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Can Leverage Constraints Help Investors?

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This paper provides causal evidence that leverage constraints can reduce the underperformance of individual investors. In accordance with Dodd-Frank, the CFTC was given regulatory authority over the retail 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 reduces average per-trade losses even after adjusting for risk. Since this causal approach holds constant contemporaneous market factors, these findings challenge the concept that individuals are better off when they are unconstrained in their risk-taking.

Keywords: Leverage Constraints, Individual Investors, Retail Foreign Exchange, Financial Market Regulation.

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What are the consequences of allowing retail investors to trade with a substantial amount of leverage? A central tenet of financial theory is that individuals are better off when they are given more choice. However, individuals that participate in risky markets often appear to do so to their own detriment.[1] Recent research has challenged the notion that retail traders lack viable information or behave irrationally,[2] implying that the consequences of providing traders with the opportunity to use leverage are uncertain, especially since a textbook model predicts welfare reductions when borrowing constraints bind.

Considering the tension between these perspective views of individual investor trading, it would be worthwhile to provide a micro-level investigation of the motivations behind trading with leverage and its impact on investor-level outcomes. However, few studies have examined leveraged trading largely due to difficulties obtaining the necessary data and challenges isolating a causal effect. This research uses a new, proprietary database provided by a Facebook-style social network for retail traders that compiles individual trading records across roughly 50 different online brokerages.[3] To overcome the problem of endogeneity due to the relationship between leverage availability, prices, and unobservable investor characteristics, 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

[1]See the survey paper Barber and Odean (2013).

[2]New evidence suggests that retail traders are information providers (Kelley and Tetlock (2013) and Giannini et al. (2014)). They may also have standard beliefs and preferences, but succumb to other factors such as information asymmetries (Linnainmaa (2010)) or have rational beliefs and are simply learning about their own ability as a trader (Linnainmaa (2011)).

[3]Heimer and Simon (2013) presents a more detailed discussion of the social networking aspects of the database.

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 0.10 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 inverse relationship between leverage and profitability is robust to controlling for per-trade factors such as the size of the trade, the holding period, direction, 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 have been caused by unrelated changes in overall market conditions.

This paper's findings help clarify our views of leveraged trading, which may generalize across many asset markets. Well over half of the traders in the myForexBook database are unprofitable and a similar number lose in the overall population of retail foreign exchange traders, across the population of brokerages, according to quarterly reports compiled by the CFTC. Likewise, retail traders in equities tend to underperform relative to standard benchmarks both in U.S. (Barber and Odean (2000)) and international studies (Barber et al. (2009b)), and their underperformance is associated with the use of leverage (Linnainmaa (2003)). Housing market speculation by out-of-town second-home buyers is also unprofitable (Chinco and Mayer (2012)) and leverage may play an important role (Ben-David (2011) and

Haughwout et al. (2011)). Even companies with overconfident managers have higher debt leverage (Ben-David et al. (2013)).

1 Related Literature

There is ample literature tying leverage constraints to asset prices, but the empirical studies are produced less frequently, because of clear challenges interpreting any results and a paucity of data. To highlight a few empirical papers, in contrast to earlier studies (Kupiec (1989) and Schwert (1989)), Foucault et al. (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 Pedersen (2014) find that leverage constraints cause investors to hold riskier assets in their portfolio, while Kahraman and Tookes (2014) studies the relation between margin requirements and liquidity.

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. (2009a) 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 fare better than others (Coval et al. (2005)) and much research attempts to explain the heterogeneity in performance. Grinblatt et al. (2011, 2012) find that high-IQ investors earn greater Sharpe ratios and are better at picking stocks. Cognitive aging outweighs the positive effect of increased experience causing older investors to perform worse (Korniotis and Kumar (2011)). Individuals earn negative excess returns buying stocks that come from firms that are in the same industry as their place of employment (Doskeland and Hvide (2011)). On the other hand, individuals use local knowledge to outperform non-local investments (Ivkovic and Weisbenner (2005)). Furthermore, investors susceptible to peer-influence trade actively and underperform relative to passive benchmarks (Han and Hirshleifer (2013); Heimer and Simon (2013); and Heimer (2014)).

2 Retail forex and the CFTC regulation

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

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

All clients, regardless of domestic location, receive spot quotes in terms of the currency pair (e.g. EUR/USD) using the nomenclature designated by standard *ISO 4217* from the *International Standards Organization*. Each pair includes a "base" and "quote" currency

(EUR is the base and USD is the quote, in the EUR/USD example). Traders decide how much of the pair to purchase or to short in terms of the base currency. The brokerage is the counter-party on all transactions, responsible for off-loading inventory into the inter-bank market. Retail clients use a domestic bank account to deposit initial funds into their forex brokerage account. Similar to a margin account, retail customers do not take receipt of the foreign currency when they trade and withdrawals are made in the client's domestic currency.

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

Regulation in the forex market

The retail forex market in the U.S. was 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 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.[4] Shortly after Dodd-Frank was written into law, the CFTC released on September 10, 2010 a finalized set of rules which required all retail brokerages to register with the CFTC and to limit the amount of leverage available to U.S. customers to 50:1 on all major pairs and 20:1 on all others (Table 1 provides a complete list of pairs).[5] The brokerages were required to come

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

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

into compliance with the new rules by October 18, 2010. Meanwhile, European regulatory authorities continue to allow retail forex brokerages full discretion over the provision of leverage to traders and the maximum available leverage tends to exceed 50:1.

A distinguishing feature of the forex market is that most brokerages have clients from all around the world. However, there is no centralized, world-wide regulatory authority. In order to comply with domestic regulations, such as those imposed by the CFTC, the brokerage is responsible for verifying the residency of their clients. Verification is done using government issued documentation, such as a passport, and a link to a domestic bank/checking account from which to withdraw and deposit funds.[6] Consequently, bypassing domestic regulation is undoubtedly costly for the majority of retail clientele, if not impossible. Thus, the structure of the market is beneficial to this research, because it is possible to compare regulated U.S. traders to their unregulated European counterparts within any given brokerage.

3 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 roughly 2.2 million trades which mostly occurred between early-2009 and December,

[6] The author's website contains an example of correspondence with a retail forex brokerage over the necessary documentation required to open an account.

2010. A more detailed discussion of the social networking aspects of the database is available in Heimer and Simon (2013). Notably, myForexBook traders have similar social behavior to those in other databases such as the Consumer Expenditure Survey, a representative household survey in the U.S. (Heimer (2014)), and the population of equity market participants in Finland (Shive (2010)).

For the purposes of this study, the data is trimmed in several ways. First, the population of traders is restricted to those claiming to reside in either the United States or Europe.[7] To ease concerns over self-reported data, the brokerages provided the operators of the social network with the primary currency of 68 percent of traders in the sample, among whom 97 percent of traders claiming to be from the U.S. also had accounts denominated in the U.S. dollar, with a similar matching rate among European respondents.[8] The data on primary currency relies on the fact that traders need to use a domestic bank account to fund an initial deposit in their forex brokerage account. Secondly, the sample is restricted to the set of traders who issued trades both before and after the CFTC regulation was implemented, thereby alleviating concerns over attrition bias.

Furthermore, 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 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

[7]Traders from other locations are present in the dataset, but the amount of leverage available to them is unknown.

[8]About 3.5 percent of all traders did not specify their location upon joining the social network. Within this group, the trader's brokerage provided the base currency for five traders, four from the U.S. and one from Europe. These five traders are included in the analysis. Furthermore, I exclude all traders who report a U.S. or European residence, but have an account denominated in a different currency.

after the regulation. This leaves a total of 256,375 trades made by 1,071 traders, almost half – 489 – are from the U.S.

Table 2 presents summary statistics on per-trade ROI, separated by U.S. and European traders. According to the notation used by the data-provider, ROI in the forex market is equal to

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

for all long positions and

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

for all short positions, where S_p is the spot price of currency pair p. S_p is equivalent to Y/X, where X is the value of the base currency and Y is the lot size of the quote currency. The subscript t refers to the second at which the position is opened, while τ is the second the position is closed. 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, which is large enough to suggest traders are unprofitable even after paying the bid-ask spread. 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 around 3.5 for both U.S. and Europeans.

The empirical analysis incorporates cross-country interest rate differentials to approximate the risk-free rate in the forex market (Menkhoff et al. (2012), among others).[9] Traders can earn the difference between short-term government-issued debt in two different countries instead of actively trading currencies. Formally, interest rate differentials are equal to $F_{p,t}$=$(i_{b,\tau} - i_{b,t}) - (i_{q,\tau} - i_{q,t})$ where i_b is the risk-free rate in the country whose currency is the base of the pair and i_q belongs to the quoted currency.[10]

[9] Alternatively, the results are robust to the inclusion of short-term interest rate changes in the trader's domestic currency.

[10] The author's website provides the one-month government yields used in this study.

European traders in the sample use more leverage on average than U.S. traders (16.7:1 versus 11.5:1, respectively), but the difference is not statistically different (Table 2). The distribution of leverage 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. Most users cite having either zero to one or one to three years of trading experience (Panel 1). Traders from both locales tend to consider themselves technical traders as opposed to basing their strategies on news, momentum, or fundamentals (Panel 2). Panel 3 presents summary statistics on the number of friendships made after joining the social network. Recent research shows that users of online social networks maintain meaningful relationships with only a handful of contacts,[11] yet U.S. traders have an average of 30.0 friends at the beginning of the sample period while Europeans have 24.0. The difference is not statistically different because the standard deviation is 94.7 and 100.6, respectively.

Do US and European traders 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 these two groups 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

[11] See the combined works of evolutionary scientist Robin Dunbar for further discussion.

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 use of leverage move together on a daily basis. I calculate the log of the first difference of average daily leverage by location (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 trading activity of U.S. and European traders is similar. Therefore, it is 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 trading behavior and subsequent outcomes.

4 Leverage and profitability

4.1 Correlation of leverage and return on investment

The standard model of a risk-averse investor predicts that a reduction in available leverage results in lower returns, because traders can no longer take on as much risk. As a first pass at examining this relationship, I estimate the influence of leverage on risk-adjusted excess-returns using the following OLS regression:

$$roi_{j,i,t} = \beta_0 + \beta_1 \cdot leverage_{j,i,t} + \beta_2 \cdot F_{p,t} + \beta_3 \cdot \sigma_{i,t}^{ROI} + \beta_4 \cdot Trade_{j,i,t} + \beta_5 \cdot Investor_i + \varepsilon_{j,i,t} \quad (1)$$

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 trading experience and trading style fixed effects. The empirical model also controls for cross-country interest rate differentials, $F_{p,t}$, as a proxy for the risk-free rate and $\sigma_{i,t}^{ROI}$, the daily standard deviation of ROI, to account for the observed risk-taking of trader i. Standard errors are clustered across two dimensions using the method outlined in Thompson (2011), which allows for correlation in residuals by trader and at the daily level.[13]

[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

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.

4.2 Empirical strategy

The CFTC regulation implemented in October, 2010 offers a quasi-natural experimental setting in which to identify the effect of leverage on investor trading. 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 activity of traders through any other channels, any change in the profitability of U.S. traders – when compared to European traders – following the regulation is likely to be attributed to the reduction in leverage.

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.

Was the CFTC trading rule binding?

Having confirmed in Section 3 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. I use forex prices provided by the retail brokerage Oanda to externally validate the data's 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.

The following regression framework formally establishes the influence of the CFTC regulation:

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

The dependent variable, $Y_{j,i,t}$, takes on one of three values. In the first specification, (1) the dependent variable is the amount of leverage used per-trade j, $leverage_{j,i,t}$. The leverage constraint should also reduce the size and frequency with which U.S. market participants trade. The dependent variable in column (2) is $trade\ size_{j,i,t}$, the size of the trade denominated in the base currency normalized around the mean of each currency pair (z-score). In the last specification, (3) the dependent variable is the number of trades issued in a given day, $trades\ day_{i,t}$. In specification (3), Equation 2 is estimated conditional on having made at least one trade during the day and is estimated at a daily frequency. The variable 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.[14]

Estimation results are presented in Table 5. The regression in Column (1) suggests that following the CFTC regulation, the amount of leverage used by U.S. traders fell by around six units relative to the control group. Conditional means from the linear model predict that U.S. traders reduced their average leverage 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 (2) shows that the regulation caused a statistically significant reduction in the size of trades made by U.S. traders relative to the control group equal to about six percent of a standard deviation. For robustness, I also use the size of the trade denominated in units of the base currency as a dependent variable. While the relationship

[14] The analysis is robust to the exclusion of trades – roughly half of a percent of the sample – opened prior to October 18, 2010 and closed afterward.

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 (3) 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.

4.3 Return on investment and the CFTC regulation

Preliminary Evidence

Preliminary evidence that the use of leverage causes lower returns is presented in Figure 5, which plots the time series 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:

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

where $US minus EUR ROI_t = \bar{roi}_{US,t} - \bar{roi}_{EUR,t}$, 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, which 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.[15]

Profitability on a per-trade basis

The above evidence, while highly informative, has its limitations. For instance, there are potentially many factors correlated with the use of leverage and a simple analysis of trends 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:

$$roi_{j,i,t} = \gamma_0 + \gamma_1 \cdot US_i + \gamma_2 \cdot constraint_t + \gamma_3 \cdot US_i \cdot constraint_t ... \\ + \gamma_4 \cdot F_{p,t} + \gamma_5 \cdot \sigma^{ROI}_{i,t} + \gamma_6 \cdot Trade_{j,i,t} + \gamma_7 \cdot Investor_i + \epsilon_{j,i,t} \quad (4)$$

[15] I also regress per-trade excess returns on market-wide excess returns among U.S. traders. The tests produce an alpha of -0.26 (s.e. = 0.01) before the regulation, and -0.17 (s.e = 0.02) following the regulation.

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 suggests that the regulation increases the ROI of leverage-constrained investors, even after controlling for observed risk-taking.

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 uses 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.

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.

The fourth and fifth columns include 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 coefficient on $US_i * constraint_t * above50_i$ is approximately 0.3 and is statistically significant at the one percent error level in both specifications. Meanwhile, the coefficient estimate for γ_3 is no longer statistically different from zero, which suggests that the results are primarily driven by the traders who are constrained by the reduction in leverage.

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, standard errors in difference-in-differences estimation can be underestimated resulting in frequent false positive results (Bertrand et al. (2004)).

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 3 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 around four, 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.

Moreover, Figure 9 conducts a similar placebo exercise while using $leverage_{ijt}$ as a dependent variable. The test evaluates the likelihood that the amount of leverage used by U.S. and European traders trend in different directions. If the two groups frequently experience divergences in their use of leverage, it would suggest that market factors are likely to produce false positive results, thereby invalidating the quasi-experiment. However, the placebo exercise produces a t-stat above 1.96 in only one out of 70 total regressions, which enhances the confidence in this paper's causal tests.

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.

5 Conclusion

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

According to a simple model of a rational agent who is free from behavioral biases, traders who use leverage take on more risk, and therefore demand higher returns. The CFTC regulation produces a contradictory result: the reduction in leverage mitigates the underperformance of the least profitable traders. Investor overconfidence – the tendency to hold beliefs that are too precise – can explain these findings. If an individual thinks he has better information than everyone else, it makes sense from his perspective to apply as much leverage as possible to his trades. The overconfident trader also overweights her own beliefs and ignores more informative signals such as price movements, which leads to trading losses. Thus, leverage constraints are capable of mitigating harmful trading behavior.

The leverage constraint imposed by the CFTC likely reached too small a fraction of the massive, highly liquid market for foreign exchange to have influenced prices. This observation is convenient for the purpose of this research, because large asset price changes could confound any conclusions about the use of leverage at the individual level. Regardless, this paper's findings may extend to our broad understanding of the relationship between asset prices and leverage, which tend to co-vary positively and is a notable features of bubble-like episodes. It is challenging to model this relationship when agents abide by textbook beliefs and preferences. However, in one of the more successful strands of that literature, overconfidence leads to optimistic beliefs among traders even if they do not necessarily possess better information.[16] Traders with the highest valuation wish to borrow in order to speculate on the resale value of the asset, which can push prices away from fundamentals, especially if it is costly to trade against the movement of prices. Therefore, this paper can be viewed as providing micro-founded evidence on the relationship between leverage and trading.

[16] Examples include Minsky (1986), Geanakoplos (2010), Hong and Sraer (2014), Scheinkman and Xiong (2003), and Simsek (2013), among others.

Appendix

A1: 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:

$$\min_{w_i} H(w) = \sum_{\{i|D=0\}} w_i log(w_i/q_i) \tag{5}$$

subject to balance and normalizing constraints,

$$\sum_{\{i|D=0\}} w_i c_{ri}(X_i) = m_r \text{ with } r \in 1, ..., R \tag{6}$$

$$\sum_{\{i|D=0\}} w_i = 1 \tag{7}$$

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

A4: An endogenous change in intraday market conditions?

As emphasized in the introduction, much research shows that retail traders influence asset prices. Therefore, a potential explanation for the increase in performance following the leverage constraint is that the reduction in retail volume among U.S. participants 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 10, 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 8 reports estimates of the following regression estimated via OLS:

$$\sigma_{c,t,h} = \gamma_0 + \gamma_1 * US\,morning_h + \gamma_2 * constraint_t + \gamma_3 * US\,morning_h * constraint_t ... + \sum_{i=2}^{11} \gamma_{4,i} * Pair_p + \epsilon_{c,t,h} \quad (8)$$

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

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

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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**

		observations	mean	std. dev.	5%	25%	50%	75%	95%
U.S.	$roi_{j,i,t}$ (%)	115,342	99.7	3.6	94.8	99.9	100.0	100.2	103.2
	$leverage_{j,i,t}$ (##:1)	115,342	11.3	28.4	0.0	0.2	1.9	10.7	45.7
	$size_{j,i,t}$ (units of base currency)	115,342	11,269.5	88,813.5	40.0	100.0	1,000.0	10,000.0	50,000.0
	$holding\ period_{j,i,t}$ (minutes)	115,342	1,023.3	4,316.1	1.2	14.1	71.0	391.5	4670.0
European	$roi_{j,i,t}$ (%)	141,050	99.8	3.6	95.0	99.9	100.0	100.3	103.5
	$leverage_{j,i,t}$ (##:1)	141,050	16.5	34.7	0.06	0.86	4.1	15.4	76.9
	$size_{j,i,t}$ (units of base currency)	141,050	19,826.9	153,817.3	100.0	1,000.0	2,000.0	10,000.0	83,000.0
	$holding\ period_{j,i,t}$ (minutes)	141,050	850.4	3,694.8	1.5	11.6	53.8	313.3	3,940.0

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.	0.0	27.6	47.4	11.0	13.9
European	0.5	33.3	46.4	9.1	10.7

Panel 2:	Trading Approach (% of traders)					
	No Response	Fundamental	Momentum	News	Technical	Not Specific
U.S.	9.8	4.1	5.7	2.9	63.2	14.3
European	10.3	5.7	5.2	2.4	63.9	12.5

Panel 3:	Number of Friendships						
	mean	std. dev	min	25%	50%	75%	max
U.S.	29.3	94.7	0	1	9	22	1,407
European	24.1	100.6	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:

$$roi_{j,i,t} = \beta_0 + \beta_1 \cdot leverage_{j,i,t} + \beta_2 \cdot F_{p,t} + \beta_3 \cdot \sigma^{ROI}_{i,t} + \beta_4 \cdot Trade_{j,i,t} + \beta_5 \cdot Investor_i + \varepsilon_{j,i,t}$$

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.

	(1)	(2)	(3)	(4)
$roi_{j,i,t}$	all trades		pre-constraint	post-constraint
$leverage_{j,i,t}$	-0.0160***	-0.0162***	-0.0188***	-0.0144***
	(0.00060)	(0.00064)	(0.00097)	(0.00088)
$log\ trade\ size_{j,i,t}$		-0.00175	0.00955	-0.0263
		(0.014)	(0.014)	(0.055)
$log\ holding\ period_{j,i,t}$		-0.0359***	-0.0348***	-0.0383***
		(0.0038)	(0.0051)	(0.0058)
$constant$	100.0***	101.0***	99.14***	101.6***
	(0.0074)	(0.34)	(0.70)	(0.39)
$F_{p,t}$	No	Yes	Yes	Yes
$\sigma^{ROI}_{i,t}$	No	Yes	Yes	Yes
direction	No	Yes	Yes	Yes
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	256,392	256,392	132,799	123,593
R^2	0.021	0.026	0.038	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:

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

where the dependent variable $Y_{j,i,t}$ is for trade j, issued by trader i, at time t. In regression (1), the dependent variable is the leverage (in units ##:1, 20:1 for example) used per-trade and in (2), $trade\ size_{j,i,t}$ is a z-score for the size of the position in the base currency conditional on each pair. In (3), 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 went into effect on October 18, 2010. Standard errors are double-clustered by day and trader.

	(1)	(2)	(3)
dependent variable	$leverage_{j,i,t}$	$trade\ size_{j,i,t}$ (z-score)	$(trades/day)_{i,t}$
US_i* $constraint_t$	-6.367***	-0.0597***	-2.251**
	(0.23)	(0.0086)	(0.85)
US_i	1.230***	-0.0327***	1.101
	(0.17)	(0.0044)	(0.75)
$constraint_t$	3.386***	-0.081***	-0.553
	(0.18)	(0.0068)	(0.41)
$log\ trade\ size_{j,i,t}$	1.592***		
	(0.14)		
$log\ holding\ period_{j,i,t}$	-1.321***	-0.00660***	
	(0.026)	(0.00087)	
$constant$	71.18***	-0.0122	5.866***
	(2.45)	(0.030)	(2.10)
$F_{p,t}$	Yes	Yes	No
$\sigma_{i,t}^{ROI}$	Yes	Yes	No
direction	Yes	Yes	No
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	256,392	256,375	22,413
R^2	0.186	0.031	0.037

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:

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

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:

$$roi_{j,i,t} = \gamma_0 + \gamma_1 \cdot US_i + \gamma_2 \cdot constraint_t + \gamma_3 \cdot US_i \cdot constraint_t + \gamma_4 \cdot F_{p,t} + \gamma_5 \cdot \sigma^{ROI}_{i,t} + \gamma_6 \cdot Trade_{j,i,t} + \gamma_7 \cdot Investor_i + \epsilon_{j,i,t}$$

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. Columns (4) and (5) use 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)	(5)
US_i* $constraint_t$	0.101***	0.132***	0.140***	0.0146	0.0259
	(0.031)	(0.033)	(0.034)	(0.022)	(0.026)
US_i* $constraint_t$*$above50_i$				0.341***	0.284***
				(0.079)	(0.084)
US_i	-0.140***	-0.175***	-0.134***	-0.0264**	-0.0159
	(0.020)	(0.022)	(0.023)	(0.012)	(0.017)
$constraint_t$	0.0436**	0.0652***	0.0590**	0.00638	0.0222
	(0.021)	(0.021)	(0.024)	(0.016)	(0.017)
$log\ trade\ size_{j,i,t}$		-0.0330**	-0.0282**		-0.00228
		(0.014)	(0.013)		(0.015)
$log\ holding\ period_{j,i,t}$		-0.0140***	-0.0120***		-0.0198***
		(0.0038)	(0.0040)		(0.0038)
$above50_i$				-0.452***	-0.308***
				(0.030)	(0.034)
US_i* $above50_i$				-0.485***	-0.465***
				(0.053)	(0.060)
$constraint_t$*$above50_i$				0.0684	0.0874*
				(0.048)	(0.051)
$constant$	99.79***	99.77***	99.73***	99.97***	99.98***
	(0.013)	(0.34)	(0.38)	(0.0086)	(0.34)
$F_{p,t}$	Yes	Yes	Yes	Yes	Yes
$\sigma^{ROI}_{i,t}$	Yes	Yes	Yes	Yes	Yes
direction	No	Yes	Yes	No	Yes
pair FE	No	Yes	Yes	No	Yes
trade size*pair FE	No	Yes	Yes	No	Yes
experience FE	No	Yes	Yes	No	Yes
trading approach FE	No	Yes	Yes	No	Yes
broker FE	No	Yes	Yes	No	Yes
entropy weights	No	No	Yes	No	No
N	256,392	256,392	256,392	256,392	256,392
R^2	0.000	0.009	0.011	0.007	0.012

Standard errors in parentheses

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

Table 8: **Did the CFTC regulation impact intraday markets?**
This table reports estimates of the following regression estimated via OLS:

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

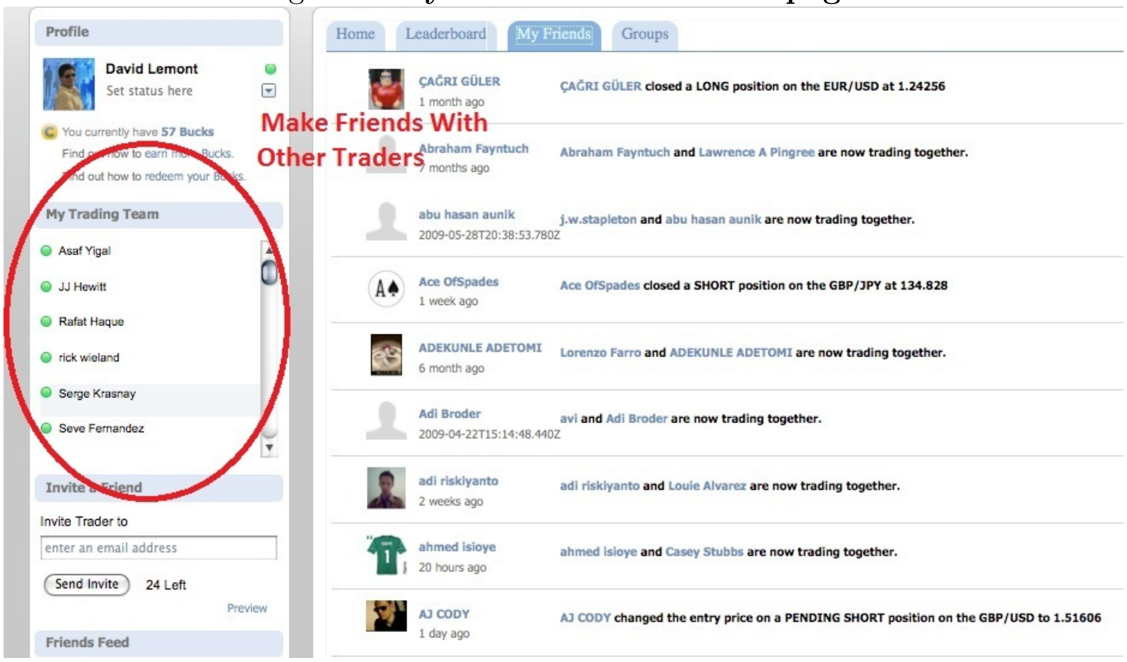
where $\sigma_{p,t,h}$ is the standard deviation of the price of currency pair p, on day t, between the hours h. $\sigma_{p,t,h}$ is calculated in two ways. In the first column, the dependent variable is the standard deviation of the difference between the high and low price within a given hour. In the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

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

Standard errors in parentheses

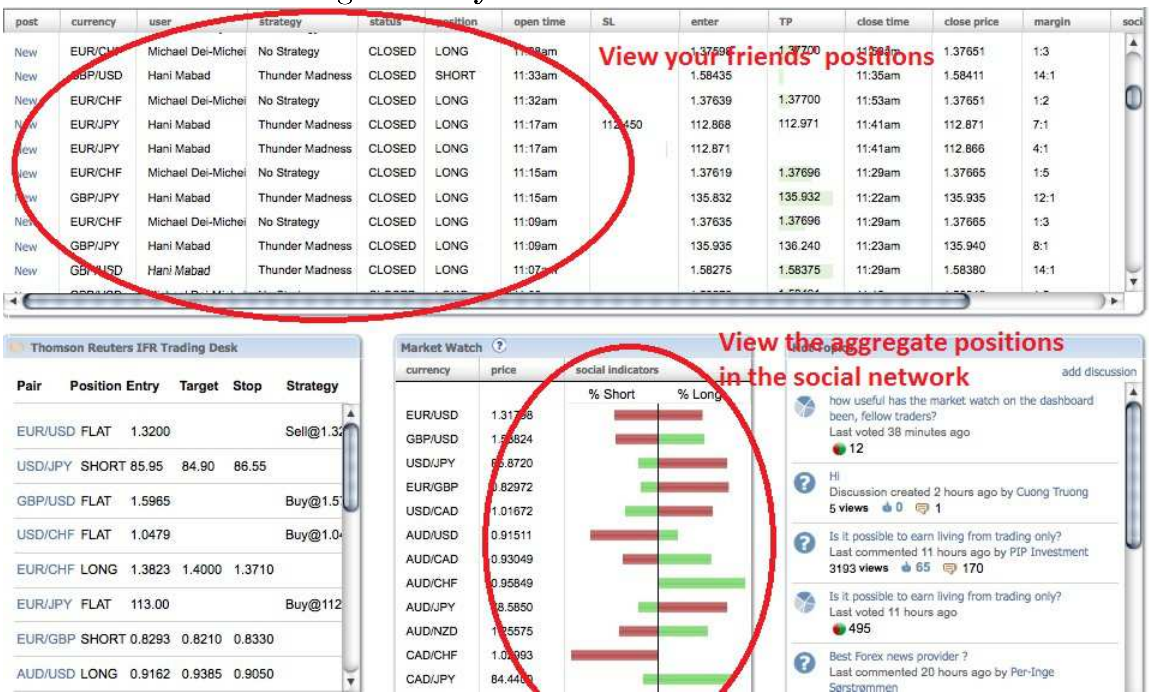
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: **myForexBook user homepage**



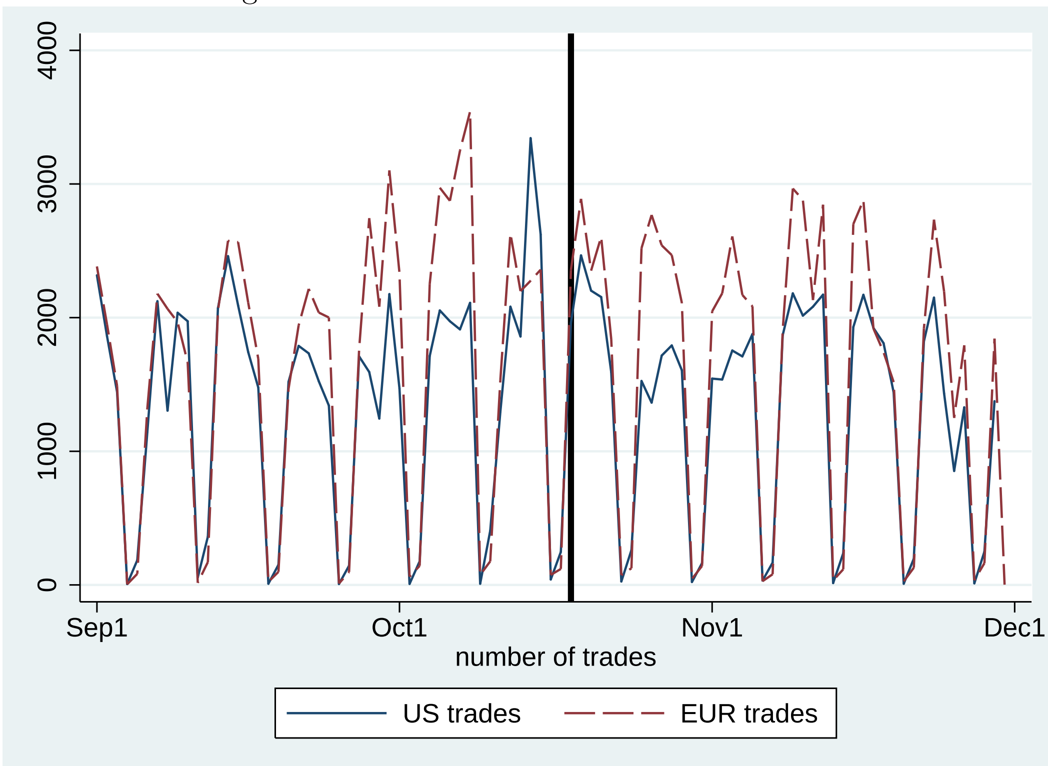
Description: This figure displays the user homepage for a member of myForexBook. Users are able to form bi-lateral friendships with other traders and communicate via private message or in the chat forum.

Figure 2: **myForexBook dashboard**



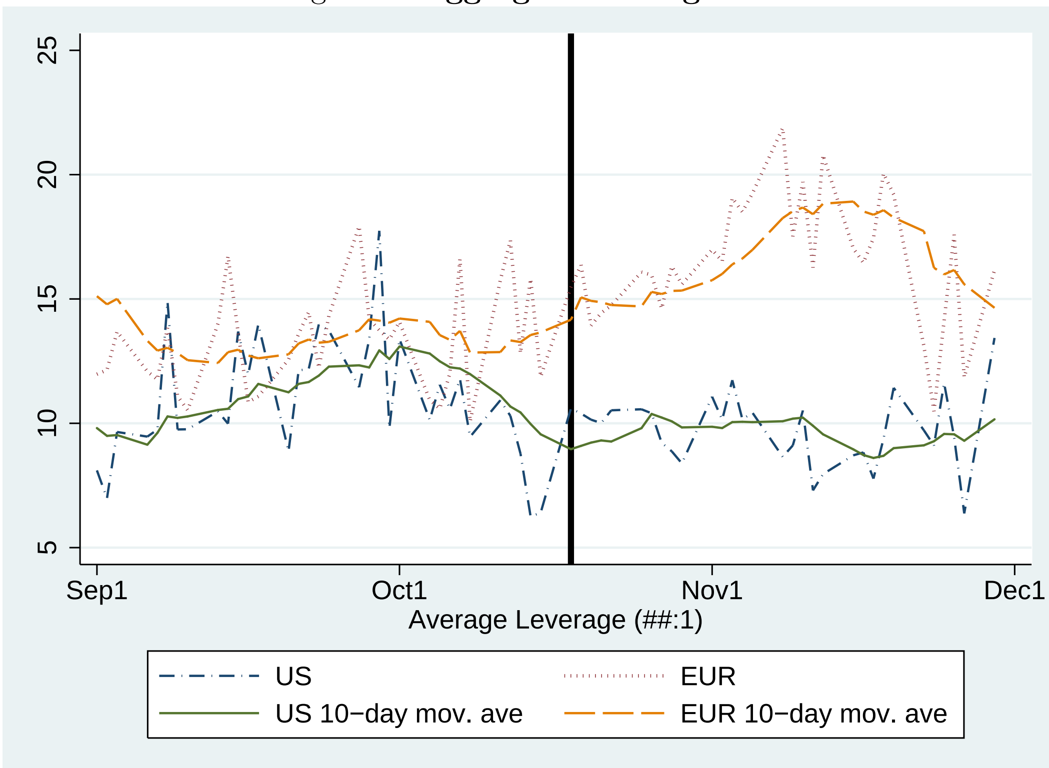
Description: This figure displays a customizable webpage dashboard available to members of myForexBook. Users are able to view their friends' positions in real-time, the aggregate positions within the network, and chat in web-forums, among other options.

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



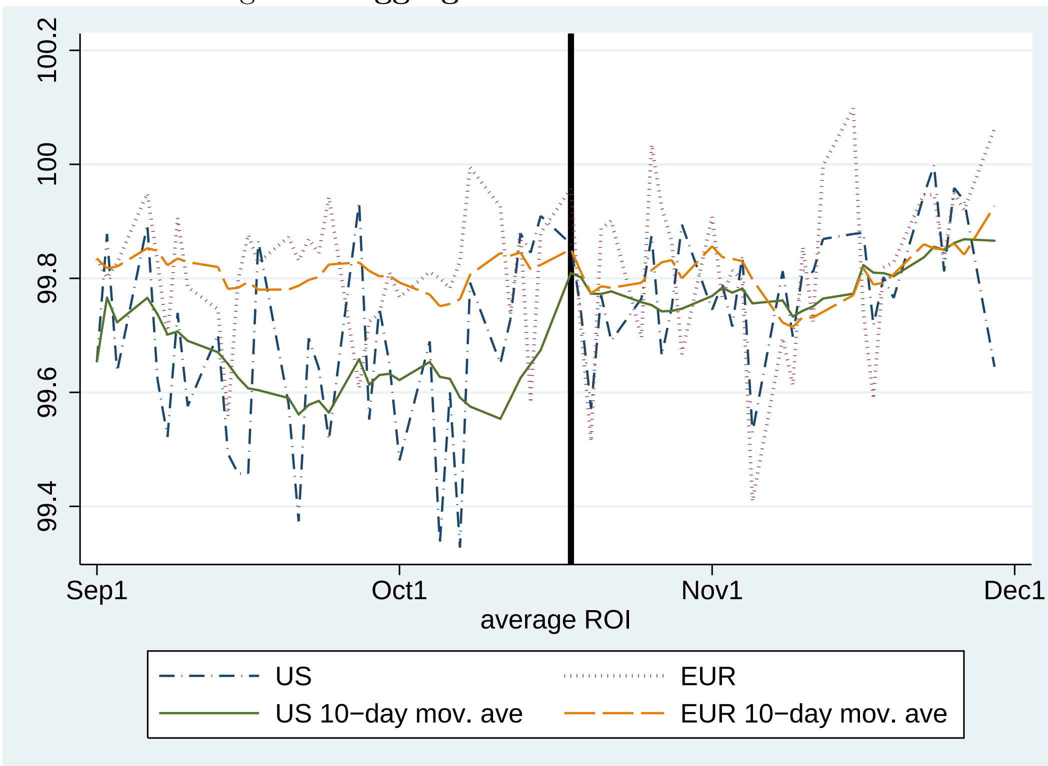
Description: This figure plots the total number of opened positions per day by U.S. and European investors in the trimmed sample described in Section 3. The valleys in the time series correspond to weekends while the majority of trading occurs during weekdays. The black vertical bar indicates the date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

Figure 4: **Aggregate leverage use**



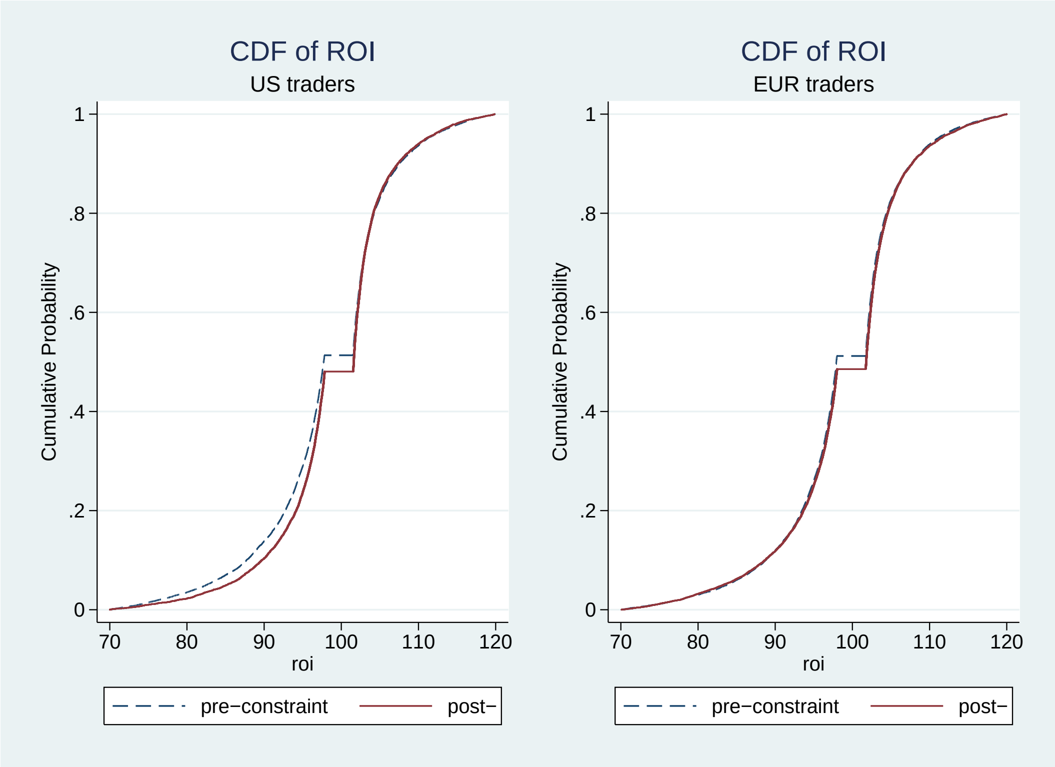
Description: This figure plots the average amount of leverage used per trade per day by U.S. and European traders in the trimmed sample described in Section 3 and a ten-day moving average of each time series. Weekends are excluded from the graph as well as the calculation of the moving average. The black vertical bar indicates the date that the CFTC trading rule was implemented, October 18, 2010.

Figure 5: **Aggregate return on investment**



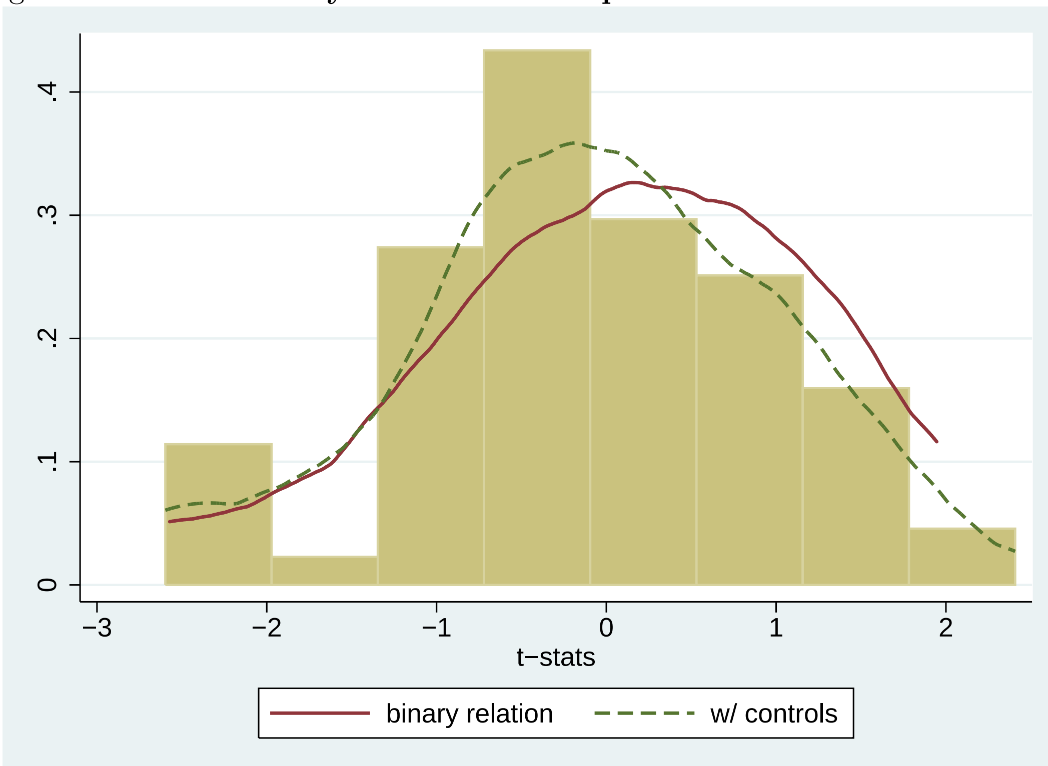
Description: This figure plots the average return on investment per trade per day by U.S. and European traders in the trimmed sample described in Section 3 and a ten-day moving average of each time series. Weekends are excluded from the graph as well as the calculation of the moving average. The black 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×constraint**



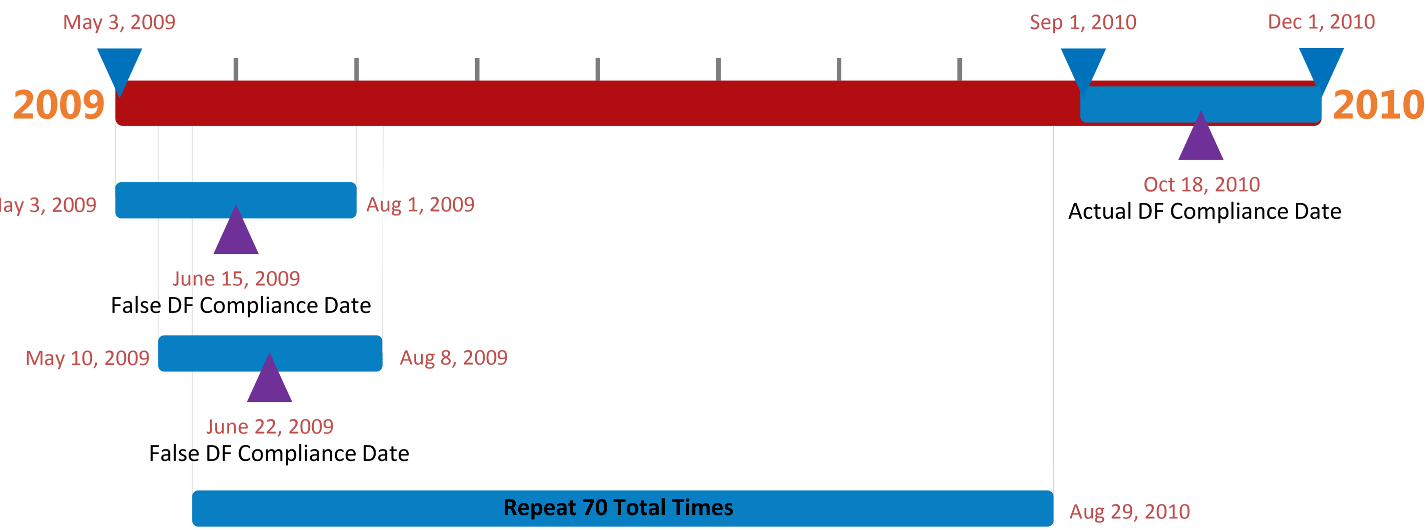
Description: This figure plots kernel density estimates using the Epanechnikov kernel function and a histogram of the t-statistics on γ_3 from a placebo test for the main difference-in-differnences regression to assess the impact of the CFTC regulation on per-trade return on investment. To conduct the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

$$binary\,relation: \quad roi_{j,i,t} = \gamma_0 + \gamma_1 \cdot US_i + \gamma_2 \cdot constraint_t + \gamma_3 \cdot US_i \cdot constraint_t + \gamma_4 \cdot F_{p,t} + \gamma_5 \cdot \sigma^{ROI}_{i,t} + \epsilon_{j,i,t}$$

$$w/controls: \quad roi_{j,i,t} = \gamma_0 + \gamma_1 \cdot US_i + \gamma_2 \cdot constraint_t + \gamma_3 \cdot US_i \cdot constraint_t + ... \\ \gamma_4 \cdot F_{p,t} + \gamma_5 \cdot \sigma^{ROI}_{i,t} + \gamma_6 \cdot Trade_{j,i,t} + \gamma_7 \cdot Investor_i + \epsilon_{j,i,t}$$

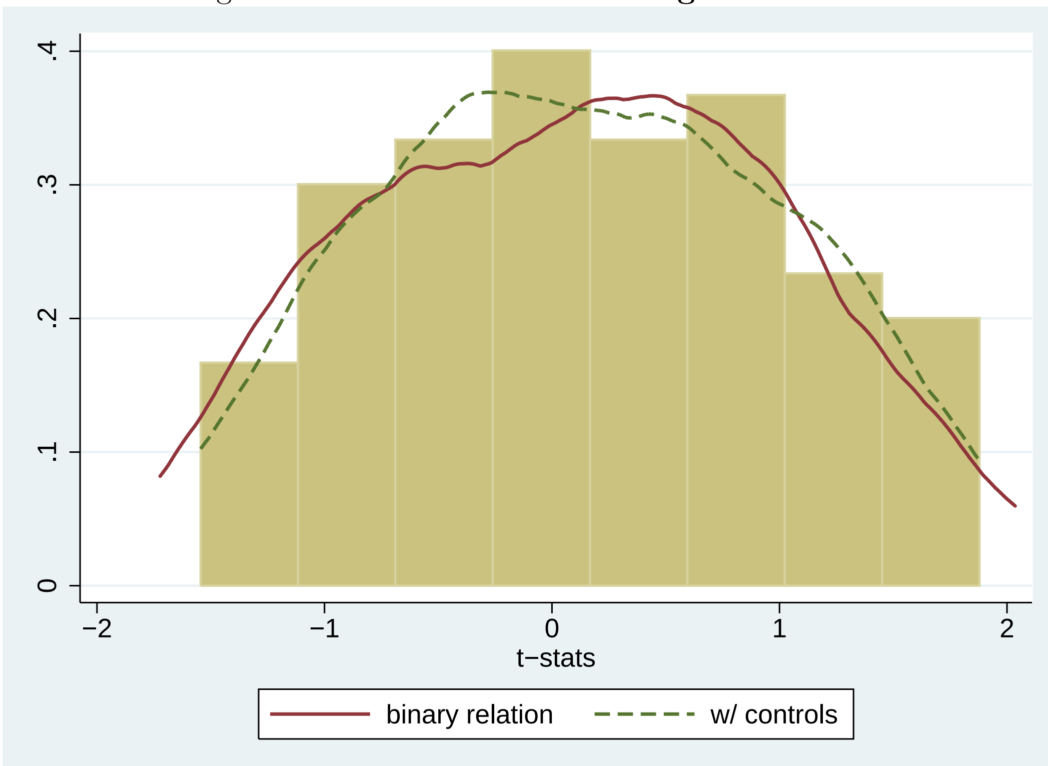
collecting the coefficient,γ_3, and the corresponding t-statistic after 70 total iterations. I change the date of $constraint_t$ each iteration, starting from Sunday, May 3, 2009 rolling forward a week at a time until Aug 29, 2010. I allow the range of the sample to encompass six weeks before and after the false date for the CFTC regulation. Prior to each iteration, I impose the data trimming exercise discussed in Section 3, 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 4.3.

Figure 9: **Placebo test for leverage difference**



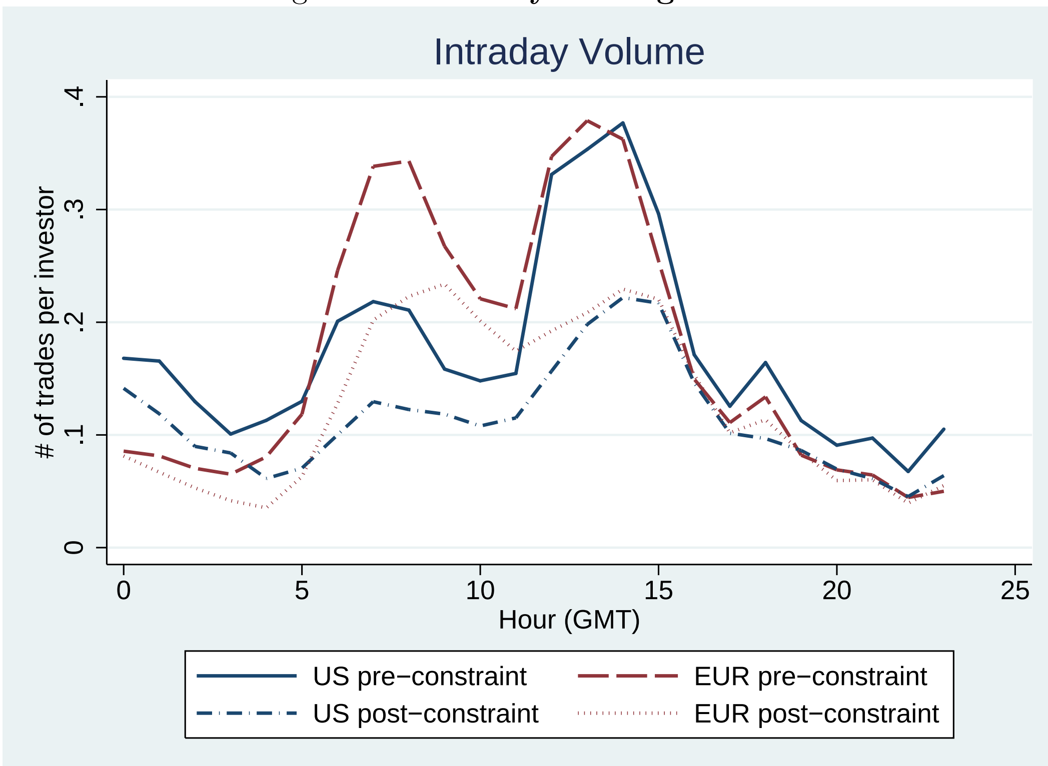
Description: This figure plots kernel density estimates using the Epanechnikov kernel function and a histogram of the t-statistics on γ_3 from a placebo test for the difference-in-differnences regression to assess the impact of the CFTC regulation on per-trade leverage. To conduct the placebo test, I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

$$binary\,relation: \quad leverage_{j,i,t} = \gamma_0 + \gamma_1 \cdot US_i + \gamma_2 \cdot constraint_t + \gamma_3 \cdot US_i \cdot constraint_t + \gamma_4 \cdot F_{p,t} + \gamma_5 \cdot \sigma^{ROI}_{i,t} + \epsilon_{j,i,t}$$

$$w/controls: \quad levereage_{j,i,t} = \gamma_0 + \gamma_1 \cdot US_i + \gamma_2 \cdot constraint_t + \gamma_3 \cdot US_i \cdot constraint_t + ... \\ \gamma_4 \cdot F_{p,t} + \gamma_5 \cdot \sigma^{ROI}_{i,t} + \gamma_6 \cdot Trade_{j,i,t} + \gamma_7 \cdot Investor_i + \epsilon_{j,i,t}$$

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 3, which restricts the sample to include only those with trades before and after the false date change.

Figure 10: **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.