Leverage Constraints, Profitability, and Risk-Shifting: Evidence from the Introduction of Dodd-Frank

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Abstract

This paper provides evidence that leverage constraints can improve investor welfare, reducing unprofitable speculation. In accordance with Dodd-Frank, the CFTC was given regulatory authority over the retail (household) market for foreign exchange and capped the maximum permissible leverage available to U.S. traders. By comparing U.S. traders on the same brokerages with their unregulated European counterparts, I show that the leverage constraint brought a reduction in average losses with no change in the volatility of their returns. Unable to use leverage to generate volatility, investors trade more frequently on days with high implied volatility, a form of risk shifting. Overconfident investors benefit most from the regulation.

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The debate among policy makers and academics regarding the role of leverage in financial markets stems back to at least the Stock Market Crash of 1929.[1] Asset price bubbles appear to be fueled by increased opportunities to use leverage, aiding speculative activity. This association has been documented as early as the South Sea Bubble of the 1700s. More recently, the global financial crisis that began in 2007-2008 was characterized by high household leverage ratios. The required down payment on a home in the U.S. hit a decade low at the peak of the housing bubble (Fostel and Geanakoplos (2012)) and the countries experiencing the largest run-up in household debt tend to have been affected most by the crisis (Glick and Lansing (2010)).

The correlation between leverage and asset prices notwithstanding, conventional theoretical models assuming a representative agent with rational expectations have difficulty producing this relationship. The interest rate is the variable of interest within this framework, while borrowing restrictions act as a friction reducing the welfare of low-wealth investors. On the other hand, heterogeneous or distorted beliefs have emerged as a key ingredient in a class of models capable of generating deviations of price above fundamentals (Hong and Sraer (2012), Geanakoplos (2010), Scheinkman and Xiong (2003), Minsky (1986)). Leverage is used herein by the most optimistic or overconfident investors to speculate on the resale value of the asset.

Despite tension between these two settings, there are few studies investigating the impact of leverage on individual trading activity largely due to difficulties obtaining the necessary data and challenges isolating a causal effect.[2] This research uses a new, proprietary database

[1] The Securities Exchange Act of 1934 gave the Federal Reserve System authority to regulate the amount of available leverage. See Galbraith (1993) and Moore (1966) for discussion.

[2] Providing empirical evidence on leverage in the housing market, Haughwout, et. al. (2011)) show that highly levered real estate speculators owned nearly half of all mortgages in the U.S. states most affected by the recent home price bubble and bust, while Chinco and Mayer (2012) show that distant home buyers may

provided by a Facebook-style social network for retail traders that compiles individual trading records across 45 different online brokerages.[3] To overcome the problem of endogeneity due to the relationship between leverage availability, prices, and unobservable investor characteristics such as sentiment,[4] I exploit the variation in leverage available across countries brought about by Commodity Futures Trading Commission (CFTC) regulation implemented in October, 2010 capping the amount available to U.S. retail forex traders at 50:1. European traders unaffected by the U.S. law change also hold accounts on the same brokerages and empirical tests show they make for a good control group with which to compare to their U.S. counterparts.

There is evidence of a strong, negative correlation between the amount of leverage used and per-trade returns. A one unit increase in the amount of leverage (for instance, 20:1 to 21:1) is associated with a decrease in the per-trade return on investment of about 0.016 percent. Indicative of a causal relationship, U.S. investors increase their profitability (reduce their losses) by around 0.1 to 0.15 percent per trade relative to the European control group. The gains in profitability are brought about by the binding impact of the regulation, as average leverage use falls afterward by about a sixth of a standard deviation and U.S. investors reduce the size of their positions by as much as a fifth.

The relationship between reductions in leverage and increased profitability is robust to controlling for per-trade factors such as the size of the trade, the holding period, direction,

behave like speculative noise traders in financial markets. This research is similar in spirit, but provides a causal link between leverage and speculative activity.

[3]In addition to chatting in forums on the website, friends in the social network are able to view each other's portfolios in real-time allowing them to track the activities of other traders. Heimer and Simon (2012) presents a more detailed discussion of the social networking aspects of the database.

[4]For example, some retail traders exhibit preferences toward lottery-type stocks – ones with lower expected value but high idiosyncratic skewness – (Kumar (2009)) and greater leverage may facilitate these types of gambles. Also, less successful traders are likely drawn towards environments offering higher leverage since trader profitability is increasing in wealth (Bonaparte and Fabozzi (2009)) and those possessing less capital require more leverage.

the currency pair, and brokerage, as well as individual specific factors such as trading style and experience. An entropy-based weighting scheme new to the finance literature accounts for pre-regulation differences in profitability between the treatment and control groups (Hainmueller (2012)). The weighting scheme calibrates to the first three moments of the treatment group's sample distribution eliminating the problem of model dependency that detracts from existing parametric methods such as propensity score matching. Furthermore, a placebo test using false dates for the CFTC regulation confirms that these results are unlikely to occur due to unrelated changes in overall market conditions.

These findings lead to the following question: why would individual investors experience an increase in returns when leverage constraints are tightened? A few explanations appear unlikely. The reduction in leverage may have led to adjustments in risk-bearing resulting in an increase in returns, consistent with the standard model of risk-averse investors. This is not the case as there is no change in the realized volatility of returns after the CFTC regulation. Instead, to compensate for the reduced ability to use leverage to generate volatility, U.S. investors trade more frequently on days with high implied volatility. Secondly, the reduction in retail trading volume may have produced an endogenous change in market conditions during the hours in which U.S. investors are most active. However, the empirical methodology obviates this concern and there is no evidence that intraday market volatility was affected by the regulation.

A more likely explanation is that a reduction in leverage mitigates the underperformance of overconfident investors by reducing the size of their positions. Two proxies for investor overconfidence enable empirical tests of this theory. Traders with poor performance ex-ante despite high trading frequency are considered overconfident, as well as those with the largest overreaction to large price movements. Concerned that the two metrics are drawn from observed trading behavior and are potentially contaminated by the quasi-experimental setting, I use an additional proxy for overconfidence new to the literature, the number of friends each trader has in the aforementioned social network as well as two measures of network centrality borrowed from graph theory, betweenness and eigenvector centrality. The proxy is justified by research in psychology showing that, "[m]ore socially dominant individuals ... make more confident judgments, holding constant their actual ability," (Burks, et al (2010)).[5] All three proxies suggest leverage constrained investors who are more overconfident have a greater reduction in losses following the CFTC regulation than other traders. Lending added support to this explanation, the empirical result is consistent with a model of investor overconfidence presented in Odean (1998) which I augment to incorporate a cap on position size.[6]

Taken as a whole, these findings are generalizable to activity by naive investors and provide micro-founded support for theoretical models that use non-standard assumptions about beliefs to derive a relationship between the availability of leverage and the propagation of asset pricing bubbles and busts.

The paper is organized as follows. Section 1 details some related findings. Section 2 describes the theoretical argument tested in this research. Section 3 provides an account of the CFTC regulation limiting the amount of leverage available to retail traders. Section 4 outlines the proprietary dataset used in the empirical analysis, the results of which are presented in Section 5. Section 6 explores three candidate explanations for the increase in returns. The final section offers policy recommendations and suggestions for future research.

[5]In several experimental studies and surveys, Anderson, et al. (2012) shows that overconfidence leads to enhanced social status.

[6]Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Kyle and Wang (1997), and Bernardo and Welch (2001) all rely on similar modeling assumptions, that overconfident traders overweight their own beliefs. Odean (1998) considers the case in which traders are price-takers. On the other hand, Schienkman and Xiong (2003) suggest overconfident investors participate in asset markets for speculative purposes, namely to have the option to resell the asset to those who mis-price it.

1 Related Literature

There are a few empirical papers with related findings. Linnainmaa (2003) documents a negative relationship between the amount of leverage used and returns among Finnish stockholders, but does not claim a causal interpretation. In contrast to earlier studies (Kupiec (1989) and Schwert (1989)), Foucault, Sraer, and Thesmar (2011) show that a reform reducing the ability of retail traders to borrow on Euronext Paris reduced the amount of speculative buying which increased idiosyncratic stock price volatility. Frazzini and Pederson (2011) find that leverage constraints cause investors to hold riskier assets in their portfolio.

Also, by showing that the use of leverage leads to poor performance among certain traders, this research contributes to the understanding of retail investors, the activities of whom can have a deleterious effect on their own welfare. For instance, Barber, et al. (2009) finds that Taiwan's retail investors underperform the market by 3.8 percent and accumulate losses that amount to 2.2 percent of Taiwan's GDP. Barber and Odean (2000) provides evidence from a discount equities brokerage in the U.S., while Grinblatt and Keloharju (2000)) examines the population of trades on the Finnish stock exchange. This study extends these findings to an asset class – foreign exchange – used heavily by retail traders since the advent of online trading.

However, some traders fair better than others (Coval, Hirshleifer, and Shumway (2005)) motivating research such as this that offers an explanation for heterogeneity in performance. Grinblatt, Keloharju, and Linnainmaa (2011, 2012) find that high-IQ investors earn greater Sharpe ratios and are better at picking stocks. According to Korniotis and Kumar (2011), cognitive aging outweighs the positive effect of increased experience causing older investors to perform worse. Døskeland and Hvide (2011) discover that individuals choosing stocks from firms that are similar to their profession earn negative excess returns. On the other hand, individuals use local knowledge to outperform non-local investments (Ivkovíc and Weisbenner (2005)). Social forces may also be a factor. Han and Hirshleifer (2012), in conjunction with Heimer and Simon (2012) and Heimer (2011), demonstrate that individuals susceptible to peer-influence trade actively and underperform passive benchmarks.

Moreover, retail traders are found to play an important role in shaping asset market characteristics, and ultimately the formation of asset prices. Kaniel, Saar, and Titman (2008) show that buying (selling) pressure by individual investors leads to positive (negative) excess returns on the NYSE. In a laboratory experiment, uninformed traders increase market volume and depth while reducing bid-ask spreads, but contribute to the deviation of price from fundamentals (Bloomfield, O'Hara, and Saar (2009)). Bender, Osler, and Simon (2011) find that a popular technical trading strategy is associated with higher volumes and lower bid-ask spreads. Additionally, several papers document that trades issued by individual investors are correlated and that their activity may influence asset prices (Barber, Odean, and Zhu (2009); Kumar and Lee (2006); and Hvidkjaer (2008)).

2 Theoretical Framework

Consider a simple model in which a representative investor cares about terminal wealth and has preferences over risk and return. Under rational expectations, leverage constraints act in an unambiguous manner, limiting the ability of investors to borrow to purchase risky assets. Therefore, constraints on leverage are a friction potentially lowering the welfare of low-wealth investors.

On the other hand, departures from rational expectations have been analyzed in theoretical settings, perhaps most prominently in the form of investor overconfidence. Odean (1998) offers the most appropriate starting point from with which to evaluate the direct influence of leverage constraints on the welfare of overconfident investors, because the investors in his frictionless model are price-takers as are likely the traders examined in the empirical tests.[7] In summary, a risk-neutral investor is given the option to purchase a risky asset that pays-out after several rounds of trading. Investors receive both a private and common signal about the value of the asset, and update their beliefs according to Baye's rule. The model differs from other work in that it relies on the assumption that some traders are overconfident causing them to hold posterior beliefs about the terminal value of the asset that is too precise, under-weighting common signals.

A key prediction of Odean (1998) is that price-taking, overconfident investors have lower welfare than a comparable investor less prone to this bias. Over-weighting one's own beliefs while downplaying more informative signals produces suboptimal risk-sharing. Thus, those with the highest (lowest) signals as to the risky asset's value hold too much (too little) of the risky asset and too little (too much) of the risk-free asset.

The introduction of a leverage constraint into Odean (1998), formalized in Appendix A1, has clear implications. The overconfident investors with the highest private valuation of the risky asset would be unable to purchase as much of it as they demand. The rest of their endowment would go towards purchasing the risk-free asset. On the other hand, those with beliefs about the asset value that are below average would be unaffected. Since all investors are price-takers, returns to both assets would be unchanged. The augmentations to the model produces the following testable hypotheses:

[7] Odean (1998) also considers the case in which overconfident investors are insiders, as well as when the marketmakers are overconfident and information is costly.

H1: *Average welfare is at least as large in the presence of constraints on leverage.*

H2: *The greater the degree of overconfidence, the larger the gains in welfare as a result of constraints on leverage.*

In summary, the activities of the most optimistic investors are mitigated and they experience improved performance (while those of others remain the same). Appendix A1 provides proof of these results.

3 Retail forex and the CFTC leverage reduction

The retail forex market has experienced unprecedented growth over the past decade. Barely in existence in the early 2000s, retail trading constituted roughly eight percent of worldwide forex trading volume in 2010 (King and Rime (2010)). It exceeded $125 to $150 billion 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, continuously offering bid and ask quotes to their customers. Each brokerage maintains a proprietary algorithm for generating quotes that is based on their own inventory and a feed from the inter-bank market. Similar to the inter-bank market, spreads are low, typically no more than two or three pips regardless of the transaction size. The brokerage is the counter-party on all transactions, responsible for off-loading inventory into the inter-bank market. The relationship between the brokerages and their clients is similar to that of a bucket shop[8] in that the customer bids on the movements of a given currency pair, but does not take receipt of the foreign currency. Clients make withdrawals from their account in their domestic currency.

[8] Warren B. Bailey is credited with providing this analogy.

The brokerages typically have clients from all around the world. However, there is no centralized, world-wide regulatory authority. In order to comply with domestic regulations, the brokerage is responsible for verifying the residency of their clients. Verification is conducted by using government issued documentation, such as a passport, and a link to a domestic bank/checking account from which to withdraw and deposit funds. As such, bypassing domestic regulation is possible, but undoubtedly costly for the majority of retail clientele.

The retail forex market was largely 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 gave the CFTC enhanced regulatory authority over the retail market. The CFTC began considering methods intended to protect consumer welfare in the forex market in anticipation of the passage of Dodd-Frank. On January 20, 2010, the CFTC released in the Federal Register a proposal to limit leverage available to retail customers to 10:1 per trade on all pairs.[9] 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 for them to limit the amount of leverage available to U.S. customers to 50:1 on all major pairs and 20:1 on all others (pairs are listed in Table 1).[10] The brokerages were required to come into compliance with the new rules by October 18, 2010.

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

[10] The CFTC lacked regulatory authority prior to the passage of Dodd-Frank, but suggested brokerages maintain a 100:1 cap on all trades.

4 The data: myForexBook

The data used in the following 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 with one of roughly 45 retail specific forex brokers. Once registered, myForexBook can access a trader's complete trading record at those brokers, even the trades they made before joining the network. New trades are entered via the retail brokerages but they are simultaneously recorded in the myForexBook database and are time-stamped to the second. Hence, there are no concerns about reporting bias. An example of a myForexBook user's homepage is displayed in Figure 1 and some of the network's features are illustrated in Figure 2. There are 5,693 traders in the database who made a total of roughly 2.2 million trades most of which occur between early-2009 and December, 2010. A more detailed discussion of the social networking aspects of the database is available in Heimer and Simon (2012).

For the purposes of this study, the data is trimmed in several ways. First, the population of traders is restricted to those claiming to be located in either the United States or Europe.[11] Traders from other locations are present in the dataset, but the amount of leverage available to them is unknown. Secondly, the sample is restricted to the set of traders issuing trades both before and after the CFTC regulation was implemented, alleviating concerns over attrition bias.

The ensuing empirical work also includes the following data trimming. The outer one percent of all observations of return on investment (ROI) are removed to prevent extreme returns in either direction from biasing any empirical estimates. This leaves the per-trade

[11]Registered users of myForexBook are asked to provide their trading region when setting up their user profile. They are able to choose between "United States", "Europe", and "Asia Pacific", or they can choose not to specify.

ROI within a range of 70 percent to 120 percent. The outer one percent on the upper tail of the distribution for leverage use is removed, censoring the data at no more than 400:1. 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. This leaves a total of 266,248 trades made by 1,071 traders, almost half – 489 – are from the U.S.

Summary statistics on per-trade ROI and leverage, separated by U.S. and European traders, are presented in Table 2. A common theme is present across both groups: while the median trade is slightly profitable, the mean trade is unprofitable losing around 0.2 percent ROI. This is not surprising since most existing research on retail investors shows that they underperform. Furthermore, the distribution has a high kurtosis with nearly half of all observations earning or losing less than 0.1 percent ROI, but a standard deviation of 3.72 for both U.S. and Europeans.

European traders in the sample consistently use more leverage than U.S. traders, averaging 16.7:1 versus 11.5:1 respectively. However, the distribution is positively skewed for both groups of traders. The median leverage is 2.0 for U.S. traders and 4.3 for Europeans. Furthermore, 7.5 percent of all trades within the sample period were issued with leverage greater than 50:1. Summary statistics on trade size and per-trade holding period are also presented in Table 2.

Registered users of myForexBook are also asked to provide profile information upon joining myForexBook, the details of which are presented in the first two panels of Table 3. Traders from both locales tend to consider themselves technical traders as opposed to basing their strategies on news, momentum, or fundamentals. Most users cite having either zero to one or one to three years of trading experience. Summary statistics on the number of friendships made after joining the social network are presented in Panel 3. U.S. traders have an average of 30.0 friends while Europeans have 24.0. The difference is not statistically different because the standard deviation is 94.7 and 100.6, respectively.

Do the US and EURs have correlated trading activities?

This section explores whether or not European traders make for a good control group with which to examine the effect of reducing the amount of leverage available to U.S. retail forex traders. I compare them in terms of how much they trade and when, when they use leverage, and if their aggregate returns trend together.

Figure 3 plots the time series of the total number of trades by U.S. and European traders, revealing that their trading volume tends to fluctuate 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.

Figure 4 plots the time series of average leverage use per day, as well as the ten-day moving average of both series. The moving average of the European leverage series is always greater than that of the U.S. reflecting the less restrictive trading environment in Europe even prior to the October, 2010 CFTC regulation. Despite the difference in levels, the moving averages trend together until a few days before the regulation's implementation. After the trading rule, the average leverage used by European traders increases while that of the U.S. traders stays roughly constant. I also investigate whether the fluctuations in their leverage use move together on a daily basis. I calculate the log of the first difference of average daily leverage per group (excluding weekends) and find that the Pearson's correlation coefficient between the two series is 32.0 percent. Again, there is a positive correlation between the two groups.

Lastly, the aggregate returns of U.S. and European investors tend to move together. The correlation coefficient of the log of the first difference of average daily ROI is 26.5 percent. Furthermore, the 10-day moving average of aggregate returns trends together both before and after the CFTC regulation (Figure 5). However, after the trading rule, the level of average ROI increases for U.S. traders while staying roughly constant for those from Europe.

Taken together, these results suggest that the activities of U.S. and European traders mirror each other. It is likely that a common set of trading strategies influence the activity of traders in the U.S. and Europe. Therefore, it seems reasonable to assume that the sample of European retail traders used in this research makes for a good control group with which to examine the effect of reduced leverage on trader welfare and behavior.

5 Leverage and profitability

5.1 Correlation of leverage and return on investment

The standard model of a risk-averse investor predicts that a reduction in available leverage results in decreased returns. As a first pass at examining this relationship, I estimate the following regression via OLS:

$$roi_{j,i,t} = \beta_0 + \beta_1 * leverage_{j,i,t} + \beta_2 * Trade_{j,i,t} + \beta_3 * Investor_i + \varepsilon_{j,i,t} \tag{1}$$

where $roi_{j,i,t}$ is the ROI for trade j, issued by trader i, at time t, the second in which the trade was placed. The variable $leverage_{j,i,t}$ is the amount of leverage used by the trader, while $Trade_{j,i,t}$ is a matrix of features that belong to each trade issued and $Investor_i$ is a matrix of trader characteristics. $Trade_{j,i,t}$ includes the logarithm of the holding period in hours, a binary variable indicating the direction of the position, brokerage fixed effects, and the logarithm of trade size as denoted in the base currency of the pair, as well as pair fixed effects interacted with the log of size.[12] Investor characteristics, captured in $Investor_i$, include experience and trading style fixed effects. Standard errors are clustered across two dimensions using the method outlined in Thompson (2009) to allow for correlation in residuals at the daily level and by trader.[13]

There is a strong negative correlation between the amount of leverage used and ROI per-trade. The first column of Table 4, presents estimates of the binary relationship between the two variables. A one unit increase in the amount of leverage (for instance, from 20:1 to 21:1) is associated with a decrease in ROI of about 0.016 percent. This implies that if a trader is using the most available leverage prior to the CFTC regulation (100:1) then the mandated reduction to 50:1 increases the per-trade ROI by about 0.8 percent. This relationship holds even after including the controls $Investor_i$ and $Trade_{j,i,t}$ (Column 2). Furthermore, the magnitude of the relationship is roughly stable across time although the coefficient on $leverage_{j,i,t}$ is slightly larger and statistically different before the CFTC regulation was implemented (Columns 3 and 4).

Thus, there is a negative association between an investor's use of leverage and the profitability of their trades. However, causality is unclear; the amount of leverage available could stimulate unprofitable trading activity, among other explanations.

[12]The size of the trade is dependent on the currency pair chosen because it is denominated in the pair's base currency.

[13]For robustness, the empirical analysis is performed using individual fixed effects estimation and random effects models, the results of which are unreported but available upon request. In all regressions, a Hausman test fails to reject the null hypothesis that the random effects model produces efficient estimates of the causal effect of the regulation. Furthermore, the results of the random effects model are not quantitatively different from the pooled OLS regression model outlined in Equation 2, although the statistical significance tends to fall to the five percent error level. As a whole, this suggests that the control variables included in $Investor_i$ are sufficient to capture the variation across traders.

5.2 Empirical strategy

The CFTC regulation implemented in October, 2010 offers a quasi-natural experimental setting in which to identify the effect of leveraged trading on investor profitability. The regulation mandated a reduction in the amount of leverage retail brokerages are allowed to offer U.S. investors. However, it did not affect European traders many of whom trade on the same brokerages. Since there is no a priori reason to believe that the trading rule directly influenced the profitability of traders through any other channels, any change in the profitability of U.S. traders – when compared to European traders – following the regulation must be attributed to the reduction in leverage.

Was the CFTC trading rule binding?

Having confirmed in Section 4 that European traders are a good control group with which to study the impact of the CFTC regulation, this section shows that the CFTC regulation had a binding effect on U.S. traders. Preliminary evidence reveals that leverage use drops substantially among U.S. investors following the CFTC trading rule from 9.4 percent to 2.6 percent of all trades utilizing greater than 50:1 margin. On the other hand, leverage used by European traders experiences a slight uptick. Respectively, 7.0 percent and 8.1 percent of all European trades use greater than 50:1 leverage prior to and after the regulation.

While there is a substantial drop in the number of instances in which U.S. traders use greater than 50:1 leverage after October 18, 2010, there are observations seemingly in violation of the CFTC's policies. The most likely explanation is that self-reporting of location by myForexBook traders contributes to measurement error, although there are other possibilities. Given that regulation in this market was a new phenomena and that there are over 45 brokerages in the dataset, the CFTC may have been unable to perfectly enforce the leverage constraint. Another possibility is that it could reflect reporting errors in the trading data, but I use forex prices provided by Oanda to externally validate its accuracy and less than 0.0001 percent of all trades fall outside the daily range of prices in the currency pair. Regardless, while some trades still use more than 50:1 leverage, the CFTC trading rule clearly had an influence, limiting the amount of leverage available to traders.

In order to implement a more formal test of the CFTC regulation's effect on leverage use, I estimate the following regression via OLS:

$$Y_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * Trade_{j,i,t} + \gamma_5 * Investor_i + \epsilon_{j,i,t} \quad (2)$$

The dependent variable, $Y_{j,i,t}$, is either (i) $leverage_{j,i,t}$, the amount of leverage used per-trade j. Since the leverage constraint should also reduce the size of U.S. trades and frequency with they trade, the dependent variable in column (ii) is $trade\,size_{j,i,t}$, a z-score for the size of the trade denominated in the base currency calculated conditional on the mean of each currency pair. In the last specification, (iii) the dependent variable is the number of trades issued in a given day, $trades\,day_{i,t}$. In this specification, the per-trade subscript j is dropped and t is at a daily frequency, and it is estimated conditional on having made at least one trade during the day. US_i indicates whether the trader's account is in the U.S., while $constraint_t$ is equal to one if the trade was opened after 00:00:00 GMT, October 18, 2010. Control variables are the same as in previous regressions and .

Estimation results are presented in Table 5. Regression (i) finds that leverage by U.S. traders falls by around six units relative to the control group following the trading rule. The linear model predicts that U.S. traders reduce their leverage use following the legislation from 14.5:1 to 11.3:1, while leverage use among European traders increased from 13.8:1 to 17.1:1. Since the distribution of leverage use is truncated at zero and heavily skewed to the right, I also estimate the following models: OLS estimation with the logarithm of $leverage_{j,i,t}$ as the dependent variable, a zero-truncated Poisson regression estimated using maximum-likelihood, and a negative binomial regression also with maximum-likelihood. The three alternative specifications (unreported, but available upon request) confirm that the regulation reduced the amount of leverage used by U.S. traders.

Also in Table 5, regression (ii) shows that the regulation caused a statistically significant reduction of about six percent of a standard deviation in the size of trades made by U.S. traders relative to the control group. For robustness, I also use the size of the trade denominated in units of the base currency as a dependent variable. While the relationship remains statistically significant, the effect of the regulation is much larger in this specification reducing the size of the trade by about two-thirds a standard deviation.

One last test verifies that the regulation had a binding effect on the activities of U.S. traders. The regression results in Column (iii) show that U.S. traders reduce the number of trades they make per-day by about 1.35 which is roughly a 13 percent decrease in trading. The regression is run conditional on having made at least one trade in said day. Since the dependent variable is count data, I also estimate the regression using a zero-truncated Poisson regression and find similar results (unreported).

Taken together, the results of the preceding analysis demonstrates that the CFTC regulation had a binding effect on the leverage employed by U.S. retail forex traders.

5.3 Return on investment and the CFTC regulation

Preliminary Evidence

Preliminary evidence that the use of leverage causes lower returns is presented in Figure 5, a time series plot of aggregate returns for both U.S. and European traders. There is a clear structural break in which U.S. traders vastly improve their profitability that occurs immediately following the CFTC regulation. Meanwhile, there is little change in average European returns over time.

In order to get a sense of the magnitude of the increase in U.S. trader profitability, I estimate the following regression using OLS:

$$US\, minus\, EUR\, ROI_t = \gamma_0 + \gamma_1 * constraint_t + \epsilon_t \tag{3}$$

where $USminusEURROI_t = \bar{roi}_{US,t} - \bar{roi}_{EUR,t}$, is the five or ten day moving average of daily ROI in the U.S. minus that in Europe. Results are presented in Table 6. γ_1 is predicted to be roughly 0.12 percent to 0.13 percent and is strongly statistically significant in all specifications. This implies that following the leverage constraint, U.S. traders increase their profitability relative to their European counterparts by about one and a quarter standard deviations.

The impact of the CFTC mandated reduction in leverage on ROI is also made apparent in Figure 6. It plots the cumulative density function (CDF) of ROI per trade before and after the regulation for both U.S. and European traders. For the European traders, the CDF barely changes. In contrast, the frequency of trades on the extreme negative tail declines noticeably for U.S investors. A Kolmogorov-Smirnov test rejects the null hypothesis that the sample distribution of ROI is the same before and after the regulation (p-value < 0.000). This suggests that limiting the amount of leverage available to traders reduces the frequency and magnitude of instances in which they lose a substantial portion of their investment.

Profitability on a per-trade basis

The above evidence, while highly informative, is flawed in that the activities of a few traders may behind the results and it may suffer from omitted variable bias. To account for this short-coming, I examine the impact of the trading rule on a per-trade basis by estimating the following regression via OLS:

$$roi_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t ... \\ + \gamma_4 * Trade_{j,i,t} + \gamma_5 * Investor_i + \epsilon_{j,i,t} \quad (4)$$

The coefficient γ_1 captures the baseline level of ROI if the trade is made by a U.S. trader, while γ_2 is the baseline ROI for trades issued after the legislation. The coefficient on the interaction term $US_i * constraint_t$, γ_3, captures the causal effect of the CFTC legislation. A positive value for γ_3 would suggest that the regulation increases the ROI of leverage-constrained investors. In other words, increased leverage use causes decreased profitability.

Estimates of Equation 4 are presented in Table 7. U.S. traders are more profitable after the mandated reduction in leverage. The first two columns provide estimates with and without $Trade_{j,i,t}$ and $Investor_i$, respectively. The per-trade ROI increases by 0.10 and 0.14 percent relative to the control group. The third column includes all control variables, but use a set of weights based on the entropy balancing technique introduced in Hainmueller (2012) and outlined in Appendix A2. The weighted regression accounts for initial differences in the distribution of returns between the U.S. and Europeans prior to the regulation. This approach produces an estimate of γ_3 equal to 0.14 and improves the fit of the model as indicated by its R-squared.

The fourth column includes an interaction with $above50_i$, a variable equal to one if trader i has used at least 50:1 leverage on at least one trade prior to the CFTC regulation. The magnitude of γ_3 is reduced to 0.043 (significant at the 10 percent error level), but this specification provides evidence that much of the gains in profitability are driven by the group of traders who have proven to use more leverage. The coefficient on $US_i * constraint_t * above50_i$ is 0.267 and is statistically significant at the one percent error level.

In terms of economic significance, the magnitude of the coefficient γ_3 encompasses a substantial portion of the distribution of ROI. Roughly 45 percent of all trades fall within 0.14 of the mean. The magnitude of the regulation is more striking when considering the fact that the average day of trading includes between seven and eight round trip trades.

A placebo test

Lastly, I employ a placebo test to verify that the change in trader performance following the CFTC regulation is unlikely to have been caused by chance. An alternative story that would explain the preceding empirical results is that the forex market undergoes frequent structural changes that affect U.S. and European traders differently. Therefore, it would not be uncommon to see a statistically significant coefficient on the interaction term in the regression outlined in Equation 4 regardless of the date chosen to implement the regime change. Furthermore, Bertrand, Duflo, and Mullainathan (2004) show that standard errors in difference-in-differences estimation can be underestimated resulting in frequent false positive results.

The placebo test involves the following procedure, illustrated in Figure 7. I run the same regressions outlined in Equation 4 using a random date instead of October 18, 2010, the date of implementation of the actual CFTC regulation. Starting with Sunday, May 3, 2009, I re-date $constraint_t$, rolling it forward each week until August 29, 2010. The data-trimming exercise outlined in Section 4 is performed before each regression which, among other things, restricts the sample group to those who have made trades both before and after the regulation. This procedure produces 70 total regressions.

Figure 8 presents a kernel-density and histogram of the estimated t-statistics on the interaction term between US_i and $constraint_t$, γ_3. The regressions assessing the actual rule change produce t-statistics of 3.66 and 4.46, which when placed in the distribution using false dates for the regulation, yield p-values less than 0.0001. Additionally, the placebo test produces false positive results at the five percent error level only two times out of 70.

In summary, the placebo test examines how likely it is that the original regressions produce false positive results. Coefficient estimates that are as precisely estimated rarely occur by chance or by factors unrelated to the leverage constraint.

6 Three candidate explanations

This section explores three candidate explanations for the finding that leverage constraints improve investor performance. First, the reduction in leverage may have led to adjustments in risk-bearing that corresponded with an increase in returns; however, the CFTC regulation is not found to cause changes in the realized volatility of trader returns. Secondly, the reduction in retail trading volume may have produced an endogenous change in market conditions during the hours in which U.S. investors are most active. Contrary to this argument, I do not find evidence that intraday currency price volatility was affected.

A more promising explanation is that the leverage constraint mitigated the underperformance of overconfident investors by reducing the size of their positions. Proxies for overconfidence enable tests of this theory. Two proxies are drawn from observed trading data. Traders with poor performance despite high trading frequency are considered overconfident, as well as those who overreact to past price movements. A third proxy draws from the social networking aspect of the dataset. Psychological research has found that overconfidence rises in conjunction with increased social prominence. It is therefore reasonable to assume that the number of friends in the network is a viable proxy. Indeed, leverage constrained investors who are more overconfident have a greater increase in profitability following the CFTC regulation than other traders.

6.1 Leverage and return volatility

The previous section presents evidence that leverage constraints can lead to more profitable trading. According to the standard risk-return tradeoff, increases in realized returns are expected to correspond to an increase in volatility. To determine if this is the case, I compute the daily standard deviation of per-trade ROI per trader i, $\sigma_{i,t}^{ROI}$, and employ a similar empirical test as in the previous sections.

Table 8 reports the estimates of the following regression using OLS:

$$\sigma_{i,t}^{ROI} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * Investor_i + \epsilon_{i,t} \quad (5)$$

In the first column, the empirical model is estimated over all days in which trader i has made at least two trades. The second column presents estimates when the regression is restricted to days with more than five trades by i. In both specifications, the empirical model predicts that the reduction in leverage causes an increase in return volatility. However, the coefficient, γ_3, is imprecisely estimated and is not statistically different from zero in either case. This suggests that investors found another channel from which to generate volatility in their returns following the reduction in leverage.

Unable to use as much leverage to generate volatility in their returns, U.S. investors traded more frequently on days with high implied volatility, a proxy for expectations of future currency volatility. This is made apparent by estimates of the following logistic regression:

$$
\begin{aligned}
Pr(Y_{j,i,t}) = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t ... \\
+ \gamma_4 * Trade_{j,i,t} + \gamma_5 * Investor_i + \epsilon_{j,i,t} \quad (6)
\end{aligned}
$$

where $Y_{j,i,t} = \{vxy_{j,i,t},\ cvix_{j,i,t}\}$ 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. The *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 *cvix* is a weighted average of the three month implied volatility across nine major currency pairs produced by Deutsche Bank.

Implied odds-ratios from estimating Equation 6 are presented in Table 9. The reduction in leverage causes an increase in the likelihood of issuing a trade on a day in which implied volatility is at its weekly high. The regression results suggest that among U.S. investors, the probability rises from around 18 to 19 percent, while for the control group of Europeans it falls from 23 to 21. The coefficient on the interaction term, γ_3, is statistically significant at the one percent error level when the dependent variable is $vxy_{j,i,t}$ and at ten percent when it is $cvix_{j,i,t}$.

This finding is suggestive of a link between the use of leverage and a speculative motive for trading. It is consistent with Frazzini and Pederson (2011), in which leverage constrained investors hold a higher fraction of high-beta stocks in their portfolio. Following the reduction in leverage imposed by the CFTC, U.S. traders are unable to use leverage to generate return volatility when prices are stable. Therefore, investors substitute (or risk-shift) towards trading more frequently when they believe the market will become turbulent.

6.2 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 re-shaped 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 9, 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 10 reports estimates of the following regression estimated via OLS:

$$\sigma_{c,t,h} = \gamma_0 + \gamma_1 * US\,morning_h + \gamma_2 * constraint_t + \gamma_3 * US\,morning_h * constraint_t ... \\ + \sum_{i=2}^{11} \gamma_{4,i} * Pair_c + \epsilon_{c,t,h} \quad (7)$$

where $\sigma_{c,t,h}$ is the standard deviation of the price of currency pair c, on day t, between the hours indicated in h. $\sigma_{c,t,h}$ 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, $\sigma_{c,t,h}$ 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. $Pair_c$ 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.

6.3 Do leverage constraints help overconfident traders?

A common explanation for the underperformance of individual investors is that they exhibit overconfidence, "specifically about the precision of their abilities" (Odean (1998)). Existing empirical studies proxy for trader overconfidence using gender (Barber and Odean (2001)), tax filings and driving records (Grinblatt and Keloharjua (2009)), and trading frequency. This research uses a proxy for overconfidence that is new to the literature, the number of friends in a trader's social network.

6.3.1 Three overconfidence proxies

The first proxy for overconfidence captures high trading frequency combined with poor performance. It is in the spirit of Barber and Odean (2001) which shows that men trade more than women despite worse performance. The authors attribute this finding to male overconfidence. The first proxy, $underperform\&intensity_i$, 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.[14] Both $\bar{roi}_{i,t}$ and trading frequency are calculated during the period prior to the CFTC rule change to avoid confounding caused by the reduction in leverage. A trader is deemed overconfident if they fall below a given percentile of the distribution of $\bar{roi}_{i,t}$ and above a percentile in trading frequency.

The second proxy relies on the tendency for overconfident investors to overreact, placing too much weight on extreme information. Idiosyncratic overreaction is captured by measuring the extent to which the decision to trade currency depends on the largest swing in the

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

previous day's price. All traders are pooled in the following regression:

$$trade\ ind_{i,t} = \beta_0 + \beta_1 * \triangle p_{t-1} + \beta_2 * trade\ ind_{i,t-1} + \beta_3 * t + \varepsilon_{i,t} \tag{8}$$

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 of the most heavily traded currency pair, EUR/USD, on day $t-1$. The estimation is conducted using t prior to the CFTC regulation. It yields an estimate of coefficient β_1 equal to 0.019 (s.e. $=$ 0.0066) which implies a standard deviation increase in $\triangle p_{t-1}$ results in a 1.5 percent point increase in the probability of trading. To capture the sensitivity of each trader to past price swings, Equation 8 is estimated for each i separately,

$$trade\ ind_t = \delta_0 + \delta_1 * \triangle p_{t-1} + \delta_2 * trade\ ind_{t-1} + \delta_3 * t + \varepsilon_t \quad for\ each\ i \tag{9}$$

and δ_1 for each i is cataloged. Idiosyncratic overreaction is the difference between aggregate overreaction and i's tendency to trade in response past price swings:

$$overreact_i = \delta_1 - \beta_1 \tag{10}$$

Similar to the first proxy, i is deemed overconfident if they are above a threshold in the distribution of $overreact_i$.

Both proxies rely on observed trading data and therefore have possible shortcomings. For instance, poor performance may reduce the subsequent trading activity of capital constrained traders. The overreaction metric may represent idiosyncratic risk tolerance which is distinct from overconfidence. Therefore, a third proxy is used, the number of friends a trader has, $friends_i$, because it potentially measures overconfidence in a manner orthogonal to individual trading records.

As described in Section 4, the traders in the sample are all participants in an online social network. They are able to communicate with other traders and form bilateral friendships. The number of friends makes for a good proxy since Anderson, et al. (2012) shows that overconfidence leads to enhanced social status in group settings. Burks, et al. (2010) also finds that, "[m]ore socially dominant individuals ... make more confident judgments, holding constant their actual ability". The authors suggest that the relationship between social dominance and overconfidence is caused by a propensity to send public signals when events occur that appear to confirm their own abilities. 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 a 0.11 increase in the number of friends a user has. Furthermore, the CFTC trading rule is unlikely to have had an effect on trader interactions within the social network, which makes this measure a better proxy than any directly related to trader activity.

6.3.2 Reductions in leverage and overconfidence: estimation results

An empirical approach similar to Section 5 is capable ofanalyzing the impact of a reduction in leverage on the trading activities of overconfident investors. Augmenting Equation 4 by incorporating the overconfident proxies as a triple interaction term with US_i and $constraint_t$

yields the following empirical model:

$$roi_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * US_i * overconfident_i ...$$
$$+ \gamma_5 * constraint_t * overconfident_i + \gamma_6 * US_i * constraint_t * overconfident_i ...$$
$$+ \gamma_7 * Trade_{j,i,t} + \gamma_8 * Investor_i + \epsilon_{j,i,t} \quad (11)$$

The variable $overconfident_i$ is equal to one if i is above a given percentile in the distribution of one of the three overconfidence proxies, $underperform\&intensity_i$, $overreact_i$, and $friends_i$. A positive value for the coefficient on the triple interaction term, γ_6, would imply that a reduction in leverage causes a larger increase in the profitability of overconfident traders.

The results from estimating Equation 11 are provided in Table 11. Columns I and II use $underperform\&intensity_i$ as a proxy for overconfidence. The coefficient estimate of γ_6 is positive in both specifications, ranging from 0.30 when $\bar{roi}_i$ is below the median and above the median trading intensity to 0.11 when below (above) the 90th percentile. The coefficient estimate is statistically significant at the one percent error level in the former, but insignificant when the cutoff for $overconfident_i$ is the 90th percentile.

The next pair of regression results, presented in Columns III and IV, use $overreact_i$ as a metric for overconfidence. According to the estimates, overconfident investors affected by the CFTC regulation increase their ROI by three basis points (s.e. = 0.065) when the median is the cutoff in the distribution of $overreact_i$. The increase in profitability is 0.37 and statistically significant at the five percent error level when the 90th percentile is the cutoff.

Columns V and VI use the number of friendships as a proxy for overconfidence. This pair of estimation results also suggest the leverage constraint has a larger positive effect on the profitability of overconfident traders, increasing the per-trade ROI by between 0.15 percent and 0.24 percent relative to the control group. The one concern is that while γ_6 should rise monotonically as the threshold number of friends needed to term the trader overconfident is increased. Despite remaining positive and statistically significant, γ_6 falls when going from the 50th (greater than eight friends) to the 90th percentile (above 40 friends) cutoff. This may suggest that those with the most friendships have achieved prominence within the network because of a reputation for good performance rather than their propensity to be boastful. Therefore, since they are less biased, they are less likely to be affected by the trading rule.

Two additional measures drawn from graph theory, betweenness and eigenvector centrality, provide robustness for the use of friendships as a proxy for overconfidence. Both are consistent with the notion that overconfidence contributes to enhanced social status (Anderson, et al. (2012)). Betweenness centrality attempts to quantify the extend to which communications within a network have to travel through a given individual. Eigenvector centrality seeks to define how prominent one is by placing a greater weight on those with ties to highly connected individuals. Technical descriptions of both variables are provided in Appendix A3. Since both variables are positively correlated with the number of friendships, 95.0 and 92.1 percent respectively, they are in accordance with the previous empirical results (regression results are not presented, but are available upon request).

The number of friendships in the network may also represent some other trader characteristics aside from their overconfidence. In a final test, I regress the log number of friends on $Investor_i$ (regression $R^2 < 0.02$) and use the residual as an alternative proxy. The residual is orthogonal to the observed characteristics of the trader by definition, but is highly correlated with the number of friendships. Therefore, the results of estimating Equation 11 with the alternative proxy are quantitatively similar (unreported but available upon request).

The body of evidence strongly supports the conclusion that overconfidence drives trader underperformance and that leverage constraints help those who are most overconfident.

7 Conclusion

This research finds that CFTC regulation reducing the amount of leverage available to U.S. traders caused individual investors to trade more profitably. While this finding might imply a change in the risk associated with their investment, there is no change in the realized volatility of their returns. This is due at least in part by risk-shifting; unable to use leverage to generate volatility, U.S. investors trade more frequently on days with high implied volatility.

Since the standard risk-return model of investor behavior fails to hold, an alternative theory explains these empirical findings. Unprofitable trading is often caused by overconfidence, a bias causing individuals to overweight their own beliefs relative to those of others. I rely on this insight to show that if investors are overconfident, leverage constraints can boost their profitability. In support of this theory, I find empirical evidence that overconfident traders are most helped by the CFTC trading rule.

A natural extension to the research conducted in this paper is to conduct a more thorough analysis on the CFTC regulation's effect on currency prices expanding on the work in Section 6.2. As mentioned in the introduction, Foucault, et al. (2011) find that an exogenous change to the share of speculative retail trading on Euronext Paris reduced idiosyncratic stock price volatility. In order to replicate a study such as theirs, it is necessary to determine the share of U.S. retail forex trading especially since other market participants may respond endogenously to the decline in their activity. Estimates from the Bank of International Settlements find that retail traders constitute approximately 10 percent of daily market volume (King and Rime (2010)), but shares may vary intraday. This requires marriage with other data sources to estimate the intraday share of retail trading volume, such as that provided by Electronic Brokerage Systems and collected by the Federal Reserve Board. In the meantime, while intraday volatility may decline as a result of the CFTC trading rule, the finding that leverage constrained investors substitute toward days with high implied volatility opens the possibility that retail traders may crowd-in during turbulent times and exacerbate large price movements.

Appendix

A1: The introduction of a leverage constraint into Odean's (1998) model of overconfidence

Odean (1998) presents a theory of overconfident, price-taking investors. Trading takes place in three rounds, $t = \{1, 2, 3\}$, and consumption takes place in $t = 4$. $N \to \infty$ traders ($i = 1, ..., N$) receive a public signal in $t = 1$ about the terminal value of a risky asset, $\tilde{v} \sim N(\tilde{v}, h_v^{-1})$. The primary divergence from standard models such as Diamond and Verrecchia (1981) and Hellwig (1980) is that each trader also receives one of $M < N$ private signals, $\tilde{y}_{ti} = \tilde{v} + \tilde{\varepsilon}_{tm}$, in $t = 2\, and\, 3$ that they believe to be correct. The noise in the private signals, $\tilde{\varepsilon}_{tm} \sim N(0, h_\varepsilon^{-1})$, is mutually independent. Since some traders are overconfident, they think they are behaving optimally, place too much weight on the private signals, and deviate from the utility maximizing quantity of the risky asset. Thus, Odean's (1998) model does not yield rational expectations equilibria.

Prior to the first round of trading, trader i is endowed with x_{0i} of the risky asset and f_{0i} units of a risk-free asset that pays out zero. In the subsequent trading rounds, i demands f_{ti} and x_{ti} of the risk-free and risky asset, respectively. Per capita supply of the risky asset $\tilde{x}$ is fixed, unchanging, and known to all.

Each trader knows that $N/M - 1$ others receive the same two signals as they do and believe the precision to be κh_ε, $\kappa \geq 1$. 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. Φ_{ti} is the information set available to trader i prior to each trading round t. Odean (1998) points out that a trader's posterior beliefs are more precise than that of the rational trader if, after receiving both signals, $\eta h_v + 2(\kappa + (M-1)\gamma)h_\varepsilon \geq h_v + 2Mh\varepsilon$.

Trader i has constant absolute risk aversion in wealth ($W_{ti} = f_{ti} + P_t x_{ti}$ for $t = \{1, 2, 3\}$, and $W_{4i} = f_{3i} + \tilde{v} x_{3i}$) with risk-aversion coefficient a. They solve

$$\max_{x_{ti}} \mathrm{E}[-\exp(-\mathrm{a}(\mathrm{W_{t+1i}})|\Phi_{\mathrm{ti}})] \text{ subject to } P_t x_{ti} + f_{ti} \leq P_t x_{t-1i} + f_{t-1i} \tag{12}$$

during each round of trading. Traders believe that the price of the risky asset, P_t, is a linear function of the average signals.

Using backwards induction, Odean (1998) solves the model and derives the following expression for average trading volume in the final round of trading (see the proof of Proposition 4, pg. 1920):

$$E\left(\sum_{i=1}^{N} \frac{|x_{3i} - x_{1i}|}{N}\right) = \frac{2(\kappa - 1)}{a} \sqrt{\frac{(M-1)h_\varepsilon}{M\pi}}. \tag{13}$$

Since traders base their first round demand for the risky asset on the correct public signal, all traders hold the same amount of the risky asset, $x_{1i} = \tilde{x}$. This amount is utility maximizing. Therefore, Equation 13 represents the expected deviation from the optimal holdings of the risky asset and the farther it is from zero, the greater the losses in trader welfare. When traders do not exhibit overconfidence, $\kappa = 1$, traders continue to hold $x_{3i} = x_{1i}$ and trading volume in this round is zero.

Using this as a starting point from which to expand on Odean's (1998) work, suppose there is an unanticipated leverage constraint imposed between the second and third round of trading. Incorporating borrowing into the model would unnecessarily complicate the algebra. As in Wang (2012), an analogous representation is to put a cap, x_c, on i's ability to purchase shares of the risky asset.

Proposition: If $\kappa > 1$ and $M \geq 2$, the imposition of x_c is welfare improving so long as some traders demand $x_{3\mathrm{i}}$ in excess of x_c.

Proof: The value of x_c can be one of two cases, $x_c \geq x_{3i}$ or $x_c < x_{3i}$. In the latter case, $l \leq N$ traders will be unaffected by the constraint while $N-(l+1)$ traders will be unable to increase their demand for the risky asset above x_c. Therefore, the left hand side of Equation 13 is now:

$$E\left[\sum_{i=1}^{l}\frac{|x_{3i}-x_{1i}|}{l}+\sum_{i=l+1}^{N}\frac{|x_c-x_{1i}|}{N-l-1}\right]\leq\frac{2(\kappa-1)}{a}\sqrt{\frac{(M-1)h_\varepsilon}{M\pi}}. \tag{14}$$

The expected value of this expression is clearly less than that of Equation 13, which represents an improvement in trader welfare.

In the case in which $x_c \geq x_{3i}$, the third round demand for the risky asset is not different from that in Equation 13 leaving welfare unchanged. Q.E.D.

A2: Entropy balancing

Entropy balancing, originally outlined in Hainmueller (2012), is a technique for estimating a set of propensity weights, $w_i \geq 0$, for n_0 observations in a control group ($D = 0$) in observational data. It uses a set of sample moments from the size n_1 treatment group ($D = 1$) as balancing constraints. According to Hainmueller (2012), the weights are chosen by minimizing the entropy distance metric:

$$\min_{w_i} H(w) = \sum_{\{i|D=0\}} w_i log(w_i/q_i) \tag{15}$$

subject to balance and normalizing constraints,

$$\sum_{\{i|D=0\}} w_i c_{ri}(X_i) = m_r \text{ with } r \in 1, ..., R \tag{16}$$

$$\sum_{\{i|D=0\}} w_i = 1 \tag{17}$$

where $q_i = 1/n_0$ is a base weight. $c_{ri}(X_i) = m_r$ denotes a set of balance constraints imposed on the moments of the covariates, X_i.

I create a variable, $roi\ mean_i$, equal to the mean of ROI per trader calculated over the pre-constraint period. The weights are estimated using the first three moments of $roi\,mean_i$. They produce the following weighted-sample moments among EUR traders.

	US			EUR **unweighted**			EUR **using** w_i		
	mean	variance	skewness	mean	variance	skewness	mean	variance	skewness
$roi\ mean_i$	99.65	1.977	-4.406	99.74	1.325	-4.704	99.65	1.977	-4.407

A3: Network centrality measures

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.
- **adjacency matrix:** $A = (a_{v,t})$. $a_{v,t} = 1$ if vertex v shares an edge with t, zero otherwise.

Centrality measures

- **Betweenness Centrality:**

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

  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 $C_B(v) \in [0, 1]$.

<u>Eigenvector Centrality</u>:

$$C_x(v) = \frac{1}{\lambda} \sum_{t \in G} a_{v,t} x_t$$

measures the centrality of node v in undirected graph G. $A = (a_{v,t})$ is the adjacency matrix and x_t is the centrality score of the neighbors of v. λ is a constant drawn from the matrix equation, $\mathbf{Ax} = \lambda\mathbf{x}$.

References

[1] Cameron Anderson, Sebastien Brion, Don A. Moore, and Jessica A. Kennedy, *A status-enhancement account of overconfidence*, Journal of Personality and Social Psychology **forthcoming** (2012).

[2] Brad M. Barber, Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, *Just how much do individual investors lose by trading?*, Review of Financial Studies **22** (2009), no. 2, 609–632.

[3] Brad M. Barber and Terrance Odean, *Trading is hazardous to your wealth: The common stock investment performance of individual investors*, Journal of Finance **55** (2000), no. 2, 773–806.

[4] ———, *Boys will be boys: Gender, overconfidence, and common stock investment*, The Quarterly Journal of Economics **116** (2001), no. 1, 261–292.

[5] Brad M. Barber, Terrance Odean, and Ning Zhu, *Do retail trades move markets?*, Review of Financial Studies **22** (2009), no. 1, 151–186.

[6] Jennifer C. Bender, Carol L. Osler, and David Simon, *Noise traders and illusory correlations in u.s. equity markets*, Review of Finance **forthcoming** (2011).

[7] Antonio E. Bernardo and Ivo Welch, *On the evolution of overconfidence and entrepreneurs*, Journal of Economics & Management Strategy **10** (2001), no. 3, 301–330.

[8] Marianne Bertrand, Esther Duflo, and Sendhil Mullainathan, *How much should we trust differences-in-differences estimates?*, The Quarterly Journal of Economics **119** (2004), no. 1, 249–275.

[9] Robert Bloomfield, Maureen O'Hara, and Gideon Saar, *How noise trading affects markets: An experimental analysis*, Review of Financial Studies **22** (2009), no. 6, 2275–2302.

[10] Yosef Bonaparte and Frank J. Fabozzi, *Household search choice: Theory and evidence*, Applied Economics, Forthcoming (2009).

[11] Stephen V. Burks, Jeffrey P. Carpenter, Lorenz Goette, and Aldo Rustichini, *Overconfidence is a social signaling bias*, Institute for the Study of Labor **Discussion Paper** (2010), no. 4840.

[12] Alex Chinco and Chris Mayer, *Distant speculators and asset bubbles in the housing market*, Working Paper (2012).

[13] Daniele Coen-Pirani, *Margin requirements and equilibrium asset prices*, Journal of Monetary Economics **52** (2005), no. 2, 449–475.

[14] Joshua D. Coval, David Hirshleifer, and Tyler G. Shumway, *Can individual investors beat the market?*, Tech. report, 2005.

[15] Kent Daniel, David Hirshleifer, and Avanidhar Subrahmanyam, *Investor psychology and security market under- and overreactions*, Journal of Finance **53** (1998), no. 6, 1839–1885.

[16] Bradford J. Delong, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, *Noise trader risk in financial markets*, Journal of Political Economy **98** (1990), no. 4, 703–38.

[17] Douglas W. Diamond and Robert E. Verrecchia, *Information aggregation in a noisy rational expectations economy*, Journal of Financial Economics **9** (1981), no. 3, 221–235.

[18] Trond M. Doskeland and Hans K. Hvide, *Do individual investors have asymmetric information based on work experience?*, Journal of Finance **66** (2011), no. 3, 1011–1041.

[19] Ana Fostel and John Geanakoplos, *Why does bad news increase volatility and decrease leverage?*, Journal of Economic Theory **147** (2012), no. 2, 501 – 525.

[20] Thierry Foucault, David Sraer, and David J. Thesmar, *Individual investors and volatility*, The Journal of Finance **66** (2011), no. 4, 1369–1406.

[21] J.K. Galbraith, *A short history of financial euphoria*, Whittle Series, Whittle Books in association with Viking, 1993.

[22] John Geanakoplos, *The leverage cycle*, NBER Macroeconomics Annual **24** (2010), no. 1, 1–66.

[23] Reuven Glick and Kevin J. Lansing, *Global household leverage, house prices, and consumption*, FRBSF Economic Letter (2010), no. Jan 11.

[24] Mark Grinblatt and Matti Keloharju, *The investment behavior and performance of various investor types: a study of finland's unique data set*, Journal of Financial Economics **55** (2000), no. 1, 43–67.

[25] Mark Grinblatt and Matti Keloharju, *Sensation seeking, overconfidence, and trading activity*, Journal of Finance **64** (2009), no. 2, 549–578.

[26] Mark Grinblatt, Matti Keloharju, and Juhani Linnainmaa, *Iq and stock market participation*, Journal of Finance **66** (2011), no. 6, 2121–2164.

[27] Mark Grinblatt, Matti Keloharju, and Juhani T. Linnainmaa, *Iq, trading behavior, and performance*, Journal of Financial Economics **104** (2012), no. 2, 339–362.

[28] Jens Hainmueller, *Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies*, Political Analysis **forthcoming** (2012).

[29] Bing Han and David Hirshleifer, *Self-enhancing transmission bias and active investing*, Working Paper (2012).

[30] Andrew Haughwout, Donghoon Lee, Joseph Tracy, and Wilbert van der Klaauw, *Real estate investors, the leverage cycle, and the housing market crisis*, Federal Reserve Bank of New York Staff Reports (2011), no. 514.

[31] Rawley Z. Heimer, *Friends do let friends buy stocks actively*, Working Paper (2011).

[32] Rawley Z. Heimer and David Simon, *Facebook finance: How social interaction propagates active investing*, AFA 2013 San Diego Meetings Paper (2012).

[33] Martin F. Hellwig, *On the aggregation of information in competitive markets*, Journal of Economic Theory **22** (1980), no. 3, 477–498.

[34] Soeren Hvidkjaer, *Small trades and the cross-section of stock returns*, Review of Financial Studies **21** (2008), no. 3, 1123–1151.

[35] Zoran Ivkovic and Scott Weisbenner, *Local does as local is: Information content of the geography of individual investors' common stock investments*, Journal of Finance **60** (2005), no. 1, 267–306.

[36] Ron Kaniel, Gideon Saar, and Sheridan Titman, *Individual investor trading and stock returns*, Journal of Finance **63** (2008), no. 1, 273–310.

[37] Michael R King and Dagfinn Rime, *The $4 trillion question: what explains fx growth since the 2007 survey?*, BIS Quarterly Review (2010).

[38] George M Korniotis and Alok Kumar, *Do older investors make better investment decisions?*, The Review of Economics and Statistics **93** (2011), no. 1, 244–265.

[39] Alok Kumar, *Who gambles in the stock market?*, Journal of Finance **64** (2009), no. 4, 1889–1933.

[40] Alok Kumar and Charles M.C. Lee, *Retail investor sentiment and return comovements*, Journal of Finance **61** (2006), no. 5, 2451–2486.

[41] Paul H. Kupiec, *Initial margin requirements and stock returns volatility: Another look*, Journal of Financial Services Research **3** (1989), 287–301.

[42] Albert S Kyle and F Albert Wang, *Speculation duopoly with agreement to disagree: Can overconfidence survive the market test?*, Journal of Finance **52** (1997), no. 5, 2073–90.

[43] Juhani T. Linnainmaa, *The anatomy of day traders*, mimeo (2003).

[44] Jianping Mei, Jose A. Scheinkman, and Wei Xiong, *Speculative trading and stock prices: Evidence from chinese a-b share premia*, Annals of Economics and Finance **10** (2009), no. 2, 225–255.

[45] Thomas Gale Moore, *Stock market margin requirements*, Journal of Political Economy **74** (1966), no. 2, pp. 158–167.

[46] Terrance Odean, *Volume, volatility, price, and profit when all traders are above average*, The Journal of Finance **53** (1998), no. 6.

[47] Jose A. Scheinkman and Wei Xiong, *Overconfidence and speculative bubbles*, Journal of Political Economy **111** (2003), no. 6, 1183–1219.

[48] G. William Schwert, *Margin requirements and stock volatility*, Journal of Financial Services Research **3** (1989), 153–164.

[49] Andrei Shleifer and Robert W Vishny, *The limits of arbitrage*, Journal of Finance **52** (1997), no. 1, 35–55.

[50] Samuel B. Thompson, *Simple formulas for standard errors that cluster by both firm and time*, Journal of Financial Economics **99** (2011), no. 1, 1–10.

[51] Yajun Wang, *Why can margin requirements increase volatility and benefit margin constrained investors?*, Working Paper (2012).

Table 1: **The CFTC trading rule and leverage constraints**

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	

Table 2: **Summary statistics**

		count	mean	std. dev.	5%	25%	50%	75%	95%
U.S.	$roi_{j,i,t}$ (%)	118,696	99.72	3.72	94.54	99.87	100.00	100.23	103.42
	$leverage_{j,i,t}$ (##:1)	118,696	11.45	28.27	0.00	0.21	1.98	11.14	45.73
	$size_{j,i,t}$ (units of base currency)	118,696	11,316.1	87,744.1	40.0	120.0	1,000.0	10,000.0	50,000.0
	$holding\ period_{j,i,t}$ (minutes)	118,696	1,058.49	4,432.52	1.22	14.58	74.20	413.80	4826.4
European	$roi_{j,i,t}$ (%)	144,693	99.81	3.72	94.78	99.85	100.04	100.36	103.67
	$leverage_{j,i,t}$ (##:1)	144,693	16.56	34.59	0.06	0.89	4.26	15.54	76.45
	$size_{j,i,t}$ (units of base currency)	144,693	21,296.6	177,366.9	100.0	1,000.0	2,000.0	10,000.0	86,000.0
	$holding\ period_{j,i,t}$ (minutes)	144,693	884.87	3828.16	1.55	11.87	55.72	327.73	4053.92

Table 3: **Trader characteristics**

The first two panels in this table provide summary statistics on self-identified trader characteristics provided upon joining myForexBook. The website allows incoming users to choose from the options specified below. The third panel presents summary statistics on the number of friendships made per trader after joining the social network.

Panel 1:	Trading Experience in years (% of traders)					
	No Response	0 - 1	1 - 3	4 - 5	5 - up	
U.S.	0.00	27.61	47.44	11.04	13.91	
European	0.52	33.33	46.39	9.11	10.65	

Panel 2:	Trading Approach (% of traders)					
	No Response	Fundamental	Momentum	News	Technical	Not Specific
U.S.	9.82	4.09	5.73	2.86	63.19	14.31
European	10.31	5.67	5.15	2.41	63.92	12.54

Panel 3:	Number of Friendships						
	mean	std. dev	min	25%	50%	75%	max
U.S.	29.28	94.70	0	1	9	22	1,407
European	24.06	100.59	0	1	7	19	1,801

U.S.: $N = 489$; Europe: $N = 582$

Table 4: **Correlation between ROI and margins**

This table reports estimates of the following regression using OLS:

$$roi_{j,i,t} = \beta_0 + \beta_1 * leverage_{j,i,t} + \beta_2 * Trade_{j,i,t} + \beta_3 * Investor_i + \varepsilon_{j,i,t}$$

where $roi_{j,i,t}$ is the return on investment in percentages for trade j, issued by trader i, at time t. $leverage_{j,i,t}$ is the amount of leverage used in each trade, while $Trade_{j,i,t}$ is a matrix of features that belong to each trade issued (its holding period and its size interacted with the currency pair, as well as main effects for both) and $Investor_i$ is a matrix of trader characteristics (trader experience, trading style, and brokerage). Standard errors are double-clustered by day and trader.

	$roi_{j,i,t}$			
	(1)	(2)	(3)	(4)
	all trades		pre-rule	post-rule
$leverage_{j,i,t}$	-0.0160***	-0.0161***	-0.0184***	-0.0145***
	(0.000557)	(0.000594)	(0.000898)	(0.000808)
$log\ trade\ size_{j,i,t}$		0.00886	0.0182	-0.00759
		(0.0145)	(0.0138)	(0.0534)
$log\ holding\ period_{j,i,t}$		-0.0324***	-0.0312***	-0.0348***
		(0.00363)	(0.00491)	(0.00557)
$direction\ (short)_{j,i,t}$		-0.133***	-0.377***	0.121***
		(0.0152)	(0.0217)	(0.0218)
$constant$	100.0***	101.0***	99.58***	101.7***
	(0.00687)	(0.317)	(0.584)	(0.376)
pair FE	No	Yes	Yes	Yes
trade size*pair FE	No	Yes	Yes	Yes
experience FE	No	Yes	Yes	Yes
approach FE	No	Yes	Yes	Yes
broker FE	No	Yes	Yes	Yes
N	266,248	266,248	137,667	128,581
R^2	0.019	0.025	0.035	0.021

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **Was the CFTC trading rule binding?**

This table reports estimates of the following regression using OLS:

$$Y_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * Trade_{j,i,t} + \gamma_5 * Investor_i + \epsilon_{j,i,t}$$

where the dependent variable $Y_{j,i,t}$ is for trade j, issued by trader i, at time t. In regression (i), the dependent variable is the leverage (in units ##:1, 20:1 for example) used per-trade and in (ii), $trade\ size_{j,i,t}$ is a z-score for the size of the position in the base currency conditional on each pair. In (iii), the number of trades are aggregated up to the daily level and the regression is run conditional on having made at least one trade. US_i is equal to one if the trader is located in the U.S. and equal to zero if located in Europe, and $constraint_t$ is equal to one if the trade was opened after the CFTC rule on margin requirements went into effect on October 18, 2010. Standard errors are double-clustered by day and trader.

	(i)	(ii)	(iii)
dependent variable	$leverage_{j,i,t}$	$trade\ size_{j,i,t}$	$trades\ day_{i,t}$
US_i* $constraint_t$	-6.278***	-0.0591***	-1.629**
	(0.226)	(0.00869)	(0.647)
US_i	1.230***	-0.0401***	0.573
	(0.164)	(0.00451)	(0.559)
$constraint_t$	3.344***	0.0801***	-0.504
	(0.172)	(0.00701)	(0.318)
$log\ trade\ size_{j,i,t}$	1.592***		
	(0.133)		
$log\ holding\ period_{j,i,t}$	-1.338***	-0.00571***	
	(0.0254)	(0.000872)	
$direction\ (short)_{j,i,t}$	-0.305**	-0.00834**	
	(0.119)	(0.00404)	
$constant$	59.94***	-0.0176	5.219***
	(2.561)	(0.0302)	(1.811)
pair FE	Yes	Yes	No
trade size*pair FE	Yes	No	No
experience FE	Yes	Yes	Yes
approach FE	Yes	Yes	Yes
broker FE	Yes	Yes	No
N	266,248	266,227	29,707
R^2	0.184	0.031	0.032

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **The impact of the CFTC trading rule on average daily ROI**

This table reports estimates of the following regression using OLS:

$$US\, minus\, EUR\, ROI_t = \gamma_0 + \gamma_1 * constraint_t + \epsilon_t$$

where $US\, minus\, EUR\, ROI_t = \bar{roi}_{US,t} - \bar{roi}_{EUR,t}$, the average daily return on investment in the U.S. minus that in Europe, and $constraint_t$ is equal to one if the day is equal to or after October 18, 2010, the day the CFTC rule constraining leverage use went into effect. The date range is September 1, 2010 to November 29, 2010, excluding weekends. The moving averages use data from prior to September 1st.

	$US\, minus\, EUR\, ROI_t$	
	5-day MA	10-day MA
$constraint_t$	0.120***	0.129***
	(0.0321)	(0.0176)
constant	-0.165***	-0.169***
	(0.0155)	(0.00851)
N	43	43
R^2	0.254	0.567

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: **The impact of the CFTC trading rule on ROI per trade**

This table reports estimates of the following regression using OLS:

$$roi_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * Trade_{j,i,t} + \gamma_5 * Investor_i + \epsilon_{j,i,t}$$

where $roi_{j,i,t}$ is the return on investment (in percentages) for trade j, issued by trader i, at time t. US_i is equal to one if the trader is located in the U.S. and equal to zero if located in Europe, and $constraint_t$ is equal to one if the trade was opened after the CFTC regulation limiting the amount of leverage went into effect on October 18, 2010. Column (3) employs a set of weights created using the entropy balancing scheme outlined in the appendix. Column (4) uses an interaction with the variable $above50_i$ which is equal to one if trader i has used more than 50:1 on at least one trade prior to the leverage constraint. Standard errors are double-clustered by day and trader.

$roi_{j,i,t}$	(1)	(2)	(3)	(4)
US_i* $constraint_t$	0.107***	0.135***	0.143***	0.0430*
	(0.0292)	(0.0303)	(0.0326)	(0.0249)
US_i	-0.134***	-0.171***	-0.125***	-0.0327*
	(0.0188)	(0.0211)	(0.0226)	(0.0173)
$constraint_t$	0.0307	0.0481**	0.0515**	0.0185
	(0.0198)	(0.0201)	(0.0232)	(0.0170)
$log\ trade\ size_{j,i,t}$		-0.0231	-0.0170	0.00780
		(0.0146)	(0.0137)	(0.0148)
$log\ holding\ period_{j,i,t}$		-0.0102**	-0.00801**	-0.0166***
		(0.00360)	(0.00379)	(0.00365)
$direction\ (short)_{j,i,t}$		-0.127***	-0.136***	-0.123***
		0.0153	(0.0163)	(0.0153)
US_i* $constraint_t$*$above50_i$				0.267***
				(0.0815)
$above50_i$				-0.312***
				(0.0327)
US_i* $above50_i$				-0.439***
				(0.0575)
$constraint_t$*$above50_i$				0.0693
				(0.0494)
$constant$	99.80***	99.81***	99.80***	100.0***
	(0.0123)	(0.318)	(0.344)	(0.320)
pair FE	No	Yes	Yes	Yes
trade size*pair FE	No	Yes	Yes	Yes
experience FE	No	Yes	Yes	Yes
trading approach FE	No	Yes	Yes	Yes
broker FE	No	Yes	Yes	Yes
N	266,248	266,248	266,248	266,248
R^2	0.000	0.008	0.011	0.012

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: **The impact of the CFTC trading rule on the volatility of returns**
This table reports estimates of the following regression using OLS:

$$\sigma_{i,t}^{ROI} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * Investor_i + \epsilon_{i,t}$$

where $\sigma_{i,t}^{ROI}$ is the standard deviation of per trade return on investment within day t, for trader i. US_i is equal to one if the trader is located in the U.S. and equal to zero if located in Europe, and $constraint_t$ is equal to one if the trade was opened after the CFTC rule on margin requirements went into effect on October 18, 2010. Units are in percentages. Standard errors are double-clustered by day and trader.

	$\sigma_{i,t}^{ROI}$	
	all days	i, t w/ $>$ 5 trades
US_i* $constraint_t$	0.168	1.117
	(2.686)	(5.836)
US_i	-0.0119	0.0341
	(0.139)	(0.385)
$constraint_t$	1.749	3.402
	(1.728)	(3.435)
constant	-2.885	-4.270
	2.222	3,566
experience FE	Yes	Yes
trading approach FE	Yes	Yes
N	22,685	10,819
R^2	0.001	0.002

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: **Do leverage constraints cause more trading when implied volatility is high?**

This table reports implied odds-ratios from estimating the following logistic regression:

$$Pr(Y_{j,i,t}) = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * Trade_{j,i,t} + \gamma_5 * Investor_i + \epsilon_{j,i,t}$$

where $Y_{j,i,t}$ is equal to one if trade j, issued by investor i, at time t is issued on the day in which implied volatility (either the *vxy* or the *cvix*) is at its weekly high, zero otherwise. US_i is equal to one if the trader is located in the U.S. and equal to zero if located in Europe, and $constraint_t$ is equal to one if the trade was opened after the CFTC regulation limiting the amount of leverage available to traders went into effect on October 18, 2010. Standard errors are double-clustered by day and trader.

	$Pr(vxy_t)$	$Pr(cvix_t)$
US_i* $constraint_t$	1.106***	1.039*
	(0.0227)	(0.0216)
US_i	0.928***	1.022
	(0.0123)	(0.0138)
$constraint_t$	0.741***	0.832***
	(0.0100)	(0.0115)
log trade size	0.997	1.00543***
	(0.00224)	(0.00226)
log holding period	1.00396**	0.974
	(0.00197)	(0.0214)
direction	0.979***	1.0517
	0.00949	(0.0571)
pair FE	Yes	Yes
trade size*pair FE	Yes	Yes
experience FE	Yes	Yes
trading approach FE	Yes	Yes
brokerage FE	Yes	Yes
constant	Yes	Yes
N	266,248	266,248
pseudo R^2	0.006	0.011

Implied Odds-Ratios; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: **Did the CFTC regulation impact intraday markets?**
This table reports estimates of the following regression estimated via OLS:

$$\sigma_{c,t,h} = \gamma_0 + \gamma_1 * USmorning_h + \gamma_2 * constraint_t + \gamma_3 * USmorning_h * constraint_t + \sum_{i=2}^{11} \gamma_{4,i} * Pair_c + \epsilon_{c,t,h}$$

where $\sigma_{c,t,h}$ is the standard deviation of the price of currency pair c, on day t, between the hours h. $\sigma_{c,t,h}$ 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, $\sigma_{c,t,h}$ 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 $Pair_c$ 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.

	(1)	(2)
$\sigma_{c,t,h}$	intra-hour high-low	10-min open
$constraint_t * US\ morning_h$	-0.00195	-0.00270
	(0.00178)	(0.00340)
$constraint_t$	-0.000420	0.0123
	(0.00108)	(0.0114)
$US\ morning_h$	0.00107	0.0000453
	(0.00138)	(0.00203)
$constant$	0.000903	0.00913
	(0.000722)	(0.00579)
pair FE	Yes	Yes
N	1,430	1,430
R^2	0.680	0.756

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: **Are overconfident traders helped more by leverage constraints?**
This table reports estimates of the following regression using OLS:

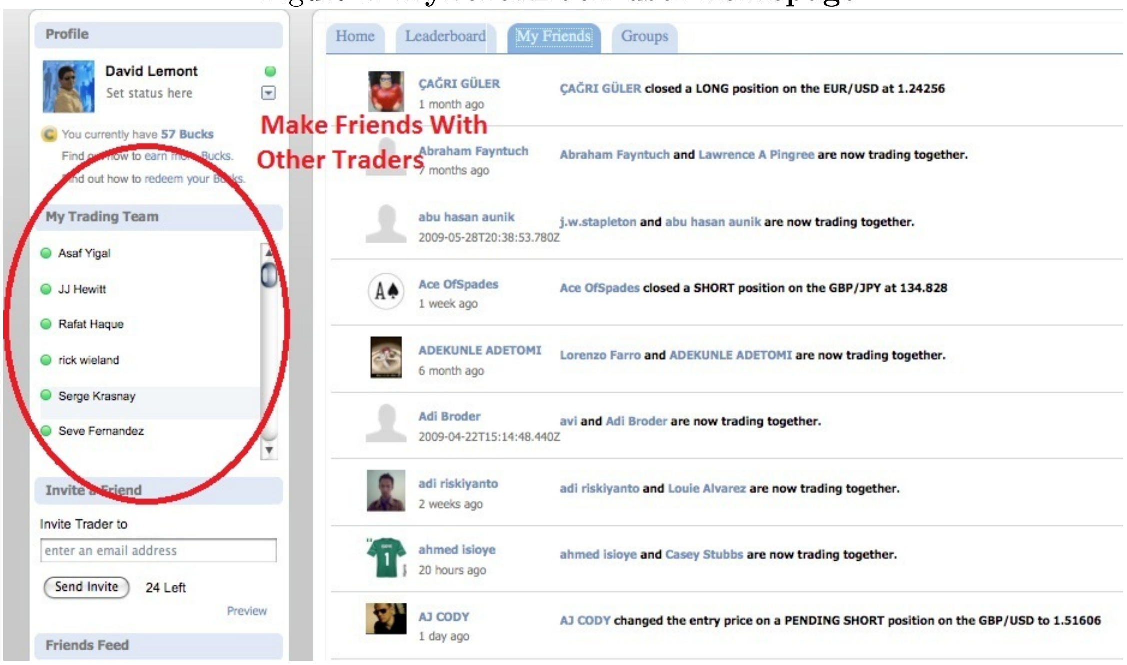
$$roi_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \gamma_4 * US_i * overconfident_i ...$$
$$+ \gamma_5 * constraint_t * overconfident_i + \gamma_6 * US_i * constraint_t * overconfident_i ...$$
$$+ \gamma_7 * Trade_{j,i,t} + \gamma_8 * Investor_i + \epsilon_{j,i,t}$$

The variable $overconfident_i$ is equal to one if trader i exceeds the 50th or 90th percentile, respectively, in one of the following three proxies. In the first pair of columns, I and II, overconfidence is captured by $underperform\&intensity_i$, a double sorting of the number of trades issued by i and their underperformance as measured by average ROI over the pre-regulation period of the sample. In Columns III and IV, i is considered $overconfident_i$ if they are above the threshold in the distribution of $overreact_i$, i's tendency to trade in response to large swings in the previous day's price. In the final pair of columns, the number of friendships made by i by the beginning of the sample period proxies for overconfidence. US_i is equal to one if the trader is located in the U.S. and equal to zero if located in Europe, and $constraint_t$ is equal to one if the trade was opened after the CFTC regulation went into effect on October 18, 2010. Standard errors are double-clustered by day and trader.

		$roi_{j,i,t}$					
		I	II	III	IV	V	VI
	$overconfident_i =$	$underperform\&intensity_i$		$overreact_i$		$friends_i$	
US_i* $constraint_t$*	$overconfident_i >$ 50th %ile	0.303***		0.0325		0.237***	
		(0.0842)		(0.0651)		(0.0635)	
	$overconfident_i >$ 90th %ile		0.114		0.370**		0.152**
			(0.437)		(0.180)		(0.0647)
	US_i	-0.0264	-0.120***	-0.0721***	-0.123***	-0.160***	-0.157***
		(0.0164)	(0.0195)	(0.0258)	(0.0214)	(0.0342)	(0.0270)
	$constraint_t$	-0.107***	-0.00938	0.00972	0.0576***	0.0527	0.0509*
		(0.0179)	(0.0197)	(0.0281)	(0.0210)	(0.0397)	(0.0261)
	US_i* $constraint_t$	0.0371	0.105***	0.139***	0.1000***	-0.00761	0.0889**
		(0.0250)	(0.0287)	(0.0374)	(0.0304)	(0.0493)	(0.0382)
	$overconfident_i$	-0.983***	-4.361***	0.0984***	-0.183***	-0.0417	0.00659
		(0.0383)	(0.258)	(0.0297)	(0.0669)	(0.0288)	(0.0292)
	US_i*$overconfident_i$	-0.291***	-0.815**	-0.253***	-0.547***	-0.0278	-0.0437
		(0.0587)	(0.368)	(0.0473)	(0.113)	(0.0459)	(0.0492)
	$constraint_t$*$overconfident_i$	0.485***	3.429***	0.0613	-0.241**	-0.0102	-0.0196
		(0.0567)	(0.286)	(0.0419)	(0.109)	(0.0462)	(0.0420)
	constant	100.6***	99.59***	99.73***	99.66***	99.79***	99.78***
		(0.322)	(0.321)	(0.321)	(0.321)	(0.320)	(0.321)
	log trade size	Yes	Yes	Yes	Yes	Yes	Yes
	log holding period	Yes	Yes	Yes	Yes	Yes	Yes
	direction	Yes	Yes	Yes	Yes	Yes	Yes
	pair FE	Yes	Yes	Yes	Yes	Yes	Yes
	trade size*pair FE	Yes	Yes	Yes	Yes	Yes	Yes
	experience FE	Yes	Yes	Yes	Yes	Yes	Yes
	trading approach FE	Yes	Yes	Yes	Yes	Yes	Yes
	brokerage FE	Yes	Yes	Yes	Yes	Yes	Yes
	N	263,389	263,389	263,389	263,389	263,389	263,389
	R^2	0.020	0.032	0.010	0.011	0.009	0.009

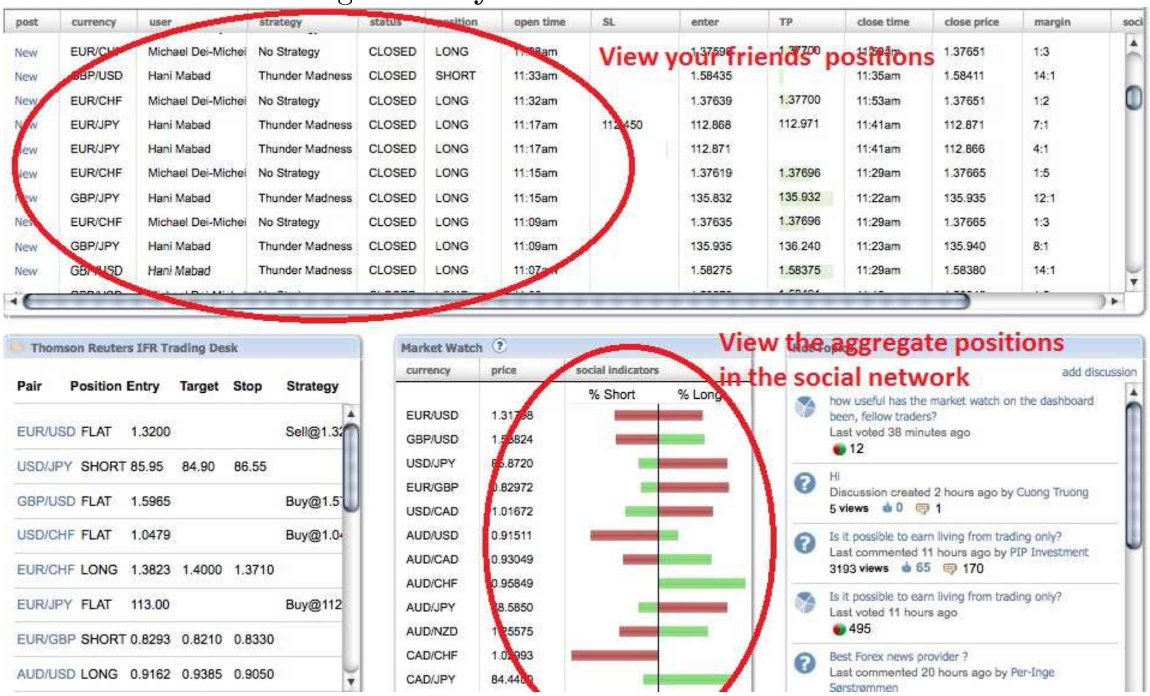
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: **myForexBook user homepage**



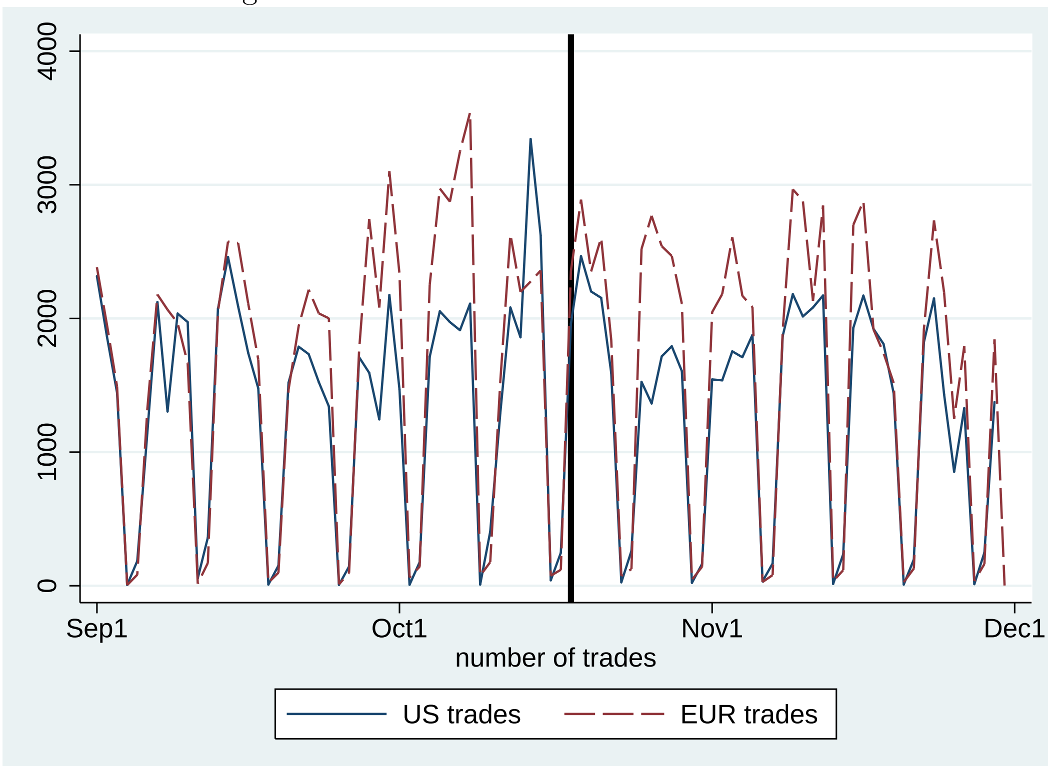
Description: This figure displays the user homepage for a member of myForexBook. Users are able to form bi-lateral friendships with other traders and communicate via private message or in the chat forum.

Figure 2: **myForexBook dashboard**



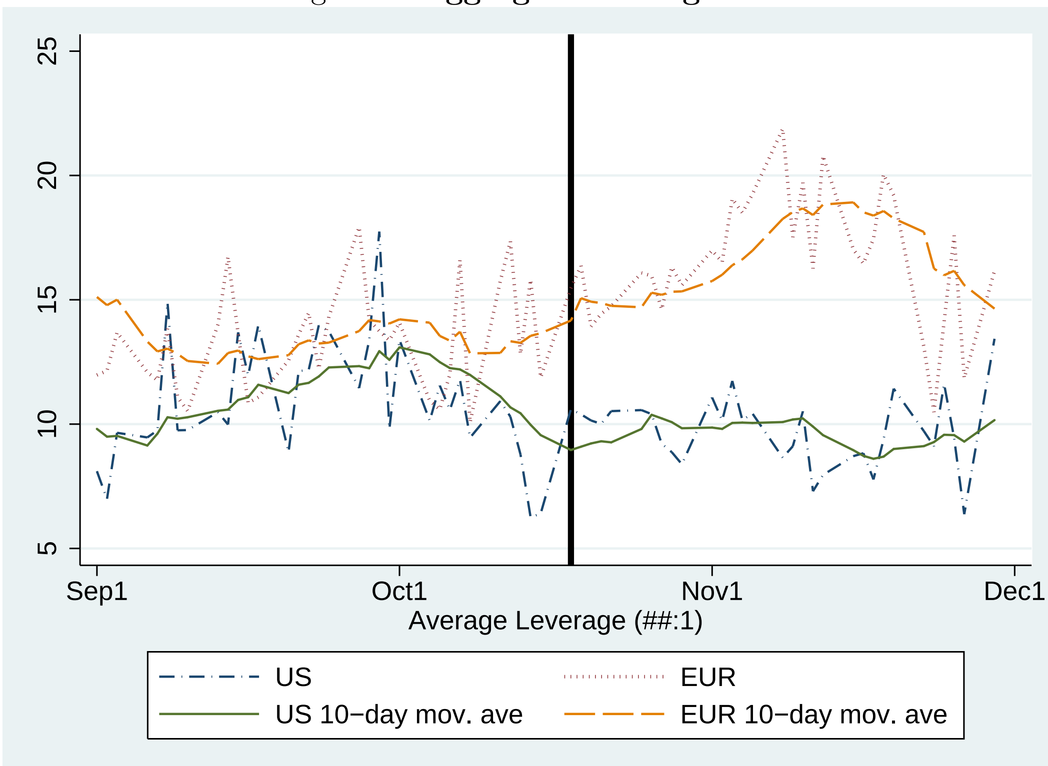
Description: This figure displays a customizable webpage dashboard available to members of myForexBook. Users are able to view their friends' positions in real-time, the aggregate positions within the network, and chat in web-forums, among other options.

Figure 3: **When do retail investors trade?**



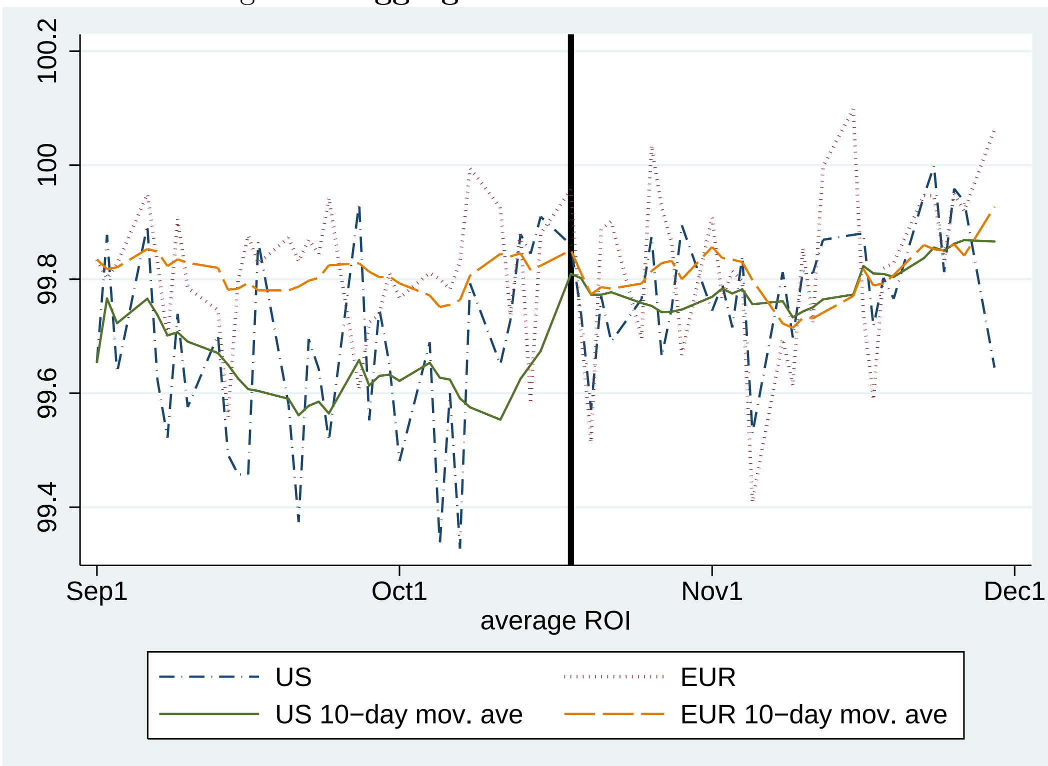
Description: This figure plots the total number of opened positions per day by U.S. and European investors in the trimmed sample described in Section 4. The valleys in the time series correspond to weekends while the majority of trading occurs during weekdays. The black vertical bar indicates the date that the CFTC trading rule was implemented, October 18, 2010.

Figure 4: **Aggregate leverage use**



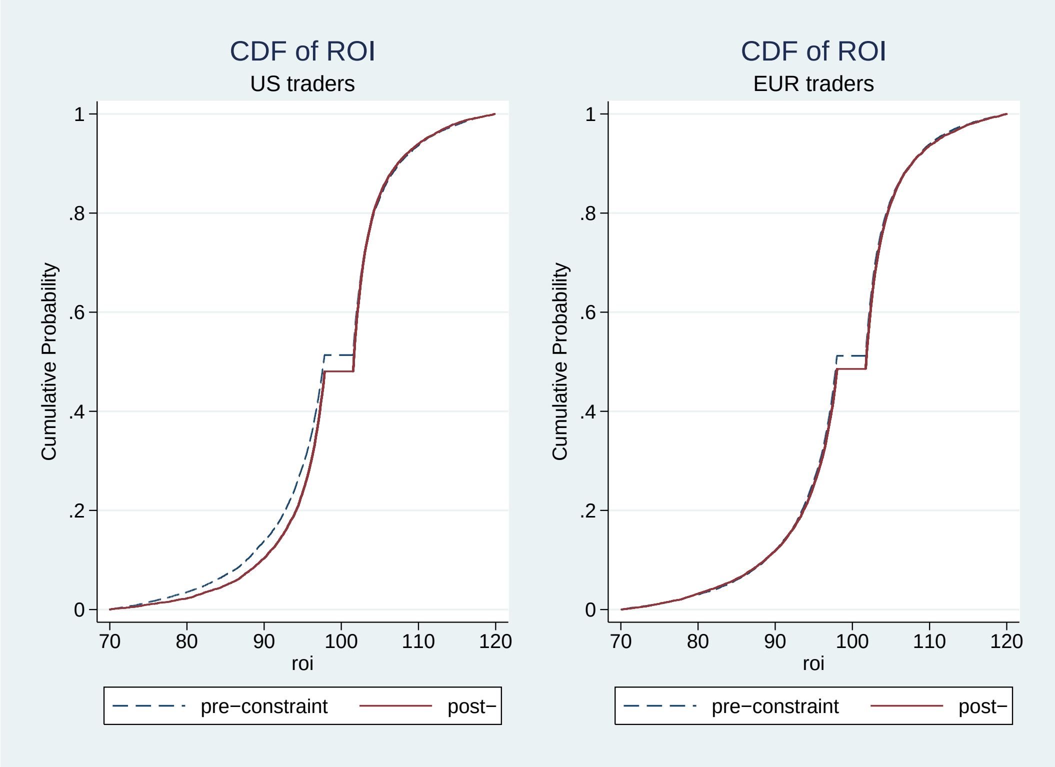
Description: This figure plots the average amount of leverage used per trade per day by U.S. and European traders in the trimmed sample described in Section 4 and a ten-day moving average of each time series. Weekends are excluded from the graph as well as the calculation of the moving average. The black vertical bar indicates the date that the CFTC trading rule was implemented, October 18, 2010.

Figure 5: **Aggregate return on investment**



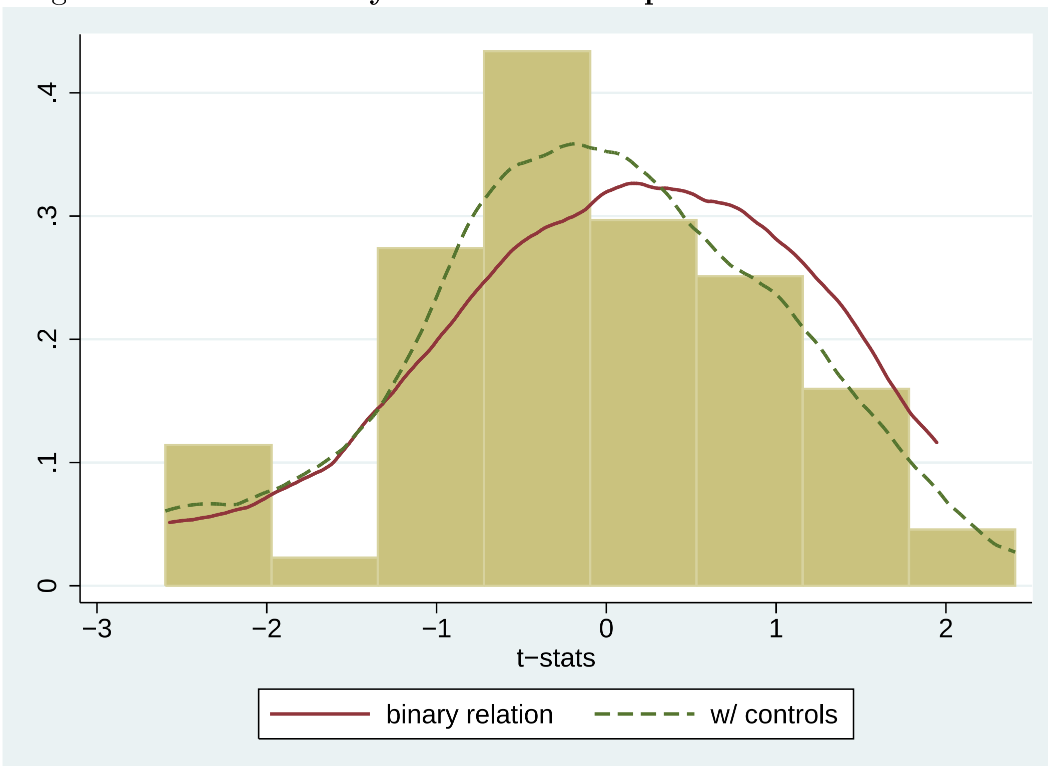
Description: This figure plots the average return on investment per trade per day by U.S. and European traders in the trimmed sample described in Section 4 and a ten-day moving average of each time series. Weekends are excluded from the graph as well as the calculation of the moving average. The black vertical bar indicates the date that the CFTC trading rule was implemented, October 18, 2010.

Figure 6: **Distribution of ROI before and after legislation**



Description: This figure plots the cumulative density function for the return on investment for all trades in the sample. For illustrative purposes, the inner 90 percent of the distribution are removed conditional on the trade being placed by the U.S. or European sub-group.

Figure 8: **Kernel density estimates from placebo test on US×Rule**



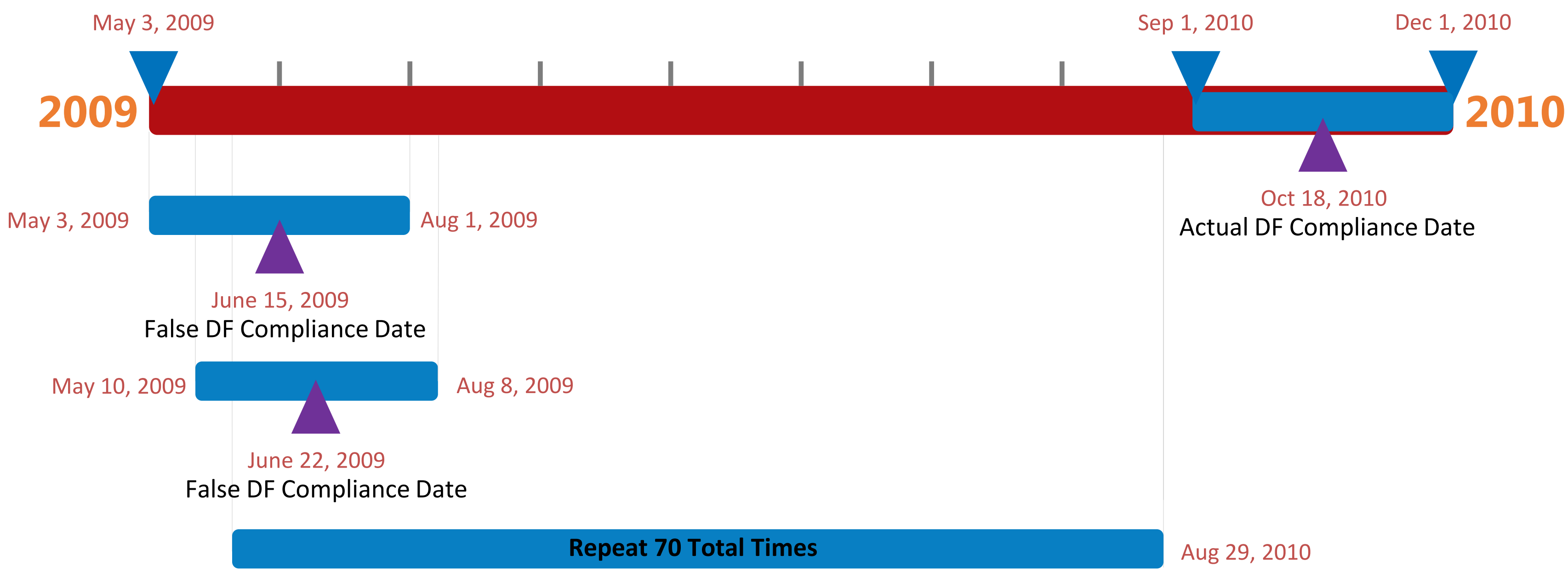
Description: This figure plots kernel density estimates using the Epanechnikov kernel function and a histogram of the t-statistics on γ_3 from a placebo test for the main difference-in-differences regression to assess the impact of the CFTC regulation on per-trade return on investment. To conduct the placebo test, I run the following regressions:

$$binary\,relation: \quad roi_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + \epsilon_{j,i,t}$$

$$w/controls: \quad roi_{j,i,t} = \gamma_0 + \gamma_1 * US_i + \gamma_2 * constraint_t + \gamma_3 * US_i * constraint_t + ...$$
$$... + \gamma_4 * Trade_{j,i,t} + \gamma_5 * Investor_i + \epsilon_{j,i,t}$$

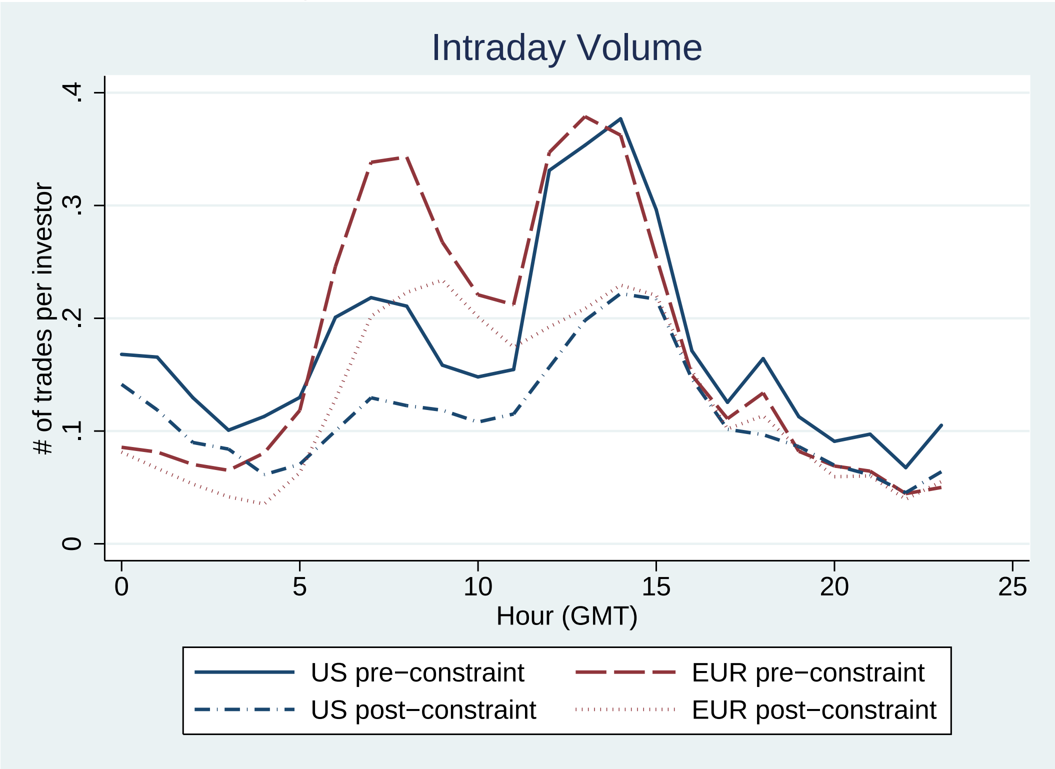
collecting the coefficient,γ_3, and the corresponding t-statistic after 70 total iterations. I change the date of $constraint_t$ each iteration, starting from Sunday, May 3, 2009 rolling forward a week at a time until Aug 29, 2010. I allow the range of the sample to encompass six weeks before and after the false date for the CFTC regulation. Prior to each iteration, I impose the data trimming exercise discussed in Section 4, which restricts the sample to include only those with trades before and after the false date change. As a reminder, the results from estimating the effect of the actual rule change are as follows. In the $binary\,relation$, $t - stat = 3.664$ and when control variables are included, $t - stat = 4.455$.

Figure 7: **Placebo test for false positive difference-in-differences test**



Description: This figure illustrates the placebo exercise described in Section 5.3.

Figure 9: **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.