**Give 'em Enough Rope?
Leveraged Trading when
Investors are Overconfident**

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Can leverage constraints mitigate overconfident financial decision-making? I examine CFTC regulation capping the maximum permissible leverage available to U.S. households that trade foreign exchange on the same brokerages as similar but unregulated European traders. The constraint reduces trading volume and alleviates up to three-quarters of per-trade losses. According to a model of portfolio choice with distorted beliefs, investor overconfidence can explain both leverage demand and underperformance. Several tests support the predictions of the model. Using common proxies to classify traders as overconfident, I find that these traders are most affected by the regulation. Consistent with overconfident, belief-based trading, traders ignore CFTC warnings of leveraged trading risks.

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Policy-makers and academics have recently expressed much interest in the regulation of consumer financial products (Campbell et al. (2011)). Some have argued that firms design and advertise financial instruments that exploit the cognitive limitations or behavioral biases of consumers.[1] This provides a role for regulators to either directly intervene in markets or mandate better information disclosure. It also necessitates research that determines why consumers are susceptible and subsequently what regulatory measures are most effective.

One way in which dealers of financial products have long been suspected to benefit at their clients' expense is by offering them the opportunity to use leverage on the financial instruments they trade (Galbraith (1993)). In contrast to a textbook model in which the provision of leverage is welfare-improving for wealth-constrained investors, increased leverage offers the promise of extraordinary returns, but consumers may underestimate, misunderstand, or be unaware of the downside risk. Naive customers are therefore the most vulnerable and would benefit from efforts to increase the awareness about the risks of levered investments. However, increased awareness might not be effective and direct intervention may be required, because some individuals may not be able to restrain themselves from using too much leverage.

Despite these concerns, which have only heightened since the financial crisis, there is not much evidence on the effectiveness of alternative measures to regulate consumer financial products – the provision of leverage included. There are at least two reasons why. First, the necessary microlevel data from financial markets has only recently been made available to researchers (e.g. Agarwal et al. (2015)). Second, rule changes often affect all market participants, making it difficult to design empirical tests that assign treatment and control groups to isolate their effectiveness.[2]

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[1]Theoretical studies include Gabaix and Laibson (2006) and Carlin (2009). The empirical evidence is limited, but includes Henderson and Pearson (2011), Vallee and Celerier (2014), and Gurun et al. (2015).

[2]For example, regulators have changed margin requirements on the Japanese Stock Exchange over 100 times since 1950, but these regulatory changes affect all market participants (Hardouvelis and Peristiani (1992)).

This paper navigates these challenges by studying intervention in a market, which is relatively unexplored by researchers and has only recently received attention from regulators – retail foreign exchange (forex). The participants in this market compare favorably to households who actively trade individual stocks and are cataloged in a seminal set of papers that follow Barber and Odean (2000). However, while Stambaugh (2014) notes that the active share of equities trading by households has declined substantially since these studies, the retail forex market has grown from close to nothing in the late 1990s to between 125 and 150 billion USD per day by 2010 (King and Rime (2010)). The market's growth can be traced to the advent of dedicated web-based trading platforms, which create and sell fractional shares of standard futures contracts, thereby making interbank currency markets accessible to ordinary households.[3] The market is characterized by extremely low transaction costs and the quick execution of trades. Most notably, brokerages provide nearly unlimited leverage, often reaching as much as 400:1 on any single transaction.

The forex market is well-suited to studying the provision and regulation of leverage, because the market operates in different countries, and therefore across different regulatory regimes. For the most part, forex trading is lightly regulated worldwide. However, following the authority granted by the Dodd-Frank Wall Street Reform and Consumer Protection Act, the Commodity Futures Trading Commission (CFTC) capped in October 2010 the amount of leverage available to U.S. retail forex traders at 50:1. Meanwhile, most brokerages serve clients from around the world and are responsible for segmenting their clientele by location and maintaining compliance with their clients' domestic regulatory authority. Conveniently, this feature enables a comparison of U.S. traders, who have been subject to tightened restrictions on leverage, to a similar set of unregulated European traders, while holding constant the differences across brokerages.

To study the effectiveness of the CFTC regulation, this research employs a novel transaction-level database compiled by an investment-specific, web-based social network that extracts individual trading records directly from

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[3]Trading in the interbank market requires a minimum of one million USD capital.

around 50 different retail-specific brokerages. The data set is useful because the forex market contains no centralized data repository. Moreover, the data include many investor characteristics and details for each trade, including the amount of leverage used when entering a new position and the client's domestic currency. Empirical tests demonstrate that European and U.S. traders are alike. In addition to having similar characteristics across locations, traders' use of leverage and realized returns covary positively.

A recent paper, Heimer (2014), shows that the CFTC's leverage constraint caused large reductions in trading volume and individual investor losses. As much as 75 percent of trading losses can be attributed to the heightened availability of leverage. Since these results are difficult to reconcile with conventional economic theory, the goal of this paper is to understand why restricting the amount of leverage available to traders makes them better off.

I argue that investor overconfidence can explain why traders demand leverage and subsequently underperform. Overconfident individuals tend to overweight the precision of their own beliefs about the distribution of an asset's return (Odean (1998)). Trading with leverage reflects a perceived lack of uncertainty, and so it makes sense from the perspective of the overconfident investor to apply leverage to their trades. Thus, a reasonable explanation is that an exogenous reduction in leverage dampens the harmful effect of overconfidence by reducing trade size. Indeed, I support this interpretation by incorporating a leverage constraint into a portfolio choice model augmented such that the investor has overconfidence beliefs. The model predicts that trading volume falls and risk-adjusted trading profits increase. This mechanism is consistent with underperformance of individual investors is frequently attributed to overconfidence (Barber and Odean (2001) and Biais et al. (2005)).

Motivated by recent psychological research, suggesting that, "[m]ore socially dominant individuals ... make more confident judgments, holding constant their actual ability," (Burks et al. (2013)) I use a trader's betweeness centrality in the social network as a proxy for overconfidence. Between centrality is a network-based statistic that captures the degree to which communications in the network are likely to travel through a given trader. Hence, it

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reflects a trader's social prominence. Traders with higher betweeness centrality also exhibit higher portfolio turnover, are more likely to respond to salient events such as large swings in prices, and tend to communicate within the social network in a self-confirming manner, all of which are associated with overconfidence to some degree. Indeed, these traders are most affected by the regulation, reducing their underperformance by an average of twenty basis points per trade.

Another way to test the relation between leveraged trading and overconfidence is by studying how traders respond when they are warned of the risks of using leverage. Prior to the implementation of the leverage constraint, the CFTC issued warnings about the risk of using leverage and conveyed its desire to regulate the market. The information treatment had no effect on traders' use of leverage or their returns, a finding that is consistent with the notion that market participants are reluctant to modify their behavior when they hold strong priors about their own ability.

This paper contributes to the debate on how to regulate consumer financial products. Some argue that no regulation is necessary, because consumers learn through trial and error (Friedman (1953)), while others suggest that increased information disclosure or "nudges" can be effective (Thaler and Sunstein (2008) and Duflo et al. (2011)). This paper shows that information treatments may not work when consumers have strong beliefs about their own ability, which differ from actual expected outcomes. In this respect, this paper's findings are widely applicable to markets that are subject to scrutiny from regulators. For example, warning labels on cigarette packets may not deter young people from smoking if they have strong ex-ante beliefs that others get sick, while they are unlikely to.

Beyond the regulatory considerations, this paper offers a fresh perspective on households that participate actively in financial markets. For over a decade, the personal finance literature has turned to Odean (1998) and Barber and Odean (2001)'s results – individuals who trade actively do not earn enough to exceed transaction costs, and trading individual stocks is indicative of subrational behavior. However, recent evidence from broader data has led scholars

to reconsider the representativeness of the empirical results (Kelley and Tet-lock (2013)). New theories have also challenged the perception that individual investors do not abide by conventional preferences and beliefs.[4] In contrast to this paper, none of these recent studies have the benefit of using a quasi-natural experiment to exclude explanations for their underperformance, which use conventional preferences and beliefs as a foundation.

Finally, this paper helps us better understand how the demand for leverage by financial market participants responds to exogenous changes in supply. Leverage is an important ingredient in many macro-financial models, and credit availability has recently been linked empirically to aggregate prices.[5] Demand for leverage potentially arises for a couple of reasons: an individual possesses superior information or they are optimistic about the asset's resale value while potentially underestimating the downside risk. The latter explanation is an important assumption for many of these theories. However, there are few studies that assess the micro-level impact of exogenous changes in leverage availability, and this paper aims to fill that gap.

1   Trading with overconfidence and leverage constraints

Consider a simple model in which a representative investor cares about terminal wealth and has preferences over risk and return. The incorporation of a leverage constraint limits the ability of investors to borrow beyond some

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[4]Linnainmaa (2010) argues that traders are unaware of adverse selection risk, while Seru et al. (2010) and Linnainmaa (2011) consider the possibility that traders underperform while learning about their ability.

[5]Some theoretical studies include Geanakoplos (2010), Scheinkman and Xiong (2003), and Simsek (2013). For empirical evidence on leverage and prices in asset markets, see Rajan and Ramcharan (2015) and Favara and Imbs (2015) for housing markets, or studies in equities markets such as Schwert (1989) and Kupiec (1989). Kahraman and Tookes (2014) and Ben-David (2011) are possibly closest to this study. The former uses a regression discontinuity design to look at changes in margin requirements on individual stocks on the Indian Stock Exchange, while the latter profiles homeowners who used high amounts of leverage to finance their purchases prior to the crisis.

fraction of their wealth. When traders have rational expectations, leverage constraints are a friction, which lowers the expected utility of low-wealth investors that are sufficiently risk-tolerant. On the other hand, departures from rational expectations have been analyzed in theoretical settings, perhaps most prominently in the form of investor overconfidence – the tendency to possess beliefs that are too precise.

I summarize a model of investor overconfidence based closely on Odean (1998), which receives formal treatment in Appendix A1. Unlike Odean (1998), the model herein incorporates borrowing and leverage constraints. Similar to much existing literature (Daniel et al. (1998); Kyle and Wang (1997); and Odean (1998), among others), overconfident traders place too much weight on their own beliefs about the ex-post value of a risky-asset. Otherwise, the model is relatively standard. A set of identical traders have constant absolute risk aversion (CARA) utility and solve their optimization problem with an eye toward terminal wealth. Traders are price-takers with respect to a risky and risk-less asset, the latter of which earns no returns. Trading takes place in one round during which all traders receive their own signal about the asset's value in addition to observing its price. When traders are not overconfident they have perfectly calibrated beliefs and the utility maximizing demand for the risky-asset is equal to the average per-trader supply.

The model produces a few testable predictions when traders are overconfident, the first of which is shared with Odean (1998). Since overconfident traders incorrectly weigh the information they receive, they underperform on average relative to the amount of risk they bear and thereby have lower expected utility. While this research is unable to provide causal tests of this hypothesis, the literature contains sufficient empirical support. The empirical setting in this paper is best suited to consider the following two hypotheses regarding the use of leverage.

First, the demand for leverage increases when market participants are overconfident. Overconfident traders believe they have better information than others, thus it makes sense from their perspective to use leverage to amplify their bets on the risky-asset regardless of their risk-tolerance. Secondly, reduc-

tions in leverage mitigate the risk-adjusted underperformance of overconfident investors. Overconfidence creates a wedge between the trader's position on the risky-asset and the optimal position size when all information is weighed properly. Exogenously imposed leverage constraints become more likely to reside within this wedge as overconfidence increases, which confines traders to a set of better outcomes.

2 Retail forex and the CFTC regulation

The retail forex market, which barely existed in the early 2000s, has experienced unprecedented growth over the past decade. According to King and Rime (2010), its volume is estimated to be between 125 and 150 billion USD per day, roughly the same as daily turnover on the entire NYSE family of stock exchanges (NYSE, Arca, and Amex).

Retail forex brokerages are organized as market-making systems, which continuously offer bid and ask quotes to their customers and earn the spread on every transaction. Each brokerage maintains a proprietary algorithm for generating quotes that are based on their own inventory and a data-feed from the interbank market. Similar to the interbank market, spreads are low, typically no more than one or two pips regardless of the transaction size. Since the brokerages do not charge any additional fees per transaction, nominal trading costs rise in proportion to the size of the trade, but are constant and relatively small in real terms.

All clients, regardless of domestic location, receive spot quotes in terms of the currency pair (e.g. EUR/USD) using the nomenclature designated by standard ISO 4217 from the International Standards Organization. Each pair includes a "base" and "quote" currency (EUR is the base and USD is the quote, in the EUR/USD example). Traders decide how much of the pair to long or to short in terms of the base currency. The brokerage is the counterparty on all transactions, responsible for off-loading inventory into the interbank market. Retail clients use a domestic bank account to deposit initial funds into their forex brokerage account. Since these are margin accounts, retail customers do

not take receipt of the foreign currency when they trade, and withdrawals are made in the client's domestic currency.

Retail brokerages also provide their clients with the option to use leverage on their trades at no additional cost. For instance, a U.S. or European trader could decide to purchase or short 100,000 EUR worth of the EUR/USD using an equivalent of 20,000 EUR of his own capital, while borrowing the difference from the brokerage. The trader uses 5:1 leverage in this example.

Regulation in the forex market

The retail forex market in the U.S. was mostly unregulated prior to the passage of the Dodd–Frank Wall Street Reform and Consumer Protection Act on July 21, 2010. Concerned with consumer welfare, the act brought widespread changes to the financial industry and strengthened the authority of the CFTC over the retail forex market. The CFTC began considering methods to protect consumer welfare in the forex market in anticipation of the passage of Dodd-Frank. On January 20, 2010, the CFTC expressed concern over the use of leverage and released in the Federal Register a proposal to restrict the leverage available to retail customers to 10:1 per trade on all pairs.[6] Shortly after Dodd-Frank was written into law, the CFTC released on September 10, 2010, a finalized set of rules which required all retail brokerages to register with the CFTC and to limit the amount of leverage available to U.S. customers to 50:1 on all major pairs and 20:1 on all others (the appendix provides a complete list of currency pairs).[7] The brokerages were required to come into compliance with the new rules by October 18, 2010. Meanwhile, European regulatory authorities continue to allow retail forex brokerages full discretion over the provision of leverage to traders, and the maximum available tends to exceed 50:1.

A distinguishing feature of the forex market is that most brokerages have clients from around the world. However, there is no centralized, worldwide

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[6]www.cftc.gov/LawRegulation/FederalRegister/ProposedRules/2010-456a

[7]Prior to the passage of Dodd-Frank, the CFTC lacked the authority to regulate retail forex leverage, and the brokerages determined their own capital requirements.

regulatory authority. Brokerages must comply with domestic regulations in each country in which they operate. This requires brokerages to segment their clientele according to country of origin. Verification of a client's home country is done using government-issued documentation, such as a passport, and a link to a domestic bank account from which to withdraw and deposit funds. Consequently, it would be challenging and costly for a retail client to search for a preferred regulatory regime. Therefore, the structure of the market is beneficial to this research, because it is possible to compare regulated U.S. traders to their lightly-regulated European counterparts while accounting for brokerage features that may otherwise vary across countries.

3   The data: myForexBook

There is no centralized data repository in the retail segment of the forex market. Thus, the data used in this paper's empirical analysis was compiled by a social networking website that, for privacy purposes, I call myForexBook. Registering with myForexBook – which is free – requires a trader to have an open account on roughly 50 retail specific forex brokers. Once a trader registers, myForexBook can access her complete trading record at those brokers, even the trades they made before joining the network. New trades are executed on a trader's brokerage, but they are simultaneously recorded in the myForexBook database and are time-stamped to the second. Hence, an advantage of the data is that there are no concerns about reporting bias. Another advantage is that the data include a broad sample of brokerages. An example of a myForexBook user's homepage and some of the network's features are presented in the appendix. There are 5,693 traders in the database who made roughly 2.2 million trades, most of which occurred between early 2009 and December 2010.

A shortcoming of the data is that it provides the domestic currency – as revealed by a link to a domestic bank account – for only 68 percent of traders in the sample. However, upon joining the social network, traders are surveyed and asked to identify whether they are from one of the following locations:

United States, Europe, or Asia-Pacific.[8] Traders provide honest answers: 97 percent of traders claiming to be from the U.S. had accounts denominated in the U.S. dollar, with a similar matching rate among European respondents.[9]

I trim the data in a few ways to increase the precision of statistical inference. I restrict the sample to traders who reside in the United States or Europe, because the market conditions they face are similar. Since the European and U.S. markets overlap within the day, traders from both locations tend to trade around the same times and they also trade similar instruments. Second, the analysis is limited to the set of traders who issue trades both before and after the CFTC regulation was implemented, thereby lessening concerns over attrition bias. The outer one percent of all observations of return-on-investment (ROI) are Winsorized to limit the influence of extreme returns. This leaves the per-trade ROI within a range of roughly 70 percent to 120 percent (100 percent implies that the trade recovered the entire initial capital and no more). I also Winsorize the top one percent of the distribution for leverage per trade. Lastly, the analysis is restricted to trades made between September 1, 2010, and December 1, 2010, so that there is roughly an equal amount of time before and after the regulation. In the main set of tests, I exclude traders on one brokerage that failed to come into compliance with the CFTC regulation by the intended date and subsequently received heavy fines for doing so. This leaves a total of 271,570 trades made by 1,069 traders, almost half – 458 – are from the U.S.[10]

Summary statistics

Table 1 presents summary statistics on per-trade ROI, separated by U.S. and European traders. According to the notation used by the data provider (and

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[8]About 3.5 percent of all traders did not specify their location upon joining the social network. Within this group, the trader's brokerage provide the base currency for five traders, four from the U.S. and one from Europe. These five traders are included in the analysis.

[9]I exclude traders who report a U.S. or European residence, but have an account denominated in a different currency.

[10]These data-trimmings are unlikely to bias the sample. In unreported tests, the sample of traders used herein compares favorably to those excluded in terms of their personal characteristic and trading behavior.

also used on the retail forex brokerages), ROI is equal to

$$\frac{(S_{p,\tau} \cdot X_t - Y_t)}{Y_t} + 100\%$$

for all long positions and

$$\frac{(Y_t - S_{p,\tau} \cdot X_t)}{Y_t} + 100\%$$

for all short positions, where S_p is the spot price of currency pair p. S_p is equivalent to Y/X, where X is the nominal value of the base currency and Y is the amount in the quote currency. The subscript t refers to the second at which the position is opened, while τ is the second the position is closed.

[insert Table 1 about here]

A common theme is present across both groups: while the median trade is slightly profitable, the mean trade is unprofitable, losing around 0.26 percent ROI, which is large enough to suggest traders are unprofitable even after paying the bid-ask spread.

Table 1 examines trading prior to and following the regulation. Prior to the regulation, European traders in the sample use more leverage on average than U.S. traders (41:1 versus 29:1, respectively), but the difference likely occurs because some brokerages implemented the CFTC's suggested guidelines weeks before the compliance date. The distribution of leverage is positively skewed for both groups of traders. The median leverage is 2:1 for U.S. traders and 4:1 for Europeans. Furthermore, around 9 percent of all trades within the sample period were issued with leverage greater than 50:1. The table also presents account level summary statistics. European and U.S. traders appear similar in many ways.

Are U.S. and European traders comparable?

While registering for myForexBook, traders are asked to provide information about themselves (Table 2). According to Panel I, the average trader is about

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27 years old. Most myForexBook users have zero to one or one to three years of trading experience. Traders from both locales tend to consider themselves technical traders as opposed to basing their strategies on news, momentum, or fundamentals. In addition to these survey responses, traders use the my-ForexBook platform to develop bilateral friendships with one another. U.S. traders have an average of 30.0 friends at the beginning of the sample period, while Europeans have 24.0, but the averages are not statistically different.

[insert Table 2 about here]

U.S. and European traders appear to have similar characteristics. Using difference-in-means tests, only a couple of the observable variables provided by the data provider – age and trading experience – are statistically different across locales. However, the magnitude of the differences is small. Similarly, the second panel presents a covariate balancing test. I use a probit model to estimate the likelihood of being a trader from the U.S. as a function of trader age, experience, trading approach, and the number of friends in myForexBook. According to the model estimates, the U.S. sample of traders is roughly two years older and has about 6 percentage point fewer novice traders, and these differences are statistically significant. Otherwise, the sample of European traders appears to be a reasonable control group relative to U.S. traders.

Do U.S. and European traders have correlated trading activities?

To further assess how European traders fare as a benchmark against regulated U.S. traders, I examine if their trading activity is comparable. I examine the comovement of trading volume, leverage use, and aggregate returns across regulatory regimes. Similar fluctuations in these variables would imply that traders may respond similarly to the reduction in leverage availability.

Figure **??** plots the time series of the total number of trades by U.S. and European traders, revealing that their trading volume tends to fluctuate

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in concert. Both groups typically take the weekends off. Furthermore, the Pearson's correlation coefficient of the log first difference of the total number of trades (excluding weekends) is 97.2 percent. This suggests that there is a strong positive correlation between the aggregate trading volume of both groups.

Table **??** also shows that returns and leverage use by U.S. and European traders tends to fluctuate in concert. Using trading days prior to the CFTC regulation, I calculate the daily changes in ROI and leverage as $log\left(y_t/y_{t-1}\right)$. Pearson's correlation coefficients between U.S. and European daily average trading are equal to 0.42 for ROI and 0.36 for leverage.

4   Leverage constraints and investor overconfidence

This section tries to understand Heimer (2014)'s result that the leverage constraint reduced investor losses. A common explanation for the underperformance of individual investors is that they exhibit overconfidence (Odean (1998)). Overconfidence is often described in two ways: either individuals think they have better-than-average ability or they hold beliefs about probability distributions that are too precise. Both definitions would increase the demand for leverage, because traders take on too much idiosyncratic portfolio risk or expect to perform better than other market participants.

Financial frictions may also affect trading profits even when traders have conventional beliefs and preferences. The appendix presents tests of several popular theories drawn from the constraint-based asset-pricing literature. In summary, financial frictions are unlikely to explain the finding that leverage constraints improve trader performance.

Three overconfidence proxies

Much empirical research ties overconfidence to excessive trading and under-performance.[11] Inspired by these findings, my first overconfidence proxy, $loss\&intensity_i$, involves sorting the sample of myForexBook traders in terms of their average ROI, $\bar{roi}_{i,t}$, and trading frequency as measured by the number of trades issued by i divided by the number of days in which i trades.[12] Both $\bar{roi}_{i,t}$ and trading frequency are calculated during the period prior to the CFTC rule change to lessen the confounding influence of the regulation. A trader is deemed overconfident if they fall below the median (90th percentile) of the distribution of $\bar{roi}_{i,t}$ and above the median (90th percentile) trading frequency.

I calculate a second proxy based on the finding that overconfident investors tend to overreact, placing too much weight on extreme events (Odean (1998)). Motivated by Barber and Odean (2008), idiosyncratic overreaction is captured by measuring the extent to which the decision to trade depends on extreme movements in past prices. All traders are pooled in the following regression:

$$trade\,ind_{i,t} = \beta_0 + \beta_1 \cdot \triangle p^2_{t-1} + \beta_2 \cdot \triangle p_{t-1} + \beta_3 \cdot trade.ind_{i,t-1} + \beta_4 \cdot t + \varepsilon_{i,t} \quad (1)$$

where $trade.ind_{i,t}$ is equal to one if i opens a position on day t, and $\triangle p_{t-1}$ is the difference between the high and low price on day $t-1$ of the most heavily traded and presumably most salient currency pair, the EUR/USD. The variable t is a daily time trend. The estimation is conducted using the time period prior to the CFTC regulation.

According to estimates of the empirical model in Equation 1, trading responds positively to past price changes. OLS estimates yield a coefficient β_1 equal to 0.06 (s.e. = 0.003) and β_2 equal to 0.01 (s.e. = 0.007). An increase

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[11] See Barber and Odean (2001), Dorn and Huberman (2005), Grinblatt and Keloharju (2009), and Biais et al. (2005).

[12] Results are robust to using the number of trades issued by i and not normalizing by the number of trading days.

in $\triangle p_{t-1}$ from the tenth to ninetieth percentile results in a 3 percentage point increase in the probability of trading on the following day.

To capture the idiosyncratic sensitivity of each individual trader to past price movements, I estimate Equation 1 for each trader separately,

$$trade.ind_t = \delta_0 + \delta_1 \cdot \triangle p_{t-1}^2 + \delta_2 \cdot \triangle p_{t-1} + \delta_3 \cdot trade.ind_{t-1}...$$
$$+ \delta_4 \cdot t + \varepsilon_t \quad for\ each\ i \quad (2)$$

and catalog δ_1 for each i. Idiosyncratic overreaction is the difference between aggregate overreaction and i's tendency to trade in response to past price swings that are more extreme,

$$overreact_i = \delta_1 - \beta_1. \quad (3)$$

The ideal proxy for overconfidence would be orthogonal to the regulatory change. However, both $overreact_i$ and $underperform\&intensity_i$ rely on observed trading data. Therefore, it is difficult to exclude the possibility that they are influenced by the pending regulation. The potential shortcomings of these measures motivates the use of a third proxy, one based on the trader's social behavior. A trader's revealed social activity is presumably independent of the CFTC's direct influence on leverage and returns.

There is reason to suspect that social behavior can be used to proxy for overconfidence. Recent experimental studies show that overconfidence leads to enhanced social status in group settings (Anderson et al. (2012)). Study participants also display greater overconfidence after having their desire for status manipulated by study administrators, which suggests causality runs in both directions. This finding may explain why some individuals receive job promotions that appear unjustified based on performance. Individuals that are unbiased in autonomous economic contexts produce overconfident self-assessments when introduced to an observational social setting (Proeger and Meub (2014)). An association between social dominance and overconfidence is also found in observational data. The relationship tends to be caused by

a propensity to send self-enhancing public signals when events occur that appear to confirm their own abilities (Burks et al. (2013)). Burks et al. (2013) also finds that, "[m]ore socially dominant individuals ... make more confident judgments, holding constant their actual ability".

Within the myForexBook database, those with more friendships tend to be the ones pursuing enhanced social status. A one percent increase in the fraction of friendships initiated relative to friendships accepted is associated with an 11 percent increase in the number of friends a user has. Traders in the myForexBook network also exhibit a tendency towards self-promotion. They send celebratory messages to other traders following short-term gains, while remaining silent after failures (Heimer and Simon (2013)). This pattern of communication suggests myForexBook traders overestimate the degree to which they contributed to past positive outcomes (Langer and Roth (1975)). Moreover, self-enhancing signals endogenously increase the level of overconfidence (Gervais and Odean (2001)) and, within myForexBook, they frequently result in friendship formation.

Motivated by this literature, an appropriate socially motivated proxy for overconfidence should reflect the concept of social prominence. An appealing metric has developed in the network sciences. The measure – betweenness centrality ($betweenness_i$) – reflects the degree by which communications in the network have to travel through a trader (node) in the myForexBook network (Appendix A.2 provides the formula used to calculate betweenness centrality). Thus, I calculate betweenness centrality for each trader using the graph of friendship connections developed prior to the regulation. Traders are deemed overconfident if they are above the median (90th percentile) value of $betweenness_i$.

Reductions in leverage and overconfidence: Estimation results

To determine the role of overconfidence in producing an inverse relation between leverage and returns, I incorporate the proxies as a triple-interaction with US_i

and $constraint_t$ in the following empirical model:

$$roi_{j,i,t} = \gamma_b + \beta_1 \cdot US_i + \beta_2 \cdot constraint_t + \beta_3 \cdot US_i \cdot constraint_t + \beta_4 \cdot US_i \cdot overconfident_i ...$$
$$+ \beta_5 \cdot constraint_t \cdot overconfident_i + \beta_6 \cdot US_i \cdot constraint_t \cdot overconfident_i ...$$
$$+ \beta_7 \cdot F_{p,t} + \beta_8 \cdot \sigma_{i,t}^{ROI} + \beta_9 \cdot Trade_{j,i,t} + \beta_{10} \cdot Investor_i + \epsilon_{j,i,t} \quad (4)$$

On the right-hand side of Equation 4, the variable US_i is equal to one if the trader is from the U.S., while $constraint_t$ is equal to one if the trade was opened after 00:00:00 GMT, October 18, 2010. The regression uses $Investor_i$ instead of trader fixed-effects, because the latter is collinear to US_i. In addition, the model includes brokerage fixed-effects, γ_b, to account for any idiosyncratic features of the brokerage that may differentially affect trader outcomes, as well any differences in the brokerage's response to the CFTC regulation. The independent variable $overconfident_i$ is one of the three proxies. A positive value for the coefficient on the triple-interaction term, β_6, implies that the reduction in losses caused by the leverage constraint can be attributed to overconfidence.

Equation 4 also incorporates the standard deviation of i's returns on a weekly basis, $\sigma_{i,t}^{ROI}$, which proxies for changes in the trader's risk tolerance over the sample. Raw returns, roi, need to be benchmarked against expected returns (comparable to the calculation of abnormal returns in studies of equities), because of time variation in macroeconomic factors. However, there is debate about how best to do so in the forex market. One possible method is to include on the right-hand side cross-country interest rate differentials as outlined in Menkhoff et al. (2012). Traders can earn the difference between short-term government-issued debt in two different countries, which makes this an approximation of the trader's expected return on a position in a given currency. Formally, interest rate differentials are equal to

$$F_{p,t} = (i_{b,\tau} - i_{b,t}) - (i_{q,\tau} - i_{q,t})$$

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where i_b is the risk-free rate in the country whose currency is the base of the pair and i_q belongs to the quoted currency.[13] Other plausible metrics for F – e.g. a global currency index – are not easily integrated in the empirical analysis in later sections of the paper, because any measure that is common to both U.S. and European traders gets differenced-out of any tests that compare traders across locations. Standard errors are double-clustered by trader and trading day.

[insert Table 3 about here]

Table 3 presents estimates of Equation 4. The estimation results support the hypothesis that overconfidence can explain why leverage constraints reduce trader underperformance. Columns (1) and (2) interact $loss\&intensity_i$ with US_i and $constraint_t$. Column (1) sets $loss\&intensity_i$ equal to one if its value is above the median, while (2) is above the 90th percentile. The coefficient estimate for β_6 is 0.38 (s.e. = 0.13) in column (1) and 0.40 (s.e. = 0.22) in column (2). Model estimates predicts that traders above the given thresholds of $loss\&intensity_i$ increase their $roi_{j,i,t}$ by 0.17 to 0.43 (columns (1) and (2), respectively) when they are from the U.S. and they trade after the regulation's implementation.

Similar results are found for the other two overconfidence proxies. When US_i and $constraint_t$ are interacted with $overreact_i$, the estimate for β_6 is not statistically different from zero when traders are above the median $overreact_i$ (column 3). However, when the threshold is increased to include only traders above the 90th percentile (column 4), the coefficient estimate is equal to 0.58 (s.e. = 0.21). This suggests that the effectiveness of the leverage constraint increases when a trader is more sensitive to extreme price changes. In column (4), the model predicts a 9 basis point increase in $roi_{j,i,t}$ among overconfident traders from the U.S. following the regulation.

Columns (5) and (6) interact US_i and $constraint_t$ with $betweenness_i$. The regressions yield coefficient estimates for β_6 of 0.16 and 0.18, when $betweenness_i$

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[13]The author's website provides the one-month government yields used in this study. The results are also robust to the inclusion of short-term interest rate changes in the trader's domestic currency (available upon request).

is above the median and 90th percentile, respectively. Both coefficient estimates are statistically significant at the 10 percent error level.

Awareness and overconfidence

Traders may not understand the risks of trading with leverage. On the other hand, overconfident traders place a disproportionate weight on their own beliefs and would therefore ignore announcements that warn of leverage's downside risk. The CFTC's announcement of its concern over the use of leverage is an ideal setting to test this prediction.

[insert Table 4 about here]

Table 4 presents estimates of the following regression:

$$Y_{j,i,t} = \gamma_b + \beta_1 \cdot US_i + \beta_2 \cdot announcement_t ...$$
$$+ \beta_3 \cdot US_i \cdot announcement_t + \epsilon_{j,i,t}. \quad (5)$$

To estimate this regression, I apply a data-trimming criterion identical to the one proposed in Section 3, which restricts the sample to trades made between December 1, 2009, and February 28, 2010. The variable $announcement_t$ is equal to one if the trade is opened following the CFTC's January 20, 2010, announcement that it was considering measures to limit leverage availability in order to protect trader welfare. The geographical variation in US_i presumably reflects differential levels of exposure and awareness to the CFTC's message. A coefficient estimate for β_3 that is not statistically different from zero would be consistent with a story in which traders are insensitive to heightened awareness of the risks of leverage. This would imply that overconfident beliefs can render an information treatment ineffective.

Estimates of Equation 5 fail to provide evidence that traders respond to the CFTC's announcement that it planned to curb leverage availability. The coefficient on the interaction term between US_i and $announcement_t$ is not statistically distinguishable from zero whether the dependent variable is roi (columns 1 and 2) or $leverage.above50 : 1$ (columns 3 and 4).

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5 Conclusion

This research analyzes new regulation imposed by the CFTC that caps the maximum permissible leverage available to retail foreign exchange traders from the U.S. Retail brokerages in the forex market have clients from around the globe and are responsible for complying with different domestic regulatory regimes. It is therefore possible to compare U.S. traders to their unregulated European counterparts, which allows for a causal interpretation of the availability of leverage on trader activity. Thus, this paper's empirical setting is uniquely suited to understanding the motivation behind trading with leverage and subsequent performance.

According to a simple model of a rational agent who is free from behavioral biases, traders who use leverage take on more risk, and therefore demand higher returns. The CFTC regulation has the opposite effect: the reduction in leverage mitigates trader underperformance. Investor overconfidence – the tendency to hold beliefs that are too precise – can explain these findings. As a result, these findings offer clarity to policy-makers interested in the welfare of consumers that invest in risky asset markets. I find that information revelation or "nudges" may be ineffective at moderating behavior when there are strong behavioral biases, such as overconfidence, that would motivate information neglect. Heavy-handed regulation is therefore more effective.

As a final consideration, I address concern that these results do not apply to household investors more broadly. There is evidence of a negative correlation between leverage and returns among retail stock traders (Goldstein and Krutov (2000)), even in frequently cited account-level data (Linnainmaa (2003)). I also find similar results when I examine all transactions on a large discount brokerage. As such, it is fair to conclude that this paper provides important lessons on the consequences of providing individuals the option to use substantial amounts of leverage on their investments.

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Table 1: **Trader and trade-level summary statistics**

Description: This table presents summary statistics from the myForexBook database, which is trimmed according to the criteria described in Section 3.

	All Traders			
Panel A: *All trades*	mean	std dev	median	N
Trades per account	254.0	885.1	95.0	1069
Fraction trades long per account	0.520	0.188	0.517	1069
Distinct currency pairs traded at least once per account	7.67	5.85	6.0	1069
Trades per account/day	8.68	26.49	3.0	31,296
Fraction traders w/ leverage 50:1 ¿ on at least one trade	0.423	0.494		1069
ROI	99.74	4.84	100.0	271,570
Fraction leverage ¿ 50:1	0.084	0.278		271,570
Leverage	29.89	139.8	3.46	271,570
Holding period (minutes)	978.3	4160.1	64.87	271,570

	U.S. Traders				European Traders			
Panel B: *Pre-CFTC regulation*	mean	std dev	median	N	mean	std dev	median	N
Trades per account	167.4	858.9	57.0	442	164.8	377.6	59.0	534
Fraction trades long per account	0.535	0.215	0.513	442	0.499	0.215	0.50	534
Distinct currency pairs traded at least once per account	6.77	5.10	6.0	442	6.42	5.25	5.0	534
Trades per account/day	9.08	39.78	3.0	442	9.02	20.21	3.0	534
Fraction traders w/ leverage 50:1 ¿ on at least one traded	0.398	0.490		8151	0.397	0.490		9756
ROI	99.63	4.98	100.0	74,003	99.74	4.91	100.0	88,007
Fraction leverage ¿ 50:1	0.084	0.278		74,003	0.106	0.307		88,007
Leverage	29.10	138.4	1.99	74,003	41.09	180.8	4.20	88,007
Holding period (minutes)	1245.2	5430.3	71.20	74,003	1063.4	4703.8	56.62	88,007

	U.S. Traders				European Traders			
Panel C: *Post-CFTC regulation*	mean	std dev	median	N	mean	std dev	median	N
Trades per account	102.5	360.2	35.5	458	114.0	261.8	39.0	549
Fraction trades long per account	0.533	0.244	0.533	458	0.516	0.240	0.517	549
Distinct currency pairs traded at least once per account	5.51	5.10	4.0	458	5.40	4.81	4.0	549
Trades per account/day	7.68	20.72	3.0	6,113	8.60	18.33	4.0	7,278
Fraction traders w/ leverage 50:1 ¿ on at least one trade	0.066	0.248		458	0.319	0.466		549
ROI	99.87	3.93	100.0	46,957	99.76	5.17	100.0	62,603
Fraction leverage ¿ 50:1	0.0031	0.0555		46,957	0.112	0.315		62,603
Leverage	8.43	29.16	2.13	46,957	31.30	122.9	5.47	62,603
Holding period (minutes)	820.2	2299.9	84.50	46,957	661.9	2220.6	58.05	62,603

Table 2: **A comparison of U.S. and European traders**

Description: This table compares traders from the United States to traders from Europe. Panel I includes a comparison of means. Panel II estimates a Probit model in which the dependent variable US_i, is equal to one if a trader is from the United States, zero otherwise.

	Panel 1:			Panel II:		
	Difference in means			Probit estimates (dep. var. $= US_i$)		
	US_i	EU_i	t^a		coef	(s.e.)
age_i	38.33	36.41	3.02	$log.age_i$	0.321	(0.14)**
$experience_i^\dagger$				$experience_i^\dagger$		
0 - 1	0.277	0.332	1.90	0 - 1	-0.252	(0.13)*
1 - 3	0.473	0.466	0.22	1 - 3	-0.131	(0.13)
3 - 5	0.110	0.91	1.05	3 - 5	-0.0271	(0.16)
5 +	0.140	0.106	1.72	5 + (omitted)		
$trading.approach_i^\ddagger$				$trading.approach_i^\ddagger$		
momentum	0.0570	0.0514	0.41	momentum	0.274	(0.24)
news	0.0285	0.0240	0.47	news	0.308	(0.30)
technical	0.631	0.639	0.25	technical	0.163	(0.18)
not specific	0.242	0.229	0.50	not specific	0.222	(0.19)
fundamental	0.0407	0.0564	1.19	fundamental (omitted)		
$number.friends_i$	29.22	23.98	0.88	$log.number.friends_i$	0.0349	(0.026)
N	480	589		N	1069	
				pseudo-R^2	0.0106	

^{a} test of equality of means among US_i and EU_i

Table 3: **Investor overconfidence and reduced leverage availability**

Description: This table reports estimates of the following regression using OLS:

$$roi_{j,i,t} = \gamma_b + \beta_1 \cdot US_i + \beta_2 \cdot constraint_t + \beta_3 \cdot US_i \cdot constraint_t + \beta_4 \cdot US_i \cdot overconfident_i ...$$
$$+ \beta_5 \cdot constraint_t \cdot overconfident_i + \beta_6 \cdot US_i \cdot constraint_t \cdot overconfident_i ...$$
$$+ \beta_7 \cdot F_{p,t} + \beta_8 \cdot \sigma_{i,t}^{ROI} + \beta_9 \cdot Trade_{j,i,t} + \beta_{10} \cdot Investor_i + \epsilon_{j,i,t}$$

where the variable $overconfident_i$ takes on one of three values: (1) $loss\&intensity_i$ is equal to one if a trader is below the median (90th percentile) of average roi and above the median (90th percentile) in the number of trades they execute, (2) $overreact_i$ is equal to one if the trader is above the median (90th percentile) in their propensity to trade in response to the one-day change in the price of the USD/EUR squared, and (3) is equal to one if the trader is above the median (90th percentile) in betweenness centality calculated using the graph of connections formed in the myForexBook network as of September 1, 2010. The other variables are described in previous tables. Standard errors are double-clustered by day and trader, and *, **, and *** denote the following significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

$overconfidence_i =$	$loss\&intensity_i$		$overreact_i$		$betweenness_i$	
	$pr(50)$	$pr(90)$	$pr(50)$	$pr(90)$	$pr(50)$	$pr(90)$
dep var $= roi_{j,i,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$overconfident_i \times constraint_t \times US_i$[†]	0.379***	0.398*	-0.0934	0.580***	0.163*	0.180*
	(0.13)	(0.22)	(0.11)	(0.21)	(0.09)	(0.11)
pair FE	x	x	x	x	x	x
$F_{p,t}$	x	x	x	x	x	x
$\sigma_{i,t}^{ROI}$	x	x	x	x	x	x
brokerage FE	x	x	x	x	x	x
$Investor_i$	x	x	x	x	x	x
N	262,274	262,274	261,635	261,635	269,100	269,100
R^2	0.014	0.014	0.015	0.015	0.014	0.014

predicted margins (setting $constraint_t = 1$ and $US_i = 1$)						
$(overconfident_i = 1) - (overconfident_i = 0)$	0.17	0.43	-0.17	0.09	0.31	0.18

[†]The complete set of possible interactions between $overconfident_i$, $constraint_t$, and US_i are unreported, but included in all regressions

Table 4: **Does the CFTC's announcement matter?**
Description: This table reports estimates of the following regression using OLS:

$$Y_{j,i,t} = \gamma_b + \beta_1 \cdot US_i + \beta_2 \cdot announcement_t + \beta_3 \cdot US_i \cdot announcement_t + \beta_4 \cdot Trade_{j,i,t} + \beta_5 \cdot Investor_i + \epsilon_{j,i,t}$$

where the variable $announcement_i$ is equal to one if the trade is executed after January 20, 2010, zero otherwise. The table includes all trades issued between November 29, 2009 and April 4, 2010. The other variables are described in previous tables. Standard errors are double-clustered by day and trader, and *, **, and *** denote the following significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

dep var =	$roi_{j,i,t}$		$leverage.above50:1_{j,i,t}$	
	(1)	(2)	(3)	(4)
$US_i \times announcement_t$	-0.0390	-0.0399	-0.00134	-0.00127
	(0.14)	(0.14)	(0.021)	(0.010)
US_i	0.0747	0.131	0.0101	0.0135
	(0.16)	(0.16)	(0.021)	(0.0083)
$announcement_t$	0.0813	0.0650	0.0159	0.0137
	(0.10)	(0.098)	(0.017)	(0.0090)
$log\ holding\ period_{j,i,t}$		-0.0807***		-0.0116***
		(0.023)		(0.0011)
$log\ trade\ size_{j,i,t}$		-0.0108		0.00598***
		(0.036)		(0.0021)
$leverage_{j,i,t}$		-0.00316*		-
		(0.0017)		-
pair FE	x	x	x	x
brokerage FE	x	x	x	x
$F_{p,t}$	x	x	x	x
$\sigma_{i,t}^{ROI}$	x	x	x	x
$Investor_i$	x	x	x	x
N	104,585	103,690	103,690	103,690
R^2	0.019	0.022	0.31	0.32

Appendix: Give'em Enough Rope? Leveraged Trading when Investors are Overconfident

A1: A model of overconfidence with leverage constraints

The model herein is closely related to [Odean, 1998]'s treatment of overconfident, price-taking investors. I preserve as closely the structure of [Odean, 1998]'s model with the intention of demonstrating that the settings implies a unique set of results regarding the use of leverage. In particular, the model differs from [Odean, 1998] in that trading takes place in a single round and investors are allowed to costlessly borrow, but may encounter a known constraint on leverage.

The asset market

The model consists of two periods, t, with trading taking place in the first, $t = 1$, and consumption in $t = 2$. To preserve the assumption that traders are price-takers, there are $N \to \infty$ traders, $i = 1, ..., N$. Prior to trading, trader i is endowed with x_{0i} of the risky asset and f_{0i} units of a risk-free asset that earns no returns. In $t = 1$, i demands x_{1i} of the risky asset, reserving the rest of the endowment for f_{1i}. Wealth is $W_{ti} = f_{ti} + P_t x_{ti}$ for $t = \{0, 1\}$ and $W_{2i} = f_{1i} + \tilde{v} x_{1i}$ in $t = 2$, where $\tilde{v}$ is the terminal value of the risky asset and has a normal distribution, $\tilde{v} \sim N(\bar{v}, h_v^{-1})$. Per trader supply of the risky asset $\bar{x}$ is fixed, unchanging, and known to all.

Each trader receives one of $M < N$ private signals prior to trading, $\tilde{y}_{1i} = \tilde{v} + \tilde{\varepsilon}_{1m}$, that they believe to be correct. The noise in the private signals, $\tilde{\varepsilon}_{1m} \sim N(0, h_\varepsilon^{-1})$, is mutually independent. Since some traders are overconfident, they think they are behaving optimally, place too much weight on their private signal, and deviate from the utility maximizing quantity of the risky asset. Equivalent to [Odean, 1998], the average signal at time $t = 1$ is $\bar{Y} = \sum_{i=1}^{N} \frac{y_{1i}}{N} = \sum_{m=1}^{N} \frac{y_{1m}}{M}$.

Traders in the model may be overconfident, which means that they place too much weight, κ, on their signal. Trader i is aware that $N/M - 1$ other traders receive the same two signals as they do and believe the precision to be κh_ε, $\kappa \geq 1$. Increases in κ can be thought of as increased overconfidence. There are $2M - 2$ other signals the precision of which the trader believes is γh_ε, $\gamma \leq 1$. The precision of $\tilde{v}$ is believed to be ηh_v, $\eta \leq 1$, by all traders. The information set available to i at $t = 1$ is $\Phi_{1i} = [y_{1i} \, P_1]^T$.

The trader's problem

Trader i has constant absolute risk aversion in wealth with risk-aversion coefficient a. They solve,

$$\max_{x_{1i}} \mathrm{E}[-\exp(-a(W_{2i}|\Phi_{1i}))] \tag{1}$$

when they trade, which according to Grossman (1976) is equivalent to choosing x_{1i} to maximize

$$\mathrm{E}[W_{2i}|\Phi_{1i}] - \frac{a}{2}\mathrm{Var}[W_{2i}|\Phi_{1i}] . \tag{2}$$

The trader's budget constraint is

$$P_t x_{ti} + f_{ti} \leq P_t x_{t-1i} + f_{t-1i} \,. \tag{3}$$

It is clear from Equation 3 that traders with the highest valuation can costlessly borrow (negative shares of f_{ti}). They can also short the asset (negative shares of x_{ti}) if they have a low valuation of $\tilde{v}$.

Substituting Equation 3 into 2 suggests the trader's problem is to maximize the trade-off between expected risk and return,

$$(\mathrm{E}(\tilde{v}|\Phi_{1i}) - P_1) \cdot x_{1i} - \frac{a \cdot x_{1i}^2}{2} \cdot \mathrm{Var}(\tilde{v}|\Phi_1) \,. \tag{4}$$

Moreover, traders correctly believe that the price of the risky asset, P_1, is a linear function of the average signals,

$$P_1 = \alpha_1 + \alpha_2 \bar{Y} \tag{5}$$

which is an identical conjecture for all traders.

Leverage constraints

Consider the imposition of a constraint on leverage exogenously imposed by a regulator. Similar to Coen-Pirani (2005) or Wang (2012), each trader is subject to the following constraint:

$$cP_t|x_{ti}| \leq P_t x_{t-1i} + f_{t-1i} \tag{6}$$

in which $c \in [0, 1]$. Equation 6 implies that i must finance a fraction c of their purchases (or short sales) of the risky asset out of their own wealth. In fact, the investor's borrowing limit is proportional to their savings. By combining equations 3 and 6 the constraint is equivalent to

$$-f_{ti} \leq \left(\frac{1-c}{c} \right) (P_t x_{t-1i} + f_{t-1i}) \tag{7}$$

when $x_{ti} > 0$ and

$$-P_t x_{ti} \leq \frac{1}{c} (P_t x_{t-1i} + f_{t-1i}) \tag{8}$$

when $x_{ti} < 0$. Otherwise, I assume it is costless to obtain leverage.

Since $N \to \infty$, total supply tends to infinity even with the constraint on leverage. Thus, the average supply available to trader i is $\bar{x}$.

Trading when leverage constraints do not bind

All traders have the same level of risk-aversion. Therefore, I differentiate Equation 4 with respect to x_{1i} to determine i's first order condition, which I rearrange to obtain the average

demand for the risky-asset,

$$x_{1i} = \frac{\mathrm{E}(\tilde{v}|\Phi_{1i}) - P_1}{a \cdot \mathrm{Var}(\tilde{v}|\Phi_1)} \ . \tag{9}$$

Equation 9 is decreasing in the price and the beliefs about volatility of the asset, but increases when the trader believes the asset can earn higher returns.

Trading when leverage constraints bind

The leverage constraint does not directly influence the trader's preferences. Therefore, i solves his maximization problem as if he is unconstrained. If the leverage constraint does not bind, i purchases x_{1i} shares of the risky asset. Similar to Coen-Pirani (2005), traders leverage their wealth to the full extent when the constraint binds. Therefore, i chooses $\frac{1}{c} \times \frac{P_1 x_{0i} + f_{0i}}{P_1}$ when $x_{1i} > \frac{1}{c} \times \frac{P_1 x_{0i} + f_{0i}}{P_1}$ and $-\left(\frac{1}{c} \times \frac{P_1 x_{0i} + f_{0i}}{P_1}\right)$ when $x_{1i} < -\left(\frac{1}{c} \times \frac{P_1 x_{0i} + f_{0i}}{P_1}\right)$. To summarize, the trader's demand function is,

$$x_{1i}^* = \begin{cases} \min\left[x_{1i}, \ \frac{1}{c} \times \frac{P_1 x_{0i} + f_{0i}}{P_1}\right], & if \ x_{1i} \geq 0 \\ \max\left[x_{1i}, \ -\left(\frac{1}{c} \times \frac{P_1 x_{0i} + f_{0i}}{P_1}\right)\right], & if \ x_{1i} < 0 \end{cases} . \tag{10}$$

Equilibrium trading

To show that leverage constraints can improve trader welfare, I solve the model for the case where the representative trader is unconstrained. The model suggests that overconfident investors engage in sub-optimal trading when they are unconstrained. The expected demand for leverage also increases as traders become more overconfident. When investors are overconfident, expected utility falls as borrowing increases, implying that leverage constraints improve welfare.

LEMMA 1: *There is a static equilibrium in which the linear price conjecture in Equation 5 produces linear demand functions. The coefficients are*

$$\alpha_1 = \frac{h_v \bar{v} - (a\bar{x})\left(1 + (\kappa - \gamma) M h_\epsilon / (M-1) \eta h_v\right)}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon} \tag{11}$$

and

$$\alpha_2 = \frac{(\kappa + \gamma M \eta - \gamma) h_\epsilon}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon}. \tag{12}$$

Proof: I solve the trader's optimization problem by calculating the trader's information set at $t = 1$. Trader i believes Φ_{1i} has a multivariate normal distribution. I include the subscript "b" to indicate that the expectations operator implies i's conjecture, while the subscript "a" denotes actual expected values. The mean and covariance matrix are believed to be,

$$\mathrm{E}_b(\Phi_{1i}) = \mathrm{E}_b[y_{1i} \ P_2]^T = [\bar{v} \quad \alpha_1 + \alpha_2 \bar{v}]^T \tag{13}$$

and

$$\Psi = \begin{bmatrix} \frac{1}{\eta h_v} + \frac{1}{\kappa h_\epsilon} & \frac{\alpha_2}{\eta h_v} + \frac{\alpha_2}{\kappa h_\epsilon M} \\ \\ \frac{\alpha_2}{\eta h_v} + \frac{\alpha_2}{\kappa h_\epsilon M} & \frac{\alpha_2^2}{\eta h_v} + \frac{\alpha_2^2(\gamma + \kappa M - \kappa)}{\kappa \gamma h_\epsilon M^2} \end{bmatrix}. \tag{14}$$

Define the covariance between the fundamental value and the information set as,

$$A^T \equiv \mathrm{cov}_b(\tilde{v}, \Phi_{1i}) = [(\eta h_v)^{-1} \quad \alpha_2(\eta h_v)^{-1}]^T. \tag{15}$$

By the projection theorem,

$$\begin{aligned} \mathrm{E}_b(\tilde{v}|\Phi_{1i}) &= \bar{v} + A\Psi^{-1}(\Phi_{1i} - \mathrm{E}_b(\Phi_{1i})) \\ &= \frac{(\kappa - \gamma)h_\epsilon y_{1i} + \gamma M \eta h_\epsilon \bar{Y} + h_v \bar{v}}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon} \end{aligned} \tag{16}$$

and since traders have identical conditional variance,

$$\begin{aligned} \mathrm{Var}_b(\tilde{v}|\Phi_1) &= (\eta h_v)^{-1} - A\Psi^{-1}A^T \\ &= \frac{1 + (\kappa - \gamma)Mh_\epsilon/(M-1)\eta h_v}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon}. \end{aligned} \tag{17}$$

Appendix A5 presents the intermediary steps used in the development of Equations 16 and 17.

To ensure the market clears, I equate average demand (Equation 9) with average supply,

$$\bar{x} = \frac{\mathrm{E}_b(\tilde{v}|\Phi_{1i}) - P_1}{a \mathrm{Var}_b(\tilde{v}|\Phi_1)} \tag{18}$$

and solve for P_1,

$$\begin{aligned} P_1 &= \frac{(\kappa - \gamma + \gamma M \eta) h_\epsilon \bar{Y} + h_v \bar{v}}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon} - \frac{1 + (\kappa - \gamma)Mh_\epsilon/(M-1)\eta h_v}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon} a\bar{x} \\ &= \frac{h_v \bar{v} - (a\bar{x})(1 + (\kappa - \gamma)Mh_\epsilon/(M-1)\eta h_v)}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon} + \frac{(\kappa + \gamma M \eta - \gamma) h_\epsilon}{\eta h_v + (\kappa + \gamma M - \gamma) h_\epsilon} \bar{Y}. \end{aligned} \tag{19}$$

The coefficient values in Equation 19 match the projected coefficient values in Equations 11 and 12. Therefore, the model produces a static equilibrium.

Before examining how overconfidence and leverage constraints affect trader welfare, this is a good point to consider how prices develop in the model. Turning to Equation 19, it is clear that prices respond positively to demand shocks, $\bar{Y}$, and negatively to supply shocks, $\bar{x}$. Prices are a multiple of the fundamental value, $\bar{v}$. The relationship between P_1 and κ is governed by the relative elasticity of supply and demand, but is otherwise indeterminate.

Overconfidence, leverage, and expected utility

PROPOSITION 1: *If $M \geq 2$ the average expected utility will be lower when $\kappa > 1$ than when $\kappa = 1$.*

Proof: To simplify the analysis, I set $\eta = 1$ and $\gamma = 1$. Maximizing utility involves finding the optimal balance between risk and return (Equation 4). To prove that overconfident investors have lower expected utility, I solve the representative trader's problem for the case in which he has perfectly calibrated beliefs about the asset's payoff, which are equal to the unconditional expectations of Equations 16 and 17 ($\mathrm{E}(\tilde{v}) = \bar{v}$ and $\mathrm{Var}(\tilde{v}) = h_v^{-1}$). I then follow the same steps as in Lemma 1, solving the trader's first order condition, setting demand equal to supply, and rearranging to obtain the equilibrium price of the risky asset. The pricing equation becomes $P_1 = \bar{v} - \left(\frac{a}{h_v}\right)\bar{x}$, which I substitute back into the demand function in Equation 9. The trader maximizes their utility by choosing a value equal to average supply, $\bar{x}$, a result that can also be found in Grossman (1976). Therefore, since $\bar{x}$ is the best the trader can do for a given set of parameter values, any deviation in demand from $\bar{x}$ represents sub-optimal trading in risk-return space as defined in Equation 4.

Following the steps outlined in [Odean, 1998], the expected average deviation from the utility maximizing demand for the risky asset is equal to:

$$\mathrm{E_a}\left(\sum_{i=1}^{N} \frac{|x_{1i} - \bar{x}|}{N}\right).$$ (20)

Expression 20 can be solved by substituting Equations 16 and 17 and the equilibrium price (Equation 19) into the trader's demand function when the trader is overconfident (Equation 9). I use the derivation of x_{1i} to develop the following expression:

$$
\begin{aligned}
x_{1i} - \bar{x} &= \frac{\frac{(\kappa-1)h_\epsilon y_{2i} + Mh_\epsilon \bar{Y} + h_v \bar{v}}{h_v + (\kappa+M-1)h_\epsilon} - \frac{h_v \bar{v} - (a\bar{x})(1+(\kappa-1)Mh_\epsilon/(M-1)h_v)}{h_v + (\kappa+M-1)h_\epsilon} - \frac{(\kappa+M-1)h_\epsilon}{h_v + (\kappa+M-1)h_\epsilon}\bar{Y}}{a\left(\frac{1+(\kappa-1)Mh_\epsilon/(M-1)h_v}{h_v + (\kappa+M-1)h_\epsilon}\right)} - \bar{x} \\
&= \frac{(\kappa-1)h_\epsilon y_{2i} + Mh_\epsilon \bar{Y} + h_v \bar{v} - h_v \bar{v} + (a\bar{x})\left(1 + (\kappa-1)Mh_\epsilon/(M-1)h_v\right) - (\kappa+M-1)h_\epsilon \bar{Y}}{a\left(1 + (\kappa-1)Mh_\epsilon/(M-1)h_v\right)} - \bar{x} \\
&= \frac{(\kappa-1)h_\epsilon}{a\left(1 + (\kappa-1)Mh_\epsilon/(M-1)h_v\right)}\left(y_{1i} - \bar{Y}\right).
\end{aligned}
$$ (21)

At this point, I return to expression 20, moving the expectations operator inside the summation and N outside the summation. The expectations of the absolute value of a random variable yields a half-normal distribution, $\sigma \frac{\sqrt{2}}{\sqrt{\pi}}$. Recalling the variance of y_{1i} and $\bar{Y}$,

$$
\begin{aligned}
\mathrm{E_a}|x_{1i} - \bar{x}| &= \sqrt{\left(\frac{(\kappa-1)h_\epsilon}{a\left(1 + (\kappa-1)Mh_\epsilon/(M-1)h_v\right)}\right)^2 \left(\left(\frac{1}{h_v} + \frac{1}{h_\epsilon}\right) - \left(\frac{1}{h_v} + \frac{1}{h_\epsilon M}\right)\right)} \times \frac{\sqrt{2}}{\sqrt{\pi}} \\
&= \frac{\kappa-1}{a\left(1 + (\kappa-1)Mh_\epsilon/(M-1)h_v\right)} \times \sqrt{\frac{2(M-1)h_\epsilon}{M\pi}}.
\end{aligned}
$$ (22)

The summation contains N identical versions of $E_a|x_{1i} - \bar{x}|$, which implies

$$E_a \left(\sum_{i=1}^{N} \frac{|x_{1i} - \bar{x}|}{N} \right) = \frac{\kappa - 1}{a\left(1 + (\kappa - 1)Mh_\epsilon/(M-1)h_v\right)} \times \sqrt{\frac{2(M-1)h_\epsilon}{M\pi}} . \qquad (23)$$

Equation 23 produces a result similar to [Odean, 1998].[1] Increases in the degree of overconfidence increase the deviation from the optimal holdings of the risky-asset within the given parameter range ($\kappa > 1$ and $M \geq 2$).[2] Considering the assumption of CARA utility, traders like higher returns, but dislike risk, and improvement along either margin increases expected utility (Equation 2). Traders believe they are behaving optimally, but in fact engage in sub-optimal trading in risk-return space.[3] ∎

PROPOSITION 2: *If $M \geq 2$ and $x_{0i} > 0$ the average expected demand for leverage will be higher when $\kappa > 1$ than when $\kappa = 1$.*

Proof: Prior to trading, i is endowed with shares of a risky and risk-less asset. Traders can use their endowment to purchase more shares (or short sell) the risky asset. Leverage is the ratio of total demand for the risky-asset, $P_1 x_{1i}$, to wealth, $P_1 x_{0i} + f_{0i}$. Thus, the average expected demand for leverage in the market is

$$E_a \left(\sum_{i=1}^{N} \frac{1}{N} \left| \frac{P_1 x_{1i}}{P_1 x_{0i} + f_{0i}} \right| \right) . \qquad (24)$$

To simplify the exposition, I set the endowment of the risk-less asset $f_{0i} = 0$.[4] I follow a similar set of steps as in the proof of Proposition 1, first developing an expression for the

---

[1] The three period version of the model in [Odean, 1998] produces a different functional form, but the same comparative statics.

[2] The partial derivative of $E_a \left(\sum_{i=1}^{N} \frac{|x_{1i} - \bar{x}|}{N} \right)$ with respect to κ is $\left(\frac{1}{(1+(\kappa-1)Mh_\epsilon/(M-1)h_v)} - \frac{(\kappa-1)Mh_\epsilon}{(1+(\kappa-1)Mh_\epsilon/(M-1)h_v)^2(M-1)h_v} \right) \times \left(\frac{1}{a} \right) \times \sqrt{\frac{2(M-1)h_\epsilon}{M\pi}}$. The first expression in parentheses can be rearranged to produce $\left(\frac{1}{(1+(\kappa-1)Mh_\epsilon/(M-1)h_v)} \right) \times \left(\frac{(M-1)h_v}{(M-1)h_v + (\kappa-1)Mh_\epsilon} \right)$ which is clearly positive when $\kappa > 1$ and $M \geq 2$.

[3] Another way to approximate the result in Proposition 1 is to examine the average difference in utility between the perfectly-calibrated and overconfidence models, $E_a[U(x) - U(x')']$, where the apostrophe belongs to the equilibrium solution from the model with overconfidence. Substituting Equation 4 into the above expression and rearranging, as well using the fact that $E_a(x)$ and $E_a(x')$ are unbiased estimates of $\bar{x}$ (the latter containing noise), yields $E_a[x \cdot (\bar{v} - P)] - E_a[x' \cdot (\bar{v} - P')]$, which is equal to $E_a(x) \cdot E_a(\bar{v} - P) - E_a(x') \cdot E_a(\bar{v} - P') + \text{cov}_a(x, \bar{v} - P) - \text{cov}_a(x', \bar{v} - P')$. Price is a projection of the fundamental value in both the perfectly-calibrated and overconfidence models, but is otherwise an indeterminate function of the parameters (Equation 19 and the first part of the proof of Proposition 1). This implies $E_a(x) \cdot E_a(\bar{v} - P) - E_a(x') \cdot E_a(\bar{v} - P')$ is centered about zero. However, overconfident traders place more weight on their own signal than they do all others signals, the latter of which plays a more prominent role in determining returns on the risky asset (recall that price is driven by the aggregate signals). Thus, $\text{cov}_a(x, \bar{v} - P)$ is strictly greater than $\text{cov}_a(x', \bar{v} - P')$, which implies $E_a[U(x) - U(x')']$ tends to be greater than zero.

[4] When $f_{0i} \neq 0$, the rightward most term in expression 25 is a weighted average of the endowment in the risky and risk-less asset, $\frac{1}{x_{0i} + (h_v + (\kappa + M - 1)h_\epsilon)f_{0i}}$.

term contained within the absolute value,

$$\frac{P_1 x_{1i}}{P_1 x_{0i}} = \frac{(a\bar{x})\left(1 + (\kappa - 1) M h_\epsilon / (M-1)h_v\right) + (\kappa - 1)h_\epsilon \left(y_{1i} - \bar{Y}\right)}{a\left(1 + (\kappa - 1) M h_\epsilon / (M-1)h_v\right)} \left(\frac{1}{x_{0i}}\right). \qquad (25)$$

I then proceed to generate N identical half-normal distributions. Therefore, the average demand for leverage in the market is clearly,

$$\mathrm{E_a}\left(\sum_{i=1}^{N} \frac{1}{N} |\frac{P_1 x_{1i}}{P_1 x_{0i} + f_{0i}}|\right) = \frac{\kappa - 1}{a\left(1 + (\kappa - 1) M h_\epsilon / (M-1)h_v\right)} \times \sqrt{\frac{2\left(M-1\right)h_\epsilon}{M\pi}} \times \left(\frac{1}{x_{0i}}\right). \qquad (26)$$

Equation 26 is equal to Equation 23 scaled by the inverse of wealth. Since Equation 23 is positive for $\kappa > 1$ and $M \geq 2$, it is clear that Equation 26 is also positive when $x_{0i} > 0$. It is also evident from Equation 26 that the demand for leverage falls as the endowment increases, so long as there is some degree of overconfidence. ∎

PROPOSITION 3: *If $M \geq 2$ and $\kappa > 1$ the average expected utility will be lower when the demand for leverage is higher.*

Proof: The proof of Proposition 3 uses the solutions derived in the proofs of Propositions 1 and 2. Equation 23 provides an expression for the average expected deviation from the utility maximizing level of demand, while Equation 26 is the average expected demand for leverage in the market. Thus, I compute how the reduction in utility changes as the demand for leverage increases by taking the total differential of the following,

$$d\left(\frac{\mathrm{E_a}\left(\sum_{i=1}^{N} \frac{|x_{1i} - \bar{x}|}{N}\right)}{\mathrm{E_a}\left(\sum_{i=1}^{N} \frac{1}{N} |\frac{P_1 x_{1i}}{P_1 x_{0i} + f_{0i}}|\right)}\right) = d\left(\frac{\frac{\kappa - 1}{a(1 + (\kappa - 1)M h_\epsilon / (M-1)h_v)} \times \sqrt{\frac{2(M-1)h_\epsilon}{M\pi}}}{\frac{\kappa - 1}{a(1 + (\kappa - 1)M h_\epsilon / (M-1)h_v)} \times \sqrt{\frac{2(M-1)h_\epsilon}{M\pi}} \times \left(\frac{1}{x_{0i}}\right)}\right)$$
$$= x_{0i} \cdot \frac{d}{dx_{0i}}. \qquad (27)$$

Equation 27 is clearly positive when there is some degree of overconfidence, which implies that an increase in the demand for leverage reduces expected utility. Owing to this result, we can make the following conjecture: when investors are overconfident, leverage constraints can improve welfare. ∎

It should be noted that an alternative approach to proving Proposition 3 is to compare the average expected utility loss when the constraint is not binding (Equation 20) to the case when the constraint binds. The average expected utility loss when demand is bound by the constraint is $\mathrm{E_a}\left(\sum_{i=1}^{N} \frac{|x_{1i}^c - \bar{x}|}{N}\right)$, where x_{1i}^c is equal to average demand when the leverage constraint holds (see the constrained case of the demand function in Equation 10). Setting demand in the constrained case equal to per-trader supply, equilibrium price becomes a function of the size of the constraint, the endowment, and the average supply. The price is perfectly revealing since it is a function of known constants, no longer reflecting

the uncertainty over interpretation of the private signals. After using the equilibrium price to solve for x_{1i}^c, it is clear the expression $\mathrm{E_a} \left(\sum_{i=1}^N \frac{|x_{1i}^c - \bar{x}|}{N} \right)$ is equal to zero, because both variables inside the absolute value consist of known constants.

Therefore, $\mathrm{E_a} \left(\sum_{i=1}^N \frac{|x_{1i} - \bar{x}|}{N} \right) - \mathrm{E_a} \left(\sum_{i=1}^N \frac{|x_{1i}^c - \bar{x}|}{N} \right)$ is equal to Equation 23, which according to Proposition 1 is greater than zero when $M \geq 2$ and $\kappa > 1$, and a positive function of κ within the given parameter range. Similar to the proof of Proposition 3, the welfare loss is greater on average when traders are overconfident and unconstrained.

A2: Betweenness centrality

Glossary

- **graph:** a set of vertices and edges.

- **vertex:** a node or point.

- **edge:** a line connecting two vertices.

- **path:** the route taken to travel between two vertices. The two vertices may be directly connected by two edges, may require travel through at least one vertices, or there may be no path connecting two vertices.

- **directed/undirected graph:** in a directed graph, travel between two vertices may only be possible in one direction, i.e. vertex i to j, but not j to i. In an undirected graph, travel is possible in both directions for all edges.

- <u>**Betweenness Centrality:**</u>

$$C_B(v) = \left(\sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}} \right) \times \left(\frac{1}{(n-1)(n-2)/2} \right)$$

measures the centrality of node v in undirected graph G. σ_{st} is the total number of shortest paths from nodes s to node t, and $\sigma_{st}(v)$ is the number of those paths that pass through v. n is the number of vertices in the graph and the second term on the right hand side of the expression normalizes the measure such that $C_B(v) \in [0, 1]$.

A3: Alternative explanations drawn from the friction-based asset-pricing literature

A recent class of theoretical models develops an inverse relation between leverage constraints and returns, even when investors have conventional beliefs. I explore the implications of these models and how they relate to the empirical setting studied in this paper.

Frictional Asset Pricing and Returns

Financial frictions potentially influence asset prices. In one example ([Frazzini and Pedersen, 2014]), when the ability to borrow is reduced, investors rebalance their portfolios toward more volatile assets, because a highly leveraged, less-volatile asset has a return distribution that is similar to an unleveraged, high-volatility asset. The required return on high-volatility assets falls as a result of the increase in demand for these assets.

An analogy to the currency markets is trading during periods of high or low volatility. According to [Frazzini and Pedersen, 2014], the leverage constraint would reduce required returns when the markets are more volatile, and the differences in profitability following the regulation could be a residual effect of risk-shifting. Therefore, the marginal effect on trader profitability following the CFTC regulation will be higher (lower) on days when currency market volatility is low (high).

The following regression model tests whether the effect of the CFTC regulation relates to currency market volatility:

$$roi_{j,i,t} = \gamma_b + \beta_1 \cdot US_i + \beta_2 \cdot IV_t + \beta_3 \cdot US_i \cdot constraint_t + \beta_4 \cdot US_i \cdot IV_t + \beta_5 \cdot constraint_t \cdot IV_t ...$$
$$+ \beta_6 \cdot US_i \cdot constraint_t \cdot IV_t + \beta_7 \cdot F_{p,t} + \beta_8 \cdot \sigma_{i,t}^{ROI} + \beta_9 \cdot Trade_{j,i,t} + \beta_{10} \cdot Investor_i + \epsilon_{j,i,t}.$$
$$(28)$$

The model introduces IV_t, which is equal to one if trade j, issued by investor i, at time t is issued on the day in which the measure of implied volatility is at its weekly high, zero otherwise. I use two different measures of IV_t. The first, vxy, is provided by JP Morgan and is calculated based on three-month at-the-moment forward volatility, which are combined with a fixed set of weights to produce a daily result. The second, $cvix$, is a weighted average of the three-month implied volatility across nine major currency pairs produced by Deutsche Bank. The coefficient of interest is on the interaction term between the group of constrained investors ($US_i \cdot constraint_t$ or $above50_i \cdot constraint_t$) and the implied volatility metric.

[insert Table A.1 about here]

Table A.1 reports estimates of the marginal contribution of marketwide implied volatility on trader returns. Columns (1) through (4) present the coefficient and standard errors from the triple-interaction between IV_t and $US_i \cdot constraint_t$ or $above50_i \cdot constraint_t$.

None of the four possible coefficients are statistically different from zero. The coefficients are small in absolute value and are just as likely to be positive or negative. There is no evidence that risk-shifting can explain why leverage has an effect on trader profits.

Other explanations in a general equilibrium setting

In a general equilibrium setting, leverage constraints combined with the interaction between the markets for risky and risk-free assets can produce increases in excess returns ([Coen-Pirani, 2005]). Reductions in leverage force investors to sell-off risky assets to meet margin calls. The rate of return on the corresponding risk-free asset has to fall in order for risk-averse investors to absorb excess supply. While the price of the risky asset remains constant and potentially rises under certain conditions (excess returns increase), its volume and volatility increase.

There are a few reasons why this explanation is unlikely. First, the empirical analysis − late-2010 − is set during a period in which the return on U.S. bonds was already close to zero, leaving little room for downward price pressure. Secondly, as illustrated in Table ??, trading volume fell in response to the CFTC regulation, at least among retail traders. Lastly, the theory produces an increase in asset price volatility. Regardless, a formal test − detailed in A.3 − provides no evidence that the regulation had an impact on currency price volatility.

Borrowing constraints in markets with information asymmetry may also affect asset prices ([Yuan, 2005]). When prices are high, informed investors can easily raise arbitrage capital, and their demand transmits price-relevant information about fundamentals. On the other hand, it tends to be more difficult for informed investors to borrow when prices are low. Uninformed traders thus have trouble discerning whether the low price is indicative of a low valuation or reflects the inability of informed investors to borrow.

The theory implies that the influence of the regulation will be strongest when prices are falling. Similar to the test in Section examining the marginal impact of implied volatility on returns following the regulation, I create a variable DXY_t which is equal to one if the daily change in a dollar index of the spot exchange rate (DXY) is at its weekly low.[5] The coefficient on the interaction term $US_i * constraint_t * DXY_t$ is 0.089, but is not statistically different from zero (s.e. = 0.08). Alternative ways of measuring DXY_t do not change the results (unreported), which suggests information asymmetries have trouble explaining the effect of the reduction in leverage.

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[5]DXY is obtained from Bloomberg.

Table A.1: **Does risk-shifting explain the increase in ROI?**

Description: This table reports estimates of the following regression using OLS:

$$roi_{j,i,t} = \gamma_b + \beta_1 \cdot US_i + \beta_2 \cdot constraint_t + \beta_3 \cdot US_i \cdot constraint_t + \beta_4 \cdot US_i \cdot IV_t ...$$
$$+ \beta_5 \cdot constraint_t \cdot IV_t + \beta_6 \cdot US_i \cdot constraint_t \cdot IV_t ...$$
$$+ \beta_7 \cdot F_{p,t} + \beta_8 \cdot \sigma_{i,t}^{ROI} + \beta_9 \cdot Trade_{j,i,t} + \beta_{10} \cdot Investor_i + \epsilon_{j,i,t}$$

where the variable IV_t is equal to one if implied volatility is at the weekly high, zero otherwise. IV_t is either from JP Morgan, vxy_t, or Deutsche Banke,$cvix_t$. The other variables are described in previous tables. Standard errors are double-clustered by day and trader, and *, **, and *** denote the following significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	$IV_t=vxy_t$	$IV_t=cvix_t$		$IV_t=vxy_t$	$IV_t=cvix_t$
dep var $= roi_{j,i,t}$	(1)	(2)	dep var $= roi_{j,i,t}$	(3)	(4)
$US_i \times constraint_t \times IV_t$†	0.0267	-0.0312	$above50_i \times constraint_t \times IV_t$†	-0.00700	0.133
	(0.12)	(0.13)		(0.13)	(0.13)
$US_i \times constraint_t$	0.309***	0.320***	$above50_i \times constraint_t$	0.263***	0.233***
	(0.11)	(0.11)		(0.11)	(0.11)
US_i	-0.0850	-0.00959	$above50_i$	-0.646***	-0.617***
	(0.097)	(0.098)		(0.10)	(0.10)
$constraint_t$	0.0164	-0.00531	$constraint_t$	0.0127	0.00597
	(0.063)	(0.064)		(0.028)	(0.028)
pair FE	x	x	pair FE	x	x
brokerage FE	x	x	brokerage FE	x	x
$F_{p,t}$	x	x	$F_{p,t}$	x	x
$\sigma_{i,t}^{ROI}$	x	x	$\sigma_{i,t}^{ROI}$	x	x
$Investor_i$	x	x	$Investor_i$	x	x
N	263,624	263,624		263,624	263,624
R^2	0.0071	0.0072		0.0096	0.0096

†The complete set of possible interactions between US_i ($above50_i$), $constraint_t$, and US_i are included in all regressions

A4: An endogenous change in intraday market conditions?

As emphasized in the introduction, much research shows that retail traders influence asset prices. Therefore, a potential explanation for the increase in performance following the leverage constraint is that the reduction in retail volume among U.S. participants reshaped the currency markets in a way favorable to U.S. investors. For the most part, any differences in market conditions would have been captured by the inclusion of European traders as a control group in the previous analysis. However, one key difference between U.S. and European traders is unaccounted for: during the morning trading hours in Europe, it is shortly after midnight in North America. Consequently, as illustrated in Figure A.1, there are intraday differences in trading volume, with U.S. investors playing less of a role during the European morning.

In order to investigate this explanation, I test if intraday currency-price volatility changed following the CFTC regulation. Table A.2 reports estimates of the following regression estimated via OLS:

$$\sigma_{c,t,h} = \gamma_0 + \gamma_1 * US\ morning_h + \gamma_2 * constraint_t + \gamma_3 * US\ morning_h * constraint_t ...$$

$$+ \sum_{i=2}^{11} \gamma_{4,i} * Pair_p + \epsilon_{c,t,h} \quad (29)$$

where $\sigma_{p,t,h}$ is the standard deviation of the price of currency pair p, on day t, between the hours indicated in h. The variable $\sigma_{p,t,h}$ is calculated in two ways. In the first column, the dependent variable is the standard deviation of the difference between the high and low price within a given hour. In the second column, $\sigma_{p,t,h}$ is the standard deviation of the price taken at ten-minute intervals. The variable, $US\ morning_h$, is equal to one if the time the price is recorded is between 11 and 16 GMT and equal to zero if between 5 and 10 GMT. All other hours are excluded from the calculation. $Pair_p$ is a categorical variable indicating each currency pair. Weekends are also removed from the analysis, and the regression is estimated with weights indicating the proportion of retail trading volume devoted to each pair during the pre-constraint period.

The coefficient on the interaction between $US\ morning_h$ and $constraint_t$, γ_3, measures the extent to which morning trading hours in the U.S. were influenced by the reduction in leverage available to retail traders relative to morning trading hours in Europe. According to the estimation results, the difference in intraday volatility is not statistically different from zero. Therefore, it is unlikely that intraday market conditions changed in a manner that would have benefited U.S. retail traders relative to Europeans.

Figure A.1: **Intraday trading volume**
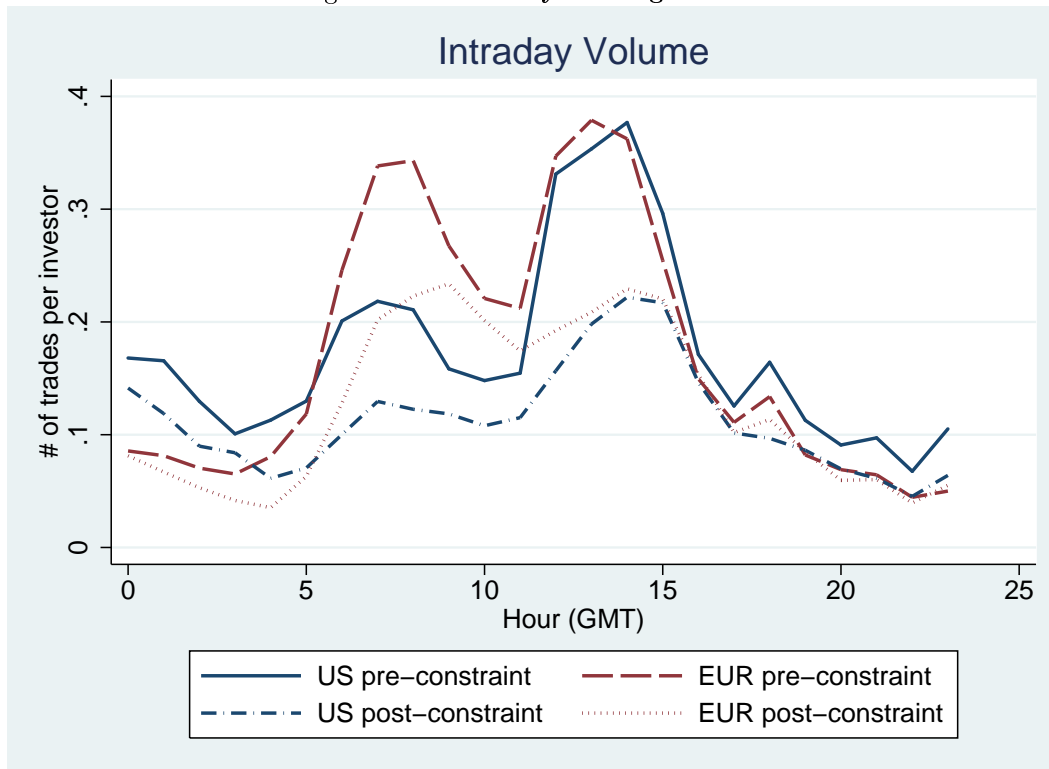
Description: This figure plots the intraday trading volume of U.S. and European retail investors before and after the CFTC mandated reduction in leverage. The measure of volume is the number of positions opened per hour divided by the number of traders by locale in the sample.

Table A.2: **Did the CFTC regulation impact intraday markets?**

Description: This table reports estimates of the following regression estimated via OLS:

$$\sigma_{p,t,h} = \gamma_0 + \gamma_1 \cdot US\,morning_h + \gamma_2 \cdot constraint_t + \gamma_3 \cdot US\,morning_h \cdot constraint_t + \sum_{i=2}^{11} \gamma_{4,i} \cdot Pair_p + \epsilon_{p,t,h}$$

where $\sigma_{p,t,h}$ is the standard deviation of the price of currency pair p, on day t, between the hours h. $\sigma_{p,t,h}$ is calculated in two ways. In the first column, the dependent variable is the standard deviation of the difference between the high and low price within a given hour. In the second column, $\sigma_{p,t,h}$ is the raw standard deviation of the price taken at ten-minute intervals. The variable, $US\,morning_h$, is equal to one if the time the price is recorded is between 11 and 16 GMT and equal to zero if between 5 and 10 GMT. All other trading hours are excluded from the calculation. $constraint_t$ is equal to one if the trade was opened after the CFTC regulation went into effect on October 18, 2010, and $Pair_p$ is a categorical variable indicating each currency pair. Weekends are removed from the analysis. The regression is run with weights indicating the proportion of trading volume devoted to each pair. Standard errors are double-clustered by day and pair.

| $\sigma_{p,t,h}$	(1) intra-hour high-low	(2) 10-min open
$constraint_t * US\,morning_h$	-0.00195	-0.00270
	(0.0018)	(0.0034)
$constraint_t$	-0.000420	0.0123
	(0.0011)	(0.011)
$US\,morning_h$	0.00107	0.0000453
	(0.0014)	(0.0020)
$constant$	0.000903	0.00913
	(0.00072)	(0.0058)
pair FE	x	x
$F_{p,t}$	x	x
N	1,430	1,430
R^2	0.680	0.756

A5. Supplementary Tables and Figures

Table A.3: **The CFTC trading rule and leverage constraints**

Description: This table lists the currency pairs effected by the CFTC trading rule reducing the amount of leverage from 100:1 to either 50:1 or 20:1.

50:1 leverage				
USD/JPY	AUD/NZD	NZD/CAD	EUR/GBP	GBP/USD
USD/CHF	USD/SEK	CHF/JPY	EUR/JPY	GBP/JPY
AUD/USD	USD/DKK	CAD/JPY	EUR/AUD	GBP/CHF
USD/CAD	USD/NOK	CAD/CHF	EUR/CAD	GBP/CAD
NZD/USD	AUD/CHF	CHF/SEK	EUR/SEK	GBP/NZD
AUD/CAD	NOK/JPY	CHF/NOK	EUR/NOK	GBP/AUD
AUD/JPY	SEK/JPY	EUR/USD	EUR/NZD	GBP/SEK
NZD/JPY	NZD/CHF	EUR/CHF	EUR/DKK	

| 20:1 leverage				
USD/MXN	USD/CZK	USD/HKD	USD/RUB	ZAR/JPY
EUR/PLN	USD/ZAR	SGD/JPY	EUR/HUF	
USD/PLN	USD/SGB	USD/TRY	USD/HUF	
EUR/CZK	HKD/JPY	EUR/TRY	TRY/JPY	

Figure A.2: **myForexBook user homepage**
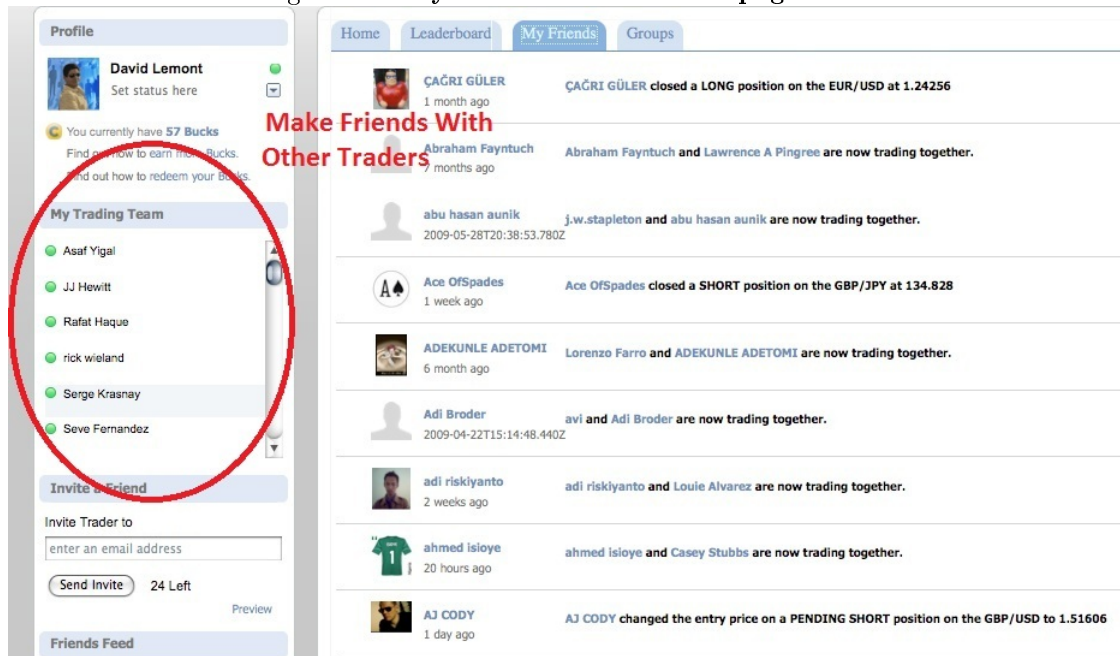
Description: This figure displays the user homepage for a member of myForexBook. Users are able to form bi-lateral friendships with other traders and communicate via private message or in the chat forum.

Figure A.3: **When do retail investors trade?**
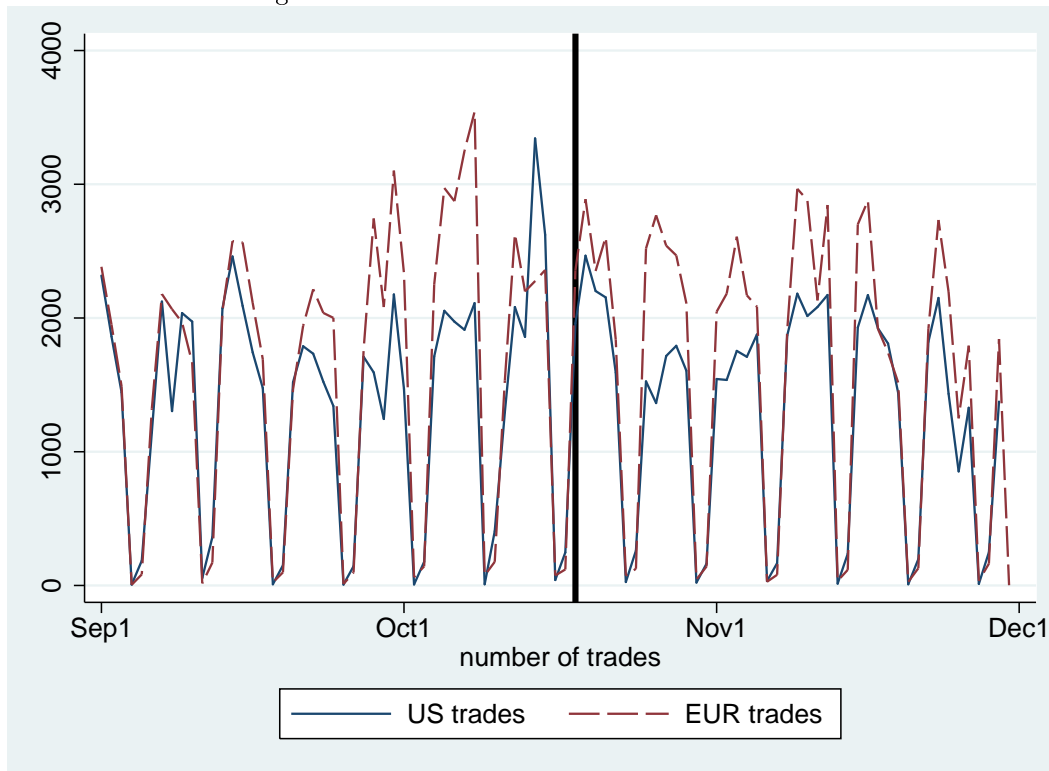
Description: This figure plots the total number of opened positions per day by U.S. and European investors in the trimmed sample described in Section **??**. The valleys in the time series correspond to weekends while the majority of trading occurs during weekdays. The black vertical bar indicates the date that the CFTC trading rule was implemented, October 18, 2010.

Table A.4: **Correlated activity between U.S. and European traders**

Description: This table presents Pearson's correlation coefficients from daily fluctuations in aggregate trading activity between U.S. and European traders i. Variables y are averaged by day t and daily changes are calculated as follows: $log\left(y_{t,i}/y_{t-1,i}\right)$. Weekends are excluded from the calculations.

	Pearson's correlation coefs
ROI	0.422
Leverage	0.357
Volume	0.965

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