The Hidden Impact of Private Money Creation on the Cross Section of Stock Returns: Evidence from the FinTech-led Boom of Cash Investing *

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Abstract

Private money creation in the form of money market funds exerts its hidden impact on the stock market via the "dual-market clientele"—a subset of investors who infrequently demand safety by systematically exploiting the distinctive features of cash investing (as opposed to stock investing). Their trading behaviour has the power to explain the stylized daily seasonality 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. For identification, we use the FinTech-led real boom of cash investing as a quasi-natural experiment, and provide difference-in-differences evidence that the permanent shock to dual-market clientele's market participation *amplifies* the cross-sectional return seasonality by more than 100 percent. The enlarged seasonality comes from the short-leg speculative stocks, and is stronger in high volatility and uncertainty periods. Overall, our findings suggest that the rise of cash investing may impose externalities on the stock market.

JEL Classification: G11, G12, G23

Keywords: Money market funds, FinTech, Cross-sectional predictability, Seasonality, Dual-market clientele

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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)

1. Introduction

The resurgence of cash investing in the recent decade—the phenomenon that investors increasingly seek high quality money-like assets—has underpinned the importance of the proper re-design of money market instruments in the modern financial markets, as there is an apparent shortage of public safe assets such as Treasury bills (Krishnamurthy and Vissing-Jorgensen, 2012; Nagel, 2016).

Money market funds are the major player in this process: They facilitate the *private money creation* that caters to the increasing demand of safety (Brunnermeier and Niepelt, 2019; Kacperczyk et. al., 2021; Cipriani and La Spada, 2021). They offer *market-based* yields, which massively reduce the cost of financial intermediation in the financial system and contribute to *interest rate liberation* in the emerging markets. More crucially, they become the centerpiece of the recent wave of FinTech revolution in China. During this massive-scale FinTech revolution, BigTech-BigData platforms (such as Alipay and Wechat Pay) partner with investment companies to re-design money market funds with a number of innovative money-likeness features, which includes, but not limited to, (i) shares of money market mutual funds (MMMFs hereafter) 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. In short, cash investing proliferates in recent years (see **Figure 1**) with customized MMMFs providing FinTech firms a huge competitive advantage, through which they bring significant challenges and *disruptions* to the incumbents (commercial banks) in the traditional banking system (Goldstein, Jiang, and Karolyi, 2019; Buchak, Hu, and Wei, 2021). Yet, little is known whether and how private money creation "spills over" to other financial assets and instruments.

In this paper, we study the **hidden** (broad) impact of private money creation in the form of money market funds on the financial markets. We argue that cash investing in money-like assets has much broader implications in financial markets long *before* the recent FinTech wave: It exerts massive impacts *outside* the money market, and reshapes the stock market in significant and seemingly *unnoticeable* ways. One major yet hidden aspect of private money creation is that it strengthens the *daily* interconnection between the stock market and the money market, as the (ongoing) re-design of money market funds ensures that they cater to the fast-paced liquidity consumption and demand for safety in the market environment where it no longer takes days for investors to transfer money between cash accounts, bank accounts, and brokerage accounts. Innovation and technology advances accelerate the speed at which payments are made and transactions with financial instruments are settled, making it possible for short-term investor clientele to trade in multiple markets (at almost the same time) within a day. Therefore, analysing the asset prices at the *daily* frequency, as opposed to the conventional *monthly* frequency, would yield more insights on the broad implications of cash investing.

There also can be a hidden impact of private money creation on the stock market. It is well known that daily asset prices exhibit a cyclical pattern.[1] Some stocks reliably earn high or low returns relative to other stocks on certain days of the week (Birru, 2018; Hirshleifer et al., 2020; Keloharju et al., 2021). An interesting and crucial question that arises is how FinTech and innovations empowered cash investing shifts (or disrupts) the daily market dynamics. Liu et al. (2019) stress that it is crucial to allow for the unique features in China to deepen our understanding of asset pricing dynamics. Carpenter et al. (2021) highlight the importance of China's financial market in allocating resources for the world's second-largest economy. Goldstein, Jiang, Karolyi (2019) call for more research on China, because it is at the forefront of the global wave of FinTech revolution and has been experiencing unprecedented financial development in recent years.

Following these leads, we offer a novel clientele-based perspective on cash investing and its broad yet hidden impact on cyclical asset prices by acknowledging the growing power of the so-called "**dual-market clientele**", a subset of short-term investors who trade in both the money market and stock market. They actively exploit the distinctive features of cash investing by systematically shifting between private safe assets (i.e., money market funds) and risky assets (i.e., stocks) on specific days of the week. One distinctive feature of cash investing as opposed to stock investing is the yields accrued on a *calendar* day basis, which guarantees a non-negative return from money

[1] 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 more towards exploring the cross-sectional patterns (see Birru, 2018; Bogousslavsky, 2016; Keloharju et al., 2021; among others).

market funds on weekends, when the stock market "sleeps". Nevertheless, 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 these distinctive features 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 cash investing via MMMFs and MMETFs in **Section 2**. Moreover, the benefit of seeking safety should be more precious and valuable for speculative stocks for at least two reasons. First, investors are reluctant to hold speculative stocks for long due to relatively high holding costs and inventory risk concerns (Liu et al., 2020). Second, speculative stocks tend to be the ones that are more susceptible to overvaluation and (potential) price crashes, and have a less liquid (or perhaps no) derivative market to hedge these risks. Therefore, the relative proportion of dual-market clientele should be more pronounced in these stocks (as opposed to non-speculative stocks). This generates the anticipated seasonality in the cross section as predicted by the Bogousslavsky (2016) infrequent rebalancing theory, as more dual-market clientele self-select to infrequently adjust their holdings by shifting between speculative stocks and money market funds on specific days of the week (i.e., Thursday and Friday).

Based on the above reasoning, the central prediction of the **dual-market clientele-based mechanism** lies 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).*

Note our dual-market clientele-based mechanism generates a distinctive prediction on the daily seasonality in the cross section: Long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks uniformly experience *low* Monday-through-Wednesday returns and *high* Thursday-through-Friday returns. Such a prediction is in sharp contrast to the return pattern implied by the investor psychology theory (Birru, 2018; Hirshleifer et al., 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), as investors' mood increases cyclically on Friday and decreases on Monday. Instead, our clientele-based mechanism reconciles with, and 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 (i.e., a symptom of temporary mispricing).[2]

Empirically, we find consistent evidence in support of the central prediction of the **dual-market clientele-based mechanism**: 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 (see **Figure 2** and **Section 4.1**). The magnitude of this daily seasonality in China 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.

Next, we examine whether the stylized daily seasonality can be explained by the demand for safety from the dual-market clientele who tend to shift funds from the stock market to the money market on particular weekdays. The approach to testing this explanation, however, is confronted with identification difficulties. 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 very likely to affect both stock returns and the incentive to seek safe assets (e.g. Hirshleifer et al., 2020). Second, the presence of seasonality in returns can drive traders to seek safe assets, representing the typical reverse-causality concern. To alleviate these concerns, we require an empirical setting where a plausible exogenous shock to the extent of the participation by the short-term dual-market clientele affects the cross-sectional stock returns. Thus, we exploit the

[2] Note although we expect a seasonal reversal within the week (i.e., a Monday-through-Wednesday reversal effect in the sense of Keloharju et al., (2021)), our central prediction is much stronger for the Thursday-through-Friday effect than for the Monday-through-Wednesday effect for at least two reasons. First, unlike the harsh deadline to leave the stock market on Thursday and Friday (in order to tap the money market yields over the weekend), there is no strict "deadline" for dual-market clientele to re-enter the stock market. Due to real-world cost concerns (i.e., bid-ask spread and price impact), they could spread their buy orders evenly on Monday through Wednesday to minimize the transaction cost. This leads to a much smaller chance for us to observe a concentrated buying pressure for speculative stocks on Monday through Wednesday (that is equally strong as the selling pressure on Thursday through Friday). Second, the demand-of-safety motive on Thursday through Friday may also indicate that some of the clientele would park their money outside the stock market for a prolong period of time (i.e., longer than a weekend), leaving their date to re-enter the stock market undecided. Therefore, all we require is that whenever these clientele decide to exit the stock market, they have a strong tendency to do it on Thursday through Friday (rather than on Monday through Wednesday).
Our definition of the dual-market clientele encompasses both retail and institutional investors, because both retail investors and institutions have the motive to demand for safety. This is consistent with the empirical evidence that both retail investors and institutions herd or engage in correlated trading (Keloharju et al., 2021). For example, Lakonishok et al. (1992) and Wermers (1999) show that pension and mutual funds herd, in particular when trading small stocks. There are also mounting evidence that individual investors engage in correlated trading in speculative stocks (Han and Kumar, 2013; Kumar et al., 2016; among others).

event of China's FinTech-led real boom of cash investing in 2013, as a quasi-natural experiment, to test the dual-market clientele-based explanation for the daily seasonality. In particular, the year of 2013 is arguably the first year of China's FinTech revolution, which is marked by the emergence of FinTech-customized MMMFs and MMETFs. These landmark events in 2013 brought revolutionary changes to money market funds, including using MMMF shares as a method of payments, lowering the minimum investment amount to one Chinese yuan, offering real-time redemption at par, and allowing trading of MMETFs in the secondary market. All of these favourable changes set new industry standards for money market funds, and ultimately lead to the real boom of cash investing in 2013 and thereafter. To the extent that an exogenous increase in the participation by short-term dual-market clientele attracts *more* of their money to shift from the stock market to the money market, we expect that the day-of-the-week seasonality of speculative stocks relative to their non-speculative counterparts is amplified following 2013 (**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**).

To test **Hypotheses 2** and **3**, we employ a difference-in-differences framework: For each anomaly variable, we compare the change in the return spread between two monthly 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-led real boom of cash investing. Empirically, we document strong evidence supporting **Hypothesis 2**. For example, for the aggregated analysis when we pool all anomaly strategies together, we find that the Thursday-through-Friday long-short benchmark-adjusted return increases by 1.15% per month more than its Monday-through-Wednesday counterpart following the 2013 FinTech-led real boom of money market funds. This confirms that the day-of-the-week seasonality is amplified after the prosperity of cash investing from 2013 onwards.

Using the same difference-in-differences framework for the long-leg and short-leg portfolios, we also find consistent evidence in support of **Hypothesis 3** that the increase of the daily seasonality stems mainly from the short-leg portfolio of speculative stocks: Their Thursday-through-Friday return drops significantly more than the Monday-through-Wednesday counterpart, following the "favourable" changes introduced by FinTech-customized MMMFs and MMETFs in 2013.

To validate the dual-market clientele-based mechanism as an explanation for the observed seasonal pattern of returns, we explore time-series variation in demand for safety. Our clientele-based mechanism implies that short-term dual-market investors have to respect the pre-determined deadline (i.e., Thursday and Friday) by either subscribing MMMFs on Thursday or buying MMETFs on Friday, so that they could reap the low-risk yields over the weekend. Under this explanation, when there is greater demand for safety, we should observe greater underperformance of speculative stocks. To be specific, we propose that the daily Thursday-through-Friday return of speculative stocks relative to the Monday-through-Wednesday counterpart should be lower on the Thursdays and Fridays with an unusually larger demand for safety from the short-term dual-market clientele who shift more money from the stock market to the money market (**Hypothesis 4**). Empirically, we use the daily abnormal order imbalance of MMETFs as the proxy of the demand of safety by the short-term dual-market investors. For ease of interpretation on its market outcome, we construct a dummy variable that identifies the (unusual) Thursdays and Fridays when there is an abnormally large order imbalance of MMETFs. Consistent with our prediction, we establish a strong empirical relation that the magnitude of the underperformance of speculative stocks (relative to the non-speculative stocks) becomes much larger when there is abnormally higher buying pressure of the MMETF shares on Thursdays and Fridays. Moreover, this amplified daily seasonality on these "abnormal" Thursdays and Fridays stems purely from the short-leg speculative stocks, confirming that the clientele-based mechanism has a disproportionate impact on speculative stocks in the cross section.

To shed more light on the time-varying demand of safety, we also test whether the impact of cash investing on the daily seasonality of anomaly returns varies over different market states. We argue that the interrelation between the magnitude of the daily seasonality and the demand of safety is likely to hold stronger in times of high volatility or high uncertainty (**Hypothesis 5**). This is because the safe haven attributes of money market funds are more precious when investors fear for market turbulence or elevated uncertainty. Thus, short-term dual-market investors have more incentives to seek safety and become more reluctant to hold speculative stocks over the weekends *precisely* when the overall market is in turbulent or uncertain states. To test this notion, we split the whole sample period into high- and low-volatility (low-uncertainty) sub-periods, and find consistent evidence that the additional daily seasonality on the Thursdays and Fridays with an unexpectedly large buying pressure of the MMETF shares holds strongly in high market volatility (uncertainty) sub-periods, but is fairly weak in the low market volatility (uncertainty) sub-periods, confirming the presence of the safe haven effect. Moreover, this incremental increase in the daily seasonality during the high market volatility (uncertainty) sub-periods stems entirely from the short-leg speculative stocks.

Next, we consider several alternative explanations, as one might argue that some of our empirical findings could arise for other legitimate reasons. Firstly, we test whether the daily seasonality is due to the timing of the macroeconomic news release. This is because macroeconomic news announcements could generate cross-sectional patterns, for instance, due to liquidity shocks that impact some stocks disproportionally more than others (Birru, 2018). By excluding days with central bank announcements and macroeconomic news releases such as GDP, PPI, and CPI, we find that the day-of-the-week pattern of the anomaly returns remains virtually intact. Therefore, the primary results are not driven by macroeconomic news announcements. Secondly, we verify whether the daily seasonality of the cross-sectional variation in average stock returns is driven by the timing of firm-specific news. After excluding days with earnings announcements from the sample, we find the magnitude of the long-short anomaly returns over different days of the week remains virtually unchanged. This indicates that the release of firm-specific news is unlikely to be the main reason for the documented daily seasonality. 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 et al., 2020). We find that the daily seasonality of the long-short anomaly returns remains virtually intact, when we exclude the third week of each month (i.e., the settlement week) in our analysis. Therefore, the result is inconsistent with the systematic trading due to derivative contracts settled on a particular week of the month. Fourthly, as short selling activity is permitted for certain stocks in the Chinese stock market, it is plausible that the observed cross-sectional pattern of returns can be induced by excessive selling pressure arising from systematically short selling speculative stocks on Thursdays and Fridays. By examining the daily change in aggregated short-selling positions across different days of the week, we find, however, exactly the opposite pattern as the alternative explanation predicts: the level of short selling is low on Thursdays and Fridays and high on the other weekdays. This evidence suggests that short-sellers tend to reduce their short positions, rather than open more short positions, on Thursdays and Fridays. Moreover, the day-of-the-week effect is more pronounced on the subset of non-eligible stocks (i.e., those cannot be short-sold by regulation) than the subset of eligible stocks (i.e., those can be short-sold by regulation). Therefore, short selling is unlikely to be the main force that drives the daily seasonality of the cross-sectional returns. Overall, none of these alternative explanations is compatible with the empirical patterns.

In addition, we also explore the portfolio implications by examining the net performance of the Thursday-through-Friday long-short strategy. We show that the relatively high return of this seasonality-based strategy more than offset the transaction costs. Moreover, an additional gain (roughly 16 bps per month) from cash investing enhances the total profits of the Thursday-through-Friday strategy, as one could invest in money market funds over the rest of the week. Collectively, transaction costs are not a major concern for our primary findings.

Finally, we also perform a battery of further analysis and robustness checks. The motive for the dual-market clientele to seek safety may not only be confined to Thursdays and Fridays, but also be shown on weekdays prior to long holidays. Consistent with this notion, we find strong daily seasonality over the two business days immediately before long holidays in China (i.e., holiday effect). We also disentangle the enhanced seasonality between Thursdays and Fridays since 2013. We argue that the Friday effect is due to the MMETF features, because MMETFs offer a *unique* last-minute solution to earn the guaranteed yields over the weekend on Friday, rather than on Thursday. In comparison, the increased Thursday effect since 2013 is largely attributed to the general FinTech-related features. The results suggest the Thursday effect is more pronounced than the Friday effect in terms of economic magnitude.

This paper makes three contributions to our understanding of asset prices in the financial markets: First, our paper complements the evolving literature on private money creation and demand for safety (Krishnamurthy and Vissing-Jorgensen, 2012; Nagel, 2016; Kacperczyk et. al., 2021; Cipriani and La Spada, 2021). To the best of our knowledge, we are the first to explore the broad implications of cash investing, a recent financial phenomenon that originates in the money market but has far-reaching implications on the financial system. By highlighting the interconnection between the money market and the stock market, our findings reveal that China's major financial development *outside* the stock market—the rise of cash investing that caters to the burgeoning demand of safety and liquidity—unintendedly impact stock prices, particularly the relative price of speculative stocks (as opposed to non-speculative stocks), leading to the striking daily seasonal pattern in the cross section.

Second, our paper contributes to the growing literature on cross-sectional return seasonality and the clientele-based explanation of asset pricing anomalies (Birru, 2018; Bogousslavsky, 2016; Keloharju, Linnainmaa, and Nyberg, 2016, 2021). We uncover a novel clientele-based mechanism that rationalizes the stylized daily seasonality in China. The dual-market clientele-based explanation—a subset of short-term investors engages in correlated trading on specific days of the week by shifting between stock investing and cash investing—provides an *exact* mechanism and direct evidence to support the perspective that daily 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 generates novel insights to understand the economic motive (i.e., demand of safety) why a subset of investors infrequently rebalance their portfolios over certain time horizon, which in turn enriches the Bogousslavsky (2016) infrequent rebalancing theory.

Thirdly, we provide novel evidence that contributes to the emerging literature on FinTech and its implications in the modern financial markets (Goldstein, Jiang, and Karolyi, 2019). 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: Recent FinTech revolution in China that caters to the increasing demand of safety and liquidity consumption 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 provides background on money market funds and the FinTech revolution in China. Section 3 describes the data and the anomaly variables. Section 4 provides the motivating evidence. Section 5 presents the main results of our empirical analysis. Section 6 performs further analysis and robustness checks. Section 7 concludes.

2. Background on money market funds and China's private money creation

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 (Kacperczyk et. al., 2021; Cipriani and La Spada, 2021). Money market funds are the major player in this process: They seek to preserve the principle of an investment at $1.00 per share, while offering a return higher than that in the bank deposit accounts (Kacperczyk and Schnabl, 2010).[3]

China introduced the money market mutual funds in the early 2000s, as an investment alternative that complements the existing products offered by investment companies (i.e., equity and bond funds). Over time, they gradually become one of the most popular investing vehicles in China: The sheer volume of cash investing—measured by the total assets under management (AUM) in money market mutual funds (MMMMFs hereafter) and money market exchange-traded funds (MMETFs hereafter)—exceeds 7.70 trillion Chinese yuan (equivalent to 1.20 trillion USD) as of June 2019, surpassing the total AUM of equity, bond, balanced, and other funds combined (see **Table A1** in the appendix).

[3] Although the MMMF shares are issued at par of 1 Chinese yuan per share in China (i.e., similar to $1.00 per share in the context of the US), an investor is required to subscribe at least 5,000 shares in the early 2000s. That is, the minimum investment is at least 5,000 Chinese yuan. The minimum investment amount has been massively reduced in recent years due to FinTech applications in 2013 (see **Section 2.2**).

The ongoing re-design of the money market funds that caters to fast-paced liquidity and safety demand of investors is vital to the rise of money market funds in China. This is achieved partly because the holdings of these funds are subject to maturity, quality, and diversification requirements designed to ensure their safety and liquidity. Due to strict regulatory requirements (which, in many ways, mimic the Rule 2a-7 of the Investment Company Act of 1947 in the US), Chinese MMMFs are restricted to investing only in short-term investment vehicles with an AA+ or a higher rating by the national credit rating agencies. The investment scope of the MMMFs in China includes call deposits, term deposits, (interbank) negotiable certificates of deposit, commercial papers, bank bills, repos, short-term government bonds, and other money market instruments that are permitted by laws and regulations and/or by the regulatory body—the China Securities Regulatory Commission (CSRC).[4]

The growth of money market funds in China is also contributed by a number of other distinctive features:

First, money market funds offer a relatively high *market-based* yield, which is better than the *regulated* deposit rates offered by commercial banks (i.e., interest rate ceilings imposed by central banks on depository institutions). For instance, the annualized yield (after fees) of the top 10 largest MMMFs ranges between 2.305% p.a. and 2.915% p.a. as of June 2019. In comparison, the 1-year bank deposit rate remains low for years at 1.5% p.a. as of June 2019.

Second, money market funds are featured with its on-demand redemption at par (i.e., a flexible investment horizon). In comparison, other competing money market instruments such as bank deposits and wealth management products (WMPs) normally have a fixed term over which the investors cannot withdraw the money early (otherwise, investors would incur a financial loss (i.e., penalty) for early withdrawals). For that reason, MMMFs (and MMETFs) are the usual place where short-term dual-market investors could temporarily park their money outside the stock market.

Third, money market funds in China adopt a "user-friendly" pro-rata fee structure from day one (i.e., since the early 2000s). Under the pro-rata fee structure, there are NO costs associated with the subscription and redemption of the MMMF shares (i.e., no front-end and back-end load fees). This

[4] The (re-)design of money market funds is a complex and dynamic process, which includes adjusting the portfolio holdings and portfolio duration, refining the fee structures, adopting proper valuation method (i.e., stable NAV), enhancing the marketability (i.e., how transaction of these funds are handled) and the money-likeness features, and other fit-for-purpose features. The (re-)designing process ensures that the funds could adapt to the continuous upgrade of financial infrastructure, and cater to the increasing liquidity and safety demand of the investors. Arguably, the re-design of money market products 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.

makes subscribing or redeeming the MMMF shares as if putting cash into or taking cash out of a real wallet. To recoup the marketing and distribution expenses, MMMFs charge the 12b-1 fee (i.e., a so-called sales and service fee in the Chinese context), which is expensed on a pro rata basis. The 12b-1 fee usually varies from 0.01% to 0.25% per annum. Therefore, all fees associated with the MMMFs are charged on a pro rata basis.[5]

2.1. The misalignment between interest accrual and trading of money market funds

One distinctive feature of cash investing via MMMFs or MMETFs (as opposed to stock investing) is the yields earned on a *calendar* day basis. Per nature of the money market instruments, interest incomes are accrued on a calendar day basis, including Saturday and Sunday. This ensures that the positive return continue to accumulate for money market funds over the weekend when the stock market "sleeps". However, trading (clearance and settlement) of money market funds is operated only on a *business* day basis. This misalignment between the interest income that accrues on *calendar* days and the clearance and settlement of money market funds that operates on *business* days induces short-term dual-market clientele—those who demand for safety by temporarily parking the money outside the stock market—to display a strong tendency to shift their stock holdings to the money-like assets at the end of the week (i.e., Thursday and Friday) rather than at the start of the (next) week.

Note the clearance and settlement for the subscription (and redemption) of money market funds take one *business* day (i.e., the next business day rule). Therefore, if a discerning short-term dual-market 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 **Figure A3** in the appendix for the timeline of the subscription and interest accrual).

[5] 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 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.

2.2. The 2013 FinTech-led real boom of cash investing

Notwithstanding the steady year-by-year growth of China's private money creation (i.e., money market funds) in the 2000s, the rise of cash investing in China is unprecedented over the recent years: 2013–present (see **Figure 1**). This overwhelming growth since 2013 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 A1** in the appendix).

[Insert **Figure 1** about here]

FinTech revolution and innovations are the key drivers behind China's recent boom of cash investing since 2013. The launch of Yu Ebao—the first FinTech-customized MMMF in China—on the Alipay platform in 2013 marks the onset of the FinTech revolution in China (Chen, 2016; Buchak, Hu, and Wei, 2021; Hua and Huang, 2021).[6] Moreover, the initiative of introducing money market exchange-traded funds over the same year further complements this FinTech and innovation-led wave of cash investing in China.

FinTech revolution. Goldstein, Jiang, Karolyi (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 wave that is led by BigTech-BigData platforms (such as Alipay and Wechat Pay) in China. For example, as the first-ever FinTech-customized MMMF in China, Yu Ebao turns out a major success: More than a third of Chinese invest in this fund, and it quickly becomes the world's largest money market mutual fund in 2017.[7] As of June 2019, the fund has a total AUM of RMB 1,033.56 billion, which is roughly four times the AUM of the second largest MMMF in China.

[6] Yu Ebao (in Chinese: 余额宝) refers to the Tianhong YuE Bao Money Market Fund (ticker: 000198) which emerges in June 2013. Note the sector of money market funds is highly competitive. The success of Yu Ebao and its FinTech-related features (as we explain in later paragraphs) quickly set the example and industry standards for other existing and newly issued money market funds. Therefore, throughout the article, we use the term **FinTech-customized MMMFs** to refer to all those 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) and are supported by FinTech and online platforms.

[7] 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
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During the recent wave of China's FinTech revolution, BigTech-BigData platforms team up with investment companies to re-design the money market funds with a number of innovative money-likeness features that fit the fast-paced digital environment:

First and most importantly, shares of the FinTech-customized MMMFs become the *de facto* money (i.e., e-currency) in the FinTech era. BigTech-BigData platforms such as Alipay and Wechat Pay set the new industry standards by adopting shares of these tailored MMMFs as the 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 revolution that enhances the money-likeness feature of money market funds. Strictly speaking, this is not just increasing the money-likeness features. Rather, it simply turns money market funds directly into real money (i.e., in the form of e-currency). 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 critical for these BigTech-BigData firms/platforms 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. In fact, the success of these FinTech-customized MMMFs provides FinTech firms/platforms a huge competitive advantage, through which they bring significant challenges and disruptions to the incumbents (i.e., commercial banks).

Second, the FinTech revolution leads most FinTech-customized MMMFs to adopt the "one-dollar" minimum investment amount. That is, the minimum investment amount has been significantly reduced to either one Chinese yuan (equivalent to 100 Chinese cents) or one Chinese cent. Note prior to the FinTech revolution, MMMFs used to have a much higher investment hurdle, as their minimum investment amount are at least 5,000 Chinese yuan. The reduction in minimum investment amount is crucial for the FinTech-customized MMMFs because they are initially 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 shares of these MMMFs can be converted into cash in real time effectively removes the conventional one-business-day redemption requirement. The shortened time in redemption significantly enhances the money-likeness features of the FinTech-customized MMMFs.

Financial innovation. 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. MMETFs bring innovative features that better cater to the increasing demand for safety and fast-paced liquidity consumption: 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). For investors who are less financially literate, the introduction of MMETFs reduces the hurdle of cash investing and enables them to shift between safe assets (i.e., cash investing) and risky assets (i.e., stock investing) with ease. MMETFs have also become a popular money market instrument since their introduction in January 2013. As of June 2019, MMETFs hold a total AUM worth RMB 236.8 billion.

One key implication of the launch of MMETFs is that they offer a last-minute solution for short-term dual-market investors to seek safety and earn the yields over the (first) weekend by trading on Friday, rather than on Thursday (see **Figure A4** in the appendix for the timeline of the purchase and interest accrual of MMETFs). Recall an investor has to submit the order to subscribe the MMMF shares on Thursday *at the latest* to earn the guaranteed yield over the weekend, given that the subscription of the MMMF shares take one business day (i.e., the next business day rule).

We are aware that the launches of Yu Ebao (FinTech revolution) and MMETFs (financial innovation) are arguably 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 on the market: 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 cash investing from 2013 onwards. Therefore, for ease of exposition, we treat them as one joint event under the grand theme of China's FinTech-led real boom of cash investing for our baseline analysis in **Section 5**. However, we do disentangle their respective impacts in further analysis (in **Section 6.4**).

2.3. The broad implications

We should stress here that the 2013 FinTech-led real boom of cash investing and its related re-design on money market funds (i.e., these tailored changes/features) should not be treated lightly. The private money creation in the form of money market funds has much broader implications *outside* the money market, and reshapes the stock market in significant yet *unnoticeable* ways. One *hidden* aspect of the 2013 real boom of cash investing is that it further strengthens the existing *daily* connection between the money market and the stock market. These "favourable" changes (such as MMMF shares as a method of payments, lowering the minimum investment amount, offering real-time redemption, and introducing MMETFs) have significantly increased the money-likeness features, and lowered the hurdles and costs in fulfilling the increasing demand for fast-paced liquidity consumption and safety, empowering *more* money to move between safety (money market funds) and risk (stocks) on a daily basis.

This increased connection between the money market and the stock market should be more pronounced for speculative stocks as opposed to non-speculative stocks, because short-term investors self-select to hold particular assets and trade at a particular time (i.e., the clientele effect). As is explained in Liu, Wang, Yu, and Zhao (2021), the positions to hold speculative stocks are short-lived for holding costs and inventory risk concerns. Cash investing offers an exit route 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 starts).

In principle, the 2013 FinTech-led real boom of cash investing represents a permanent shock to the market participation by short-term dual-market clientele, and following the shock we should expect that there is *more* of their money to move *cyclically* in and out of the stock market and the money market on specific days of the week.[8] Irrespective of the investors' preference of MMMFs or MMETFs, the rigid cut-off date to earn the yields over the weekend dictates that when it comes to shifting from stock investing (i.e., speculative stocks) to cash investing, they tend to leave the stock market on Thursday and Friday rather than on Monday, Tuesday, and Wednesday. Therefore, the proliferation of money market funds from 2013 onwards offers a natural experiment for us to validate the causal effect of the increased market participation by the dual-market clientele (i.e., more demand for past-paced liquidity consumption and safety) on the daily seasonality of cross-sectional returns (see **Section 5**).

3. Data and variables

3.1. Data and data sources

[8] We are aware that the FinTech-led real boom of cash investing also encourage other investors (such as online consumers), not just the dual-market clientele, to put their money into money market funds. This is actually beneficial to dual-market clientele, because more participation by heterogeneous investors reduces the run risk of the money market funds, so that the collective trading behaviour of dual-market clientele (on specific days of the week) would less likely to cause liquidity issues for these large-sized funds.

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 et al. (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 & 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.

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 et al., 2016). These anomaly measures include idiosyncratic volatility (Ivol), lottery demand (Max), turnover ratio (Turnover), return volatility (Volatility), and market beta (Beta). As all of these anomaly measures capture a certain dimension of the speculative nature of the stock, 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 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.

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.

3.3. Descriptive statistics

In this section, we show that the portfolios of our interests have the return patterns that are consistent with the empirical literature: Speculative stocks earn lower average returns than non-speculative stocks (Bali et al., 2011; Kumar, 2009). Each month we sort stocks (in ascending order) into decile portfolios based on one of the anomaly variables (in **subsections 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 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 the non-speculative stocks and selling the speculative stocks. The design of the long-short portfolios is to ensure that it produces the positive expected returns 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.

[Insert **Table 1** here]

4. Motivating evidence

4.1. The day-of-the-week effect

In this section, we first examine the day-of-the-week effect of the long-short anomaly strategies over the full sample period. The central prediction of the dual-market clientele-based mechanism 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), as the short-term dual-market clientele trade in concert to reduce their stock holdings for safety (i.e., less risk-taking) by the end of the week. 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 anomaly portfolios (as in **Section 3.3**). The portfolios are value-weighted and rebalanced monthly. We then calculate the monthly Monday-through-Wednesday (Thursday-through-Friday) portfolio returns by accumulating the daily returns on Mondays, Tuesdays, and Wednesdays (on Thursday and Friday) within each month.

Figure 2 visualizes the average performance of the anomaly strategies on Monday-through-Wednesday and Thursday-through-Friday, respectively. It depicts a striking daily seasonality 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 Monday through Wednesday and *highly positive* returns Thursday through Friday. In **Table 2**, the average excess returns of the long-short anomaly strategies are uniformly negative on Monday-through-Wednesday, ranging from –48 bps to –7 bps per month over the sample period. In comparison, the excess returns become highly positive on Thursday-through-Friday, which are all statistically significant at the 1% level. From an economic perspective, the Thursday-through-Friday returns are 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 usually larger than their all-weekday counterparts in **Table 1**).

[Insert **Figure 2** about here]

The same salient pattern emerges when we evaluate the risk-adjusted performance under alternative factor models. For example, these 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.

Overall, long-short anomaly strategies that buy non-speculative stocks and sell speculative stocks experience *low* returns Monday through Wednesday and *high* returns Thursday through Friday in China. When interpreting the evidence from **Tables 1** and **2** collectively, it becomes clear that the magnitude of this daily seasonality in China 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. This striking day-of-the-week effect is consistent with the central prediction of our dual-market clientele-based mechanism (**Hypothesis 1**).

[Insert **Table 2** here]

4.2. Asymmetry in long and short legs

We also examine the daily seasonality for the long-leg and short-leg portfolios, respectively. **Table 3** compares the performance of the non-speculative stocks in the long-leg portfolio with that of the speculative stocks in the short-leg portfolio. As it stands, both the excess returns and the risk-adjusted returns for the non-speculative stocks (i.e., the long-leg portfolio) are indistinguishable from zero on Thursday and Friday, indicating that there are no material price changes for these stocks at the end of the week. In comparison, the speculative stocks (i.e., the short-leg portfolio) experience large price drops on Thursday and Friday: The raw returns are highly negative and sizeable, ranging from –0.94% (*t*-statistics = –3.14) to –1.59% (*t*-statistics = –4.34) per month for the anomaly variables. 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).

[Insert **Table 3** here]

Table 4 reports the Monday-through-Wednesday performance of the non-speculative stocks (i.e., long leg) and the speculative stocks (i.e., short leg), respectively. Moving across the table, it appears that average Monday-through-Wednesday returns are positive for both the speculative stocks and non-speculative stocks. This general pattern holds for both the raw returns and the risk-adjusted returns. However, the positive Monday-through-Wednesday phenomenon is fairly weak, and none of these returns are statistically significant.

When interpreting the evidence from **Tables 2, 3, and 4** collectively, it becomes clear that speculative stocks tend to vastly underperform their non-speculative counterparts at the end of the week: Thursday and Friday. However, the return differential on the remaining part of the week (Monday through Wednesday) is fairly small between speculative and non-speculative stocks. This is somewhat expected, because our central prediction (**Hypothesis 1**) speaks mainly to the concentrated selling pressure for speculative stocks on Thursday through Friday (i.e., increased demand of safety over the forthcoming non-trading weekend). Unlike the harsh deadline to leave the stock market on Thursday through Friday, there is no such "deadline" for dual-market clientele to re-enter the stock market on Monday through Wednesday. Instead, they could execute their buying orders (for speculative stocks) on any weekdays. Therefore, the seasonal reversal on Monday-through-Wednesday is much weaker in magnitude compared to the Thursday-through-Friday phenomenon. Nevertheless, much of the daily seasonality in the cross section is driven by speculative stocks in the short-leg portfolio.[9]

[9] Consistent with our central prediction, we 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 exists a similar unbalanced buying pressure of MMETFs (i.e., cash investing) at the end of the week (see **Figure 3**), suggesting the strong interconnection between stock investing and cash investing. We formally test this interconnection in **Section 5**.

[Insert **Table 4** here]

5. Empirical analysis

As stated in the introduction (**Section 1**), our remaining four testable hypotheses are summarized as follows.

The former two hypotheses (**Hypotheses 2** and **3**) are related to the causal effect of increased market participation by the dual-market clientele on the day-of-the-week effect of the cross-sectional stock returns.

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-led real boom of cash investing.*

Hypothesis 3: *The increased day-of-the-week seasonality following the 2013 FinTech revolution-led real boom of cash investing 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 prosperity of cash investing since 2013.*

We also test two additional hypotheses, **Hypotheses 4** and **5**, which are based on the daily observations.

Hypothesis 4a: *The day-of-the-week seasonality in long-short anomaly returns is more pronounced on Thursday and/or Friday with an unusually large demand of safety. That is, the daily Thursday-through-Friday return relative to the Monday-through-Wednesday counterpart is further increased on Thursday and/or Friday with an unusually large abnormal order imbalance of Money Market ETFs.*

Hypothesis 4b: *The increased daily Thursday-through-Friday return relative to the Monday-through-Wednesday counterpart on Thursday and/or Fridays with an unusually large abnormal order imbalance of Money Market ETFs stems mainly from the short-leg anomaly portfolios.*

Hypothesis 5a: *The day-of-the-week seasonality in long-short anomaly returns is more pronounced in high market volatility (uncertainty) periods than in low market volatility (uncertainty) periods. That is, the daily Thursday-through-Friday return relative to the Monday-through-Wednesday* *counterpart is further increased on periods with high market volatility (uncertainty) than in periods with low market volatility (uncertainty).*

Hypothesis 5b: *The increased daily Thursday-through-Friday return relative to the Monday-through-Wednesday counterpart during the high market volatility (uncertainty) periods stems mainly from the short-leg anomaly portfolios.*

5.1. The difference-in-differences framework

In this subsection, we validate the two main hypotheses, **Hypotheses 2** and **3**. As discussed in **Section 1**, the 2013 FinTech revolution (and innovations) leads to the real boom of cash investing in recent years, empowering money market funds to better cater to the increased demand for past-paced liquidity consumption and safety. One key implication of this FinTech-related boom in cash investing is that it enables *more* money (of the short-term dual-market clientele) to moves *cyclically* between the stock market and the money market on specific days of the week. Therefore, we would expect this exogenous shock to the market participation by the short-term dual-market clientele to have a permanent impact on the daily seasonality of the asset pricing anomalies. To validate this notion, we employ the difference-in-differences (DiD) framework with the following model specification:

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

where α_t is the time fixed effect, 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 and innovation-led real boom of money market funds), and zero otherwise. Following Chu, Hirshleifer, and Ma (2020), we do not include the individual term $Post_t$, which 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 Thursday-through-Friday strategy and the Monday-through-Wednesday strategy following the real boom of cash investing since 2013. The coefficient λ_1 is expected to be positive, as we expect the prosperity of cash investing since 2013 to have a positive and permanent impact on the daily seasonality of the asset pricing anomalies.

[Insert **Table 5** about here]

We perform the DiD test for the long leg, the short leg, and the long-short portfolio, respectively. **Table 5** 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 1.15% with a t-statistics of 3.78. This confirms **Hypothesis 2** that the cross-sectional return seasonality is *amplified* after the real boom of cash investing in 2013. In particular, the average Thursday-through-Friday long-short return has an *additional* increase of 1.15% per month relative to the Monday-through-Wednesday counterpart following the 2013 boom. 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 the daily seasonality increases more than 100 percent after the real boom of cash investing in 2013.

Consistent with the mispricing interpretation and our projection that the demand of safety (and liquidity) is more valuable for short-term holders of 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. For the aggregated analysis on the FF3-adjusted returns, the DiD coefficient amounts to –1.75% with a t-statistics of –5.21, 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 boom of cash investing. Similar patterns also hold for the raw and CAPM-adjusted returns.

Overall, we find consistent evidence that the 2013 FinTech revolution (and innovation) and the prosperity of cash investing afterwards have a permanent impact on the daily cross-sectional stock return seasonality. The results reinforce the dual-market clientele mechanism: The real boom of money market funds enables *more* short-term dual-market capital to move *cyclically* between the stock market and the money market over specific days of the week, which drives (and amplifies) the day-of-the-week seasonality in the cross section.

5.2. Daily evidence

In this subsection, we perform additional tests with daily observations to generate more insights on the dual-market clientele-based mechanism. We validate the notion that an *unusual* increase of the demand of safety (via cash investing) ahead of the incoming weekend is associated with more pronounced daily seasonality of the long-short portfolio returns.

To zoom in on the impact of cash investing and also for ease of interpretation on its market outcome, we construct a dummy variable that captures the salient increase in the demand of safety based on the daily **order imbalance** measured in dollar terms (i.e., in Chinese yuan) reported by the MMETFs. Note we rely on the order imbalance data of MMETFs simply because daily observations of MMETFs are readily available, while MMMFs do not report similar daily statistics (such as daily subscription and redemption). 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 invest in very similar money market instruments and are popular alternatives (i.e., homogenous products) when investors seek safety. To account for the daily seasonality and the time trend of the order imbalance, we first compute the daily *abnormal* order imbalance, which is defined as the difference between the daily order imbalance and the mean value on the same day of the week over the prior 12-month rolling window. Next, we construct a dummy variable of the abnormal order imbalance, denoted as IMB, that equals one if the daily abnormal order imbalance on the Thursdays or Fridays 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 measure is *ex ante* with no look-ahead bias.

[Insert **Figure 3** about here]

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

$$y_t = \alpha + \beta_1 DOW_t + \beta_2 IMB_t + Controls_t + \varepsilon_t, \qquad [2]$$

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 dummy of the 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 slope coefficient on the DOW_t dummy captures the day-of-the-week effect (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 interests is the slope coefficient on the dummy of abnormal order imbalance, which captures the *additional* daily seasonality on Thursdays or Fridays under *unusual* conditions—when there is a salient increase in the demand for safety by investing in the money market.

[Insert **Table 6** here]

Table 6 presents the estimation results for the slope coefficient on the dummy of abnormal order imbalance. The coefficients for the long-short anomaly portfolios are uniformly positive and statistically significant, providing strong supports to **Hypothesis 4a**. That is, the daily seasonality in the anomaly returns is more pronounced on Thursdays or Fridays with an unusually large abnormal buying pressure of MMETFs (i.e., an increasing amount of short-term dual-market capital flows out of the stock market and into the money market). The magnitude of the increased daily seasonality on these unusual Thursdays or Fridays amounts to at least 20 basis points (bps) per day, which is three or four times of its usual level (i.e., 4 to 6 bps per day).

When comparing the coefficients on the IMB_t dummy for the long-leg and short-leg portfolios, we also find consistent evidence to support **Hypothesis 4b**. Consistent with our clientele-based explanation that the demand of safety via cash investing has a disproportionally large impact on speculative stocks relative to non-speculative stocks, 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 amplified daily seasonality of the anomaly returns on the unusual Thursdays and Fridays (with a sudden increase in the demand for MMETFs) stems purely from the short-leg anomaly portfolios.

Overall, the interrelation between cash investing and the long-short anomaly returns reinforces the impact of short-term dual-market clientele on the daily seasonality of cross-sectional stock returns. The underperformance of speculative stock (relative to non-speculative stocks) becomes more pronounced precisely on these Thursdays and Fridays when there are unusually more money of the short-term dual-market clientele (as captured by the abnormal buying pressure for MMETFs) fleeing from the stock market to safety, consistent with the short-term dual-market clientele-based mechanism.

5.3. Time variation in the demand of safety

In this subsection, we provide further evidence on the time variation in the demand of safety. We explore whether the impact of cash investing on the daily seasonality of anomaly returns varies over different market states. 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). We posit that the safe-haven attribute is more precious and it is more likely to influence the trading behavior of the short-term dual-market clientele in high volatility or uncertainty states, because holding costs and inventory risk of speculative stocks escalate precisely when it is in market downturns or panic states. Therefore, when short-term dual-market investors fear for (or are experiencing) market turbulence, they become more reluctant to hold speculative stocks over the weekend, and are more likely to shift their holdings towards safe assets—the money market funds (i.e., the safe haven effect). That is, these dual-market investors have a stronger tendency to liquidate their stock holdings on the Thursdays and Fridays in stressful states, as it becomes more lucrative to consume liquidity and seek safety (i.e., the guaranteed yield over the weekend). Thus, the day-of-the-week seasonality should be strengthened when the market volatility (uncertainty) is high. In comparison, in calm or upward market states, these traders are more likely to hold stocks for longer periods such as over the weekends (forfeiting the yields from the money market), which weakens the day-of-the-week seasonality.

To test this conjecture, we divide the sample into high and low volatility (uncertainty) periods and re-estimate **Equation 2** 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.

[Insert **Table 7** here]

Table 7 presents the estimation results for the slope coefficient on the dummy of abnormal order imbalance. 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, proxied by the dummy of abnormal order imbalance in MMETFs, 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 cash investing 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 on the safe haven effect with the Baker, Bloom, and Davis (2016) China-specific economic policy uncertainty (EPU) index constructed by Davis et al. (2019). We divide the sample into high and low uncertainty periods and re-estimate **Equation 2** for the two subsamples. For each daily return observation, it is classified as in high/low uncertainty periods if the prior month-end demeaned EPU value is above/below average.[10] 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 A5** in the appendix).

Overall, these results provide supportive evidence that the day-of-the-week seasonality of the anomaly returns are strengthened during the high volatility or uncertainty periods, confirming the safe haven effect of money market funds.[11]

5.4. Alternative explanations

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

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[10] 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.

[11] In unreported analysis, we also use investor sentiment as an alternative fear measure to validate the safe haven effect. Using the Han and Li (2017) China investor sentiment index, we divide the sample into high and low sentiment periods and re-estimate **Equation 2** 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). Given that investor sentiment is inversely related to market volatility, the evidence lends further support to the safe haven effect.

5.4.1. Macroeconomic 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, Gosnell, and Lasser 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 announcement 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) also 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 **Table 8** shows 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.

[Insert **Table 8** about here]

5.4.2. Firm-specific news

The announcements of firm-specific earnings news on Fridays may also explain 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 **Table 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.

[Insert **Table 9** about here]

5.4.3. 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 10 presents the Fama-French three-factor alphas of the expiration strategy and the non-expiration strategy, respectively. For either of the 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.

[Insert **Table 10** about here]

5.4.4. 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 et al. (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 et al., 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 et al., 2012; Boehmer et al., 2020). Given that value-relevant information flows are disseminated to the market on a continuous basis, 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 only allowed in China from 2010 onwards and is still in a limited scope: Only the stocks in the short-selling list that is approved by China Securities Regulatory Commission (CSRC) are eligible for short-selling (Chang et al., 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 A6** in the appendix, 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.

Third, 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 et al., 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 **Figure 4**). 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. Therefore, we can rule out short selling as the main force that drives our documented daily seasonality of the cross-sectional returns in China.

[Insert **Figure 4** about here]

5.5. Portfolio implications

In this subsection, we explore the portfolio implications of our findings on the day-of-week-effect of the cross-sectional returns (in **Section 4)**. In principle, the Thursday-through-Friday long-short strategies represent betting against the concentrated selling pressure induced by the short-term dual-market clientele on Thursday and Friday. Given that these anomaly strategies generate sizeable positive (risk-adjusted) returns on Thursday and Friday, we first use the time-series spanning test to compare the performance of the monthly Thursday-through-Friday long-short anomaly strategies with that of the benchmark (buy-and-hold) long-short anomaly strategies that invest over all days of the week. To be specific, we regress the excess return of the Thursday-through-Friday strategy on that of the benchmark (buy-and-hold) strategy for each of the anomalies. **Table 11** displays the results of the time-series spanning tests. As it stands, the intercepts are highly positive (ranging from 0.87% to 1.20% per month), and statistically significant at the 1% level for all the prominent anomalies. These highly positive intercepts indicate at least two things. First, the returns of Thursday-through-Friday anomaly strategies are largely not subsumed by their benchmark buy-and-hold counterparts. Second, these Thursday-through-Friday strategies offer incremental returns over, and a better risk-return trade-off than, their benchmarks.

[Insert **Table 11** about here]

We are aware that the above spanning test is a simplified analysis, because it ignores transaction costs. The Thursday-through-Friday strategy would incur higher transaction costs than the benchmark strategy, as seasonality-based strategies require active trading and thus more frequent portfolio rebalancing (Keloharju et al., 2021). Therefore, we examine the net performance of the Thursday-through-Friday strategy that takes into account transaction costs.

Table 12 reports the net performance of the Thursday-through-Friday strategy. In principle, our Thursday-through-Friday strategy requires to reform the portfolio every week, which corresponds to a portfolio turnover of 400% per month (i.e., assuming four weeks per month). Therefore, the monthly net portfolio return—the dependent variable in **Panel A** of the table—is computed as the monthly raw return subtracted by four times of the average portfolio-level bid-ask spread. The average portfolio-level bid-ask spread is updated each month, which is defined as the value-weighted average of individual means of the (daily) bid-ask spreads of the composite stocks over that month. As it stands, the performance of the Thursday-through-Friday strategy survives the transaction costs. For example, the net excess returns are highly positive, which range from 42 bps to 107 bps per month, and are statistically significant at the 5% or finer levels.

In **Panel B** of the table, we investigate the "enhanced" Thursday-through-Friday strategy for the prominent anomalies. Note savvy investors are able to further increase the total return by investing in money market funds over the remaining (calendar) days of the week. Therefore, the net return of the "enhanced" strategy is defined as the net return of the Thursday-through-Friday strategy in **Panel A** plus the four-seventh of the monthly yield of the money market funds. This (roughly) adds an additional yield of 16 bps per month over the full sample period. As expected, the "enhanced" Thursday-through-Friday strategy delivers even better portfolio performance (than their counterparts in **Panel A**) due to the additional gains from the money market. For example, the net excess returns range from 58 bps to 123 bps per month, and are statistically significant at the 5% or finer levels for all the long-short portfolios. Similar patterns apply to the CAPM- and FF3-adjusted returns as well.

[Insert **Table 12** about here]

Overall, the net portfolio performance indicates that transaction costs are not a major concern for implementing the Thursday-through-Friday strategy. The relatively high return of the seasonality-based strategy more than offset the transaction costs. Moreover, the additional gains from the money market provide an additional source to the profits of the Thursday-through-Friday strategy.

6. Further analysis and robustness checks

6.1. Holiday effect

In this subsection, we provide further evidence on the short-term dual-market clientele-based mechanism 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 more attractive to the short-term dual-market clientele. Thus, the tendency for these dual-market 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 any 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 relative high returns over the two working days prior to the long holidays. As is shown in **Figure A1** in the appendix, the average daily excess return of the long-short anomaly strategies over the two days prior to holidays are nearly two times that of their Thursday-through-Friday counterparts. Overall, the documented holiday effect is consistent with the short-term dual-market clientele-based mechanism, and reinforces the view that short-term traders care about the guaranteed yields over long holidays.

6.2. Falsification test

To ensure that the documented difference-in-differences patterns are specific to actual event of the 2013 FinTech-led real boom of money market funds, rather than a general phenomenon for any date, we thus conduct a falsification test. Empirically, we create a pseudo-event that starts at January 2005 and ends at June 2011. The pseudo-event has the same window length as our actual event, and is not overlapping with the actual event. We then replicate the difference-in-differences analysis based on the randomly selected pseudo-event.

Table A4 in the appendix presents the slope coefficients on the DiD term for the pseudo-event. As it stands, the DiD coefficients for the long-short portfolios are all small in magnitude and indistinguishable from zero, indicating that there is no change in the day-of-the-week effect following the pseudo-event. Similarly, the DiD coefficients for the short-leg portfolios are also indistinguishable from zero, suggesting that the daily seasonality for the speculative stocks (relative to non-speculative stocks) exhibits no difference between the pre and the post pseudo-event periods.

Overall, the comparison between the placebo test results and our main difference-in-differences results in **Section 4.2** reinforces that the impact of the 2013 FinTech revolution (i.e., its induced real boom of cash investing) on the seasonal cross-sectional stock returns is genuine and unlikely to be a general phenomenon for any date.

6.3. Short event window: 2011 - 2014

In this subsection, we also perform an alternative univariate difference-in-differences test that focuses on the four-year "event" window spanning from January 2011 to December 2014. The years 2011 and 2012 correspond to the pre-event period: The two years immediately before the 2013 FinTech-led real boom of cash investing. In comparison, the latter two years 2013 and 2014 correspond to the post-event period marked by the launches of FinTech-customized MMMFs and innovative MMETFs. Again, we use the Thursday-through-Friday anomaly strategy as the treatment group, while the Monday-through-Friday counterpart as the control group.

For each of the anomaly strategy (which can be the long leg, the short leg, or the long-short portfolio), we first compute the average monthly Thursday-through-Friday and Monday-through-Wednesday FF3-adjusted returns in the pre- and post-event periods, respectively. Next, we evaluate the two-sample difference along two dimensions: For the Thursday-through-Friday and Monday-through-Wednesday portfolios, we evaluate the (two-sample) return difference between the pre- and post-event periods. For the pre-event and post-event periods, we evaluate the (two-sample) return difference between the Thursday-through-Friday and Monday-through-Wednesday portfolios. Finally, our key variable of interests is the difference-in-difference term, which is the post-minus-pre difference in the return spread between the Thursday-through-Friday (treatment) and the Monday-through-Wednesday (control) portfolios. For brevity purpose, we present only the results for the combo strategy (see **Table A7** in the appendix).[12] A number of salient features emerge from the table:

First, for the long-short anomaly portfolio, there exists a dramatic increase in the return spread between the Thursday-through-Friday (treatment) and the Monday-through-Wednesday (control)

[12] The main features are robust across the six individual anomaly strategies as well, which are available in the internet appendix.

portfolios. The pre-event return spread between the two groups amounts to 1.68% per month, while the post-event return spread jumps to 4.35% per month. The post-minus-pre difference (i.e, the DiD term) amounts to 2.67% per month and is statistically significant at the 1% level.

Second, the post-minus-pre return difference stems from both the Thursday-through-Friday and the Monday-through-Wednesday portfolios. The post-minus-pre difference amounts to –1.96% per month for the Monday-through-Wednesday portfolio, indicating that speculative stocks outperform the non-speculative stocks significantly on Monday through Wednesday following the launches of MMETFs and FinTech-customized MMMFs in 2013. In comparison, the post-minus-pre difference amounts to 0.71% per month for the Thursday-through-Friday portfolio, implying that speculative stocks underperform the non-speculative stocks on Thursday through Friday in the post-event periods (i.e., 2013–2014). The fact that the both the Thursday-through-Friday and the Monday-through-Wednesday portfolios experience large changes in *opposite* directions after 2013 reinforces our short-term dual-market clientele-based mechanism, as the 2013 FinTech revolution and innovations lower the hurdles and costs of cash investing, mobilizing *more* money to cyclically flow into the stock market (from the money market) at the beginning of the week (i.e., Monday through Wednesday) and flow out of the stock market (into the money market) at the end of the week (i.e., Thursday through Friday).

Third, consistent with the temporary mispricing view, the dramatic post-minus-pre difference is solely driven by the short-leg portfolio—speculative stocks. After the introductions of FinTech-customized MMMFs and innovative MMETFs in 2013, the speculative stocks experience a large post-event return increase (relative to the pre-event period) on Monday through Wednesday, indicating a temporary buying pressure at the beginning of the week. Similarly, these speculative stocks experience a large post-event return drop (relative to the pre-event period) on Thursday through Friday, implying a temporary selling pressure at the end of the week. In comparison, there are no significant changes for the long-leg portfolio (i.e., non-speculative stocks) after the 2013 FinTech-led real boom of cash investing.

Overall, these salient features are consistent with our baseline DiD analysis (with longer sample period) in **Section 5.1**. It is clear that starting from 2013, there emerges a sharp increase in the return spread between the Thursday-through-Friday and Monday-through-Wednesday long-short strategies (See **Figure A2** in the appendix), which corroborates with the “unintended” consequence of the FinTech and innovation-led real boom of cash investing. That is, the re-design of money market funds with revolutionary and innovative features (i.e., FinTech-customized MMMFs and MMETFs) strengthens the daily connection between the stock market and the money market, and enlarges the day-of-the-week effect because it mobilizes more money to systematically shift between risk and safety on specific days of the week. This increased recurring in- and out-flows enlarges the day-of-the-week effect.

6.4. Disentangling the respective impacts of FinTech-customized MMMFs and MMETFs

In this subsection, we disentangle the respective impact of FinTech-customized MMMFs and MMETFs during the recent boom of cash investing. Note in our main analysis (in **Section 5**), we treat the launches of FinTech-customized MMMFs (i.e., Yu Ebao) and MMETFs as one *joint* event under the grand theme of China's FinTech-led real boom of cash investing. This is because these two salient events not only coincide with each other in time (i.e., both are launched in the first half of 2013), but also are homogenous in nature in the sense that they both utilize the combination of financial and technical advances to increase the money-likeness attributes of money market funds, lower the investment hurdles and costs, and provide alternative routes to allow investors to demand for safety. Therefore, they *jointly* contribute to the real boom of cash investing in 2013 and afterwards.

However, one distinctive feature of the launch of MMETFs (as opposed to that of FinTech-customized MMMFs) is that it offers a last-minute solution for short-term dual-market investors to seek safety and earn the yields over the weekend by trading on Friday, rather than on Thursday (see **Figure A4** in the appendix for the timeline of the purchase and interest accrual of MMETFs). Recall an investor has to submit the order to subscribe the MMMF shares on Thursday at the latest to earn the guaranteed yield over the weekend, given that the subscription of the MMMF shares take one business day (see **Figure A3** in the appendix). For that reason, to the extent that the underperformance of speculative stocks over non-speculative counterparts on Friday increases since 2013, we could attribute the increased Friday effect almost *exclusively* to the MMETF features, because MMETFs offer dual-market clientele a unique way to earn the yields over weekends by trading on Friday (rather than on Thursday). In comparison, to the extent that there is an increase in such underperformance on Thursday since 2013, the increased Thursday seasonality could be largely attributed to the FinTech-customized MMMF features. The patterns in **Figure 3** support our predictions, as we observe that the strongest buying pressure of MMETF shares happens on Friday, but not on Thursday. In short, the emergence of MMETFs redistributes the dual-market clientele's increased demand for safety from Thursday to Friday (i.e., a redistribution effect). Without the introduction of MMETFs, we should expect a much-concentrated demand for money market funds on Thursday.

Empirically, to disentangle the respective impacts of FinTech-customized MMMF features (Thursday) and MMETF features (Friday), we first generate the (monthly) Thursday-only portfolio and Friday-only portfolio, together with the Monday-through-Wednesday portfolio (which is scaled by a factor of 1/3). Next, we modify the difference-in-difference analysis in **Section 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 day-of-the-week effect attributed to the FinTech-customized MMMF features (i.e., the Thursday DiD term) and the MMETF features (i.e., the Friday DiD term).

Table A3 in the appendix presents the slope coefficients on the two DiD terms. As expected, both DiD coefficients are positive and large in magnitude, indicating that the launches of MMETFs and FinTech-customized MMMFs both amplify the day-of-the-week seasonality in the long-short anomaly returns, because the permanent shock to the dual-market clientele’s market participation leads to *more* money that are mobilized and become available to cyclically move in between stock market and money market on specific days of the week. Overall, it confirms the redistribution effect that the existence of MMETFs partially shifts the aggregate demand of safety at the end of the week from Thursday to Friday.

6.5. Other robustness checks

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

Other anomalies. We also validate whether our documented day-of-the-week pattern also holds for other well-known cross-sectional anomalies. 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 4.1**, we calculate the monthly excess returns for the Monday-through-Wednesday and Thursday-through-Friday long-short portfolios, respectively. **Table A8** 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 4** is that the risk factors could also vary over different day 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 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 stocks returns.

7. Conclusion

This paper generates new insights on how private money creation—in the form of money market funds—exerts the hidden and broad impact on the stock market. FinTech applications and financial innovations in China's money market funds offer us a unique laboratory to explore how financial development and technological advances *outside* the stock market could unintentionally reshape the stock market dynamics.

The emergence of dual-market clientele represents a novel economic phenomenon that a subset of short-term investors, who are active in both markets, systematically exploit the distinctive features of cash investing as opposed to stock investing. Their collective trading behaviour (i.e., infrequent rebalancing over specific horizons) explains the stylized daily seasonality 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.

We also provide difference-in-differences evidence to support the dual-market clientele-based mechanism. Using the 2013 FinTech-led real boom of cash investing as a plausible exogenous shock to the dual-market clientele's market participation, we show that the daily seasonality increases more than 100 percent following the shock, and the enlarged daily seasonality comes entirely from the short leg of speculative stocks. The novel evidence indicates that FinTech revolution and technological advances, which facilitate short-term investors to trade in multiple markets at almost the same time within a day, 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 two markets via the dual-market clientele.

Our work is the first to address the economic consequence of FinTech-led cash investing on the financial markets. 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) for investors unexpectedly worsen price efficiency with the symptom of *amplified* cross-sectional return predictability and temporary mispricing.

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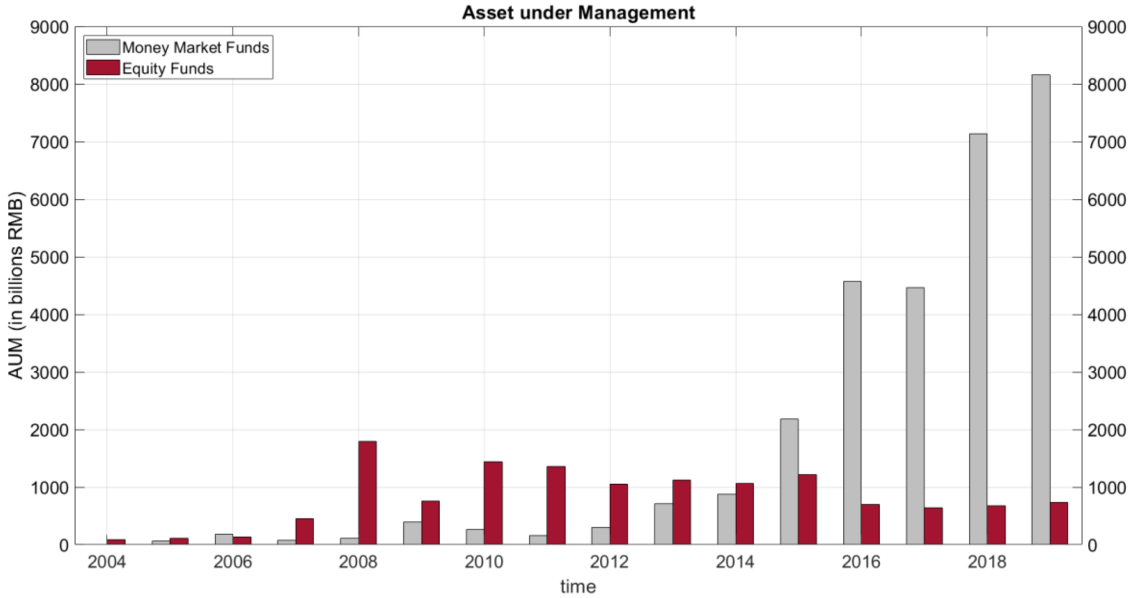
Figure 1. Assets under management of money market funds and equity mutual funds

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. All figures are measured in billions of RMBs.



Source: WIND

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

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.

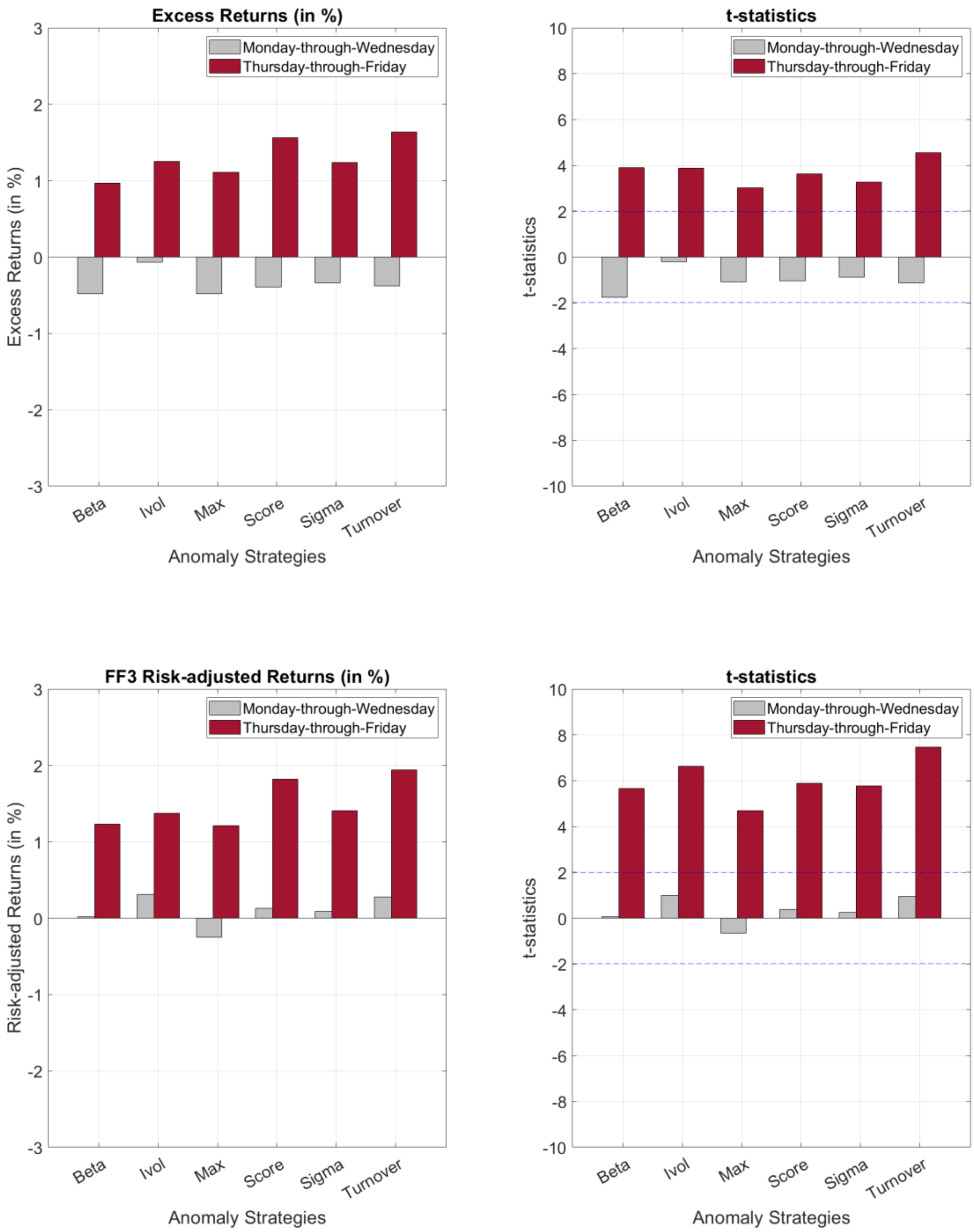


Figure 3. Order imbalance of Money Market ETFs

The figure plots the demeaned order imbalance of the Money Market ETFs (measured in millions of RMB) on specific day of the week. Daily order imbalance is aggregated over the top 5 largest MMETFs, which represents more than 99% of the AUMs among all MMETFs. The sample period spans from January 2013 to June 2019.

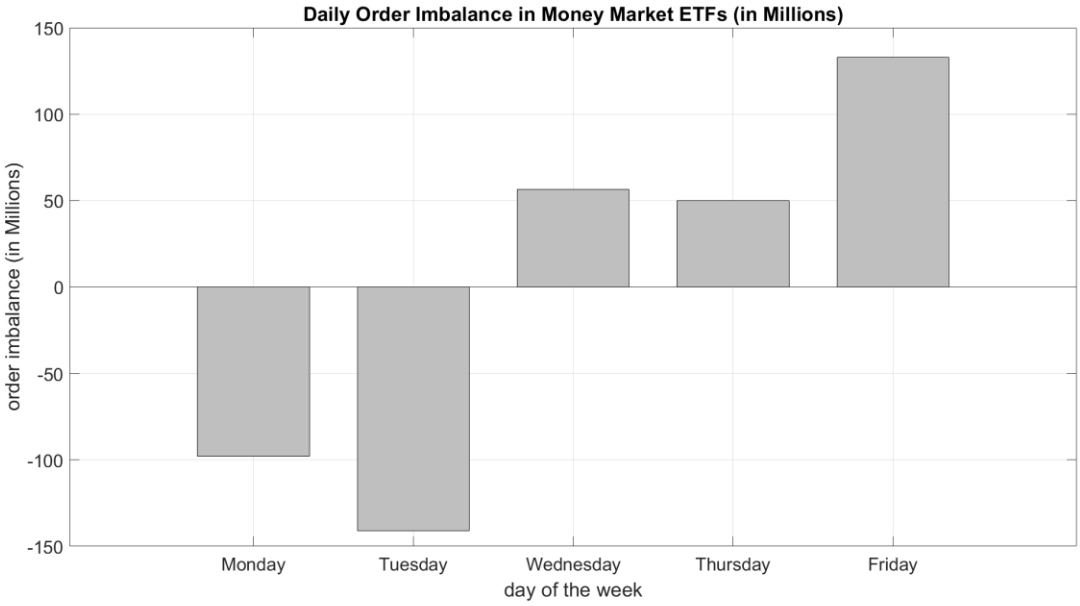


Figure 4. Daily change in short-selling balance

The figure 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).

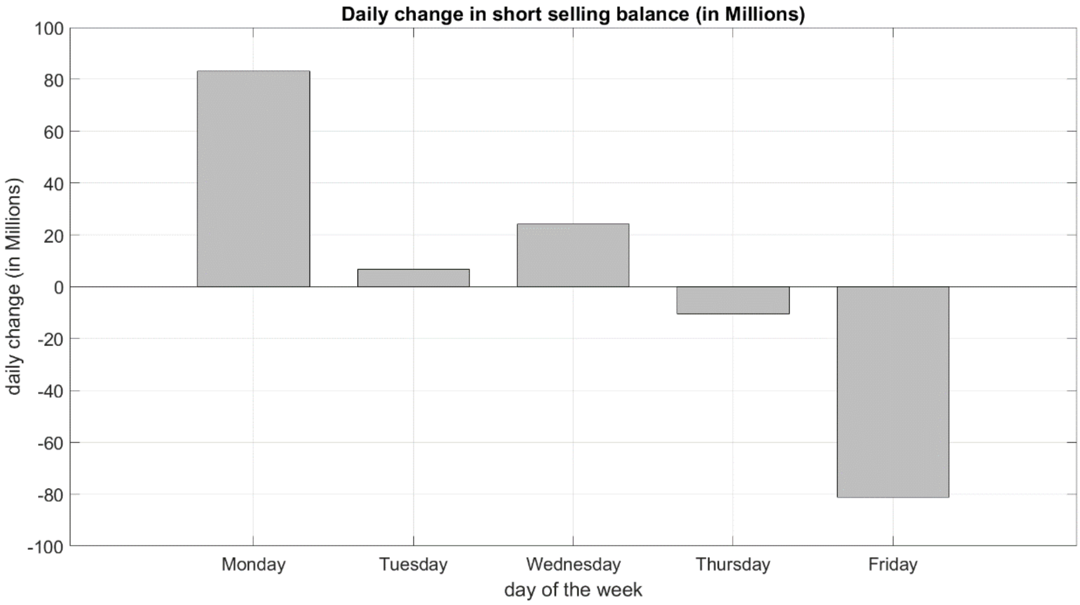


Table 1. Description of the long-and-short strategies

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.

Panel A: Formation of the long-and-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

Table 2. Monday through Wednesday and Thursday through Friday

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.

	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]

Table 3. Short leg versus long leg, Thursday through Friday

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. The portfolios only invest on Thursday through Friday. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to June 2019.

	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]

Table 4. Short leg versus long leg, Monday through Wednesday

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. The portfolios only invest on Monday through Wednesday. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to June 2019.

	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]

Table 5. Difference-in-differences results

The table reports the DiD coefficient λ_1 from the regression $R_{i,t} = \alpha_t + \lambda_0 Treat_i + \lambda_1 Treat_i \times Post_t + \varepsilon_{i,t}$ 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 could either invests on Monday through Wednesday or on Thursday through Friday. $Treat_i$ is the treat dummy that equals 1 if portfolio i is formed based on the strategy that invests only on Thursday through Friday, and zero otherwise. $Post_t$ is the post-event dummy that equals 1 following the 2013 FinTech-led real boom of cash investing (i.e., from 2013 onwards), and zero otherwise. α_t denotes time fixed effects. The results for the long-leg portfolios, short-leg portfolios, and long-minus-short (LMS) 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.

	Excess Returns			CAPM-Adjusted Returns			FF3-Adjusted Returns		
	Long	Short	LMS	Long	Short	LMS	Long	Short	LMS
Ivol	0.02	–1.05	1.07	0.07	–0.96	1.03	0.13	–1.01	1.14
	[0.03]	[–1.42]	[1.92]	[0.16]	[–1.60]	[2.00]	[0.31]	[–1.70]	[2.43]
Max	–0.40	–1.05	0.65	–0.34	–0.96	0.62	–0.30	–0.97	0.67
	[–0.87]	[–1.36]	[1.07]	[–0.89]	[–1.49]	[1.06]	[–0.82]	[–1.51]	[1.17]
Turnover	–0.24	–1.23	0.10	–0.18	–1.12	0.94	–0.11	–1.13	1.02
	[–0.49]	[–1.56]	[1.68]	[–0.43]	[–1.77]	[1.74]	[–0.28]	[–1.79]	[2.03]
Sigma	–0.16	–1.24	1.09	–0.10	–1.15	1.05	–0.04	–1.17	1.13
	[–0.34]	[–1.59]	[1.87]	[–0.24]	[–1.78]	[1.92]	[–0.11]	[–1.83]	[2.18]
Beta	–0.06	–0.91	0.85	0.01	–0.80	0.81	0.05	–0.82	0.87
	[–0.13]	[–1.23]	[1.61]	[0.02]	[–1.35]	[1.64]	[0.14]	[–1.37]	[1.82]
Score	–0.28	–1.19	0.91	–0.22	–1.09	0.87	–0.16	–1.09	0.93
	[–0.60]	[–1.47]	[1.44]	[–0.57]	[–1.62]	[1.45]	[–0.45]	[–1.63]	[1.60]
Combo	–0.17	–1.10	0.93	–0.11	–1.00	0.89	–0.05	–1.02	0.96
	[–0.36]	[–1.47]	[1.78]	[–0.27]	[–1.67]	[1.84]	[–0.15]	[–1.71]	[2.12]
Aggregate	–0.57	–1.70	1.13	–0.63	–1.78	1.15	–0.61	–1.75	1.15
	[–1.90]	[–3.58]	[3.23]	[–2.71]	[–5.22]	[3.59]	[–2.68]	[–5.21]	[3.78]

Table 6. Impact of abnormal order imbalance

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.

	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]

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

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.

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]

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]

Table 8. Excluding macro announcement days

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. The monthly return series are reconstructed by 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 Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from January 2007 to June 2019.

	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]

Table 9. Excluding earnings announcement days

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. The monthly return series are reconstructed by excluding the earnings announcement days. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to June 2019.

	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]

Table 10. Expiration and non-expiration dates

The table reports the Fama-French three-factor alpha (FF3) 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.

	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]

Table 11. Portfolio implications

This table reports the outputs of the time-series spanning test. The dependent variable is the long-short anomaly strategy returns that only invests on Thursday and Friday, and the independent variable is the benchmark buy-and-hold anomaly strategy that invests over the entire month. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to June 2019.

	Ivol	Max	Turnover	Sigma	Beta	Score	Combo
Intercept	0.87	0.88	1.20	0.93	0.79	1.11	0.93
	[4.24]	[3.51]	[5.40]	[4.17]	[4.80]	[4.47]	[4.71]
Benchmark	0.34	0.38	0.37	0.36	0.39	0.39	0.37
	[9.88]	[10.91]	[11.94]	[14.34]	[13.59]	[11.79]	[11.92]
$Adj. R^2$	0.38	0.42	0.47	0.45	0.49	0.47	0.44
Obs.	276	276	276	276	276	276	276

Table 12. Net portfolio returns

The table reports the monthly average excess return (Excess), the CAPM alpha (CAPM), and the Fama-French three-factor alpha (FF3) to each long-short anomaly strategy that invests only on Thursday through Friday. The dependent variable in Panel A (B) is the portfolio return net of transaction cost that excludes (includes) the yield from investing in money market funds over the rest of the week. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to June 2019.

Panel A: Net returns of the long-short strategies, without MMMF yields

	Ivol	Max	Turnover	Sigma	Beta	Score	Combo
Excess	0.68	0.52	1.07	0.68	0.42	0.98	0.67
	[2.85]	[2.04]	[4.25]	[2.71]	[2.11]	[3.72]	[3.15]
CAPM	0.78	0.61	1.21	0.77	0.52	1.09	0.78
	[3.39]	[2.38]	[4.57]	[2.94]	[2.52]	[3.89]	[3.54]
FF3	0.79	0.60	1.41	0.82	0.65	1.27	0.85
	[3.63]	[2.46]	[5.10]	[3.41]	[3.04]	[4.21]	[4.05]

Panel B: Net returns of the long-short strategies, with MMMF yields

	Ivol	Max	Turnover	Sigma	Beta	Score	Combo
Excess	0.84	0.68	1.23	0.83	0.58	1.14	0.83
	[3.48]	[2.62]	[4.87]	[3.31]	[2.87]	[4.28]	[3.84]
CAPM	0.94	0.77	1.36	0.93	0.68	1.25	0.94
	[4.03]	[2.95]	[5.16]	[3.50]	[3.26]	[4.41]	[4.21]
FF3	0.94	0.76	1.56	0.98	0.80	1.42	1.01
	[4.31]	[3.06]	[5.65]	[4.00]	[3.74]	[4.69]	[4.74]

Appendix:

Figure A1. Holiday Effect

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.

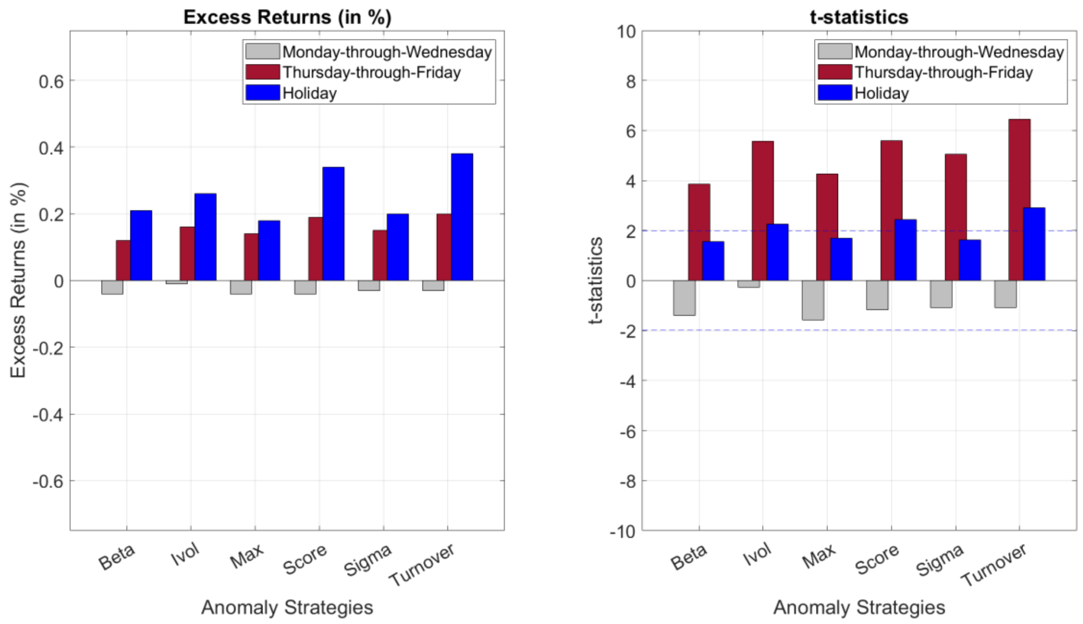


Figure A2. Difference in average returns between the Thursday-through-Friday and Monday-through-Wednesday long-short anomaly strategies

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).

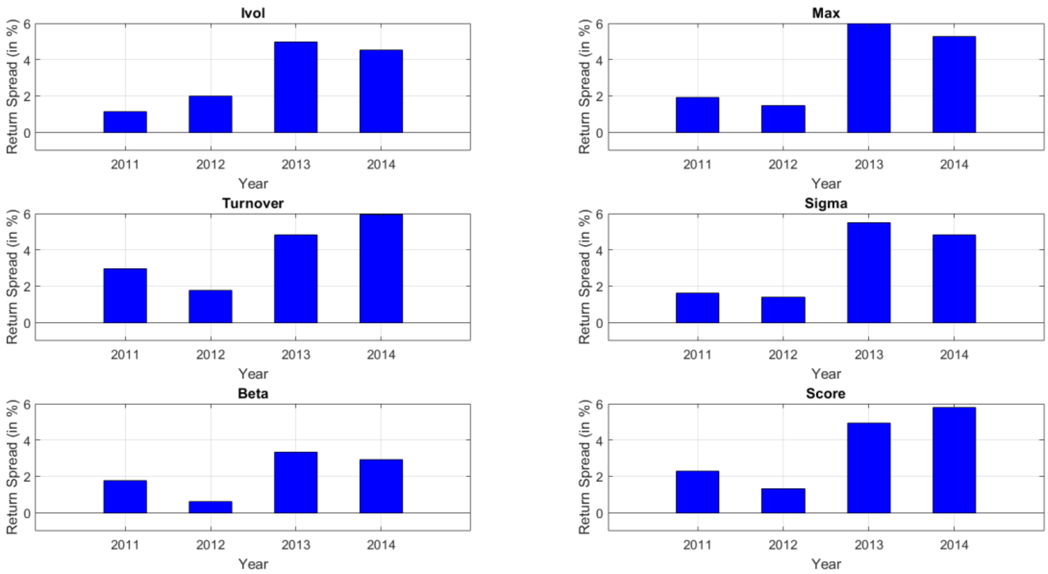


Figure A3. Illustration of the subscription of the shares of a money market mutual fund on Thursday

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.

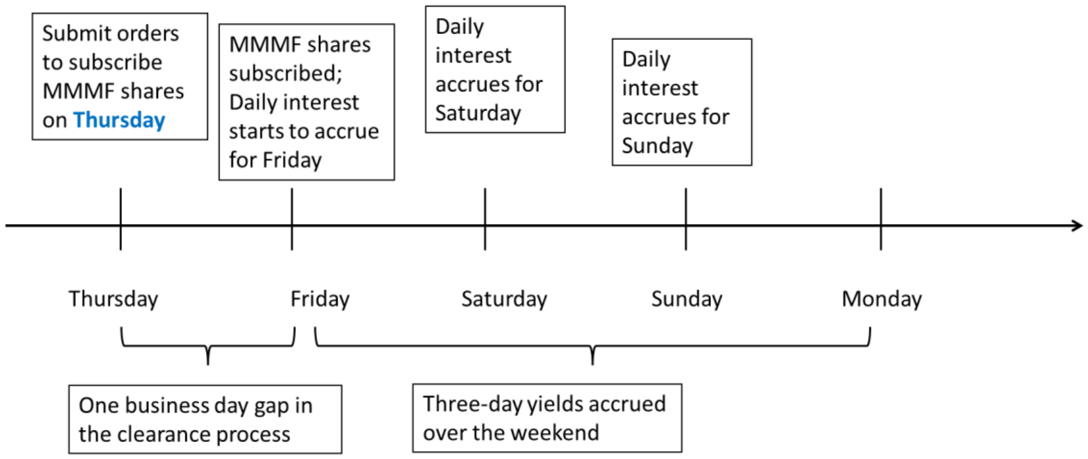


Figure A4. Illustration of the purchase of the shares of a money market exchange-traded fund on Friday

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.

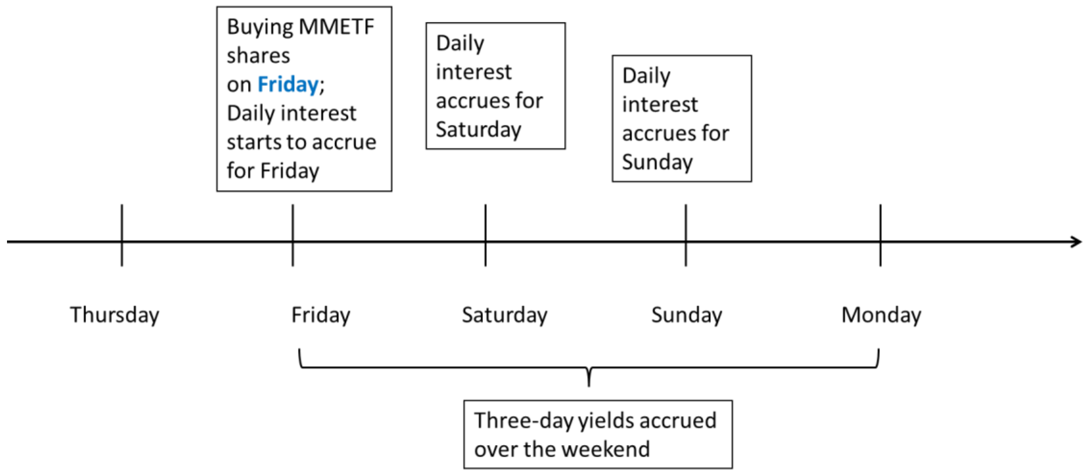


Table A1. Mutual funds by investment classification as of 30 June 2019

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

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

Table A2. Day of the week

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.

	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]

Table A3. Disentangling the impacts of FinTech-customized MMMF features and MMETF features

The table reports the two DiD coefficients λ_{Thur} and λ_{Fri} from the modified DiD regression:

$$R_{i,t} = \alpha_t + \lambda_0 Thur_i + \lambda_1 Fri_i + \lambda_{\mathrm{Thur}} Thur_i \times Post_t + \lambda_{\mathrm{Fri}} Fri_i \times Post_t + \varepsilon_{i,t}.$$

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). Note we scale the Monday-through-Wednesday return (i.e., the control group) by 1/3 to ensure a fair comparison to the Thursday return and Friday return. $Thur_i$ is the Thursday-treatment dummy that equals 1 if the portfolio return is the Thursday strategy, and zero otherwise. Fri_i is the Friday-treatment dummy that equals 1 if the portfolio return is the Friday strategy, and zero otherwise. $Post_t$ is the post-event dummy that equals 1 following the 2013 FinTech-led real boom of cash investing (i.e., starting from 2013 onwards), and zero otherwise. α_t denotes time fixed effects. The results for the long leg portfolios, short leg portfolios, and long-minus-short (LMS) 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.

Panel A: The Thursday DiD coefficient, λ_{Thur}, capturing the impact of FinTech-customized MMMF features

	Excess Returns			CAPM-Adjusted Returns			FF3-Adjusted Returns		
	Long	Short	LMS	Long	Short	LMS	Long	Short	LMS
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	–0.5	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	0.56	–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	–0.27	–0.93	0.66	–0.28	–0.94	0.66	–0.26	–0.93	0.67
	[–1.81]	[–3.74]	[3.56]	[–2.13]	[–4.58]	[3.80]	[–2.08]	[–4.61]	[4.03]

Panel B: The Friday DiD coefficient, λ_{Fri}, capturing the impact of MMETF features

	Excess Returns			CAPM-Adjusted Returns			FF3-Adjusted Returns		
	Long	Short	LMS	Long	Short	LMS	Long	Short	LMS
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	–0.18	–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	0.44	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	–0.09	–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	–0.19	–0.60	0.42	–0.20	–0.62	0.42	–0.19	–0.61	0.42
	[–1.34]	[–2.71]	[2.44]	[–1.65]	[–3.17]	[2.51]	[–1.53]	[–3.13]	[2.60]

Table A4. Placebo test: Difference-in-differences results

The table reports the DiD coefficient λ_1 from the regression $R_{i,t} = \alpha_t + \lambda_0 Treat_i + \lambda_1 Treat_i \times Post_t + \varepsilon_{i,t}$ 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 could either invests on Monday through Wednesday or on Thursday through Friday. $Treat_i$ is the treat dummy that equals 1 if portfolio i is formed based on the strategy that invests only on Thursday through Friday, and zero otherwise. $Post_t$ is the post-event dummy that equals 1 over the period January 2005 to June 2011 for the pseudo event and zero otherwise. α_t denotes time fixed effects. The results for the long leg portfolios, short leg portfolios, and long-minus-short (LMS) 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.

	Excess Returns			CAPM-Adjusted Returns			FF3-Adjusted Returns		
	Long	Short	LMS	Long	Short	LMS	Long	Short	LMS
Ivol	–0.11	0.64	–0.75	–0.47	0.03	–0.50	–0.42	–0.07	–0.35
	[–0.21]	[0.90]	[–1.55]	[–1.01]	[0.06]	[–1.16]	[–0.92]	[–0.13]	[–0.83]
Max	–0.28	0.84	–1.12	–0.67	0.24	–0.91	–0.64	0.19	–0.84
	[–0.53]	[1.10]	[–1.95]	[–1.62]	[0.38]	[–1.65]	[–1.59]	[0.31]	[–1.50]
Turnover	0.16	0.11	0.04	–0.22	–0.62	0.40	–0.15	–0.62	0.47
	[0.29]	[0.13]	[0.07]	[–0.49]	[–1.00]	[0.73]	[–0.36]	[–1.00]	[0.92]
Sigma	–0.27	0.67	–0.94	–0.67	0.04	–0.71	–0.63	–0.01	–0.62
	[–0.53]	[0.90]	[–1.75]	[–1.60]	[0.06]	[–1.37]	[–1.53]	[–0.01]	[–1.20]
Beta	0.10	0.40	–0.31	–0.33	–0.26	–0.07	–0.34	–0.29	–0.04
	[0.19]	[0.49]	[–0.56]	[–0.86]	[–0.43]	[–0.14]	[–0.93]	[–0.49]	[–0.09]
Score	0.03	0.63	–0.60	–0.37	–0.06	–0.31	–0.34	–0.07	–0.27
	[0.06]	[0.75]	[–0.93]	[–0.85]	[–0.09]	[–0.52]	[–0.83]	[–0.11]	[–0.46]
Combo	–0.08	0.53	–0.61	–0.47	–0.12	–0.35	–0.43	–0.16	–0.27
	[–0.16]	[0.71]	[–1.33]	[–1.20]	[–0.21]	[–0.87]	[–1.15]	[–0.29]	[–0.67]
Aggregate	–0.71	–0.33	–0.39	–0.46	–0.01	–0.44	–0.37	0.00	–0.38
	[–2.13]	[–0.68]	[–1.14]	[–1.74]	[–0.04]	[–1.42]	[–1.47]	[0.01]	[–1.24]

Table A5. Impact of abnormal order imbalance in high and low EPU periods

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-minus-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.

Panel A: High EPU periods

	Long leg	Short leg	Long–Short
Ivol	0.03	–0.11	0.14
	[0.43]	[–1.21]	[1.07]
Max	0.04	–0.24	0.28
	[0.64]	[–2.45]	[2.47]
Turnover	0.09	–0.19	0.28
	[1.37]	[–2.15]	[2.42]
Sigma	0.06	–0.18	0.24
	[0.81]	[–1.63]	[1.79]
Beta	–0.02	–0.13	0.12
	[–0.33]	[–1.50]	[0.95]
Score	0.05	–0.22	0.27
	[0.68]	[–2.13]	[2.13]
Combo	0.04	–0.17	0.21
	[0.73]	[–2.06]	[2.03]

Panel B: Low EPU periods

	Long leg	Short leg	Long–Short
Ivol	–0.05	–0.08	0.02
	[–1.14]	[–1.36]	[0.28]
Max	–0.04	–0.07	0.03
	[–0.73]	[–0.93]	[0.3)]
Turnover	0.00	–0.14	0.14
	[–0.06]	[–2.03]	[1.68]
Sigma	–0.05	–0.12	0.07
	[–1.13]	[–1.76]	[0.75]
Beta	–0.01	–0.09	0.08
	[–0.19]	[–1.79]	[1.03]
Score	–0.04	–0.14	0.10
	[–0.88]	[–1.65]	[0.86]
Combo	–0.03	–0.10	0.07
	[–0.76]	[–1.76]	[0.88]

Table A6. Subsample analysis of the stocks eligible for short selling and the non-short-selling stocks

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.

Panel A: The subset of eligible stocks in the short-selling list

	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: The subset of Non-short-selling stocks

	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]

Table A7: Univariate difference-in-differences analysis of the FF3-adjusted returns

The table reports the univariate difference-in-differences tests of the monthly Fama-French three-factor alpha of the Monday-through-Wednesday and Thursday-through-Friday combo strategy during the pre-event (i.e., 2011–2012) and post-event (i.e., 2013–2014) periods. It presents the results for long-leg, short-leg, and long-short portfolios, respectively. The Newey-West adjusted *t*-statistics are reported in brackets. The sample period spans from January 2011 to December 2014.

Combo

	Long leg			Short leg			Long–Short		
	2011–2012	2013–2014	Diff	2011–2012	2013–2014	Diff	2011–2012	2013–2014	Diff
Mon. to Wed.	–0.19	0.44	0.63	–0.39	2.20	2.59	0.20	–1.76	–1.96
			[1.19]			[4.78]			[–3.44]
Thurs. to Fri.	0.77	0.44	–0.32	–1.11	–2.14	–1.03	1.88	2.59	0.71
			[–0.52]			[–1.30]			[0.90]
Diff	0.96	0.00	–0.95	–0.72	–4.35	–3.62	1.68	4.35	2.67
	[1.28]	[0.00]	[–0.93]	[–0.64]	[–3.68]	[–3.15]	[2.32]	[4.59]	[2.78]

Table A8. Other anomalies: Monday through Wednesday and Thursday through Friday

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 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.

	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]
Illiquidity	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]