excess returns (risk-free rate is subtracted). Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am (risk-free rate is subtracted). lnME is the natural logarithm of firm's market capitalization. Turnover is the firm's daily turnover ratio. All the returns are reported in basis points. The t-statistics in parentheses are Newey-West adjusted with a lag of 12. The sample spans from July 1999 to June 2019.

Moreover, the return spread between the CGO5 and the CGO1 for the last half-hour return, 3:00 pm (2:30 to 3:00 pm), is significantly negative with a substantial magnitude, –7.99 bps with a *t*-statistic of –13.42. The spread between the top and bottom CGO quintiles for 2:30 pm (2:00 to 2:30 pm) and 2:00 pm (1:30 to 2:00 pm) is still statistically significant, while smaller in magnitude than 3:00 pm, which equals to –2.24 bps and –1.41, with a *t*-statistic of –5.31 and –3.14. Evidently, during the day trading, stocks with capital gains are more likely to be sold out for the paper gain realized, which induces the relatively lower recent returns for the higher CGO quintile portfolios. Strikingly, this disposition effect related asset rebalancing happens mainly at the end of the day.

3.4.2. Double sorts

In this subsection, we conduct a double-sorting portfolio analysis to examine the effect of CGO on mispricing factor cross-section return predictability for different trading intervals. The double-sorting approach allows us to test whether a variable still has predictive power for returns after being sorted by another variable. This approach is robust as it benefits from the diversification of individual stocks across quintile portfolios and there is no need to assume a linear relationship between the sorting variable and the dependent variable. Also, the concerns of noises and outliers are attenuated, which enhances the applicability of variable tests.

The double-sorting is done in two ways: first sort on CGO (then Score) and first sort on Score (then CGO). We calculate the average returns of portfolios obtained by double-sorting both on Score and CGO variables. Specifically, for each day, we first sort stocks into quintiles by the stock's mispricing anomaly, Score. Within each Score quintile, we further sort stocks into quintiles based on daily CGO. Next, we calculate the value-weighted average returns for 25 portfolios respectively and report the return differential between the highest and lowest CGO quintiles. Then, ceteris paribus, we reverse the sort order. The result of portfolio returns first sorted by Score (CGO) is reported on the left (right) panel of **Table 3.4**.

To have the overview of the disposition effect on the return predictability of mispricing anomaly, we first test the double sorting for total returns (close-to-close). [19] The results are reported in **Panel A** of **Table 3.4**. The left panel of **Table 3.4** shows that the average return spread between CGO5 and CGO1 decreases monotonically with their Score quintile. For the

[19] We also calculate the double sorting return results for other intervals, for example, the intraday and overnight returns. The results and analyses are reported in the online appendix.

most speculative stocks (Score5), high CGO stocks underperform low CGO stocks by 12.49 basis points (*t*-statistic equal to –5.23), suggesting that the disposition effect is significant for speculative stocks. In contrast, for the unspeculative stocks (Score1), the negative correlation between CGO and future returns is reserved to be positive (C5-C1 equals 11.84 with *t*-statistic 4.63). On the other aspect, Column S1-S5 of the right panel (first sorted by CGO) reports the return spread between extreme mispricing portfolios (S1-S5) among different CGO quintiles. For stocks with the highest previous capital gains (CGO5), as expected, low-Score stocks outperform high-Score stocks by 13.20 bps (*t*-statistic equal to 4.61). In contrast, for stocks with the highest capital losses (CGO1), low-Score stocks underperform high-Score stocks by 15.31 bps (*t*-statistic equal to –6.67). Therefore, the difference-in-differences is 28.54 bps per day, with a *t*-statistic of 9.62. This is consistent with the finding of An et al. (2020) that when facing prior losses, the demand for speculative assets increases; when facing prior gains, the selling pressure for speculative assets is extremely larger than for unspeculative stocks.

Then, our key focus is on the relationship between the disposition effect and the end-of-day cross-section return seasonality. **Panel B** of **Table 3.4** reports the double-sorting results for the return interval of 2:30 to 3:00 pm. Consistent with the one-way sorting results, the result in the **left panel of Panel B** shows that for each given Score quintile, the average last half-hour interval returns of portfolios decrease monotonically with their CGO quintile. The difference between the returns of the highest and lowest CGO quintiles within each of the Score quintiles is significantly negative, ranging from –6.89 to –10.48. The difference-in-differences result is significantly positive, with 3.60 bps (*t*-statistic equal to 4.61).

Our main concern is that speculative stocks with extreme capital gains are more likely to be sold at the end of the trading day, which induces the end-of-the-day mispricing correction. As shown in the **right panel of Panel B**, when facing capital gains (CGO5 quintile), the portfolio returns are significantly positive for the Score1 to Score4 portfolios, ranging from 0.53 to 4.18 basis points, with the *t*-statistics from 0.68 to 5.98. As a comparison, the portfolio of Score5 in the highest CGO quintile experiences negative returns, which is about –5.36 basis points, with the *t*-statistic equal to –5.84. This confirms our MA/PT framework prediction, that is, when investors face prior gains, they are more risk-aversion. Thus, they are more likely to sell speculative stocks relative to unspeculative stocks and this induces selling pressure for the short leg. Importantly, this disposition effect happens mostly over the end of the trading day.

Moreover, the difference between the returns of the lowest and highest Score quintiles, shown in the S1-S5 column of the **right panel in Panel B**, is generally significant within each CGO quintile, ranging from about 6.63 to 9.53 bps per day, with *t*-statistics from 9.87 to 12.83. It is noteworthy that the predictability of the Score for future end-of-day returns exists not only in the extreme CGO group but also in the middle CGO groups. These groups consist of stocks that are typically neither winners nor losers, with a CGO value close to zero. This finding indicates that the mispricing cross-sectional last-hour effect is prevalent among different CGO groups.

Panel C and Panel D of Table 3.4 report the double-sorting average return results for 2:00 to 2:30 pm and 1:30 to 2:00 pm intervals. For the 2:00 to 2:30 pm interval, in each Score quintile, the CGO has a negative relationship with returns, which is consistent with our on-way sorting results before. The differences between the highest and lowest CGO portfolios are significantly negative, while the magnitude is smaller than that of 2:30 pm, ranging from –1.68 to –3.07 bps, with *t*-statistics from –3.54 to –5.62. Moreover, the Score predictability is not pronounced anymore in all the CGO quintiles. Those results are consistent with the notion that returns of the second last half-hour interval don't exhibit mispricing anomaly's predictability while do experience the disposition effect-related trading. For 1:30 pm, there is no material pattern between CGO and future returns. The return spreads between the high-CGO stocks and low-CGO stocks in different Score quintiles are mostly statistically insignificant. On the other side, the Score has a positive relationship with future returns. That is, for each CGO quintile, the strategy that goes long the most unspeculative stocks (Score5) and goes short the most speculative stocks (Score1) receives significant negative returns, ranging from –2.48 to –3.37 bps, with the *t*-statistics from –3.87 to –6.04. This finding is consistent with the pattern of cross-sectional intraday returns reported in **Table 3.1**, which shows that during the day trading time, except for the last half-hour trading interval, the mispricing factor performs poorly and earns negative returns.

Overall, we treat the disposition effect as the most possible mechanism for the end-of-day effect of cross-sectional returns. Specifically, when facing high capital gains, investors have a strong tendency to sell speculative stocks to achieve the gains on paper at the end of the day, which induces massive relative negative returns of speculative stocks at the end of the day. In contrast, unspeculative stocks across different CGO portfolios experience uniformly buying pressure at the end of the day, which is consistent with the positive returns for the long-leg portfolio.

Table 3. 4 Portfolio double-sorted by Score and CGO

Panel A: Total Return

First sort by Score, then CGO						
	Score1	Score2	Score3	Score4	Score5	
CGO1	2.58	9.52	9.90	12.91	16.86	
	[0.87]	[2.85]	[2.91]	[3.60]	[4.32]	
CGO2	7.64	7.66	7.28	7.54	7.43	
	[2.98]	[2.47]	[2.21]	[2.17]	[2.03]	
CGO3	8.29	5.76	6.45	5.34	0.34	
	[3.48]	[1.98]	[2.09]	[1.60]	[0.10]	
CGO4	6.40	8.76	6.87	3.95	–1.45	
	[2.74]	[3.15]	[2.24]	[1.25]	[–0.41]	
CGO5	14.41	8.64	9.77	9.61	4.37	
	[4.66]	[2.98]	[3.10]	[2.71]	[1.11]	
C5–C1	11.84	–0.88	–0.14	–3.30	–12.49	24.33
	[4.63]	[–0.43]	[–0.07]	[–1.49]	[–5.23]	[8.79]

First sort by CGO, then Score						
	CGO1	CGO2	CGO3	CGO4	CGO5	
Score1	–0.56	5.62	5.72	7.72	16.09	
	[–0.17]	[2.05]	[2.30]	[3.12]	[4.93]	
Score2	9.75	7.38	6.62	7.76	8.77	
	[2.87]	[2.36]	[2.23]	[2.79]	[2.97]	
Score3	9.89	7.35	6.21	7.64	9.51	
	[2.85]	[2.24]	[2.01]	[2.49]	[3.01]	
Score4	12.58	6.91	5.67	4.40	8.46	
	[3.50]	[2.00]	[1.69]	[1.38]	[2.45]	
Score5	14.85	5.70	0.00	–0.59	2.92	
	[3.82]	[1.54]	[0.00]	[–0.17]	[0.76]	
S1–S5	–15.31	–0.08	5.73	8.30	13.20	28.54
	[–6.67]	[–0.04]	[2.59]	[3.54]	[4.61]	[9.62]

Panel B: 2:30–3:00 pm

First sort by Score, then CGO							First sort by CGO, then Score						
	Score1	Score2	Score3	Score4	Score5			CGO1	CGO2	CGO3	CGO4	CGO5	
CGO1	11.84	10.52	9.55	8.43	4.76		Score1	13.02	8.93	7.73	5.78	4.18	
	[18.92]	[15.38]	[12.62]	[10.60]	[5.29]			[19.70]	[13.72]	[13.09]	[10.02]	[5.98]	
CGO2	8.95	7.17	6.46	4.85	1.47		Score2	10.84	7.22	6.00	4.81	3.42	
	[15.19]	[10.86]	[9.03]	[6.32]	[1.75]			[15.27]	[10.96]	[8.97]	[7.48]	[4.76]	
CGO3	8.28	5.91	4.88	3.47	–0.10		Score3	9.66	6.68	4.48	4.56	1.65	
	[13.70]	[8.93]	[7.00]	[4.78]	[–0.12]			[12.65]	[9.33]	[6.35]	[6.53]	[2.29]	
CGO4	6.20	5.07	4.20	2.36	–1.81		Score4	8.10	5.08	3.49	2.71	0.53	
	[10.54]	[7.97]	[5.88]	[3.17]	[–2.18]			[10.02]	[6.75]	[4.73]	[3.60]	[0.68]	
CGO5	4.95	3.50	1.84	0.55	–5.72		Score5	4.07	1.53	0.13	–0.87	–5.36	
	[7.47]	[4.93]	[2.56]	[0.69]	[–6.32]			[4.55]	[1.85]	[0.16]	[–1.02]	[–5.84]	
C5–C1	–6.89	–7.01	–7.71	–7.88	–10.48	3.60	S1–S5	8.95	7.40	7.60	6.63	9.53	0.57
	[–10.11]	[–11.06]	[–12.57]	[–12.82]	[–14.16]	[4.61]		[13.18]	[12.16]	[13.02]	[9.87]	[12.83]	[0.72]

Panel C: 2:00–2:30 pm

First sort by Score, then CGO							First sort by CGO, then Score						
	Score1	Score2	Score3	Score4	Score5			CGO1	CGO2	CGO3	CGO4	CGO5	
CGO1	1.29	1.23	1.50	2.03	1.81		Score1	0.25	–0.39	–1.00	–0.94	–1.49	
	[2.13]	[1.70]	[1.95]	[2.49]	[2.01]			[0.41]	[–0.65]	[–1.72]	[–1.62]	[–2.32]	
CGO2	0.14	0.34	0.52	0.82	0.47		Score2	0.30	–0.47	–0.79	–1.26	–1.91	
	[0.25]	[0.49]	[0.71]	[1.02]	[0.53]			[0.40]	[–0.68]	[–1.15]	[–1.88]	[–2.69]	
CGO3	0.19	–0.08	0.05	–0.04	–0.31		Score3	0.65	–0.51	–1.03	–1.15	–1.83	
	[0.35]	[–0.11]	[0.06]	[–0.05]	[–0.34]			[0.85]	[–0.70]	[–1.40]	[–1.56]	[–2.41]	
CGO4	0.08	–0.12	–0.58	–0.56	–0.74		Score4	0.91	–0.39	–0.95	–1.41	–1.93	
	[0.14]	[–0.17]	[–0.80]	[–0.70]	[–0.81]			[1.12]	[–0.48]	[–1.20]	[–1.78]	[–2.29]	
CGO5	–0.39	–0.90	–0.70	–0.88	–1.26		Score5	0.44	–0.41	–1.24	–1.57	–2.28	
	[–0.64]	[–1.29]	[–0.93]	[–1.03]	[–1.31]			[0.49]	[–0.45]	[–1.37]	[–1.70]	[–2.40]	
C5–C1	–1.68	–2.13	–2.20	–2.91	–3.07	1.39	S1–S5	–0.16	0.02	0.23	0.60	0.79	0.97
	[–3.54]	[–4.55]	[–4.34]	[–5.54]	[–5.62]	[2.19]		[–0.28]	[0.03]	[0.42]	[1.01]	[1.21]	[1.48]

Panel D: 1:30–2:00 pm

First sort by Score, then CGO							First sort by CGO, then Score						
	Score1	Score2	Score3	Score4	Score5			CGO1	CGO2	CGO3	CGO4	CGO5	
CGO1	2.64	3.60	3.65	5.01	6.38		Score1	2.73	2.16	1.98	1.93	2.56	
	[4.68]	[5.49]	[5.33]	[6.54]	[7.37]			[4.76]	[3.69]	[3.78]	[3.52]	[4.19]	
CGO2	2.20	3.02	3.74	3.82	5.20		Score2	3.71	3.07	2.82	2.19	2.23	
	[4.10]	[4.87]	[5.40]	[5.34]	[6.14]			[5.53]	[4.90]	[4.71]	[3.51]	[3.47]	
CGO3	1.68	2.66	3.34	3.75	4.87		Score3	3.82	3.41	3.46	2.91	3.08	
	[3.21]	[4.47]	[4.96]	[5.05]	[5.80]			[5.54]	[4.99]	[5.12]	[4.35]	[4.41]	
CGO4	1.88	2.53	2.79	3.37	4.35		Score4	4.98	3.66	3.76	3.23	3.86	
	[3.65]	[4.10]	[4.19]	[4.68]	[5.22]			[6.57]	[5.10]	[5.09]	[4.41]	[5.08]	
CGO5	2.27	2.08	3.09	3.83	5.09		Score5	6.09	5.27	4.77	4.44	5.03	
	[3.85]	[3.28]	[4.40]	[5.04]	[5.72]			[7.10]	[6.45]	[5.63]	[5.29]	[5.76]	
C5–C1	–0.37	–1.52	–0.56	–1.18	–1.29	0.92	S1–S5	–3.37	–3.12	–2.79	–2.50	–2.48	0.88
	[–0.72]	[–3.41]	[–1.22]	[–2.39]	[–2.47]	[1.46]		[–6.04]	[–5.88]	[–4.94]	[–4.36]	[–3.87]	[1.36]

Note: This table presents the results of **value-weighted excess returns** (in basis points) of portfolios sorted by mispricing anomaly (Score), and CGO. The left (right) panel of the table shows the returns of portfolio sorted first by Score (CGO) then CGO (Score). For each day, stocks are first ranked in ascending order on the basis of the mispricing anomaly (CGO index). Within each Score (CGO) quintile, stocks are further sorted into five portfolios by their previous day's CGO (Score) from the lowest CGO1 (Score1) to the highest CGO5 (Score5). Then, within each CGO (Score) portfolio, we calculate the value-weighted average excess return as well as the CGO5 (Score1) minus CGO1 (Score5) portfolio return differentials for the day that follows. The t-statistics in parentheses are Newey-West adjusted with a lag of 12. The sample spans from July 1999 to June 2019.

3.4.3. Fama-MacBeth regression

The double-sorting test in the preceding section is simple and intuitive, but it lacks explicit control over the potential variables that may influence returns. To exclude other possible mechanisms, we perform the Fama-MacBeth methodology that simultaneously controls for a set of well-established return predictors. More specifically, for each trading interval, we run the following cross-sectional regressions:

$$ret_{i,t} = \alpha_t + \beta_t CGO_{i,t} + \gamma_t Score_{i,t-1} + \delta_t CGO_{i,t} \times Score_{i,t-1} + \theta_t lnME_{t-1} + \vartheta_t lnBTM_{t-1} + \mu_t OP_{t-1} + \rho_t INV_{t-1} + \sigma_t MOM_{t-1} + \tau_t STREV_{t-1} + \varphi_t AvgTurn_{t-1} + \varepsilon_t \tag{6}$$

where $ret_{i,t}$ is the returns for different trading intervals each day in basis points. lnME is the natural logarithm of a firm's market capitalization measured at the end of the prior month. lnBTM is the natural logarithm of a firm's book-to-market equity measured at the end of the previous fiscal year. OP is the ratio of operational profits and book equity measured at the end of the previous fiscal year. INV is the growth of total assets for the end of the previous fiscal year. MOM is the past 12-month cumulative return, skipping the most recent month. STREV is the past one-month return. AvgTurn is the average daily turnover (in percentage) over the last year. Independent variables are all winsorized at their 5^{th} and 95^{th} percentiles.

In **Table 3.5**, we report the time-series averages of daily coefficients for regressions of different trading interval returns. The benchmark regression is in column (1). The result for total returns shows that the coefficient of CGO is significant and negative, indicating that stocks with more unrealized capital gain experience lower recent returns. Note that Grinblatt and Han (2005) find that stocks with higher capital gain overhang would have higher future returns (in the next month). Our findings are consistent with their analysis, which suggests investors have a tendency to sell stocks with higher CGO in order to realize gains on paper. This overselling of high CGO stocks leads to undervaluation, resulting in the predictability of CGO for future returns. Moreover, the results of benchmark regression for the intraday half-hour intervals, 3:00 pm, 2:30 pm, and 2:00 pm, have a similar pattern with total returns, in which the coefficients of CGO are significantly negative. These results are consistent with our findings in the preceding one-way sorting results.

Table 3. 5 Fama-MacBeth regressions using CGO and Score

Dep.=	Total		3:00 pm		2:30 pm		2:00 pm	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Coef.	26.97	31.18	37.76	44.83	5.13	5.60	3.47	1.89
	[3.47]	[4.22]	[24.38]	[29.60]	[4.21]	[5.09]	[3.27]	[1.82]
CGO	–60.61	122.64	–62.71	–49.71	–22.49	–22.78	–7.88	0.74
	[–5.54]	[5.74]	[–19.55]	[–10.92]	[–11.40]	[–7.25]	[–3.95]	[0.23]
Score		–1.03		–1.18		–0.08		0.31
		[–3.51]		[–16.06]		[–1.35]		[5.08]
Score × CGO		–34.48		–2.42		–0.01		–1.30
		[–11.63]		[–3.95]		[–0.02]		[–2.68]
lnME	–2.66	–2.71	–2.62	–2.86	–0.65	–0.66	–0.31	–0.25
	[–4.28]	[–4.43]	[–18.96]	[–21.33]	[–6.24]	[–6.46]	[–3.13]	[–2.58]
lnBTM	1.98	1.93	–0.80	–1.01	0.38	0.35	0.45	0.48
	[3.33]	[3.28]	[–4.78]	[–5.98]	[3.38]	[3.25]	[4.29]	[4.64]
OP	0.03	0.03	0.04	0.03	0.01	0.01	–0.01	–0.01
	[1.36]	[1.37]	[7.11]	[6.67]	[1.05]	[1.16]	[–1.99]	[–1.84]
INV	0.01	0.01	0.01	0.01	–0.01	–0.01	0.01	0.01
	[0.12]	[0.26]	[1.67]	[2.46]	[–0.75]	[–0.35]	[0.07]	[0.04]
MOM	–27.17	–18.37	–4.57	2.92	–1.92	–0.96	0.87	–0.94
	[–5.96]	[–3.71]	[–4.23]	[2.58]	[–2.40]	[–1.22]	[1.10]	[–1.21]
STREV	0.38	1.04	6.46	6.01	0.09	0.16	–1.04	–0.91
	[0.20]	[0.58]	[12.23]	[12.81]	[0.32]	[0.63]	[–3.48]	[–3.30]
AvgTurn	–4.03	–2.95	–6.69	–4.37	–1.13	–1.06	0.84	0.15
	[–5.82]	[–5.24]	[–22.79]	[–19.89]	[–5.69]	[–6.78]	[3.80]	[0.92]
$Adj.R^2$	0.07	0.08	0.03	0.04	0.03	0.04	0.03	0.04
Firms	1164	1164	1164	1164	1164	1164	1164	1164
Periods	4820	4820	4820	4820	4820	4820	4820	4820

Note: The table presents the Fama-MacBeth (1973) cross-sectional regressions at the firm level. Every day, we run a cross-sectional regression of returns on lagged variables. The time-series average of the regression coefficients is reported. The dependent variables are returns for different trading interval in basis points. Total is the close-to-close interval returns. 3:00 (2:30 and 2:00) pm indicates the regression result of taking the half-hour interval returns that starts at 2:30 (2:00 and 1:30) pm and ends at 3:00 (2:30 and 2:00) pm as the dependent variable. CGO is defined as in Section 2.2.3. Score is the Average Score index, which is the proxy of mispricing anomaly. lnME is the natural logarithm of firm's market capitalization measured at the end of the prior month. lnBTM is the natural logarithm of a firm's book-to-market equity measured at the end of the previous fiscal year. OP is the ratio of operational profits and book equity measured at the end of the previous fiscal year. INV is the growth of total assets for the end of the previous fiscal year. MOM is the past 12-month cumulative return, skipping the most recent month. STREV is the past one-month return. AvgTurn is the average daily turnover (in percentage) over the last year. t-statistics in parentheses are Newey-West adjusted with a lag of 12. $Adj.R^2$ is the adjusted R-square. Firms is the average number of firms in the cross-sectional regression, and Periods is the number of days for the period-by-period cross-sectional regressions. The sample spans from July 1999 to June 2019.

Next, we investigate the role of CGO in the predictability of Score strategy. The interaction term of Score and CGO, coefficient δ_t, is our main coefficient of interest. The regressions in column (2) report the regressions with the mispricing proxy Score and the interaction term between the CGO and Score. For the coefficient of the interaction term of Total returns, the result is negative and significant. For the end of the day half-hour intervals, the coefficient of interaction terms is significantly negative at 3:00 pm, which equals –2.42 with a *t*-statistic corresponding to –3.95. The interaction term coefficient is smaller in magnitude for 2:30 pm and 2:00 pm, which equals –0.01 and –1.30 (with *t*-statistic –0.02 and –2.68), respectively. This indicates that only for the last half-hour interval, speculative stocks with capital losses have higher returns than speculative stocks with capital gains, confirming that our results based on double sorts still hold even after we control for size, book-to-market ratios, profitability, investment ratio, momentum, reversal, and average turnover characteristics.

We also find consistent evidence to support the salient negative predictability of Score at the end of the day that the coefficient of Score itself at 2:30 pm typically is significantly negative, which equals to –1.18 with *t*-statistics corresponding to –16.06. The negative predictability of the mispricing factor disappears at the 2:30 pm interval, and even reverses to be positive at 2:00 pm, which is consistent with our results shown in **Table 3.1**.

Overall, our regression results are generally consistent with the previous single-sorting and double-sorting findings. The analysis provides strong evidence suggesting that CGO plays an important role in the mispricing anomaly's end-of-day effect.

3.5. Additional evidence

In this section, we provide additional evidence about the end-of-the day trading.

3.5.1. Market quality

The presence of the disposition effect mechanism and its association with the end-of-day return pattern may have broader implications for the stock market. One consequence is the potential impact on market efficiency, which may be worsened by the pronounced end-of-day effect observed in the mispricing anomaly. From the inverse perspective, the increased trading volume with lower transaction costs and reduced price impact at the end of the day may facilitate trading for the investors who chose to reshuffle their portfolio prior to market close.

To further investigate these effects, **Table 3.6** presents average value-weighted measures of liquidity, volatility, and market efficiency in the long and short leg of the Score portfolio across different half-hours of the trading day in 2018.

We measure liquidity using the Amihud ratio, RQS (relative quoted spread), and Turnover. Amihud is the Amihud illiquidity measure (Amihud 2002), which is defined as the absolute return divided by the trading dollar volume (in millions of RMB) in the specific half-hour. RQS is the relative quoted spread, proxied by the 1-min average of the ratio of the bid-ask spread to the midpoint. Turnover is the half-hour interval share trading volume turnover, constructed by using the half-hour share trading volume divided by the number of tradable shares. Note that for ease of interpretation, RQS and Turnover is presented in percentage. Panel A of **Table 3.6** presents the value-weighted liquidity measures for long and short Score portfolios, respectively. Amihud is 9.76% (8.18%) lower at 3:00 pm than at 2:30 pm for stocks in the long (short) leg and the differential between those two intervals is statistically significant, –0.0036 (–0.0028) with *t*-statistic of –3.21 (–2.90). This indicates that trades executed at the last half-hour are likely to have a smaller price impact than trades executed before. Consistent with the Amihud pattern, RQS is 7.84% (18.34%) lower at 3:00 pm than at 2:30 pm for stocks in the long (short) leg, with the differential statistically significant, –0.0134 (–0.0179) and *t*-statistic of –4.86 (–17.20). Moreover, the RQS at the end-of-day is the smallest over the whole day, meaning that the transaction cost is lowest at the end-of-day. Turnover is 43.84% (40.14%) higher at 3:00 pm than at 2:30 pm for stocks in the long (short) leg portfolio. Consistent with previous studies (Bogousslavsky 2021; Lou et al. 2019), turnover dips during the day and then rises near the close. Overall, our results imply that investors with large trade orders may have a strong tendency to execute the trade at the end-of-day due to the higher liquidity, lower trading cost, and smaller price impact.

Our measures of volatility are AbsRet and StdRet, calculated using the absolute return of the specific half-hour interval and the standard deviation of 1-min stock returns in half-hour. It is worth noting that the AbsRet and StdRet are highly correlated with each other. Panel B of **Table 3.6** shows the average value-weighted half-hours volatility for long and short-leg portfolios. AbsRet is 21.15% (8.06%) higher at 3:00 pm than at 2:30 pm for stocks in the long (short) leg, and the differential between those two intervals is statistically significant, 0.0582 (0.0508) with t-statistic of 4.60 (3.10). This indicates that the trading during the end-of-day is highly volatile, especially for the long-leg portfolio.

Table 3. 6 Market quality of the long leg and long leg Score stocks

Panel A: Liquidity

	Amihud		RQS		Turnover	
	Long	Short	Long	Short	Long	Short
10:00 am	0.0429	0.0351	0.1762	0.1213	0.0464	0.6439
10:30	0.0383	0.0367	0.1725	0.1031	0.0260	0.3410
11:00	0.0431	0.0425	0.1729	0.1039	0.0208	0.2476
1:00 pm	0.0490	0.0501	0.1752	0.1070	0.0179	0.1989
1:30	0.0406	0.0465	0.1727	0.1035	0.0186	0.1951
2:00	0.0403	0.0431	0.1706	0.0997	0.0188	0.2162
2:30	0.0379	0.0391	0.1710	0.0976	0.0203	0.2317
3:00	0.0342	0.0363	0.1576	0.0797	0.0293	0.3247
Diff (3:00-2:30pm)	–0.0036	–0.0028	–0.0134	–0.0179	0.0090	0.0931
t-stat	[–3.21]	[–2.90]	[–4.86]	[–17.20]	[7.83]	[16.75]

Panel B: Volatility

	AbsRet		StdRet	
	Long	Short	Long	Short
10:00 am	0.5603	1.3416	0.2826	0.6540
10:30	0.3432	0.8175	0.1836	0.4178
11:00	0.2975	0.7040	0.1605	0.3615
1:00 pm	0.2804	0.6674	0.1518	0.3281
1:30	0.2467	0.5805	0.1502	0.3237
2:00	0.2634	0.6303	0.1470	0.3357
2:30	0.2752	0.6301	0.1527	0.3442
3:00	0.3334	0.6809	0.1755	0.3389
Diff (3:00-2:30pm)	0.0582	0.0508	0.0228	–0.0053
t-stat	[4.60]	[3.10]	[7.34]	[–1.25]

Panel C: Market efficiency

	AR		VR	
	Long	Short	Long	Short
10:00 am	0.1738	0.1565	1.0867	0.8904
10:30	0.1714	0.1592	0.9657	0.8518
11:00	0.1697	0.1617	0.9500	0.8291
1:00 pm	0.1780	0.1666	1.0704	0.8455
1:30	0.1732	0.1684	1.0165	0.8346
2:00	0.1730	0.1721	0.9846	0.7716
2:30	0.1755	0.1764	0.9871	0.7272
3:00	0.1928	0.1794	1.1998	0.7715
Diff (3:00-2:30pm)	0.0172	0.0029	0.2127	0.0442
t-stat	[4.77]	[2.71]	[3.66]	[2.99]

Note: The table reports the value-weighted liquidity, volatility, and market efficiency measures of the Score portfolio's long and short legs in 2018. All the measures are computed at the stock level and value-weighted across stocks each half-hour interval on each day. Liquidity measures reported in Panel A consist of the Amihud ratio, relative quoted spread (RQS), and Turnover. Amihud is computed as $\frac{|r|}{DVol} \times 10^6$, where r denotes the quote midpoint return and $DVol$ denotes the dollar volume in RMB. RQS is computed as the 5-min average relative quoted spread (ask bid spread over the quote midpoint). Turnover is computed as the half-hour share trading volume divided by the number of tradable shares of the stock. Volatility measures reported in Panel B consist of absolute half-hour quote midpoint returns (AbsRet) and standard deviation (stdRet) of 5-min quote midpoint returns. Market efficiency measures reported in Panel C consist of the autocorrelation (AR) and variance ratio (VR). AR is computed using the absolute value of 1-min quote midpoint return autocorrelations. VR is computed as $|1 - VR(1min, 5min)|$, where $VR(n, m)$ is the ratio of the midpoint return variance over 1-min interval to the return variance over 5-min interval, both divided by the length of the period. Note that RQS, Turnover, and Volatility measures are scaled by multiplying 100. The first intraday interval starts at 9:30 am; 13:00 indicates the half-hour interval that starts at 10:00 am and ends before 10:30 am. The differences of results for 3:00 pm and 2:30 pm are also reported in the row Diff (3:00-2:30pm). The t-statistics in parentheses are Newey-West adjusted with a lag of 12. The sample is from 1 January 2018 to 31 December 2018.

We use two measures to capture the high-frequency market efficiency: Autocorrelation (AR) and Variance Ratio (VR). Panel C of **Table 3.6** presents results for market efficiency measures for long and short Score portfolios. If prices are efficient and follow a random walk, these measures should be close to zero, because deviations from zero in either direction indicates departures from a random walk. We use the absolute value of the autocorrelation coefficient as our AR measure (Boehmer, Fong, and Wu 2020; Boehmer and Kelley 2009; Chordia, Roll, and Subrahmanyam 2005). We first obtain returns from quote midpoints to abstract from bid-ask bounce and then compute 1-minute return autocorrelation for each stock in each half-hour interval. The results in the first and second columns of Panel C of **Table 3.6** show that the AR at 3:00 pm is the largest over the day, for both long- and short-leg portfolios. The differences between 2:30 pm interval and 2:00 pm are uniformly significant positive for long- and short-leg, 0.0172 (*t*-statistic equal to 4.77) and 0.0029 (*t*-statistic equal to 2.71). Therefore, during the end-of-day the price is far more away from the random walk and the market is more inefficient.

We construct an alternative efficient measure based on the variance ratio. A random walk price implies that the ratio of long-term to short-term return variances, measured per unit of time, equals 1. Since we are interested in the gap between actual and efficient prices in either a negative or positive direction, we define | 1−VR (n, m) | as the variance ratio measure, where VR(n, m) is the ratio of the quote midpoint return variance over m periods to the return variance over n periods, both divided by the length of the period. [20] The result for VR is consistent with AR. The VR in the long leg at the end-of-day is the largest. For the short leg portfolio, the VR at 3:00 pm is not the largest, but still significantly larger than 2:00 pm. Our results imply that for both long- and short-leg portfolios, the market is less efficient at the end of the day.

Our empirical results reveal that trading during the end-of-day is more liquid with less transaction cost and smaller price impact. On the other hand, the market volatility increases, and the market efficiency decreases for both long- and short-leg portfolios during the last half-hour trading. The result suggests that it would be more convenient for investors to execute their large trades at the end of the day, while the occurrence of these substantial portfolio rebalancing has a detrimental effect on the price efficiency, resulting in a more volatile and less efficient

[20] Note that n is larger than m. This method is used in Chordia, Roll, and Subrahmanyam (2008) and Boehmer and Kelley (2009). Autocorrelations are related to variance ratios because VR(n, m) can be expressed as a linear combination of the first n − 1 autocorrelation coefficients. Empirically, we find no qualitative differences in results between AR and VR computed over comparable intervals.

market.

3.5.2. Order imbalance

It is presumed that price pressure arises from imbalanced trading volume rather than balanced trading. Thus, we look at the behavior of order imbalance as a relevant factor. Order imbalance (OI) is defined as the buyer-initiated volume minus seller-initiated volume divided by their sum (total trading volume). In light of the analysis before, we would expect that in the last half-hour trading interval, relative to the long-leg portfolio (unspeculative stocks), the short-leg portfolio (speculative stocks) would experience notable selling pressure and thus exhibit a smaller order imbalance.

Table 3.7 presents the value-weighted average order imbalance measure for stocks in the long-leg and short-leg of the mispricing portfolio across various daytime trading intervals spanning from January 2014 to June 2019. Due to the data limitation, the intraday trading period (9:30 am to 3:00 pm) is only divided into 3 intervals, 9:30 to 10:00 am, 10:00 am to 2:30 pm, and 2:30 pm to 3:00 pm. As expected, we document a relatively stronger selling pressure for speculative stocks during the final half-hour of trading. Specifically, for the interval 2:30 to 3:00 pm, the OI of stocks in the short-leg portfolio is observed to be 2.87% lower compared to the long-leg portfolio, with a *t*-statistic of 7.14. This notable difference in OI indicates a prominent selling pressure for short-leg relative to long-leg at the end of the day. Furthermore, we find that the OI difference between the long-leg and short-leg remains positive during the 10:00 am to 2:30 pm interval, which spans three hours, albeit with a smaller magnitude of 1.63% (*t*-statistic equal to 5.64). However, for the first half-hour trading, the OI of the short-leg is 2.42% larger than the long-leg (*t*-statistic equal to –3.71), which is consistent with the negative returns of the long-short portfolio at the open. Therefore, the results from the order imbalance test provide further evidence that speculative stocks experience significant selling pressure at the end of the day.

Table 3. 7 Order imbalance

	Long leg		Short leg		Long- short	
	mean	t-stat	mean	t-stat	mean	t-stat
9:30-10:00 am	–10.42	–14.47	–8.00	–29.25	–2.42	–3.71
10:00 am-2:30 pm	–3.42	–12.86	–5.05	–27.77	1.63	5.64
2:30-3:00 pm	–1.37	–3.86	–4.24	–13.79	2.87	7.14
Intraday	–3.59	–11.97	–4.86	–28.36	1.27	4.14

Note: This table reports the intraday value-weighted average order imbalance for long, short and long-short Score portfolio. Portfolios are value-weighted and are re-adjusted for one month. Order imbalance is defined as the ratio (scaled by 100) of the difference between active purchase amount and active selling amount to the sum of active purchase amount and active selling amount on a given trading interval. The intraday trading (9:30 am to 3:00 pm) is divided into 3 intervals, 9:30 to 10:00 am, 10:00 am to 2:30 pm, and 2:30 pm to 3:00 pm. The *t*-statistics are based on Newey-West standard errors with 12 legs. The sample spans from January 2014 to June 2019.

3.5.3. Infrequent rebalancing

Return autocorrelations in the absence of infrequent traders typically exhibit negative values across all horizons in the economy, unless liquidity shocks are highly persistent. Only with infrequent rebalancing, autocorrelations can switch signs around traders' rebalancing horizon and become positive (Bogousslavsky 2016). As we proposed, the end-of-day cross-sectional pattern observed in China is induced by the infrequent rebalancing behavior of speculative investors who experience capital gains. Consequently, we would expect that the positive predictability for cross-sectional returns is more pronounced at the end of the day, as a result of this infrequent rebalancing dynamic.

For each intraday half-hour interval return and for each lag, k , in the spirit of Jegadeesh (1990) and Heston et al. (2010), we run the following cross-sectional regressions,

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{it} \qquad (10)$$

where $r_{i,t}$ is the return of stock i for day t; $r_{i,t-k}$ is the return of stock i for day $t-k$; k is the lag, with values 1 through 8 (past 8 trading days). We calculate the pattern of return predictability by averaging return responses, $\gamma_{k,t}$, over time for lag k. It is worth pointing out that our method is different from measuring the autocorrelation of individual stock returns, as our cross-sectional regression subtracts an overall market effect, which reduces variance and devotes to returns relative to other stocks.

Table 3.8 reports the coefficient results for the regression. Columns 1 and 2 show that the regression return responses of 2:30 to 3:00 pm intervals are significantly positive for all lags. At lag1 (day1) the time-series average $\gamma_{k,t}$ is 0.67 with a t-statistic of 3.81. The predictability effect is more pronounced for the longer lag, lag4 and lag5, with the coefficient results of 1.97 and 1.80 (t-statistics equal to 19.05 and 18.57), respectively. Note that the cross-sectional last half-hour return's predictability lasts more than one week. For returns of 2:30 pm and 2:00 pm, the return effect is only significantly negative at lag1 and there is no marked pattern for the longer lags, supporting the view of short-term return reversal without infrequent rebalancing.

Table 3. 8 Cross-sectional Regressions

	3:00 pm		2:30 pm		2:00 pm	
Lag	Est	t-stat	Est	t-stat	Est	t-stat
1	0.67	3.81	–0.98	–8.89	–0.82	–7.88
2	1.31	9.87	–0.15	–1.56	–0.09	–0.92
3	1.70	15.41	–0.02	–0.22	0.04	0.38
4	1.97	19.05	0.06	0.67	0.09	1.08
5	1.80	18.57	–0.07	–0.86	0.13	1.38
6	1.53	15.89	0.15	1.78	0.16	1.83
7	1.79	18.80	0.01	0.16	0.08	0.98
8	1.73	17.56	0.14	1.63	0.04	0.46

Note: The table reports the cross-sectional regression results of the intraday returns and overnight returns. First, we divided the 9:45 am to 3:00 pm trading day to 8 disjoint half-hour intervals. 3:00 pm indicates the return of a half-hour interval that starts at 2:30 pm and ends at 3:00 pm. For every half-hour interval returns, we run the simple univariate cross-sectional regression $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{it}$. The variable $r_{i,t}$ is the return of stock i for day t, and the variable $r_{i,t-k}$ is the return of stock i for day $t-k$. The cross-sectional regressions are calculated for all combinations of stock i, from July 2015 through June 2019, and lag k, with values 1 through 8 (past 8 trading days). The table reports the time-series averages of $\gamma_{k,t}$ in percentages and the respective Newey-West t-statistics adjusted with 12 legs.

Overall, our results indicate that a positive autocorrelation is observed for returns in the last half-hour trading interval, while for other half-hour intervals during the daytime the positive autocorrelation return pattern doesn't exist. The results support the statement of Heston et al. (2010), who postulate that systematic trading and institutional fund flows lead to positive predictability in cross-sectional stock returns. They also point out that the predictability return effect is quite concentrated in the first and last half-hours of trading.

3.6. Robustness checks

Also, we conduct a series of tests to assess the robustness of our results.

3.6.1. Mispricing anomalies

The Score strategy utilized in the previous analysis is based on the average mispricing measure which captures the speculative features of a stock by aggregating the five prominent anomaly measures, idiosyncratic volatility (Ivol), lottery demand (Max), Trunover ratio (Turnover), return volatility (Sigma), and Market beta (Beta).

To provide an additional test, this subsection examines all the anomalies included in the construction of Score measure. Similar to the presentation in **Table 3.1**, in **Table 3.9** we report the total, overnight, and intraday returns for each of those long-short anomalies. All those anomalies display a pronounced end-of-week pattern, in line with our findings before. During the last half-hour interval (2:30 to 3:00 pm), the average returns range from 5.60 bps to 10.57 bps, with corresponding *t*-statistics ranging from 8.82 to 16.21. The alpha values of 3:00 pm show similar results, ranging from 7.45 bps to 13.46 bps, with corresponding *t*-statistics ranging from 11.89 to 21.71. Also, during the intraday period excluding the last half-hour, most of these anomalies tend to earn negative returns.

We also validate whether our end-of-week pattern also holds for other well-known cross-sectional anomalies. Specifically, we explore the total, overnight, and intraday returns of long-short strategies based on Size, Value (Book-to-market), Profitability, Illiquidity, and short-term return reversal (Reversal). Following Liu et al. (2019), we exclude investment and momentum strategies as they are not priced in China. It is worth noting that for Size and Illiquidity, the speculative leg is the long leg, so the anomaly return is expected to be reversed and thus negative at the end of the day. As a result, we would expect negative end-of-day returns for these anomalies. Among the five anomalies examined, Size and profitability exhibit statistically significant end-of-day alphas. Value, Illiquidity, and Reversal display no pattern at all. Overall, **Table 3.9** reinforces the robustness of the intraday seasonality of the cross-sectional stock returns across various anomalies.

3.6.2. Days of the week

In this subsection, we provide further evidence on the cross-sectional return's end-of-day pattern by exploring the days of the week effect. We propose that the cross-sectional end-of-day return seasonality would be more pronounced towards the end of the week (Thursday to Friday) compared to the beginning of the week (Monday to Wednesday). First, after a full week of gambling, investors are more likely to engage in asset rebalancing and sell the speculative stocks with positive capital gain overhang to realize gains on paper at the end of the week, confirming the disposition effect. Second, over the weekend period when the stock market is closed, the guaranteed yield (accrued from Friday to Sunday) in the shadow banking market may become more attractive for the stock market investors.

Figure A1 visualizes the total, overnight, and intraday long-short Score strategy's alphas cross days of the week. Consistent with the results of Han et al. (2023), Total alpha shows stylized seasonality that the long-short strategy experiences low Monday-through-Wednesday returns and high Thursday-through-Friday returns. Han et al. (2023) states that the Fintech revolution and its related expanding market access mechanism are the possible explanations for this unique cross-sectional seasonality in China. For the intraday half-hour intervals, our result shows that the end-of-day effect is more pronounced during Thursday-through-Friday compared to other days. Specifically, the magnitude of the returns on Thursday-through-Friday is roughly twice as large as those on Monday-through-Tuesday.

Therefore, the Score portfolio performs particularly well on Thursday and Friday, especially at the last half-hour interval. The results align with our prediction, providing consistent evidence for the presence of the end-of-day effect.

Table 3. 9 Other anomalies: long-short portfolios

	Total	Intraday	OV	10:00	10:30	11:00	11:30	1:00	1:30	2:00	2:30	3:00
						Idiosyncratic volatility (IVol)						
AveRet	–0.01	–5.36	5.18	–1.04	–3.02	–1.15	–0.75	–0.08	–2.72	–2.42	0.07	5.60
	[0]	[–3.29]	[3.12]	[–1.63]	[–4.45]	[–1.94]	[–1.32]	[–0.24]	[–5.32]	[–4.56]	[0.12]	[8.82]
Alpha	2.96	–2.13	5.09	–0.96	–2.56	–1.90	–0.91	0.33	–2.58	–1.33	0.03	7.45
	[1.29]	[–1.39]	[3.3]	[–1.65]	[–4.13]	[–3.49]	[–1.69]	[1.17]	[–5.5]	[–2.82]	[0.06]	[11.89]
						Lottery demand (Max)						
AveRet	–0.98	–4.02	2.92	–2.67	–3.10	–1.38	–0.70	1.11	–2.11	–3.15	0.10	7.64
	[–0.35]	[–2.45]	[1.39]	[–3.84]	[–4.42]	[–2.29]	[–1.17]	[3.11]	[–3.95]	[–5.5]	[0.18]	[12.17]
Alpha	2.42	–0.07	2.83	–2.56	–2.46	–2.34	–0.92	1.67	–1.91	–1.64	0.06	10.02
	[0.92]	[–0.04]	[1.35]	[–4.21]	[–3.9]	[–4.52]	[–1.77]	[5.66]	[–4.23]	[–3.53]	[0.12]	[16.94]
						Turnover						
AveRet	2.01	0.16	1.84	–1.30	–2.96	–0.52	0.13	–0.24	–3.00	–2.93	1.19	9.84
	[0.7]	[0.09]	[1.07]	[–1.96]	[–4.34]	[–0.83]	[0.23]	[–0.8]	[–5.52]	[–5.14]	[2.05]	[14.96]
Alpha	5.35	3.84	1.76	–1.22	–2.51	–1.26	–0.05	0.14	–2.85	–1.65	1.15	12.11
	[2.12]	[2.34]	[1.09]	[–2]	[–3.93]	[–2.16]	[–0.1]	[0.55]	[–5.82]	[–3.35]	[2.29]	[19.23]
						Return volatility (Sigma)						
AveRet	–0.45	–5.22	4.61	–2.23	–3.44	–1.45	–0.76	–0.15	–2.28	–3.56	–0.21	8.73
	[–0.17]	[–2.96]	[2.72]	[–3.1]	[–4.61]	[–2.3]	[–1.27]	[–0.4]	[–3.9]	[–5.86]	[–0.34]	[13]
Alpha	3.70	–0.67	4.49	–2.11	–2.75	–2.53	–1.00	0.47	–2.07	–1.93	–0.26	11.50
	[1.58]	[–0.43]	[2.88]	[–3.53]	[–4.24]	[–4.72]	[–1.89]	[1.6]	[–4.19]	[–3.95]	[–0.54]	[18.43]
						CAPM Beta (Beta)						
AveRet	2.48	3.89	–1.35	–0.88	–2.63	–0.21	0.45	–0.96	–1.29	–2.29	1.09	10.57
	[1.09]	[2.36]	[–1]	[–1.47]	[–4.23]	[–0.35]	[0.85]	[–3.95]	[–2.61]	[–4.44]	[1.97]	[16.21]
Alpha	6.67	8.49	–1.47	–0.75	–1.93	–1.24	0.20	–0.49	–1.09	–0.60	1.04	13.46
	[3.62]	[6.29]	[–1.13]	[–1.59]	[–3.76]	[–2.7]	[0.49]	[–2.31]	[–2.87]	[–1.56]	[2.51]	[21.71]

(*continued on next page*)

Table 3.9 (*continued*)

	Total	Intraday	OV	9:45	10:00	10:30	11:00	11:30	1:00	1:30	2:00	2:30
						Size						
AveRet	7.57	5.21	2.73	0.16	0.52	0.05	–0.09	1.55	2.40	1.58	0.21	–1.21
	[2.28]	[3.24]	[1.05]	[0.29]	[0.93]	[0.1]	[–0.2]	[5.23]	[5.78]	[3.99]	[0.51]	[–2.32]
Alpha	6.14	3.82	2.77	0.15	0.46	0.22	–0.05	1.43	2.39	1.27	0.22	–1.94
	[1.95]	[2.42]	[1.07]	[0.28]	[0.84]	[0.51]	[–0.11]	[5.81]	[5.76]	[3.28]	[0.55]	[–3.53]
						Book–to–market						
AveRet	1.82	2.84	–1.00	0.51	0.13	–0.10	0.27	0.79	–0.34	1.37	0.97	–0.49
	[0.85]	[2.03]	[–0.80]	[0.89]	[0.22]	[–0.20]	[0.59]	[2.93]	[–0.79]	[3.20]	[2.28]	[–0.95]
Alpha	2.06	3.00	–1.02	0.52	0.07	–0.18	0.26	0.85	–0.35	1.30	0.97	–0.90
	[0.95]	[2.1]	[–0.83]	[0.90]	[0.12]	[–0.35]	[0.58]	[3.49]	[–0.80]	[3.08]	[2.28]	[–1.54]
						Gross profitability						
AveRet	–0.71	–2.91	1.88	0.06	–0.88	–0.01	–0.69	–1.26	–1.21	–1.48	0.03	2.20
	[–0.35]	[–2.27]	[1.50]	[0.13]	[–1.85]	[–0.02]	[–1.94]	[–5.27]	[–3.83]	[–4.29]	[0.09]	[5.96]
Alpha	–0.20	–2.29	1.88	0.07	–0.81	–0.15	–0.71	–1.17	–1.20	–1.25	0.02	2.86
	[–0.10]	[–1.80]	[1.50]	[0.16]	[–1.73]	[–0.39]	[–2.03]	[–5.54]	[–3.81]	[–3.69]	[0.06]	[7.29]
						Illiquidity						
AveRet	6.58	3.73	3.17	–0.28	0.12	–0.87	–0.32	2.10	1.48	0.80	0.42	0.31
	[2.17]	[2.40]	[1.38]	[–0.55]	[0.22]	[–1.92]	[–0.73]	[7.04]	[3.46]	[1.93]	[1.04]	[0.65]
Alpha	5.62	2.84	3.21	–0.28	0.13	–0.80	–0.31	2.05	1.50	0.77	0.42	–0.03
	[1.94]	[1.87]	[1.41]	[–0.55]	[0.23]	[–1.72]	[–0.71]	[8.26]	[3.53]	[1.89]	[1.05]	[–0.06]
						Reversal						
AveRet	3.43	1.04	2.25	–1.14	–0.56	–0.12	0.42	2.49	–1.10	–0.20	–0.01	0.97
	[1.54]	[0.68]	[1.58]	[–1.94]	[–0.96]	[–0.24]	[0.93]	[8.56]	[–2.7]	[–0.47]	[–0.01]	[1.95]
Alpha	3.39	1.11	2.25	–1.13	–0.52	–0.22	0.40	2.64	–1.05	–0.04	–0.01	1.24
	[1.53]	[0.74]	[1.58]	[–1.94]	[–0.89]	[–0.42]	[0.88]	[10.86]	[–2.59]	[–0.11]	[–0.03]	[2.24]

Note: This table reports the total, intraday, and overnight average returns (AveRet) and alphas in basis points of long-short decile anomaly portfolio. Portfolios are value-weighted and are re-adjusted for one month. Stock returns are computed using quote midpoints. The *t*-statistics shown in brackets are based on Newey-West standard errors with 12 legs. The sample spans from July 1999 to June 2019.

3.6.3. Equal-weighted portfolio returns

The average returns of the long-short portfolio we constructed in the paper are all value-weighted. In this subsection, we validate whether the cross-sectional intraday return pattern also holds for the equal-weighted portfolio returns. **Table 3.A2** shows that the end-of-day pattern is persistent for the equal-weighted long-short Score portfolio returns. Also, the massive positive returns are consistent across sub-samples.

Following **Table 3.A2**, we also report the equal-weighted returns for long and short leg portfolio, respectively. The results support our finding before that for the last half-hour interval, long leg portfolio experiences significant positive returns while short leg experiences significant negative returns.

3.6.4. Opening price

The analysis above uses the midquote price at 9:45 am to compute the open, intraday, and overnight returns. This section checks whether the results are still robust with an earlier sampling of the opening price at 9:30 am.[21] Based on the market quality results in **Table 3.7**, the relative quoted spread and volatility are highest at the open, supporting the finding of Lee et al. (1993) that the spreads widen and depths fall at the open. We would expect the mispricing to worsen at the open due to the massive trading of retail investors.

Table 3.A3 reports long-short Score strategy opening, intraday, and overnight returns using midquotes sampled at 9:30 am and 9:45 am. Sampling at 9:30 am decreases opening returns, and thus decreases the intraday returns and increases the overnight returns. The results are uniformly consistent over the different mispricing anomalies. Our results show that the mispricing is worsened at the earlier sampling and the overnight mispricing correction is larger in magnitude with the open auction price as the opening price. The trading mechanism at the open should be focused on for further research.

[21] In the US stock market, the tug of war between overnight and intraday alphas appears only with the 9:35 midquote (Bogousslavsky 2021; Lou, Polk, and Skouras 2019).

3.7. Conclusion

In this paper, we document the intraday cross-sectional seasonality in China. More specifically, we find that mispricing anomaly portfolios that go long the unspeculative stocks and go short the speculative stocks experience negative returns over most of the daytime but earn significantly sizable positive returns in the last half-hour of trading. In other words, mispricing worsens over the daytime and gets corrected at the end of the day.

We consider several possible explanations for this cross-sectional intraday seasonality. First, the end-of-day seasonality pattern is opposite to the US, where the mispricing anomalies perform well over the day but poorly at the end. As a result, the institutional constraints and overnight risk mechanism proposed by Bogousslavsky (2021) for the explanation of the intraday seasonality in the US are not appliable in China. Then, we take the prospect theory/mental accounting-based disposition effect as the most plausible explanation. The performance of the long-short mispricing strategy varies substantially across portfolios with different levels of capital gains or losses. Consistent with the end-of-day seasonality, the disposition effect is more pronounced at the last 30-minute trading interval. Moreover, the end-of-day cross-sectional return seasonality is more pronounced for stocks with prior high capital profits. Specifically, when facing high capital gains, relative to unspeculative stocks, investors have a strong tendency to sell speculative stocks to achieve the gains on paper at the end of the day.

Our analysis reveals a striking cross-sectional end-of-day pattern for mispricing factors in the Chinese stock market. It is desirable for future research to analyze the high-frequency trading patterns from the alternative perspective, which would contribute to a deeper understanding of the underlying mechanisms in the mispricing anomalies.

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Appendix

Section A

Anomaly measures

Idiosyncratic volatility (Ivol): Idiosyncratic volatility is defined as the standard deviation of the residuals obtained from regressing the daily excess returns of a stock on the Fama-French (1993) three-factors over the prior month. Ang et al. (2006) find that stocks with low idiosyncratic volatility earn relatively high average returns compared to those with high idiosyncratic volatility.

Lottery demand (Max): The lottery demand measure is computed as the average of the largest five daily returns in the prior month. Bali et al. (2011) document a negative relation between the lottery demand measure and the subsequent stock returns. They attribute the negative relation to the lottery demand of gambling investors, who are willing to overpay the positive-skewed stocks.

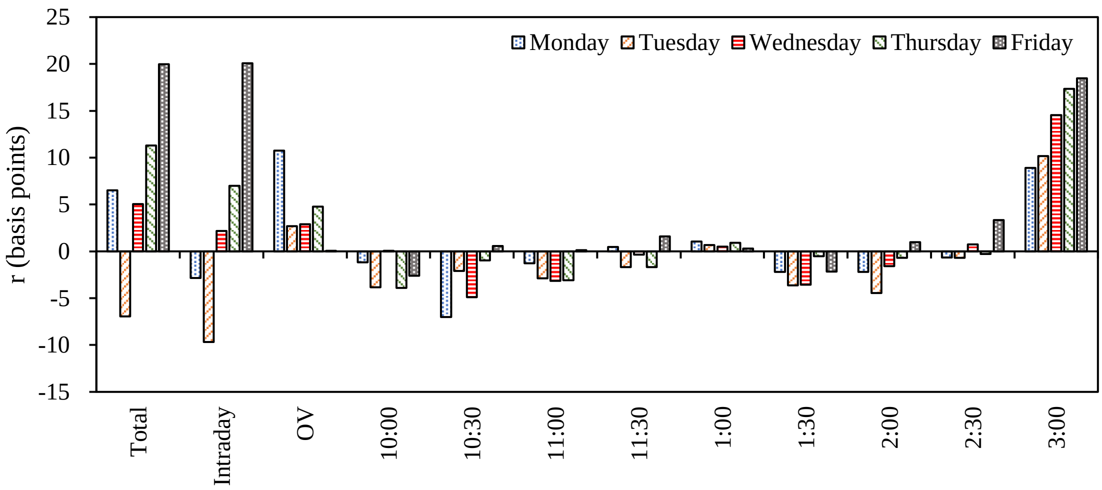
Turnover ratio (Turnover): Turnover ratio is defined as the average of daily turnover ratios over the past month. Liu et al. (2019) suggest that turnover is a stock-level sentiment measure in China, and document that stocks with low turnover ratio outperform counterparts with high turnover ratio.

Return volatility (Sigma): Return volatility is measured as the standard deviation of daily returns over the prior month. Blitz et al. (2021) interpret return volatility as a firm-level speculative measure, and they document that the low-volatility effect is stronger and more persistent than the low-beta effect in China.

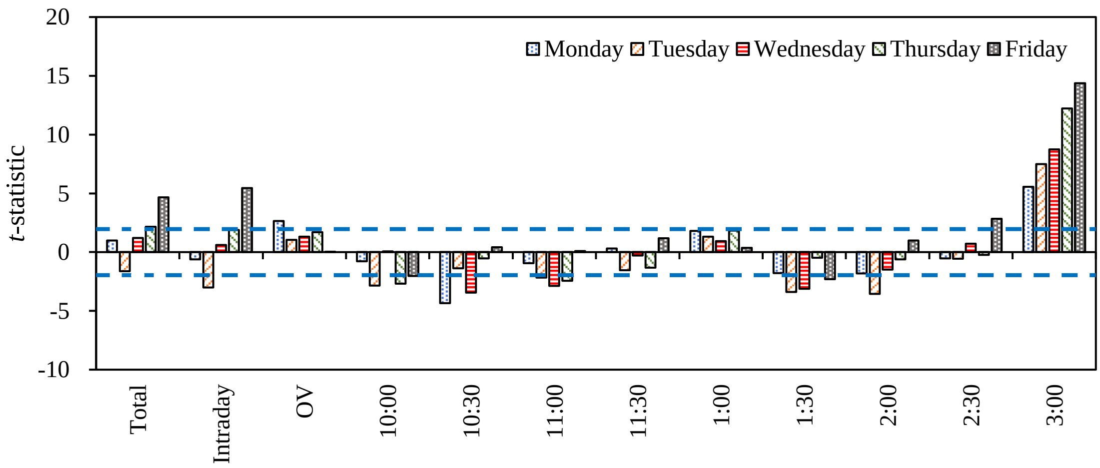
Market beta (Beta): Market beta is constructed as the product of the return correlation (with the market portfolio) and the market-adjusted volatility, using the approach in Frazzini and Pedersen (2014). Han et al. (2020) document that the low-beta anomaly is strong in China, and the magnitude of the low-beta anomaly varies with investor overconfidence over time.

Figure 3.A 1 Score portfolio alphas across days of the week

Score portfolio α



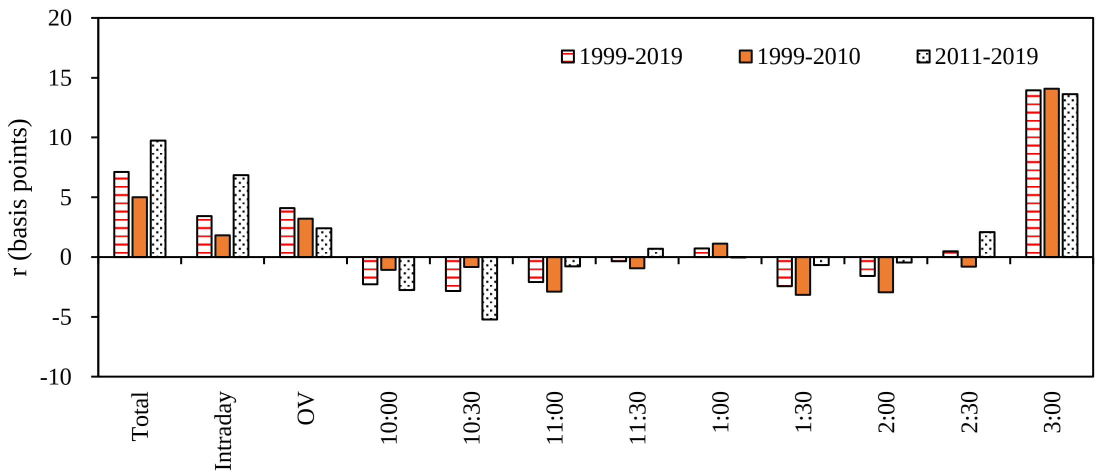
t-statistic



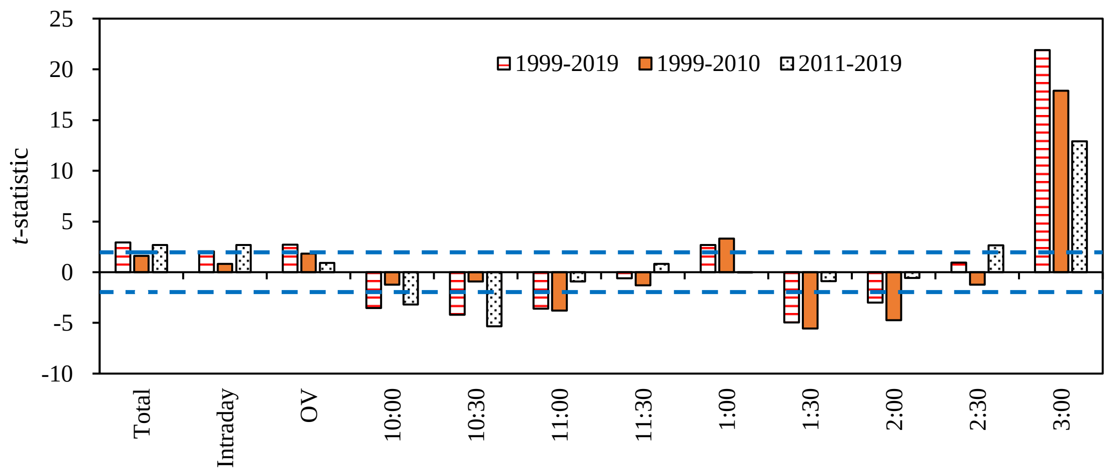
Note: The figure visualizes the long-short Score portfolio's total, intraday, and overnight alphas (in basis points) and *t*-statistics across days of the week. Stock returns are computed using quote midpoints. The first intraday interval 10:00 starts at 9:45 am and ends before 10:00 am; 10:30 indicates the half-hour interval that starts at 10:30 am and ends before 11:00 am. Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am. The upper panel reports the total, intraday and overnight alphas (in basis points). The lower panel plots the associated Newey-West adjusted *t*-statistics with a lag length of 12. The dashed horizontal line denotes the 5% significant level. The sample period is from July 1999 to June 2019.

Figure 3.A 2 Score portfolio average sub-sample return

Score portfolio α



t-statistic



Note: The figure visualizes the long-short Score portfolio's total, intraday, and overnight average alphas (in basis points) and *t*-statistics across different time-series subsamples. Score is the mispricing measure calculated with the average score of mispricing anomalies (idiosyncratic volatility, lottery demand, turnover, return volatility, and CAPM beta). Portfolios are value-weighted and are re-adjusted for one month. Stock returns are computed using quote midpoints. The first intraday interval 10:00 starts at 9:45 am and ends before 10:00 am; 10:30 indicates the half-hour interval that starts at 10:30 am and ends before 11:00 am. Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am. The upper panel reports the total, intraday and overnight average returns (in basis points). The lower panel plots the associated Newey-West adjusted *t*-statistics with a lag length of 12. The dashed horizontal line denotes the 5% significant level. The sample period is from July 1999 to June 2019.

Table3.A 1 Controlling for Size: Score portfolio return

	Total	Intraday	OV	10:00	10:30	11:00	11:30	1:00	1:30	2:00	2:30	3:00
						Panel A: Small						
Long leg	23.37	13.41	10.12	0.33	1.22	–2.56	–0.10	2.59	1.46	2.67	0.28	7.55
	[4.39]	[6.04]	[2.28]	[0.52]	[1.62]	[–4.01]	[–0.15]	[7.48]	[2.47]	[4.69]	[0.45]	[12.50]
Short leg	7.09	15.90	–8.67	1.47	4.13	–1.10	0.37	2.94	3.79	4.89	–0.38	–0.05
	[1.71]	[5.70]	[–4.18]	[1.62]	[4.13]	[–1.18]	[0.40]	[5.85]	[4.48]	[5.86]	[–0.41]	[–0.07]
lms	16.28	–2.49	18.79	–1.14	–2.91	–1.46	–0.47	–0.35	–2.34	–2.21	0.66	7.61
	[3.90]	[–2.22]	[4.66]	[–2.49]	[–5.87]	[–3.35]	[–1.11]	[–1.46]	[–6.07]	[–5.51]	[1.55]	[16.07]
						Panel B: Medium						
Long leg	12.97	11.73	1.58	–0.44	0.73	–2.59	–0.22	2.34	0.80	2.54	0.30	8.29
	[3.78]	[5.76]	[0.74]	[–0.72]	[1.01]	[–4.16]	[–0.34]	[7.07]	[1.4]	[4.56]	[0.49]	[14.59]
Short leg	7.09	11.68	–4.51	1.22	4.72	–1.82	–0.04	2.02	3.42	4.40	–0.86	–1.22
	[1.75]	[4.28]	[–2.23]	[1.31]	[4.67]	[–1.97]	[–0.04]	[3.97]	[3.92]	[5.12]	[–0.91]	[–1.44]
lms	5.88	0.05	6.09	–1.66	–3.99	–0.77	–0.19	0.32	–2.62	–1.86	1.16	9.51
	[2.94]	[0.04]	[3.78]	[–3.48]	[–7.71]	[–1.72]	[–0.43]	[1.29]	[–6.40]	[–4.42]	[2.64]	[18.85]
						Panel C: Large						
Long leg	7.81	10.76	–2.97	0.01	1.54	–1.44	0.43	0.73	0.70	1.97	–0.12	7.02
	[3.18]	[6.44]	[–2.16]	[0.01]	[2.39]	[–2.53]	[0.70]	[2.49]	[1.23]	[3.76]	[–0.21]	[12.96]
Short leg	7.72	11.60	–3.80	1.19	4.56	–0.76	0.71	0.06	3.20	4.81	–0.45	–1.45
	[1.96]	[4.42]	[–1.76]	[1.20]	[4.40]	[–0.79]	[0.74]	[0.11]	[3.49]	[5.20]	[–0.46]	[–1.68]
lms	0.09	–0.84	0.83	–1.18	–3.03	–0.68	–0.27	0.68	–2.50	–2.84	0.33	8.47
	[0.03]	[–0.45]	[0.50]	[–1.61]	[–3.96]	[–1.01]	[–0.43]	[1.88]	[–4.18]	[–4.31]	[0.52]	[12.42]

Note: This table reports the total, intraday, and overnight average returns (AveRet) in basis points of Score portfolio. The Score strategies are performed separately for three equally sized groups sorted by firm market capitalization at the end of the previous month. Portfolios are value-weighted and are re-adjusted for one month. Stock returns are computed using quote midpoints. The first intraday interval 10:00 starts at 9:45 am and ends before 10:00 am; 10:30 indicates the half-hour interval that starts at 10:30 am and ends before 11:00 am. Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am. The *t*-statistics shown in brackets are based on Newey-West standard errors with 12 legs. The sample spans from July 1999 to June 2019.

Table3.A 2 Equal-weighted returns for Score portfolio

	Total	Intraday	OV	10:00	10:30	11:00	11:30	1:00	1:30	2:00	2:30	3:00
Panel A: Long-short portfolio												
AveRet	5.91	–0.20	6.19	–1.83	–3.61	–1.33	0.09	0.21	–2.33	–2.88	0.72	10.68
	[2.41]	[–0.15]	[3.29]	[–3.24]	[–6.31]	[–2.65]	[0.19]	[0.79]	[–5.02]	[–5.82]	[1.42]	[19.67]
Alpha	9.46	3.74	6.10	–1.72	–2.97	–2.25	–0.13	0.71	–2.13	–1.25	0.67	13.36
	[4.14]	[3.27]	[3.20]	[–3.8]	[–6.13]	[–5.82]	[–0.33]	[3.66]	[–6.15]	[–3.47]	[1.83]	[26.2]
Panel B: Long and short legs (AveRet)												
Long leg	4.85	7.08	–1.97	–0.84	–0.05	–2.63	–0.42	1.76	–0.11	1.78	–0.02	7.82
	[1.62]	[4.23]	[–0.92]	[–1.74]	[–0.08]	[–5.23]	[–0.8]	[6.48]	[–0.23]	[4.03]	[–0.03]	[16.19]
Short leg	–1.06	7.27	–8.16	0.99	3.56	–1.30	–0.51	1.55	2.22	4.66	–0.74	–2.86
	[–0.29]	[2.86]	[–4.22]	[1.12]	[3.73]	[–1.49]	[–0.58]	[3.37]	[2.7]	[5.71]	[–0.84]	[–3.58]
Panel C: Long and short legs (Alpha)												
Long leg	–1.57	0.40	–1.79	–1.00	–1.09	–1.23	–0.09	0.97	–0.38	–0.33	0.06	4.01
	[–0.88]	[0.65]	[–1.13]	[–4.69]	[–4.89]	[–6.4]	[–0.52]	[9.09]	[–2.37]	[–2.04]	[0.36]	[16.15]
Short leg	–11.02	–3.34	–7.89	0.72	1.88	1.02	0.04	0.25	1.75	0.91	–0.61	–9.35
	[–6.51]	[–2.87]	[–8.41]	[1.68]	[4.04]	[2.73]	[0.12]	[1.38]	[5.33]	[2.68]	[–1.74]	[–20.65]
Panel D: Subsamples (2002-2010, 2011-2019) (Alpha)												
Pre2011	11.66	3.27	8.44	–0.98	–2.02	–2.78	–0.28	0.91	–2.34	–2.11	–0.39	14.16
	[5.01]	[2.31]	[5.04]	[–1.58]	[–3.27]	[–5.3]	[–0.63]	[3.82]	[–5.56]	[–4.9]	[–0.81]	[21.55]
Post2011	6.42	4.81	1.64	–2.32	–4.21	–1.48	0.09	0.41	–1.47	–0.44	2.06	12.32
	[1.47]	[2.57]	[0.42]	[–3.63]	[–5.44]	[–2.63]	[0.13]	[1.23]	[–2.83]	[–0.74]	[3.84]	[15.71]

Note: This table reports the total, intraday, and overnight average returns (AveRet) and alphas in basis points of Score portfolio. Portfolios are equal-weighted and are re-adjusted for one month. Stock returns are computed using quote midpoints. The first intraday interval 10:00 starts at 9:45 am and ends before 10:00 am; 10:30 indicates the half-hour interval that starts at 10:30 am and ends before 11:00 am. Total indicates the total daily close-to-close interval; Intraday indicates the intraday interval from 9:45 am to 3:00 pm; OV indicates the overnight interval from 3:00 pm on the previous day to the current day's 9:45 am. The *t*-statistics shown in brackets are based on Newey-West standard errors with 12 legs. The sample spans from July 1999 to June 2019.

Table3.A 3 Opening price and return

	Opening return		Intraday return		Overnight return	
	9:30 am	9:45 am	9:30 am	9:45 am	9:30 am	9:45 am
Score	–13.11	–2.40	–12.27	–1.50	14.75	4.20
	[–9.66]	[–3.14]	[–5.22]	[–0.80]	[12.47]	[2.60]
IVol	–9.83	–1.04	–14.19	–5.36	13.69	5.18
	[–8.16]	[–1.63]	[–6.94]	[–3.29]	[9.97]	[3.12]
Max	–12.28	–2.67	–13.64	–4.02	12.31	2.92
	[–10.06]	[–3.84]	[–6.72]	[–2.45]	[6.28]	[1.39]
Turnover	–10.62	–1.30	–9.26	0.16	10.98	1.84
	[–8.24]	[–1.96]	[–4.10]	[0.09]	[8.02]	[1.07]
Sigma	–11.03	–2.23	–14.07	–5.22	13.18	4.61
	[–8.48]	[–3.10]	[–6.27]	[–2.96]	[9.18]	[2.72]
Beta	–5.92	–0.88	–1.23	3.89	3.70	–1.35
	[–5.87]	[–1.47]	[–0.64]	[2.36]	[3.43]	[–1.00]

Note: This table reports the opening, intraday and overnight value-weighted average returns in basis points of long-short portfolios computed using midquotes at 9:30 am and 9:45 am. For instance, with the opening midquote at 9:30 am, the overnight return is computed between 3:00 pm on the previous day and 9:30 am on the current day, while the opening return and intraday return is computed from 9:30 am until 10:00 am and 3:00 pm on the current day. Portfolios are value-weighted and are re-adjusted for one month. The *t*-statistics shown in brackets are based on Newey-West standard errors with 12 legs. The sample spans from July 1999 to June 2019.

Chapter 4

Ownership Concentration and Market Quality Evidence from Economic Stimulus Package of China

Abstract:

This paper investigates the relationship between ownership concentration and market performance by analyzing the effects of the 2008 economic stimulus package implementation on market quality and stock returns in China. The government-related ownership concentration in SOEs (State-Owned Enterprises) becomes more pronounced after the implementation of the stimulus package, which may lead to ineffective corporate governance concerns and further deteriorate market quality. Empirically, we first show that the stimulus package injects liquidity into the capital market, resulting in overall improvements in market quality. Furthermore, our finding demonstrates that following the stimulus policy, SOEs exhibit less liquidity, volatility, and efficiency than other entities, relative to the pre-stimulus period. We also find that the stimulus package shock leads to decreased profitability for SOEs and increased profitability for POEs (Private-Owned Enterprises) in the stock market. Finally, to confirm the validity of our results, we conduct the difference-in-differences analysis and test the investment inefficiency during the stimulus period.

JEL Classification: E32, E62, G14, G38

Keywords: Ownership Concentration, Government Intervention, 2008 Stimulus Package of China, Liquidity, Efficiency

4.1. Introduction

Corporate ownership concentration plays a pivotal role in corporate governance research studies. It is well noted that ownership control in the hands of a few leads to adverse selection and managerial entrenchment problems. In this context, large shareholders are more likely to possess superior information compared to outside shareholders, inducing information asymmetry (Easley and O'Hara 1987; Morck, Yeung, and Yu 2000). This disproportional ownership[22] associated information asymmetry may further impair the market liquidity (Chung, Elder, and Kim 2010), increase the stock price synchronicity (Gul, Kim, and Qiu 2010), and even destroy share values (Gompers, Ishii, and Metrick 2003). Yet, some argue that ownership concentration can serve as a credible commitment, facilitating the alignment of interests between controlling and minority shareholders, ultimately reducing the information asymmetry and improving market liquidity (Grossman and Stiglitz 1980; Merton 1987; Rubin 2007). Thus, the net effect of corporate concentrated ownership on the market performance remains unclear. In this study, we analyze whether and to what extent ownership discrimination responds to the 2008 economic stimulus package in China to shed light on the relationship between ownership structure and market dynamics, such as market quality and stock returns.

Compared to the developed economies, corporate ownership is highly concentrated in China. Large controlling shareholders, especially government-related entities, are actively involved in the managerial process and typically possess full control over major corporate decisions (Gul et al. 2010). Thus, the primary agency problem in China is the horizontal agency conflict, which refers to the conflict of interest between controlling and minority shareholders. On the other hand, the prevalent vertical agency problem is alleviated by the effective discipline exerted by large shareholders over managers (Jiang and Kim 2020). Given this unique institutional environment, we expect that the ownership concentration in China increases the information asymmetry, potentially undermining the market quality and stock value. Additionally, as highlighted by Carpenter, Lu, and Whitelaw (2020), China has become the second-largest economy globally, and it is crucial to explore its unique features to enhance our comprehension of global resource allocation. Therefore, it is worthwhile to investigate the consequences of the disproportional ownership structure in China.

One of the most distinctive features of the ownership concentration of Chinese listed firms is

[22] Disproportional ownership means the deviation from the "one share-one vote" principle, that is, the mechanism that allows some block shareholders to control the votes that are larger than their corresponding rights to the firm's cash flow (Adams and Ferreira 2008).

the identity of the largest shareholder, which is typically government-related, e.g., a central government agency, a regional government, or a large state-owned enterprise. Many listed firms in China are still partially privatized and closely tied to the government, although the Chinese government implements a series of reforms for SOEs' (state-owned enterprises) privatization and regulatory mechanisms[23]. SOEs typically receive disproportionately larger support from the banks and government, a phenomenon known as ownership discrimination. Notably, unlike other enterprises that solely pursue the profit objective, SOEs have an additional objective: Act as a fiscal instrument to help government accomplish social and political goals. This departure from profit maximization may jeopardize corporate performance and lead to the entrenchment effect, whereby controlling shareholders have the incentive to divert firm resources at the expense of outside investors (Fan and Wong 2002; Johnson et al. 2000; Kim and Yi 2006).

Poor corporate governance is associated with low financial and operational transparency[24], which in turn, increases information asymmetries between insiders (e.g., managers and large shareholders) and outside investors (e.g., outside owners and liquidity providers), as well as among outside investors (Chung et al. 2010). Specifically, controlling shareholders, in this case, government shareholders, may withhold private information from the outsider or selectively disclose the information to the market to mask their self-serving behaviors. This can deter the flow of firm-specific information to the market, leading to less informative stock prices and a more opaque market (Gul et al. 2010; Morck et al. 2000). Therefore, the cost of analyzing the private information of SOEs is likely to be higher than the profitability of trading for outside investors. This discourages informed trading, hinders mispricing correction, impairs stock market liquidity, and further makes the stock price more inefficient. In this study, we explore the link between the performance of the stock market and the unique government-concentrated ownership structure in China that is deemed to increase the information asymmetry.

This examination poses several empirical challenges. Most importantly, many differences in characteristics between SOEs and non-SOEs are unobservable and endogenous to misconduct. We attempt to overcome these challenges through multiple complementary empirical

[23] Since late 1978, SOEs in China have undergone several types of reforms. These include 1980s' initial decentralization; partial privatization through share issue privatization (SIP) in the early 1990s; privatization via negotiated transfer of nontradable controlling stakes in the mid-1990s; and the 2005 split-share structure reform.
[24] Transparency, as described by the Organization for Economic Co-Operation and Development (OECD) Principles of Corporate Governance, involves the timely disclosure of adequate information concerning a company's financial performance, as well as commercial objectives, ownership structures, remuneration, related party transactions, governance structures, and internal controls.

approaches. Our primary methodology exploits the effect of the Chinese stimulus package policy on firms' trading performance through the exogenous increases in government controls for SOEs, relative to private-owned enterprises (POEs). We examine whether and to what extent the shock of the stimulus package exacerbates the ownership discrimination effect on the market quality and stock returns.

The 4 trillion RMB fiscal stimulus policy was launched by China's central government in November 2008, an amount more than 12% of the annual GDP in China, right after the 2007 to 2008 financial crisis hit the export-driven Chinese economy extremely hard,[25] to promote economic recovery by encouraging the investment. As indicated before, SOEs serve as a fiscal instrument for the government, a role that becomes more pronounced during the stimulus period. Prior studies also have shown that, compared to the pre-stimulus period, SOEs receive much more subsidies and loans than POEs during the implementation of the economic stimulus package (Huang et al. 2020; Wen and Wu 2019).

As did many countries, the Chinese government injected massive amounts of money into its banking system in late 2008 and 2009 to stimulus the economy. Cong et al. (2019) show that during the stimulus years—new credit was allocated relatively more toward state-owned or state-controlled firms and firms with lower initial marginal productivity of capital[26]. Thus, SOEs receive low interest loans and more government subsidies.

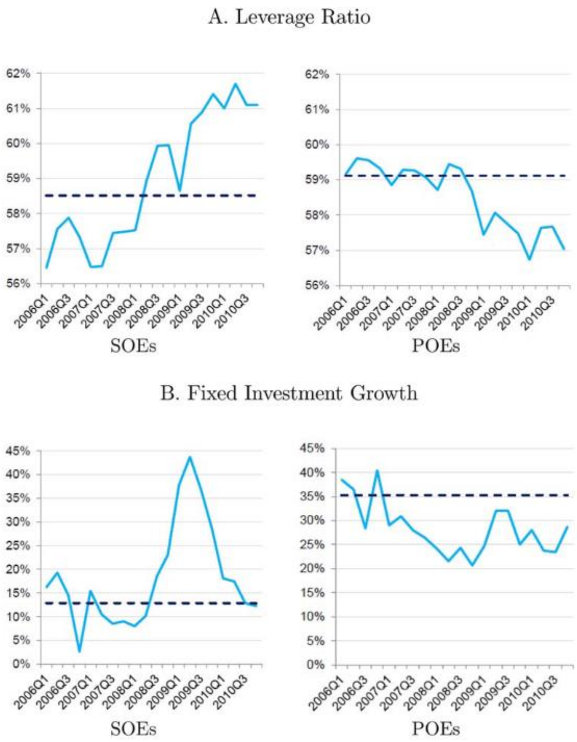
Figure 4.1 shows the differences of leverage ratio and fixed investment growth between SOEs and POEs around the period of implementation of stimulus package, spanning from 2006 to 2010. The results show that only SOEs were willing to expand their debts promptly after the crisis, thus inducing the expansion of the fixed asset investments. The loans that SOEs get mainly come from the credit support of LGFV (local government financing vehicle). From the view of firm's borrowing behavior, we can see the effectiveness of China's stimulus package is largely driven from the contribution of the public sector (SOEs).

The economic support from the stimulus policy can lead to both advantages, such as a quick recovery from the crisis,[27] and disadvantages, such as distortions and inefficiencies (Huang, Pagano, and Panizza 2020; Liu, Pan, and Tian 2018). Additionally, Liu et al. (2018)

[25] The annualized GDP growth dropped from 13.9% in 2007Q4 to 6.4% in 2009Q1. The unemployment rate among registered urban households increased by 2 percentage points in 2008, which certainly understates the increase for unregistered urban households (Feng, Hu, and Moffitt 2015).
[26] The basic structure of Chinese stimulus policy is shown in Figure 4.A 1 in the Appendix
[27] The Chinese economy recovered fast, the GDP grew by 8.7% in 2009 and by 10.4% in 2010.

demonstrate that after the implementation of the stimulus package, investments and loans issued by SOEs became less efficient.

Figure 4.1: Behaviors of Chinese State-owned enterprises and private-owned enterprises



Note: This figure presents the SOEs and POEs' average leverage ratio and fixed investment growth. The data are published by the National Bureau of Statistics of China (NBSC).

Taking together, we can see that the implementation of the stimulus package resulted in a closer connection between SOEs and their controlling shareholders, the government. Therefore, we expect that the increased government control may adversely affect the market performance of SOEs compared to POEs, following the implementation of stimulus package.

To measure the state ownership, following the approach of Carpenter et al. (2020), we first aggregate the number of shares held by the top ten holders that are state entities. Then we define a firm as state-owned (SOE) if it has more than 50% of shares owned by the state, suggesting that the government has dominant controlling power. Conversely, we consider a firm private-owned (POE) if it has less than 5% of shares owned by the state. For other firms with 5% to 50% of shares owned by the government, we use them as the benchmark. Note that due to the limited availability of shareholding information for only the top ten holders, we cannot determine whether other smaller shareholders are state entities. Therefore, we adopt this approach to avoid potential misclassification and ensure the accuracy of our state and private ownership categorization.

In our first analysis, we examine the relationship between liquidity and ownership discrimination. As indicated above, the departure of SOEs' objectives from value maximization can lead to conflicts of interest between the state controlling shareholder and minority shareholders, potentially jeopardizing corporate performance. According to the adverse selection theory, government-related controlling shareholders for SOEs possess superior information compared to minority shareholders, resulting in decreased the SOEs' financial and operational transparency, and further impairing the market liquidity. Besides, given the more prominent government intervention for SOEs after the stimulus package in 2009, we would expect that the lower liquidity for SOEs is more pronounced compared to other firms following the implementation of the stimulus policy. Empirically, our analysis first reveals that the aggressive monetary policy and stimulus policies inject huge liquidity into the stock market, leading to higher liquidity for both SOEs and non-SOEs after the implication of the stimulus policy. To identify the effect of enhanced government control on liquidity, we adopt a primary empirical strategy inspired by Bertrand, Schoar, and Thesmar (2007) using OLS panel data regression analysis. This approach allows us to exploit the dynamic change in liquidity for firms with different ownership controls after the implementation of the economic stimulus package. We find that SOEs exhibit lower market liquidity compared to other benchmark firms after the implementation of the stimulus policy: lower trading turnover, wider relative quoted spread, and larger price impact of trades. These findings indicate that concentrated ownership, particularly the enhanced state control in SOEs, has a significant negative impact on liquidity in the stock market.

Second, we attempt to establish a more direct link between information asymmetries and trading performance by examining the effect of the stimulus package on the return volatility in the stock market. We observe that compared to non-SOEs, intraday volatility has decreased to a greater extent for SOEs in the post-stimulus period compared to before. This volatility reduction can be attributed to the increased government intervention through stimulus package, which makes SOEs to be more reluctant to release new firm-specific information and the market becomes opaquer. Lower volatility, in this context, reflects information withholding by SOEs, and thus, it could be considered undesirable.

To shed more light on the consequences of government concentrated ownership structure, we then investigate the impact of the implementation of the stimulus package on price efficiency. Gul et al. (2010) test the effects of largest-shareholder ownership concentration on the amount of firm-specific information incorporated into share prices, as measured by stock price synchronicity. They find that synchronicity is higher when the largest shareholder is government related, meaning that the market efficiency is worse for SOEs. However, Gul et al. (2010) use the dataset from 1996 to 2003. Therefore, we first retest the link between synchronicity and corporate governance characteristics from 2003 to 2018. We find that the managerial entrenchment effect of ownership concentration, especially the government related concentration, on stock price synchronicity is persistent over the last two decades. Furthermore, we investigate the economic stimulus package shock on the market efficiency. As mentioned above, the discrimination between SOEs and POEs for resource allocation and government intervention is more prominent after the implementation of the stimulus package. Thus, we hypothesize that relative to other firms the market efficiency of SOEs has deteriorated more after the implementation of the stimulus package. Except for stock price synchronicity, we construct a new measure: variance ratio for the market efficiency proxy. Empirically, we show that compared to the other firms, the prices of SOEs deviate more from the random walk and have higher price synchronicity following the stimulus policy implementation, which supports the hypothesis as well.

We next examine whether the firms' ownership structure influences equity performance. Gompers, Ishii, and Metrick (2003) relate corporate governance with equity prices and find that firms with stronger shareholder rights have earned abnormal returns compared to firms with weaker rights. Therefore, we propose that more serious ownership discrimination after the stimulus package implementation also can be reflected in the return performance of the stock market. Consistent with our prediction, we find that the SOEs underperform the other firms by about 91 basis points per month during post-stimulus period, relative to that pre-stimulus period. However, the difference in returns between POEs and the other firms is positive, around 131 basis points. That is, compared to the benchmark portfolio, SOEs became less profitable and POEs became more profitable after the implementation of the stimulus policy. Furthermore, as discussed above, the information asymmetry of SOEs may discourage informed trading for outside investors, and thus hinder the mispricing correction. Our findings show that compared to the benchmark firms, the mispricing is stronger for SOEs after the exit of the stimulus policy, and there are no significant results for POEs.

We conduct a battery of exploratory analyses and robustness tests. Specifically, to eliminate the concerns of the endogeneity problems, we conduct a difference-in-differences regression with propensity score matching methodology (PSM). The results reinforce our conclusions that the economic stimulus package genuinely has a prominent effect on the corporate governance of SOEs. With more government control, compared to POEs, SOEs experience less liquidity, lower price efficiency, and lower returns following the implementation of the stimulus package.

We also test the effect of the stimulus policy in the short window from 2006 to 2012, three years before and after the plan implementation. We find that SOEs exhibit worse market quality compared to POEs following the implementation of the stimulus policy. However, the impact of the stimulus plan on the equity returns for SOEs becomes significant only in the long-run period.

Besides, we examine the investment efficiency for the validation test. Based on our premise, the implementation of the stimulus package is associated with resource misallocation and investment inefficiency for SOEs, which further leads to the market dynamics. Empirically, we find that average investment expenditures during the stimulus period (2008-2010) have negative relations with the succeeding returns after 2011. More crucially, this effect is more salient for SOEs. Also, we take the average investment expenditure during the stimulus period as a coarse proxy for the degree of government ties with the firm. We find that SOEs with higher investment expenditures during the stimulus period do have lower returns than others after the implementation of the stimulus policy. Overall, our results indicate a significant and robust relationship between the ownership discrimination and trading performance, including market quality and stock prices, in the secondary market, and suggest an important role for macro-economic stimulus policy in amplifying this disproportional ownership structure in China.

Our contribution to literature is threefold. First, we extend the burgeoning literature examining the effect of corporate management on the secondary market, which has primarily been examined in two ways, trading hypothesis and adverse selection hypothesis (Adams and Ferreira 2008; Demsetz and Villalonga 2001; Merton 1987; Rubin 2007). Our results add support for the adverse selection theory, specifically, ownership concentration leads to information asymmetries and distorts market quality. We use the stimulus package policy as a natural experiment to validate the causal effect of government intervention and ownership structure on the firm’s performance and market efficiency in the stock market. Second, our study contributes to macroeconomic literature examining the role of stimulus package policy after the crisis in the microstructure. Works of literature on the effectiveness of the stimulus package mainly focus on their effect on the macro economies, such as employment and GDP (Ouyang and Peng 2015; Xue, Yilmazkuday, and Taylor 2020); it is still a controversial issue whether and how the micro-economy is influenced by the stimulus policy. Our study shows that the stimulus package can inject liquidity differently among firms with different ownership characteristics. Our paper offers a particularly important insight in light of the impact of the stimulus package on corporate governance. Also, the dataset in the past literature working on stimulus policy is limited to the early 2010s. We update the dataset to 2018, 9 years after the stimulus package implementation, which is possible for us the check the long-term influence of the macro-policy. Finally, our results can be of interest to regulators and policymakers concerned about the role of stimulus package implementation and ownership discrimination structure.

The paper is organized as follows. Section 4.2 provides background information about the economic stimulus package. Section 4.3 describes our sample and measure constructions and presents descriptive statistics. Section 4.4 represents the model specification and then reports the empirical results of our main regressions. Section 4.5 reports the results of our robustness checks. Section 4.6 concludes.

4.2. Background for the 2008 stimulus package in China

The financial crisis of 2008 began in the US but soon spread like wildfire to the whole world. Central banks and governments reacted with unprecedented stimulus programs to combat the recession. The US enacted fiscal stimulus projects including the Economics Stimulus Act of 2008 and the American Recovery and Reinvestment Act of 2009, which in total were as large as 5 percent of the gross domestic product (GDP) in the US.

In response to the global financial crisis, China likewise undertook large-scale fiscal and monetary stimulus measures. At the end of 2008, China’s central bank adopted an aggressive monetary policy by relaxing the credit constraint faced by commercial banks, which was achieved by cutting the prime lending rate, relaxing credit limits, and injecting liquidity into the economy. Additionally, the Chinese government enacted a 4 trillion RMB fiscal stimulus policy in November of 2008, an amount of more than 12% of the GDP in China, with the aim of promote investment. Of the total four trillion plan, the central government directly funded 1.18 trillion,[28] which is 30% of the overall program, and the rest was funded by local governments to support investment projects.[29] These combined fiscal and monetary measures were designed to stimulate economic growth, boost investment, and enhance market stability during the economic recovery period.

The dispersion of China's stimulus was far more politically directed than it was in developed countries. Chinese stimulus directors were not only concerned with economic objectives but also political ones. Thus, the connection between SOE and the government is closer after the stimulus policy. Wen and Wu (2019) state that SOEs considerably increase their credit borrowing and fixed investment during the stimulus period, which leads to the rapid revival of investment for the economy and GDP growth. Huang et al. (2020) insist that Chinese non-SOEs are often discriminated against in regard to applying for bank loans in comparison to SOEs. Liu et al. (2018) also show that during China's stimulus, SOEs received more loans and invested more than non-SOEs, while those loans and investments are less efficient for SOEs. Cong et al. (2019) insist that the expanded credit was allocated relatively more to SOEs, although SOEs are generally less productive than POEs. They show that while the private sectors were the main drive of China's economic growth before the 2008 crisis, they received disproportionately less of resources from the stimulus package, which would have dampened the policy's success. Overall, the Chinese government cleverly used its SOEs as a fiscal instrument to implement its aggressive programs to stimulate the economy in 2009 (Wen and Wu 2019).

The stock market is the mirror of the economy. Based on the past literature, Carpenter et al. (2020) test the stock price informativeness and the investment informativeness about future profits. They state that state-owned firms have stock prices that are economically and statistically less informative regarding investment and profits in the latter after stimulus subperiod. Additionally, Harrison et al. (2019) analyze a comprehensive dataset of all medium and large firms in China between 1998 and 2013. They demonstrate that SOEs continue to benefit from government support relative to private enterprises even after the stimulus package

[28] In reality, the central government input to the stimulus totaled RMB 1.6 trillion (36% larger than the CNY 1.18 trillion envisioned at the start): 108 billion in the fourth quarter of 2008, 130 billion, 70 billion, 80 billion and 223.8 billion, respectively, in the first to fourth quarters of 2009, and 992.7 billion in 2010. (Website of National Development and Reform Commission, China)

[29] Within less than a month of the announcement of the stimulus package, local governments, in aggregate, had proposed a staggering total of RMB 18 trillion in investment projects.

period. However, despite this support, SOEs exhibit significant underperformance in profitability, leading to a misallocation of resources. Thus, government support made profitability at firms with large government-related ownership harder to predict. The consequences of the stimulus package shock on the ownership discrimination of firm performance warrants further examination. In the following sections, we will comprehensively expound on these issues.

4.3. Data and variable measurement

In this section we discuss our data sources, variable measurement procedures, and descriptive statistics of the key variables used in the study.

4.3.1. Data

We construct a comprehensive dataset from multiple sources. Daily and monthly equity data are retrieved from the China Stock Market & Accounting Research (CSMAR) database. Our sample contains all available A-shares listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange. Following common practice, we adopt some filtering rules to compile the dataset: First, we exclude stocks that have just become public within the past three months to avoid the IPO effect. Second, we filter out stocks having consecutive zero returns over the past three months to prevent our result from being influenced by stocks with trading suspensions. The quarterly accounting data, including cash flow and balance sheet data, are also from CSMAR. Our sample runs from January 2003 to May 2018, with the beginning chosen to reflect when the China Securities Regulatory Commission (CSRC) required all listed firms to file quarterly financial reports.

The shareholder data are obtained from CSMAR and Wind Information Inc. (WIND). We aggregate the number of shares held by the top ten holders that are state entities. The mean and median state ownership proportions are 22% and 9.6%. We define a firm as SOE if it has more than 50% shares owned by the state. In our observations (2003-2018), 20% of firms are state-owned. We define a firm as POE if it has less than 5% of shares owned by the state, which contains 46% of firms in our sample. Other firms, whose shares are 5% to 50% owned by state entities, are used as a benchmark in the analysis below, which contains 34% of firms in our sample.

The intraday 5-min frequency trading data used for market quality measures' construction are retrieved from Thomson Reuters Tick History (TRTH). To emanate the effect of bid-ask bounce, we calculate the 5-min mid-quote price using the best ask and bid price provided by TRTH. We apply a uniform data filtering rule for the high-frequency data: First, we require a stock to have at least ten 5-min frequency trading information a day. Second, we require a stock to have at least one year of high-frequency data. Finally, we merge the market quality measures and equity return measures together.

Table 4. 1 Variables and definitions

Variable	Definitions
Amihud	The ratio of the absolute daily return (percent) to the daily trading volume (in millions of RMB)
Turnover	Monthly share trading volume divided by the number of tradable shares over the month
RQS	Relative quoted spread
TV	Total dollar trading volume (in millions of RMB)
HLrange	The ratio of the difference of highest and lowest price of the day to the close price
Vol5	The daily volatility of 5-min midpoint returns
Vol30	The daily volatility of 30-min midpoint returns
VR30_5	Variance ratio is constructed as the absolute value of the difference between 1 and six times the variance of 5-min quote midpoint returns divided by the variance of 30-min mid quote returns.
VR30_10	Variance ratio is constructed as the absolute value of the difference between 1 and three times the variance of 10-min quote midpoint returns divided by the variance of 30-min mid quote returns.
SYNCH	Stock price synchronicity
SOE	Indicator variable that equals one if one if a stock has more than 50% shares owned by the state
POE	Indicator variable that equals one if one if a stock has more than 5% shares owned by the state
Post	Indicator variable that equals one for observations since 2011
lnME	Natural logarithm of market value for a firm
lnBTM	Natural logarithm of the ratio of the market value to the book value of equity
Ret	Monthly firm-specific returns, multiplied by one hundred
E/P ratio	Earning to price ratio, defined as net earning divided by the product of the share price and total number of shares
Tskew	Skewness of the firm-specific daily returns in a month
Sigma	Standard deviation of the firm-specific daily returns in a month
ANALYST	Number of analysts following a firm in a year
Industry	Industry classification based on the classification by the China Securities Regulatory Commission (CSRC) in 2012
TOPHOLD	The percentage of shares held by the largest shareholder

Investment expenditure	Investment expenditure is measured as cash payments for fixed assets, intangible assets, and other long-term assets from the cash flow statement minus cash receipts from selling these assets, scaled by beginning total assets
Inv1	The average investment expenditure in 2009 to 2010
Inv2	The average investment expenditure in 2006 to 2007

Our final sample comprises 319,114 firm-month observations for 3,009 valid stocks in total. Following the convention, we use the monthly rate of the one-year bank time-deposit, derived from WIND, as the proxy for the risk-free rate for the performance calculation. All the continuous variables are winsorized at the 1% level to eliminate the outlier effects. **Table 4.1** provides detailed definitions of the variables used in our analysis.

4.3.2 Market quality measures

In this subsection, we construct variables to capture different dimensions of market quality for each firm, focusing on liquidity, volatility, and price efficiency.

4.3.2.1. Liquidity

We compute three standard measures of liquidity, focusing on the *Amihud* (price impact), *RQS* (relative quoted spread), and *Turnover*.

One frequently used measure of stock market liquidity is the extent to which an asset can be bought or sold without affecting its price. We measure the price impact measure for liquidity by Amihud (2002). The daily *Amihud* measure is defined as follows:

$$Amihud_{it} = |Ret_{it}|/VOLD_{it}, \qquad (1)$$

where $Ret_{i,t}$ is the daily return for stock i in day t, and $VOLD_{i,t}$ is the respective daily trading volume (in millions in renminbi (RMB)). Firms with larger *Amihud* are less liquid.

We also compute the relative quoted spread to capture the transaction cost of the trade. For a given interval t, for each stock, the relative quoted spread, *RQS*, is defined as follows:

$$RQS_{it} = (Ask_{it} - Bid_{it})/((Ask_{it} + Bid_{it})/2), \qquad (2)$$

where Ask_{it} and Bid_{it} are the best ask and bid price in the 5-min interval t for stock i. Then, after standardizing the quoted bid-ask spread by the mid-quote price, we can get the *RQS*. Then we calculate the daily relative quoted spread measure using the time-weighted average *RQS* for each stock. The narrower the *RQS* is, the more liquid the stock is.

Turnover ratio is constructed by using the share trading volume divided by the number of tradable shares.

4.3.2.2. Volatility

We construct two measures, *HLrange* and *Vol*, to capture the possible volatility changes after the stimulus package policy implementation.

HLrange is measured using the intraday range between the highest and lowest prices of a day standardized by the daily closing price. Price high-low range is simple and widely used in volatility measure that gives weight to extreme values. Studies have shown that the extreme value volatility estimators have good empirical performance and are closely related to market structure (Boehmer, Fong, and Wu 2020).

Vol is the short-term return volatility measured as the standard deviation of 5-min or 30-min midpoint returns for each stock. Price movements during short intervals contain less fundamental news and can reflect transitory price changes (Bennett and Wei 2006; Chordia, Roll, and Subrahmanyam 2011; O'Hara and Ye 2011). Note that trade-based volatility measures are quite noisy due to bid-ask bounce, and this problem is even worse for the very high frequency measures. Thus, to emanate the bid-ask bounce, we complement the analysis with midpoint returns based on 5 min (*Vol5*) and 30 min (*Vol30*) time intervals during the day.

4.3.2.3. Price efficiency

We employ two different approaches, VR (variance ratio) and SYNCH (synchronicity) to measure how efficient stock prices incorporate information in the stock market.

Our first measure for market efficiency is the variance ratio (VR) test as suggested by Lo and MacKinlay (1989). Chordia et al. (2011) also mention this measure, which is also called the comparison of short- and long-horizon variance ratios. We define the variance ratio of mid-quote returns as

$$VR = \left| \frac{\sigma^2_{y-min\ Returns} \times \left(\frac{x}{y}\right)}{\sigma^2_{x-min\ Returns}} - 1 \right|, \qquad (3)$$

where $\sigma^2_{y-min\ Returns}$ ($\sigma^2_{x-min\ Returns}$) is mid-quote return variance with an interval of y-min (x-min) and we assume that $x > y$, that is, x belongs to the long period and y belongs to the short period. We compare the variance of price returns in 5-to-30min and 10-to-30 min daily variance ratio, VR30_5 and VR30_10 for each stock on that day. If prices are efficient and follow a random walk, these measures should be close to zero.

Chordia, Roll, and Subrahmanyam (2008) state that the variance ratio reveals the degree of private information produced by the trading process. If quote midpoints prices are not affected by autocorrelation and follow random walks, thus, quote changes are permanent on average and variances variance ratios will not systematically deviate from one (Bessembinder 2003). Therefore, in a more liquid market, stock prices are closer to a random walk and VR is closer to zero.

Another proxy we use for market efficiency is stock price synchronicity (SYNCH). Morck et al. (2000) test worldwide synchronicity at the country level and find that developed markets have higher idiosyncratic risks than emerging markets. They suggest that stock prices contain market-wide and firm-specific information and hence the magnitude of idiosyncratic risk reflected by stock returns can be used to measure the price efficiency of a security.

To measure the stock price synchronicity, first, we need to separate total return movements into two components: market common factors and firm idiosyncratic factors. To construct a more powerful test, we modify Morck et al. (2000)'s approach to compute monthly, rather than yearly, stock price synchronicity using daily data. Daily data allow the synchronicity index to be calculated more accurately than weekly, although it is more computationally intensive. We estimate the following market model for each month:

$$RET_{it} = \alpha + \beta_1 MKTRET_t + \varepsilon_{it}, \qquad (4)$$

In estimating Eq. (4), we require that daily return data be available for at least fifteen days per firm per month to run the regression. To circumvent the bounded nature of R^2 within [0,1], we use a logistic transformation of R^2:

$$SYNCH_i = log\left(\frac{R_i^2}{1-R_i^2}\right), \qquad (5)$$

where $SYNCH_i$ is the monthly stock price synchronicity for firm i. The higher the *SYNCH*, the higher the stock price synchronicity, implying that the stock price movements are more synchronous and less efficient.

4.3.3. Summary statistics

Panel A and B of **Table 4.2** reports the descriptive statistics and correlation matrix for all for the specific measures of liquidity, volatility, and price efficiency. As shown, *Amihud* is highly positively correlated with *RQS* and negatively with *Turnover*, which is consistent with the convention. The measures of volatility (*HLrange*, *Vol5* and *Vol30*) are highly correlated. Referring to price efficiency measures, *VR30_5* (*VR30_10*) and *SYNCH* are positively correlated, but the correlation coefficients are relatively low, 0.16 and 0.04, respectively. This shows that variance ratio and synchronicity measures capture different aspects of price efficiency while they also have common components.

Panel C presents the changes in market quality variables over different periods, pre-stimulus (January 2003-Octomber 2008) and post-stimulus (January 2011-May 2018), for SOEs, POEs, and other firms, respectively. Note that we exclude the policy implementation period, from November 2008 to December 2010. As discussed above, the economic stimulus package injects huge liquidity into the real economy as well as the stock market. Panel C shows that the average liquidity increases for all the firms. The magnitude of the liquidity increase for POEs is larger than for SOEs. Regarding measures of Volatility, all kinds of firms have lower volatility after the implementation of the stimulus package. The results also show that both SOEs and POEs have experienced price efficiency improvement in recent years. Compared to SOEs, the magnitude of price efficiency improvement for POEs is larger. This evidence is consistent with the result of Carpenter et al.(2020) which shows that stock prices are more informative recently in China's stock market. There are two possible reasons for price efficiency improvement. First, increased competition in liquidity provision makes the prices more informative. Second, more cross-market arbitrage activities may decrease pricing errors and improve price efficiency (Xu et al. (2020)).

Overall, the implementation of stimulus package and aggressive monetary policy, which inject liquidity, indeed enhances the informativeness of stock prices in China's stock market. However, the changes in market quality measures for SOEs and POEs differ in magnitude. These findings provide preliminary evidence suggesting that the shock of the stimulus package amplifies the ownership discrimination effect on the corporate governance and market performance.

Table 4. 2 Descriptive statistics

Panel A:

Variable	Mean	Median	Std	Min	Max
Amihud	0.0769	0.0238	0.1127	0.0049	0.4540
Turnover	0.0085	0.0075	0.0051	0.0015	0.0280
RQS	0.0017	0.0016	0.0005	0.0010	0.0031
HLrange	0.0367	0.0330	0.0116	0.0209	0.0864
Vol5	0.0033	0.0030	0.0011	0.0019	0.0078
Vol30	0.0068	0.0061	0.0022	0.0040	0.0167
VR30_5	0.8254	0.7822	0.3475	0.0002	4.4402
VR30_10	0.6274	0.5943	0.2789	0.0002	3.0255
SYNCH	–0.5589	–0.3089	1.5740	–2.3829	7.8378

Panel B:

Liquidity:

Variable	Amihud	Turnover	RQS	TV
Amihud	1			
Turnover	–0.5450	1		
RQS	0.7239	–0.5625	1	

Volatility:

Variable	Hlrange	Vol5	Vol30
HLrange	1		
Vol5	0.9951	1	
Vol30	0.9928	0.9955	1

Price Efficiency:

Variable	VR30_5	VR30_10	SYNCH
VR30_5	1		
VR30_10	0.8700	1	
SYNCH	0.1569	0.0363	1

Panel C:

	SOE			POE			Others		
	Pre	Post	Diff	Pre	Post	Diff	Pre	Post	Diff
Amihud	0.1338	0.0110	–0.1228	0.2458	0.0326	–0.2132	0.2128	0.0175	–0.1954
Turnover	0.0039	0.0049	0.0011	0.0097	0.0143	0.0046	0.0082	0.0128	0.0046
RQS	0.0020	0.0017	–0.0003	0.0024	0.0013	–0.0011	0.0021	0.0012	–0.0009
HLrange	0.0380	0.0277	–0.0103	0.0430	0.0396	–0.0035	0.0428	0.0349	–0.0079
Vol5	0.0034	0.0025	–0.0010	0.0039	0.0034	–0.0005	0.0039	0.0030	–0.0009
Vol30	0.0072	0.0051	–0.0021	0.0081	0.0072	–0.0009	0.0081	0.0064	–0.0017
VR30_5	0.9659	0.9433	–0.0227	0.9696	0.8980	–0.0715	0.9675	0.9115	–0.0561
VR30_10	0.6878	0.6341	–0.0537	0.6674	0.6066	–0.0608	0.6693	0.6140	–0.0553
SYNCH	–0.3579	–0.5295	–0.1716	–0.3474	–0.8037	–0.4563	–0.3912	–0.5973	–0.2061

Note: Panel A reports descriptive statistics for main variables. Panel B reports the correlation between liquidity, volatility, and market efficiency measures, respectively. Panel C shows the mean statistics for different ownership structure firms after and before the stimulus package. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

4.4. Empirical design and results

In this section, we first present our baseline regression model. Subsequently, we examine the impact of the stimulus package on market performance, encompassing market quality and stock prices, for firms with different ownership structures.

4.4.1. Model specification

We study the impact of the stimulus package implementation on several outcomes for both SOEs and POEs, including kinds of aspects of market quality measures and return performance. The empirical design is consistent across different measures, and we detail our main strategy here.

Since the 4-trillion stimulus package constitutes a nationwide exogenous shock, we first establish an OLS panel data regression to explain the determinants of stock's return performance following the method of Bertrand et al. (2007). This method helps us explore the dynamic change in market quality for different kinds of firms based on ownership structure following the implementation of the economic stimulus package.

In our regression analysis, we include a dummy variable "Post" to account for the days after the stimulus package ended, covering the period from January 2011 to May 2018. To avoid the influence from the policy execution, we exclude the period during the stimulus policy implementation, spanning from November 2008 to December 2010.[30] Thus, we can focus on evaluating the impact of the stimulus package after its active implementation phase. We divide the stocks into three portfolios: SOE, POE, and Others, based on the proportions of shares owned by the state. We introduce the dummy variables SOE and POE to investigate the potential differences in market quality and stock returns based upon ownership discrimination. SOE is an indicator, which equals to one if the firm has more than 50% of shares owned by the state, and zero otherwise. POE represents the firm that has less than 5% of shares owned by the state. In order to explore changes in SOEs and POEs, the other firms with 5% to 50% shares owned by state entities are used as a benchmark. Notably, due to the restricted access to shareholding information for only the top ten holders, we cannot ascertain whether other smaller shareholders are state entities. To mitigate potential misclassification, we adopt this

[30] We also do the robustness check without excluding the policy implementation period, that is, the Post is the dummy variable equal to one if it is after November 2008. We find qualitatively similar results.

approach to ensure the accuracy of our state and private ownership categorization. The regression equation is expressed as follows:

$$MQ_{i,t} = \alpha_0 + \beta_1 \, SOE_{\,i,t} \times Post_{\,t} + \beta_2 \, POE_{\,i,t} \times Post_{\,t} + \beta_3 lnME_{\,i,t-1} + \beta_4 lnBTM_{i,t-1} + \beta_5 MQ_{\,i,t-1} + \varepsilon_{i,t}, \qquad (6)$$

where $MQ_{\,i,t}$ is the specific market quality measure that we construct in Section 3.2 for firm i in month t. The control variables contain logarithm of the market capitalization (*lnME*), logarithm of the book-to-market ratio (*lnBTM*), and the first lag of the dependent variable. Following Boehmer and Kelley (2009), we lag all control variables by one month to ensure explanatory variables are predetermined. The regression includes firm and year fixed effects, so we exclude the variables of $SOE_{\,i,t}$, $POE_{\,it}$, and $Post_{\,t}$ in the equation. Standard errors are corrected to allow for clustering of the error terms at the firm level and time level, which helps to avoid potential biases that may arise from serial dependency in the panel data.[31]

The interaction term $SOE \times Post$'s coefficient β_1 is the main coefficient of interest. It captures the difference in market quality measures between SOEs and other benchmark firms following the implementation of the stimulus package in 2009, relative to that in the pre-stimulus period. In the next analysis, we run the regression in equation (6) for each market quality measure, including liquidity, volatility, and efficiency, and for stock returns.

4.4.2. Liquidity

Several previous studies have investigated the effect of ownership structure on market liquidity. Brockman, Chung, and Yan (2009) find a negative relationship between block ownership and market quality due to the real friction effect of the disproportional ownership on the trading activity. Rubin (2007) finds that the liquidity-ownership relation is mostly driven by institutional ownership and approves the adverse selection hypothesis. In contrast to the above studies, we focus on the differences in liquidity due to internal ownership identity.

Based on the adverse selection theory, government-related controlling shareholders of SOEs possess superior information compared to minority shareholders, which impairs SOEs' financial and operational transparency and further reduces market liquidity (Chung et al.

[31] Petersen (2009) discuss the use of clustered standard errors to correct the residual serial correlation in financial panel dataset regression.

2010; Easley and O'Hara 1987; Grossman and Stiglitz 1980). Specifically, the increased information asymmetry would lead to higher costs for outside investors to acquire and analyze information. Thus, investors could be reluctant to trade under incomplete or uncertain information (Kyle 1985). Moreover, enhanced government intervention, aligned with the stimulus package, strengthens the managerial entrenchment effect of the government-related ownership concentration. Therefore, with the increased government intervention for SOEs after the economic stimulus package, we expect that the lower liquidity for SOEs would be more pronounced compared to other firms following the implementation of the stimulus policy.

In this section, we explore whether the stimulus package led to differences in liquidity measures for SOEs relative to non-SOEs. We follow the main OLS panel regression method reported in equation (6). Specifically, we apply the liquidity measures of *Amihud*, *Turnover*, and *RQS*, as the dependent variable. The coefficient of $SOE \times Post$ is our main coefficient of interest. It captures the difference in liquidity measures between SOEs and other benchmark firms following the implementation of the stimulus package in 2009, relative to that in the pre-stimulus period. The results are reported in **Table 4.3**.

In Column 1 of **Table 4.3**, the dependent variable is Amihud, which measures price impact, the extent to which a trade alters the share price. The coefficient result of $SOE \times Post$ is 0.01 (t-statistic equal to 3.39), indicating that liquidity significantly declines for SOEs relative to the benchmark firms after the stimulus package shock. In contrast, the sign for coefficient of $POE \times Post$ is reversed to be negative, equal to –0.013 with t-statistic of –4.20, suggesting that POEs are more liquid relative to others after the implementation of the stimulus package. These results support our prediction that the shock of the stimulus package exacerbates the ownership discrimination effect on the market quality.

The dependent variable in Column 2 is the Turnover ratio, which captures the trading activity in a given share in a given quarter. The coefficient result of $SOE \times Post$ is –0.37 (t-statistic equal to –4.76), implying that the SOEs' turnover ratio is significantly reduced following the stimulus package implementation. However, the average difference in turnover ratio between POEs and other firms following the stimulus package shock is 0.005, but not statistically significant, with a t-statistic of 1.37. We also test the effect of the stimulus package on the transaction cost, *RQS* (relative quoted spread). Column 3 shows that the coefficient of $SOE \times Post$ is 0.003, with t-statistic equal to 3.51, while the estimated coefficient on

$POE \times Post$ is –0.002, with a t-statistic equal to –2.48. These results suggest that relative to other benchmark firms, the average trading cost for SOEs (POEs) is significantly larger (smaller) after the implementation of the stimulus package, which is consistent with the findings for *Turnover* and *Amihud*.

The increased government intervention prompted by the stimulus package makes it more challenging for investors to access private information and earn profits from SOEs. As a result, their willingness to trade declines. We find that compared to the other firms, SOEs exhibit lower market liquidity after the implementation of the stimulus policy: lower trading turnover, wider relative quoted spread, and larger price impact of trades. These findings emphasize that concentrated ownership, particularly the enhanced state control in SOEs, has a significant impact on liquidity in the stock market.

Table 4. 3 Effect of stimulus package on liquidity

VARIABLES	(1) Amihud	(2) Turnover	(3) RQS
SOE × Post	0.010***	–0.037***	0.003***
	(3.39)	(–4.76)	(3.51)
POE × Post	–0.013***	0.005	–0.002**
	(–4.20)	(1.37)	(–2.48)
$lnME_{t-1}$	–0.015***	–0.019**	–0.010***
	(–3.75)	(–2.48)	(–7.09)
$lnBTM_{t-1}$	–0.034	1.019*	0.105
	(–0.10)	(2.04)	(0.69)
$Amihud_{t-1}$	0.744***		
	(16.89)		
$Turnover_{t-1}$		0.593***	
		(44.06)	
RQS_{t-1}			0.791***
			(41.77)
Constant	0.170***	0.248***	0.116***
	(3.91)	(4.19)	(7.73)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	276,439	276,439	276,439
R–squared	0.80	0.60	0.85
Adj. R–squared	0.799	0.600	0.851

Notes: This table reports the results of the following regression:

$$\text{Liquidity}_{i,t} = \alpha_0 + \beta_1 \text{SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{POE}_{i,t} \times \text{Post}_{i,t} + \beta_3 \text{lnME}_{i,t-1} + \beta_4 \text{lnBTM}_{i,t-1} + \beta_5 \text{Liquidity}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are liquidity measures, including Amihud, Turnover, and RQS. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state. POE $_{i,t}$ is the dummy variable equal to one if a stock has less than 5% shares owned by the state. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

4.4.3. Volatility

In this section, we examine the effect of the economic stimulus package on volatility by estimating our equation (6) with *HLrange*, *Vol5*, and *Vol30* as our dependent variables. The results are reported in **Table 4.4**.

In Column 1, the dependent variable is *HLrange*. The result for the coefficient of $SOE \times Post$ is –0.056, with t-statistics equal to –3.03, indicating that compared to other firms, the volatility for SOEs decreases after the implementation of the stimulus package. The coefficient of $POE \times Post$ is 0.015 (t-statistics equal to 0.79), but not significant at the conventional level, implying that compared to the benchmark firms, the volatility of POEs remains stable around the policy shock. To examine high-frequency price changes, 5-min and 30-min intraday returns are computed for each stock between 9:30 AM and 3:00 PM. Note that we use the midpoints prices, rather than transactions prices, to emanate the effect of bid-ask bounce. Then, the standard deviations of the 5-min and 30-min intraday returns are measured for each stock in each trading day as the proxies for volatility: $Vol5$ and $Vol30$. Columns 2 and 3 show that for Vol5 and Vol30, the coefficients of $SOE \times Post$ are –0.004 (t-statistics equal to –2.40) and –0.09 (t-statistics equal to –2.68). The results are consistent with before.

Overall, the results imply that return volatility for SOEs has decreased compared to the benchmark firms after the stimulus package policy. As presented by Boehmer (2020), volatility can be an indicator of how prices adjust to new information. That is, the observed changes in return volatility might simply reflect the information flows. Given that with increased government intervention, SOEs would be less inclined to disclose new information, resulting in an opaquer market. Under this scenario, lower volatility of SOEs reflects information withholding and therefore could be undesirable for market transparency and efficiency. We will test the dynamic changes in market efficiency in the next section to support our analysis.

Table 4. 4 Effect of stimulus package on volatility

VARIABLES	(1) HLrange	(2) Vol5	(3) Vol30
SOE × Post	–0.056***	–0.004**	–0.009***
	(–3.03)	(–2.40)	(–2.68)
POE × Post	0.015	0.001	0.002
	(0.79)	(0.55)	(0.67)
$lnME_{t-1}$	0.134**	0.008	0.021**
	(2.49)	(1.62)	(2.17)
$lnBTM_{t-1}$	8.558*	0.823**	1.559**
	(1.94)	(2.18)	(2.17)
$HLrange_{t-1}$	0.545***		
	(15.73)		
$Vol5_{t-1}$		0.567***	
		(15.46)	
$Vol30_{t-1}$			0.553***
			(15.52)
Constant	0.419	0.062	0.102
	(0.76)	(1.24)	(1.05)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	276,439	276,439	276,439
R–squared	0.62	0.65	0.62
Adj. R–squared	0.613	0.645	0.620

Notes: This table reports the results of the following regression:

$$\text{Volatility}_{i,t} = \alpha_0 + \beta_1 \text{ SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{ POE}_{i,t} \times \text{Post}_{i,t} + \beta_3 \text{lnME}_{i,t-1} + \beta_4 \text{lnBTM}_{i,t-1} + \beta_5 \text{Volatility}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are volatility measures, HLrange, Vol5 and Vol30. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state. POE is the dummy variable equal to one if a stock has less than 5% shares owned by the state. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. t-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

4.4.4. Price efficiency

In this section, we first follow the methodology of Gul et al. (2010) to test whether the ownership discrimination effect on market efficiency still holds in the last two decades. Then, we investigate the effect of the stimulus package on the market efficiency measures.

4.4.4.1. Retest the effect of ownership concentration on stock price synchronicity

Stock price synchronicity measures the degree to which individual stock prices move in tandem with the overall market, reflecting the amount of firm-specific information incorporated into share prices. Morck et al. (2000) state that among 40 sample countries, China has the second highest synchronicity, where poor investor protection discourages informed trading and thus leads to a less efficient market. Gul et al. (2010) then investigate whether and how stock price synchronicity is associated with firm-level corporate governance characteristics, such as ownership structure and audit quality, over the 1996-2003 period. They find that due to the managerial entrenchment effect, synchronicity is higher for firms with government-related ownership concentration in China.

The Chinese government has made a ton of efforts to improve the stock price efficiency in the last two decades, but there are still many firms partially privatized and closely connected with the government. Thus, it is important to investigate whether the effect of government-related ownership concentration on stock price synchronicity still exists in China in recent years. Following the methodology of Gul et al. (2010), we test the effects of ownership concentration on stock price synchronicity, over the period from 2003 to 2018. **Table 4.A1** represents the results.

Following Gul et al. (2010), we first construct a new variable $TOPHOLD$, which is defined as the percentage of shares held by the largest shareholder, to represent the level of ownership concentration for listed firms. To explore potential non-linear relationships, we include a quadratic term $TOPHOLD^2$ in our regression analysis. This allows us to examine whether the relation between synchronicity and ownership concentration exhibits a concave pattern, whereby as concentration increases, synchronicity increases at a decreasing rate up to its maximum threshold, after which it begins to decrease. We include control variables that may influence synchronicity, firm size (*lnME*), market-to-book ratio (*lnBTM*), trading volume turnover (*Turnover*), and earning-to-price ratio (*E/P*). SOE and POE, defined the same as before, refer to the government closely tied firms and non-government related firms.[32]

Column 1 of **Table 4.A1** presents the results of the relationship between ownership concentration and synchronicity. As expected, the estimated coefficient on $TOPHOLD^2$ is –0.409, with *t*-statistic equal to –1.74. The coefficient on $TOPHOLD$ is positive, 0.069 with a *t*-

[32] Gul et al. (2010) use TOPGOV as the proxy for government-related firms. TOPGOV is an indicator that equals one if the firm's largest shareholder is government-related, and zero otherwise.

statistic 3.09, which is statistically significant at the 1% level. Thus, consistent with the results of Gul et al. (2010), the stock price synchronicity still maintains a concave function of ownership concentration over the period from 2003 to 2018. Column 2 shows that the estimated coefficient on SOE is significantly positive, 0.069, with *t*-statistics equal to 3.52, while for POE, the result is not statistically significant. The results are supportive of the notion that government related ownership concentration is more likely to lead to price inefficiency. Column 3 presents the estimated results for the full-model regression including all the variables. All estimated coefficients remain significant with the expected sign.

Overall, the results show that despite the continuing efforts of the Chinese government to reform its financial system, the issue of stock price synchronicity remains significant for firms with concentrated ownership, particularly for firms with government-related large shareholders, e.g., SOEs. We will test the effect of the stimulus package on this linkage in the next section.

4.4.4.2. The effect of the stimulus package on price efficiency

Next, we provide further insight into the association between ownership concentration and stock price informativeness by introducing the effect of the stimulus package shock. Given the unique institutional environment of China, SOEs get more loan/credit support from the government's stimulus package. With more government interventions, government-related controlling shareholders in SOEs have more incentive to cover up their private information to outside investors to camouflage their self-serving behaviors. We posit that after the implementation of the stimulus package, the managerial entrenchment effect of the ownership concentration would be more prominent for the listed SOEs, contributing to less transparency information environments. Thus, the stimulus package shock would result in information asymmetry and further deteriorate SOEs' price efficiency compared to non-SOEs.

Except for the stock price synchronicity, we construct another measure, variance ratio, to proxy the price efficiency. Chordia et al. (2011) present that the variance ratio reveals the degree of private information produced by the trading process. Deviations from a random walk can arise because noise trading can cause return serial correlation (Grossman and Miller, 1988). If the prices are affected by autocorrelation, the return variances variance ratios will systematically deviate from one, indicating that the stock market itself was unable to provide sufficient liquidity. We expect that the stock price synchronicity and variance ratio would be larger for

SOEs in recent years after the stimulus package shock as the increased government intervention has deteriorated the market quality of SOEs.

Table 4.5 presents the results for equation (8) with price efficiency measures as the dependent variable. The coefficient of $SOE \times Post$ is the main coefficient of interest, indicating the efficiency difference between SOEs and other firms after the stimulus package shock, relative to pre-stimulus period. Column 1 presents the regression analysis results for price synchronicity. Consistent with our prediction, the estimated coefficient of $SOE \times Post$ is significantly positive, 0.087, with t-statistics equal to 2.94. The result indicates that with the shock of the stimulus package, synchronicity is higher for SOEs relative to other non-government-related firms. However, the coefficient of $POE \times Post$ is reversed to be negative, which is equal to –0.002, but not statistically significant with a t-statistic of –0.84. As shown in columns 2 and 3, the estimated coefficients of $SOE \times Post$ are highly significant for both *VR30_5* and *VR30_10*, with the expected positive signs, which equal to 0.021 (*t*-statistic equal to 3.39) and 0.019 (*t*-statistic equal to 3.31). These results show that compared to other firms, SOEs' prices experience larger deviations from the random walk following the implementation of the stimulus package.

Overall, due to the government intervention accompanied by the stimulus package, the effect of government-related ownership concentration on stock price efficiency has become more salient in recent years.

Table 4. 5 Effect of stimulus package on price efficiency

	(1)	(2)	(3)
VARIABLES	SYNCH	VR30_5	VR30_10
SOE × Post	0.087***	0.021***	0.019***
	(2.94)	(3.39)	(3.31)
POE × Post	–0.020	–0.005	–0.006
	(–0.84)	(–0.93)	(–1.32)
$lnME_{t-1}$	–0.129***	–0.064***	–0.053***
	(–3.20)	(–8.08)	(–7.53)
$lnBTM_{t-1}$	1.882***	0.037	–0.331
	(7.97)	(0.05)	(–0.51)
$SYNCH_{t-1}$	–0.180***		
	(–10.02)		
$VR30\_5_{t-1}$		0.149***	
		(13.28)	
$VR30\_10_{t-1}$			0.133***
			(12.32)
Constant	0.557	1.237***	1.261***
	(1.64)	(15.29)	(17.37)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	276,439	276,439	276,439
R–squared	0.17	0.13	0.11
Adj. R–squared	0.161	0.120	0.104

Notes: This table reports the results of the following regression:

$$\text{Efficiency}_{i,t} = \alpha_0 + \beta_1 \text{ SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{ POE}_{i,t} \times \text{Post}_{i,t} + \beta_3 \text{lnME}_{i,t-1} + \beta_4 \text{lnBTM}_{i,t-1} + \beta_5 \text{Efficiency}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are market efficiency measures, stock price synchronicity and variance ratio. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state. POE $_{i,t}$ is the dummy variable equal to one if a stock has less than 5% shares owned by the state. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

4.4.5. Return performance

In this section, we investigate the influence of the firms' ownership structure on equity performance. Prior research by Gompers, Ishii, and Metrick (2003) establish a link between corporate governance and equity prices, showing that firms with stronger shareholder rights tend to earn higher abnormal returns compared to firms with weaker rights. Chung et al. (2010)

also state that corporate governance can affect a firm's market value. In our study, the identifying assumption is that compared to non-SOEs, SOEs should be more affected by the stimulus package intervention, from the aspects of both micro-structure and trading performance. Our primary goal in this sector is to provide direct evidence supporting this identification assumption in terms of return performance.

4.4.5.1. Stock return performance

First, we examine the effect of the economic stimulus package on firms' return performance by estimating equation (6). The results are reported in **Table 4.6**. In this regression, we apply the monthly excess returns of the stock as the dependent variable.

The coefficients β_1 and β_2 of $SOE\times Post$ and $POE\times Post$ are the main coefficients of interest, which capture the difference in stock returns between the SOEs (POEs) and other benchmark firms after the stimulus policy exit, relative to that pre-stimulus. As discussed above, we posit that less responsive loan lending and investment inefficiency for SOEs after the stimulus package implementation can also be reflected in the return performance of the stock market. We would expect β_1 to be negative, implying that the SOEs would experience lower returns after the shock of the stimulus package, relative to the benchmark firms.

Column 1 of **Table 4.6** shows that the estimated coefficient on $SOE\times Post$ is –0.428 and significant at the 1% level, indicating that after the introduction of the stimulus package, the average monthly returns for SOEs are lower by 43 basis points than the other benchmark firms, relative to the pre-stimulus period. However, the estimated coefficient on $POE\times Post$ is 0.426, positive and significant at a 1% conventional level, showing that compared to the other firms, POEs with less connection with the government earn higher returns, 42.6 basis points per month, following the implementation of the stimulus package. Column 2 takes control of size (*lnME*), book-to-market ratio (*lnBTM*), trading turnover ratio (*Turnover*), and the one lag of return (Ret_{t-1}). Note we lag all control variables by 1 month to ensure that explanatory variables are predetermined. The results are consistent with before, after the execution of the economic stimulus package, SOEs earn less than 91.3 basis points while POEs earn more than 130.7 basis points compared to the other firms. As for the effects of the control variables, we find that firms with higher market capitalization or higher turnover ratio in the prior month experience higher returns, which is consistent with the predictability characteristics of those variables.

Liu et al. (2018) find that with the implementation of the economic stimulus package after the financial crisis, both SOEs and POEs receive more bank loans and apply more investments, while bank lending and investment are less responsive to firm profitability and investment opportunities for SOEs compared to POEs. Consistent with Liu et al. (2018)'s finding, we show that after the implementation of the economic stimulus policy, SOEs become less profitable and POEs become more profitable in the stock market. This indicates that the stimulus package has different impact on the market performance of SOEs and POEs.

Table 4. 6 Effect of stimulus package on returns

VARIABLES	(1) Ret	(2) Ret
SOE × Post	–0.428**	–0.913***
	(–2.17)	(–2.91)
POE × Post	0.426**	1.307***
	(2.27)	(5.44)
$lnME_{t-1}$		–4.026***
		(–5.88)
$lnBTM_{t-1}$		0.656
		(1.14)
$Turnover_{t-1}$		–6.167***
		(–3.71)
Ret_{t-1}		–0.016
		(–0.41)
Constant	0.576	34.013***
	(0.81)	(5.04)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	280,889	276,439
R–squared	0.09	0.12
Adj. R–squared	0.0770	0.110

Notes: This table reports the results of the following regression:

$$\text{Ret}_{i,t} = \alpha_0 + \beta_1 \text{ SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{ POE}_{i,t} \times \text{Post}_{i,t} + \beta_3 \text{lnME}_{i,t-1} + \beta_4 \text{lnBTM}_{i,t-1} + \beta_5 \text{Turnover}_{i,t-1} + \beta_6 \text{Ret}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are liquidity measures. Ret $_{i,t}$ is the excess monthly return in percentage. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state. POE is the dummy variable equal to one if a stock has less than 5% shares owned by the state. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), Turnover ratio, and the first lag of the dependent variable. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

4.4.5.2. Mispricing

Next, we investigate whether the performance changes documented above differ systematically based on the firm's speculative characteristics, which we measure as the monthly turnover ratio for each firm. Under the adverse selection and entrenchment effect theory, large government-related shareholders of SOEs have more incentive to cover up their non-profit maximizing behaviors by withholding unfavorable information or selectively disclosing such information. Thus, the higher cost of acquiring and analyzing firm-specific information on SOEs for outside investors, especially after the stimulus package implementation, would deter the trading of informed investors and then lead to a more salient mispricing phenomenon.

High sentiment toward a stock can affect its price by adding liquidity to optimistic irrational investors, driving it higher than justified by fundamentals and thereby lowering its expected future returns. Hence, high liquidity is a symptom of overvaluation. Baker and Wugler (2006) state that turnover, or more generally liquidity, can be used as a sentiment measure. Two assumptions are under this scenario: short-sales constraints, and irrational, sentiment-driven investors participate.[33] Lee (2013) uses turnover empirically as a sentiment measure at the individual level. Thus, we use the Turnover index as a proxy for speculative mispricing in our analysis.

In **Table 4.7**, we add our mispricing proxy, Turnover, to the regression model of equation (6). The key variable of interest is the coefficient on the triple interaction term $SOE \times Post \times Turnover$, which is predicted to be negative, meaning that the less profitable effect for SOEs following the stimulus package shock is more pronounced for mispricing firms. We also include the double interaction terms $SOE \times Turnover$ and $Post \times Turnover$ for the control variables in these regressions. The dependent variables are monthly returns for all the regressions. In columns 1 and 2, **Table 4.7**, we test the triple interaction term $SOE \times Post \times Turnover$ and $POE \times Post \times Turnover$, respectively. The coefficient of $SOE \times Post \times Turnover$ is significantly negative, –6.168, with a t-statistic of –2.75. For column 2, the coefficient on $POE \times Post \times Turnover$ is positive, 1.669, but the result is not significant at a conventional level. Column 3 shows the estimated results for the full-model regression with all variables included. The estimated coefficient of $SOE \times Post \times Turnover$ remains significant at the 5% level with expected sign. The results present that the negative relative

[33] China's stock market is especially suited to the assumptions. First, short-selling is only allowed in China from 2010 and is still in a limited scope. Second, individual retail investors, normally recognized as sentiment traders, are the major sentiments in China's stock market, holding over 80% of all free-floating shares.

returns for SOEs in the post-stimulus period are especially pronounced for stocks with higher turnover, suggesting that SOEs may have suffered from more mispricing after the implementation of the stimulus package.

Overall, we find that compared to the other firms, the mispricing is stronger for SOEs after the implementation of the stimulus policy, and there are no significant results for POEs.

Table 4. 7 Effect of stimulus package on returns mispricing

VARIABLES	(1) Ret	(2) Ret	(3) Ret
SOE × Post × $Turnover_{t-1}$	–6.168***		–5.115**
	(–2.75)		(–2.36)
POE × Post × $Turnover_{t-1}$		1.668	0.880
		(1.32)	(0.69)
SOE × Post	–0.359		–0.166
	(–0.87)		(–0.49)
POE × Post		1.071***	0.959***
		(3.03)	(3.23)
SOE × $Turnover_{t-1}$	1.980		1.403
	(1.14)		(0.75)
POE × $Turnover_{t-1}$		–0.316	–0.029
		(–0.33)	(–0.03)
Post × $Turnover_{t-1}$	–2.926	–4.011	–3.456
	(–0.69)	(–0.97)	(–0.87)
$lnME_{\mathrm{t}-1}$	–3.963***	–4.028***	–4.012***
	(–5.83)	(–5.90)	(–5.88)
$lnBTM_{\mathrm{t}-1}$	0.587	0.565	0.594
	(1.05)	(1.02)	(1.07)
Ret_{t-1}	–0.018	–0.018	–0.018
	(–0.44)	(–0.45)	(–0.44)
$Turnover_{t-1}$	–3.450	–3.305	–3.404
	(–0.79)	(–0.76)	(–0.82)
Constant	34.100***	34.245***	34.109***
	(5.06)	(5.07)	(5.07)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	276,439	276,439	276,439
R–squared	0.12	0.12	0.12
Adj. R–squared	0.111	0.111	0.111

Notes: This table reports the results of the following regression:

$$\text{Ret}_{i,t} = \alpha_0 + \beta_1 \text{ SOE}_{i,t} \times \text{Post}_{t} \times \text{Turnover}_{i,t-1} + \beta_2 \text{ POE}_{i,t} \times \text{Post}_{t} \times \text{Turnover}_{i,t-1}$$
$$+\beta_3 \text{ SOE}_{i,t} \times \text{Post}_{i,t} + \beta_4 \text{ POE}_{i,t} \times \text{Post}_{i,t} + \beta_5 \text{ SOE}_{i,t} \times \text{Turnover}_{i,t-1} + \beta_6 \text{ POE}_{i,t} \times \text{Turnover}_{i,t-1}$$
$$+\beta_7 \text{ Post}_{t} \times \text{Turnover}_{i,t-1} + \beta_8 \text{lnME}_{i,t-1} + \beta_9 \text{lnBTM}_{i,t-1} + \beta_{10} \text{Ret}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are liquidity measures. Ret $_{i,t}$ is the excess monthly return. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state. POE is the dummy variable equal to one if a stock has less than 5% shares owned by the state. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

4.5. Robustness tests

4.5.1. Difference-in-differences regression

A potential concern with the panel data regression approach is that there could exist endogeneity problems that are not captured by the control variables. To mitigate this endogeneity problem, we also conduct a difference-in-differences test with propensity score matching methodology (PSM) to offer robust results.

The treatment group includes the SOEs who have more than 50% shares owned by the state. For each treatment firm, we select matched control firms from the POEs portfolio based on a propensity score after a logit model is estimated, using all the firms without missing variables in a year before the stimulus policy was abandoned (January 2010 to December 2010). Note that the ownership discrimination problem starts to become serious after the bailout stops. We select our matching variables as those likely to be associated with stock performance and market quality. We match firms based on several predictors, including *Analyst*, *lnBTM*, *E/P ratio*, *Tskew*, *Sigma*, and *Industry*. *Analyst* is the number of analysts (group) following in a firm. We use the analyst coverage as the proxy for the reputation of the firm, instead of market capitalization, as the difference in the size between SOEs and POEs is extremely large. *lnBTM* is the ratio of the market value to the book value of equity. *E/P ratio* is another proxy for the value factor proposed by Liu et al. (2019), which is defined by net earning divided by the product of the share price and total number of shares. *Tskew* and *Sigma* are defined as the skewness and standard deviation of firm-specific daily returns in a month, used to control the firm-specific information for investors. We take *Tskew* and *Sigma* as the speculative characteristic proxies for stocks to control for any mispricing differences before the stimulus policy between SOEs and POEs. We also control for the industry fixed effect, *Industry*, which is defined based on the classification by the China Securities Regulatory Commission in 2012.

The pre-treatment period is from January 2003 to October 2008, and the post-treatment period is after the stimulus policy stops, from January 2011 to May 2018. Note that we exclude the period during the stimulus policy implementation to avoid the influence of the policy execution. The difference-in-differences regression model is specified as follows to test the effect of the implementation of the stimulus policy on market quality and return performance:

$$\begin{aligned} MQ_{i,t} &= \alpha_0 + \beta_1 SOE_{i,t} \times Post_{i,t} + \beta_2 lnME_{i,t-1} \\ &+\beta_3 lnBTM_{i,t-1} + \beta_4 MQ_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \quad (7)$$

$$Ret_{\ i,t} = \alpha_0 + \beta_1\ SOE_{\ i,t} \times Post_{\ i,t} + \beta_2 lnME_{\ i,t-1} + \beta_3 lnBTM_{\ i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Ret_{i,t-1} + \varepsilon_{i,t}, \quad (8)$$

where the dependent variables in equation (7) are the market quality measures, including liquidity, volatility, and price efficiency measures, for firm i, at month t; the dependent variable in equation (8) is the excess returns for firm i, at month t; $SOE_{\ i,t}$ is a dummy variable that equals to 1 if a stock belongs to the treatment group and 0 for the control group. $Post_{\ i,t}$ is a dummy variable that equals 1 if a stock is in the year of the post period. To ensure that our results are not due to poor matches, we include market capitalization value (*lnME*), book-to-market ratio (*lnBTM)*, and turnover (*Turnover*) as control variables in the difference-in-differences regressions. As *Turnover* is a measure of liquidity, we exclude it from the control variables in equation (7). Consistent with before, we lag all control variables by one month to ensure explanatory variables are predetermined. We also include the first lag of dependent variables in the regression. We estimate the difference-in-differences regression with stock fixed effects and time fixed effects to account for any unobserved time-invariant characteristics of specific stocks and stock-invariant time fixed effects.

The result of the logit regression for the propensity score matching is reported in Table 4.A2. After matching, we have a total of 350 (350) unique treatment (control) firms, which we use in the regressions of equations (7) and (8). We find that our logit model explains the choice variable well. The coefficients of *lnBTM*, *Anaylst*, and *Tskew* are positively significant at better than the 1% level, respectively, implying that firms with higher value, larger size, and higher return skewness are likely to be SOEs. The coefficient of Sigma is negatively significant at a 1% level, suggesting that the stock prices of SOEs are less volatile than POEs. Panel B presents the comparison of variables between treatment and control firms before and after matching. The results show that matched treatment and control firms are comparable after our propensity score matching procedure.

Similar to Section 4.4.2, we first test the policy effect on the liquidity for treatment and control firms, SOEs and POEs. Column 1 to 3 of **Table 4.A3** reports the coefficients of the regression of equation (7) with liquidity measures as the dependent variable. The results remain robust for liquidity changes, showing that the difference in market liquidity between SOEs and POEs increases following the stimulus package shock. We then re-test the effect of the economic stimulus package on volatility. The results are reported in Column 1 to 3 of **Table 4.A4**. The estimated coefficients of $SOE \times\ Post$ are significant at the 10% level with an expected negative sign. Finally, we re-evaluate the effect of the stimulus package on market quality. Column 1 to 3 of **Table 4.A5** presents the DiD regression results, which are consistent with the results of **Table 4.6**. Compared to POEs, the implementation of the stimulus package leads to more government intervention for SOEs and then deteriorates their price efficiency. Column 1 to 2 of **Table 4.A6** reports regression results for equation (8). The results provide strong support for the hypothesis that after the exit of the stimulus package, SOEs perform worse than the POEs, relative to the pre-stimulus period. The result of Column 2 is also consistent with the results reported in **Table 4.8** that the stimulus package shock deters informed trading for SOEs and leads to a more salient mispricing problem.

Overall, the result in this subsection reinforces the robustness of the fact that stimulus package shock amplifies the ownership discrimination effect on the market quality and return performance.

4.5.2. DiD regression for short-term period

In our main specification, we test the effect of the stimulus policy on the market dynamics for a long time, over 15 years. However, using a long sample period may increase the likelihood that the omitted variables, e.g., macro factors, and firm reforms, influence the market quality and performance, thus invalidating our causal inference. To mitigate this concern, we re-estimate the DiD regression using data from the short-term period spanning 2006 to 2012. Also, this test offers a particularly important insight into the short-term impact of stimulus policy on the market dynamics.

Consistent with our previous analysis, we exclude the policy implementation period, from November 2008 to December 2009. This approach allows us to isolate the effect of the stimulus plan on the market dynamics of SOEs compared to POEs over the three-year period after the policy implementation.

Columns 4 to 6 of **Table 4.A3** report the coefficients of the regression of equation (7) with liquidity measures as the dependent variable for the sample from 2006 to 2012. The results of Aminud and Turnover are statistically significant, even though the magnitude of the coefficients is smaller than it is in Columns (1) and (2) for the long-run sample period. However, the coefficient of transaction cost, RQS, is not significant anymore. Moreover, Columns 4 to 6 of **Table 4.A4** and **Table 4.A5** report the coefficients of the DiD regression with volatility and market efficiency measures as the dependent variable in the short-run sample. The results are consistent with the analysis with the full-time sample, indicating the prompt effect of the stimulus package on the market quality.

Next, we test the influence of the firm's ownership structure on equity performance in the short-term period. Columns 3 to 4 of **Table 4.A6** reports regression results for equation (8) using the data from 2006 to 2012. We find that there is no marked pattern for the difference in market performance between SOEs and POEs, following the implementation of the stimulus package in the short-run period.

Overall, our results document that in the short run, compared to the POEs, SOEs exhibit lower market quality after the implementation of the stimulus policy. However, the impact of the stimulus plan on the equity returns for SOEs can only be observed in the long-run period.

4.5.3. Investment inefficiency

We perform a validity test to see whether the inefficient investments during the execution of stimulus package for SOEs genuinely have a negative effect on the stock performance. Chen et al. (2011) show that government intervention in an emerging and transitional economy is another type of friction that drives SOEs into less optimal investment decisions. We posit that the investments during the stimulus package implementation period are likely to lead to the resources' misallocation and inefficiencies, especially for SOEs, which then results in the market dynamics.

Following Chen et al. (2011)'s method, we first construct the investment expenditure, which is measured as cash payments for fixed assets, intangible assets, and other long-term assets from the cash flow statement minus cash receipts from selling these assets, scaled by beginning total assets.[34] Then, we calculate *Inv1* for the proxy of the average quarterly investment expenditure in 2009 to 2010, the period of the execution of the stimulus package. Inv1 also can serve as a coarse proxy for the degree of government ties for a firm during the execution of the stimulus package period. We still use the difference-in-differences regression method mentioned in the last sub-section. The results are reported in **Table 4.A7**.

First, we test the relationship between the investment expenditure during the stimulus package

[34] Our definition of investment expenditure is similar to capital expenditure used in the U.S.-based studies (COMPUSTAT Item 128#)

period, Inv1, and the firm's returns afterwards using the dataset from January 2011 to May 2018. Column 1 of **Table 4.A7** shows that the firms who invest more during the stimulus period earn less returns after 2011. In Column 2, we insert the indicator variable SOE into our regression. The coefficient of $SOE \times Inv$ is significantly negative, –1.299, with t-statistics equal to –2.46. The result shows that SOEs with higher investment expenditures during the stimulus period has lower returns on the succeeding period than POEs, which is consistent with our hypothesis that the investment for SOEs during the stimulus package period is more inefficient than it for POEs.

We then establish a difference-in-differences regression using the dataset from 2003 to 2018 to test whether returns of SOEs with higher investment during the stimulus package period, are lower than the POEs', following the execution of the stimulus package. Note that $Inv1$ refers to the closeness of government and firms. We insert Inv into the regression of equation (6). The key variable of interest is the coefficient on the triple interaction term $SOE\times Post\times Inv$, which presents the differences in stock returns between the SOEs with higher $Inv1$ and other firms after the execution of the stimulus policy, relative to the pre-stimulus period. The result reported in Column 3, **Table 4.A7** shows that the coefficient of $SOE\times Post\times Inv$ is equal to –1.647, with a t-statistic of –2.20. This indicates that compared to POEs, SOEs who receive more support from the government and invest more, may have suffered lower returns in the stock market after the implementation of the stimulus package.

To ensure that the documented inefficient investment pattern is specific to the investment during the stimulus package period, rather than a general phenomenon for investment at any date, we thus conduct the pseudo test. Empirically, we create a pseudo investment expenditure variable, $Inv2$, which refers to the average expenditure from 2006 to 2007. The pseudo-event has the same window length as our actual event and does not overlap with the actual event. To eliminate the influence of the financial crisis, we skip the year 2008. We then replicate the regressions based on the randomly selected pseudo-event. Columns 4 to 6, **Table 4.A7**, present the results of the pseudo-test. As it stands, the coefficients on the Inv, $SOE \times Inv$, and $SOE\times Post\times Inv$ are all small in magnitude and not significant at the conventional level. Overall, the comparison of the placebo test results strengthens the hypothesis that the investment for SOEs during the stimulus period is inefficient.

4.6. Conclusion

In this paper, we go beyond the widely debated existence and impacts of ownership concentration on the market dynamics based on the exogenous 2008 economic stimulus package shock, offering valuable insights into the implications of government interventions on firms' performance in the stock market. Specifically, we employ a panel data regression model to provide solid evidence that the stimulus package implication exacerbates the disparities between SOEs and non-SOEs in terms of market quality and stock returns.

Compared to other firms with less connection with the government, the SOEs receive more resources, subsidies, and loans, from the economic stimulus policy. This phenomenon is widely referred to as ownership discrimination. However, this is also related to the resources' misallocation and inefficiencies. The economic stimulus package offers us a natural experiment to test the managerial entrenchment and adverse selection effect on firms with different ownership structures. We test whether this ownership discrimination effect holds on the market performance aspect, which enhances our understanding of the consequences of government-related ownership concentration.

First, we find that the implementation of the stimulus package after the financial tsunami inserts liquidity into the capital market and improves the market quality for all firms, which is helpful for economic recovery. We further examine the macro shock of the stimulus package on the micro-structure of firms. We find that compared to other firms, SOEs have less liquidity and lower volatility after the exit of the stimulus package policy, relative to the pre-stimulus period. Next, we test the changes in market efficiency referring to SOEs and POEs. Our results show that relative to other firms, the market efficiency of SOEs has deteriorated more after the exit of the stimulus package. This is consistent with the increased government interventions in SOEs through the resources support of the stimulus package, and this also reflects the distinct nature of political connections between SOEs and POEs. Then, from the perspective of return performance, we find that after the exit of the stimulus package, SOEs became less profitable and POEs became more profitable in the stock market, relative to the pre-stimulus period. Also, due to the stronger concentrated controlling power by the government, SOEs are more reluctant to release firm-specific information, which deters informed trading and leads to a more salient mispricing problem. We conclude that government intervention for SOEs related to the stimulus package implication in China distorts their return performance and market quality.

Overall, this paper sheds light on the effects of ownership structure on firm's performance in the stock market from the view of the 2008 stimulus package implementation in China. We also reveal the economic consequences of stimulus packages in emerging markets, focusing on firms' performance and microstructure implications. With political connections forced upon SOEs, the government in an emerging economy is capable of extracting resources from these firms to suit its social or political goals, especially during the stimulus package implication periods, which negatively affects the firms' performance and market quality. In this sense, the results presented in this paper may apply outside the context of China and offer valuable insights for both academia and policymakers.

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Appendix

Figure 4.A 1 The structure of the China economic stimulus policy

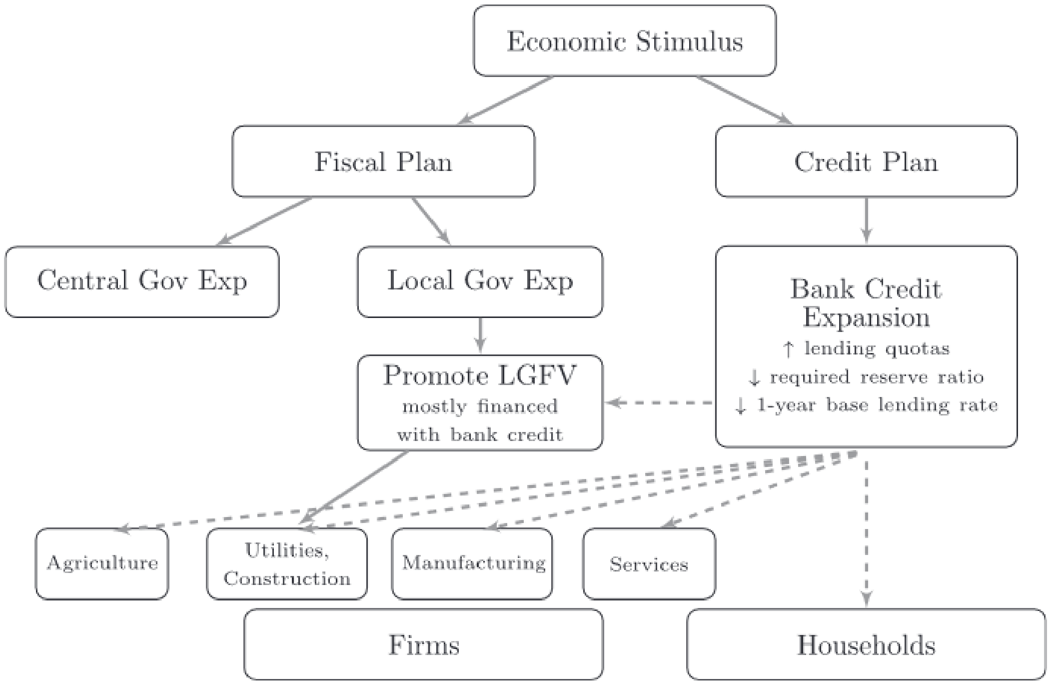

Table 4.A 1 The effect of ownership concentration on synchronicity

	(1)	(2)	(3)
$TOPHOLD^2$	–0.409*		–0.463*
	(–1.74)		(–1.68)
$TOPHOLD$	0.646***		0.644**
	(3.09)		(2.43)
SOE		0.069***	0.043**
		(3.52)	(2.01)
POE		–0.002	–0.006
		(–0.12)	(–0.27)
$lnME_{t-1}$	–0.095***	–0.095***	–0.096***
	(–10.60)	(–10.61)	(–2.73)
$lnBTM_{t-1}$	0.155***	0.157***	0.155***
	(20.24)	(20.46)	(4.25)
E/P_{t-1}	0.017***	0.017***	0.017***
	(14.58)	(14.84)	(7.88)
$Turnover_{t-1}$	0.368***	0.362***	0.370***
	(24.82)	(24.57)	(3.11)
$SYNCH_{t-1}$	–0.187***	–0.186***	–0.186***
	(–82.43)	(–82.38)	(–10.39)
Constant	–0.505***	–0.359***	–0.494
	(–5.41)	(–4.37)	(–1.34)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	309,300	309,300	309,300
R–squared	0.17	0.17	0.17
Adj. R–squared	0.164	0.164	0.164

Note: This table reports the results of the following regression:

$$SYNCH_{i,t} = \alpha_0 + \beta_1 TOPHOLD_{i,t}^2 + \beta_2 TOPHOLD_{i,t} + \beta_3 SOE_{i,t} + \beta_4 POE_{i,t} + \beta_5 lnME_{t-1} + \beta_6 lnBTM_{t-1} + \beta_7 E/P_{t-1} + \beta_8 Turnover_{t-1} + \beta_9 SYNCH_{t-1} + \varepsilon_{i,t},$$

where the dependent variable is the stock price synchronicity, $SYNCH$. $TOPHOLD$ is the percentage of shares held by the largest shareholder. $SOE_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state, and zero otherwise. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), E/P ratio, Turnover, and the first lag of the dependent variable. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

Table 4.A 2 Propensity score matching

Panel A: propensity score regression (pre-matching)

	z-stats
lnBTM	0.571
	(3.78)
E/P ratio	0.001
	(0.07)
Analyst	0.016
	(5.27)
Tskew	1.739
	(3.89)
Sigma	–5.02
	(–3.16)
Industry	Yes
Obs.	961
Pseudo R^2	0.05

Panel B:

	Pre-matching				Post-matching			
	Treated	Control	Diff	t-stat	Treated	Control	Diff	t-stat
lnBTM	3.38	3.27	0.11	2.88	3.37	3.31	0.06	1.50
E/P ratio	2.93	2.71	0.22	0.66	2.53	2.30	0.23	1.09
Analyst	12.82	9.43	3.39	4.91	12.73	11.68	1.05	1.19
Tskew	0.00	–0.04	–0.04	–4.51	0.01	–0.01	0.02	0.96
Sigma	0.03	0.03	0.00	4.06	0.03	0.03	–0.00	–1.02

Note: This table presents the diagnostics and results for the propensity score matching. The sample is all the firms without missing matching variables in the year 2010, before the prudent monetary policy starts. The firms are matched using one-to-one nearest-neighbor logit model propensity score matching, without replacement, on a set of variables. Panel A reports the results from the logit model used in estimating the propensity scores for the treatment and control groups. The treatment group is the SOE portfolios, which contains firms with more than 50% of equity owned by the state. The control group is the POE portfolio, which contains firms with less than 5% of equity owned by the state. The dependent variable in the logit model is the SOE dummy, and indicator variable that equals to one for treatment firms, and zero otherwise. The matching variable contains lnBTM, EP ratio, Analyst, Tskew, Sigma, and industry. The coefficient estimates are reported with the z-statistics displayed in brackets below. Panel B reports the balance test results for the pairs of treatment and control firms before and after the matching.

Table 4.A 3 Difference-in-differences regression analysis for liquidity

	2003-2018			2006-2012		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Amihud	Turnover	RQS	Amihud	Turnover	RQS
SOE × Post	0.007**	–0.027***	0.002**	0.001***	–0.01***	0.01
	(2.19)	(–4.73)	(2.08)	(2.89)	(–3.46)	(0.78)
$lnME_{t-1}$	–0.006***	–0.01**	–0.01***	–0.04***	–0.03***	–0.02***
	(–3.60)	(–2.39)	(–6.79)	(–14.51)	(–14.82)	(–13.66)
$lnBTM_{t-1}$	0.01	0.93	0.10	–1.03***	1.26***	0.14
	(0.23)	(1.56)	(0.46)	(–4.58)	(6.21)	(1.52)
$Amihud_{t-1}$	–0.002***			0.59***		
	(–5.97)			(20.22)		
$Turnover_{t-1}$		0.634***			0.57***	
		(24.93)			(70.71)	
RQS_{t-1}			0.815***			0.66***
			(39.58)			(34.86)
Constant	0.190***	0.185***	0.121***	0.46***	0.33***	0.27***
	(3.83)	(3.14)	(6.21)	(14.57)	(15.69)	(14.22)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,094	77,094	77,094	30,143	30,143	30,143
R–squared	0.80	0.65	0.86	0.59	0.59	0.72
Adj. R–squared	0.797	0.650	0.855	0.585	0.584	0.710

Note: This table reports the results of the following difference-in-differences regression:

$$\text{Liquidity}_{i,t} = \alpha_0 + \beta_1 \text{ SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{lnME}_{i,t-1} + \beta_3 \text{lnBTM}_{i,t-1} + \beta_4 \text{Liquidity}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are liquidity measures. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state, and zero otherwise. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. We use a propensity score matched sample based on TableA1. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

Table 4.A 4 Difference-in-differences regression analysis for volatility

	2003-2018			2006-2012		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HLrange	Vol5	Vol30	HLrange	Vol5	Vol30
$SOE \times Post$	–0.04*	–0.003	–0.008*	–0.13***	–0.01***	–0.03***
	(–1.66)	(–1.43)	(–1.69)	(–5.37)	(–5.40)	(–5.45)
$lnME_{t-1}$	0.11**	0.006	0.02**	0.08***	–0.01	0.01***
	(2.50)	(1.45)	(2.21)	(5.18)	(–0.02)	(3.72)
$lnBTM_{t-1}$	9.23*	0.903*	1.74*	15.18***	1.53***	3.21***
	(1.80)	(1.92)	(1.87)	(10.86)	(11.73)	(10.52)
$HLrange_{t-1}$	0.55***			0.36***		
	(15.01)			(61.20)		
$Vol5_{t-1}$		0.58***			0.39***	
		(14.88)			(62.70)	
$Vol30_{t-1}$			0.56***			0.36***
			(14.12)			(59.43)
Constant	0.430	0.061	0.086	1.70***	0.21***	0.37***
	(0.82)	(1.27)	(0.89)	(11.83)	(15.12)	(11.71)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,094	77,094	77,094	30,143	30,143	30,143
R–squared	0.67	0.69	0.66	0.66	0.68	0.65
Adj. R–squared	0.669	0.691	0.656	0.651	0.675	0.646

Note: This table reports the results of the following difference–in–differences regression:

$$\text{Volatility}_{i,t} = \alpha_0 + \beta_1 \text{ SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{lnME}_{i,t-1} + \beta_3 \text{lnBTM}_{i,t-1} + \beta_5 \text{Volatility}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are volatility measures. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state, and zero otherwise. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain log market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. We use a propensity score matched sample based on TableA1. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

Table 4.A 5 Difference-in-differences regression analysis for price efficiency

	2003-2018			2006-2012		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	VR30_5	VR30_10	SYNCH	VR30_5	VR30_10	SYNCH
$SOE \times Post$	0.02**	0.02**	0.08**	0.01*	0.01	0.08**
	(2.53)	(2.59)	(2.28)	(1.81)	(1.50)	(2.51)
$lnME_{t-1}$	–0.08***	–0.07***	–0.12***	–0.08***	–0.07***	–0.08***
	(–8.69)	(–8.11)	(–3.45)	(–18.97)	(–17.43)	(–4.13)
$lnBTM_{t-1}$	1.01	0.59	2.20***	1.81***	1.20***	11.60***
	(1.02)	(0.66)	(7.95)	(4.53)	(3.29)	(6.56)
$VR30\_5_{t-1}$	0.17***			0.08***		
	(13.73)			(13.61)		
$VR30\_10_{t-1}$		0.15***			0.07***	
		(12.84)			(11.27)	
$SYNCH_{t-1}$			–0.19***			0.14***
			(–12.05)			(22.67)
Constant	1.39***	1.33***	0.58*	1.21***	1.27***	0.06
	(12.74)	(14.15)	(1.83)	(29.46)	(33.93)	(0.31)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,094	77,094	77,094	30,143	30,143	30,143
R–squared	0.14	0.12	0.18	0.12	0.10	0.21
Adj. R–squared	0.129	0.111	0.17	0.104	0.0807	0.191

Note: This table reports the results of the following difference-in-differences regression:

$$\text{Efficiency}_{i,t} = \alpha_0 + \beta_1 \text{SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{lnME}_{i,t-1} + \beta_3 \text{lnBTM}_{i,t-1} + \beta_4 \text{Efficiency}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are price efficiency measures. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state, and zero otherwise. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. We use a propensity score matched sample based on TableA1. t-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

Table 4.A 6 Difference-differences regression analysis for return

	2003-2018		2006-2012	
	(1)	(2)	(3)	(4)
$\text{SOE} \times \text{Post} \times Turnover_{t-1}$		–2.40*		–1.94
		(–1.91)		(–0.70)
$SOE \times Post$	–1.87***	–1.37***	–1.33	–1.12
	(–5.00)	(–2.91)	(–1.75)	(–1.15)
$\text{SOE} \times Turnover_{t-1}$		–1.74		–0.11
		(–1.08)		(–0.07)
$\text{Post} \times Turnover_{t-1}$		–2.84		–1.15
		(–1.51)		(–0.34)
$lnME_{\mathrm{t-1}}$	–2.89***	–2.83***	–6.02	–5.97
	(–4.28)	(–4.26)	(–1.52)	(–1.48)
$lnBTM_{\mathrm{t-1}}$	1.09	0.99	1.02	94.55
	(1.37)	(1.32)	(0.44)	(0.40)
$Turnover_{t-1}$	–5.31**	–1.87	–2.68	–1.92
	(–2.57)	(–0.82)	(–1.07)	(–0.50)
Ret_{t-1}	–0.02	–0.02	–0.08	–0.08
	(–0.43)	(–0.33)	(–1.15)	(–1.14)
Constant	23.89***	23.62**	49.45	49.29
	(3.09)	(2.46)	(1.28)	(1.27)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	77,094	77,094	30,143	30,143
R–squared	0.12	0.12	0.21	0.21
Adj. R–squared	0.113	0.114	0.190	0.190

Note: This table reports the results of the following difference-in-differences regression:

$$\text{Return}_{i,t} = \alpha_0 + \beta_1 \text{SOE}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{lnME}_{i,t-1} + \beta_3 \text{lnBTM}_{i,t-1} + \beta_4 \text{Turnover}_{i,t-1} + \beta_6 \text{Ret}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are price efficiency measures. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state, and zero otherwise. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), and the first lag of the dependent variable. We use a propensity score matched sample based on TableA1. *t*-statistics based on errors clustered by firm and time are presented in parentheses. The sample period is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded.

Table 4.A 7 Difference-in-Differences regression analysis for investment

	(1) Inv1	(2) Inv1	(3) Inv1	(4) Inv2	(5) Inv2	(6) Inv2
$SOE \times Post \times Inv$			–1.647**			–1.043
			(–2.20)			(–1.19)
$Treat \times Post$			1.637***			–0.815
			(2.80)			(–1.70)
$SOE \times Inv$		–1.299**	–0.814***		–1.064	0.715
		(–2.46)	(–3.01)		(–1.49)	(1.07)
Inv	–1.085*	–0.336	–0.970**	–0.897	–0.350	–0.476*
	(–1.98)	(–0.80)	(–2.47)	(–1.80)	(–1.19)	(–1.78)
$lnME_{t-1}$	–1.254***	–1.229***	–0.908***	–1.293	–1.262	–0.949*
	(–4.10)	(–4.07)	(–3.65)	(–1.77)	(–1.77)	(–1.80)
$lnBTM_{t-1}$	0.483	0.491	0.894**	0.435	0.449	0.790**
	(1.30)	(1.33)	(2.12)	(1.21)	(1.24)	(2.32)
$Turnover_{t-1}$	–7.500***	–7.557***	–6.049***	–7.799**	–7.862**	–6.071**
	(–3.91)	(–3.93)	(–3.25)	(–3.08)	(–3.06)	(–2.70)
Ret_{t-1}	0.013	0.013	–0.908***	0.015	0.015	–0.030
	(0.24)	(0.24)	(–3.65)	(0.26)	(0.26)	(–0.68)
Constant	13.230***	12.963***	7.190**	13.824	13.505	7.775
	(3.68)	(3.64)	(2.36)	(1.85)	(1.85)	(1.61)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,296	43,296	80,113	34106	34106	68775
R–squared	0.05	0.05	0.11	0.05	0.05	0.11
Adj. R–squared	0.0513	0.0515	0.110	0.0508	0.0505	0.113

Note: This table reports the results of the following difference-in-differences regression:

$$\text{Ret}_{i,t} = \alpha_0 + \beta_1 \text{SOE}_{i,t} \times \text{Post}_{i,t} \times \text{Inv} + \beta_2 \text{SOE}_{i,t} \times \text{Post}_{i,t} + \beta_3 \text{SOE}_{i,t} \times \text{Inv} + \beta_4 \text{Inv} + \beta_5 \text{lnME}_{i,t-1} + \beta_6 \text{lnBTM}_{i,t-1} + \beta_7 \text{Turnover}_{i,t-1} + \beta_8 \text{Ret}_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variables are price efficiency measures. SOE $_{i,t}$ is the dummy variable equal to one if a stock has more than 50% shares owned by the state, and zero otherwise. Post $_{i,t}$ is a dummy variable that equals one for observations since 2011. Inv is a firm's average investment expenditure in the 2009 and 2010, which is measured as cash payments for fixed assets, intangible assets, and other long-term assets from the cash flow statement minus cash receipts from selling these assets, scaled by beginning total assets. The control variables contain logarithm of the market capitalization (lnME), logarithm of the book-to-market ratio (lnBTM), Turnover, and the first lag of the dependent variable. We use a propensity score matched sample based on TableA1. The sample period for (1), (2), (4), and (5) is from January 2011 to May 2018. The sample period for Column (3) and (6) is from January 2003 to May 2018 and the policy implementation period from November 2008 to December 2010 is excluded. *t*-statistics based on errors clustered by firm and time are presented in parentheses.

Chapter 5

Conclusion

5.1. Summary

This dissertation studies the unique patterns of the Chinese stock market through the view of empirical asset pricing, including the day-of-week return seasonality, cross-sectional end-of-day effect, and the ownership concentration relationship with the market dynamics. Compared to the U.S. and other developed countries, the Chinese capital market has its own characteristics in several key aspects of market structure and participants, trading and settlement regulations, and regulatory environments. All those differences further induce different investors' trading behaviors and return patterns in the stock market.

The investigation of the **first paper (Chapter 2)** shows that the cross-sectional return seasonality in the Chinese stock market is related to the private money creation: the distinctive features of the money fund market incentivize speculative investors to rebalance their portfolio on specific days of the week. We find that the long-minus-short portfolio, going long the speculative stocks and going short the unspeculative stocks experiences significantly high positive returns on Thursdays and Fridays, while receive relatively low returns on the other days (Monday through Wednesday). This pattern contradicts the cross-sectional returns in the U.S. market, where long-minus-short portfolios receive positive returns on Monday and negative returns on Friday (Birru 2018).

This paper contributes to the existing literature in three aspects. First, this paper complements the knowledge on the topic of private money creation, which addresses the discussion of how privately provided assets can substitute publicly provided assets to provide investors with safe and liquid values. We extend this line of research to the stock market by studying whether private money creation can exert its disproportionate impact on stock prices. Second, this paper has provided a deeper insight into cross-sectional return seasonality and the explanation of asset pricing anomalies. To the best of my knowledge, we are the first to use the interconnection between the stock market and the money market to explain the daily seasonality of cross-sectional stock returns.

Our study also enriches Keloharju, Linnainmaa, and Nyberg (2021) mispricing explanation and Bogousslavsky (2016) infrequent rebalancing theory. Besides, we discuss the FinTech innovation in China and its implications in the modern financial markets. This paper presents a challenge to the conventional belief that the FinTech revolution and technology would improve market efficiency by reducing transaction costs and trading frictions in the financial system. Our findings suggest that the recent FinTech wave starting in 2013 in China enlarges the cross-sectional return predictability thus worsening the market price efficiency.

The **second paper (Chapter 3)** works on exploring the distinctive end-of-day pattern in stock cross-sectional returns in China. Compared to the pattern in the US, where the mispricing correction happens throughout the day except the last half-hour of trading, the intraday seasonality pattern in China is reversed (Bogousslavsky 2021). We find that the long-minus-short mispricing factor experiences significantly positive returns at the last half-hour trading interval (2:30-3:00 pm) but performs poorly during the other trading periods. The disposition effect of speculative stockholders could be the most potential explanation for this distinctive intraday seasonality in China. Specifically, investors have the incentive to sell out stock with prior capital gains at the end of the day, when the market is most liquid, and the transaction cost is the lowest.

This paper contributes to literature through three streams. First, this paper adds to the literature that works on the cross-sectional return seasonality. Our findings related to intraday half-hour interval cross-sectional returns provide insightful information to evaluate asset pricing mechanisms and to study the properties of the seasonality predictability. Our disposition effect mechanism provides an economic channel and direct evidence to support the statement that cross-sectional seasonality could arise from the predictable in- and out-flows (Keloharju, Linnainmaa, and Nyberg 2021).

Second, to the best of my knowledge, we are the first to study the disposition effect on the seasonality of asset returns. Based on the model of asset prices incorporating prospect theory built by Barberis, Jin, and Wang (2021) the behavioral model of either beliefs or preferences can be used to predict a wide range of anomalies. Our finding adds support to their arguments that the prospect theory and the disposition effect can be potential “behavioral” explanations for the asset pricing anomalies.

Third, we are the first one to decompose the intraday and overnight cross-sectional returns of the Chinese stock market. We uncover that the intraday cross-sectional return pattern is different from the U.S. and other developed countries. Our findings can deepen our understanding of the Chinese stock market and the importance of the investors’ trading behavior effect on the market performance.

In the **third paper (Chapter 4)**, using the panel data OLS regression analysis, our analysis reveals that ownership control by large shareholders, especially government-related institutions, hurts the stock market quality. In this paper, we use the Chinese stimulus package policy implementation after the 2008 global financial crisis as the exogenous shock to the ownership concentration status of state-owned enterprises (SOEs).

Empirically, we first show that the stimulus package injects liquidity into the capital market, resulting in overall improvements in market quality. Furthermore, our finding demonstrates that following the stimulus policy, SOEs exhibit less liquidity, volatility, and efficiency than other entities, relative to the pre-stimulus period. We also find that the stimulus package shock leads to decreased profitability for SOEs and increased profitability for POEs (Private-Owned Enterprises) in the stock market. Finally, to confirm the validity of our results, we conduct the difference-in-differences analysis and test the investment inefficiency during the stimulus period.

The contribution of this paper is twofold. First, we contribute to existing knowledge of the effect of corporate management on the secondary market. Our findings provide support for the adverse selection theory that ownership concentration induces information asymmetries and thus distorts market quality. We use the stimulus package policy as a natural experiment to validate the causal effect of government intervention and ownership structure on the firm’s performance and market efficiency in the stock market.

Second, this paper sheds new light on arguments for the effectiveness of the stimulus package implementation. The existing literature mostly focuses on the effect of the stimulus policy on the macro economies, such as employment and GDP (Ouyang and Peng 2015; Xue, Yilmazkuday, and Taylor 2020). Our findings offer a unique insight into the impact of the stimulus package on corporate governance. Previous literature on stimulus policy was limited to datasets from the early 2010s. We have updated the dataset to include data up to 2018, allowing us to examine the long-term effects of the macro-policy nine years after the implementation of the stimulus package.

5.2. Policy implications

The findings in this dissertation have important implications for policy makers and capital market investors.

In terms of the first paper (**Chapter 2**), based on the analysis before, the implications for policy design are that the shortage of assets with safety and liquidity values needs to be addressed. Safe assets are needed as stores of value and collateral (Gorton and Ordoñez 2022). Safe assets are provided both publicly, eg., government bonds, and privately, eg., ABS, MMFs. Private safe assets take the form of promises that private agents can make by transforming otherwise riskier and potentially non-pledgeable private assets. Thus, besides the development of public safe assets, the regulators should also encourage the existence of the safe private assets to improve the capital liquidity. For example, the regulators can promote the increase of private money creation by reducing the regulation constraints or implementing supportive policies.

Besides, the side-effects of the FinTech revolution also need to be noticed. As we discussed in the paper, the 2013 FinTech shock could exert a hidden impact on the other financial market, i.e., the stock market. Our results show that the recent FinTech revolution on money market funds in China unexpectedly exerts adverse externalities on the stock market by worsening price efficiency in general and amplifying the cross-sectional stock return predictability in particular. Thus, another important implication is that regulatory authority needs to pay close attention to the interconnection between the different financial sectors.

For the second paper (**Chapter 3**), the general policy implication is that the capital market regulators should pay attention to the trading in specific daily short-term intervals, especially the last half-hour. As shown in our results, the trading volatility is higher, and the market efficiency worsens before the market closes. Besides, the short-term return reversal is highly significant during the last half-hour trading interval. Regulators are supposed to implement efficient policy to make sure the market stability and market liquidity. This may involve establishing a regular reporting system for market participants to ensure the information transparency, developing an advanced surveillance system to monitor trading activities in real-time, and maintaining clear and open communication channels with different regulatory departments to provide guidance and reduce uncertainty during times of market stress.

Taken together the results of Chapters 2 and 3, for the capital market investors, including abroad and overseas, first, they should have a better understanding of the special features of the Chinese stock market. China has the world's second-largest stock market, which plays a crucial role in financing an economy that some forecasts predict will become the world's largest within the next decade. China's political and economic environments are notably different from those of the U.S. and other developed countries. In terms of the return seasonality, the day-of-the-week, and the intraday patterns contradict that of the U.S. Empirically, short-term investors with speculative stock holdings who have the tendency to leave the stock market need to pay more attention to the huge selling pressure during the last half-hour trading period and the end of the week (Thursday and Friday). Investors can also achieve the mispricing correction if they trade on the long-minus short strategy at the end of the week or at the end of the day.

For the third paper (**Chapter 4**), our work provides insightful findings for the macro policy makers and the state-owned firms managers.

Our results offer policy implications for the efficiency of the stimulus package implementation and the role of SOEs in economic recovery. Our study shows that the stimulus package can directly inject liquidity differently among firms with different ownership characteristics. Our paper also offers a particularly important insight in light of the impact of the stimulus package on corporate governance. For the stimulus policymakers, it is essential for them to accurately measure the efficiency of stimulus package implementation. In the short run, the stimulus policy may have a direct impact on the economic recovery, but in the long run, it may sabotage the market efficiency by giving unbalanced support to the government-related firms, e.g., more capital credits (loan support) going to the SOEs during the 2009 economic stimulus policy period. In the context of the Chinese market, to foster a balanced economic environment, market regulators should give more capital credits to private firms, which often face financial constraints unlike their state-owned counterparts. Furthermore, promoting an equitable business environment is important for the development of the Chinese economy. Regulators can mitigate the dominance of the SOEs by ensuring that POEs receive fair treatment in government contracts and credit support. Those measures can help to foster a more competitive and open market environment.

Based on our analysis, despite the continuing efforts of the Chinese government to reform its financial system, the issue of stock price inefficiency remains significant for firms with concentrated ownership, particularly for firms with government-related large shareholders, e.g., SOEs. To enhance market efficiency, it is vital that Chinese market regulators implement stringent policies requiring corporations, especially government related firms, to maintain higher standards of transparency in their news disclosures. This could include mandatory reporting of both financial and non-financial information in a timely and consistent manner, ensuring that all market participants have open access to critical data that may influence investment decisions. By establishing regular and detailed reporting cycles, regulators can minimize information asymmetry, thus stabilizing market volatility and bolstering investor confidence.

5.3. Limitations and suggestions for future research

There are some limitations in this dissertation that need to be addressed, which would be helpful for future studies on those topics.

In the first and second papers (**Chapters 2 and 3**), we gathered data from many different sources. The dataset lasts from 1996 (1999) to 2019 for Chapter 2 (3). Therefore, the seasonality patterns after 2019 are not taken into consideration. For future research, it would be interesting to test the effect of the Covid-19 pandemic on the stock market cross-sectional return seasonality. During the pandemic, the market had a period of turbulence, experiencing extremely high volatility and turnover. We would expect that the day-of-the-week effect fades during this period since the capital has the tendency to leave the stock market temperately and flow to safe heaven, e.g., money market fund, deposit market.

In this case, our prediction seems to contradict the findings of ‘Section 2.6.2: Time variation in the demand of safety’, where we hold that the association between abnormal demand of money market funds and the seasonal anomaly returns gets stronger in high market volatility (uncertainty) state than in low market volatility (uncertainty) state. For this section, our assumption is strict under the condition that the market is not in an extreme situation, i.e., financial crisis. For further research, we can take the situation of market turbulence into consideration.

Moreover, based on the data limitation, in this paper, we state that all types of investors, including individuals and institutions, have the tendency to do the portfolio rebalancing unevenly within the week and at the end of the day. Future studies can distinguish the trading behavior between different types of investors in the market. For **Chapter 2**, we would expect that the shock of the demand-for-safety driven by the Fintech revolution is more pronounced for individual investors than institutional investors. The institutional investors have the interbank and Repo market to get the market-level interest rate. In contrast, for individual investors, the emergence of the FinTech customized MMFs firstly offers them the chance to place the capital for market-level interest rate. Further empirical tests need to be done to test our predictions.

Next, for **Chapter 3**, the mechanism in terms of the end-of-day effect from the specific market perspective is not clear. In the current version, we explain the difference in the end-of-day pattern between China and the U.S. using the disposition effect mechanism. Also, we state that due to the limitation of the margin trading and short selling in the Chinese stock market, the overnight risk and institutional constraints factors that are used to explain the end-of-day effect in the U.S. are not applicable in the context of China. However, the disposition effect is a generalized concept that is also applicable in the U.S. market. Thus, confusion arises, why does not the disposition effect influence the U.S. market in this way? In the further study, we will try to address this question using the different market features of China. We propose that the shadow banking market offers the option for investors to place their capital before the stock market closes. For further research study, we plan to find the mechanism of the last half-hour trading from the shadow banking market as the complement for our disposition effect mechanism.

In terms of the methodologies, in the third paper (**Chapter 3**), the double sorting method is not enough, we need more direct evidence to show the impact of the disposition effect on the intraday return predictability. We can only see that compared to the low CGO decile, the high CGO decile with higher speculative characteristics has low returns, indicating the selling pressure for the speculative stocks with capital gain. However, we can observe that the predictability of the mispricing factor is consistent for all the CGO deciles. To check the effect of the disposition effect on the last half-hour trading behavior more accurately, we are planning to apply the Regression Discontinuity Design. For example, we can employ a RDD model to study stock investors' end-of-the-day response to CGO around the $0 (i.e., zero CGO) cutoff.

For the third paper (**Chapter 4**), the definition of state-owned enterprises (SOE) should be given more attention for further revision. Due to the data limitations, we define a firm as state-owned (SOE) if it has more than 50% of shares owned by the state, suggesting that the government has dominant controlling power. However, this definition is a bit controversial. For further study, it is necessary to add some new measures as the robustness test, e.g., using the ultimately controlling shareholder to define the SOE and POE.

Besides, for the methodology, we use the panel OLS regression to test the relationship between the ownership concentration and the market performance. However, in the long-term test, there may exist some omitted variables that influence the results and are not included in our regression, i.e., macro events, company innovations, and policy regulations. For further study, we need to address those concerns. Also, more work will need to be done to determine the effect of the stimulus package policy on the financial markets, not only from the side of the macro market but also from the micro-economy, i.e., trading behavioral, and corporate governance.

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