Losing money on the margin

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Abstract: Margin trading is popular with retail investors around the world. To limit the scale of these investors' potential losses, regulators impose a system of collateral requirements and margin calls. We show in this paper, however, that the collateral requirement imposed by margin calls results in negative expected returns for these traders whilst also inducing positive skew in the returns distribution. Investments in assets with symmetric returns, when traded on margin, instead offer limited losses and a small chance of a large gain, much like lottery stocks and other gambles. We demonstrate this theoretically and then show empirically, using a unique database of account data from a Chinese retail brokerage, that the realized losses of margin traders are often substantial. This leads us to question whether current regulation is appropriate.

Keywords: Margin Trading, Margin Requirement, Financial Regulation, Retail Investors

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1 Introduction

"The Little Crash in '62", as described in the classic account of Brooks (2014), was the result of limited liquidity and panic. In particular it was the result of the limited liquidity and panic of retail investors trading on the margin, that is, trading mostly with borrowed money secured with a small amount of collateral. Kindleberger (2000) identifies a similar role for margin traders and their brokers in the 1929 crash while Brunnermeier and Pedersen (2009) discuss their role in more recent crises.[1] Margin trading, however, remains a common but relatively understudied feature of financial markets. This is surprising since, as this paper shows, trading on the margin leads retail investors to receive substantially lower returns.

Regardless of whether a crash is transitory like in 1962, or not as in 1929, liquidity spirals as described anecdotally by Brooks (2014) and formally by Brunnermeier and Pedersen (2009), lead to the ruin of many margin investors. Of course, in crises, large numbers of investors suffer (and profit) but, as we will show, margin traders risk the loss of their entire investment even during tranquil periods. In this paper we study the effect of margin trading on the distribution of returns. We present a theoretical model of margin trading that shows that whilst margin requirements limit losses they also reduce expected returns. We test these predictions using a unique dataset containing the full portfolio histories of individual clients of a leading Chinese retail brokerage. We show that Rebar futures traders trading on margin on the Shanghai Futures Exchange (SHFE)

[1] Brooks (2014) describes how the Dow Jones incurred its second largest ever loss on the Monday and fell further on Tuesday morning. That afternoon, however, the market started to recover, and its losses had been eliminated completely one trading day later by the end of Thursday. Brooks, citing the NYSE official reports, emphasizes the role of private individuals' behavior in precipitating the crash and that the majority of private investors traded on the margin. As the market fell, reducing the value of their portfolios and thus eliminating their collateral, these investors – presumably unable or unwilling to provide additional collateral – were issued margin calls and forced by their brokers to liquidate their positions to eliminate their debts. Many had already faced such calls over the prior weekend, providing the initial downwards acceleration. The large volume of selling induced by this led to further price falls, further margin calls, and a downwards spiral. In Brooks's account, the precipitous fall in the market – so rapid the Dow Jones ticker tape was unable to keep up – was arrested only by the entry of institutional investors who perceived value in the market, and who crucially, had ample liquidity.

consistently under perform the market and in fact make negative expected returns.[2] This negative return is not due to the performance of the asset, rather it is caused by the investors trading on margin as both those individuals who take long positions and those who take short positions on margin lose money over the period.

Given then, the obvious hazards of trading on the margin, the natural question is, why is margin trading ubiquitous? Our explanation is that the collateral requirement imposed by margin calls induces positive skewness in the distribution of these returns. If a trader fails to produce additional capital given a fall in the value of their portfolio then this portfolio is closed. The distribution of returns is therefore truncated from below. Investments in otherwise low risk assets will instead offer lower average returns but with limited losses and a small but positive chance of a large gain. In other words they resemble lotteries. We will rule out alternative explanations based on portfolio management by showing that the traded asset never forms part of an optimal portfolio and that combinations of any other asset alongside the riskless asset dominates diversification with Rebar.

Previous work, which we discuss below, has largely focused on the understanding the aggregate effects of margin trading in terms of liquidity, stability, price dynamics or investors willingness to enter the market. This paper complements this literature by studying the implications of margin trading at the individual level, an area which has seen relatively little work. One notable exception is Heimer (2015) who studies the impact of leverage constraints by comparing leverage-limited US traders with their unconstrained EU counterparts. By studying contemporaneously traded FX markets he shows that leverage constraints limit losses. In his view, leverage constraints serve to limit poor decisions by over-confident traders. Our study shows that traders pay for these limited losses through a lower expected return. In essence traders remove the possibility of large losses at the cost of making small losses more likely. In this sense our

[2] Rebar are reinforcing steel bars, widely used with concrete in the construction of buildings.

work also relates to that of Dybvig (1988) who finds that employing a strategy using stop loss orders has a cost to the trader.

Our explanation that margin trading is popular because it skews the distribution of returns is consistent with the literature that documents preferences for investments with positively skewed returns. An important early contribution was that of Golec and Tamarkin (1998) who showed that investors prefer so called lottery stocks: those with high skewness in the returns. More recently, skewness has been shown to have a negative relationship with the returns of equity options (Byun and Kim, 2016) and that option prices partly reflect retail investors compensating intermediaries for the additional risk associated with lottery-type payoffs (Boyer and Vorkink, 2014). Bali et al. (2011) shows that lottery stocks command a price premium whilst Conrad et al. (2013) shows that more positively skewed options have lower returns. Bhattacharya and Garrett (2008) provides evidence that lotteries that offer more skewness offer lower returns, suggesting a similar trade-off. There have been various explanations for this effect focusing on cumulative prospect theory and the overweighting of tail probabilities (see, for instance, Polkovnichenko and Zhao (2013)).

The small chance of a large return associated with margin trading is also related to the literature that studies *trading as gambling*. Kumar (2009) has shown that lottery-ticket purchasers tend to buy lottery-type stocks, and investors in regions with a greater proportion of Catholics compared to Protestants, and thus fewer religious presumptions against gambling trade, buy more lottery-type stocks (Kumar et al., 2011). Similarly, investors who say they enjoy investing are found to trade more (Dorn and Sengmueller, 2009) and investors trade less, especially in lottery stocks when real world lottery prizes are large (see, Gao and Lin, 2015, Dorn et al., 2015).

The previous literature on margin trading has predominantly focused on the effects on the market as a whole. Limits to margin trading have been shown to reduce market volatility; see for instance Hardouvelis (1990) and Chowdhry and Nanda (1998). Brunnermeier and Pedersen (2009) use a formal model to understand the effects of margin trading on markets. In their model, market liquidity interacts with the ability of investors to borrow to trade. They show how this interaction can destabilize markets, increase volatility and induce 'liquidity spirals' like those in 1929 and 19nan62, and those from the early 1980s onwards that they describe in their study.[3] Margin requirements have also received attention as regulatory tools with Hardouvelis and Theodossiou (2002) showing how they may be used to limit price instability and Lensberg et al. (2015) examining their effectiveness in enhancing financial stability. Booth et al. (1997) looks at the appropriate level of margin requirements for futures exchanges to balance default risk against liquidity while Koudijs and Roth (2016) studys how the individual experiences of Dutch lenders of a crisis in 1772 affected their willingness to extend margin loans and the terms on which they did so.

Empirical work has sought to shed further light on the relationship between margin trading and liquidity. Hardouvelis and Peristiani (1992) and Hardouvelis and Kim (1995) both study the relationship between margin requirement levels and market participation finding a negative relationship. Kahraman and Tookes (Forthcoming) exploits the staged introduction of margin trading for different assets in India to provide evidence that margin trading leads to a substantial reduction in the spread. On the other hand, Wang (2014), using data for Chinese exchange traded funds (ETF), shows that allowing margin trading and short selling can reduce liquidity by discouraging trading by uninformed investors. This paper relates to this work by showing that margin trading may encourage trading by investors seeking lottery-type payoffs.

The literature has also considered the related issue of short selling. Often, although not exclusively, short positions are purchased on margin. Empirically short selling has been shown to improve the incorporation of negative information into market prices (Bris et al., 2007, Chang et al., 2014) whilst having little effect on volatility or crash risk (Crane et al., 2018). Theoretically Xu (2007) present a model of short selling where

[3] These results contrast with those of Seguin and Jarrell (1993) who argue that margin trading did not induce greater falls in prices during the crash of 1989.

they are able to show that short selling constraints increase skewness in asset returns. The analysis underlying all of these tests and result is distinctly different from our findings. Both the theoretical and empirical pieces concern the effect of short selling on the distribution of asset price changes observed in the market. In contrast we find that even for an asset with a symmetric distribution of raw returns, the returns of traders trading on margin will be positively skewed. As such the margin requirement induces skewness in the individuals returns but not the market returns.

Thus, from a regulatory perspective, the previous literature may be thought of as a debate about the social value of margin trading. On one hand, the literature has found that retail margin trading is valuable because it may boost market liquidity, limit price instability, and thus boost market stability. On the other hand, it may also occasionally lead to the negative spirals identified by Brunnermeier and Pedersen (2009). Our results complement this dilemma with another. We find that the provision of liquidity comes at the cost of substantial losses for the investors who provide it and generate stability by entering the market. Moreover, increases in collateral requirements to prevent liquidity spirals can exacerbate these losses. That being said, it seems investors seek the lottery-type returns distribution offered by margin trading distribution and thus it is not necessarily the case that the large financial losses incurred equate to reductions in welfare.

This paper is organized as follows. Section 2 demonstrates theoretically that margin trading results in lower returns and more skewness. Section 3 extends this with a numerical analysis that provides quantitative estimates of the scale of losses due to margin trading. Section 4 introduces our data and provides contextual information about Rebar trading on the SHFE. Section 5 presents empirical evidence of the losses of margin traders in our data and that these are concentrated on those who are identified as less able to provide additional capital in response to a margin call. Section 6 shows that this behavior can not be understood as part of a portfolio strategy. Section 7 studies the characteristics of the small number of traders in our data who achieved substantial returns. Section 8 closes the paper.

2 Margin trading

Traders, whether private individuals or institutions, can often use the assets they trade as collateral to finance other trades. Given that such assets are risky, they are unable to borrow the full value of these assets and must provide some additional collateral. For individual investors, this process often takes the form of a margin account in which investors are able to purchase assets up to the value of some multiple of the collateral they have provided. This limit is known as the margin requirement. For example a trader who posts $\$1,000$ of collateral with a margin requirement of 10% may purchase assets up to the value of $\$10,000$ with the trader's broker providing the additional cash to make the purchase. This leverage will increase the variance of the returns, a 10% appreciation in the value of the assets now doubles the investor's initial collateral whilst a similar depreciation eliminates it. Leverage does not in the absence of margin requirements, change the expected return of an investment – whilst gains are multiplied so are losses. In reality, however, losses, such as those in the second case, will increase the trader's leverage and so violate the margin requirement. As a result, in the event of losses the trader is required to provide additional funds to maintain the margin ratio.[4] This requirement for additional funds is known as a *margin call*. If the investor does not provide additional funds the brokerage reduces the position to maintain the margin ratio and ultimately closes it completely to prevent losses beyond the investors original stake.

The margin call and subsequent liquidation of part of or a whole position if no margin is provided means that there is no chance of an investor losing more than their original stake without further investment. It is this constraint that separates margin trading

[4]Brokers frequently specify a "maintenance margin" requirement. This is lower than the initial market requirement and prevents traders having to post collateral immediately after opening a position in the event of a small loss.

from a purely leveraged position. Leverage naturally means that gains and losses are both multiplied, adding variance and therefore risk to the returns distribution. The result of margin calls, however, is to induce asymmetry. Where previously the time series may have been well-described by a Brownian motion, and thus memoryless, it now becomes a first-hitting process in which once a boundary value has been crossed (the margin requirement) the asset value is effectively fixed at that boundary thereafter and even if the underlying asset appreciates the value of the investor's position will not increase. This has important implications for investors buying and holding the asset: longer time periods increase the chance of hitting the boundary and locking in a negative return. Intuitively, we can see that this will have two effects. Firstly, the transformation to a first-hitting process reduces the mean return. Secondly, as the margin requirement truncates the returns distribution, this naturally leads to skewness, even when the underlying asset is symmetrically distributed.

It is important to note that this argument is different from the well understood affect of constraints on portfolio positions, for instance limits to short selling. Even if a margin requirement is not binding at the creation of a portfolio, allowing the non-margin constrained optimal portfolio to be constructed, if there is some leverage in the portfolio the margin constrain still dynamically reduces expected returns.

The argument we present also has some similarities to the strategic use of stop loss rules (see the results of Dybvig (1988) and Barberis (2012)) but is subtlety different in that the use of stop loss rules is a particular strategy, whilst margin constraints potentially have a much wider effect that is more difficult to recognize and avoid. Margin trading is heavily used by retail traders in a range of markets around the world. Adverts attracting traders to trade on these platforms at high margin ratio's are prevalent both on the internet and traditional press often associated with inducements for new participants but without any suggestion of the effect of margin trading on returns.[5] The ability to leverage also is a common assumption in portfolio construction which is

[5] A parallel may be drawn here with internet casinos and gambling platforms.

frequently achieved through margin accounts. Again their is no suggestion in these cases that the use of leverage has its own unique perils. The effect of margin on these two cases, whilst following from the assumption of Brownian motion, has not been previously noted, however, is clearly far reaching.

The insights regarding skewness and reduced returns are important for our following argument and so in the remainder of this section we provide a more formal argument to make the insight for both effects more rigorous.

2.1 Margin trading has a reduced expected return (at any horizon)

Denote the return of an investment of a specified quantity of asset x which has positive expected returns over a period t as r_t^x when not invested on the margin, and as R_{tc}^x for the same quantity of asset x when invested on the margin such that a realization of $x \leq c$ triggers a margin call. A margin call always involves some loss, but the exact amount will depend on the degree of leverage and the size of the price movement. The reason for this is that a margin call will only ever be trigged when the current price of the asset x_t is less than the purchase price x_0. The mean return on the asset, conditional on a price change that takes it below the margin threshold, is negative. Thus, formally, a margin requirement c transforms the stochastic process describing the evolution of the price of x into a super-martingale. Then we have the following proposition:

Proposition 1. *The expected return $E[R_{ct}^x]$ of an asset x over a period t with margin requirement c is decreasing in c and always lower than the return of the same asset x in the absence of a margin requirement $E[r_t^x] \geq 0$.*

Here we explicitly consider the effect of investments of the same size, with and without a margin requirement, to demonstrate the effect of this constraint. Later in the paper we consider numerically the related impact of leverage in the context of margin requirements and show a similar result.

We now present a heuristic form of this argument to provide additional intuition. Consider a period $(0, t)$, then denoting the minimum value of the asset x over the period as

$$\overset{\vee}{x}_t = \min_{s \in (0,t)} (x_s)$$

The expected returns of the two investments over the time interval then may be written as:

$$E[r_t^x] = E[r_t^x | \overset{\vee}{x}_t > c] \cdot P(\overset{\vee}{x}_t > c) + E[r_t^x | \overset{\vee}{x}_t \leq c] \cdot P(\overset{\vee}{x}_t \leq c) \tag{1}$$

$$E[R_{tc}^x] = E[R_c^x | \overset{\vee}{x}_t > c] \cdot P(\overset{\vee}{x}_t > c) + \gamma \cdot P(\overset{\vee}{x}_t \leq c) \tag{2}$$

where in the asbence of a margin call the returns with and without leverage are the same, that is, $E[R_{tc}^x | \overset{\vee}{x}_t > c] = E[r_t^x | \overset{\vee}{x}_t > c]$. While, since a margin call is always costly as $x_c < x_0$, and the returns on the asset x in the absence of leverage are weakly positive, then we have that $\gamma = E[R_{tc}^x | \overset{\vee}{x}_t \leq c] < E[r_t^x | \overset{\vee}{x}_t \leq c]$ is the return in the event of a margin call. It then follows that $E[R_c^x] < E[r_t^x]$. The difference between $E[R_c^x]$ and $E[r_t^x]$ is determined by the chance of the margin call $P(\overset{\vee}{x}_t \leq c)$ and the loss it implies $\gamma - E[r_t^x | x \leq c]$. Focusing on the former, we can write the probability of the price, $P(\overset{\vee}{x}_t > c)$, having being sufficient to avoid a margin call at all periods in the interval, $(0, t)$, as a first-hitting process with boundary x_c:

$$P(\overset{\vee}{x}_t > c) = 1 - \frac{1}{\sqrt{2\pi\sigma^2 t}} \left\{ \exp(-\frac{(x_t - x_0)^2}{2\sigma^2 t}) - \exp(-\frac{(x_t - (x_0 - 2x_c))^2}{2\sigma^2 t}) \right\} \tag{3}$$

Inspection of (3) shows that $P(x \leq c)$, the probability of a margin call is increasing in the volatility, σ^2, and the holding period, t. This is natural, as an asset with no volatility would never trigger a margin call. But, this also highlights that if margin requirements are well matched to assets' properties then more volatile assets would be associated with higher margin requirements.

This result has parallels with the consequences of position constraints on the return of a portfolio. It is different, however, in the important sense that it is not dependent on a constraint upon the composition of the portfolio at creation. Normally a constraint on an asset position, such as leverage limits, may prevent the formation of certain portfolios and therefore move the efficient portfolio down and to the right in mean variance space. Our result is different, even if under a margin constraint the optimal portfolio may be created the possibility of margin calls means that if that portfolio is leveraged the overall return will be reduced. Importantly this result applies even with only a single risky asset and is not dependent on diversification between two risky assets.

Figure A1 highlights this. For unleveraged positions, to the left of A, corresponding to a position solely invested in the risky asset, the risk–return trade-off is a straight line between the risky and riskless assets. Beyond point A, however, the gradient of the line decreases due the effect detailed above. We will show later that this gradient may be negative.

[Figure 1 about here.]

2.2 Skewness

The previous section showed the effect of a margin requirement on mean returns. This section will formalize the intuitive relationship between truncating a distribution and its skewness. We show that the presence of a margin requirement induces right-skewed, 'lottery', returns. We do so by analyzing the properties of a truncated normal distribution, extending the work of Pender (2015), who characterizes the moments of a truncated normal distribution using Hermitian polynomials, the following can be shown:[6]

[6] It is important to note that the below result is dependent on the underlying distribution. For example, truncation does not necessarily result in skewness in a Pareto distribution. However, as can be seen in Figure A10, raw returns for the market we consider are well approximated by the normal distribution.

Proposition 2. *The derivative of the skewness with respect to the lower truncation point A is positive, thus a larger margin requirement increases the skewness of the returns of a given asset X*

$$\frac{\partial Skew_X}{\partial A} \equiv \frac{\partial E[(x-\mu_x)^3]}{\partial A} > 0 \tag{4}$$

Proof. See Appendix B. □

Proposition 2 relates to the analysis of Barberis (2012) who studies how the use of a stopping rule, such as when an individual who has lost their gambling money then leaves the casino, leads to a skewed distribution of returns even given binomial gambles. In a financial market there is normally no such stopping rule and an investor may hold a position and thus wait, potentially indefinitely, to obtain the average return. Even if a position is closed it is unlikely to lead to the loss of all of one's funds. Margin trading changes this. The combination of greater leverage and limited liquidity means that the probability at any given horizon of losing the entire initial investment is substantial.

3 Margin requirements and returns

We extend the result above to analyze the quantitative effects of margin trading on the distribution of returns. We study numerically how the existence of a margin call skews individual returns given the empirical asset returns distribution and reduces the expected return. The results suggest that although the distribution of single-period asset returns is approximately normal, that distribution of individual's returns, taking into account the margin requirement, are highly skewed. Indeed the key quantitative and qualitative feature of the simulated returns data is the relationship between skewness and margin calls, as predicted by Proposition 2. The simulation we present below includes limits on daily price changes in line with those present in the SHFE described later. If these limits are reached then trading is suspended. This means that whilst the magnitude of the upside return is limited on any given day, by reinvesting the original gains plus or minus any losses on subsequent days we will still observe the familiar lottery-type returns pattern. Losses are always truncated to be at most the original stake, whilst gains are unbounded. These limits complicate an analytical extension of Barberis (2012) making a numerical analysis necessary.

To understand the effect of margin requirements on the skewness of individual returns we run a numerical simulation of the effect of asset price changes on trader returns in the presence of margin requirements and forced liquidation through margin calls. At time 0 a single trader enters the market with an integer number, m_0, of contracts in Rebar futures each of which is for n hands of Rebar.[7] Along with their futures position each trader also has capital, c_0, equal to a percentage, λ, of the value of the underlying Rebar contracts to finance the position. If the initial price of the underlying Rebar contract is x_0 at time 0 the trader has $\lambda c_0 = m_0 n x_0$ capital. A price path of the underlying asset is then simulated for a period of 21 days with changes in the asset price being added/subtracted from the margin account. If the asset price changes by δ_t on day t the value of the margin account changes by $\delta_t m_t n$. If the value of the margin account decreases such that the margin requirement, R is violated, i.e. $c_t < R m_t n x_t$ the number of contracts the trader holds is reduced to the highest integer number such that this is no longer the case. Note that initially $\lambda > R$ such that the trader can afford their initial position.

We fit this model to empirical data by estimate a GARCH(1,1) ARIMA(1,1,0) model based on Rebar future prices for the period covered by our data March 2009 to September 2013. In order to treat long and short positions equally we set the drift term equal to zero. Using this model, we simulate five million independent twenty-one day price paths. For each path we calculate the returns of the trader. We contrast the returns of the margin trader with those of a trader holding the asset without leverage. For margin traders, we calculate results for long and short positions and for different numbers of

[7] A hand is the unit of trade of Rebar. We describe the specifics of the Rebar market in detail at the start of the data section.

initial contracts, m. In line with market rules, the margin requirement is set to $R = 7\%$ and the maximum price change on any day is 7%.[8] Each contract is for $n = 10$ hands of Rebar and the initial price for each hand is $x = 3000$ RMB. Traders start the simulation with initial wealth $\lambda = 15\%$ of the contract value.

Panels A2a and A2b of Figure A2 show the simulated returns distribution of traders' returns. The left-hand figure illustrates the case of traders with a single long futures contract, whilst the right-hand figure shows the distribution for traders who initially holds five contracts. We first consider the case with traders with a single long or single short contract. The average return for non-leveraged traders over the period is 0 whilst the leveraged traders' returns are approximately -1%.[9]

Importantly, regardless of whether a trader takes a long or short position the margin account results in negative returns, and in both cases, by the end of the simulation, approximately 88% of traders have incurred sufficient losses that they can no longer meet their margin requirements and so have a position of zero. Both distributions have a negative mean and are heavily skewed, as predicted by Propositions 1 and 2 respectively. The lower skewness for the larger initial position reflects that individuals faced with a margin call may close one or more open positions and continue to hold the remainder of their portfolio. As we will see below, most of the investors we study open one position at a time and so are subject to a more heavily skewed distribution of returns.

[Figure 2 about here.]

[8] Whilst the brokers' requirement is 12%, this is understood to often be negotiable; thus, assuming only the SHFE required margin represents the minimum chance of margin calls, and thus the least skewed distribution.

[9] Throughout we calculate returns as $\frac{m_t - m_0 - c}{m_0}$ where m_0 is the initial cash in the margin account, m_t is the final cash in the account after positions have been liquidated and c is any cash transferred into the margin account between times 0 and t. Note c may be negative if cash is withdrawn.

4 Context and data

Before moving to the empirical evidence we first outline the salient features of the Rebar futures market that is this paper's focus. Rebar are steel bars mainly used in construction. China is the largest market for Rebar, by volume, and has been for over 20 years. In order to manage risk and provide for the hedging of exposure to the Rebar market, the SHFE introduced Rebar futures contracts on March 27, 2009. Subsequently, Rebar futures contracts have become one of the most actively traded commodity futures in the Chinese financial markets. At the same time, the Rebar futures market has become the biggest metallic futures market in the world based on trading volumes and turnover.

Rebar futures are similar to other commodity futures. There are 12 Rebar futures contract delivery dates each year. Each contract is deliverable in the middle of the month and starts trading 12 months earlier. Each contract has a unique identifier RB, the commodity code of Rebar futures, followed by the year of delivery and month of delivery. For instance, RB1210 specifies the Rebar futures contract which started trading in the middle of October in 2011 and delivered in the middle of October in 2012. Excluding holidays and weekends, the number of trading days for each contract is approximately 230. Daily trading time, as set by SHFE is 3.75 hours per day (3.58 hours before June 27, 2010). Price changes on the SHFE are limited to a maximum of 7% per day. If these limits are met, the market is closed until the next trading day.[10]

Chinese futures can be traded by anyone willing to open an account with one of the, at the time of writing, 198 registered Chinese futures companies (henceforth, brokerages). After opening and funding a margin account, individuals may trade any exchange traded futures in Chinese markets. The sole role of brokerages is to execute their clients' orders on the relevant Chinese futures exchanges. Orders may be submitted by customers

[10]This limit places both a lower and upper truncation on the distribution of prices changes. The lower truncation, however, is in almost all cases less tightly binding than the margin requirement. Whilst, Propositions 1 and 2 abstract from this, we do include this effect in the numerical analysis.

through telephone or computer; the brokerage then submits orders to exchanges by computer only, and thus precise timings are recorded of when orders are submitted and fulfilled. There are no market makers within the market and the market operates as an electronic limit order book. As such the high liquidity and trading volumes coupled with the ease of trade make this an ideal instrument to study retail investor behavior.

The SHFE has strict rules that only registered institutional traders can take delivery of commodities. Individual traders, who still hold open positions one month before delivery have their positions liquidated.[11]

Rebar futures are traded such that, the trading unit "one hand" is equal to 10 tons of Rebar. SHFE set the margin ratio based on market conditions. During the period studied, the transaction fee for Rebar futures is between 0.007% and 0.03%. The minimum margin ratio imposed by the SHFE is varied between 5% and 12%, although it is 7% for almost the whole period we study. This is identical to the maximum allowable price move to ensure that even in the scenario of a trader being maximally leveraged at the start of the day the price may not move so far that the position has a negative value. Although in this case the trader would lose all of their investment. Brokerages also set a further margin ratio, which is generally $4\% - 5\%$ higher than the margin ratio of the SHFE. This is designed to protect traders from frequent mandatory liquidation. Based on these two margin ratios traders have two margin requirement "deadlines". Assuming a trader has open positions, they must ensure sufficient funds are in their margin account, as given by the brokerage's margin ratio. When the money in a trader's account is lower than the margin requirement of the brokerage, the brokerage gives the trader a margin call in order to provide them the opportunity to provide additional funds as collateral. If the trader does not deposit funds into their margin account and further losses are incurred such that the lower margin requirement of SHFE is violated, then the SHFE will liquidate all positions of the trader. Given the difference between the brokerage and

[11] Registered institutional traders must own production capacity or a storage warehouse to be eligible to take delivery. The Chinese Securities Regulatory Commission (CSRC) checks these requirements are met in order to protect both trading parties.

SHFE margin requirements is less than the maximum possible daily price change (7%) even a trader who satisfies both requirements at the start of the day may be forced to liquidate due to intra-day price changes.

Our data are provided by one of the 198 brokerage firms. They cover the period March 27, 2009 to September 30, 2013 (50 contracts). During this period we observe the exact trading history for all of the $22,411$ clients of this brokerage firm. That is, for a given client, we observe each order submitted (for Rebar), its form (limit or market), size, price, and the precise time it was submitted. We also observe, for a total of $5,652,091$ trades, the precise details of how, when and if the order was fulfilled. Further, we observe the state of every trader's margin account including any daily gains or losses from trading, including from other assets, and any funds added or withdrawn from the account.

Whilst impossible to verify, there is no reason to believe that the individuals who use the brokerage we study are not representative of retail traders in this market as a whole. Importantly, the fee structure and margin requirements of competing firms are comparable to the firm we study. The only noteworthy feature is that our firm is amongst the largest. There may additionally be other institutional participants within the market for whom our set is not representative, however, these traders are unlikely to be capital constrained in the way we outline above and so will not be subject to the same effects. Similarly there is no reason to believe the retail traders that use this market are unrepresentative of retail futures traders in other markets around the world. The SHFE Rebar market is the largest commodities futures market in China and one of the largest globally. It is therefore not a small or niche market and would be expected to attract a wide range of traders. Furthermore, empirically, the results in Tables A4 and A5 discussed in Section 6 show that the market is not efficient with little relationship between the future price and the price of the underlying Rebar, which is consistent with the majority of market participants being similar to those in our data, and not better funded or more sophisticated. Finally, it is worth noting that our data start on the same day as Rebar are first traded on the SHFE thus ensuring that we can be confident that none of our results are unique to some episode of Rebar trading history.

[Table 1 about here.]

Table A1 summarizes the trading histories in our dataset. The key feature of the data is that they are extremely skewed – a small number of traders made large profits and traded heavily. We analyze the characteristics of these traders further in Section 7. The data on traders' average and maximum positions reveals that the majority of traders only ever open relatively small positions. Looking at profit we see evidence of skew in the profits traders make. The median trader's average return on a trade is a loss of 1.4% whilst the average trade of the average trader gives a positive return of 0.8%. Notably, now looking at fees this mean profit is smaller than the average fee, suggesting that whilst the median trader is making a loss before fees, both the mean and median trader are making a loss once fees are taken into account. The skewness is also reflected in the average and maximum amounts traders hold in the brokerage account. While the mean trader holds $366,000$ RMB, the median holds only $48,000$ RMB, their maximum balances are $878,000$ and $114,000$ RMB respectively. Thus, while there are a small number of traders making substantial profits, most traders only ever open small positions and on average make small, but appreciable, losses on each trade.

4.1 Aggregate behavior

Figure A3 describes the market properties of Rebar. We focus on 2012 for clarity, but the conclusions are the same for other years in our sample.[12] Panel A3a describes the prices of the 12 contracts traded during 2012. The thick blue line is the average of the Tianjin and Shanghai spot prices.[13] It can be seen that whilst the individual future prices tend

[12]Figures A16–A18 in the Appendix reproduce Figure A3 for the other years in our sample.

[13]Unsurprisingly, given the distances and transaction costs involved, the two are closely related but not identical, as can be seen in Figure A20 in the Appendix.

to follow the spot price, their changes are often quite different, indicating the possibility of arbitrage profits. We discuss this possibility more formally below.

Panel A3b describes an important feature of the market – almost all of the trading volume is concentrated on three contracts: January, March, and October. Moreover, one contract is traded almost exclusively at any one time. Specifically, the most heavily traded contract on any given day accounted for 95% of daily volume in 2011 rising to over 98% of the volume in 2013.[14] Panel A3c shows the total market position by contract which makes it clear that not only are only three contracts being traded but positions are only being opened in these three contracts.[15]

Why trading is concentrated on these three contracts in particular is unclear but does not seem to have any substantive economic basis. Figure A19 in the Appendix reports net Chinese imports of steel, and Rebar specifically, by month. It is clear that whilst there is some seasonal fluctuation – imports are lower in the first few months, perhaps due to Chinese New Year and cold winter weather preventing building – there is no reason for traders' exclusive focus on January, March, and October. Notably, there is almost no activity in the other contracts. However, by restricting trading to a single contract at any point in time liquidity is increased, reducing trading costs for all traders (albeit with an increase in basis risk). The benefits conferred by each additional trader are enjoyed by all other traders, and these economies of scale lead to a single contract being traded at a time, even if the choice of which is largely arbitrary.

[Figure 3 about here.]

[14]Figure A14 which is a stacked bar chart showing the composition of total trading volumes over time makes this same point graphically – almost all of the volume is accounted for by one of these three contracts at any point throughout the whole period.

[15]All twelve contracts are plotted; but, the other nine are indistinguishable from the x-axis.

4.2 Financial constraints

In order to verify the effect of margin constraints on returns it is first necessary to show that traders are regularly affected by margin requirements. For margin requirements to be meaningful it is necessary that the trader does not have sufficient available capital to fully finance their position, i.e. that they have used the margin facility of the broker to multiply their money to purchase a larger position. If they do this fully they will be liquidity constrained – unable to open further positions, even on margin, without depositing additional capital. Figure A4 describes how often traders are in this position. Specifically, it describes the proportion of all days in which their accounts are active that they fall into one of four categories. Panel A4a describes how often individuals are unable to trade – that is, they have no open positions and insufficient available funds in their margin account to open one. We can see that this is only rarely the case – perhaps because traders in this situation cease using their account. Panel A4b shows that, similarly, very few traders ever have sufficient funds in their account to open a position and do not do so that day. Panels A4c and A4d do the same for traders who already have one position open. It can be seen in Panels A4a and A4c that, ignoring the large numbers of traders who are never constrained, the distributions are otherwise approximately uniform, suggesting that those traders who are at some point liquidity constrained are constrained on average around half of the time. One reason for this is that traders may not keep unnecessary funds in their account, moving money only when necessary for a trade. This implies that these traders either do not anticipate trading again or do not anticipate needing to transfer more funds for their future trades (i.e., they bet that the initial trades would be profitable). The other, non-contradictory, explanation is that traders, treat their actions in this market as a form of gambling and like visitors to casinos, have a fixed budget to "play" with. Note, that this also explains the 12% of individuals reported by the left-hand spike in Panel A4d who, given they have an open position, never have enough funds in order to be able to open another. That is, they only ever trade one contract. The spike in Panel A4c suggests that there are similarly around a quarter of traders who are never constrained given that they have an open position. This may comprise individuals who choose not to use their full margin, richer individuals who tend to trade many contracts, or simply those who know they will trade more in the future and leave funds in their account for this purpose. Taken together, there is a substantial proportion of traders who are invested to their limit much of the time and therefore subject to binding margin requirements.

[Figure 4 about here.]

Here we focus on one individual asset, however, there is a large number of other contracts that may be traded (approx $9,000$ through our brokerage). In order to understand the effect of margin requirements it is important to understand how traders wealth is affected by trading not just in Rebar but also in other assets as the profits and losses from these may affect their need to liquidate. We do not observe the positions or trading history of other assets, but we do observe changes in individuals' margin accounts due to this trading.[16] We are thus able to reconstruct the aggregate extent and outcomes of their trades in all other assets. That is the extent to which observed changes in margin accounts are not due to (observed) Rebar trading or (observed) funds transfers they must be due to (unobserved) losses or gains in other assets. Figure A5 shows that 60% of traders trade exclusively Rebar. Further, nearly all individuals have a ratio of non-Rebar trade volumes to Rebar volumes of 1 or less, suggesting that they trade as much Rebar as anything else. We can, therefore, say that the majority of these traders only trade one or two assets. That there is a long tail of individuals trading significantly more of these other assets than Rebar might suggest that there is a fraction of relatively sophisticated investors who maintain larger, more diversified, portfolios.

[16] Implicitly, we also do not observe whether the trader has other trading accounts with other brokerages. Whilst it is possible that some traders do this we believe it is unlikely that it is commonly the case. The brokerage we consider offers the ability to trade a large range of assets. This includes equities as well as the futures on many other commodities. At the same time Rebar futures are a major asset and can be traded through many brokerages. Therefore it would seem unlikely that traders would commonly set up accounts with other brokers to trade other assets.

Further, inspection of Figure A6 suggests that almost all traders trade on a given day Rebar *or* another asset. Thus, whilst some traders' preferred asset may vary over the period very few frequently trade more than one on any one day. This is perhaps unsurprising given the lack of liquidity that characterizes most traders, as seen in Figure A4. The above evidence taken together shows that a large fraction of the traders we consider are constrained by margin requirements. Further the need of these traders to liquidate will in most cases be solely or significantly dependent in the changes in the Rebar futures prices.

[Figure 5 about here.]

[Figure 6 about here.]

5 Losses

The model described previously predicted that on average traders subject to margin requirements lose money. In this section we use the individual account histories of futures traders to show that most traders lose money at, at least, the predicted rate. We first consider the overall distribution of average daily returns, and then provide evidence for the margin call as the source of lower returns and excess positive skew by analyzing the distribution of returns, per position.

The traders in our data do not trade every day and often go months without trading or having open positions. Key to our argument is that traders' returns are affected by the margin calls inherent in leveraged positions. If a trader is not leveraged, or alternatively has sufficient cash that they are effectively not leveraged, they are not bound by the constraint we outline above. In considering traders' gains and losses from positions it is therefore intuitive to consider individual trading episodes – collections of temporally close trades – and to treat different episodes separately. This way any difference in a trader's available capital, and therefore, the degree to which they are constrained , over time can be picked up. We split each trader's trading history into a set of mutually exclusive episodes using a clustering algorithm described in Appendix D.

Figure A7 shows traders' average daily returns in each of the episodes. Both panels present kernel density plots, truncated for clarity of observation. Panel A7a limits the returns to between -2% and 5% and Panel A7b to between -0.6% and 0.4%. In both cases the dashed vertical line describes the mean daily return of -0.123%,[17] equivalent to an annualized return of -25%.[18] Put differently, this distribution implies that 88% of traders will lose money on an average day and, conditional on losing, their average return that day will be -0.274%.[19] The large difference in the conditional and unconditional return reflects the positive skew in the data. This skewness can be seen in both Panel A7a and more easily in the truncated distribution in Panel A7b.[20] Inspecting Panel A7b we can see clearly the positive skew in the distribution of returns. Comparing the distribution either side of the mean line shows that whilst losses are clustered near the mean, the positive returns are much more dispersed. Measured numerically, the skewness is 5.69; this is greater than in the numerical analysis where it is 1.4. The model and calibration are deliberately simple and this discrepancy therefore likely reflects additional, non-modeled, sources of variation in the empirical data such as trading frequency, and willingness to reinvest, along with the assumption of no drift in the simulated price paths. It is important to highlight that this skew is endogenous. It is not driven by skewness in the asset returns, which themselves are not skewed, rather it is the effect of margin trading on each individual traders returns. To further emphasize this the skewness is present

[17]This is significantly different from zero at the 1% level.

[18]This figure is based on a trading year of 230 days.

[19]We consider the behavior of traders in the upper tail of the distribution in Section 7. It should be noted, however, that there are no market makers so the profitable traders do not have privileged access to the market.

[20]Our preferred measure excludes episodes for which there is less than 10 days of trading activity. This is to ensure our results are not driven by new traders who may not understand the market, or who only trade once or twice before exiting the market. All of our results are robust to this choice and a comparison is reported in Figure A12 in the Appendix.

for both long and short traders who's profits/losses from a given price move would be of opposite signs.

The implication of Figure A7 is clear: the margin traders we study almost all obtain returns substantially worse than 0. Without margin trading the returns of short traders should be of opposite sign and but equal magnitude to that of the long traders. It is the effect of trading on margin on individual traders' returns, rather than the raw return of the asset which is driving this. Given that traders may take a long or a short position, the negative price trend over the period we study cannot be the cause. Notably, traders open very similar numbers of long and short positions (55.8% long).[21] Whilst due to the large number of observations the means of the distributions are statistically different they are not substantively different. This is unsurprising given that the expected returns of the long and short positions should be the same. The results we describe for the complete sample, including the negative returns of trades, also hold in both the subsamples of long and short positions.[22]

To demonstrate that it is the returns distribution of leveraged traders that induces the skewness, we now seek to identify those most likely to not be in a position to underwrite their trades. To do so we treat the amount an individual is willing to commit to trading as being fixed in each episode of trading. We then treat the amount an individual is willing to invest in a given episode as a strictly increasing function of the amount invested and any profits, in that episode to date. That is, even if they withdraw money from their trading account we assume that they will be willing to redeposit those funds in the current episode. This definition of constrained traders is conservative in that it will classify some unconstrained traders as constrained. To see this, consider that some of the traders who have withdrawn money may have used it for other purposes and so not be able to reinvest it. Thus, constrained traders are those for whom the maximum

[21]This is calculated solely from the opening of positions and does not include those contracts used to close positions. As such it measures the willingness of traders to speculate on upwards or downwards movements.

[22]The negative returns from margin trading more than wipe out the possible gains for traders taking short positions in a market with a downward trend over the period.

committed funds has already been reached, and whom have insufficient funds in their brokerage account to open additional positions. The length-distribution of the episodes is described in Figure A13 in the Appendix. This shows the average position is relatively small and held for under a day. Such relatively frequent, high-cost trading has previously been documented as a key reason why retail investors often fare badly (see, Barber and Odean, 2000, Barber et al., 2009).

We now test directly the prediction that leveraged traders, and in particular those that are constrained to not be able to open further positions, obtain inferior returns. Table A2 presents results of regressions run on the complete sample of trading episodes. To test precisely the theory that it is being unable to respond to a margin call that reduces returns, and not simply an absence of capital, we contrast the returns for constrained and unconstrained traders with a given level of available capital. Available capital is defined as a percentage of the maximum capital available to that trader in that trading episode. By controlling for this we are comparing only the effects of being unable to meet a margin call and not any other consequence of capital availability or position size. That is, we compare the average return conditional on a given level of capital availability for those who are, and those who are not, constrained. In the notation of Proposition 1, this is the difference between the expected return for a given price without a margin constraint, $E[r_t^x|x \leq c]$ and with it, $\gamma = E[R_{tc}^x|x \leq c]$. This difference is given by β_3 in the following regression:

$$\text{returns}_{it} = \alpha_i + \beta_1 \frac{K_t}{Max\ K}_{it} + \beta_2 \left(\textit{Constrained}_{it} \times \frac{K_t}{Max\ K}_{it} \right) + \beta_3 \textit{Constrained}_{it} + \lambda_t + \varepsilon_{it} \tag{5}$$

Where $i \in \{1, \ldots, N\}$ denotes each particular trading episodes. Similarly, $t \in \{1, \ldots, T\}$ denote individual trading days. A binary variable, *Constrained*, distinguishes when individuals are constrained. Note, that given the interaction term $\textit{Constrained}_{it} \times \textit{Capital}_{it}$ the coefficient on *Constrained*, β_3, is the effect of being constrained when a trader has no available capital. Thus, here, this term captures the mechanical effect of being kept out of the market. This is distinct from the reduced return associated with being unable to meet a margin call captured by β_2.

To control for the fact that higher returns might lead to higher available capital, and these higher returns might reflect unobserved heterogeneity in daily market returns or in trader characteristics, we include two sets of fine-grained fixed effects. Our results therefore reflect variation in returns within a given trading episode, compared to average returns for all traders on each day. The trader-episode fixed effects allow not only for unobservable trader specific effects, but for these to vary in an unrestricted way from one episode to another. Similarly, the inclusion of the trading-day effects means that any possibility that, for example, there is a relationship between having available capital and market performance are controlled for. As well as controlling for unobserved heterogeneity these fixed effects also assuage potential concerns about reverse causality, that is that changes in the distribution of returns induce changes in behaviour by traders. Our focus on individual traders means that we take a different approach to ruling out endogeneity than recent related work, of Chang et al. (2014) or Kahraman and Tookes (Forthcoming), that exploits natural experiments to establish the causal effects of short selling and margin trading on market efficiency and liquidity respectively. Our approach instead relies upon the inclusion of two high-dimensional sets of fixed effects. We argue that given including day fixed-effects controls for any average response of traders to daily market conditions, and including trader-episode fixed effects controls for individual responses of traders to market conditions over a period of a few days or weeks, that it is hard to think of ways in which individuals' returns and participation are simultaneously determined. Thus, we argue that our identification assumption that individuals' returns are conditionally random is extremely plausible.

Table A2 reports results for both daily returns including trading costs in columns 1, 3, 5, and 7 and excluding them in columns 2,4,6, and 8. These daily returns are unsurprisingly small and so we multiply them by 100 so that coefficients can be understood as percentage point changes in returns. Columns 1 and 2 report results excluding any fixed effects, thus the estimated coefficients are the unconditional effects of capital availability and being constrained. Looking first at column (1) we see that, as expected, β_1 is positive implying that higher capital availability is associated with higher returns. Crucially, we find that β_2 the difference in returns associated with being not able to meet a margin call for a given level of capital availability, is negative. Finally, the effect of being out of the market, β_3 is positive, reflecting the negative average returns captured by the constant term. All coefficients are significant at the 1% level, with standard errors clustered by trading day to allow for correlations induced by overall market performance. Column (2) shows that the estimates are quantitatively and qualitatively unaffected by excluding trading costs. Columns (3)-(6) report the results including first only the trader-episode fixed effects, and then only the trading day fixed effects. The results are again similar, albeit slightly smaller when including only trading-day effects. Finally, our preferred specification is reported in columns (7) and (8). This includes both sets of fixed effects, the results are again similar, with slightly larger magnitudes than in the other columns. Most importantly, the magnitude of β_2 is now approximately double β_1, i.e. $\beta_1 - \beta_2 \approx -\beta_1$ unlike in column (1) and (2) where it was only slightly larger in magnitude implying only a slightly negative daily return. Looking at columns (3)–(6) suggests that this might be mostly attributed to a failure to control for trading-day effects. But, in all specifications, there is a reduced return associated with trading on the margin without being able to meet a margin call.

[Table 2 about here.]

[Figure 7 about here.]

[Figure 8 about here.]

6 Margin trading and the optimal portfolio

Given negative expected returns, why are Rebar futures so heavily traded on the margin? One explanation of this is that individuals have a preferences for lottery-type payoffs. For example Byun and Kim (2016), Bali et al. (2011), Conrad et al. (2013), Bhattacharya and Garrett (2008) all highlight a willingness of investors to sacrifice returns for positive skewness. The positive skew and limited losses resulting from margin constraints means that the returns distribution of any given asset may be transformed into one resembling a lottery-type stock. As such margin trading may be attractive to many individual investors with this bias.

An alternative to the skewness-seeking behavior described above is that traders are using their position as a hedge as part of a diversified portfolio. In this section we show that cannot be the case. In order to be viable such an investment, whilst bearing a negative expected return, would have to allow investors to achieve a sufficient reduction in the variance of their portfolio returns to be worthwhile. We take this claim seriously and show that it is effectively impossible for Rebar to be used to hedge risk efficiently.[23] For any feasible asset, it is shown that the investor would be better taking a combination of the asset and cash, paying a return of zero, than a portfolio including Rebar.

We consider two assets, a and b, with returns r_a and r_b with standard deviations σ_a and σ_b respectively. The portfolio comprising these two assets with weight w of asset a has return r:

$$r = wr_a + (1 - w)r_b \tag{6}$$

And variance:

$$\sigma^2 = w^2\sigma_a^2 + (1 - w)^2\sigma_b^2 + 2\rho w(1 - w)\sigma_a\sigma_b \tag{7}$$

[23] On a practical note, given the difference in observed returns of Rebar futures and the underlying asset it would be rapidly apparent to anyone that tried that this was not a viable strategy.

Where ρ is the covariance of assets a and b. The range of possible portfolio returns and standard deviations is shown in Figure A9. Rearranging and solving for r gives:

$$r = \frac{r_b\sqrt{\sigma_a^2\sigma_b^2\left(\rho^2-1\right)+\sigma^2\left(\sigma_a^2-2\sigma_a\sigma_b\rho+\sigma_b^2\right)} - r_a\sqrt{\sigma_a^2\sigma_b^2\left(\rho^2-1\right)+\sigma^2\left(\sigma_a^2-2\sigma_a\sigma_b\rho+\sigma_b^2\right)} + \sigma_a^2 r_b - \sigma_a\sigma_b\rho(r_a+r_b) + r_a\sigma_b^2}{\sigma_a^2-2\sigma_a\sigma_b\rho+\sigma_b^2} \tag{8}$$

Equation 8 describes the typical risk return trade-off for a portfolio. We refer to the asset with lower return, corresponding to Rebar, as asset A, and the asset with higher return corresponding to another asset, or portfolio of assets, as B. To demonstrate that Rebar never appears in an optimal portfolio, we show that for all portfolio's a higher expected return, for a given level of variance, may be obtained by taking a combination of asset B and the riskless asset than by including Rebar.

[Figure 9 about here.]

Importantly, unlike standard portfolio theory, taking a short position in Rebar does not extend the efficient frontier beyond asset B. The negative return of Rebar comes from margin trading and not from the asset itself – therefore, taking a short position in Rebar does not result in a positive return. Whilst Rebar may provide diversification benefits, it has such a high negative return that it never increases expected returns. The highest expected return is, therefore, found in the portfolio solely consisting of B.

In order to demonstrate that the diversification benefit of Rebar is outweighed by its negative expected return it is shown that for all levels of risk the efficient frontier is dominated by the return that may be obtained from taking an appropriate portfolio of asset B and the riskless asset paying r_f. In other words for all levels of risk the efficient frontier always lies below the straight line connecting r_f and asset B. To do this it is sufficient to prove that the derivative of the efficient frontier at asset B is less than that of the straight line representing portfolios composed of a mixture of asset B and a riskless asset. This is because the two lines intersect at B and the second derivative of the risk–return curve is negative in the upper portion; therefore, if the condition is met, the efficient frontier will always be below the straight line.

The return at point B is dependent on the identity and characteristics of asset B. For assets with higher returns, the straight line becomes progressively steeper. Thus, at some point, given $-1 < \rho < 1$ the optimal portfolio will include some Rebar. However, we show that this will only be the case given annualized returns of Rebar of -0.25, with a standard deviation of 0.13 and a correlation of -0.15, for assets with returns far in excess of those realistically observable.[24] In particular, it is not true if assets have returns less than 1000%. The derivative of the straight line linking the risk free rate with asset B is $\frac{r_b - r_f}{\sigma_b}$ whilst the derivative of the efficient frontier at B is given by:

$$\frac{\partial r}{\partial \sigma} = \frac{s(r_b - r_a)}{\sqrt{\sigma_a^2 \sigma_b^2 \left(\rho^2 - 1\right) + \sigma^2 \left(\sigma_a^2 - 2\sigma_a \sigma_b \rho + \sigma_b^2\right)}} \tag{9}$$

Then it may be verified that if $r_f = 0.0$, $r_a = -0.25$, $\sigma_a = 0.13$, $0 \leq w \leq 1$, $\sigma_b > 0$, $-1 < \rho < 1$, and $r_b > 0$ then no point exists such that:

$$\frac{s(r_b - r_a)}{\sqrt{\sigma_a^2 \sigma_b^2 \left(\rho^2 - 1\right) + \sigma^2 \left(\sigma_a^2 - 2\sigma_a \sigma_b \rho + \sigma_b^2\right)}} - \frac{r_b}{\sigma_b} < 0 \tag{10}$$

If $0 < r_b \leq 1000$ and $\sigma_b = 0.13$ (equal to that of Rebar). Note that this range can be much larger but, given no asset normally exists with a Sharpe ratio near to $\frac{r_b}{\sigma_b} = \frac{1000}{0.13}$ there is no need to look further. □

In further support of this argument, in Appendix C, we demonstrate that Rebar does not ever appear in the optimal portfolio given the assets available to Chinese investors during the period. We find no evidence that an optimal portfolio, of any size, would contain leveraged Rebar investments. Examination of the behavior of traders in the previous section showed, further, that the modal position is opened for less than a day. Such frequent trading is incompatible with an explanation of portfolio optimization given

[24]The correlation of -0.15 is the largest absolute negative correlation between Rebar and any of 9000 other Chinese assets over our time period.

that traders face substantial trading costs. Thus, we can see that a portfolio explanation is not only unlikely in theory, it is rejected by the data.

Analyzing market efficiency provides additional evidence that margin trading reflects a preference for lotteries and not sophisticated behavior by traders. If the Rebar market were efficient then the correlation between the change in the spot price Δs_t and the change in the future price, Δf_t should be close to unity. In fact, as reported by Table A4 they are always substantially lower. Cointegration-based tests of market efficiency, allowing for risk aversion or risk loving (see, Chowdhury, 1991), tell the same story and are reported in Table A5. This may reflect the practical difficulties involved in Rebar arbitrage: Rebar are bulky and there are restrictions on who may take delivery. But, these difficulties should be far from insurmountable. Rebar are not perishable and are easily saleable and so it is perhaps surprising that no arbitrageur owning production or storage capacity has emerged. Alternatively, if the futures market were largely comprised of speculators then there would be less reason to believe that there should be an equilibrium relationship between the spot and forward price. This itself may place limits on arbitrage as argued by Shleifer and Vishny (1997), making the costs associated with possessing the necessary physical infrastructure prohibitive.

7 Small fraction of traders make large profits

Whilst the majority of traders make significant losses, there are a small number of traders who enjoy very substantial profits. By examining these traders we can understand how they avoid the negative returns associated with margin trading. Whilst the positive returns of these traders will in some cases reflect good luck, it may also reflect differences in behavior or resources. Table A3 shows that one key way in which they differ is that the most successful traders maintain their positions for much longer. For the most successful 0.01% the average is a week compared to less than a day for the modal trader. If instead the top 1% are considered, the average positions are still held for substantially longer than their less successful peers. These longer holding periods indicate that these traders are holding the asset longer and not being forced to liquidate as a result of a margin call. Earlier theoretical results suggested that longer holding periods made margin liquidation more likely, however, for these traders the longer periods may be a consequence of success as well as a cause. Given the scale of these traders' profits they are often in a position to fully underwrite their positions, allowing them to avoid the negative returns from margin calls and enjoy a higher average return than their leveraged peers.

A second key difference is described in the next panel of Table A3. The most successful traders trade very frequently, with 400 trades a day not being uncommon. This again may reflect affluence, perhaps itself caused by their success, but it might also suggest a form of algorithmic trading. The heaviest traders execute over 3000 trades a day or one every 5 seconds. Alternatively, it might be one account being operated by a number of individuals concurrently.[25] It is worth re-emphasizing that there are no designated market makers in the market and the fee structure, including no rewards for liquidity provision, makes operating as market maker expensive. Like all of the traders in our data, they almost exclusively use marketable limit orders and the fees they pay mean that such market making would not be profitable.

Our explanation for their profits is that these traders act as net providers of skewness. That is, they are sufficiently liquid to underwrite the occasional large profit made by the small, skewness-seeking investors, and so can earn excess returns as the counterpart of the expected losses of margin traders as per Proposition 1. That is they receive an expected return equivalent to the average losses incurred by the margin traders. Given that the losses of margin traders are large in percentage terms, it is easy to see how these traders make such large aggregate profits by opening many such positions. In this

[25] All of the results in the paper are robust to excluding this tiny number of (very profitable) accounts. That they are unimportant for the results of this section can be verified by comparing the 90^{th} percentile of the top 1% of traders in Table A3 with all other traders. In general, excluding these traders strengthens our findings.

interpretation that these successful traders hold their positions for longer reflects that they never prefer to close their position, instead waiting for their counterparty being forced to do so by a margin call.

[Table 3 about here.]

[Table 4 about here.]

[Table 5 about here.]

8 Conclusion

Whilst ubiquitous in modern finance, margin trading has received relatively little attention. In particular there has been little work looking at the effect of trading on margin on an individual's returns. In this paper we show that the collateral requirement imposed by margin calls has two important effects. Firstly it lowers mean returns, whilst margin calls may protect traders from losing more than their initial investment they pay for this benefit. Secondly it induces positive skew in individual trader's returns even for assets who's raw returns are not skewed. As a result, investments offer limited losses and a small but positive chance of a large gain. We quantified the scale of these effects using a unique dataset on the full trading histories of Rebar futures traders on the SHFE. We show that both expected and observed losses from leveraged traders are substantial and positively skewed despite returns on the underlying asset not exhibiting these properties. Traders' acceptance of these terms is consistent with previous findings in the literature of traders' preferences for positive skewness. Margin trading offers the same skewed returns associated with lottery-type stocks. Our empirical findings are based on the trade of futures contracts, we were able to show, however, that it is infeasible that traders are using these contracts to hedge other positions. Rather traders are specifically aiming to make positive returns on their Rebar positions. Our results are therefore generalisable to other markets, and classes of asset, where traders can trade on margin.

Our results are also important from a regulatory perspective. Essentially, we find that rather than deriving a return from providing liquidity as might be expected margin traders incur substantial losses. Thus, other market participants derive the benefits of the liquidity they provide, with the compensation for margin traders being restricted to the hedonic gains associated with the skewed returns distribution a collateral requirement induces. Thus, perhaps unusually for financial regulation, given that the traders we follow seem to repeatedly and willingly participate in the market this becomes, similarly to gambling, an issue of what degree of regulatory paternalism is appropriate, a partly normative question we leave for future research.

A Additional figures

[Figure 10 about here.]

[Figure 11 about here.]

[Figure 12 about here.]

[Figure 13 about here.]

[Figure 14 about here.]

[Figure 15 about here.]

[Figure 16 about here.]

[Figure 17 about here.]

[Figure 18 about here.]

[Figure 19 about here.]

[Figure 20 about here.]

[Figure 21 about here.]

[Figure 22 about here.]

B Proof of proposition 1

Pender (2015) shows that $X \sim N(q, v)$ with upper and lower truncation points A and B has skewness:

$$\text{Skew}(A, B, q, v) = \frac{\left(\frac{h_2(\chi)\psi(\chi) - h_2(\phi)\psi(\phi)}{\theta(\phi)-\theta(\chi)} - \frac{3(((\chi\psi(\chi)-\phi\psi(\phi))(\psi(\chi)-\psi(\phi)))(\theta(\phi)-\theta(\chi)))}{\theta(\phi)-\theta(\chi)} + \frac{2(\psi(\chi)-\psi(\phi))^3}{(\theta(\phi)-\theta(\chi))^3}\right)}{\left(1 - \frac{(\psi(\chi)-\psi(\phi))^2}{(\theta(\phi)-\theta(\chi))^2} + \frac{\chi\psi(\chi)-\phi\psi(\phi)}{\theta(\phi)-\theta(\chi)}\right)^{3/2}} \tag{11}$$

Differentiating (11), and setting both the mean, $m = 1$, and the variance, $q = 1$ with respect to A gives:

$$\frac{\partial \text{Skew}(X)}{\partial A} = \frac{N}{D} = \frac{N_1 + N_2 + N_3 + N_4 + N_5 + N_6}{(D_1 + D_2)^{3/2}} \tag{12}$$

Where:

$$
\begin{aligned}
N_1 =& \frac{24e^{-2(A-1)^2-\frac{3}{2}(B-1)^2}\left(-e^{\frac{1}{2}(A-1)^2}+e^{\frac{1}{2}(B-1)^2}\right)^3}{\pi^2\left(\operatorname{erf}\left(\frac{A-1}{\sqrt{2}}\right)-\operatorname{erf}\left(\frac{B-1}{\sqrt{2}}\right)\right)^4}\\
N_2 =& \frac{2(A-2)Ae^{-(A-1)^2-\frac{1}{2}(B-1)^2}\left(-e^{\frac{1}{2}(A-1)^2}+e^{\frac{1}{2}(B-1)^2}\right)}{\pi\left(\operatorname{erf}\left(\frac{A-1}{\sqrt{2}}\right)-\operatorname{erf}\left(\frac{B-1}{\sqrt{2}}\right)\right)^2}\\
N_3 =& \frac{3(A-2)Ae^{-A^2+A-\frac{B^2}{2}-1}\left(-e^{\frac{A^2}{2}+B}+e^{\frac{B^2}{2}+A}\right)}{2\pi}\\
N_4 =& \frac{3(A-1)e^{-(A-1)^2}\left(A-(B-1)e^{\frac{1}{2}(A-B)(A+B-2)}-1\right)}{2\pi}\\
N_5 =& \frac{(A-1)e^{-\frac{A^2}{2}+A+B-\frac{B^2}{2}-1}\left(e^{\frac{1}{2}(B-1)^2}((A-2)A-2)+2e^{\frac{1}{2}(A-1)^2}\right)\sqrt{\frac{2}{\pi}}}{\operatorname{erf}\left(\frac{A-1}{\sqrt{2}}\right)-\operatorname{erf}\left(\frac{B-1}{\sqrt{2}}\right)}\\
N_6 =& \frac{12\sqrt{2}(A-1)e^{\frac{1}{2}(-3)(A-1)^2-(B-1)^2}\left(e^{\frac{1}{2}(A-1)^2}-e^{\frac{1}{2}(B-1)^2}\right)^2}{\pi^{3/2}\left(\operatorname{erf}\left(\frac{A-1}{\sqrt{2}}\right)-\operatorname{erf}\left(\frac{B-1}{\sqrt{2}}\right)\right)^3}\\
D_1 =& -\frac{2e^{-(A-1)^2-(B-1)^2}\left(e^{\frac{1}{2}(A-1)^2}-e^{\frac{1}{2}(B-1)^2}\right)^2}{\pi\left(\operatorname{erf}\left(\frac{A-1}{\sqrt{2}}\right)-\operatorname{erf}\left(\frac{B-1}{\sqrt{2}}\right)\right)^2}\\
D_2 =& \frac{\left((A-1)e^{-\frac{1}{2}(A-1)^2}-(B-1)e^{-\frac{1}{2}(B-1)^2}\right)\sqrt{\frac{2}{\pi}}}{\operatorname{erf}\left(\frac{B-1}{\sqrt{2}}\right)-\operatorname{erf}\left(\frac{A-1}{\sqrt{2}}\right)}+1
\end{aligned}
\tag{13}
$$

We consider the relevant case where there is only lower truncation, that is $B=\infty$. Some algebraic manipulation gives:

$$
\left.\frac{\partial\text{Skew}}{\partial A}\right|_{B=\infty}=\frac{3(A-1)^2e^{-(A-1)^2}}{2\pi\left(1-\frac{\sqrt{\frac{2}{\pi}}(A-1)e^{-\frac{1}{2}(A-1)^2}}{\operatorname{erf}\left(\frac{A-1}{\sqrt{2}}\right)}\right)^{3/2}}>0
\tag{14}
$$

Given that $A\neq 1$, this is always positive confirming that the skewness is almost everywhere increasing in the truncation point. $\square$

C Optimal portfolio

We initially consider empirically the composition of the optimal portfolio. This composition depends on the set of assets available. We obtained daily price data for around $8,500$ other financial assets and commodities available to Chinese investors. Note, that limitations on foreign investment mean that we can be confident this represents, broadly speaking, the universe of available financial investments.[26] We exclude real estate assets, as the implied investment size and time horizon for such investments is very different to that observed for Rebar, and thus, it is implausible that Rebar could be part of a hedging strategy for such assets. Solving for the optimal portfolio for a broad range of time periods and time horizons we never find that margin-traded Rebar are included. One might attribute this result to the consistent negative trend across the period but, given that traders could open short or long positions this argument carries little weight.

D Trading periods algorithm

A given episode may be regarded as a group of trades that are close together in time and separated from other groups of trades by a period of no trades. We identify these periods separately for each individual automatically using the k-means algorithm. This looks at the history of an individual's trading volumes (or total position size). The optimal number of clusters for each trader is determined by applying an automated version of the "elbow" heuristic. This approach identifies the number of clusters such that adding additional clusters only has a small effect on explaining further variance. The optimal number of clusters is then the point in variance explained/clusters space that is furthest from the 45 degree line – the elbow or corner in the graph of variance explained against clusters. For example, in the case presented in Figure A23 this suggests that 4 is the optimal

[26]This list is available upon request.

number of clusters. Alternative clustering algorithms such as hierarchical clustering were also considered and did not qualitatively change the results.

[Figure 23 about here.]

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Table A1: Summary statistics for $22,087$ traders executing $5,652,091$ trades

Variable	Mean	Std. Dev.	P1	P10	P50	P90	P99
Position:							
Mean	.222	.689	.001	.002	.016	.355	3.82
Max	.726	2.268	.001	.004	.047	1.422	9.5
Profit:							
Mean	.008	1.19	-2.31	-.404	-.014	.252	2.93
Fees:							
Mean	.03	.026	.003	.007	.02	.07	.114
Total	279	913	.161	1.23	18.78	494	6,006
Margin Account: ($N = 725,939$)							
Mean	366	2,015	6	11	48	529	5,793
Max	878	4,559	8	21	114	1,312	14,005

All figures are in 1000s of RMB. *Mean Position* is the average value of a given trader's position excluding positions of size zero. *Max Position* is the maximum position value ever opened by a given trader. *Mean* and *Median Profit* describe the average monetary profit per trade of a given trader. *Mean* and *Total Fees* similarly describe the monetary value of transaction costs paid by a given trader on their average trade, and across all of trades respectively. *Mean Margin Account* describes the capital in a given traders margin account averaged across all days it was opened. *Max Margin Account* describes the highest capital recorded in a given trader's account.

Table A2: Financial constraints and Returns

	Dependent variable: Percentage daily returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\frac{K_t}{Max\ K}$	0.04***	0.04***	0.03***	0.03***	0.01***	0.01***	0.03***	0.03***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)	(0.000)	(0.000)
Constrained $\times \frac{K_t}{Max\ K}$	−0.041***	−0.042***	−0.047***	−0.051***	−0.029***	−0.031***	−0.051***	−0.057***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constrained	0.11***	0.13***	0.11***	0.13***	0.10***	0.12***	0.09***	0.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.293***	−0.144***	−0.289***	−0.140***	−0.278***	−0.124***		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Fixed Effects	None	None	Trader × Cluster	Trader × Cluster	Trading Day	Trading Day	Both	Both
Observations	725,939	725,939	725,939	725,939	725,939	725,939	725,939	725,939

Note: $\frac{K_t}{MaxK}$ is the capital available to the trader on day t as a percentage of the total capital available in that trader episode. *Constrained* is a dummy variable which takes a value of 1 when a trader is identified as having no additional investable funds, and 0 when traders are able to meet a margin call with additional funds. $\frac{K_t}{Max\ K}$ is standardized to have mean 0 and standard deviation 1.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors, clustered by trading day, in parentheses.

Table A3: Trading behavior of the most successful traders

Variable	Obs	Mean	Std. Dev.	P90	P99
Average Holding Period					
Top 0.01%	9	8.4	6.0	19.1	19.1
Top 0.1%	22	6.4	6.1	16.5	19.1
Top 1%	221	3.9	7.1	8.7	25.5
All Other Traders	21,866	2.0	5.6	4.3	23.0
Trades Per Day					
Top 0.01%	2,179	91.8	133.5	235.0	675.0
Top 0.1%	5,042	68.6	122.6	175.0	595.0
Top 1%	2,8062	28.3	71.1	63.0	316.0
All Other Traders	697,877	7.0	19.1	14.0	63.0
Value Per Trade					
Top 0.01%	2,179	492,587.4	66,136.0	589,975.7	673,218.9
Top 0.1%	5,042	472,215.6	93,998.8	583,273.5	761,253.6
Top 1%	28,062	334,900.6	129,218.0	484,283.7	731,847.0
All Other Traders	697,877	113,178.5	101,092.6	248,800.5	499,007.0

Traders are ranked by their total profit. Rankings based on total or average return are similar. Summary statistics are within group, thus $P90$ of the Top 1% is the 90^{th} percentile of the top 1% of traders.

Table A4: Correlations between the price of Rebar futures and the spot price by contract

Code	Spot Opening	Spot Closing	Spot Settlement	Δ Opening	Δ Closing	Δ Settlement
RB0909	0.93	0.94	0.93	0.54	0.39	0.48
RB0910	0.93	0.94	0.94	0.57	0.41	0.53
RB0911	0.92	0.93	0.92	0.49	0.35	0.48
RB0912	0.90	0.90	0.90	0.48	0.31	0.43
RB1001	0.89	0.90	0.89	0.41	0.28	0.42
RB1002	0.85	0.86	0.85	0.43	0.23	0.37
RB1003	0.82	0.82	0.82	0.42	0.27	0.39
RB1004	0.72	0.74	0.74	0.38	0.25	0.37
RB1005	0.56	0.55	0.55	0.40	0.24	0.39
RB1006	0.36	0.34	0.34	0.42	0.24	0.38
RB1007	0.29	0.27	0.28	0.37	0.22	0.36
RB1008	0.14	0.13	0.13	0.19	0.13	0.22
RB1009	0.17	0.14	0.15	0.41	0.25	0.38
RB1010	0.09	0.07	0.08	0.40	0.25	0.38
RB1011	-0.00	-0.02	-0.02	0.32	0.27	0.37
RB1012	0.22	0.22	0.22	0.38	0.30	0.45
RB1101	0.49	0.49	0.49	0.44	0.23	0.39
RB1102	0.70	0.69	0.69	0.41	0.28	0.41
RB1103	0.86	0.86	0.85	0.41	0.28	0.39
RB1104	0.94	0.94	0.94	0.42	0.27	0.37
RB1105	0.96	0.95	0.96	0.38	0.22	0.33
RB1106	0.96	0.96	0.96	0.23	0.22	0.32
RB1107	0.90	0.89	0.90	0.30	0.15	0.29
RB1108	0.89	0.89	0.90	0.31	0.26	0.33
RB1109	0.79	0.79	0.77	0.31	0.16	0.23
RB1110	0.50	0.48	0.49	0.30	0.10	0.26
RB1111	0.70	0.70	0.67	0.19	0.29	0.34
RB1112	0.80	0.80	0.80	0.14	0.22	0.22
RB1201	0.85	0.84	0.85	0.33	0.23	0.30
RB1202	0.91	0.91	0.91	0.19	0.25	0.26
RB1203	0.93	0.93	0.93	0.24	0.13	0.22
RB1204	0.95	0.95	0.95	0.24	0.18	0.24
RB1205	0.95	0.95	0.95	0.21	0.23	0.29
RB1206	0.95	0.95	0.95	0.26	0.25	0.28
RB1207	0.93	0.92	0.93	0.25	0.26	0.26
RB1208	0.93	0.93	0.93	0.26	0.18	0.24
RB1209	0.94	0.94	0.94	0.27	0.16	0.28
RB1210	0.94	0.93	0.93	0.27	0.22	0.30
RB1211	0.94	0.95	0.95	0.23	0.26	0.30
RB1212	0.97	0.97	0.98	0.34	0.23	0.30
RB1301	0.97	0.96	0.97	0.36	0.13	0.31
RB1302	0.96	0.95	0.96	0.27	0.15	0.28
RB1303	0.94	0.94	0.94	0.24	0.13	0.26
RB1304	0.90	0.89	0.89	0.32	0.21	0.26
RB1305	0.82	0.81	0.81	0.33	0.10	0.26
RB1306	0.81	0.80	0.81	0.27	0.15	0.27
RB1307	0.85	0.85	0.85	0.29	0.16	0.24
RB1308	0.83	0.83	0.84	0.24	0.08	0.20
RB1309	0.78	0.76	0.77	0.23	0.11	0.24
RB1310	0.80	0.79	0.79	0.26	0.07	0.21

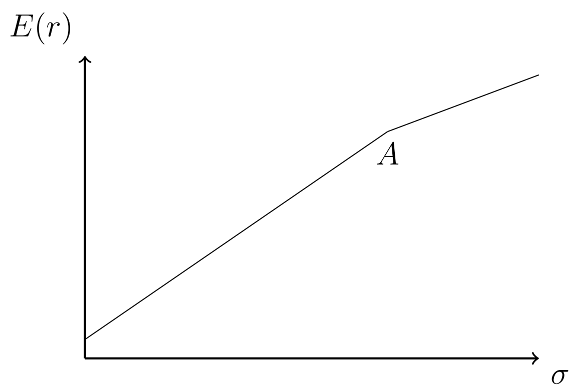
The column Spot Opening is the correlations between the spot price of Rebar and the opening price of Rebar futures. Spot Closing is the correlation between the spot price of Rebar and the closing price of Rebar futures, and Settlement similarly the correlation with the reported settlement price. The columns Δ Opening, Δ Closing, and Δ Settlement report the correlations between the first differences of the spot prices. Bold-font contract-code denotes that a contract was one that was heavily traded as discussed in Section 4.1.

Table A5: Cointegration coefficients between Rebar future and spot prices

Code	$Z_{settlement}$	Z_{close}	Z_{open}	Code	$Z_{settlement}$	Z_{close}	Z_{open}
RB0909	-2.06	-2.31	-2.02	RB1110	-2.18	-2.28	-2.18
RB0910	-2.14	-2.46	-2.21	RB1111	-1.77	-1.95	-2.75
RB0911	-2.06	-2.43	-2.41	RB1112	-1.27	-1.23	-2.13
RB0912	-2.37	-2.66	-2.76	RB1201	-1.52	-1.73	-1.70
RB1001	-2.55	-2.99	-3.15	RB1202	-2.07	-2.08	-2.87
RB1002	-2.21	-2.56	-2.84	RB1203	-2.85	-2.97	-3.17
RB1003	-1.66	-2.08	-2.05	RB1204	-2.99	-3.11	-3.46*
RB1004	-0.85	-1.20	-1.69	RB1205	-2.46	-2.88	-3.43*
RB1005	-0.03	-0.40	-0.66	RB1206	-2.75	-2.87	-3.40*
RB1006	-0.77	-0.88	-0.85	RB1207	-2.66	-2.59	-2.69
RB1007	-0.81	-0.88	-0.87	RB1208	-2.70	-2.74	-2.92
RB1008	-0.60	-0.61	-0.61	RB1209	-2.32	-2.72	-2.92
RB1009	-0.57	-0.62	-0.53	RB1210	-2.94	-3.34	-3.32
RB1010	-1.59	-1.60	-1.57	RB1211	-3.37*	-3.46*	-3.87*
RB1011	-0.77	-0.76	-0.78	RB1212	-3.66*	-4.01**	-3.94*
RB1012	-1.23	-1.23	-1.23	RB1301	-2.75	-3.35	-3.06
RB1101	-1.66	-1.71	-1.57	RB1302	-2.69	-3.15	-3.28
RB1102	-2.51	-2.48	-2.50	RB1303	-2.76	-2.98	-3.44*
RB1103	-3.18	-3.43*	-2.96	RB1304	-2.57	-2.76	-2.98
RB1104	-3.15	-3.64*	-3.60*	RB1305	-2.31	-2.61	-2.49
RB1105	-4.70**	-5.78**	-5.17**	RB1306	-2.61	-2.77	-2.93
RB1106	-4.29**	-4.86**	-7.02**	RB1307	-2.87	-3.01	-2.94
RB1107	-1.55	-2.77	-2.67	RB1308	-2.27	-2.50	-2.63
RB1108	-3.20	-3.66*	-3.94*	RB1309	-1.68	-1.95	-2.12
RB1109	-2.11	-2.37	-2.91	RB1310	-2.42	-2.60	-2.59

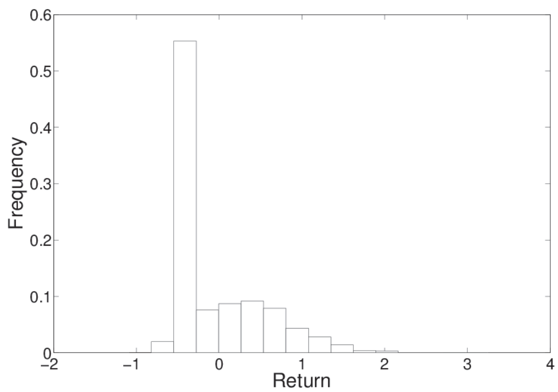
Column $Z_{settlement}$ reports the test statistics for the second stage of an Engel–Granger cointegration test between the settlement price and the spot market. Z_{close} and Z_{open} report the same for cointegration tests between the closing price and the opening price respectively. * denotes significance at the 5% level, and ** at the 1% level.

Figure A1: Effect on returns

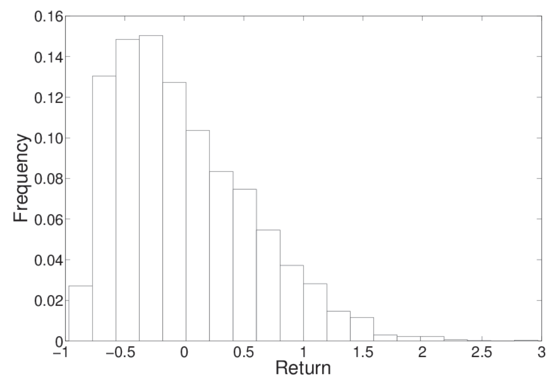


The figure shows the expected return and standard deviation of returns for a portfolio comprising a single risky and riskless (cash) asset. For points on the line to the left of point A the investor is long in both assets whilst to the right they are long in the risky asset and short in the riskless i.e. they are leveraged on margin.

Figure A2: Simulated returns from margin trading



(a) Initial position of 1 contract

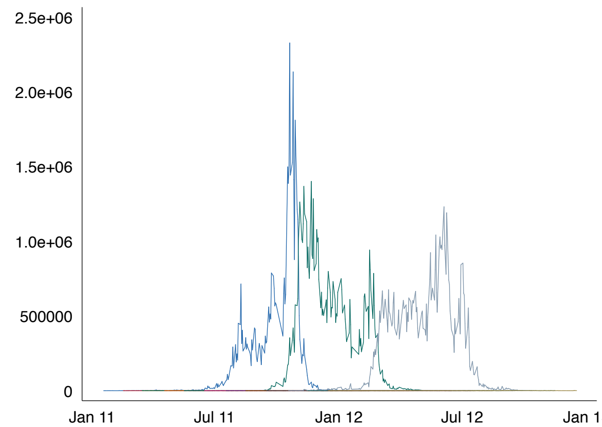


(b) Initial position of 5 contracts

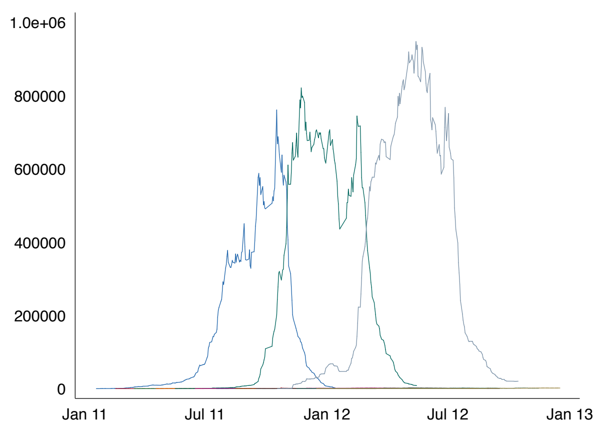
Graphs present absolute returns of traders from the numerical simulation. Each trader has an initial position of 1 contract or 5 contracts respectively, and wealth of 15% of the value of these position. This is equivalent to $4,500$ RMB and $22,500$ RMB respectively. Returns are calculated over 21 trading days. Traders are assumed to partially close positions, whilst maintaining whole numbers of contracts, in response to margin calls and to use any profits to open additional positions. The simulated distribution of prices is estimated using a GARCH(1,1) ARIMA(1,1,0) model for the Rebar future price over the period March 2009 to September 2013. In order to treat long and short positions equally the drift term is set equal to zero.

Figure A3: 2012 Rebar contracts

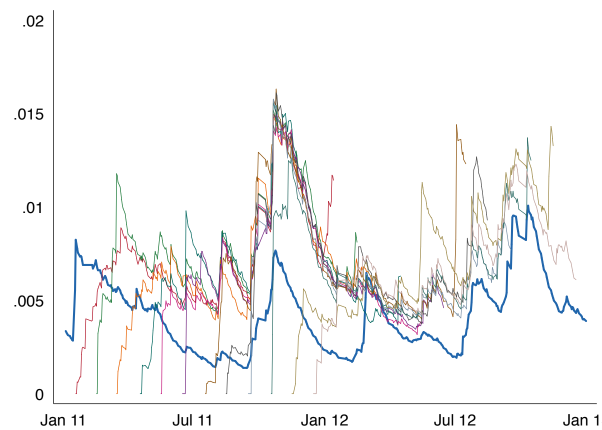
(a) Price



(b) Volume



(c) Market Position

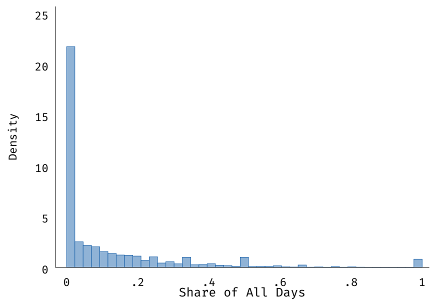


(d) Volatility

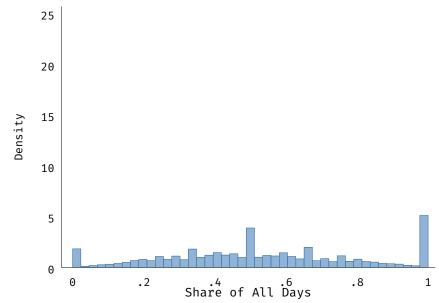
Figures present summary information about the trade of Rebar contracts expiring in 2012. The top left figure shows prices of the 12 contracts, RB1202–RB1212 expiring in 2012, in RMB. The dark blue line is the volume-weighted average price over these contracts. The top right figure shows the traded volume of each of the 12 contracts, although note that only 3 have substantial trading. The bottom right figure shows the net market position (Open Interest) of each of the 12 contracts (although again only 3 are distinguishable from zero). The bottom right figure shows the daily volatility of returns as measured by an exponential weighted moving average of returns with $\lambda = 0.94$. The thick blue shows the average daily price volatility of all contracts.

Figure A4: A lack of liquidity often prevents traders increasing their position

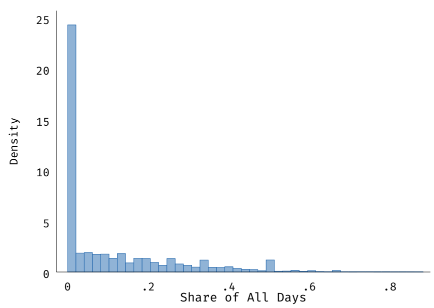
(a) No position, can not open one



(b) No position, could open one



(c) Open position, can not open more



(d) Open position, could open more

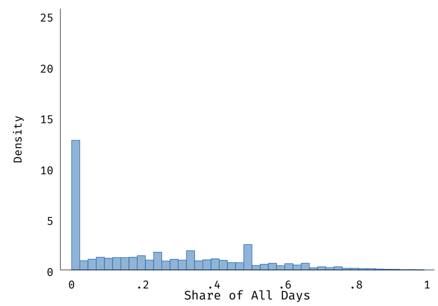


Figure A4a plots the proportion of all trader-day observations (one trader-day observation is based on the position of one trader on a given day, thus each calendar day is associated with one trader-day observation for each trader active in the market on that day) in which a trader has insufficient funds in their account to open a position and where they do not already have an open position. Figure A4b similarly describes the proportion of trader-days in which a trader has no open position but could afford to open one. Figure A4c describes the share of trader-days in which an individual with at least one open position can not afford to open another. Figure A4d describes the fraction of trader-days in which a trader has an open position and sufficient liquidity to open further positions. For all figures the distributions are calculated across the full sample of data March 2009-September 2013 for all traders and all positions opened during this period.

Figure A5: Ratio of trade values in non-Rebar assets to Rebar futures

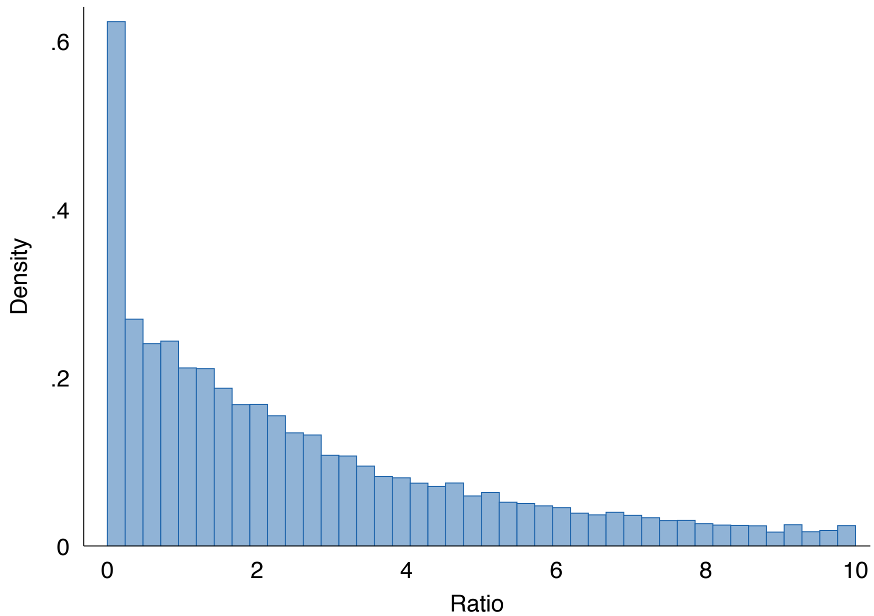
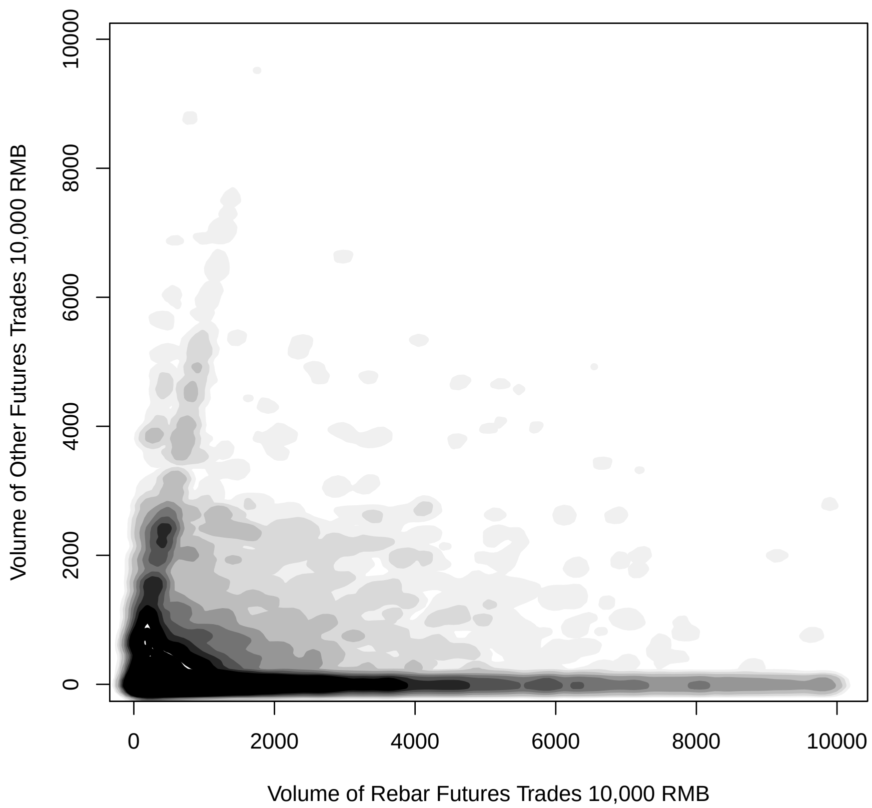


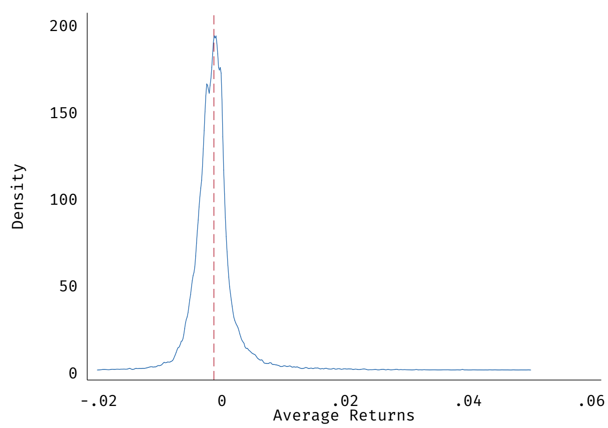
Figure shows a histogram of the ratio of the total value of trades in non-Rebar assets to the total value of Rebar trades for each trader on each day. Value of Rebar trades is calculated from the observed trading record of each trader. The value of non-Rebar trades is calculated from the net change in the margin account excluding cash-inputs and withdrawals and Rebar trades. Non-Rebar trades could be in any asset available to the clients of the brokerage. For all figures the distributions are calculated across the full sample of data March 2009-September 2013 for all traders and all days during this period.

Figure A6: Trading volumes in non-Rebar assets to Rebar futures

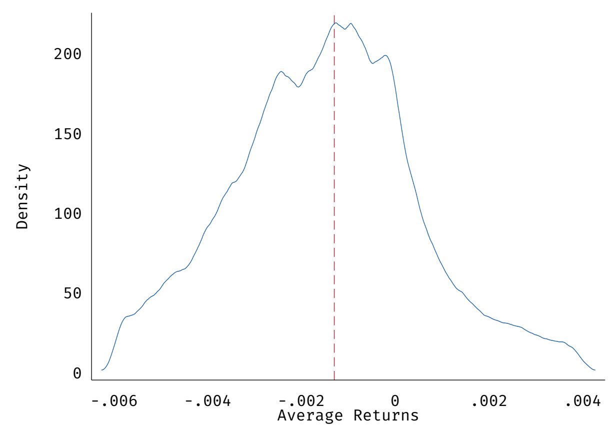


The plot is a heatmap describing the 2-dimensional kernel density surface estimated with an unconstrained bandwidth matrix chosen by smoothed cross-validation and a Gaussian kernel. The x-axis describes the volume of Rebar futures trades, while the y-axis is the total trading volume in all other assets. Units in both cases are in 10,000 RMB.

Figure A7: Average daily returns including transaction costs



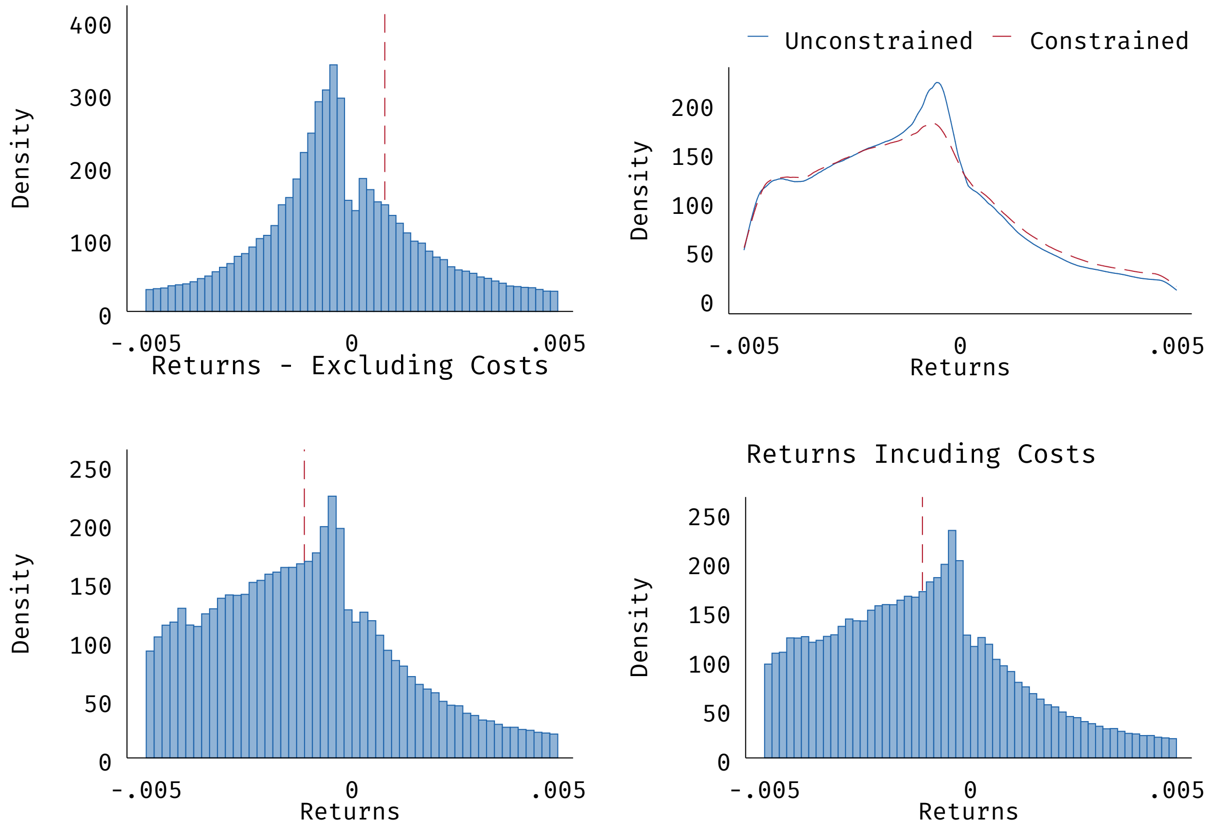
(a)



(b)

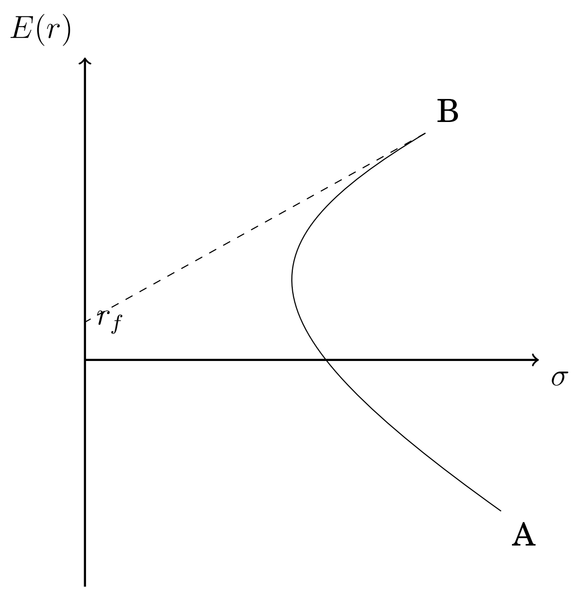
Figures present the average daily returns of traders including transition costs. Average daily returns are calculated across all positions held by all traders in the complete sample. The right figure is a close up of the center of the distribution presented on the left. Both figures present kernel density plots truncated for clarity at -0.02 and 0.05 and -0.006 and 0.004 for the left and right panels. Returns include the observed trading costs which vary between 0.0068% and 0.03%. The red dashed vertical line is the mean daily return.

Figure A8: Average daily returns for constrained and unconstrained Traders



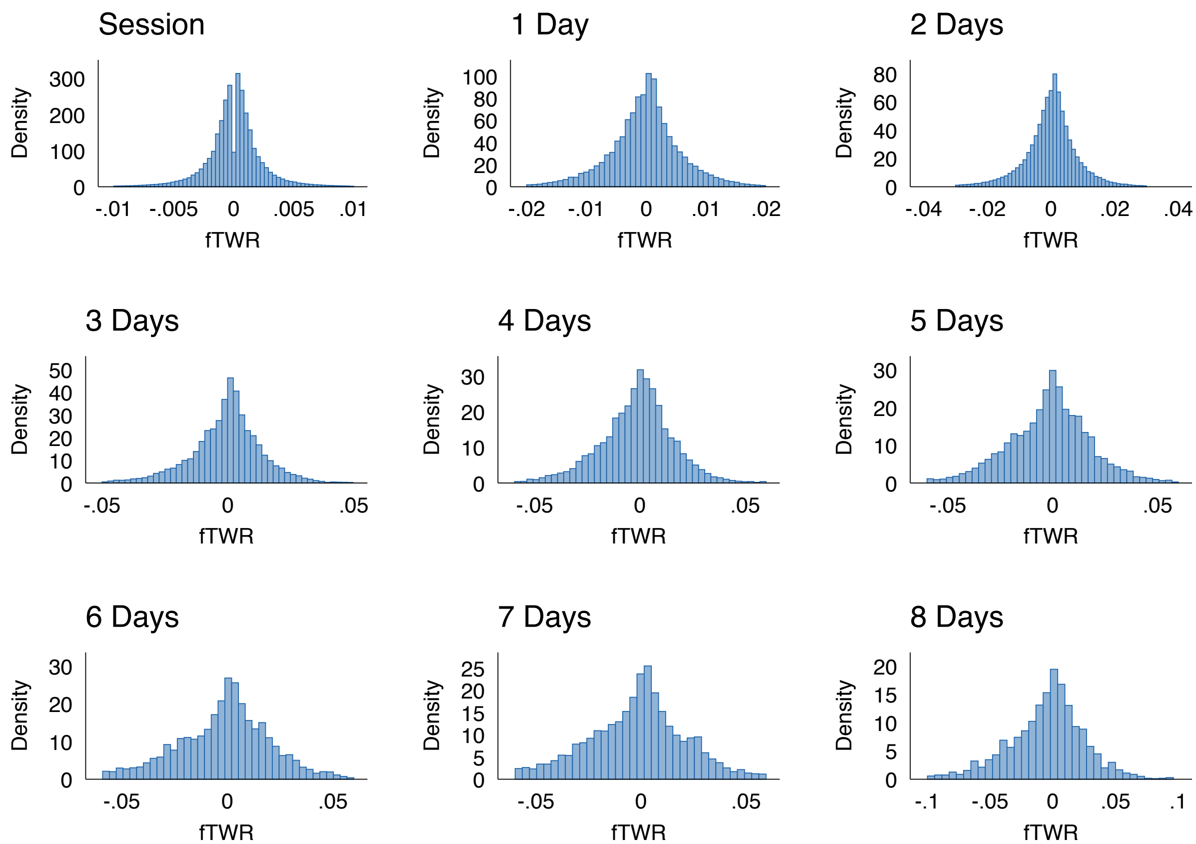
The figures present the difference in the average daily returns obtained by *constrained* and *unconstrained traders* including and excluding transaction costs. Transaction costs are directly observed from the trading record. Constrained traders are those identified as having no additional investable funds whilst unconstrained traders are those able to meet a margin call with additional funds. Average daily returns are calculated across all positions held by all traders in the complete sample. The top left histogram plots the distribution of average daily returns excluding transaction costs for all traders. The top right figure plots two kernel density plots showing the distributions of returns obtained by constrained and unconstrained traders. The lower left histogram plots the distribution of returns obtained by unconstrained traders before trading costs. The bottom right histogram describes the distribution of average daily returns after costs for all traders. All distributions are truncated at -0.005 and 0.005 for clarity. Returns include the observed trading costs which vary between 0.0068% and 0.03%. In all histograms the red dashed vertical line is the mean daily return.

Figure A9: Optimal portfolio frontier



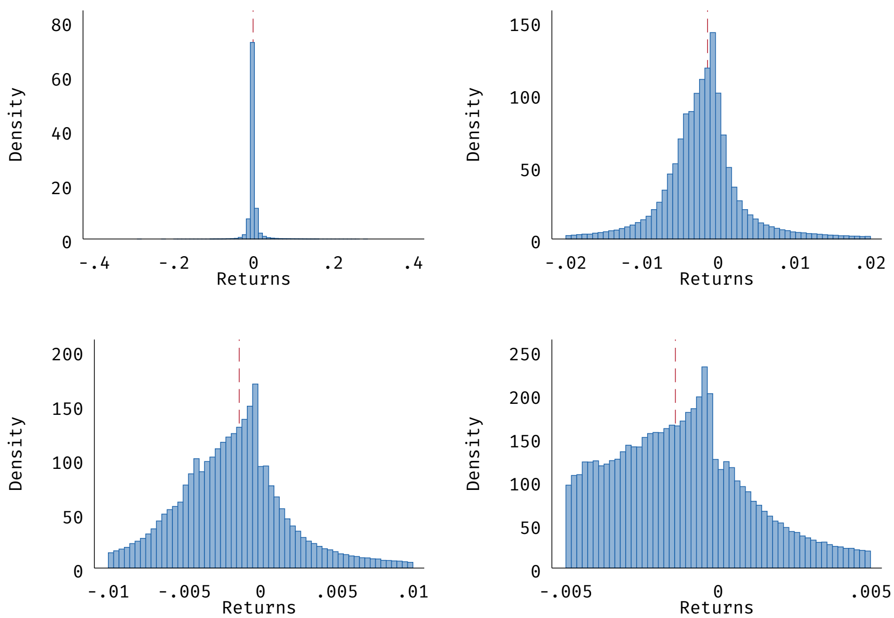
The figure shows the efficient frontier for two assets A and B (solid dark line) and the return from a portfolio including cash and asset B in different fractions (dashed line). In all cases short selling is excluded.

Figure A10: Final total weighted return by position duration



Graphs showing the distribution of returns for positions held for a maximum specified period. A period is defined from the opening of a position to the position returning to zero. *fTWR* is the absolute return of each position for a given maximum period, weighted by its size. The top left histogram shows the size-weighted distribution of returns for positions held for one trading session or less. The eight remaining plots are describe holding periods of between one and two days, two and three days, etc. The distribution is truncated for clarity at ± 0.01 for Sessional returns, and $\pm\{0.02, 0.03, 0.05, 0.06, 0.06, 0.06, 0.06, 0.1\}$ for the 1-Day, 2-Day returns, etc.

Figure A11: Returns including transaction costs



Figures present the distributions of returns, per position, obtained by *constrained traders* including transaction costs. Constrained traders are those traders identified as having no additional investable funds. Returns are calculated across all positions held by all traders in the complete sample. The red dashed vertical line is the mean daily return. For clarity, the top right distribution is truncated at ± 0.02; the bottom left distribution at ± 0.01; and the bottom right distribution at ± 0.005.

Figure A12: Average returns measure

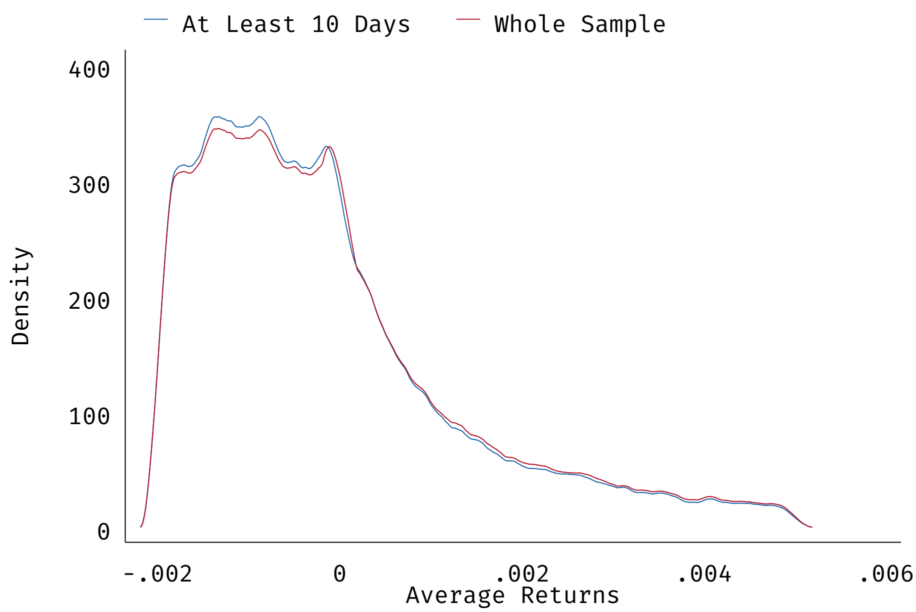


Figure shows the distribution of average returns when calculated from trading periods (blue line) held at least 10 days and from all periods (red line). The graph shows the average daily return over the period. Trading periods are identified using a k-means clustering algorithm described in Appendix D to identify clusters of trades. Returns are calculated across all positions held by all traders in the complete sample.

Figure A13: Number of days in trading episodes

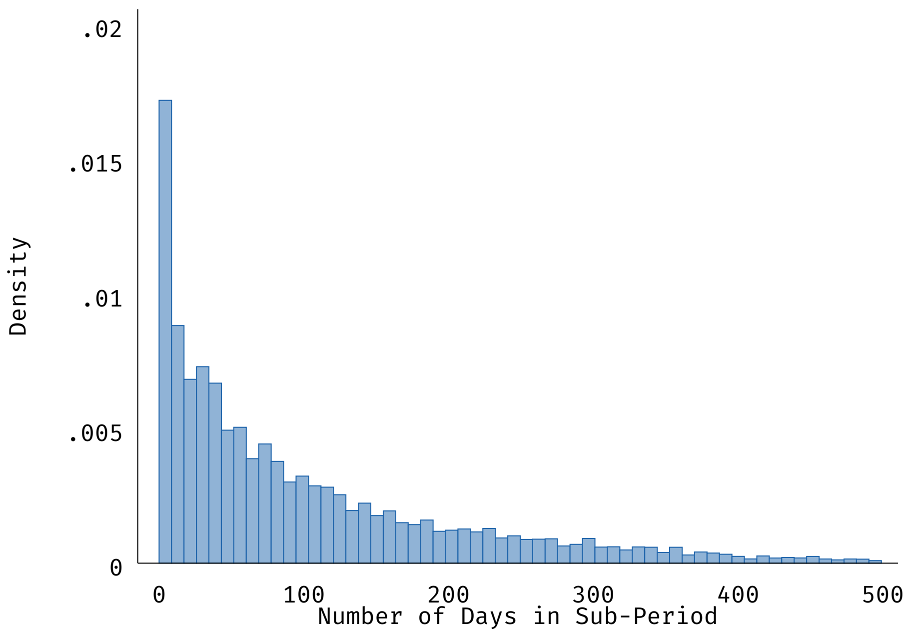


Figure presents the distribution of days in trading periods identified by the k-means clustering algorithm described in Appendix D. The distribution is truncated at 500 days for clarity and is calculated across all positions held by all traders in the complete sample.

Figure A14: One Rebar contract accounts for almost all trading volume at any given time

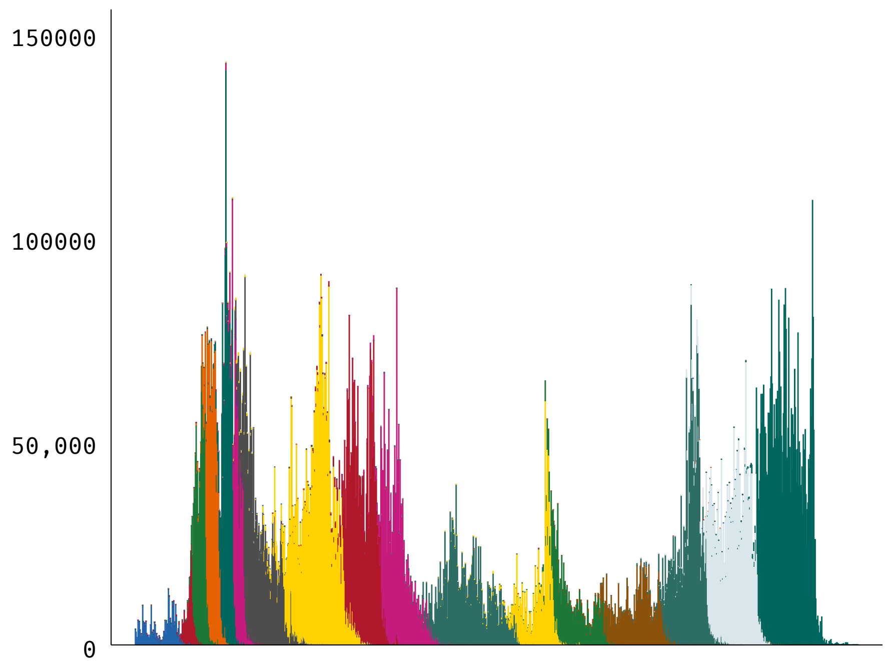
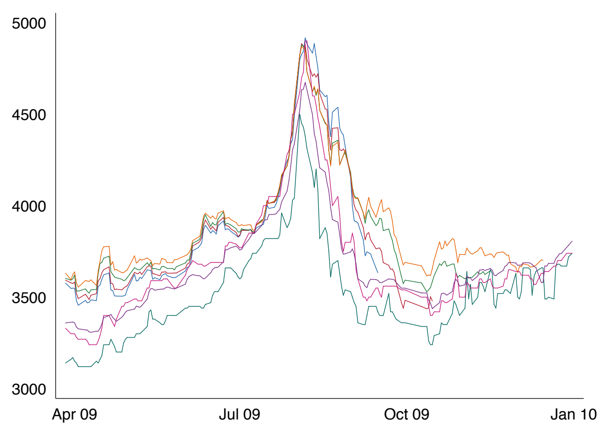
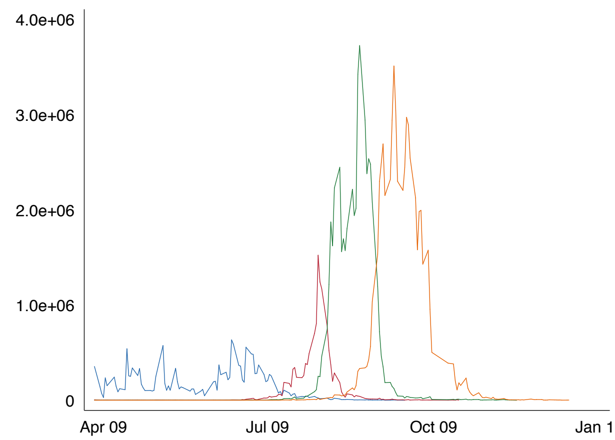


Figure presents the total trading volume, measured in contracts, for all contracts at each point in time. Data are presented as a stacked bar chart, however, at any one time generally only one contract is being actively traded. The number of visible contracts is therefore relatively small.

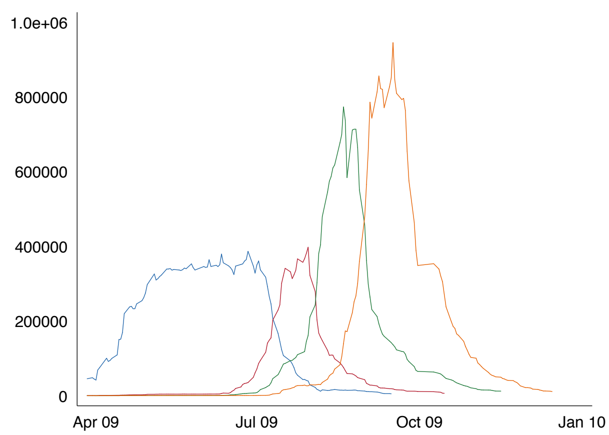
Figure A15: 2009 Rebar contracts



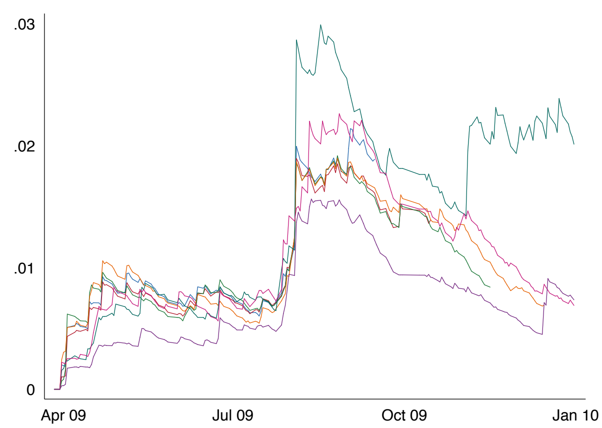
(a) Price



(b) Volume



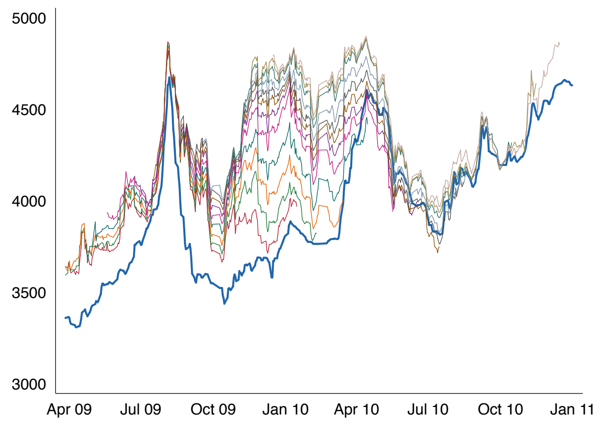
(c) Market Position



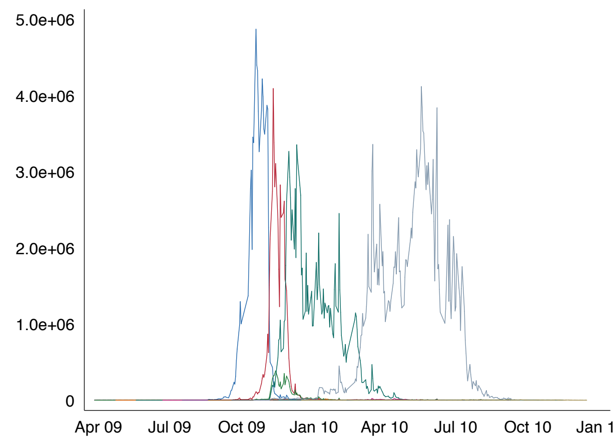
(d) Volatility

Figures present summary information about the trade of Rebar contracts expiring in 2009. The top left figure shows the price of the 4 contracts, RB0909–RB0912 expiring in 2009, in RMB. The dark blue line is the volume-weighted average price over these contracts. The top right figure shows the traded volume of each of the 4 contracts, although note that only 3 have substantial trading. The bottom left figure shows the net market position (Open Interest) of each of the 4 contracts. The bottom right figure shows the daily volatility of returns as measured by an exponential weighted moving average of returns with $\lambda = 0.94$. The thick blue shows the average price volatility of all contracts.

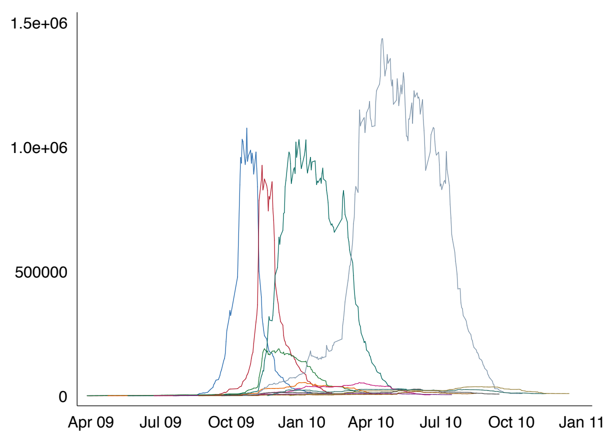
Figure A16: 2010 Rebar contracts



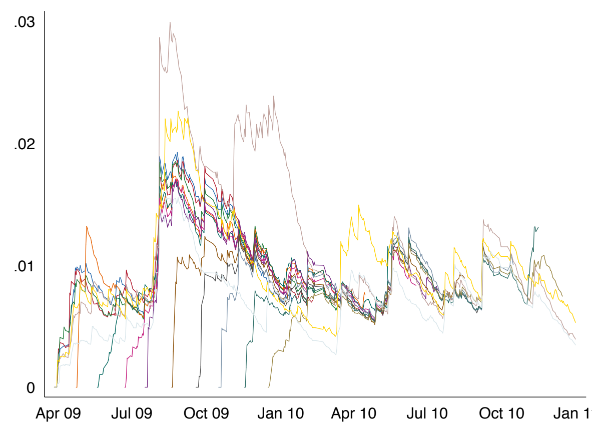
(a) Price



(b) Volume



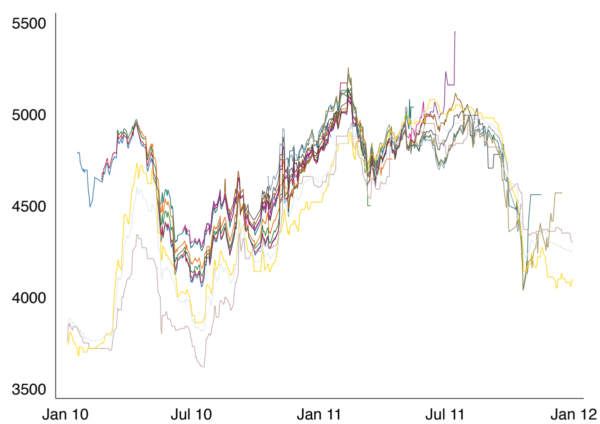
(c) Market Position



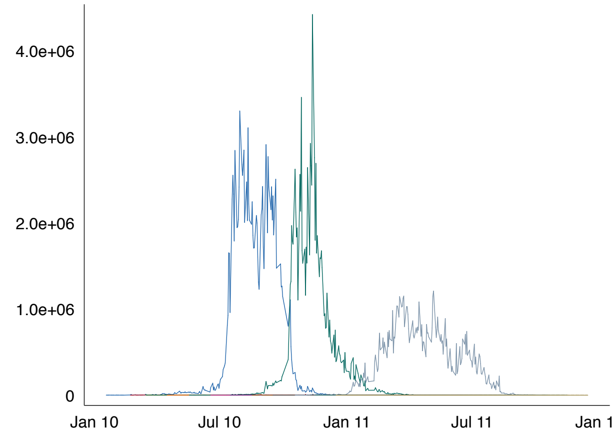
(d) Volatility

Figures present summary information about the trade of Rebar contracts expiring in 2010. The top left figure shows the price of the 12 contracts, RB1201–RB1212 expiring in 2012, in RMB. The dark blue line is the volume-weighted average price over these contracts. The top right figure shows the traded volume of each of the 12 contracts, although note that only 3 have substantial trading. The bottom left figure shows the net market position (Open Interest) of each of the 12 contracts. The bottom right figure shows the daily volatility of returns as measured by an exponential weighted moving average of returns with $\lambda = 0.94$. The thick blue shows the average price volatility of all contracts.

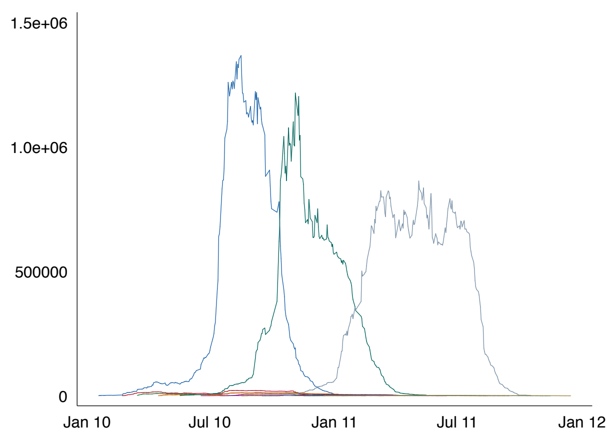
Figure A17: 2011 Rebar contracts



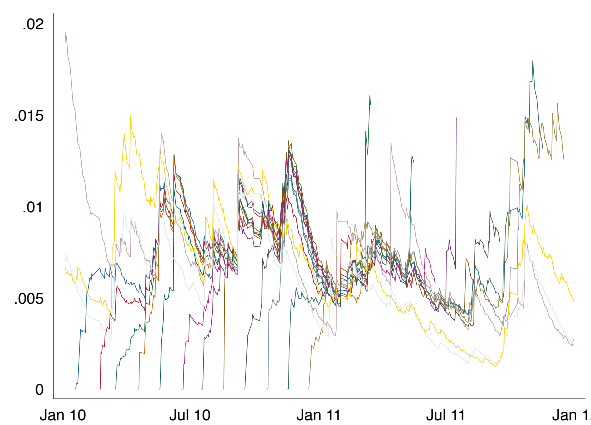
(a) Price



(b) Volume



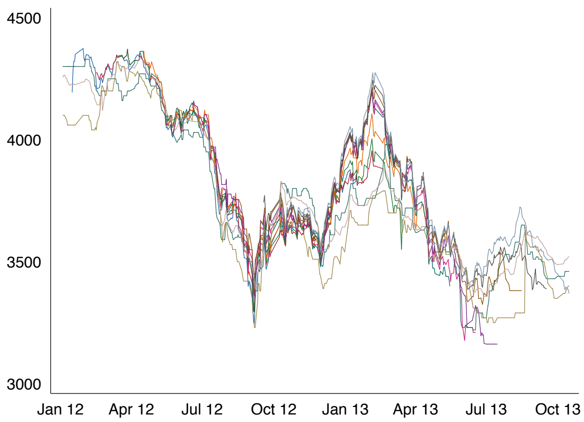
(c) Market Position



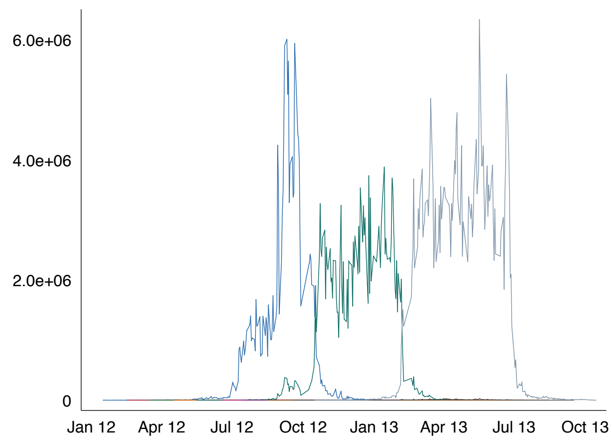
(d) Volatility

Figures present summary information about the trade of Rebar contracts expiring in 2011. The top left figure shows the price of the 12 contracts, RB1101–RB1112 expiring in 2011, in RMB. The dark blue line is the volume-weighted average price over these contracts. The top right figure shows the traded volume of each of the 12 contracts, although note that only 3 have substantial trading. The bottom left figure shows the net market position (Open Interest) of each of the 12 contracts. The bottom right figure shows the daily volatility of returns as measured by an exponential weighted moving average of returns with $\lambda = 0.94$. The thick blue shows the average price volatility of all contracts.

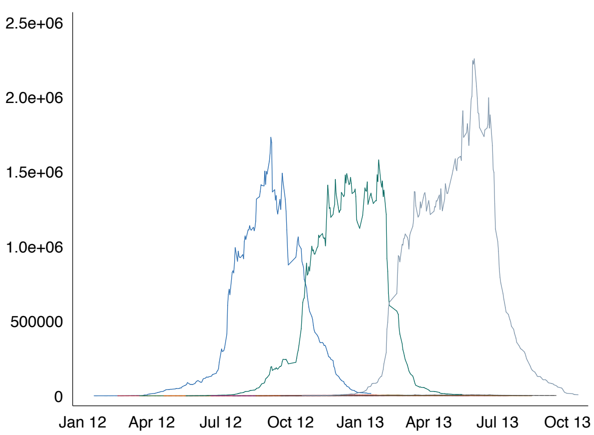
Figure A18: 2013 Rebar contracts



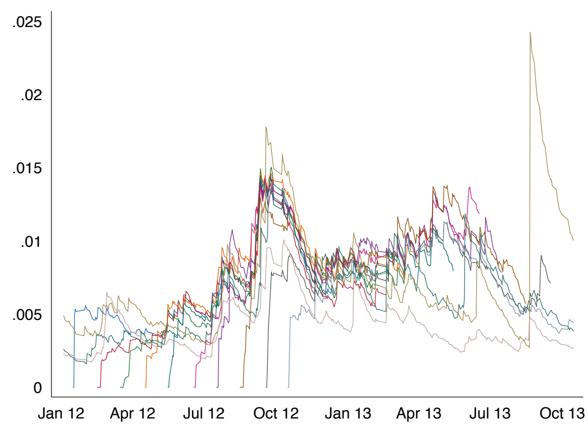
(a) Price



(b) Volume



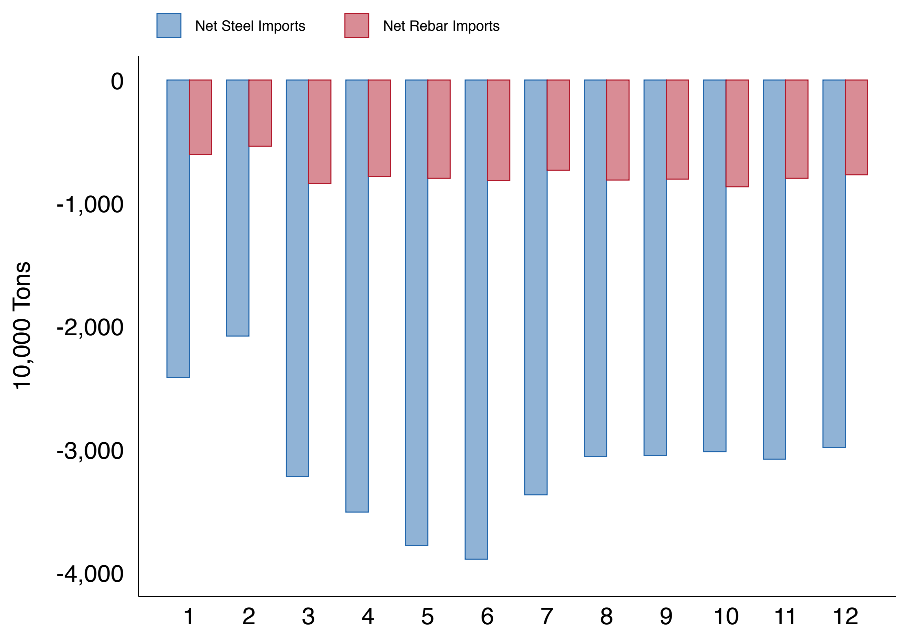
(c) Market Position



(d) Volatility

Figures present summary information about the trade of Rebar contracts expiring in 2013. The top left figure shows the price of the 10 contracts, RB1301–RB1310 expiring in 2013, in RMB. The dark blue line is the volume-weighted average price over these contracts. The top right figure shows the traded volume of each of the 10 contracts, although note that only 3 have substantial trading. The bottom left figure shows the net market position (Open Interest) of each of the 10 contracts. The bottom right figure shows the daily volatility of returns as measured by an exponential weighted moving average of returns with $\lambda = 0.94$. The thick blue shows the average price volatility of all contracts.

Figure A19: Monthly net steel imports



For each month, the graph describes the net imports of all forms of steel and net imports of Rebar. Whilst overall net steel imports fluctuate a little over the year, Rebar imports are comparatively stable with only a small decrease in January and February.

Figure A20: Rebar spot prices

The graph plots the spot price for the Shanghai market as well as the other (smaller) market of Tianjin, and the average of the two. It is clear that, whilst there are sometimes variations between the two, deviations do not tend to last for more than a few days, except perhaps with the exception of early 2011.

Figure A21: Price volatility – whole sample

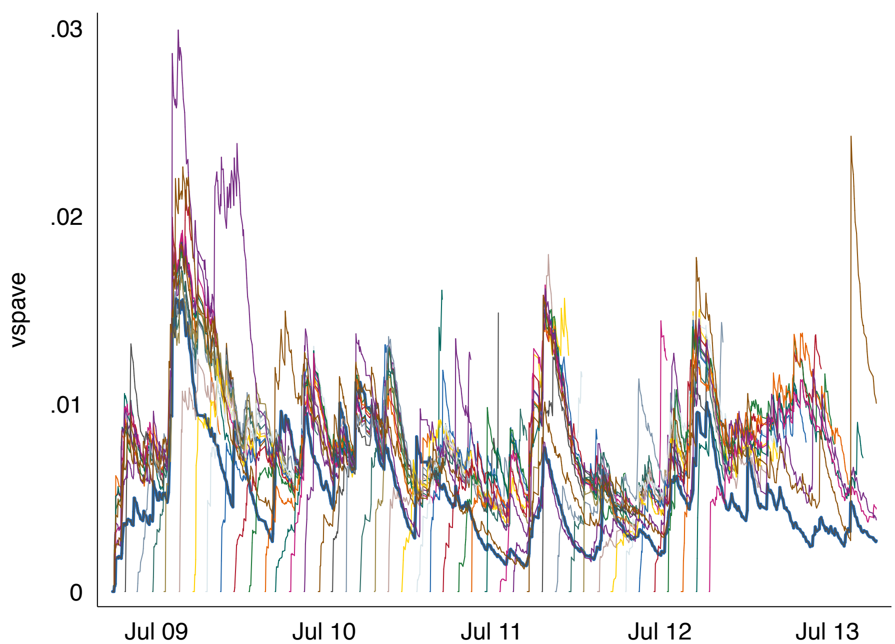
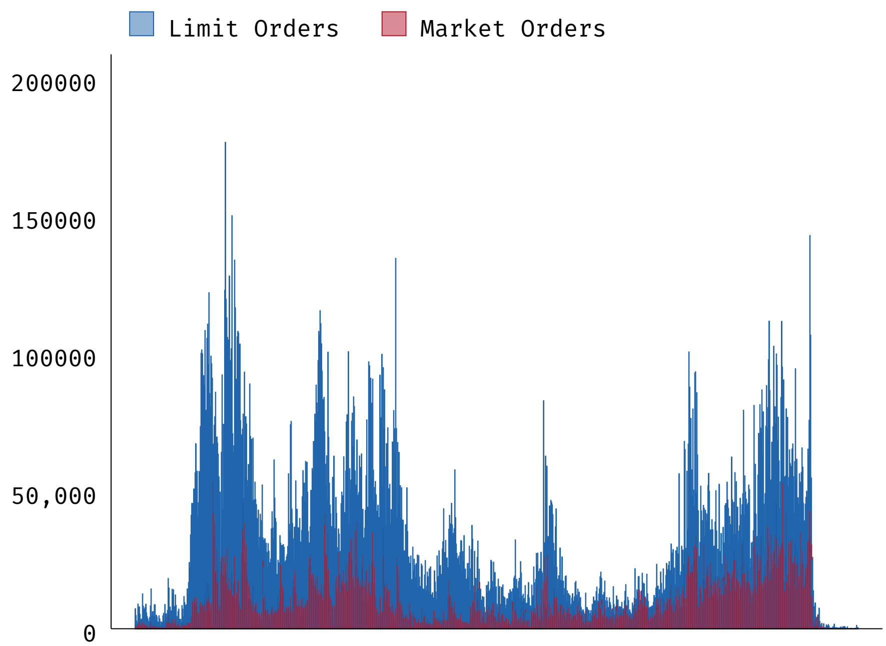


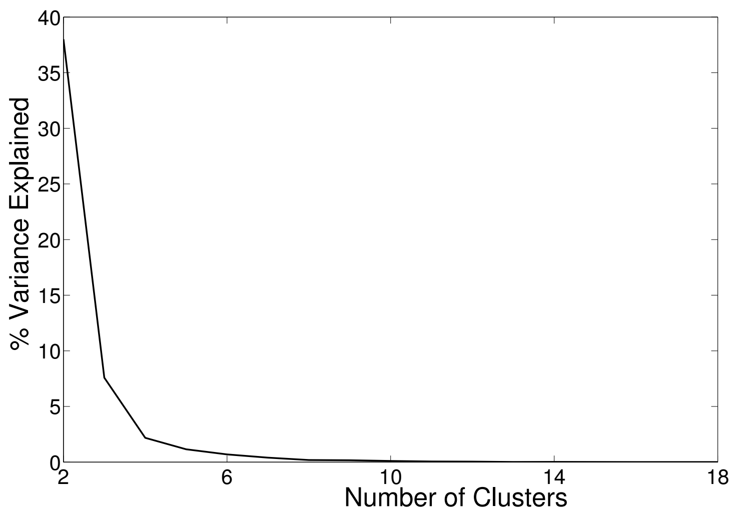
Figure plots the volatility of each Rebar contracts in the full sample, March 2009 to September 2013, over its lifetime. Volatility of each contract is calculated using an exponentially weighted moving average of changes in return (with $\lambda = 0.94$). The thick blue line is the volume-weighted average volatility across all contracts.

Figure A22: Market and limit orders



The figure contains a stacked bar chart describing the total number of daily orders over the sample period, and the proportion of this accounted for by limit and market orders respectively. The preponderance of blue reflects that most orders in the data are limit orders and that the two seem to be in relatively constant proportion over the period.

Figure A23: Identifying the number of separate trading episodes



The vertical axis reports the proportion of variance explained by the last cluster while the horizontal axis reports the total number of clusters. Thus, in the example the second cluster explains around 40% of the variance, the third around 7% the fourth around 3%, and the 18^{th} approximately 0% of the variance.