Leverage is a Double-Edged Sword*

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Abstract

We use proprietary data on intraday transactions at a futures brokerage to analyze the link between implied leverage, trading performance, and the sources of profits/losses, conditional on investor skill. We measure skill during a training period, and analyze performance out of sample. Levered positions stimulate de facto liquidity provision by skilled investors, who earn 19.3 bps per leverage unit. Unskilled investors' leverage amplifies their losses, particularly those stemming from gambling proclivity. Across all individuals and institutions, forced liquidations largely account for the negative impact of leverage on performance. Regulatory increases in required margins decrease (enhance) skilled (unskilled) investors' performance.

Keywords: Leverage, futures, margin calls, investor skill, trading performance

JEL Classification: D03, D81, G02, G12, G23

1 Introduction

The implicit leverage afforded by derivatives offers the prospect of magnified profits to individual and institutional investors. There are, however, several examples of investors that became financially distressed due to derivatives-induced losses. For instance, Archegos Capital Management lost $20 billion within two trading days due to a levered derivatives position (see Dahlquist, Sokolovski, and Sverdrup 2021). As described in Rafeld, Fritz-Morgenthal, and Posch (2017), the substantially levered position of Nick Leeson in derivatives bankrupted Barings Bank. In the 1990s, the oft-cited billion-plus dollar losses incurred by Metallgesellschaft and Robert Citron, the Orange County treasurer, both involved derivatives bets.[1] Admonitions that individual investors should avoid leveraged derivatives via discount brokerages such as Robinhood are commonplace in the popular press, although individual success stories are sometimes highlighted.[2]

While there are many instances and anecdotes surrounding derivatives leverage, there remains the issue of how exactly such leverage affects the cross-section of trading performance. In this paper, we use high-frequency data to consider the links between leverage, overall performance, and the sources of profits/losses in futures markets, conditional on traders' skill. Notably, we measure skill during a training period, and examine the leverage-performance link out of sample. We also investigate how forced liquidations (due to margin calls) affect levered profits. At the outset, we clarify that our focus in this paper is not spot leverage from borrowed funds, but the leverage levels implied by the actual derivatives positions of traders. Thus, "leverage" refers to the effective leverage implied by traders' marked-to-market positions in the contracts we consider.

Our dataset, kindly provided by a major futures broker in China, includes traded orders, intraday time-stamped transaction histories, day-end holdings, and account cash flows (injection and withdrawals) encompassing a three-year period for more than 10,000 investors. While the majority of investors are individuals, some institutions are included as well. To the best of our knowledge, our paper is the first to analyze the interaction between traders' skill, leverage, and performance, and the mechanisms by which leverage impacts performance. Our principal

[1] These cases are among the highest account-level trading losses of all time; viz. http://tinyurl.com/kpxhvmj4.

[2] See for example, https://tinyurl.com/3p9yupu2 and http://tinyurl.com/bwwcrbe8.

metrics at the trader level are the following: a daily rate of return (DRR) measure, a turnover (DTO) measure, and a leverage level (DLV) implied by traders' nominal positions relative to the capital at stake. We construct two versions of DRR, gross and net of brokerage commissions.

To identify traders' skill, we use Sharpe ratios of net DRRs to stratify investors. As in Ivković, Sialm, and Weisbenner (2008), Barber et al. (2009), Grinblatt, Keloharju, and Linnainmaa (2012), and Barber et al. (2014), we find that performance varies considerably in the cross-section. We show that investors' performance is *persistent* in that investors with higher Sharpe ratios in the first year of the sample tend to obtain higher Sharpe ratios in subsequent years. We use a bootstrap procedure based on Fama and French (2010) to further separate skilled from unskilled investors in the first sample year. We then explore the relation of leverage with their performance in the remainder of our sample. None of the skilled or the unskilled investors are institutions, indicating that institutional investors' ability to trade profitably is moderate.[3]

Conditional on skill, leverage is a double-edged sword for individual investors: The out-of-sample net returns of the skilled are enhanced (decreased) by levered positions. We analyze the reasons for these intuitive findings. Existing research suggests that unskilled investors might have a tendency to gamble (Dorn, Dorn, and Sengmueller 2015, Luo and Subrahmanyam 2019, Liu et al. 2021) or trend-chase (Barberis et al. 2018). On the other hand, skilled investors might earn profits from informed trading (Black 1975), de facto market making (Adrian, Etula, and Muir 2014) or arbitrage activities (Hugonnier and Prieto 2015). The question then is how leverage impacts these activities. Turning to unskilled investors first, we find that levered positions amplify unskilled investors' investment losses due to gambling proclivity, where the latter is measured as a tendency to trade on days with greater amplitudes in prices. We do not find evidence of trend-chasing trades. For skilled investors, we uncover the following evidence. First, these investors gain by using higher implied leverage: On average, a one unit increase in leverage for these investors implies a 19.3 bps increase in net DRR (about 47% annually). We show that such investors tend to open long positions in rising markets, and close out the position at market peaks, and vice versa. This behavior is consistent with *de facto* market making, i.e., intraday liquidity provision; see, for example, Grossman and Miller (1988) and Nagel (2012).

[3]The term "skill" is all-encompassing, and for our purposes, it can, for example, mean lower costs of information acquisition, or lower opportunity costs of being present in the market continuously.

We find that these skilled investors also indulge in basis arbitrage. We do not find supportive evidence of informed trading by skilled investors at a daily or longer horizon.

Note that leverage can adversely impact DRR in two ways: one is persistent trading at unfavorable prices (Barber and Odean 2000), the effects of which might be magnified by leverage, and the other is the forced liquidations that arise from margin calls. We are not aware of previous studies that explicitly consider the second channel,[4] and our data indeed allow us to do so. We introduce an indicator that is triggered for investor-day observations with forced intraday liquidation events. Such events explain a large portion of the aggregate underperformance due to high DLV: The magnitude of the coefficient of DLV in the gross DRR regression decreases by more than 90% and becomes statistically insignificant on non-event days; while that of the net DRR is reduced by about 60% during such days.[5]

We also perform a difference-in-differences (DiD) analysis of performance around regulatory increases in required margin ratios. We show that following this policy shift, highly levered investors prior have greater decreases in chosen leverage post-shift relative to investors with low leverage. Further, the net returns of these highly levered investors increase post-shift relative to the other investors. But the policy that effectively constrains leverage has heterogeneous impacts on traders: The performance of unskilled investors increases, whereas that of skilled investors and institutions, as a group, deteriorates. Thus, our identification scheme confirms the "double-edged" aspect of implied derivatives leverage.

Two streams of literature closely link to our paper. One is related to trading performance, and the other is connected to leverage. The seminal work of Odean (1999), Barber and Odean (2000), Barber and Odean (2001), and Barber et al. (2009) focuses on the effect of behavioral biases on investors' trading behavior and their wealth. Bauer, Cosemans, and Eichholtz (2009) show that options trading is harmful to most individual investors. Li, Subrahmanyam, and Yang (2018) show that investors' skewness (lottery) preference can explain the extreme popularity of the world's largest callable options market, and that issuers earn large rents (investors lose

[4] Santa-Clara and Saretto (2009) consider the impact of simulated margin requirements on the profitability of derivatives strategies; we add to their findings by using data on actual forced liquidations.

[5] A recent article on Bloomberg (https://tinyurl.com/p4n4p746) discussed how highly leveraged positions impact trader losses in cryptocurrency markets and quoted Jeffery Wang of the Amber Group, a crypto trading firm, as saying: "We've seen a lot of higher leverage positions be liquidated in a short span of time... This was a large flushout and if the market wants to continue higher it was likely necessary to remove some of the froth from overleveraged positions."

billions) by catering to investors' lottery preference via offering more lottery-like products. Using account-level data, Pearson, Yang, and Zhang (2021) and Li, Subrahmanyam, and Yang (2021) study how market participants behave and perform in a warrants market bubble. Frazzini and Pedersen (2021) show that options and ETFs with high embedded leverage (which are, by definition, more risky) provide lower abnormal returns (alphas), suggesting they might be overpriced. We add to these papers by using actual trading and performance data to analyze how trader skill interacts with implied leverage.

There are many significant theoretical papers that analyze the effect of margin trading on asset price dynamics, and tackle the issue of how to regulate (manage) leverage to improve market quality (see, e.g., Chowdhry and Nanda 1998; Brunnermeier and Pedersen 2009; Geanakoplos 2010; Garleanu and Pedersen 2011; Fostel and Geanakoplos 2012; Jacobs and Levy 2012; Jin and Zhou 2013; and Santos and Veronesi 2021). Our analysis of cross-sectional dispersion in the performance of levered portfolios allows for additional avenues of future theoretical research.

As for empirical work on leverage and margined trades, Hong, Kubik, and Fishman (2012) find that, after good earnings news, the price of highly shorted stocks (usually on margin) surges more compared with that of otherwise similar stocks. Using the unique features of the margin trading system in India, Kahraman and Tookes (2017) quantify the impact of trader leverage on market liquidity; they show that liquidity increases when stocks become eligible for margin trading, and that the aforementioned relationship reverses during crises.[6] Richardson, Saffi, and Sigurdsson (2017) find that securities with more leveraged investors tend to experience more extreme returns. Making use of publicly available data, Santa-Clara and Saretto (2009) show that margin requirements make the writing of put options less profitable. Bessembinder and Seguin (1993) analyze the links between volume and volatility in futures markets. Koudijs and Voth (2016) find that the bankruptcy of an investor consortium exposed lenders' activity, and following this bad experience, lenders increased the cost of leverage. Our high-frequency data at the account level allow us to contribute to this literature by explicitly consideration of the

[6] Taking more of a macro perspective, Schularick and Taylor (2012) study the behavior of money, credit, and macroeconomic indicators over the years 1870-2008, and find that credit growth is a powerful predictor of financial crises. Baron and Xiong (2017) find similar results in the banking sector, i.e., bank credit expansion implies higher crash risk. Di Maggio and Kermani (2017) study the effect of the supply of credit the real macroeconomy.

link between trader skill and leverage, and of the rationales for why leverage boosts or reduces performance.

In two important papers, Heimer and Simsek (2019) and Heimer and Imas (2021) analyze the impact of leverage restrictions on retail currency traders using DiD on a self-reported trader database at a social media website. This analysis uses the fact the U.S. retail traders' leverage was capped by regulation in 2010 but that of European traders was not. They focus on the effects of the leverage regulation on aggregate trader performance in the spot foreign exchange market. They show that the constraint reduces trading volume, improves trading performance, and has little effect on the relative bid-ask spread. We add to these papers in three ways. First, we focus on cross-sectional variation in the relation between implied derivatives leverage and profits at the individual account level (individuals versus institutions; skilled versus unskilled). Second, we are able to perform high-frequency analyses of why skilled and unskilled investors over- or under-perform. Third, we pin down the cause of leverage-induced underperformance (margin calls vs. trading at unfavorable prices). Thus, our work is complementary to theirs.[7]

Margin trading in the Chinese stock market has attracted much attention recently. Via a regression discontinuity design, Hansman et al. (2018) quantify the effects of introducing margined investing on the Chinese stock market bubble of 2010-2015. Hu, Liu, and Zhu (2019) study how (de)leveraging contributes to stock market quality by using stock-level margin trading data. Feng, Lu, and Xiao (2020) claim that the unregulated (shadow-financed) margin trading exhibits stronger explanatory power for time-series and cross-sectional asset returns than its regulated (brokerage-financed) counterpart. Taking advantage of both regulated (brokerage-financed) and unregulated (shadow-financed) account-level margin trading data, Bian et al. (2021) study investor behavior during the 2015 market turmoil in China. They show how leverage-induced trading causes contagion and thus affects asset returns and volatilities. Our paper complements these papers by considering the links between trader skill, leverage, and performance. Using account-level data, Gao et al. (2021) show that the complexity embedded in levered investment funds benefits sophisticated investors and hurts small and naïve investors.

At this point, it worth reiterating what our Chinese context adds to the typical finance

[7]In a recent paper, Davydov and Peltomäki (2021) consider leverage accruing from instruments such as leveraged ETFs and come to a conclusion similar to Heimer and Simsek (2019).

academic trying to learn more about finance in general. In this regard, our account-level intraday data from futures markets offer a unique opportunity for studying the effect of derivatives leverage on the cross-section of trading performance. To the best of our knowledge, our paper is the first to directly document the heterogeneous impact of leverage and to uncover mechanisms underlying the leverage-return relationships across traders. Our results indicate that skilled investors benefit from leveraged derivatives positions, and the sources of superior performance are de facto market making and traditional basis arbitrage. The value of leverage for unskilled investors is negative, mainly due to margin calls.[8] Further, the differential impacts of margin constraints on skilled investors, institutions, and unskilled investors is a cautionary note against derivatives regulation based on treating investors as a homogeneous group. This point is relevant to the debate on regulating access to derivatives (and the concomitant leverage) at U.S. discount brokerages,[9] particularly because the trading characteristics of Chinese investors are similar to those in the U.S. (viz. Liu et al. 2021).

The paper proceeds as follows. We describe the data, measures and methods in Section 2. Section 3 considers the impact of leverage on portfolio volatility and returns for individuals and institutions, and also reveals how forced liquidations (margin calls) affect performance. Section 4 investigates how unskilled investors' performance is affected by the combination of leverage and gambling proclivity. Section 5 analyzes how skilled investors use leverage to obtain their superior performance. Section 6 performs a difference-in-differences analysis around regulatory increases in the margin ratio. Section 7 concludes.

2 Data and Measures

In this section, we first describe our proprietary data set. We then move to describe our measures of performance, trading intensity, and leverage. Finally, we present our method for distinguishing skill from luck.

[8]While hedging may play a role in derivatives trading, it should not be associated with leverage. Thus, the connection between performance and leverage should be delinked from hedging. Further, the median time to fully turning around a position is a mere 53 minutes in our sample. The first page of the online appendix considers the regulatory environment surrounding futures hedging, and indicates that hedging is unlikely to be a source of underperformance within our sample.

[9]See, for example "Opinion: Robinhood needs more regulatory oversight" at https://tinyurl.com/wv69p9cf.

2.1 Dataset

Our dataset, provided by a brokerage firm, spans the period January 2, 2014 to December 30, 2016, and includes 733 trading days. While we were unable to persuade the broker to give us more data, our time span compares with the sample of equity trades in Barber and Odean (2001), Grinblatt and Keloharju (2001), Barber et al. (2009), and Liu et al. (2021), in which the data encompass periods ranging from one to six years. Our dataset has the additional feature that we have time-stamped data on intraday transactions. Note also that all our markets are in zero net supply, where buying and selling are treated symmetrically. Thus, we are able to abstract from issues such as whether the period spanned a bull or bear market, which are pertinent to net long securities such as equities. Further, our period was not unusual in terms of trading activity for the futures markets in our sample,[10] indicating no pitfalls in generalizing our findings.

The data include six tables: These consist of account details, capital, transactions, holding, delivery, and entrust. The account details table contains the account ID, birth date, account open date, and account close date. The capital table contains investor-day level information about marking-to-market profit/loss, as well as money injected and withdrawn. Each trading record in the transaction table contains the following information: account ID, transaction series number (reset daily), variety code (indicating the underlying asset), delivery month (indicating maturity date), trading price, trading volume, trading date, trading time (accurate to one second), trading direction (buy or sell), position change (open or close), a forced offset indicator, and the commission fee incurred by the trade. The holding table contains account ID, date, variety code, delivery month, the day-end holding position (long or short), the corresponding day of the opened position, the daily holding return, the aggregate holding return, and the settlement price for both the current and previous trading days. The delivery table contains account ID, date, variety code, delivery month, delivery amount, delivery price, and the settlement price for the previous trading day. The entrust table, which documents submitted orders, contains account ID, entrust series number (reset daily), variety code, delivery month, order price, order volume, order date, order time (accurate to one second), entrust direction (buy or sell), position flag (open or close), forced offset indicator, and a cancel flag.

[10] Annual trading activity in the relevant markets is available at https://tinyurl.com/xtdhss2x.

There are 39.4 million futures trading records (including futures deliveries) by 10,822 investors, among which 315 (2.91%) are institutional investors. We have 1086 contracts written on 51 different underlying assets.[11] Table 1 reports summary statistics of variables used in this paper, including the number of trades (in thousands), the notional value traded in our sample (in billions), the gross profits (in millions) and the net profits (in millions) earned by investors. Futures written on the CSI 300 Index contribute the most turnover in notional value terms, and their investors also suffer the greatest losses. The second to last column of Table 1 shows the number of forced liquidation trades, which total 12,182 in our sample. The last column shows the number of investors that had ever traded futures written on each particular underlying asset.

Panel A of Table 2 shows that the total notional value traded is 8.86 trillion yuan (about U.S. $1.36 trillion, or 0.9% of the market), and the average turnover value for individuals (institutions) is 809.8 million (568.0 million) yuan. Panel B shows that the aggregated gross loss for individuals (institutions) is 464.1 million (33.2 million) yuan. In Panel C, we see the aggregated net loss for individuals (institutions), which is 998.1 million (52.5 million) yuan. Investors in our sample lost 1,050.6 million yuan in total, and more than half ($1050.6 - 497.3 = 553.3$ million yuan) of the aggregate loss is due to transaction costs. The distribution of gross profits for individuals is right skewed, indicating that there are a few individual investors who can earn high gross profits. However, net of transaction fees, the distribution of profits is slightly left skewed. Panel C shows that, on average, at this single brokerage, individual investors lost 93 thousand yuan, which is higher than the per capita Chinese gross domestic product (64,644 yuan) in the year 2016, and also higher than the total of the contemporaneous (years 2014 to 2016) disposable income per capita of Chinese residents ($20,167 + 21,966 + 23,821 = 65,954$ yuan).[12]

Panel D of Table 2 shows that the mean value of the average day-end assets for individuals (institutions) is 90.3 (433.0) thousand yuan. More than 1% of investors have an average day-end asset value higher than 1.2 million yuan (U.S. $200,000). Panel E demonstrates that the mean (median) value of net profit per unit of notional turnover is about -0.15% (-0.04%).

To investigate investors' holding periods, we introduce the term "trading cycle," which is

[11] From the "Investor Accounts of Securities and Futures Market" section of the Yearbook of Chinese Securities and Futures Market (available at https://data.cnki.net/yearbook/), the contemporaneous overall market has 1842 contracts written on 51 underlying assets. Contract positions are marked-to-market on a daily basis, as in the U.S. There are required margins on each contract; however, there is no distinction between initial and maintenance margin.

[12] Data from National Bureau of Statistics: http://www.stats.gov.cn/tjsj/zxfb/201902/t20190228_1651265.html.

a round-trip transaction for a specific contract. Specifically, a trading cycle begins at the time when an investor opens a position in a futures contract, and ends when the trader *completely* clears the position in that contract. We define the duration of each cycle as the elapsed trading time between the beginning and end of the cycle. Panel F of Table 2 reports the distribution of investors' median duration of trading cycles. We find that, for more than 25% of investors, the median duration is less than 16 minutes, which indicates that there is a considerable portion of investors who conduct intraday futures trading. The median of investors' median duration is 51.6 minutes, and the mean is more than ten hours, which implies that the distribution of the duration of trading cycles is highly right-skewed. Institutions hold positions of longer duration relative to individuals; their median is almost seven hours. The same panel also shows that there are more than 100 high frequency traders in our sample: for more than 1% of investors, the median duration is less than 0.5 minute.

2.2 Trader-Level Metrics: Return, Turnover Ratio, and Implied Leverage

We define performance and trading activity measures that incorporate intraday trading information.[13] Specifically, on day t, investor i's daily rate of return (DRR) is given by

$$\text{DRR}_{i,t} = \frac{\text{Daily\_Profit}(i,t)}{\text{Cash\_Injection}(i,t) + \text{Day\_End\_Asset}(i,t-1)}, \tag{1}$$

where $\text{Day\_End\_Asset}(i,t-1)$ represents the total assets (cash plus margin) of investor i at the end of day $t-1$. In the denominator, we also add the amount of money that is injected into the futures account during day t, since the money is immediately available after injection. $\text{Daily\_Profit}(i,t)$ is available directly within our dataset based on the marking-to-market mechanism on day t. We construct two versions of DRR: gross and net DRR, which, respectively, exclude and include transaction costs.

[13] In our sample, in nearly one-third of cases, investors who trade futures on one day have zero holdings of futures on the previous day; also, the aggregate number of contracts held at end-of-day-close account for only 16.1% of the number of contracts traded. Thus, as in Li, Subrahmanyam, and Yang (2021), a within-day calculation is more relevant than the holdings-based return calculation method of Barber and Odean (2001) for equity trades.

Our daily turnover (DTO) measure is defined similarly to DRR in Eq. (1) as follows:

$$\text{DTO}_{i,t} = \frac{\text{Turnover\_Value}(i,t)/2}{\text{Cash\_Injection}(i,t) + \text{Day\_End\_Asset}(i,t-1)}, \tag{2}$$

where "Turnover_Value(i,t)" is defined as the sum of notional values of all trades on day t by investor i. Since futures trading is usually leveraged, and intraday trading is prevalent, the above defined DTO measure can be well over 100%. Unlike Barber and Odean (2001) (see their Section II.C), we therefore do not cap our DTO measure at the 100% level.

A key measure used in our paper is the implied leverage, i.e., the notional value held relative to the capital at stake. Again, since the day-end holding positions only account for a small (zero for more than 30% of the cases) portion of trading volume, we need to consider intraday positions. In this paper, we define daily implied leverage (DLV) as follows

$$\text{DLV}_{i,t} = \frac{\text{Maximum\_Value\_Held}(i,t)}{\text{Cash\_Injection}(i,t) + \text{Day\_End\_Asset}(i,t-1)}, \tag{3}$$

where the "Maximum_Value_Held(i,t)" in the numerator is the maximum notional value held by investor i during day t, and is defined as:

$$\text{Maximum\_Value\_Held}(i,t) = \max_{0 \le j \le n_{i,t}} \text{Notional\_Value}_{j,i,t}, \tag{4}$$

where $n_{i,t}$ is the total number of trades by investor i on day t, and Notional_Value$_{j,i,t}$, $0 \le j \le n_{i,t}$ is the aggregate notional value of all held contracts computed as:

$$\text{Notional\_Value}_{j,i,t} = \sum_{k=1}^{m_{j,i,t}} N_{k,j,i,t} \times P_{k,t-1}, \tag{5}$$

where $m_{j,i,t}$ is the number of different contracts held by investor i immediately after the j-th trade during day t, $N_{k,j,i,t}$ is the net position for the k-th contract, and $P_{k,t-1}$ is the settlement price of contract k on day $t-1$. When $j = 0$, $\{N_{k,0,i,t}\}$ records the positions held by investor i at the end of the previous trading day. Note that if there is no trading on day t, our DLV measure is exactly the leverage level at the end of day $t-1$. We impose a purchase price of $P_{k,t-1}$ for day t contract purchases rather than the real time price, since there may exist a confounding effect that increased prices might tend to increase the leverage level contemporaneously. In all three measures DRR, DTO, and DLV, we do not consider cash withdrawals. Equivalently, we assume that all cash injection occurs at the very beginning of each day, while all cash withdrawal occurs at the end of the day after the marking-to-market.

Note that DLV represents the chosen level of leverage, and not a mandated maximum level. That is, the numerator of DLV is also a proxy for trading aggressiveness, in that it measures how much of a nominal amount the trader is willing to put at stake. The denominator of course, is a measure of the total personal capital available, so that the DLV ratio captures the level of implied leverage. Our focus is on how and why such DLV influences trader performance, unconditionally, as well as conditional on trader skill. To prevent possible mechanical connections between ex-post measures of skill, DLV, and performance, we identify trader skill out of sample, as described in Section 2.3.

Panels G and H of Table 2 show the distributions of gross and net DRR, respectively. On average, traders earn negative DRRs. The cross sectional mean of the average gross DRR for individuals (institutions) is −47.9 (−16.1) basis points, and that of the net DRR for individuals (institutions) is −70.4 (−23.1) basis points. Both gross and net DRRs are left skewed. The better performance of institutions relative to individuals is consistent with Barber et al. (2009) and Bian et al. (2021) for equities.

Panels I and J of Table 2 report the distributions of DTO and DLV, respectively. The mean DTO for individuals is 15.66, more than three times higher than that for institutions (4.51). About 1% of investors have a DTO higher than 160.[14] Panel J shows that the average DLV is 5.76 (4.88) for individuals (institutions). The DLV exceeds 14 at the 99th percentile, indicating that at least some investors tend to hold extremely leveraged positions.

2.2.1 Alternative Measures for Implied Leverage

Since implied leverage is our primary focus in this paper, we now define some alternative DLV measures, which are used for robustness checks.

[14]These numbers should be interpreted carefully as we compute DTO using notional values traded but do not base it on the money in margin accounts. For example, if the leverage is 10, then a DTO of 160 means investor positions changed hands 16 times, rather than 160 times.

The first is the *contemporaneous* leverage measure ConDLV which is defined similarly as DLV except that the notional value in Eq. (5) is now computed at prices when trading occurs:

$$\text{Notional\_Value}_{j,i,t} = \sum_{k=1}^{m_{j,i,t}} N_{k,j,i,t} \times P_{k,s_{j,i,t}}, \tag{6}$$

where $P_{k,s}$ is the price of the contract k at time s, and $s_{j,i,t}$ is the time that investor i's j-th trade on day t occurs.

The second alternative is the *lagged* leverage measure LagDLV, which is the one-day lagged version of ConDLV. Specifically, for each investor i on day t, $\text{LagDLV}_{i,t} = \text{ConDLV}_{i,t-1}$. Note that although the LagDLV addresses the reverse causality problem between the leverage and return measures, the lagged leverage measure may contain less information about the real leverage level for high frequency traders who seldom hold overnight positions.

We also propose a third alternative, a measure of *predicted* leverage. Specifically, for each investor i on day t, we estimate an autoregressive model with four lags using all observations of ConDLV up to day $t-1$, and compute the $\text{PredDLV}_{i,t}$ using the estimated coefficients and the most recent four lags.[15] We term the predicted time series PredDLV.

2.3 Luck versus Skill

To study whether leveraged investors exhibit persistent skill, we apply a bootstrap method used in Fama and French (2010). In this method, the authors first calculate fund alphas using a three- or four-factor model (as per Fama and French 1993 or Carhart 1997) on gross and net returns. They then compute zero-α returns for each fund via the fund's α net of its monthly return. Finally, they use the t-statistic on the α [$t(\alpha)$] from 10,000 bootstrap simulations of the zero-α returns to test whether actual fund returns have a nonzero true α. We mimic this procedure to test whether leveraged investors' performance is due to luck. Since futures market DRRs are high frequency (daily) performance measures intended to capture intraday trading, they are unlikely to be related to traditional risk factors (normally computed at monthly horizons). Hence our abnormal performance measure simply adjusts for mean returns. We call this bootstrap approach

[15] The number of lags used in the autoregression is determined by studying the time series of the cross-sectional averages (across all investors) of ConDLV; lags beyond four are insignificant for this series. The results when using two or three lags are virtually the same.

the "FF procedure."

An investor is said to pass the FF-test if the t(mean) of that investor's net DRR is higher than the entire set of t(mean)-s from 10,000 bootstrap simulations on adjusted returns.[16] We define the p-value for the "FF-test" (the null is that investors' performance is luck) as the proportion of the 10,000 simulated t(mean)-s on adjusted returns that surpass the corresponding t(mean) on unadjusted returns. Note that for top-performing investors with a positive t(mean) on net DRRs, the smaller the p-value, the more unlikely that investors' performance is due to luck. However, to test whether the performance of investors suffering *negative* returns is due to (bad) luck, we define a different p-value, i.e., the proportion of the 10,000 simulated t(mean)-s on adjusted returns that are *lower* than the corresponding t(mean) on unadjusted returns. We measure skill at the trader level, and not at the contract level, which is consistent with Fama and French (2010), who measure skill at the fund level. In unreported analyses, we find that skilled and unskilled leverage is not unusually concentrated in certain contracts; thus justifying our aggregation to the trader level. In the entire analysis conditional on skill, we measure skill in the first year of the sample, and consider the link between leverage and performance in the remainder of the sample (as well as in sample).

3 Implied Leverage and Investment Performance

In this section, we analyze the relationship between leverage, volatility and returns for the entire sample of traders; and then explore the impact of forced liquidations on performance. To obtain a first impression about the relation between the use of leverage and other investors' characteristics, Table 3 shows summaries of quantities of interest for investors grouped by their average DLV. We use steps of ten percentile points for the grouping, with the exceptions that we also consider the top and bottom 1%. We find that high DLV investors tend to trade more and incur more trading costs. Specifically, Table 3 shows that DTO decreases monotonically from 212.8 for the top 1% to 2.5 for the bottom 1%, and that the average daily trading cost decreases

[16]The bootstrap procedure in both Fama and French (2010) and our work accounts for cross correlation by a joint sampling of months for all funds in a simulation run, but not for autocorrelation. Fama and French (2010) indicate that autocorrelation is not a major problem in their data. We also verify in unreported analysis that the autocorrelations in investors' DRR time series are weak.

(almost) monotonically from 2342 yuan to 194 yuan. As a matter of fact, the top DLV group possesses the lowest median duration of trading cycles, the highest trade size, and the highest number of trades per day. Thus, in general, the traders with the highest leverage are also the most active ones. The natural question that arises then is whether the higher leverage translates to better investment performance. We explore this issue below.

3.1 Implied Leverage and Risk

High leverage is usually accompanied by high risk, and thus high volatility in portfolio returns. Accordingly, we conduct cross-sectional regressions of the standard deviation of investors' gross DRR and net DRR on leverage. Table 4 reports the results. We find from Column (1) that a unit increase in leverage implies a 0.7% increase in the daily standard deviation of investors' gross DRR, equivalent to an 11% increase in annualized volatility. Column (2) shows that turnover ratio (DTO) also varies positively with standard deviation of investors' gross DRR, and the effect mostly stems from using leverage (DLV): Columns (3) and (4) of Table 4 show that the orthogonal part of DTO with respect to DLV only explains a small part of changes in the standard deviation of investors' gross DRR. The results for net DRR reported in Panel B of Table 4 are similar.

To show how leverage affects institutional investors' risk, we include a dummy variable "Inst" (1 for institutions; 0 for others) and an interaction term "Inst$\times$DLV" in regression analyses reported in Table 4. The coefficients of "Inst" show that institutional investors on average bear lower risk than individuals, which is consistent with the finding (see Panel J of Table 2) that institutions tend to use lower leverage than individuals. The coefficients of the interaction term show that the marginal effect of leverage on institutions' volatility is virtually the same as that on individuals' volatility.

Overall, Table 4 confirms that high leverage leads to high risk in individual investors' portfolios. The next issue we explore is whether the higher risk translates to higher average returns.

3.2 Implied Leverage and Returns

High risk is assumed by rational investors for earning high returns. To get a first impression about the relationship between investors' returns and their implied leverage, we plot equally weighted average returns for each leverage bin in Figure 1. Barber et al. (2009) and Barber and Odean (2000) document that investors over-trade, i.e., high trading intensity is associated with reduced performance. To control for the effect of trading frequency, we perform a dependent double sort (first sorting by DTO) on turnover ratio (DTO) and leverage (DLV) in Figure 1. Since most returns are negative, we plot the corresponding opposite numbers in Figure 1 to get a better perspective. The upper plot in Figure 1 shows that higher leverage implies lower gross returns. After taking transaction costs into account, another factor, i.e., turnover, emerges: a high turnover ratio corresponds to low net returns (which accords with Barber and Odean 2000). Another interesting finding is that investors earn high gross returns by trading extremely actively and using high leverage (the upper left corner in the upper plot of Figure 1); however, the accompanying high trading cost almost perfectly offsets these returns.

To further examine the effect of leverage, we conduct panel regressions of investors' gross DRR and net DRR on our leverage proxy, DLV. To see if the leverage effect is different for institutional investors, we also incorporate a dummy variable "Inst" (1 for institutions; 0 for others) and an interaction term "Inst×DLV" in regression analyses. Investors' ages, account ages, the value-weighted futures' time-to-maturity, and DTO are included as controls together with day fixed effects in the regressions. Table 5 reports the results of the regressions.

Panel A of Table 5 shows that a unit increase in leverage implies a decrease in individual investors' daily gross (net) return by 3.23 (5.30) bps when controls are included.[17] The magnitude is large: assuming similar leverage applies each day within a year, the accumulated underperformance in gross (net) return terms is in annualized terms about 8% (13%) per additional unit of leverage. Although the point estimate of the effect of leverage on institutional investors' performance is negative, it is statistically insignificant.[18] In ancillary results, we find

[17]Note that the mechanism of generating leverage in futures markets is quite different from that of margin trading using borrowed funds in stock markets. The key point surrounding the latter is that such trading is always accompanied by funding (borrowing) costs, which are not relevant for futures markets and are thus not related to the results reported in this paper.

[18]Tables IA.1 and IA.2 in the internet appendix, which are the equivalents of Tables 4 and 5 for institutions alone, confirm that high DLV is associated with higher volatility and lower net DRRs for institutions.

that investors with higher account age on average have higher returns and lower turnover ratio, while chronological age depicts the opposite pattern.

We next use the three alternative measures of DLV in Section 2.2.1 to eliminate confounding effects arising from potential joint determination of DRR and DLV. First, we use information up to day $t-1$ when predicting the investors' returns at day t via the measure PredDLV, i.e., the predicted leverage using lagged leverage up to $t-1$. Panel B of Table 5 shows the regression results, which depict similar patterns as those in Panel A. We also perform two further robustness checks on Table 5 by using the lagged and contemporaneous leverage measures (LagDLV and ConDLV). The results are shown in Tables IA.3 and IA.4 of the online appendix, and are consistent with those in Table 5. From this point we use the main measure of DLV; however, all the reported results are robust to the alternative DLV measures in Section 2.2.1.

3.3 Forced Liquidation and Returns

Intuitively, leverage is an amplifier for portfolio returns, and it should have symmetric effects when investments make or lose money; however, why is it associated with reduced performance even gross of commissions? This, of course, may happen because of simple "overtrading" at persistently unfavorable prices (Barber and Odean 2000), the effects of which may be magnified by leverage. But another aspect that operates in leveraged markets is the phenomenon of forced liquidations (or fire sales) that accompany margin calls.[19] The higher the effective leverage, the higher is the probability of being mandatorily liquidated within a trading day. Investors may find it challenging to recover from these intraday liquidation events. The role of such events on trader performance has not yet been explicitly explored in previous work.

We introduce a dummy variable which we term "Force," that is set to 1 if a forced liquidation occurs within an investor-day, and zero otherwise. The first columns in Panels A and B of Table 6 report the counterparts of the last columns in Panels A1 and A2 of Table 5 with the "Force" dummy added. Comparing Table 6 with Table 5, we find that, after including "Force" as a control

[19]The exchanges have exact rules for margin calls, which are strictly enforced. The rule is defined via a variable "*Risk_Degree*", which is defined as "$Margin/(Margin + Cash)$". Brokerage firms require higher margin ratios than exchanges, which results in higher *Margin* required, and thus higher "*Risk_Degree*". When "$Risk\_Degree >= 1$" under brokerage rules, the brokerage issues a notice of margin call, and investors must then top up cash so that "$Risk\_Degree < 1$" before the deadline specified in the notice. Otherwise the brokerage closes part (or all) of the position to release margin such that "$Risk\_Degree < 1$".

variable, the magnitudes of the DLV coefficients in the DRR regressions decrease considerably; for example, the coefficient of DLV for gross DRR changes from -3.23 bps to -0.05 bps with an insignificant t-value of -0.07. This informs that after controlling for forced liquidations, leverage does not play any significant role in gross DRR; in other words, the impact of leverage on gross investment returns occurs mainly via forced liquidations.

Furthermore, the first column of Panel B in Table 6 shows that the DLV coefficient in the net DRR regression changes from -5.30 bps to -2.11 bps (with a t-statistic of -3.39) as a result of forced liquidation, a percentage decrease of about 60%. Compared with the nearly zero corresponding coefficient in Panel A, the significant coefficient of -2.11 in Panel B indicates a positive relationship between trading costs and leverage. This confirms the notion that large leverage enlarges trading positions, and hence should increase trading costs. Overall, the evidence indicates that both forced liquidation and increased trading costs cause leveraged investors to lose money (net of commissions) in futures trading.[20]

Note that the "Force" dummy is not determined by the day-end DRR because the investor can adjust trading strategies following the intraday forced liquidation. Traders avail of ample such opportunities to recover from liquidation, given the median duration of just 52 minutes documented in Panel F of Table 2. Nonetheless, to address this issue, in the second columns of Panels A and B in Table 6 we show that the results are robust to using a predicted "Force" variable based on a logit model with past daily lags of DLV, DRR, and DTO. Indeed, the coefficients barely change using this alternative variable.

In Table IA.5 within the internet appendix, we consider the impact of forced liquidation via a sorting procedure. We sort investors into 5×5 groups by full sample average DLV and DTO, and for each group, document the difference in net DRRs including and excluding days of forced liquidation. The table confirms that those traders that carry the highest DLV are impacted the most by forced liquidation, and the difference across DLV quintiles are significant for the entire sample, and for four of five DTO groups. Interestingly, among all groups, forced liquidation has the maximal proportional impact on those with the lowest DTO and highest DLV, suggesting a positive link between DTO and skill.

To explicitly quantify the liquidity (or price pressure) effects of forced liquidation, we conduct

[20]The coefficients of age, account age, and time-to-maturity in Table 6 are consistent with those in Table 5.

an event study around investors' forced trades. Figure 2 shows returns on volume-weighted average prices (VWAP) around investors' forced buys and sells separately. We find that forced sell trades suffer more severe liquidity costs than forced buys, which is consistent with Brennan et al. (2012). Quantitatively, forced sell trades bear a 50 bps liquidity cost within a 30 minute period, while the corresponding number for forced buy trades is less than 10 bps. Figure 3, which plots the best bid (ask) price around the forced sell (buy) trades, also confirms that on average there is a price rebound of more than 10 bps right after the forced sells. These empirical findings are consistent with the notion of predatory trading proposed by Brunnermeier and Pedersen (2005), who propose that "if one trader needs to sell, others also sell," which then results in a less liquid market and a shrinking liquidation value for the distressed investor.[21]

4 Unskilled Investors

We have shown that investors on average pay for leverage. In this section, we intend to ascertain what type of trading patterns contribute to the relatively unskilled investors' losses. Of course, that unskilled individual investors are subject to trading biases is well-known; for example, they seem to treat trading as gambling, a form of entertainment, and naïvely extrapolate from past returns; see, for example Liu et al. (2021) and Barberis et al. (2018). The question, however, is whether unsophisticated investors are self-aware enough to not use leverage in a counter-productive way that exacerbates their bias. This issue has not yet received attention in the literature. To this end, we do two things in this section. First, we identify unskilled investors out of sample. Then, we consider the effect of leverage on their trading biases.

To reliably investigate the aforementioned issues, we need to identify investors who consistently evidence a lack of skill in our sample period. To this end, in this section, we stratify investors by trading performance based on their Sharpe ratios of net DRR in a training period (year 2014), and analyze their performance and trading behavior in the years of 2015 and 2016.

We group investors by their Sharpe ratios of net DRRs, and report the cross-sectional averages (within each group) of each investor's time series averages of net DRR (in percent), DTO, and

[21] Tables IA.6-IA.8 in the internet appendix show that the results on forced liquidation are robust to alternative measures of DLV.

DLV in Table 7. The reported numbers also include the cross-sectional averages of Sharpe ratios associated with DRRs, the cross-sectional median of the median duration of trading cycles, the number of investors in each group, and the number of investors who pass the FF-test as per Section 2.3. We find that the monotonicity in Sharpe ratios and net DRRs remains (but statistically weakens) in the out-of-sample period, which implies persistence in investors' performance. This latter claim can be further verified by noting that there are more FF-passers in the high Sharpe ratio groups, which is true for both in-sample as well as out of sample.

We find from Table 7 that the median duration of trading cycles exhibits a hump shape, i.e., both top- and bottom-performing investors trade very actively: the median values of median durations for extreme groups are less than 8 minutes in both the in- and out-of-sample periods; in the out-of-sample period, the top 1% of investors tend to trade more actively than those in the bottom 1% group. Consistent with the duration of trading cycles, DTO exhibits a U shape: in the in-sample period, the average notional turnover is higher by as much as 6 times for investors in extreme groups relative to the middle group; the pattern is similar in the out-of-sample period. Investors' DLV exhibits only modest heterogeneity both in and out of sample for the Sharpe ratio stratification. For example, the cross-sectional average of DLV ranges from 6.15 to 8.23 in the in-sample period; the values for top and bottom groups are slightly higher than those for other groups, while the difference is statistically insignificant. Overall, these findings imply that investors' trading activity and DLV also exhibit persistence.

4.1 Identifying Unskilled Investors

Although we have shown that investors' performance and trading behavior are persistent, Table 7 shows that, except for DTO, both the size and the statistical significance of the difference between extreme groups are lower out of sample than in-sample. This latter fact suggests that both top and bottom (stratified by Sharpe ratios of net DRRs) investors' performance might be due to chance. In order to better understand investor behavior, we need to further mitigate the effect of luck to identify unskilled (this section) and skilled (Section 5.1) investors.

In this section, we term unskilled investors as those who traded at least on 24 trading days during the year 2014 and satisfy all of the following criteria: (1) investors' Sharpe ratios of DRRs during the year 2014 are negative and amongst the bottom 5% of all investors who traded at least on 24 days during the year, and (2) the p-value for "testing whether the performance of investors suffering negative returns is due to luck" (as per Section 2.3) is zero (i.e., their t-statistics are below the FF-bootstrap in each of the simulations). Using this approach, we identify 79 unskilled investors; all of them are individuals.

Table 8 presents the unskilled investors' percentiles on their Sharpe ratios of net DRR, median of duration of trading cycles (in minutes), average net DRR (in percent), average DTO, average DLV, number of trading days (NoDays), number of trades per trading day (NoTperDay), and their p-values of the "FF-test" defined as per Section 2.3. Table 8 shows that a large portion of unskilled investors trade very actively: more than half of them trade more than 23 times per trading day in both in- and out-of-sample periods; more than one fourth of them trade on more than half of the trading days. In the out-of-sample period, only two out of the 79 unskilled investors earn positive average net DRRs which, however, is likely due to luck (with out-of-sample p-values higher than 0.3).[22]

In Table 9, we present the net and gross DRRs for the unskilled investors, sorted by DLV quintiles, both in-sample and out of sample. We find that in the year of identification, both gross and net DRRs decline with DLV, and the differences across the extreme quintiles are statistically significant. In the out-of-sample period, however, gross DRR presents less of a clear picture across DLV quintiles, and the difference between the high and low DLV quintiles is positive and marginally significant (t=2.36). However, the net DRR presents a pattern similar to the in-sample period; it is clearly declining in DLV, with the difference between high and low DLV quintiles amounting to almost -200 basis points with a t-statistic of almost -10. The gross DRR numbers may reflect a mild tendency on the part of the unskilled to learn from experience (Seru, Shumway, and Stoffman 2010). In terms of DRR after accounting for trading costs, however, leverage has a negative impact on unskilled performance, both in-sample and out of sample.

[22]Skill may be overstated in our sample, since the out-of-sample period spans the latter two years, requiring a three-year survival for traders. We acknowledge this issue, but it is reassuring that 77 of the 79 unskilled investors identified during the first year continue to underperform in the latter two years, indicating that we are truly picking up a lack of skill.

4.2 Sources of Unskilled Investors' Losses

It is of interest to understand what contributes to unskilled investors' losses. We consider two important biases studied in earlier literature: extrapolation (see, e.g., Barberis et al. 2018) and a proclivity towards gambling (see, e.g., Liu et al. 2021).[23]

Specifically, Barberis et al. (2018) propose that many investors form their demand for risky assets by extrapolating past returns. This implies trend-chasing trades, which might contribute to naïve investors' losses. We next investigate if unskilled investors in futures markets also conduct such trades. Table 10 shows results from panel regressions of unskilled investors' OIB on past returns over periods spanning 1 minute to 5 days. We find no evidence that unskilled investors are trend-chasers; on the contrary they tend to buy (sell) in falling (rising) markets. In fact, Figure 4, which plots returns around unskilled investors' open trades, shows that unskilled investors try to time rebounds after big price changes. However, such timing is ineffective.

Using data from a nationwide survey of Chinese retail investors, Liu et al. (2021) find that gambling preference is a key factor in explaining investors' trading motives. We next study the relation between gambling proclivity and leverage. Gambling-motivated trading should be higher when asset prices are more prone to large swings; we therefore use a measure daily amplitude in prices as a proxy for gambling proclivity. The daily amplitude on day t is defined as $Amp_t = \frac{High_t - Low_t}{Close_{t-1}}$, where $Close_{t-1}$ is the settlement price on day $t-1$, and $High_t$ (Low_t) is the highest (lowest) trading price on day t. For both the in- and out-of-sample periods, Table 11 reports results of panel regressions of unskilled investors' DRR and DTO on DLV and amplitude. To investigate the effect of leverage, we also include the interaction term between amplitude and a HDLV dummy (1 if DLV is higher than the sample median, and 0 otherwise).[24]

The results in Panels A3 and B3 of Table 11 show that DTO is indeed higher when Amp is larger. The coefficient for the interaction term is positive and significant, indicating that high leverage amplifies the gambling effect. Panels A2 and B2 of Table 11 show that net DRRs are

[23]Another well-studied bias is the disposition effect, which is the reluctance to liquidate losing positions and eagerness to realize gains (see, e.g., Odean 1998). Heimer and Imas (2021) show that this bias contributes to investors' losses in spot foreign exchange markets. In unreported analyses, we find that unskilled investors are indeed subject to the disposition effect (which is magnified by leverage), while skilled investors (who are specifically identified in Section 5.1) are not. The results are available upon request.

[24]In Figure IA.1 within the internet appendix, we provide DRR stratified by volatility (computed using one-minute returns) and show that the unskilled losses are higher when they trade on contract-days with higher volatility. This is consistent with the results on amplitude in Table 11.

lower when amplitude is higher: a one percent increase in amplitude implies about a 122 (63) bps decrease in unskilled investors' net DRR during the in-sample (out-of-sample) period. The negative and significant coefficients for the interaction term in Panels A2 and B2 show that the pattern is more prominent when DLV is higher. These results indicate that leverage amplifies the deleterious impact of gambling proclivity on unskilled investors' performance.

5 Skilled Investors

We now turn to the other side of the coin: Are there skilled investors who benefit from derivatives leverage? If so, what is the source of their leverage-induced superior performance? Again, we go through a sequence of steps. First, we identify skilled investors in sample. We then analyze their trading performance out of sample. Finally, we investigate the source of their superior performance and how it is linked to leverage.

Similarly to the previous section, we first identify skilled investors by applying the bootstrap procedure as per Section 2.3, and then study the effect of leverage on their performance. We investigate the sources of skilled investors' superior performance by considering evidence of intraday market timing strategies and basis arbitrage trades.

5.1 Identifying Skilled Investors

In this section, we identify skilled investors by the intersection implied by the following routine: (1) investors who traded at least on 24 days during the year 2014; (2) investors whose Sharpe ratios of DRRs during 2014 are amongst the top 5% of all investors who traded at least on 24 days during the year; and (3) investors whose DRR time series in 2014 passes the luck-skill test as per Section 2.3. In this way, we identify eight skilled investors; none of them are institutions.[25]

Table 12 provides some characteristics for skilled investors. In this table, we sort (in descending order) these investors by their Sharpe ratios of net DRR in the year 2014, and report annualized Sharpe ratios of net DRR, median of trading cycles' duration (in minutes), average net DRR (in basis points), average DTO, average DLV, number of days with trading (NoDays),

[25]This finding is consistent with Coval, Hirshleifer, and Shumway (2021) who conclude that there are individual investors in equities who can persistently beat the market. Our focus is on the issue of whether skilled investors benefit from the implied leverage of derivatives positions.

number of trades per trading day (NoTperDay), and the p-values for the "FF-test" defined as per Section 2.3. Panel A and B report results in-sample and out of sample, respectively.

In Panel A, we find that the Sharpe ratios of net DRR range from 3.20 to 7.65, and that the net return ranges from 8 bps to 336 bps per day. Skilled investors' median duration ranges from 0.15 minute to 3.73 minutes, their average number of trades per day ranges from 42.4 to 478.7, and their DTO ranges from 29.5 to 721.3, all of which indicate that they are high frequency traders. The number of days with trading also implies high participation rates by skilled investors. Skilled investors' average DLV shows high heterogeneity: it ranges from 1.94 to 13.96.

Panel B indicates that skilled investors identified in 2014 also perform very well in years 2015 and 2016: their average net returns exceed 21 bps per day, and the corresponding Sharpe ratios exceed 2.8. Moreover, all p-values for the "FF-test" during the out-of-sample period are less than 1%, which indicates that our proposed skilled investors do have trading skill. In fact, skilled investors tend to trade more actively in the out-of-sample period: for 6 out of 8 skilled investors, their median durations of trading cycles are shorter out-of-sample than in-sample, and their numbers of trades per trading day in the out-of-sample period are also higher.

5.2 Skilled Investors' Performance

To examine if skilled investors can earn higher profits by taking advantage of leverage, we first generate a counterpart of Figure 1 for skilled investors, which is Figure 5. This figure shows that skilled investors obtain higher gross DRR by trading more actively and using higher leverage. Interestingly, even the skilled investors suffer from large transaction costs due to their excessive trading: two out of the five bars in the highest turnover decile become negative in the bottom plot of Figure 5. Leverage seems to facilitate at least some skilled performance: two of the most prominent bars in the bottom plot of Figure 5 are located at the highest leverage quintile.

We formally study the effect of using leverage for skilled investors by conducting panel regressions of DRR on DLV, using a Top dummy (1 for skilled investors), and its interactions with DLV and DTO. Table 13 reports the results. Here the Top dummy is defined ex-ante since we identify skilled investors using 2014 data, and Table 13 only includes observations in years 2015–2016. We also include "Force" and its interaction terms as controls. Since no skilled investors experienced forced liquidations, the interaction term between Top and Force is unnecessary. For comparison, we also report results without the Top dummy in the first column of each panel.

We find that the coefficients of DLV, DTO, Age, AccAge, TtM, and Force in the regression results reported in Table 13 are qualitatively similar to those in Table 6 (the results in the first columns of the panels in Table 13 are different from the first columns of the corresponding panels in Table 6 because we only use data for years 2015–2016 in Table 13). The second columns of Panels A and B in Table 13 show that skilled investors earn superior returns via leverage: the coefficient on DLV$\times$Top implies that a one unit leverage increase implies a 29.6 (20.4) bps increase in gross (net) DRR compared to other investors, which indicates that skilled investors earn about 50% higher annual net returns relative to others per unit of additional leverage.

Note that the DLV and the DLV$\times$Top coefficients in the last column of Table 13 imply that the net effect of using an additional leverage unit on skilled investors' net DRR is 19.3 bps (about 47% annually). The results are robust if we use the predicted value of the "Force" dummy and loosen the criteria for choosing skilled investors (relative to the stringent FF p-value of zero), but are economically weaker in the latter case; interested readers can refer to Tables IA.9-IA.13 in the internet appendix.

5.3 Sources of Skilled Investors' Profitability

It is of interest to understand how skilled investors profit from the leverage implied by futures positions. Such leverage can benefit traders along many dimensions. For example, Black (1975) suggests that informed traders can benefit from leverage, Adrian, Etula, and Muir (2014) suggest that leverage can enhance the efficacy of de facto market making, and Hugonnier and Prieto (2015) suggest that arbitrage activity can be more effective with higher leverage. So the question is how leverage impacts these activities. To address this issue, we next conduct some formal tests.

We first check if skilled investors tend to open long (short) futures positions when they are under-(over-) priced, using the futures-spot basis.[26] Since it is difficult to estimate theoretical

[26] Another arbitrage strategy involves trading futures on the same underlying asset, but with different maturities. Simple summaries show that we only observe 11 investor-days when skilled investors hold opposite positions in such futures. So skilled investors' performance is unlikely related to this type of arbitrage.

values for commodity futures owing to the challenge in estimating convenience yield, here we focus on financial futures. We define the basis as the difference between market quotes and their corresponding theoretical estimates: $Basis_{t,T} = F_{t,T} - S_t \times e^{(r_{t,T} - d_{t,T})(T-t)}$, where $F_{t,T}$ is the time-t market quote for a futures contract maturing at time T, $r_{t,T}$ is the risk-free rate,[27] and $d_{t,T}$ is the dividend rate.[28] Figure 6 depicts the distribution of $Basis_{t,T}$ at the minute frequency. The top plot shows the raw $Basis_{t,T}$, and the bottom plot shows the basis relative to the theoretical value, i.e., $\frac{Basis_{t,T}}{S_t \times e^{(r_{t,T} - d_{t,T})(T-t)}}$. Figure 6 shows that $Basis_{t,T}$ is negative in more than 80% of the cases. As a matter of fact, the median raw (resp. relative) basis is -65.52 index points (resp. -2.04%), which is consistent with strict spot constraints on short-sales.[29]

Given that the "fair" basis tends to be negative, if skilled investors conduct arbitrage strategies, then (1) skilled investors' open order imbalance (OIB) should be higher when the basis widens (i.e., becomes more negative) and, (2) this OIB should be negatively related to changes in the absolute basis. We define OIB in an interval t as[30]

$$\text{OIB}(t) = \frac{Buy\_Volume(t) - Sell\_Volume(t)}{Buy\_Volume(t) + Sell\_Volume(t)}.$$

Since skilled investors' daily OIB is trivially different from zero across all observations, we conduct the analyses of arbitrage strategies at the one-minute frequency. Table 14 reports results from panel regressions relating changes in the absolute basis to skilled investors' OIB of open trades. To reveal the effect of leverage, we also include DLV and its interaction term with OIB as independent variables. We find that, both in-sample and out of sample, skilled investors' open OIB is higher after the basis widens, and OIB positively predicts a narrowing of the basis in the following minutes. We thus find supportive evidence that skilled investors can earn rents by conducting arbitrage strategies. Interestingly, high leverage also implies a narrowing of the basis

[27] The risk-free rate $r_{t,T}$ is obtained by using a linear interpolation technique on the most recent SHIBOR (Shanghai Interbank Offered Rate) rate term structure.

[28] We estimate the dividend rate using data on the underlying index (unadjusted for cash dividends) and the corresponding total return index (reinvesting dividends); both are available in the CSMAR (China Stock Market & Accounting Research) database. Specifically, we estimate the dividend rate as $d_{t,T} = \frac{\ln(H_T/H_t) - \ln(S_T/S_t)}{T-t}$, where H and S represent the total return index and the raw index, respectively.

[29] During market crashes in the year 2015 caused by the de-leveraging policy of Chinese authorities, the raw basis was as low as -1500 index points, and the corresponding relative basis was about -25%.

[30] As a robustness check, we also define another measure $\text{OIB\_}N(t) = \frac{Number\_of\_Buys - Number\_of\_Sells}{Number\_of\_Buys + Number\_of\_Sells}$. The results are virtually the same when using OIB_N.

during the in-sample period: a one unit increase in DLV implies a one basis point $(-1.2 + 0.2)$ narrowing in the relative basis during the following five minutes; for other time periods, leverage also helps for a moderate level of OIB (absolute value less than $0.90/1.38 = 0.65$). Although a similar pattern exists out of sample, the corresponding statistical significance is weak.

To examine if skilled investors' net buying can predict futures market movements, in Table 15 we report the results from panel regressions of holding period returns over several horizons on OIB. We find that, in-sample as well as out of sample, skilled investors' OIB positively predicts returns over the next day and week, but the predictive power is very weak.

We also conduct analogous analyses for the investor set complementary to skilled investors. We term these "non-skilled" investors, as opposed to the "unskilled" investors of the previous section. We present the results for non-skilled investors in Panels C and D in Table 15. We find that these investors' OIB *negatively* predicts returns on the next day (week) suggesting that they exhibit a perverse ability to time the market. During the in-sample period, non-skilled investors' leverage is also negatively related to futures returns on the next day (week).

Recall from Table 12 that all skilled investors conduct high frequency intraday trading. We thus conduct an analysis similar to Table 15 at the one-minute frequency. Table 16 reports the results. We find that skilled investors tend to buy when the returns in the previous minute and the contemporaneous minute are negative, and their OIB significantly and positively predicts returns in the following minutes. While the predictability of future returns from OIB accords with informed trading, such trading does not accord with the negative relation of skilled investors' OIB with past returns. Indeed, such a pattern indicates that skilled investors step in to provide liquidity when it is needed. Thus, their behavior is consistent with de facto market making, or intraday liquidity provision.[31]

Comparing the magnitude of the coefficients of r_1, $r_{1:5}$, and $r_{1:10}$ (one-, five- and ten-minute returns), we find that OIB's predictive power mainly stems from the one minute right after trade. The coefficients of the interaction term show that higher leverage further strengthens the OIB effect. Panels C and D of Table 16 reports the results for non-skilled investors. Interestingly, such investors also tend to buy when the returns of the previous minute and the contemporaneous

[31] Figure IA.2 in the internet appendix shows that skilled investors earn greater returns by trading on contract-days with higher volatility. This accords with the finding that unskilled losses are greater in such contracts (Figure IA.1).

minute are negative; but after their trades, prices continue to move in an unfavorable direction.

Of course, in futures markets, there are position-opening trades and covering (closing) trades. It is reasonable to conjecture that the opening trades of skilled investors are more consistent with liquidity provision than closing trades. We thus conduct similar analyses as those in Table 16 for open trades only. Table IA.14 reports the results. We find that the predictive power of skilled investors' OIB for future returns is economically larger. To provide further detail, we plot average VWAP returns around skilled investors' open buys and sells in Figure 7, which, together with Tables 16 and IA.14, indicates that skilled investors tend to open long positions at pullback in a rising market, and close these positions after price increases, and vice versa. In fact, across all buy (sell) open trades of skilled investors, the average return across minutes -60 through -3 is significantly positive (negative), and that in the minute -1 is significantly negative (positive). Thus, there is a consistent picture that skilled investors are adept at liquidity provision.[32]

6 Heterogeneous Impact of Increases in Required Margins

In an apparent effort to curb excessive speculation and volatility in commodity futures, the three major commodity futures exchanges in China issued a series of announcements during April 5 to 29, 2016, warning of the risk inherent in Chinese futures markets. They also raised the margin ratio requirement for futures written on 16 underlying commodities.[33] This policy shock provides us a natural experiment to confirm our earlier findings about the heterogeneous impact of leverage on the cross-section of investors' portfolios. We carry out our analyses by adopting a difference-in-differences (DiD) design.[34] Note that our DLV is defined on a portfolio basis; hence we conduct our DiD at the investor level, rather than at the contract level.

We first consider the entire group of investors (Table 17), and then consider the cross-section (Table 18). For the former case, we define treatments (resp. controls) as the group of investors

[32]There is other evidence that skilled or informationally advantaged traders outperform others. For example, Fishman and Longstaff (1992) document that dual traders in futures markets earn greater profits than other floor traders. There also is evidence that biases can be costly in futures markets (Coval and Shumway 2005), and that some retail investors may act as liquidity providers (Kaniel, Saar, and Titman 2008). Our work expands on these papers by focusing on the impact of leverage (DLV) on skilled and unskilled traders.

[33]See, for example, https://tinyurl.com/kn8jhn3.

[34]Heimer and Simsek (2019) focus on how retail investors are affected by a CFTC regulation that capped domestic leverage in foreign exchange spot markets. Our additional focus on the heterogeneous effect of the margin regulation distinguishes our analysis from theirs.

whose time-series average DLV (during a 100-day period before April 5) is higher (resp. not higher) than the sample median DLV. This is motivated by the observation that traders who choose high DLV are more likely to be affected by the policy change than the low leverage group. In this way, we have 2617 treatments and 2618 controls. We use data over roughly a one-year window (November 6, 2015 to October 28, 2016) to conduct the DiD analyses. Table IA.15 in the internet appendix shows that we cannot reject the null hypothesis of parallel trends.

Panel A of Table 17 presents results from the DiD on DLV, DRRs (in basis points), and the standard deviation of investors' DRRs (in percent). We find that, compared with the pre-event period, the post-event average DLV for the high leverage group decreases by as much as 1.15 ($= 1.263 - 0.113$). Further, the high leverage group's average gross (net) DRR increases by more than 20 (10) basis points. We note that regulators also increased transaction fees in the post-event period, the results on net DRRs might be contaminated in the sense that the coefficient might contain information other than the impact of the margin constraint. To this end, we define a new measure "NetAdj" DRR, which assumes the same transaction fee for the post-event period as that for the pre-event period. The fifth column of Table 17 reports the results, which are similar to those for gross DRR. Turning to volatility, the last two columns in Table 17 show that the standard deviation of portfolio returns following the event is lower by more than 0.7% per day for highly levered investors. This result supports the regression-based evidence in Table 4. As a robustness check, Panel B of Table 17 considers the counterpart of Panel A when ex-ante skilled investors (identified as per Table 12) are excluded from the analyses, and finds similar results.

Our analysis in earlier sections highlights the heterogeneous impact of DLV on performance across investors. To examine the robustness of those results, we now turn to DiD analyses for unskilled, skilled, and institutional investors.[35] The results are reported in Table 18. We find from Panel A that margin constraints improve unskilled investors' risk-reward tradeoff: The event has little effect on portfolio risk and significantly increases portfolio returns. Panel B shows that the event, which limits skilled investors' leverage, also limits their earning power. Panel C shows that the effect on institutions is qualitatively similar to that for skilled investors. Panel D conducts the DiD on the *union* of skilled and institutions, and shows that the treatment effect on net DRR is economically large and statistically significant. Specifically, the net DRR of highly levered

[35] In unreported analyses, the analogs of Table IA.15 for these cases continue to support the null of parallel trends.

investors is lowered by more than 70 bps per day, while that for investors with low DLV remains virtually unchanged. Hence the leverage constraint has a heterogeneous impact in the cross-section; it increases the net DRR of unskilled individuals, but has the opposite impact on skilled investors and institutions.[36] The DiD analysis is therefore consistent with our earlier findings in Sections 4 and 5 on the association of DLV with skilled and unskilled traders' performance.

7 Summary and Concluding Remarks

We all teach our students that derivatives trades imply levered control of notional spot market positions. But what does such implied leverage entail? Does the link between chosen levels of implied leverage and performance vary by investors' ex ante skill levels? How does leverage affect the sources of gains and losses for investors? How do margin calls, and the ensuing forced liquidations, affect the leverage-performance link? Addressing these questions requires granular data for derivatives positions and performance. We attempt to make headway on the issues by using a unique dataset on Chinese futures trading, which allows us to measure daily implied leverage as well as performance metrics in the cross-section of investors. The data comprise individuals and institutions (although the majority are the former), and are available at high frequency, allowing us to ascertain intraday trading patterns as well. We use an identification period to measure trader skill, and then consider the impact of implied leverage on the cross-section of trading performance out of sample.

We find that the usage of derivatives leverage amplifies unskilled investors' losses due to gambling proclivity (Liu et al. 2021), but also boosts skilled investors' profits from intraday liquidity provision (Adrian, Etula, and Muir 2014). Overall, therefore, the implied leverage of derivatives is a double-edged sword. In aggregate, leverage reduces trading performance, even as it makes investment returns more volatile. The effect of leverage on institutional trading performance is not statistically different from that on individuals. We explore, for the first time, the contribution of forced liquidations (induced by margin calls) on the relation between leverage

[36] In Tables IA.16 and IA.17 within the online appendix, we conduct an analysis of whether the changes in the margin ratio regulations in the futures market led to increased market efficiency. We measure the latter by the absolute basis and absolute autocorrelations at the one-minute frequency. The treated group in this case is the group of contracts that underwent the regulatory change. We find no evidence that the shifts in margin ratios (and the associated changes in implied leverage) materially altered market efficiency metrics.

and performance. We find that these events largely account for the negative relation between leverage on gross returns.

We conduct a difference-in-differences analysis around regulatory increases in required margin ratios. These policy changes have a heterogeneous impact on traders; while they cut the leverage carried by both skilled and unskilled investors, trading performance improves for the unskilled, and that for skilled individuals and institutions deteriorates. Thus, caution is warranted in framing leverage policies under the assumption that retail investors are unsophisticated. Indeed, our results indicate that some retail investors are persistently successful at de facto liquidity provision, and constraining leverage has an adverse effect on these traders' performance.

One issue our paper has not touched upon is *why* the embedded leverage in derivatives positions exhibits cross-sectional variation.[37] Note that in the futures markets we analyze, leverage can fluctuate simply because of inattention combined with large price moves. It may also vary across investors due to differences in wealth levels or other account attributes. Ascertaining the sources of such variation is clearly an important area for future research.

[37] Other studies have considered leverage variation in a time-series context. For example, Adrian and Shin (2010) and Ang, Gorovyy, and Van Inwegen (2011) consider time-series variations in the leverage of market making intermediaries and hedge funds, respectively.

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Table 1: **Summary Statistics for Futures by Underlying Asset**

This table reports, for all futures traded in our sample, which spans January 02, 2014 to December 30, 2016. Reported are summaries grouped by their underlying assets. We provide futures' codes, listing exchange (Exch.), underlying asset, number of trades (NTrade, in thousand) in our sample, notional value (Notional, in billion) traded in our sample, gross profits (GProfit, in million), net profits (NProfit, in million), number of forced offsets (NForce) that occurred in our sample, and number of investors (NoI) who traded those futures. In the column "Exch.", CFE represents the China Financial Futures Exchange, CZC the Zhengzhou Commodity Exchange, DCE the Dalian Commodity Exchange, and SHF the Shanghai Futures Exchange. There were 51 different underlying assets. Futures written on Methanol changed their codes from ME to MA in June 2015, while those written on Thermal Coal changed their codes from TC to ZC in May 2016.

Code	Exch.	Underlying asset	NTrade	Notional	GProfit	NProfit	NForce	NoI
IC	CFE	CSI 500 Index	93.85	176.92	-21.72	-29.38	9	324
IF	CFE	CSI 300 Index	1581.53	1934.06	-119.76	-185.70	62	1199
IH	CFE	Shanghai 50 Index	145.78	130.16	-28.09	-33.51	20	510
T	CFE	10-year Treasury Bond	15.44	21.74	0.19	0.12	0	96
TF	CFE	5-year Treasury Bond	18.28	20.98	-0.55	-0.64	3	157
CF	CZC	Cotton No. 1	964.91	170.97	4.39	-11.53	576	3467
FG	CZC	Glass	506.34	29.66	-10.18	-15.64	380	3821
JR	CZC	Japonica Rice	0.08	0.01	-0.03	-0.03	0	13
LR	CZC	Late Indica Rice	0.98	0.09	-0.05	-0.05	0	27
MA	CZC	Methanol (1506)	2422.59	260.60	-5.56	-22.59	731	3964
ME	CZC	Methanol (old)	220.17	49.68	-1.71	-4.81	21	1012
OI	CZC	Rapeseed Oil	332.55	48.28	-4.13	-6.63	163	2203
PM	CZC	Common Wheat	0.00	0.00	-0.01	-0.01	0	2
RI	CZC	Early Indica Rice	2.30	0.16	-0.09	-0.11	2	108
RM	CZC	Rapeseed Meal	4670.79	525.24	-10.04	-39.11	1830	5701
RS	CZC	Rapeseed	0.48	0.02	0.01	0.00	0	46
SF	CZC	Silicoferrite	57.50	2.81	2.04	1.80	0	330
SM	CZC	Silicomanganese	36.07	1.96	0.55	0.43	0	326
SR	CZC	Sugar	3395.74	526.39	-21.48	-45.82	1065	5457
TA	CZC	Terephthalic Acid	2361.81	275.75	18.15	-18.64	542	4884
TC	CZC	Thermal Coal (old)	103.99	16.39	-1.87	-3.05	29	956
WH	CZC	Wheat	23.82	2.92	0.63	0.38	6	417
ZC	CZC	Thermal Coal (1605)	507.62	57.12	1.22	-4.03	216	1637
A	DCE	Yellow Soybean No.1	796.53	133.64	0.45	-6.34	88	2836
B	DCE	Yellow Soybean No.2	0.01	0.00	-0.00	-0.00	0	3
BB	DCE	Plywood	211.52	49.27	-2.34	-6.05	40	1019
C	DCE	Yellow Corn	445.29	45.69	10.29	6.93	109	3475
CS	DCE	Corn Starch	443.61	50.41	-6.41	-9.86	91	2186
FB	DCE	Fiberboard	96.60	11.97	-3.15	-4.27	21	838
I	DCE	Iron Ore	850.13	247.32	-22.69	-56.31	1081	4127
J	DCE	Smelter Coke	511.79	250.34	-62.01	-92.51	385	3052
JD	DCE	Eggs	672.73	93.49	29.81	12.63	74	3896
JM	DCE	Coking Coal	293.52	61.59	-23.48	-33.15	233	2849
L	DCE	Polyethylene	2034.53	565.33	-1.87	-24.34	253	3487
M	DCE	Soybean Meal	3710.49	640.34	-16.55	-52.23	616	6775
P	DCE	Palm Oil	2217.91	531.50	-26.97	-53.88	301	4805
PP	DCE	Polypropylene	904.43	103.76	-3.08	-12.27	212	2886
V	DCE	Polyvinyl Chloride	160.31	17.05	5.71	4.72	16	1105
Y	DCE	Soybean Oil	1743.21	516.77	-10.14	-33.24	515	4482
AG	SHF	Silver	1036.66	185.72	-13.08	-22.55	236	4056
AL	SHF	Aluminium	113.54	19.11	-6.03	-7.06	12	1598
AU	SHF	Gold	154.66	68.66	-1.11	-4.04	17	1638
BU	SHF	Petroleum Pitch	267.32	21.73	3.42	0.48	115	2685
CU	SHF	Copper	371.02	145.26	-4.96	-17.17	90	2587
FU	SHF	Fuel Oil	0.03	0.00	0.00	0.00	0	6
HC	SHF	Hot Rolled Coil	141.41	11.31	7.62	6.30	10	1114
NI	SHF	Nickel	431.46	72.78	-11.61	-18.91	61	1770
PB	SHF	Lead	29.87	3.76	-1.31	-1.64	2	464
RB	SHF	Screw Thread Steel	2810.60	441.36	-46.72	-89.02	1372	6712
RU	SHF	Natural Rubber	1138.09	261.11	-80.55	-102.18	511	3739
SN	SHF	Tin	14.17	2.13	-0.34	-0.41	0	281
WR	SHF	Wire Rod	0.02	0.00	-0.01	-0.01	0	3
ZN	SHF	Zinc	337.27	60.81	-12.11	-15.64	66	2240

Table 2: **Distribution of Turnover Value, Gross Profits, Net Profits, Day-End Asset, Net Profit per Turnover, Duration of Trading Cycle, Gross DRR, Net DRR, DTO, and DLV.**
This table reports percentiles of aggregate turnover by notional value, aggregate gross profits, aggregate net profits, average day-end assets, net profit per unit turnover, median of duration of trading cycles, average gross DRR, average net DRR, average DTO, and average DLV for each investor. We first consider the sample with all investors; then we split the sample into institutions and individuals. The sample mean, sample skewness, and total value are also reported. There are 10822 investors in total, 315 of them are institutions.

Investor Type	Percentiles					Mean	Skew.	Total
	1st	25th	Median	75th	99th			
	Panel A: Turnover value (million yuan; "Total" in this panel is measured in billion yuan)							
All	0.086	7.268	42.216	215.365	12936.424	802.621	32.971	8864.149
Institutions	0.051	9.560	47.059	245.708	9862.420	567.992	13.806	185.733
Individuals	0.087	7.184	41.925	214.575	12996.440	809.780	32.780	8678.416
	Panel B: Gross profit (million yuan)							
All	-1.766	-0.055	-0.008	0.000	1.430	-0.045	13.754	-497.278
Institutions	-3.327	-0.170	-0.014	0.057	1.768	-0.101	-0.603	-33.155
Individuals	-1.685	-0.053	-0.008	0.000	1.390	-0.043	14.441	-464.124
	Panel C: Net profit (million yuan)							
All	-2.091	-0.076	-0.014	-0.000	0.975	-0.095	-2.474	-1050.595
Institutions	-3.351	-0.192	-0.019	0.043	1.298	-0.161	-3.244	-52.510
Individuals	-1.985	-0.074	-0.014	-0.001	0.937	-0.093	-2.361	-998.085
	Panel D: Day-end asset (thousand yuan)							
All	0.14	4.92	18.16	66.05	1416.21	100.48	5.58	—
Institutions	1.63	50.85	182.38	509.15	2461.92	433.02	2.20	—
Individuals	0.14	4.72	17.14	61.17	1216.96	90.34	5.90	—
	Panel E: Net profit per turnover (%)							
All	-3.27	-0.12	-0.04	-0.01	1.03	-0.15	-7.87	—
Institutions	-5.49	-0.32	-0.04	0.09	3.87	-0.18	-1.54	—
Individuals	-3.14	-0.12	-0.04	-0.01	0.91	-0.15	-8.38	—
	Panel F: Median of duration of trading cycle (minutes)							
All	0.45	15.42	51.63	203.27	13110.58	625.93	11.89	—
Institutions	0.32	83.17	413.32	1988.50	38145.64	2639.94	4.82	—
Individuals	0.47	15.20	49.35	191.58	12392.00	567.00	12.81	—
	Panel G: Average gross DRR (bps)							
All	-560.06	-80.23	-25.38	9.40	273.51	-46.95	-3.94	—
Institutions	-611.20	-30.47	-2.76	22.19	399.93	-16.12	-6.72	—
Individuals	-560.68	-81.37	-26.36	8.95	265.44	-47.88	-3.82	—
	Panel H: Average net DRR (bps)							
All	-596.13	-103.19	-38.76	-0.45	191.68	-68.95	-4.78	—
Institutions	-612.37	-38.87	-7.89	16.93	350.54	-23.07	-7.01	—
Individuals	-596.22	-105.40	-40.35	-1.23	185.97	-70.35	-4.71	—
	Panel I: Average DTO							
All	0.53	3.03	6.17	13.12	162.11	15.33	12.95	—
Institutions	0.14	0.99	1.77	3.32	43.34	4.51	15.30	—
Individuals	0.56	3.16	6.35	13.43	164.34	15.66	12.84	—
	Panel J: Average leverage							
All	0.94	3.98	5.49	7.08	14.47	5.74	1.19	—
Institutions	0.24	2.82	4.40	6.50	17.09	4.88	1.44	—
Individuals	0.99	4.02	5.52	7.09	14.46	5.76	1.20	—

Table 3: **Various Characteristics for Different Groups of Investors Grouped by Average DLV**
We group investors by their time series averages of DLV, and report the cross-sectional averages (within each group) of each investor's time series averages of DLV, DTO, trade size (notional value, in thousands of Chinese yuan), number of trades per day (NoTperDay), and transaction costs per day (Chinese yuan). The fourth column reports the cross-sectional medians (within each group) of each investor's time series median duration of trading cycles. The last column report the number of investors (NoI) in each group. We only include investors who traded on at least 36 days in our sample. 7,357 investors satisfy this criterion. We then stratify these 7,357 investors by their average DLV. In the last two rows of each panel, we report the differences between the top 1% group and the bottom 1% group, as well as the corresponding t-statistics for testing the null of no difference. t-statistics are based on cluster-robust standard errors accounting for auto- and cross-correlation. The p-values for differences in medians of durations are based on the Mood's median test. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Investor Group	DLV	DTO	Duration	TradeSize	NoTperDay	Cost	NoI
Top 1%	17.16	212.80	15.44	286.92	175.42	2341.92	74
[1%, 10%)	10.82	42.32	42.35	172.20	55.80	771.51	662
[10%, 30%)	7.76	18.37	51.50	130.83	24.62	358.49	1471
[30%, 70%)	5.69	13.00	46.93	148.24	16.30	306.64	2943
[70%, 90%)	3.79	6.73	56.56	163.56	16.50	308.92	1471
[90%, 99%)	2.37	4.02	56.87	157.62	17.08	227.79	662
Bottom 1%	1.14	2.51	39.61	134.88	20.64	193.88	74
Difference	16.02***	210.29***	-24.17	152.04***	154.78***	2148.04***	—
(t-stat)	(49.07)	(31.81)	(p=)0.10	(3.48)	(4.02)	(2.75)	—

Table 4: **Implied Leverage and Volatility of Investors' DRR**

This table presents results of regressions of the standard deviation (σ) of investors' gross DRR (in percent) and net DRR (in percent) on DLV. Only investors who traded on at least 36 trading days are included in this analysis; there are 168 institutional investors satisfying this criterion. We control for DTO in regressions. DTOOrth $=$ DTO $- \hat{\beta} *$ DLV is the orthogonal part of DTO with respect to DLV, where $\hat{\beta}$ is the loading on DLV from the following OLS regression: $\text{DTO}_i = \alpha + \beta * \text{DLV}_i + \hat{\epsilon}_i$. "Inst" is a dummy variable, which equals 1 for institutional investors, and 0 for individuals. Panel A reports results for gross DRR, and Panel B reports the results for net DRR. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. The last two lines report the number of observations and the adjusted R^2 (in percent) for each regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: σ(Gross DRR)				Panel B: σ(Net DRR)			
DLV	0.70***	—	—	0.66***	0.69***	—	—	0.65***
	(65.18)			(54.40)	(64.58)			(54.10)
DTO	—	0.92***	—	0.18***	—	0.90***	—	0.16***
		(31.72)		(6.43)		(31.14)		(5.91)
DTOOrth	—	—	0.17***	—	—	—	0.15***	—
			(4.80)				(4.41)	
Inst	-0.97**	0.00	-0.84***	-0.78**	-1.00**	-0.02	-0.85***	-0.83**
	(-2.49)	(0.01)	(-3.56)	(-2.01)	(-2.57)	(-0.07)	(-3.62)	(-2.13)
Inst×DLV	0.08	—	—	0.08	0.09	—	—	0.08
	(1.27)			(1.23)	(1.35)			(1.32)
Intercept	1.80***	3.48***	5.71***	1.54***	1.83***	3.52***	5.71***	1.59***
	(25.75)	(41.05)	(92.42)	(19.10)	(26.37)	(41.73)	(93.12)	(19.89)
Obs	7,357	7,357	7,357	7,357	7,357	7,357	7,357	7,357
Adjusted R^2 (%)	37.56	12.23	0.53	37.90	37.15	11.84	0.49	37.44

Table 5: **Panel Regressions of Investors' DRR for Full Sample**

This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on leverage. The regressions include day fixed effects. Panel A uses DLV as the independent variable, while Panel B uses the predicted DLV as the independent variable. On each day t, we estimate an autoregression model with 4 lags using ConDLV up to day $t-1$, and compute the predicted leverage measure PredDLV using the estimated coefficients and the latest 4 lags. In both panels, "Inst" is a dummy variable which equals 1 for institutional investors, and 0 for individuals. Investors' demographic information (age and account age), time-to-maturity (TtM, in days), and DTO (in logarithmic scale) are included as independent variables. Age and account age are measured in years computed on January 1, 2017. Time-to-maturity is defined as the notional-value weighted mean (*across all trades*) for each investor-day. t-statistics are based on robust standard errors clustered by investor and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: Regression on DLV					
	Panel A1: Gross DRR			Panel A2: Net DRR		
DLV	0.774	0.480	-3.226***	-5.672***	-5.952***	-5.304***
	(0.897)	(0.571)	(-4.516)	(-10.096)	(-10.668)	(-8.367)
Inst	34.987**	5.934	33.349**	40.902***	24.982*	20.188
	(1.988)	(0.322)	(1.990)	(3.435)	(1.888)	(1.492)
Inst×DLV	-3.042	-2.430	-2.572	-2.033	-1.596	-1.571
	(-0.724)	(-0.571)	(-0.699)	(-0.827)	(-0.634)	(-0.602)
Age	—	-0.599***	-0.531***	—	-0.279**	-0.290**
		(-3.381)	(-3.119)		(-1.970)	(-2.080)
AccAge	—	4.843***	4.894***	—	3.248***	3.239***
		(6.766)	(7.015)		(5.762)	(5.788)
TtM	—	0.203***	0.293***	—	0.269***	0.253***
		(4.992)	(7.466)		(6.780)	(6.611)
DTO	—	—	22.508***	—	—	-3.936**
			(10.269)			(-2.270)
Obs	1,376,035	1,376,035	1,376,035	1,376,035	1,376,035	1,376,035
	Panel B: Regression on PredDLV					
	Panel B1: Gross DRR			Panel B2: Net DRR		
PredDLV	0.728	0.480	-2.302***	-4.913***	-5.147***	-4.355***
	(0.872)	(0.592)	(-3.124)	(-8.333)	(-8.853)	(-6.527)
Inst	35.452**	6.365	36.603**	47.094***	33.607***	25.003*
	(2.077)	(0.356)	(2.250)	(3.988)	(2.607)	(1.865)
Inst×PredDLV	-3.160	-2.543	-3.098	-2.891	-2.446	-2.289
	(-0.703)	(-0.562)	(-0.766)	(-0.989)	(-0.832)	(-0.749)
Age	—	-0.604***	-0.504***	—	-0.219	-0.247*
		(-3.321)	(-2.921)		(-1.531)	(-1.766)
AccAge	—	4.856***	4.828***	—	3.134***	3.142***
		(6.730)	(6.912)		(5.526)	(5.608)
TtM	—	0.205***	0.286***	—	0.267***	0.244***
		(5.053)	(7.247)		(6.697)	(6.347)
DTO	—	—	20.996***	—	—	-5.974***
			(9.186)			(-3.407)
Obs	1,359,995	1,359,995	1,359,995	1,359,995	1,359,995	1,359,995

Table 6: **Panel Regressions of Investors' DRR with Force Dummy**
This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on leverage. The regressions include day fixed effects. Investors' demographic information (age and account age), time-to-maturity (TtM, in days), and DTO (in logarithmic scale) are included as independent variables. Age and account age are measured in years computed on January 1, 2017. Time-to-maturity is defined as the notional-value weighted mean (*across all trades*) for each investor-day. In the first column of each panel, we include a dummy variable "Force", which equals 1 for observations on which force offset occurs, and 0 for others. In the second column of each panel, we replace the dummy variable "Force" by a new variable "PredForce", which is the fitted logit probability of the "Force" dummy as a function of four lags of DRR, DTO, and DLV (additional lags are insignificant). t-statistics are based on robust standard errors clustered by investor and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: Gross DRR		Panel B: Net DRR	
DLV	-0.048	0.683	-2.110***	-1.553**
	(-0.067)	(0.860)	(-3.390)	(-2.152)
DTO	16.159***	17.033***	-10.195***	-9.097***
	(7.957)	(8.126)	(-6.552)	(-5.476)
Age	-0.674***	-0.599***	-0.381***	-0.309***
	(-4.911)	(-4.319)	(-3.448)	(-2.708)
AccAge	5.678***	4.861***	3.950***	3.144***
	(8.039)	(7.134)	(6.855)	(5.660)
TtM	0.213***	0.279***	0.173***	0.239***
	(5.629)	(7.133)	(4.713)	(6.261)
Force	-2668.356***	—	-2658.976***	—
	(-26.363)		(-26.354)	
PredForce	—	-2824.875***	—	-2693.983***
		(-7.591)		(-7.226)

Table 7: **Various Characteristics for Different Groups of Investors Grouped by Sharpe Ratios** We group investors by their Sharpe ratios of net DRRs, and report the cross-sectional averages (within each group) of each investor's time series averages of net DRR (in percent), DTO, and DLV. The second column reports the cross-sectional averages of Sharpe ratios, which are annualized via multiplying the daily ratios by the square root of 244, which is the typical number of trading days in a year in China. The third column reports the cross-sectional medians (within each group) of each investor's time series median duration of trading cycles. The last two columns report the number of investors (NoI) and the number of FF-test passers in each group. We first identify investors who traded on at least 24 days in year 2014. 3422 investors satisfy this criterion. We then stratify these 3422 investors by their Sharpe ratios of net DRRs. This table only reports summaries for those 3391 investors who traded on at least 24 days in year 2014 *and* at least 2 days after 2014. In the last two rows of each panel, we report the differences between the top 1% group and the bottom 1% group, as well as the corresponding t-statistics for testing the null of no difference. t-statistics for Sharpe ratios are based on a simple two sample t-test. t-statistics for NetDRR, DTO, and DLV are based on cluster-robust standard errors accounting for auto- and cross-correlation. The p-values for differences in medians of durations are based on the Mood's median test. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Investor Group	SharpeRatio	Duration	NetDRR	DTO	DLV	NoI	FF-passer
	Panel A: In sample (year 2014)						
Top 1%	4.883***	7.700	1.172***	75.817	6.768	33	7
[1%, 10%)	1.936***	106.717	0.525***	28.475	6.191	308	1
[10%, 30%)	0.294***	113.942	0.088**	12.134	6.154	682	0
[30%, 70%)	-1.233***	73.658	-0.421***	10.638	6.484	1352	0
[70%, 90%)	-2.891***	32.367	-0.967***	15.173	6.428	680	0
[90%, 99%)	-4.968***	13.938	-1.661***	37.448	6.758	302	0
Bottom 1%	-9.347***	4.533	-2.544***	94.756	8.230	34	0
Difference	14.231***	3.167*	3.716***	-18.939***	-1.462	—	—
(t-stat)	(37.302)	(p=)0.080	(11.925)	(-2.906)	(-1.461)	—	—
	Panel B: Out of sample (years 2015-2016)						
Top 1%	0.631	1.450	0.095***	83.110	6.831	33	7
[1%, 10%)	-0.322	85.358	-0.182*	25.466	6.087	308	6
[10%, 30%)	-0.929***	111.317	-0.430***	12.368	6.108	682	2
[30%, 70%)	-1.037***	81.967	-0.459***	12.312	6.284	1352	1
[70%, 90%)	-1.910***	35.767	-0.821***	15.675	6.228	680	0
[90%, 99%)	-2.977***	16.717	-1.098***	43.959	6.695	302	1
Bottom 1%	-4.813***	7.950	-1.320***	52.407	7.095	34	0
Difference	5.444***	-6.500	1.415***	30.703***	-0.263	—	—
(t-stat)	(5.167)	(p=)0.121	(5.248)	(7.647)	(-0.322)	—	—

Table 8: **Unskilled Investors' Characteristics**
This table presents characteristics of unskilled investors. Unskilled investors are identified as the intersection of the following: (1) they traded on at least 24 days in year 2014; (2) their Sharpe ratios of net DRR in year 2014 are lower than the 5th percentile of the full sample and, (3) their actual t-values of net DRRs are lower than all 10,000 t-values generated by the FF-procedure. In this way, we identify 79 unskilled investors. We compute summaries for in-sample and out-of-sample, separately. Reported include Sharpe ratios of net DRR, median of duration of trading cycles (in minute), average net DRR (in percent), average DTO, average DLV, number of trading days (NoDays), number of trades per trading day (NoTperDay), and the p-values of the "FF-test" defined as per Section 2.3. Sharpe ratios are annualized by multiplying the daily ratios by the square root of 244, which is the typical number of trading days in a year in China.

Percentiles	SharpeRatio	Duration	NetDRR	DTO	DLV	NoDays	NoTperDay	FF-test
Panel A: In sample (year 2014; 245 trading days)								
Min	-14.20	0.38	-5.84	1.05	1.32	24	1.5	0.0000
5th	-11.69	0.77	-5.10	3.62	2.57	30	4.6	0.0000
10th	-9.81	1.11	-4.40	7.99	4.26	46	5.8	0.0000
25th	-7.87	2.25	-3.00	22.05	6.27	93	13.0	0.0000
Median	-6.34	5.88	-1.99	41.27	7.29	138	23.6	0.0000
75th	-5.43	11.48	-1.27	101.67	8.84	181	52.0	0.0000
90th	-5.09	28.46	-0.84	239.01	13.21	222	110.6	0.0000
95th	-4.97	51.32	-0.52	389.04	15.40	238	140.8	0.0000
Max	-4.95	179.98	-0.33	683.49	17.97	245	215.5	0.0000
Panel B: Out of sample (years 2015-2016; 488 trading days)								
Min	-11.38	0.20	-6.09	0.82	1.99	2	1.0	0.0000
5th	-9.23	0.72	-4.25	2.99	2.96	9	3.8	0.0000
10th	-8.32	0.95	-3.34	5.40	3.55	23	5.8	0.0000
25th	-5.65	3.32	-2.29	16.27	5.20	59	10.2	0.0000
Median	-3.84	7.30	-1.44	37.70	6.63	157	23.6	0.0005
75th	-2.65	14.88	-0.73	77.77	8.83	298	47.2	0.0129
90th	-1.50	34.13	-0.44	175.52	12.03	412	111.0	0.1825
95th	-1.05	134.55	-0.23	360.67	14.79	448	173.0	0.3553
Max	4.35	1167.55	1.38	1766.24	19.27	484	419.9	0.6984

Table 9: **Unskilled Investors' DRRs by DLV**
This table groups unskilled investors' investor-day observations by DLV, and reports the averages of DLV, gross DRR, and net DRR within each quintile. Unskilled investors are identified as per Table 8. In Panel A and Panel B, we compute summaries for the in-sample and out-of-sample periods, separately. Gross DRR and net DRR are reported in basis points. In the last two rows of each panel, we report the differences between the extreme groups along with the corresponding t-statistics for testing the null of no difference. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

DLV Group	DLV	Gross DRR	Net DRR
Panel A: In sample (year 2014; 245 trading days)			
High	15.33	-116.65***	-370.69***
2	9.41	-151.52***	-279.33***
3	7.59	-138.54***	-235.51***
4	6.00	-108.81***	-170.82***
Low	3.20	-27.96***	-56.76***
High-Low	12.12***	-88.69***	-313.93***
(t-stat)	(82.08)	(-3.76)	(-13.62)
Panel B: Out of sample (years 2015-2016; 488 trading days)			
High	14.97	55.15***	-207.40***
2	8.62	-56.40***	-195.12***
3	6.80	-101.56***	-227.70***
4	5.03	-42.08***	-117.46***
Low	2.55	2.04	-15.58***
High-Low	12.42***	53.11**	-191.81***
(t-stat)	(67.74)	(2.36)	(-9.83)

Table 10: **Trend Chasing: Regression of Unskilled Investors' OIB on Past Returns**
This table presents results of panel regressions of unskilled investors' order imbalance on past returns. Unskilled investors are identified as per Table 8. The regressions include contract and maturity fixed effects. For each minute t, OIB is computed as $\frac{Buy\_Volume-Sell\_Volume}{Buy\_Volume+Sell\_Volume}$, r_i is the return realized during the day (minute) $t+i$, and $r_{i:j}$ is the return realized during days (minutes) $t+i$ to $t+j$. We rescale all returns to daily units (assuming 360 trading minutes per day). t-statistics are based on robust standard errors clustered by contract and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Unskilled investors' daily OIB					
A1: In-sample			A2: Out-of-sample		
r_{-1}	-0.21	—	r_{-1}	-0.15	—
	(-0.86)			(-1.15)	
$r_{-5:-1}$	—	0.28	$r_{-5:-1}$	—	0.12
		(0.56)			(0.44)
Obs	8,604	8,455	Obs	22,177	22,013

	Panel B1: Unskilled investors' OIB by minute; in-sample				
r_{-1}	-0.14***	—	—	—	—
	(-9.19)				
$r_{-5:-1}$	—	-0.40***	—	—	—
		(-10.66)			
$r_{-10:-1}$	—	—	-0.44***	—	—
			(-9.59)		
$r_{-30:-1}$	—	—	—	-0.32***	—
				(-6.97)	
$r_{-60:-1}$	—	—	—	—	-0.24***
					(-4.30)
Obs	247,104	247,091	247,073	247,023	246,961

	Panel B2: Unskilled investors' OIB by minute; out-of-sample				
r_{-1}	-0.13***	—	—	—	—
	(-7.36)				
$r_{-5:-1}$	—	-0.36***	—	—	—
		(-8.00)			
$r_{-10:-1}$	—	—	-0.38***	—	—
			(-7.77)		
$r_{-30:-1}$	—	—	—	-0.41***	—
				(-7.14)	
$r_{-60:-1}$	—	—	—	—	-0.39***
					(-6.03)
Obs	391,023	391,022	391,022	391,020	391,019

Table 11: **Gambling: Panel Regressions of Unskilled Investors' DRR and DTO**

This table presents results of panel regressions of investors' gross DRR (in basis points), net DRR (in basis points), and DTO (in logarithmic scale) on amplitude (Amp, in percent) and DLV. For contract i on day t, amplitude is defined as $Amp_{i,t} = \frac{High_{i,t} - Low_{i,t}}{Close_{i,t-1}} \times 100$, where $Close_{i,t-1}$ is the settlement price on contract i on day $t-1$, and $High_{i,t}$ ($Low_{i,t}$) is the highest (lowest) trading price on day t. The variable "Amp" is then defined as the notional-value weighted mean (across all trades) for each investor-day. HDLV is a dummy variable which takes value 1 if DLV higher than sample median and 0 otherwise. We conduct the regressions separately for the in- and out-of-sample periods. The regressions for DRR include day fixed effects, and those for DTO include investor fixed effects. Controls include investors' demographic information (age and account age), time-to-maturity (TtM), and a "Force" dummy. Age and account age are measured in years computed on January 1, 2017. Time-to-maturity is defined as the notional-value weighted mean (across all trades) for each investor-day. The "Force" dummy takes value 1 for observations on which forced offset occurs and 0 for others. Unskilled investors are identified as per Table 8. t-statistics are based on robust standard errors clustered by investor and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: In sample (year 2014; 245 trading days)								
	Panel A1: Gross DRR			Panel A2: Net DRR			Panel A3: DTO	
DLV	-0.036	5.165*	5.242*	-21.115***	-16.236***	-15.795***	0.133***	0.133***
	(-0.017)	(1.882)	(1.892)	(-10.451)	(-6.041)	(-5.815)	(31.965)	(31.853)
Amp	—	-103.041***	-100.405***	—	-123.590***	-122.245***	0.137***	0.132***
		(-6.697)	(-6.490)		(-7.926)	(-7.820)	(10.774)	(10.435)
HDLV×Amp	—	-48.691***	-49.266***	—	-48.120***	-47.974***	0.026**	0.029**
		(-3.876)	(-3.919)		(-3.785)	(-3.774)	(1.968)	(2.200)
Controls	No	No	Yes	No	No	Yes	No	Yes
Obs	10,763	10,763	10,763	10,763	10,763	10,763	10,763	10,763
Panel B: Out of sample (years 2015-2016; 488 trading days)								
	Panel B1: Gross DRR			Panel B2: Net DRR			Panel B3: DTO	
DLV	9.207**	8.819	8.768	-7.573***	-5.314**	-5.533**	0.080**	0.080**
	(1.990)	(1.414)	(1.392)	(-4.245)	(-2.037)	(-2.127)	(2.136)	(2.138)
Amp	—	-56.040***	-55.708***	—	-64.189***	-62.545***	0.066***	0.065***
		(-4.620)	(-4.603)		(-5.859)	(-5.708)	(2.787)	(2.717)
HDLV×Amp	—	-2.195	-2.487	—	-24.399**	-25.016**	0.119***	0.119***
		(-0.141)	(-0.162)		(-2.404)	(-2.457)	(2.609)	(2.608)
Controls	No	No	Yes	No	No	Yes	No	Yes
Obs	14,738	14,738	14,738	14,738	14,738	14,738	14,738	14,738

Table 12: **Skilled Investors' Characteristics**

This table presents characteristics of the eight skilled investors. In this table, skilled investors are identified by the following routine: (1) their Sharpe ratios of DRRs during the year 2014 are amongst the top 5% of all investors who traded at least on 24 days during the same year and, (2) their DRR time series in year 2014 can pass the luck-skill test proposed in Section 2.3. We compute characteristics for in-sample and out-of-sample, separately. For each skilled investor, we report Sharpe ratios of net DRR, median of duration of trading cycles (in minutes), average net DRR (in percent), average DTO, average DLV, number of trading days (NoDays), number of trades per trading day (NoTperDay), and the p-values of the "FF-test" defined as per Section 2.3. Sharpe ratios are annualized by multiplying the daily ratios by the square root of 244, which is the typical number of trading days in a year in China.

SN	SharpeRatio	Duration	NetDRR	DTO	DLV	NoDays	NoTperDay	FF-test
Panel A: In sample (year 2014; 245 trading days)								
1	7.65	1.72	1.08	176.09	11.74	244	252.5	0.0000
2	6.69	1.70	0.67	101.54	7.09	241	170.2	0.0000
3	6.09	0.62	0.87	168.79	7.48	141	72.1	0.0000
4	5.70	0.62	3.36	721.29	13.96	157	344.0	0.0000
5	5.22	1.55	1.26	92.22	11.56	237	51.6	0.0000
6	4.87	0.28	0.08	29.50	1.94	162	208.1	0.0000
7	4.58	3.73	0.29	37.68	5.51	241	42.4	0.0000
8	3.20	0.15	0.26	49.01	3.27	178	478.7	0.0000
Panel B: Out of sample (years 2015-2016; 488 trading days)								
1	7.18	1.08	0.80	83.55	4.70	485	224.7	0.0000
2	4.28	1.10	0.86	209.32	8.14	486	380.6	0.0000
3	5.48	0.42	1.05	183.56	5.68	403	140.8	0.0000
4	3.12	0.92	2.87	825.87	17.79	303	556.1	0.0002
5	2.86	0.93	0.87	53.36	9.11	477	92.7	0.0000
6	4.01	0.35	0.21	14.70	1.57	47	142.7	0.0095
7	4.78	0.78	0.46	96.57	5.18	473	129.6	0.0000
8	4.72	0.12	0.25	53.95	4.41	178	485.6	0.0000

Table 13: **Panel Regressions of Investors' DRR in Years 2015-2016 with Top Dummy**
This table presents the results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on DLV. In this table, we only include observations in years 2015-2016. The regressions include day fixed effects. Investors' demographic information (age and account age), time-to-maturity (TtM), and DTO (in logarithmic scale) are included as independent variables. Age and account age are measured in years computed on January 1, 2017. Time-to-maturity is defined as the notional-value weighted mean (*across all trades*) for each investor-day. In the second column of each panel, we include a Top dummy (1 for skilled investors; 0 for others) and its interaction terms with other variables. Skilled investors are identified as per Table 12. Force is a dummy variable (1 for observations on which force offset occurs; 0 for others). *t*-statistics are based on robust standard errors clustered by investor and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: Gross DRR		Panel B: Net DRR	
DLV	0.639	0.492	-1.132*	-1.180**
	(1.063)	(0.819)	(-1.891)	(-1.968)
DTO	16.433***	15.608***	-10.820***	-11.396***
	(13.881)	(13.227)	(-9.234)	(-9.759)
Age	-0.719***	-0.684***	-0.454***	-0.440***
	(-8.921)	(-8.482)	(-5.637)	(-5.461)
AccAge	6.447***	6.361***	4.695***	4.639***
	(15.145)	(14.948)	(11.269)	(11.131)
TtM	0.256***	0.248***	0.234***	0.226***
	(5.582)	(5.376)	(5.070)	(4.885)
Force	-2792.482***	-2792.039***	-2783.266***	-2783.140***
	(-26.714)	(-26.711)	(-26.700)	(-26.701)
Top	—	-596.051***	—	24.567
		(-8.660)		(0.380)
DLV×Top	—	29.636***	—	20.443***
		(5.699)		(4.066)
DTO×Top	—	106.476***	—	-5.644
		(6.941)		(-0.387)
Obs	964,542	964,542	964,542	964,542

Table 14: **Regression of Changes in Basis on Skilled Investors' Open OIB by Minute**
This table presents results of panel regressions of changes in financial futures basis on skilled investors' order imbalance by minute. The regressions include contract and maturity fixed effects. Skilled investors are identified as per Table 12. For each minute t, OIB is computed as $\frac{Buy\_Volume - Sell\_Volume}{Buy\_Volume + Sell\_Volume}$ (volume only accounts for open trades), r_i is the signed change in absolute value of $RelBasis_{t,T}$ in the minute $t+i$, and $r_{i:j}$ is the signed change in absolute value of $RelBasis_{t,T}$ realized during minutes $t+i$ to $t+j$, where $RelBasis_{t,T}$ is defined as $\frac{F_{t,T} - S_t \times e^{(r_{t,T} - d_{t,T})(T-t)}}{S_t \times e^{(r_{t,T} - d_{t,T})(T-t)}} \times 10000$. For each minute t, DLV is the average (across all skilled investors traded in the minute) contemporaneous leverage computed in the minute frequency. t-statistics are based on robust standard errors clustered by contract and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$r_{-15:-1}$	$r_{-10:-1}$	$r_{-5:-1}$	r_{-1}	r_0	r_1	$r_{1:5}$	$r_{1:10}$	$r_{1:15}$
	Panel A: Skilled investors; in sample (year 2014)								
OIB	6.13***	3.64***	3.59***	1.07***	2.50***	-5.91***	-9.32***	-7.28**	-6.59**
	(13.55)	(4.23)	(5.66)	(3.57)	(4.45)	(-17.65)	(-2.95)	(-2.38)	(-2.55)
OIB × DLV	0.14	0.45	-1.20***	-0.23	-0.33	1.38**	0.20	1.13**	1.67**
	(0.13)	(0.38)	(-8.57)	(-1.38)	(-0.75)	(2.11)	(0.64)	(2.54)	(2.25)
DLV	0.78	0.06	0.92	0.07	-0.05	-0.90***	-1.23***	-0.99*	-1.59***
	(1.00)	(0.05)	(1.28)	(0.18)	(-0.19)	(-5.69)	(-7.85)	(-1.66)	(-15.27)
Obs	728	755	788	806	811	813	807	796	781
	Panel B: Skilled investors; out of sample (years 2015-2016)								
OIB	5.89***	4.87***	3.03***	1.03*	2.78***	-3.92***	-3.93***	-3.95***	-3.09***
	(4.42)	(3.77)	(2.95)	(1.87)	(3.63)	(-5.59)	(-5.02)	(-3.06)	(-3.18)
OIB × DLV	-1.03**	-0.81	-0.31	-0.21	0.21	0.15	-0.76*	0.04	0.44
	(-2.54)	(-1.49)	(-0.87)	(-0.94)	(0.65)	(0.98)	(-1.70)	(0.05)	(0.71)
DLV	1.23***	0.49**	0.43***	0.04	0.20	-0.05	-0.48	-0.54	-0.36
	(2.75)	(2.02)	(2.93)	(0.60)	(0.94)	(-0.43)	(-0.92)	(-0.86)	(-0.55)
Obs	1,492	1,557	1,611	1,652	1,657	1,664	1,652	1,639	1,603

Table 15: **Regression of Returns on Investors' Daily Order Imbalance (OIB)**
This table presents results of panel regressions of daily future returns on skilled and non-skilled investors' daily order imbalance. Given each group of investors, we conduct the analyses for in-sample and out-of-sample periods, separately. The regressions include contract and maturity fixed effects. In this table, skilled investors are identified as per Table 12. For each day t, OIB(t) is computed as $\frac{Buy\_Volume - Sell\_Volume}{Buy\_Volume + Sell\_Volume}$, DLV is defined as per Eq. (3), r_i is the return on the next trading day $t+i$, and $r_{i:j}$ is the return across days $t+i$ to day $t+j$. Reported are daily returns (all returns are divided by the number of days during the holding period) in basis points. t-statistics are based on robust standard errors clustered by contract and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
	$r_{-5:-1}$	r_{-1}	r_0	r_1	$r_{1:5}$
	Panel A: Skilled investors; in sample (year 2014)				
OIB	137.31**	-11.50	77.99***	97.25	75.12
	(2.02)	(-0.38)	(2.79)	(1.37)	(0.43)
OIB × DLV	-18.70***	0.42	-6.50***	-7.80	3.56
	(-3.06)	(0.15)	(-2.65)	(-1.44)	(0.21)
DLV	-2.48	2.21	1.79	-1.00	-5.26
	(-0.63)	(1.58)	(1.17)	(-0.67)	(-1.35)
Obs	2,972	3,007	3,016	3,022	3,022
	Panel B: Skilled investors; out of sample (years 2015-2016)				
OIB	175.41*	49.83	48.28	-7.72	-38.28
	(1.70)	(1.41)	(0.64)	(-0.14)	(-0.31)
OIB × DLV	-11.76	-5.24	-8.38	1.32	10.39
	(-1.25)	(-1.36)	(-0.93)	(0.27)	(0.95)
DLV	5.37	1.09	0.79	-0.86	-2.42
	(1.64)	(0.88)	(0.60)	(-0.61)	(-0.76)
Obs	8,769	8,823	8,836	8,846	8,828
	Panel C: Non-skilled investors; in sample (year 2014)				
OIB	17.38	14.97	-3.74	-2.18	-24.63
	(0.65)	(1.33)	(-0.28)	(-0.16)	(-0.78)
OIB × DLV	-1.60	-1.31	-0.17	-0.51	1.61
	(-0.58)	(-1.12)	(-0.12)	(-0.37)	(0.49)
DLV	4.40***	-4.07***	-6.13***	-2.37***	-5.60***
	(2.90)	(-6.73)	(-9.12)	(-3.42)	(-3.34)
Obs	22,909	23,449	23,595	23,719	23,652
	Panel D: Non-skilled investors; out of sample (years 2015-2016)				
OIB	31.35*	15.10**	-2.11	-13.31*	0.21
	(1.82)	(2.09)	(-0.29)	(-1.66)	(0.01)
OIB × DLV	-3.58**	-1.77**	-0.66	0.63	-0.67
	(-2.02)	(-2.42)	(-0.89)	(0.77)	(-0.38)
DLV	6.93***	-0.54	-1.37***	1.00**	-0.02
	(7.38)	(-1.38)	(-3.73)	(2.43)	(-0.02)
Obs	69,560	70,466	70,698	70,868	70,551

Table 16: **Regression of Returns on Investors' OIB by Minute**

This table presents results of panel regressions of future returns on skilled and non-skilled investors' order imbalance by minute. Given each group of investors, we conduct the analyses for in-sample and out-of-sample periods, separately. The regressions include contract and maturity fixed effects. Skilled investors are identified as per Table 12. For each minute t, OIB is computed as $\frac{Buy\_Volume - Sell\_Volume}{Buy\_Volume + Sell\_Volume}$, r_i is the return realized in the minute $t+i$, $r_{i:j}$ is the return realized during minutes $t+i$ to $t+j$, and DLV is the average (across all skilled investors traded in the minute) contemporaneous leverage computed in the minute frequency. Reported are holding period returns in basis points. t-statistics are based on robust standard errors clustered by contract and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$r_{-60:-3}$	r_{-2}	r_{-1}	r_0	r_1	$r_{1:5}$	$r_{1:10}$
	Panel A: Skilled investors; in sample (year 2014)						
OIB	2.95***	0.15**	-0.47***	-1.63***	0.39***	0.50***	0.49***
	(5.73)	(2.17)	(-4.45)	(-15.14)	(5.57)	(4.81)	(4.88)
OIB × DLV	-0.42***	-0.07***	-0.08***	0.07	0.04**	0.05***	0.05**
	(-2.97)	(-3.37)	(-3.22)	(1.56)	(2.43)	(2.85)	(1.98)
DLV	-0.06	0.01	-0.00	0.01	-0.00	0.03	-0.01
	(-0.27)	(0.58)	(-0.08)	(0.70)	(-0.19)	(1.07)	(-0.16)
Obs	83,929	83,929	83,929	83,929	83,931	83,931	83,931
	Panel B: Skilled investors; out of sample (years 2015-2016)						
OIB	1.49***	0.37***	-0.03	-2.57***	0.43***	0.47***	0.51***
	(5.06)	(4.21)	(-0.23)	(-12.07)	(5.35)	(5.43)	(8.65)
OIB × DLV	-0.11	-0.09***	-0.11***	0.15***	0.03***	0.02	0.02
	(-1.30)	(-5.59)	(-4.86)	(4.36)	(3.17)	(1.31)	(1.56)
DLV	-0.04	0.01	0.01	0.02	-0.02**	-0.05**	-0.06*
	(-0.23)	(1.58)	(0.39)	(1.62)	(-1.96)	(-2.41)	(-1.95)
Obs	202,890	202,890	202,890	202,890	202,890	202,890	202,890
	Panel C: Non-skilled investors; in sample (year 2014)						
OIB	-0.23	-0.22***	-0.32***	-0.91***	-0.34***	-0.23***	-0.20**
	(-0.71)	(-7.10)	(-7.98)	(-13.47)	(-7.51)	(-3.41)	(-2.29)
OIB × DLV	-0.15*	-0.01	-0.04***	0.02	0.01	-0.00	-0.01
	(-1.76)	(-1.57)	(-3.51)	(1.31)	(1.00)	(-0.13)	(-0.20)
DLV	-0.67**	-0.06***	-0.06***	-0.10***	-0.03	-0.05	-0.09
	(-2.01)	(-2.80)	(-2.89)	(-3.68)	(-1.34)	(-0.98)	(-1.07)
Obs	1,429,960	1,430,453	1,430,465	1,430,486	1,430,515	1,430,515	1,430,515
	Panel D: Non-skilled investors; out of sample (years 2015-2016)						
OIB	-2.19***	-0.35***	-0.60***	-1.63***	-0.35***	-0.26***	-0.21**
	(-7.62)	(-7.40)	(-7.84)	(-14.29)	(-6.09)	(-3.44)	(-2.37)
OIB × DLV	0.13*	0.02	0.03*	0.16***	0.02	0.02	0.02
	(1.75)	(1.43)	(1.69)	(5.83)	(1.17)	(0.87)	(0.77)
DLV	0.42	0.05**	0.10***	0.06**	-0.02	-0.09	-0.15*
	(1.30)	(2.52)	(4.43)	(2.49)	(-0.89)	(-1.55)	(-1.68)
Obs	3,127,713	3,127,941	3,127,943	3,127,950	3,127,955	3,127,954	3,127,954

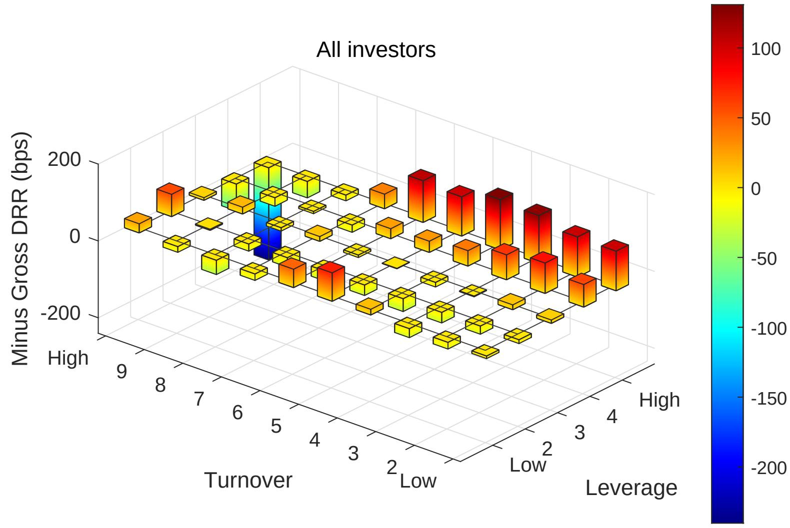
Table 17: **Risk and Return Around Margin Ratio Change: Full Sample**

This table presents difference-in-difference (DiD) analyses on DLV, DRRs (in basis points), and the standard deviation of investors' DRRs (in percent). The regulator increased margin ratios for futures written on 16 underlying assets during the event window April 5 to 29, 2016. The treatment (resp. control) group includes investors whose average DLV (during a 100-day period before April 5) is higher (resp. not higher) than the sample median DLV. In this way, we have 2617 treatments and 2618 controls. "NetAdj" DRR represents a transaction fee adjusted version of net DRR, which assumes the same transaction fee for the post event period as that for the pre event period. Observations during November 6, 2015 to October 28, 2016, except for the event window, are used in this table. "Treat" and "After" are two dummy variables which take on the value 1 for the treatment and post-event periods, respectively. We control for DTO, age, account age, and time-to-maturity in all regressions. Panel A reports results for the full sample, and Panel B reports results when ex-ante skilled investors (identified as per Table 12) are excluded from the analyses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

		DRR			std(DRR)	
	DLV	Gross	Net	NetAdj	Gross	Net
	Panel A: With skilled investors					
Treat	3.875***	-29.085***	-27.833***	-30.169***	4.246***	4.229***
	(48.294)	(-3.431)	(-3.307)	(-3.584)	(42.905)	(42.965)
After	0.113***	5.159	-1.390	2.570	0.953***	0.956***
	(2.695)	(0.993)	(-0.268)	(0.495)	(13.638)	(13.646)
Treat×After	-1.263***	21.899**	14.752*	20.411**	-0.705***	-0.707***
	(-17.022)	(2.449)	(1.652)	(2.295)	(-5.660)	(-5.690)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Without skilled investors					
Treat	3.874***	-29.273***	-28.109***	-30.461***	4.250***	4.232***
	(48.275)	(-3.438)	(-3.324)	(-3.601)	(42.906)	(42.969)
After	0.118***	5.155	-1.388	2.580	0.955***	0.957***
	(2.820)	(0.993)	(-0.267)	(0.497)	(13.655)	(13.661)
Treat×After	-1.262***	22.412**	15.393*	21.063**	-0.702***	-0.703***
	(-17.009)	(2.489)	(1.709)	(2.347)	(-5.625)	(-5.654)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 18: **Risk and Return Around Margin Ratio Change: Subsamples**
This table presents difference-in-difference (DiD) analyses on DLV, DRRs (in basis points), and the standard deviation of investors' DRRs (in percent). The regulator increased margin ratios for futures written on 16 underlying assets during the event window April 5 to 29, 2016. The treatment (resp. control) group includes investors whose average DLV (during a 100-day period before April 5) is higher (resp. not higher) than the median DLV of the corresponding subsample. "NetAdj" DRR represents a transaction fee adjusted version of net DRR, which assumes the same transaction fee for the post event period as that for the pre event period. Observations during November 6, 2015 to October 28, 2016, except for the event window, are used in this table. "Treat" and "After" are two dummy variables which take on the value 1 for the treatment and post-event periods, respectively. We control for DTO, age, account age, and time-to-maturity in all regressions. Panel A reports results for unskilled investors (identified as per Table 8), Panel B reports results for skilled investors (identified as per Table 12), Panel C reports results for institutional investors, and Panel D reports results for the combined sample of institutional and skilled investors. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

		DRR			std(DRR)	
	DLV	Gross	Net	NetAdj	Gross	Net
	Panel A: Unskilled investors (26 treatments; 27 controls)					
Treat	2.413***	-97.609*	-62.999	-68.982	4.498***	4.447***
	(4.051)	(-1.950)	(-1.298)	(-1.401)	(5.666)	(5.591)
After	-0.100	2.174	-18.725	-14.665	0.486	0.546
	(-0.279)	(0.119)	(-0.888)	(-0.707)	(1.024)	(1.160)
Treat×After	-1.300*	133.102***	59.029	77.863*	0.526	0.485
	(-1.872)	(3.037)	(1.248)	(1.899)	(0.554)	(0.545)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Skilled investors (3 treatments; 3 controls)					
Treat	3.342***	69.585	8.677	4.055	4.955	5.142
	(5.358)	(1.133)	(0.201)	(0.099)	(1.526)	(1.544)
After	-0.614	30.423	-60.623**	-59.350**	-1.003***	-0.951***
	(-1.205)	(1.214)	(-2.174)	(-2.129)	(-2.694)	(-2.802)
Treat×After	-1.315**	-169.076	-121.885	-109.816	-0.297	-0.206
	(-2.512)	(-1.347)	(-1.279)	(-1.228)	(-0.164)	(-0.117)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
	Panel C: Institutional investors (58 treatments; 58 controls)					
Treat	4.614***	24.564	23.398	23.101	4.223***	4.207***
	(8.398)	(0.917)	(0.888)	(0.876)	(4.623)	(4.692)
After	-0.064	1.496	1.329	1.913	0.561*	0.566*
	(-0.241)	(0.122)	(0.115)	(0.165)	(1.712)	(1.723)
Treat×After	-1.836***	-28.983	-42.832	-41.742	-0.893	-0.899
	(-2.725)	(-0.851)	(-1.252)	(-1.216)	(-0.846)	(-0.864)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
	Panel D: Institutional and skilled investors (61 treatments; 61 controls)					
Treat	4.597***	22.770	29.569	28.740	4.105***	4.080***
	(8.485)	(0.808)	(1.176)	(1.147)	(4.710)	(4.756)
After	-0.052	2.122	1.425	2.026	0.652*	0.657*
	(-0.196)	(0.163)	(0.128)	(0.181)	(1.916)	(1.928)
Treat×After	-1.811***	-54.733	-72.909**	-70.693**	-1.177	-1.175
	(-3.222)	(-1.489)	(-2.307)	(-2.253)	(-1.181)	(-1.196)
Controls	Yes	Yes	Yes	Yes	Yes	Yes



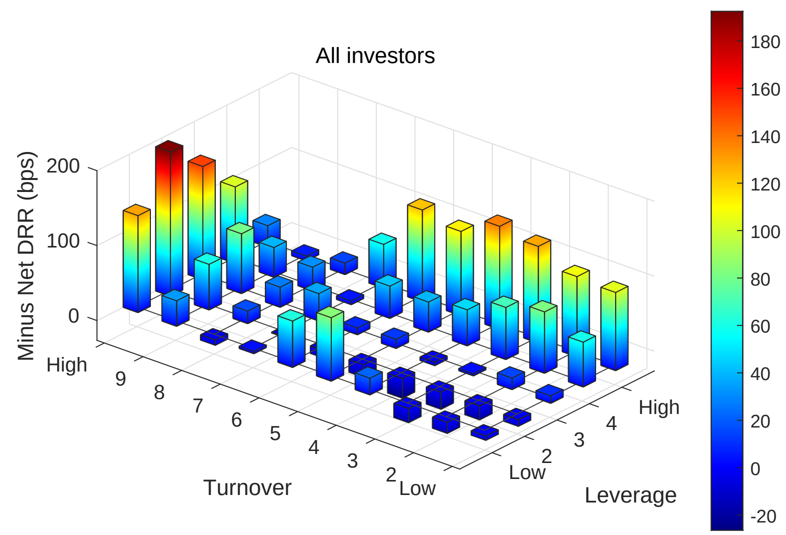


Figure 1: Opposite-signed average returns in different bins of turnover (DTO) and leverage (DLV). We perform dependent double sorts across all investor-day observations. Specifically, we first sort all observations into DTO deciles and then, in each DTO decile, we sort observations into DLV quintiles. For each double sorted group, we report the equally weighted average DRRs in basis points. The upper (bottom) panel shows results for gross (net) returns. Because most numbers are negative, we show the corresponding opposite-signed numbers in both plots to get a better view.

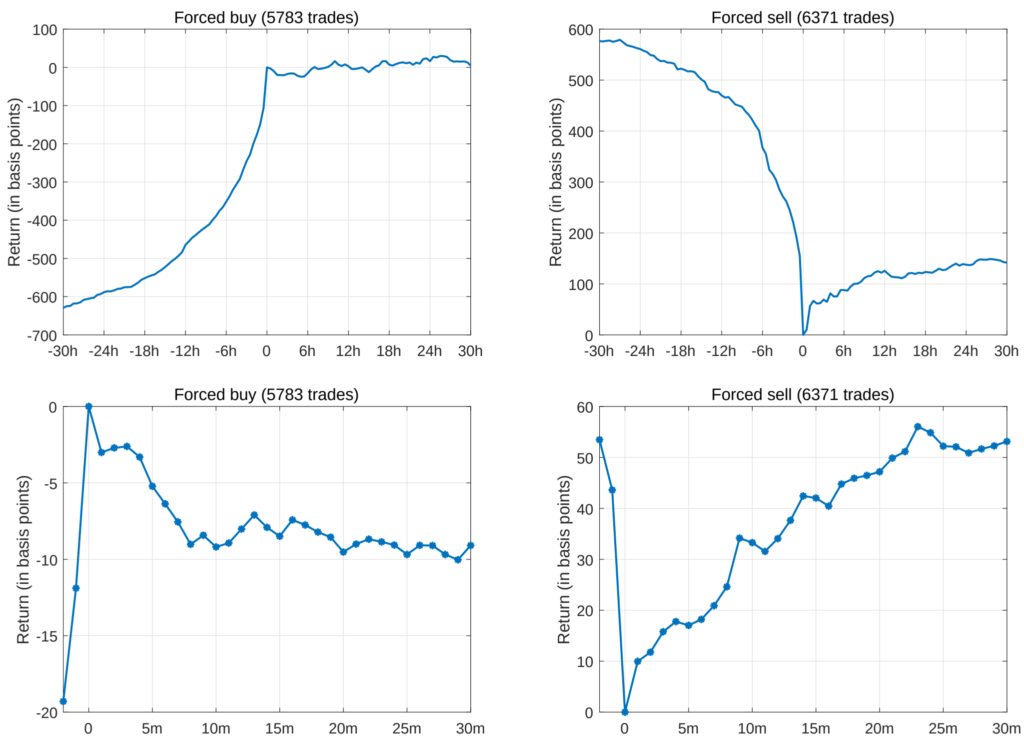


Figure 2: Average return (in basis points) around forced buy (left plots) trades and forced sell (right plots) trades. This figure conducts an event study around investors' forced offsets. We plot average returns on VWAP (volume-weighted average price). Returns are calculated as the simple return with respect to the transaction price of the forced trade: $r_{VWAP} = \frac{\text{VWAP} - P_0}{P_0}$, where P_0 is the transaction price of the forced trade.

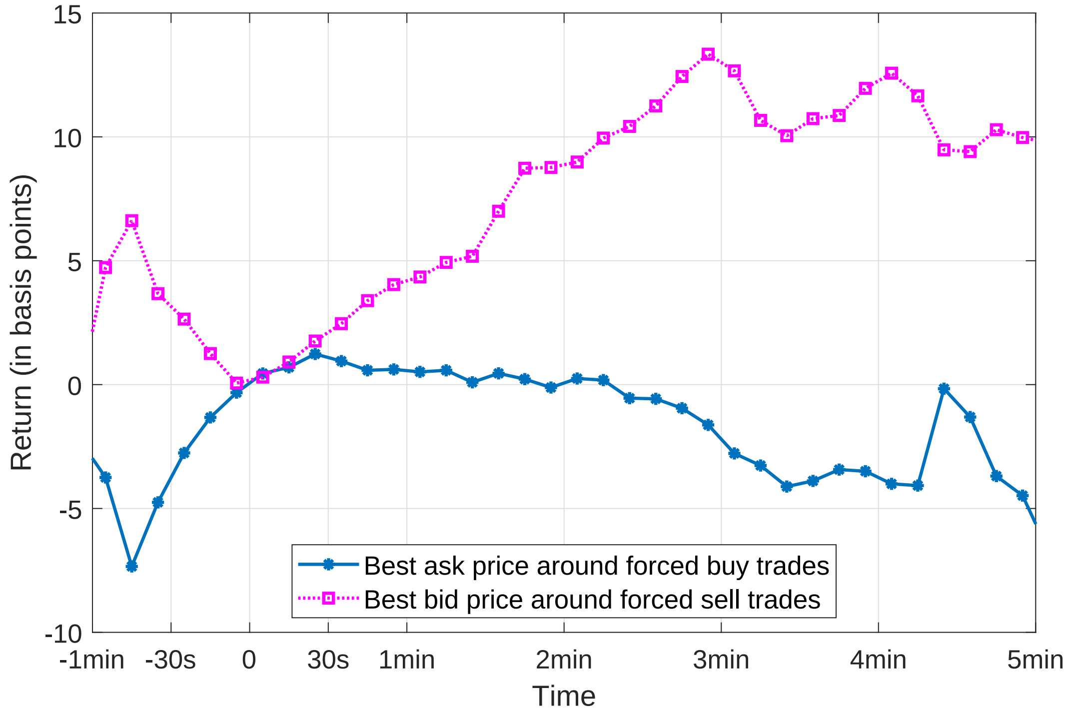


Figure 3: Average return (in basis points) around forced buy trades and forced sell trades. This figure conducts an event study around investors' forced offsets. We plot the average return on the best bid (ask) price around the forced sell (buy) trades. Returns are calculated as the simple return with respect to the price of the forced trade: $r_{bid,ask} = \frac{P_{bid,ask} - P_0}{P_0}$, where P_0 is the transaction price of the forced trade.

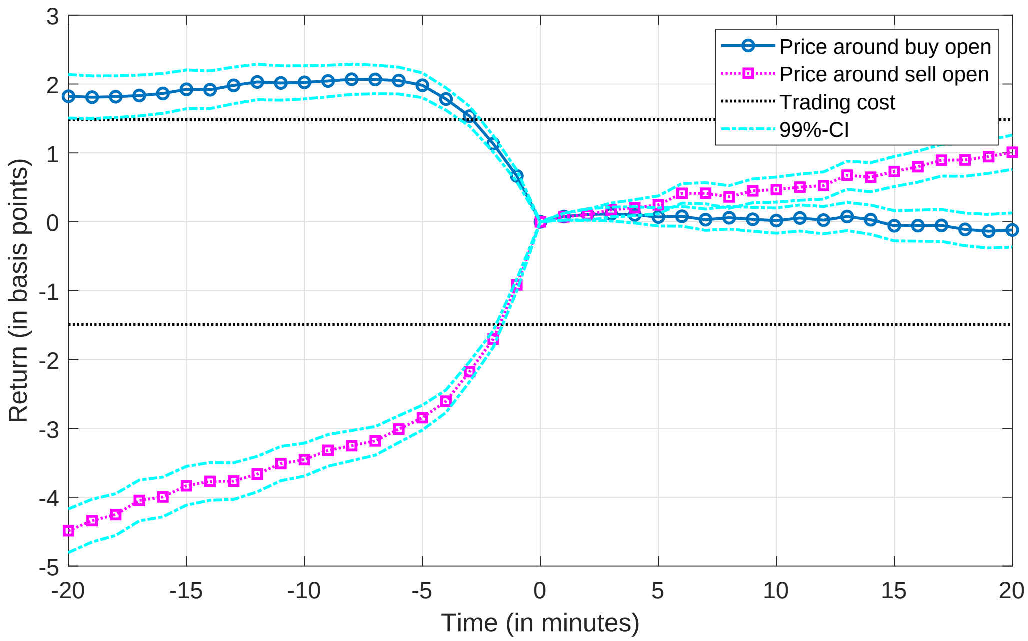


Figure 4: VWAP around unskilled investors' open trades. This figure conducts an event study around unskilled investors' open buys and sells, separately. Unskilled investors are identified as per Table 11. We plot average returns of VWAP (volume-weighted average price) together with their 99% confidence intervals. Returns are calculated as the simple return with respect to the transaction price of the current trade: $r_{VWAP} = \frac{\mathrm{VWAP}-P_0}{P_0}$, where P_0 is the transaction price of the current trade. The upper (lower) horizontal dotted line represent unskilled investors' average transaction cost of buy-then-sell (sell-then-buy).

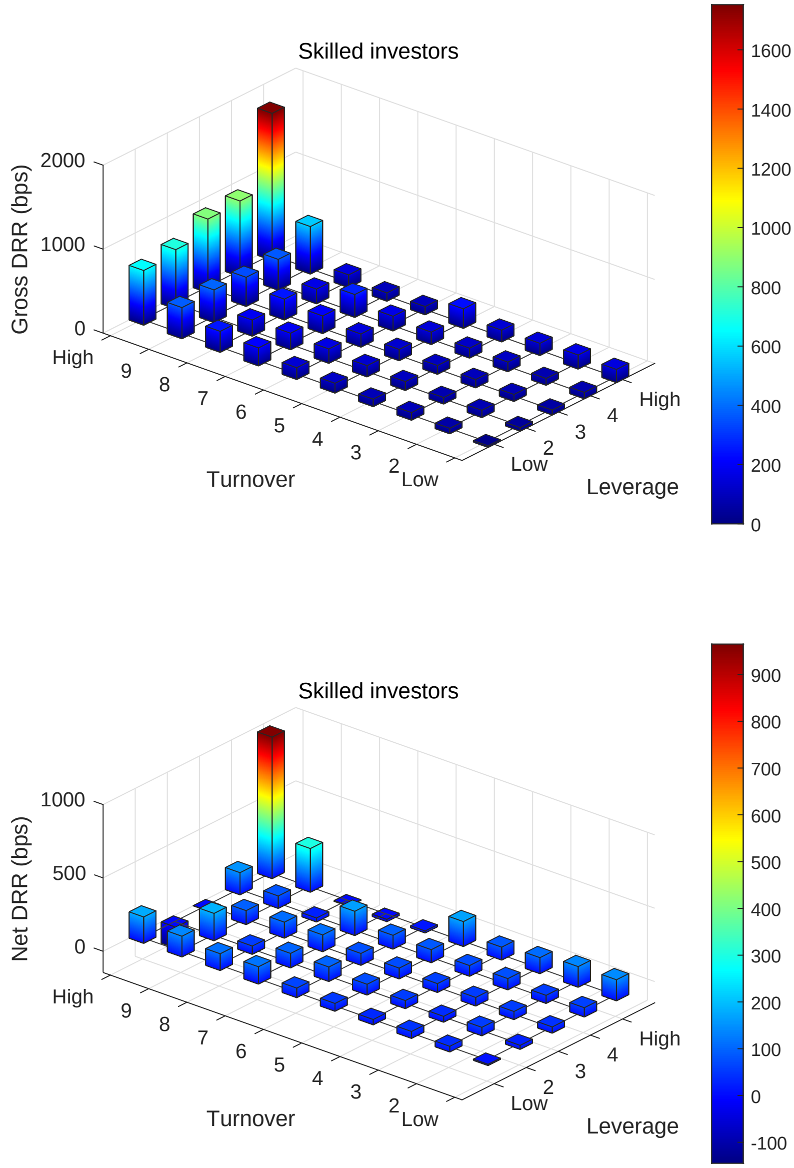


Figure 5: Average returns in different bins of turnover (DTO) and leverage (DLV) for skilled investors. We perform dependent double sorts across all investor-day observations. Only skilled investors' observations are included in this analysis. In this figure, skilled investors are identified as per Table 12. Specifically, we first sort all observations into DTO deciles and then, in each DTO decile, we sort observations into DLV quintiles. For each double-sorted group, we report the equally weighted average DRRs in basis points. The upper (bottom) panel shows results for gross (net) returns.

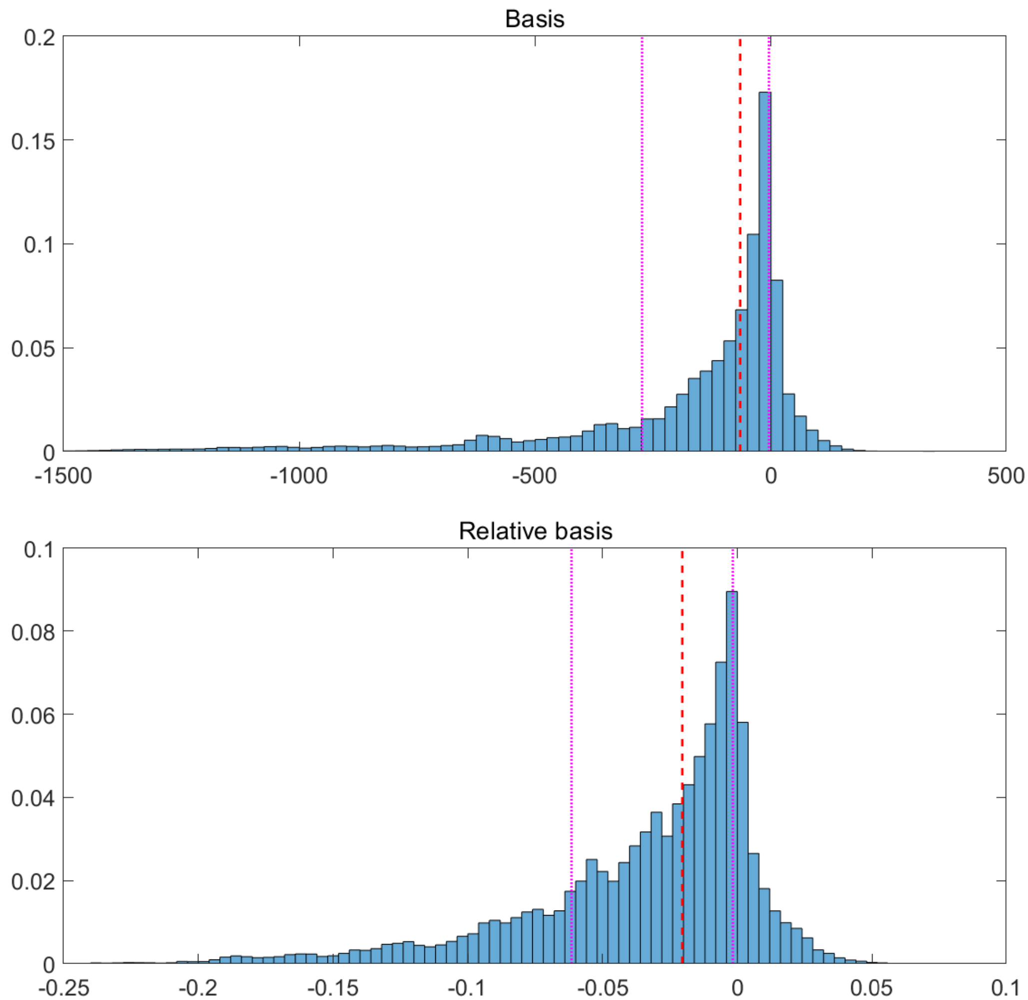


Figure 6: The basis for financial futures during the years 2014–2016. This figure plots the histogram (probability distribution) of the bases for all financial futures at the one-minute level during 2014–2016. The basis is defined as the closing price of futures less the corresponding theoretical value $F_{t,T} = S_t \, e^{-(r_{t,T}-d_{t,T})(T-t)}$ at the end of each trading minute t, where T is the maturity time, and $r_{t,T}$ and $d_{t,T}$ are the corresponding risk-free rate and dividend rate. In each plot, the dashed line indicates the median, and the dotted lines represent the 20th and the 80th percentiles.

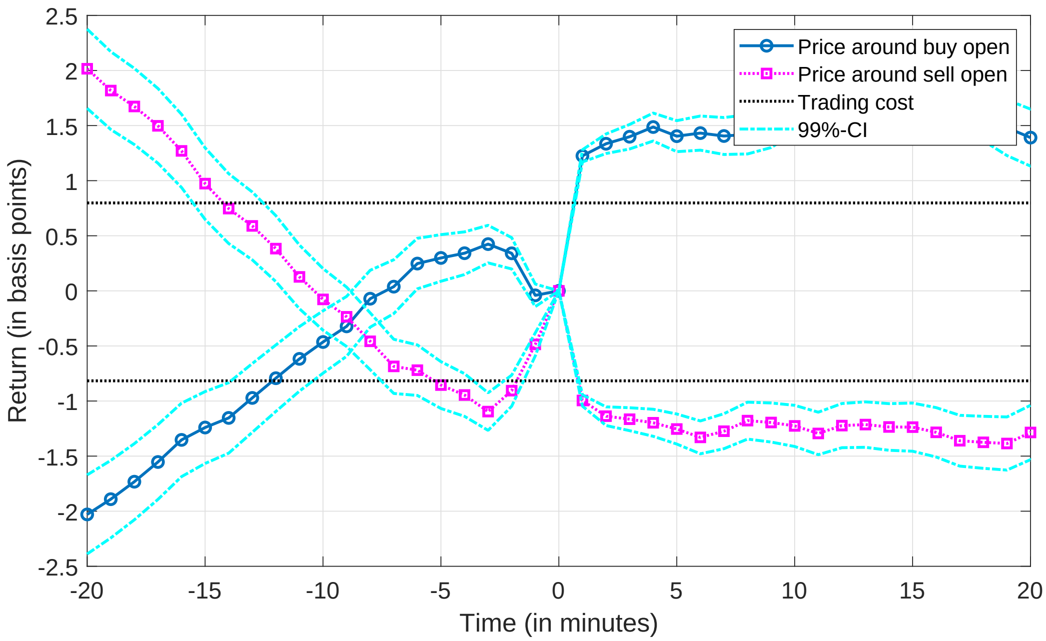


Figure 7: VWAP around skilled investors' open trades. This figure conducts an event study around skilled investors' open buys and sells, separately. Skilled investors are identified as per Table 12. We plot average returns on VWAP (volume-weighted average price) together with their 99% confidence intervals. Returns are calculated as the simple return with respect to the transaction price of the current trade: $r_{VWAP} = \frac{\text{VWAP}-P_0}{P_0}$, where P_0 is the transaction price of the current trade. The upper (lower) horizontal dotted line represents top investors' average transaction cost of buy-then-sell (sell-then-buy).

Internet Appendix to

“Leverage is a Double-Edged Sword”

Avanidhar Subrahmanyam, Ke Tang, Jingyuan Wang, and Xuewei Yang

November 2, 2021

In this Appendix we provide some ancillary discussion and empirical results.

Speculation vs. Hedging in Chinese Futures

In the futures markets we study, hedging trades enjoy preferential treatment (including more favorable trading limits and commission fees), and thus are strictly supervised. According to a document titled "Regulatory Measures for the Hedging Business," published jointly by the four major futures exchanges, we find that:

- For commodity futures, only institutional investors are allowed to perform hedging.
- For financial futures, investors are required to carry out hedging in accordance with their proposed hedging plan, which is submitted when applying for permissions to hedge, and hedges are subject to position limits.
- For both commodity and financial futures, investors engaged in hedging are not allowed to **frequently** open and close positions.

As per Table 2, institutional investors' notional trading value accounts for 2.1% of the total.[1] Specifically, for commodity futures, institutional investors' notional trading value accounts for 2.67% of the total. Taking the length of trading cycles as a proxy of trading frequency, we find that for financial futures, 94.5% (resp. 97.9%) of trading cycles are completed within one hour (resp. one day); for commodity futures, and 77.0% (resp. 87.8%) of trading cycles are completed within one hour (resp. one day). The above indicates that hedging activity is unlikely to account for investors' performance in the futures markets we consider.

[1]Unreported analysis shows that institutional investors' aggregated notional value of positions accounts for 8.1% of the total.

Table IA.1: **Implied Leverage and Volatility of Institutional Investors' DRR**

This table presents results of regressions of the standard deviation (σ) of institutional investors' gross DRR (in percent) and net DRR (in percent) on DLV. Only institutions that traded on at least 36 trading days are included in this analysis. We control for DTO in regressions. DTOOrth $=$ DTO $- \hat{\beta} *$ DLV is the orthogonal part of DTO with respect to DLV, where $\hat{\beta}$ is the loading on DLV from the following OLS regression: $\text{DTO}_i = \alpha + \beta * \text{DLV}_i + \hat{\epsilon}_i$. Panel A reports results for gross DRR, and Panel B reports the results for net DRR. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. The last two lines report the number of observations and the adjusted R^2 (in percent) for each regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: σ(Gross DRR)				Panel B: σ(Net DRR)			
DLV	0.78***	—	—	0.79***	0.77***	—	—	0.79***
	(16.12)			(13.36)	(16.03)			(13.36)
DTO	—	1.11***	—	-0.04	—	1.09***	—	-0.06
		(6.22)		(-0.28)		(6.11)		(-0.41)
DTOOrth	—	—	-0.04	—	—	—	-0.06	—
			(-0.18)				(-0.26)	
Intercept	0.83***	3.18***	4.97***	0.84***	0.83***	3.19***	4.96***	0.86***
	(2.83)	(9.10)	(20.22)	(2.82)	(2.86)	(9.15)	(20.27)	(2.88)
Obs	168	168	168	168	168	168	168	168
Adjusted R^2 (%)	60.77	18.40	-1.42	60.55	60.52	17.86	-1.44	60.32

Table IA.2: **Panel Regressions of Institutional Investors' DRR**

This table presents results of panel regressions of institutional investors' gross DRR (in basis points) and net DRR (in basis points) on leverage. The regressions include day fixed effects. Panel A uses DLV as the independent variable, while Panel B uses the predicted DLV as the independent variable. On each day t, we estimate an autoregression model with 4 lags using ConDLV up to day $t-1$, and compute the predicted leverage measure PredDLV using the estimated coefficients and the latest 4 lags. Investors' demographic information (account age), time-to-maturity (TtM, in days), and DTO (in logarithmic scale) are included as independent variables. Account age are measured in years computed on January 1, 2017. Time-to-maturity is defined as the notional-value weighted mean (*across all trades*) for each investor-day. t-statistics are based on robust standard errors clustered by investor and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: Regression on DLV					
	Panel A1: Gross DRR			Panel A2: Net DRR		
DLV	-1.976	-2.162	-6.075**	-7.371***	-7.557***	-8.881***
	(-0.486)	(-0.540)	(-2.132)	(-3.153)	(-3.221)	(-3.980)
AccAge	—	-1.968	-1.491	—	-1.758	-1.596
		(-1.115)	(-0.856)		(-0.986)	(-0.898)
TtM	—	-0.036	-0.005	—	0.006	0.017
		(-0.411)	(-0.060)		(0.074)	(0.193)
DTO	—	—	23.097***	—	—	7.817
			(2.940)			(1.237)
Obs	28,061	28,061	28,061	28,061	28,061	28,061
	Panel B: Regression on PredDLV					
	Panel B1: Gross DRR			Panel B2: Net DRR		
PredDLV	-2.228	-2.413	-5.854*	-7.572***	-7.737***	-8.699***
	(-0.507)	(-0.558)	(-1.862)	(-2.644)	(-2.721)	(-3.409)
AccAge	—	-1.850	-1.294	—	-1.550	-1.395
		(-1.126)	(-0.814)		(-0.957)	(-0.856)
TtM	—	-0.042	-0.018	—	-0.005	0.001
		(-0.470)	(-0.196)		(-0.062)	(0.014)
DTO	—	—	21.840***	—	—	6.104
			(2.909)			(1.097)
Obs	27,684	27,684	27,684	27,684	27,684	27,684

Table IA.3: **Panel Regressions of Investors' DRR for LagDLV**

This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on lagged leverage measure LagDLV. The setting for this table is the same as that for Table 5, except that this table uses LagDLV instead of DLV. LagDLV is defined as per Section 2.2.1.

	Panel A: Gross DRR			Panel B: Net DRR		
LagDLV	-2.329***	-2.588***	-5.437***	-7.499***	-7.735***	-7.326***
	(-2.640)	(-2.998)	(-6.395)	(-10.868)	(-11.299)	(-9.114)
Inst	20.036	-10.771	23.156	31.858***	15.864	10.996
	(1.267)	(-0.640)	(1.522)	(2.838)	(1.276)	(0.873)
Inst×LagDLV	-0.537	0.049	-0.685	-0.375	0.051	0.156
	(-0.127)	(0.011)	(-0.181)	(-0.135)	(0.018)	(0.055)
Age	—	-0.650***	-0.547***	—	-0.284**	-0.299**
		(-3.539)	(-3.159)		(-1.974)	(-2.108)
AccAge	—	5.031***	5.027***	—	3.364***	3.364***
		(6.837)	(7.090)		(5.891)	(5.927)
TtM	—	0.212***	0.302***	—	0.271***	0.259***
		(5.249)	(7.699)		(6.883)	(6.787)
DTO	—	—	23.603***	—	—	-3.387*
			(9.854)			(-1.818)
Obs	1,374,516	1,374,516	1,374,516	1,374,516	1,374,516	1,374,516

Table IA.4: **Panel Regressions of Investors' DRR for ConDLV**

This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on the contemporaneous leverage measure ConDLV. The setting for this table is the same as that for Table 5, except that this table uses ConDLV instead of DLV. ConDLV is defined as per Section 2.2.1.

	Panel A: Gross DRR			Panel B: Net DRR		
ConDLV	0.872	0.580	-3.119***	-5.600***	-5.877***	-5.217***
	(1.006)	(0.687)	(-4.315)	(-9.900)	(-10.466)	(-8.126)
Inst	34.870**	5.911	33.122**	40.571***	24.723*	19.865
	(2.001)	(0.324)	(1.994)	(3.448)	(1.885)	(1.482)
Inst×ConDLV	-3.007	-2.398	-2.528	-1.965	-1.531	-1.508
	(-0.723)	(-0.570)	(-0.694)	(-0.812)	(-0.619)	(-0.587)
Age	—	-0.597***	-0.530***	—	-0.277*	-0.289**
		(-3.370)	(-3.110)		(-1.960)	(-2.071)
AccAge	—	4.837***	4.890***	—	3.245***	3.235***
		(6.766)	(7.014)		(5.761)	(5.787)
TtM	—	0.202***	0.293***	—	0.269***	0.253***
		(4.986)	(7.452)		(6.770)	(6.597)
DTO	—	—	22.414***	—	—	-4.002**
			(10.205)			(-2.296)
Obs	1,376,035	1,376,035	1,376,035	1,376,035	1,376,035	1,376,035

Table IA.5: **The Effect of Forced Liquidation on Investors' Net DRRs**

This table presents the effect of removing observations with forced liquidation on investors' average net DRRs. Panel A reports the within-group cross-sectional averages of investors' time-series mean net DRRs. Panel B reports the within-group cross-sectional averages of the difference $mean(\widehat{DRR}_{i,t}) - mean(DRR_{i,t})$, where $DRR_{i,t}$ is the observed DRR time series for investor i, and $\widehat{DRR}_{i,t}$ is the corresponding time series obtained by omitting observations where forced liquidation occurs. The second column of Panel A reports the average DLV for each DLV quintile. The third columns in Panel A and Panel B report averages for each DLV quintile. The remaining columns in these panels perform independent double sorts on DLV and DTO, and report averages for each intersection of the resulting quintiles. Panel C reports the improvement ratios which are obtained via dividing the entries in Panel B by the absolute values of the corresponding entries in Panel A.

DLV Group	Mean DLV	DTO Group					
		All	Low	2	3	4	High
Panel A: Averages of mean net DRRs (in basis points)							
Low	2.54	-19.32	-2.28	-28.53	-37.99	-54.21	-64.62
2	4.30	-49.07	-13.69	-34.10	-40.85	-72.72	-133.40
3	5.50	-77.47	-19.46	-36.57	-62.07	-91.62	-153.15
4	6.73	-88.75	-32.47	-59.11	-57.02	-85.49	-147.85
High	9.62	-109.15	-26.47	-95.91	-104.22	-90.25	-143.67
Panel B: Averages of differences in net DRRs (in basis points)							
Low	—	0.20	0.13	0.16	0.59	0.00	0.23
2	—	1.34	2.14	1.57	1.19	0.75	0.56
3	—	3.81	4.22	4.45	4.89	3.33	2.31
4	—	7.91	6.00	11.42	8.75	6.64	7.09
High	—	18.88	15.16	20.89	30.81	19.77	12.73
High-Low	—	18.68	15.03	20.73	30.21	19.77	12.50
(t-stat)	—	(14.27)	(17.42)	(10.66)	(5.81)	(5.51)	(1.67)
Panel C: Improvement ratios (in percent)							
Low	—	1.02	5.64	0.56	1.56	0.00	0.35
2	—	2.73	15.66	4.60	2.91	1.04	0.42
3	—	4.91	21.67	12.17	7.87	3.63	1.51
4	—	8.91	18.47	19.33	15.35	7.77	4.80
High	—	17.30	57.28	21.78	29.56	21.91	8.86

Table IA.6: **Panel Regressions of Investors' DRR with Force Dummy and PredDLV**
This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on predicted leverage from an autoregression model with 4 lags. The setting for this table is the same as that for Table 6, except that this table uses PredDLV instead of DLV. PredDLV is defined as per Section 2.2.1.

	Panel A: Gross DRR		Panel B: Net DRR	
PredDLV	1.502**	2.366***	-0.549	0.086
	(2.355)	(3.063)	(-0.981)	(0.123)
DTO	14.890***	15.813***	-11.988***	-10.832***
	(7.161)	(7.317)	(-7.898)	(-6.564)
Age	-0.666***	-0.594***	-0.361***	-0.291**
	(-4.809)	(-4.260)	(-3.258)	(-2.559)
AccAge	5.635***	4.809***	3.882***	3.068***
	(7.985)	(7.084)	(6.731)	(5.538)
TtM	0.205***	0.273***	0.164***	0.231***
	(5.439)	(6.968)	(4.469)	(6.050)
Force	-2692.121***	—	-2680.905***	—
	(-26.666)		(-26.647)	
PredForce	—	-2887.196***	—	-2737.663***
		(-7.762)		(-7.357)

Table IA.7: **Panel Regressions of Investors' DRR with Force Dummy and LagDLV**

This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on the lagged leverage measure LagDLV. The setting for this table is the same as that for Table 6, except that this table uses LagDLV instead of DLV. LagDLV is defined as per Section 2.2.1.

	Panel A: Gross DRR		Panel B: Net DRR	
LagDLV	-0.763	-0.913	-2.656***	-3.044***
	(-1.177)	(-1.183)	(-4.508)	(-4.306)
DTO	16.731***	18.477***	-10.153***	-8.155***
	(7.861)	(8.239)	(-6.501)	(-4.724)
Age	-0.684***	-0.620***	-0.383***	-0.322***
	(-4.927)	(-4.397)	(-3.446)	(-2.796)
AccAge	5.714***	4.939***	3.980***	3.222***
	(8.035)	(7.172)	(6.867)	(5.753)
TtM	0.217***	0.288***	0.174***	0.246***
	(5.795)	(7.416)	(4.804)	(6.487)
Force	-2667.973***	—	-2653.876***	—
	(-26.675)		(-26.640)	
PredForce	—	-2747.479***	—	-2588.276***
		(-7.461)		(-7.042)

Table IA.8: **Panel Regressions of Investors' DRR with Force Dummy and ConDLV**
This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on the contemporaneous leverage measure ConDLV. The setting for this table is the same as that for Table 6, except that this table uses ConDLV instead of DLV. ConDLV is defined as per Section 2.2.1.

	Panel A: Gross DRR		Panel B: Net DRR	
ConDLV	0.059	0.793	-2.023***	-1.463**
	(0.083)	(0.984)	(-3.209)	(-1.997)
DTO	16.053***	16.919***	-10.274***	-9.181***
	(7.883)	(8.042)	(-6.557)	(-5.484)
Age	-0.673***	-0.597***	-0.380***	-0.308***
	(-4.901)	(-4.309)	(-3.436)	(-2.696)
AccAge	5.673***	4.855***	3.946***	3.140***
	(8.039)	(7.133)	(6.854)	(5.658)
TtM	0.212***	0.278***	0.172***	0.239***
	(5.618)	(7.122)	(4.702)	(6.251)
Force	-2668.783***	—	-2659.324***	—
	(-26.367)		(-26.357)	
PredForce	—	-2829.221***	—	-2697.558***
		(-7.601)		(-7.233)

Table IA.9: **Panel Regressions of Investors' DRR in Years 2015-2016 with Top Dummy (Criteria=99.9%; 17 Skilled Investors)**

This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on DLV. In this table, we only include observations in years 2015-2016. The regressions include day fixed effects. DTO (on a logarithmic scale), investors' demographic information (age and account age), and time-to-maturity (TtM) are included as independent variables. Age and account age are measured in years computed on January 1, 2017. Time-to-maturity is defined as the notional-value weighted mean (*across all trades*) for each investor-day. "Force" is a dummy variable (1 for observations on which force offset occurs; 0 for others). In the second column of each panel, we also include a Top dummy (1 for skilled investors; 0 for others) and its interaction terms with other variables. Skilled investors are identified as per Table 12 except that we require skilled investors' actual t-value of net DRR to be higher than the corresponding 99.9% quantile of the simulated t-values. In this way, we identify 17 skilled investors. t-statistics are based on robust standard errors clustered by investor and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: Gross DRR		Panel B: Net DRR	
DLV	0.639	0.513	-1.132*	-1.166*
	(1.063)	(0.853)	(-1.891)	(-1.942)
DTO	16.433***	15.380***	-10.820***	-11.618***
	(13.881)	(13.166)	(-9.234)	(-10.051)
Age	-0.719***	-0.699***	-0.454***	-0.440***
	(-8.921)	(-8.670)	(-5.637)	(-5.464)
AccAge	6.447***	6.254***	4.695***	4.513***
	(15.145)	(14.705)	(11.269)	(10.829)
TtM	0.256***	0.241***	0.234***	0.222***
	(5.582)	(5.218)	(5.070)	(4.780)
Force	-2792.482***	-2792.106***	-2783.266***	-2783.084***
	(-26.714)	(-26.713)	(-26.700)	(-26.702)
Top	—	-287.828***	—	-52.659*
		(-9.136)		(-1.754)
DLV×Top	—	23.652***	—	13.280***
		(6.269)		(3.626)
DTO×Top	—	56.186***	—	17.781**
		(7.521)		(2.448)
Obs	964,542	964,542	964,542	964,542

Table IA.10: **Panel Regressions of Investors' DRR in Years 2015-2016 with Top Dummy (Criteria=99%; 36 Skilled Investors)**

This table presents results of panel regressions of investors' gross DRR (in basis points) and net DRR (in basis points) on DLV. In this table, we only include observations in years 2015-2016. The regressions include day fixed effects. DTO (on a logarithmic scale), investors' demographic information (age and account age), and time-to-maturity (TtM) are included as independent variables. Age and account age are measured in years computed on January 1, 2017. Time-to-maturity is defined as the notional-value weighted mean (*across all trades*) for each investor-day. "Force" is a dummy variable (1 for observations on which force offset occurs; 0 for others). In the second column of each panel, we also include a Top dummy (1 for skilled investors; 0 for others) and its interaction terms with other variables. Skilled investors are identified as per Table 12 except that we require skilled investors' actual t-value of net DRR to be higher than the corresponding 99% quantile of the simulated t-values. In this way, we identify 36 skilled investors. t-statistics are based on robust standard errors clustered by investor and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: Gross DRR		Panel B: Net DRR	
DLV	0.639	0.445	-1.132*	-1.224**
	(1.063)	(0.735)	(-1.891)	(-2.028)
DTO	16.433***	15.374***	-10.820***	-11.604***
	(13.881)	(13.053)	(-9.234)	(-9.963)
Age	-0.719***	-0.694***	-0.454***	-0.437***
	(-8.921)	(-8.600)	(-5.637)	(-5.426)
AccAge	6.447***	6.125***	4.695***	4.427***
	(15.145)	(14.362)	(11.269)	(10.595)
TtM	0.256***	0.240***	0.234***	0.221***
	(5.582)	(5.192)	(5.070)	(4.763)
Force	-2792.482***	-2792.642***	-2783.266***	-2783.404***
	(-26.714)	(-26.737)	(-26.700)	(-26.718)
Top	—	-91.974***	—	-18.422
		(-6.348)		(-1.305)
DLV×Top	—	18.621***	—	10.169***
		(8.081)		(4.499)
DTO×Top	—	19.211***	—	11.087***
		(5.785)		(3.382)
Obs	964,542	964,542	964,542	964,542

Table IA.11: **Panel Regressions of Investors' DRR in Years 2015-2016 with Top Dummy**
The setting for this table is the same as that for Table 13, except that we replace the "Force" dummy with "PredForce", which is the fitted logit probability of the "Force" dummy as a function of four lags of DRR, DTO, and DLV.

	Panel A: Gross DRR		Panel B: Net DRR	
DLV	0.759	0.598	-1.180	-1.238
	(1.000)	(0.786)	(-1.556)	(-1.628)
DTO	18.792***	18.016***	-8.253***	-8.787***
	(13.266)	(12.728)	(-5.995)	(-6.386)
Age	-0.612***	-0.578***	-0.350***	-0.337***
	(-7.148)	(-6.742)	(-4.095)	(-3.934)
AccAge	5.475***	5.394***	3.736***	3.684***
	(13.086)	(12.882)	(9.115)	(8.976)
TtM	0.338***	0.330***	0.316***	0.309***
	(6.936)	(6.746)	(6.452)	(6.283)
PredForce	-2665.609***	-2656.905***	-2544.739***	-2540.410***
	(-6.942)	(-6.918)	(-6.624)	(-6.613)
Top	—	-598.206***	—	22.188
		(-8.664)		(0.343)
DLV×Top	—	29.663***	—	20.630***
		(5.681)		(4.086)
DTO×Top	—	105.295***	—	-7.000
		(6.825)		(-0.477)
Obs	964,542	964,542	964,542	964,542

Table IA.12: **Panel Regressions of Investors' DRR in Years 2015-2016 with Top Dummy (Criteria=99.9%; 17 Skilled Investors)**

The setting for this table is the same as that for Table IA.9, except that we replace the "Force" dummy with "PredForce", which is the fitted logit probability of the "Force" dummy as a function of four lags of DRR, DTO, and DLV.

	Panel A: Gross DRR		Panel B: Net DRR	
DLV	0.759	0.618	-1.180	-1.226
	(1.000)	(0.811)	(-1.556)	(-1.609)
DTO	18.792***	17.796***	-8.253***	-9.000***
	(13.266)	(12.690)	(-5.995)	(-6.604)
Age	-0.612***	-0.592***	-0.350***	-0.336***
	(-7.148)	(-6.916)	(-4.095)	(-3.932)
AccAge	5.475***	5.288***	3.736***	3.558***
	(13.086)	(12.603)	(9.115)	(8.649)
TtM	0.338***	0.323***	0.316***	0.305***
	(6.936)	(6.597)	(6.452)	(6.183)
PredForce	-2665.609***	-2656.983***	-2544.739***	-2539.963***
	(-6.942)	(-6.919)	(-6.624)	(-6.612)
Top	—	-274.069***	—	-39.297
		(-8.758)		(-1.318)
DLV×Top	—	24.197***	—	13.969***
		(6.369)		(3.790)
DTO×Top	—	51.558***	—	13.032*
		(6.911)		(1.793)
Obs	964,542	964,542	964,542	964,542

Table IA.13: **Panel Regressions of Investors' DRR in Years 2015-2016 with Top Dummy (Criteria=99%; 36 Skilled Investors)**
The setting for this table is the same as that for Table IA.10, except that we replace the "Force" dummy with "PredForce", which is the fitted logit probability of the "Force" dummy as a function of four lags of DRR, DTO, and DLV.

	Panel A: Gross DRR		Panel B: Net DRR	
DLV	0.759	0.585	-1.180	-1.248
	(1.000)	(0.766)	(-1.556)	(-1.634)
DTO	18.792***	17.752***	-8.253***	-9.024***
	(13.266)	(12.597)	(-5.995)	(-6.590)
Age	-0.612***	-0.592***	-0.350***	-0.338***
	(-7.148)	(-6.897)	(-4.095)	(-3.940)
AccAge	5.475***	5.174***	3.736***	3.487***
	(13.086)	(12.265)	(9.115)	(8.428)
TtM	0.338***	0.322***	0.316***	0.303***
	(6.936)	(6.562)	(6.452)	(6.157)
PredForce	-2665.609***	-2656.544***	-2544.739***	-2539.353***
	(-6.942)	(-6.919)	(-6.624)	(-6.612)
Top	—	-85.431***	—	-12.214
		(-5.791)		(-0.849)
DLV×Top	—	16.015***	—	7.683***
		(6.848)		(3.360)
DTO×Top	—	20.977***	—	12.759***
		(6.243)		(3.816)
Obs	964,542	964,542	964,542	964,542

Table IA.14: **Regression of Returns on Investors' Open OIB by Minute**

This table presents results of panel regressions of future returns on skilled investors' order imbalance by minute. The regressions include contract and maturity fixed effects. Skilled investors are identified as per Table 12. For each minute t, OIB is computed as $\frac{Buy\_Volume - Sell\_Volume}{Buy\_Volume + Sell\_Volume}$, r_i is the return realized in the minute $t+i$, and $r_{i:j}$ is the return realized during minutes $t+i$ to $t+j$. Reported are holding period returns in basis points. t-statistics are based on robust standard errors clustered by contract and date. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) $r_{-60:-3}$	(2) r_{-2}	(3) r_{-1}	(4) r_0	(5) r_1	(6) $r_{1:5}$	(7) $r_{1:10}$
	Panel A: Skilled investors; in sample (year 2014)						
OIB	3.44**	-0.13	-0.25	0.85	0.79***	1.09***	1.01***
	(2.24)	(-0.57)	(-0.68)	(1.44)	(7.50)	(7.02)	(4.93)
OIB × DLV	-0.81***	-0.09***	-0.17***	-0.32***	-0.01	0.00	-0.00
	(-3.58)	(-2.97)	(-3.30)	(-3.73)	(-0.35)	(0.11)	(-0.13)
DLV	-0.02	0.02	0.01	0.01	-0.00	0.03	-0.02
	(-0.05)	(1.26)	(0.44)	(0.49)	(-0.19)	(0.75)	(-0.42)
Obs	53,418	53,418	53,418	53,418	53,418	53,418	53,418
	Panel B: Skilled investors; out of sample (years 2015-2016)						
OIB	2.36	-0.50**	-1.11***	-1.22***	0.85***	0.96***	0.99***
	(1.52)	(-2.04)	(-2.72)	(-4.70)	(10.91)	(8.10)	(5.46)
OIB × DLV	-0.27**	-0.04	-0.00	-0.04	-0.02	-0.03*	-0.03
	(-2.18)	(-1.38)	(-0.11)	(-0.86)	(-1.59)	(-1.67)	(-1.34)
DLV	0.04	0.02	0.00	0.00	-0.01	-0.04	-0.06
	(0.23)	(1.44)	(0.32)	(0.03)	(-0.76)	(-1.53)	(-1.45)
Obs	127,622	127,622	127,622	127,622	127,622	127,622	127,622
	Panel C: Non-skilled investors; in sample (year 2014)						
OIB	-0.59	-0.29***	-0.11*	-0.10	-0.03	-0.01	-0.08
	(-1.40)	(-6.67)	(-1.94)	(-1.49)	(-0.91)	(-0.17)	(-1.25)
OIB × DLV	-0.12	-0.02	-0.12***	-0.23***	-0.09***	-0.08***	-0.07***
	(-1.22)	(-1.36)	(-7.35)	(-15.47)	(-7.34)	(-5.06)	(-3.19)
DLV	-0.81**	-0.06***	-0.08***	-0.12***	-0.03	-0.04	-0.07
	(-2.06)	(-2.78)	(-3.18)	(-3.40)	(-1.19)	(-0.65)	(-0.84)
Obs	1,029,938	1,030,348	1,030,358	1,030,377	1,030,405	1,030,405	1,030,405
	Panel D: Non-skilled investors; out of sample (years 2015-2016)						
OIB	-0.99**	-0.29***	-0.19***	-0.42***	0.10***	0.17***	0.16**
	(-2.26)	(-6.28)	(-2.65)	(-7.35)	(3.09)	(3.23)	(2.09)
OIB × DLV	-0.34***	-0.02	-0.10***	-0.25***	-0.12***	-0.11***	-0.09***
	(-2.92)	(-1.34)	(-5.14)	(-14.61)	(-9.24)	(-6.23)	(-3.73)
DLV	0.47	0.05**	0.11***	0.08***	-0.01	-0.08	-0.13
	(1.28)	(2.28)	(4.18)	(3.25)	(-0.51)	(-1.29)	(-1.39)
Obs	2,172,170	2,172,352	2,172,354	2,172,360	2,172,365	2,172,365	2,172,365

Table IA.15: **Parallel Trend Tests for DiD Analyses**
This table presents results of parallel trend tests for the difference-in-difference (DiD) analyses in Table 17. We split the 100-day pre-event period into three subintervals (33, 33, 34). T_3 is a dummy variable that equals 1 for the first 33-day period, and T_2 is a dummy variable that equals 1 for the next 33-day period. Other aspects of the table are the same as those for Table 17.

		DRR		
	DLV	Gross	Net	NetAdj
	Panel A: With skilled investors			
Treat $\times T_3$	0.143	-20.192	-17.685	-17.666
	(1.490)	(-0.732)	(-0.639)	(-0.638)
Treat $\times T_2$	0.003	20.290	24.477	24.885
	(0.038)	(1.091)	(1.301)	(1.323)
Treat	3.830***	-30.374*	-31.430*	-33.922**
	(42.808)	(-1.836)	(-1.883)	(-2.030)
Treat × After	-1.218***	23.072	18.222	24.035
	(-15.003)	(1.391)	(1.085)	(1.430)
After	0.113***	5.149	-1.401	2.558
	(2.697)	(0.992)	(-0.270)	(0.493)
Controls	Yes	Yes	Yes	Yes
	Panel B: Without skilled investors			
Treat $\times T_3$	0.138	-20.226	-17.713	-17.692
	(1.433)	(-0.725)	(-0.633)	(-0.632)
Treat $\times T_2$	0.002	20.774	25.152	25.565
	(0.028)	(1.103)	(1.320)	(1.342)
Treat	3.831***	-30.727*	-31.944*	-34.453**
	(42.765)	(-1.834)	(-1.891)	(-2.038)
Treat × After	-1.219***	23.748	19.098	24.924
	(-14.979)	(1.411)	(1.121)	(1.463)
After	0.118***	5.145	-1.400	2.569
	(2.821)	(0.992)	(-0.270)	(0.495)
Controls	Yes	Yes	Yes	Yes

Table IA.16: **DiD Analyses for the Futures Basis**

This table presents results of difference-in-difference (DiD) analyses on futures basis around policy changes that occurred in April 2016. We use data during a 40-day pre event period and during a 40-day post event period in this analysis. The dependent variable is the absolute value of the basis (futures prices minus spot prices). In column "(1)" futures with margin requirement changes are taken as the treated group, and all other futures are taken as controls. In column "(2)" futures with margin requirement changes are taken as the treated group, and futures without any regulatory changes are taken as controls. In column "(3)" futures with any regulatory changes (margin requirements, price limits, and commission fees) are taken as the treated, and futures without any regulatory changes are taken as controls. *t* statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	AbsBasis	AbsBasis	AbsBasis
Treat	-0.0251	-0.0346	-0.0373
	(-0.7913)	(-1.0498)	(-1.2131)
After	1.0749***	0.9389***	0.9389***
	(19.3405)	(17.3254)	(17.3269)
Treat×After	-0.0214	0.1147	0.2420***
	(-0.2438)	(1.3220)	(2.8526)
Obs	3194	2794	3194

Table IA.17: **DiD Analyses for Autocorrelations in High Frequency Futures Prices**
This table presents results of difference-in-difference (DiD) analyses on the first-order autocorrelation of futures prices (at 1-minute frequency) around policy changes occurred in April 2016. We use data during a 40-day pre event period and during a 40-day post event period in this analysis. The dependent variable is the absolute value of the first-order autocorrelation coefficient. In column "(1)" futures with margin requirement changes are taken as the treated group, and all other futures are taken as controls. In column "(2)" futures with margin requirement changes are taken as the treated group, and futures without any regulatory changes are taken as controls. In column "(3)" futures with any regulatory changes (margin requirements, price limits, and commission fees) are taken as the treated group, and futures without any regulatory changes are taken as controls. *t* statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	AbsCorr	AbsCorr	AbsCorr
Treat	0.0102*	0.0176***	0.0209***
	(1.7420)	(2.9769)	(4.0442)
After	0.0081*	0.0126**	0.0120**
	(1.7945)	(2.5569)	(2.5404)
Treat×After	0.0001	-0.0044	-0.0071
	(0.0074)	(-0.5302)	(-0.9651)
Obs	720	580	720

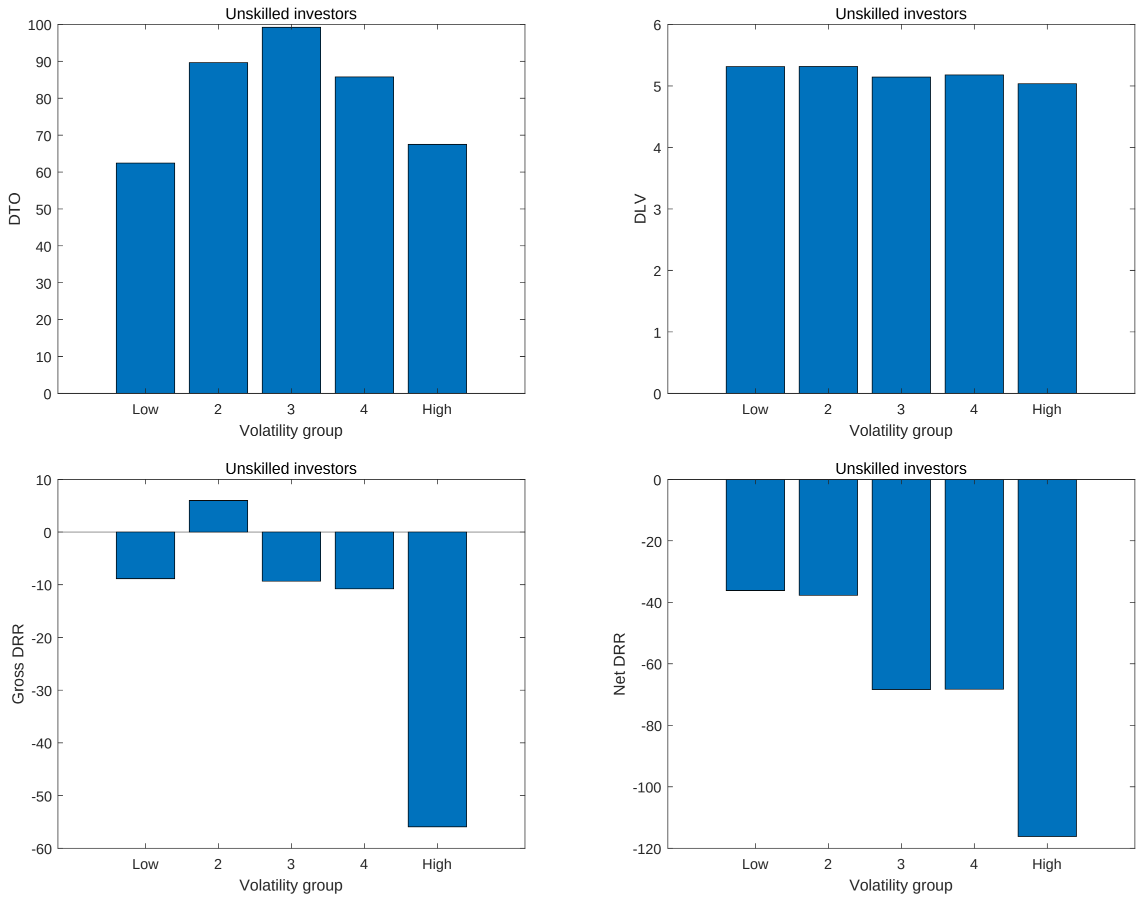


Figure IA.1: Unskilled investors' average DTO, DLV, gross DRR, and net DRR within quintiles of contract-day observations grouped by intra-day 1-min volatility. [The differences in gross and net DRRs across the extreme volatility groups are each statistically significant at the 5% level.]

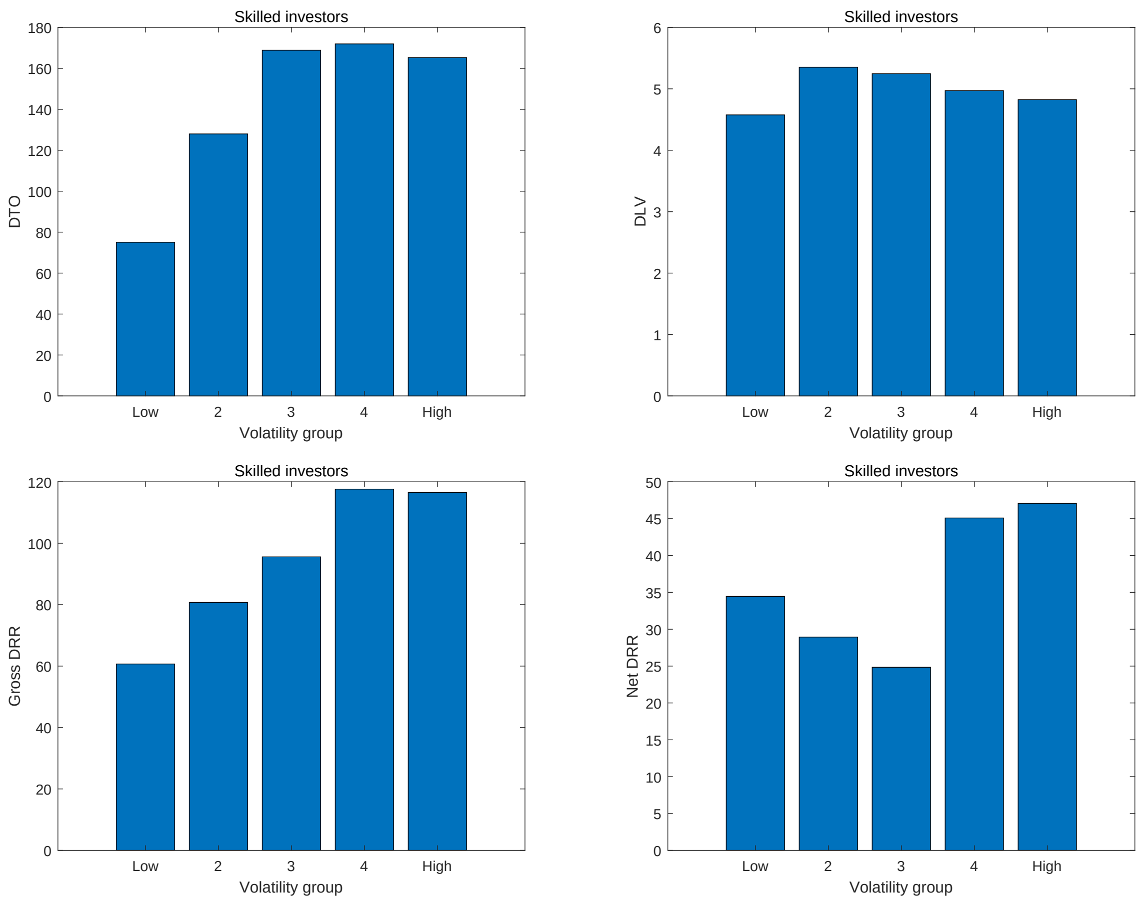


Figure IA.2: Skilled investors' average DTO, DLV, gross DRR, and net DRR within quintiles of contract-day observations grouped by intra-day 1-min volatility. [The differences in gross and net DRRs across the extreme volatility groups are each statistically significant at the 5% level.]