NBER WORKING PAPER SERIES

SHOULD RETAIL INVESTORS' LEVERAGE BE LIMITED?

Rawley Z. Heimer
Alp Simsek

Working Paper 24176
http://www.nber.org/papers/w24176

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2017, Revised June 2019

We thank the operators of the social network for providing us the data, Alex Dusenbery for helping with the database, Jonathon Hazell for providing outstanding research assistance, and Adrien Verdelhan for giving us data from Brusa et al., 2014. We acknowledge the financial support of NSF Early Career Grant under Grant Number SES-1455319. Any remaining errors or omissions are the authors' responsibility. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Should Retail Investors' Leverage Be Limited?
Rawley Z. Heimer and Alp Simsek
NBER Working Paper No. 24176
December 2017, Revised June 2019
JEL No. G02,G11,G12,G18,G2

ABSTRACT

Does the provision of leverage to retail traders improve market quality or facilitate socially inefficient speculation that enriches financial intermediaries? We evaluate the effects of 2010 regulations that cap leverage in the U.S. retail foreign exchange market. Using three unique data sets and a difference-in-differences approach, we document that the leverage-constraint reduces trading volume by 23%, alleviates high-leverage traders' losses by 40%, and reduces brokerages' operating capital by 25%. Yet, the policy does not affect the relative bid-ask prices charged by the brokerages. These results suggest the policy improves belief-neutral social welfare without reducing market liquidity.

Rawley Z. Heimer
Boston College,
Carroll School of Management
heimer@bc.edu

Alp Simsek
Department of Economics, E52-552
MIT
50 Memorial Drive
Cambridge, MA 02142
and NBER
asimsek@mit.edu

Should Retail Investors' Leverage Be Limited?[★]

Rawley Heimer[a,*], Alp Simsek[b,c]

[a] *Boston College, Carroll School of Management, 140 Commonwealth Avenue, Chestnut Hill, MA 02467, United States*
[b] *Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, United States*
[c] *NBER, United States*

Abstract

Does the provision of leverage to retail traders improve market quality or facilitate socially inefficient speculation that enriches financial intermediaries? We evaluate the effects of 2010 regulations that cap leverage in the U.S. retail foreign exchange market. Using three unique data sets and a difference-in-differences approach, we document that the leverage-constraint reduces trading volume by 23%, alleviates high-leverage traders' losses by 40%, and reduces brokerages' operating capital by 25%. Yet, the policy does not affect the relative bid-ask prices charged by the brokerages. These results suggest the policy improves belief-neutral social welfare without reducing market liquidity.

Keywords: Leverage restriction policy, foreign exchange market, retail trading, speculation, consumer financial protection
JEL classification: G18, G11, G12, G24, D84

1. Introduction

In recent decades, the financial services sector in the U.S. has grown rapidly, with its contribution to gross domestic product (GDP) increasing from 2.8% in 1950 to 8.3% in 2006 (Greenwood and Scharfstein, 2013). Policymakers and economists raise concern that the rapid growth of finance might in part reflect rent-seeking activities, which do not necessarily benefit society (Zingales, 2015).

A specific concern is that the financial sector features excessive trading volume that does not necessarily benefit market participants, but that enriches the institutions that intermediate those trades. Established theories show that behavioral distortions (such as overconfidence) naturally induce investors to undertake speculative trades that lower their own risk-adjusted returns as well as their (appropriately defined) welfare (e.g., Odean, 1998; Gervais and Odean, 2001). In practice, however, there are other motives for trade, and the net effect on investors' welfare depends on the quantitative strength of the speculative motive. Moreover, even purely speculative "noise" trading can mitigate adverse selection and improve market liquidity (see, for instance, Grossman and Stiglitz, 1980; Kyle, 1985; Black, 1986). Therefore, the effect of speculation on social welfare and market quality remains an empirical question. Addressing this question is important, because in the aftermath of the recent financial crisis, policies that restrict trading activity (such as financial transaction taxes or leverage restrictions) are seriously considered, and sometimes adopted, by policymakers around the world.

[★] We thank the operators of the social network for providing us the data, Alex Dusenbery for helping with the database, Jonathon Hazell for providing outstanding research assistance, and Adrien Verdelhan for giving us data from Brusa et al., 2014. We acknowledge the financial support of NSF Early Career Grant under Grant Number SES-1455319. Any remaining errors or omissions are the authors' responsibility.

[*] Corresponding author at Boston College, Carroll School of Management, 140 Commonwealth Avenue, Chestnut Hill, MA 02467, USA. Phone: +1 (216) 774-2623. Fax: +1 (617) 552-0431.

Email addresses: heimer@bc.edu (Rawley Heimer), asimsek@mit.edu (Alp Simsek)

In this paper, we systematically evaluate the effects of a policy that restricts leverage in the retail foreign exchange market. Leverage is a major catalyst of speculative trading, because it increases the scope for extreme returns, and enables investors to take larger positions than what they can afford with their own money. The retail foreign exchange market is an ideal venue, because unlike mature markets that have longstanding restrictive leverage policies (e.g., the Securities and Exchange Commission (SEC) permits just 2:1 leverage on long positions in U.S. stocks, a policy that dates back to the Securities Exchange Act of 1934), the provision of leverage by retail forex brokerages has only recently been regulated. In October 2010, under the authority of the Dodd-Frank Act, the Commodity Futures Trading Commission (CFTC) capped the amount of leverage brokers can provide to U.S. traders at 50:1 on all major currency pairs and 20:1 on others. Meanwhile, European regulatory authorities continued to allow retail forex brokerages full discretion over the provision of leverage to traders, and the maximum available almost always exceeded 50:1. These features of the market—time-series variation in available leverage and a suitable control group of unregulated traders—allow us to use a difference-in-differences design to evaluate the costs and benefits of the leverage-constraint policy.

To characterize the welfare effects of the policy, we guide our empirical analysis with a stylized model that captures key features of the retail market for foreign exchange. The model features traders with heterogeneous and dogmatic beliefs that reflect behavioral distortions (such as overconfidence) but that can also contain some information about asset returns. Specifically, some beliefs might generate better-than-average return (before transaction costs), which we refer to as "information," whereas others generate neutral or lower return, which we refer to as "noise." Traders take positions based on their beliefs, and a competitive retail broker intermediates these positions. The broker incurs technological intermediation costs, which can be thought of as the infrastructure and the labor it employs, as well as informational costs. In particular, similar to Glosten and Milgrom (1985), the broker sets bid and ask prices after taking into account the information content of traders' orders.

The model predicts that the leverage-constraint policy reduces trading volume, because the leveraged positions are downscaled to satisfy the constraint. The decline in volume improves traders' expected return by reducing the intermediation costs that they ultimately pay (via bid-ask spreads). This also shrinks the intermediation revenues, as well as the size of the brokerage sector. Moreover, as in Brunnermeier et al. (2014), these effects represent belief-neutral improvements in social welfare. In particular, a planner that uses a fixed belief to evaluate traders' utilities can conclude that the policy improves social welfare without taking a stand on whose belief is correct. Intuitively, speculation transfers wealth among traders while lowering aggregate wealth due to intermediation costs. The policy improves welfare by reducing these costs, and by enabling the productive resources utilized by the brokerage sector to be employed elsewhere. On the other hand, to the extent that the policy improves the information in the average trade (which happens if the highly leveraged trades are "noisier" than other trades), then it also increases the bid-ask spreads. Hence, from the lens of this model, the leverage-constraint policy represents a trade off: It mitigates socially inefficient intermediation costs, but it can also worsen market liquidity—which the planner might independently care about.

To empirically study the effects of the leverage-constraint policy, we bring together three novel data sets that speak to different aspects of the market. First, we employ a transaction-level database compiled by a website that directly extracts individuals' trading records from close to 50 different retail-specific brokerages. The data include many investor characteristics and details for each trade. The data also contain nearly the same number of U.S. and European traders. The European traders are an ideal control group for studying the leverage-constraint, because their personal characteristics and trading activities prior to the CFTC regulation are similar to the U.S. traders'. Second, we compile a panel data set of brokerages' operating capital and retail forex obligations from filings at the CFTC. Third, we use proprietary data from a company that records intra-second forex pricing quotes by approximately 80 banks that are active in wholesale FX markets.

Motivated by how our model characterizes welfare in this market, our empirical analysis comes in three parts. First, we investigate the effect of the policy on trader-level outcomes: their trading volume and portfolio returns. Second, we investigate the policy's effect on the brokerage sector by examining their excess capital. Third, we examine market liquidity, by testing the execution prices paid by traders in this market, relative to bid and ask prices in the interbank market. To summarize our findings, the announcement of regulation has no effect on traders' activity. However, the actual leverage-constraint lowers trading volume and it significantly reduces traders' underperformance. The constraint also lowers the excess capital of the brokerage sector, but it does not significantly affect (relative) bid-ask spreads. Consistent with theory, these results suggest that the leverage-constraint policy improves social welfare by mitigating socially excessive intermediation, while having no adverse consequences for market liquidity.

More specifically, our analysis identifies the effect of the regulation on trading volume and returns by comparing U.S. to European traders' activities before and after the leverage-constraint. Using this empirical approach, we find that the leverage-constraint policy leads to a 23% reduction in monthly trading volume. The policy also improves traders' average monthly returns, with stronger effects for traders that use more leverage. Before the leverage-constraint policy, traders in the highest quintile of the leverage-use distribution have 30 to 40 percentage points worse net monthly return than traders in the lowest quintile. The policy substantially improves high-leverage traders' monthly return without having a significant impact on low-leverage traders' return. Specifically, high-leverage traders increase their relative performance by 18 percentage points per month, which we interpret as the treatment-on-treated effect of the regulation. Seeing as, prior to the policy, the average high-leverage U.S. trader loses 44% per month (in absolute terms), the leverage-constraint policy mitigates these traders' losses by about 40%.

To the extent that our tests can accommodate, we show that our results on trading activity are robust to trader and time fixed effects, and to fixed effects for the trader's brokerage and their choices of which currency pairs to trade. The results further satisfy tests for parallel trends, placebo tests for false dates of regulation, and are similar when we use alternative control and treatment groups—traders that use more leverage prior to the constraint versus traders that use less leverage.

Our model predicts that, by reducing trading volume, the regulation reduces the intermediation revenues and the size of the brokerage sector. We test these effects by comparing the excess capital (capital in excess of the regulatory requirement) of brokerages that have retail forex obligations to a control group of brokerages that are regulated by the CFTC, but do not offer retail forex accounts. The excess capital of the affected brokerages falls by about 25% relative to brokerages without forex obligations. The reduction in excess capital is most pronounced for brokerages that offered traders more leverage prior to the CFTC regulation, precisely the brokerages we expect to be more sensitive to leverage restrictions. We also conjecture that the reduction of intermediation revenues precipitated significant concentration of brokerages in the retail forex market. At the time of the CFTC regulations, close to 25 brokerages were registered with the CFTC and had retail forex obligations. Only four brokerages have survived until today, with the smaller brokerages being the quickest to go out of business or be acquired by larger entities.

Our model also predicts that, by changing the information content of traders' orders, the regulation might increase bid-ask spreads and reduce market liquidity. To the extent that the brokers are constrained and need some of their own capital to intermediate positions, a reduction of their excess capital can further reduce market liquidity (as in Brunnermeier and Pedersen, 2008). To test these predictions, we merge our proprietary intra-second quote data with actual trades in the account-level data to estimate the execution prices charged by brokerages relative to price quotes in the interbank market. We find no evidence that brokerages charged higher spreads as a result of the CFTC regulation. This observation can be reconciled with our model if the leverage-constraint policy does not substantially change the information content of the average trade. Indeed, our back-of-the-envelope calculations suggest that the policy has little effect on traders' gross returns (gross of trading costs) that provide a measure of their information. Put differently, our results on portfolio returns seem to be largely driven by the reduction in trading volume and associated trading costs as opposed to changes in information.

A plausible alternative mechanism for regulators to curtail speculation is to issue warnings about the use of leverage. Some argue that, in lieu of heavy-handed regulations, guidance in financial decision-making can improve social welfare (e.g., Thaler and Benartzi, 2004). In our setting, warnings could make traders aware of levered trading risks and brokerages, threatened with regulations, adopt alternative practices to stimulate traders' demand. In January 2010, several months prior to imposing the leverage-constraint regulation, the CFTC announced that it wished to restrict the provision of leverage with the intent of protecting traders' welfare. Though the announcement attracted market participants' attention, it did not significantly affect trading volume, traders' demand for leverage or their returns, nor did it affect brokerages' capital or bid-ask spreads. These results suggest that the physical leverage-constraint is the most effective policy.[1]

Our paper is part of a large literature that analyzes the role of retail trading in financial markets: specifically, we focus on whether retail trading can be socially excessive. A longstanding view is that retail trading is driven by behavioral distortions ("noise"). Indeed, several empirical papers provide evidence that they trade for purely speculative reasons, such as overconfidence (Barber and Odean, 2001), sensation-seeking (Grinblatt and Keloharju, 2009), or skewed preferences (Kumar, 2009). Our results highlight the role of leverage in enhancing speculation and financial intermediation in foreign exchange markets. We show that highly leveraged trades generate low after-fee returns, consistent with their driving force being speculation, and that the leverage-constraint policy mitigates trading volume and improves traders' returns. More originally, we also show that the leverage-constraint policy reduces the excess capital of financial intermediaries.

The literature also focuses on the impact of retail traders on aggregate outcomes, such as prices and liquidity. The older view is that retail traders are subject to correlated distortions ("aggregate noise" or "sentiment") that might increase price volatility (see, for instance, Shleifer and Summers, 1990). Recent literature emphasizes that retail traders can also reduce price volatility by providing liquidity to other market participants (e.g., Barber et al., 2008; Dorn et al., 2008; Kaniel et al., 2008; Barrot et al., 2016), or that retail trades are informed on average (e.g., Berkman et al., 2014; Ben-David, Birru, and Rossi, 2017; Kelley and Tetlock, 2013; Kaniel et al., 2012). We connect this literature to increasingly important research on the market-wide effects of providing leverage to market participants or changes in margin requirements (Kupiec, 1989; Schwert, 1989; Hardouvelis and Peristiani, 1992; Seguin and Jarrell, 1993; Foucault et al., 2011; Kahraman and Tookes, 2017). Our paper is different from these works in that we study a market in which we would not expect changes in retail traders' leverage to globally affect asset prices (in our setting, retail traders do not have enough market-share to affect exchange rates).[2,3] This lets

[1] Seeing as the announcement comes several months before the actual leverage-constraint, it can also be thought of as a placebo test that checks for common trends between treatment and control groups prior to the leverage-constraint. This test adds confidence in our difference-in-difference identifying assumptions, because the announcement does not significantly affect any of our main outcome measures.

[2] On the other hand, as our model illustrates, retail traders' leverage can still affect local market liquidity: specifically, the bid-ask spreads charged by the brokerages. Our analysis of bid-ask spreads builds upon Glosten and Milgrom (1985) with some differences that we clarify in Section 2.2.

[3] There is a notable literature on the microstructure of and liquidity in the foreign exchange market that mainly focuses on interdealer trading (e.g., King et al., 2013; Mancini et al., 2013). Because of the decentralized nature of FX markets, it is most appropriate to view retail foreign exchange traders and retail brokers as price-takers.

us test the leverage-constraints' effect on other outcomes—such as trading volume and traders' returns, the brokerage sector's revenues, and the execution prices charged by brokerages—without concern about disentangling the effects due to leverage-constraints from the effects due to concurrent changes in asset prices. And indeed, to our knowledge, ours is the first paper to study how leverage-constraints affect account-level trading outcomes, the understanding of which *can* help clarify relationships between leverage and aggregate prices that have been proposed in the theoretical literature (e.g., Geanakoplos, 2003, 2010; Fostel and Geanakoplos, 2008; Simsek, 2013a; Adrian and Shin, 2010; Garleanu and Pedersen, 2011; Wang, 2015; Cao, 2017).[4]

Relatedly, our paper is part of a recent surge of research on the regulation of consumer financial products (Campbell et al., 2011). This literature argues for paternalistic regulations when sophisticated intermediaries take advantage of individuals' cognitive limitations—such as shrouded information or limits to attention (e.g., Gabaix and Laibson, 2006; Carlin, 2009)—to "dupe" consumers (e.g., Bertrand and Morse, 2011; Gurun et al., 2016), or when correlated financial mistakes by individuals have negative externalities, such as the 2000s housing boom and bust. However, it is less clear how to analyze welfare when individuals have full information sets, but their idiosyncratic beliefs cause them to behave differently than a "rational" model would suggest. Our paper tackles this conceptual challenge by joining a growing literature arguing that the standard Pareto criterion (that respects individuals' own beliefs) is not appropriate and recommends more paternalistic welfare criteria (e.g., Stiglitz, 1989; Summers and Summers, 1989; Posner and Weyl, 2013; Brunnermeier et al., 2014; Gilboa et al., 2014). We provide an empirical application of the belief-neutral criterion developed by Brunnermeier et al. (2014), which enables the planner to do welfare analysis according to the objective belief without knowing exactly what it is. According to our findings, even though traders appear to only harm themselves when they act on their misguided beliefs, their excessive trading reduces social welfare by utilizing productive resources to intermediate speculation. In this sense, we provide compelling evidence that supports Zingales's (2015) conjecture that some parts of the financial sector do not necessarily benefit society.

This paper is organized as follows. Section 2 describes the retail foreign exchange market as well as the CFTC regulation. This section also summarizes our stylized model of this market, and describes how the leverage-constraint policy affects the equilibrium outcomes and welfare in the model. Section 3 describes the data. Section 4 explores the regulation's effect on trader outcomes. Section 5 analyzes the effect of the regulation on broker outcomes. Section 6 studies the impact of the regulation on relative bid-ask spreads. Section 7 concludes. The Internet Appendix contains the details of the theoretical model as well as the empirical results omitted from the main text.

2. Retail forex market and the CFTC regulation

The retail forex market barely existed in the early 2000s, but has experienced unprecedented growth for more than a decade. According to King and Rime (2010), its volume in 2010 was 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.

Retail forex brokerages are market-making specialists. Each brokerage continuously offers bid and ask quotes to its clients. The brokerage is the counterparty on all transactions, that is, it actually trades with clients as opposed to simply matching trades (though over time it can offload these positions to other clients or to the interbank market). Each brokerage maintains a proprietary algorithm for generating bid and ask quotes that are based on

[4] Though we analyze the foreign exchange market, our results are consistent with a growing empirical literature that illustrates leverage might have also facilitated speculation in the housing market in the run-up to the recent subprime crisis (Ben-David, 2018; Haughwout et al., 2011; Favara and Imbs, 2015; Bailey et al., 2018).

its own inventory and a data feed from the interbank market. These quotes typically represent a spread over the interbank (mid) price. Therefore, clients' trading costs are in proportion to the size of the trade, and depend on the bid-ask spreads charged brokers. Brokerages do not charge any additional fees per transaction. Moreover, they also give clients the option to use leverage on their trades at no additional upfront cost. For example, a U.S. or European trader could decide to take a 100,000 EUR position in the EUR/USD using 20,000 EUR (or the USD equivalent) of their own capital, while borrowing the difference from the brokerage. The trader uses 5:1 leverage in this example.

All clients use a domestic bank account to deposit initial funds into their forex brokerage account. Regardless of their domestic location, clients 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 (ISO). Each pair includes a "base" and "quote" currency (in the EUR/USD example, EUR is the base and USD is the quote). Clients do not take receipt of the foreign currency when they trade, and withdrawals are made in the client's domestic currency.

2.1. Regulation in the forex market

The retail forex market in the U.S. was mostly unregulated prior to the passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act on July 21, 2010. Concerned with consumer welfare, the Act strengthened the CFTC's authority over the retail forex market. The CFTC began considering methods to protect consumer welfare in the forex market in anticipation of the passage of Dodd-Frank. On January 20, 2010, the CFTC expressed concern over the use of leverage and released in the Federal Register a proposal to restrict the leverage available to retail customers to 10:1 per trade on all pairs.[5]

Shortly after Dodd-Frank was written into law, the CFTC released on September 10, 2010, a finalized set of rules which required retail brokerages that had U.S. accounts to register with the CFTC. The rule also capped the amount of leverage available to U.S. customers to 50:1 on all major pairs and 20:1 on all others (Table A.1 in the Internet Appendix provides a complete list of currency pairs).[6] The brokerages were required to comply with the new rules by October 18, 2010. Some brokerages appear to have imposed the leverage restriction before October 18, 2010, while at least one high volume brokerage did not comply with the regulation until several months later and subsequently received heavy fines for doing so. Meanwhile, European regulatory authorities during this period continued to allow retail forex brokerages full discretion over the provision of leverage to traders, and the maximum available almost always exceeds 50:1.

A distinguishing feature of the forex market is that a significant number of brokerages have clients from around the world. However, there is no centralized, worldwide regulatory authority. Brokerages must comply with domestic regulations in each country that they operate. This requires brokerages to segment their clientele according to country of origin. Verification of a client's home country is done using government-issued documentation, such as a passport, and a link to a domestic bank account from which to withdraw and deposit funds. Consequently, it would be challenging and costly for a retail client to search for a preferred regulatory regime. Therefore, the structure of the market is beneficial to this research, because it is possible to compare regulated U.S. traders to their lightly regulated European counterparts while accounting for brokerage features that may otherwise vary across countries.

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

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

2.2. A stylized theoretical model of the retail forex market

To guide our empirical analysis, we construct a stylized model motivated by the key features of the retail forex market. We relegate the details to the Internet Appendix and present here a summary. The model features a single asset (the currency), and traders with heterogeneous beliefs about the return of this asset. Traders' beliefs are dogmatic in the sense that a trader believes his/her belief is correct (and thus, she does not learn from prices or other traders' beliefs). Driven by their beliefs, traders take speculative positions on the asset in pursuit of high expected returns. Because the objective return distribution is unique, belief heterogeneity captures various behavioral distortions, such as overconfidence (which we leave unmodeled for simplicity). On the other hand, we also allow traders' beliefs to contain some information about the objective distribution. Specifically, some beliefs might generate better-than-average return (before transaction costs) according to the objective belief, which we refer to as "information," whereas others generate neutral or lower return, which we refer to as "noise." Traders have their own capital but they can also use leverage. Leverage is initially unrestricted (for simplicity) and it becomes constrained after the implementation of the policy.

A competitive brokerage sector intermediates traders' positions (while also providing them with leverage free of additional charge). The representative broker incurs technological intermediation costs, which can be thought of as capturing the infrastructure and labor it employs. For simplicity, we take these costs to be linear in the size of the intermediated positions. The broker might also incur informational costs, because traders might have some information on average. Similar to Glosten and Milgrom (1985), the broker quotes bid and ask prices that take into account the information content of traders' orders. In a competitive equilibrium, the ask spread is equal to the sum of the technological cost and the expected return according to the objective distribution conditional on traders submitting a buy order (and a similar expression applies for the bid spread).[7]

We first use the model to analyze the determinants of traders' expected profit, which is a key outcome variable in our empirical analysis. The model reveals that traders' expected profit is decreasing in trading volume. Intuitively, technological intermediation costs are passed to traders via bid-ask spreads. The more traders trade, the more they incur these costs, and the lower is their expected return. Perhaps surprisingly, traders' average information does not affect their expected return (over the longer run). If traders' information increases, meaning that they generate higher return before transaction costs, this tends to increase their expected return. However, it also induces the broker to face more adversely selected orders. The broker eventually raises the bid-ask spreads (otherwise, it would consistently make losses), which neutralizes the impact of improved information on traders' expected return. The flip side of these results is that the broker's expected revenue (its compensation for technological intermediation costs) as well as its size are decreasing in trading volume.

We then analyze the determinants of social welfare. Normative analysis is challenging in this environment, because investors have heterogeneous beliefs that reflect behavioral distortions. Moreover, the planner might not know which trader (if any) has the objective belief. Following Brunnermeier et al. (2014), we assume the planner evaluates traders' utility according to a single belief, but she also makes the welfare comparisons robust to the choice of the belief (specifically, she considers any convex combination of traders' beliefs). We find that the social welfare in this setting is actually independent of (and therefore robust to) the choice of the single belief. This is because, under any fixed belief, the expected gain of a trader is the expected loss of another trader (or the bro-

[7] The market-maker in Glosten and Milgrom (1985) trades with a mix of informed and liquidity traders, whereas in our model it trades with speculators with heterogeneous and dogmatic beliefs. This modeling difference leads to two main differences in results. First, the traders in our model can also have negative information on average, in which case the market-maker would actually face advantageous selection that would *lower* bid-ask spreads. Second, our model generates considerable trading volume (driven by speculation) even though we do not introduce any liquidity traders.

ker). This formally captures the idea that speculation transfers wealth among agents without creating social value. Once properly accounted for, these transfers do not affect social welfare regardless of whose belief we use for welfare calculations. We refer to the resulting expression as belief-neutral welfare, and show that it is decreasing in trading volume and traders' portfolio risks. Intuitively, speculation generates technological intermediation costs, which are increasing in volume, and which reduce social welfare (because the resources or people used to intermediate speculative trades could also be used elsewhere). In addition, speculation also induces investors to hold risky portfolios despite their risk aversion (in pursuit of perceived expected returns), which further reduces social welfare.

We next characterize how the introduction of the leverage-constraint policy affects the equilibrium variables and social welfare. The policy reduces trading volume, as well as traders' portfolio risks, because highly leveraged trades are downscaled to satisfy the constraint. By reducing volume, the policy increases traders' expected profit while reducing the broker's expected revenue and size. By reducing volume and portfolio risks, the policy also improves belief-neutral social welfare.

The effect of the policy on the bid-ask spreads depends on how it influences traders' average information—measured as the objective expected return (before transaction costs) of an average buy or sell order. For instance, if leveraged trades are "noisier" than average, restricting those trades will improve the average information, which will eventually translate into higher spreads as we described earlier. While the rise in spreads would not affect the social welfare in our model (because the spreads represent transfers among agents), it would reduce market liquidity, which a regulator might independently care about. It could also reduce social welfare in alternative formulations of our model, for example, if some traders take positions for non-speculative reasons (e.g., to hedge their background risks) and if the planner overweights these traders' utility relative to the speculative traders.

To summarize, the model makes both positive (testable) and normative predictions regarding the effect of the leverage-constraint policy. On the positive side, the model predicts that the policy will reduce trading volume, increase traders' expected profit, reduce the brokerages' expected revenue and size, and increase bid-ask spreads if and only if it improves traders' average information. On the normative side, the model predicts that the policy lowers the belief-neutral social welfare by economizing on the productive resources used to intermediate speculation, but it can also have an adverse effect on market liquidity (bid-ask spreads).

3. Three unique data sets

Our model predicts that the leverage-constraint policy can affect trader-level outcomes, broker-level outcomes, and market-level outcomes (e.g., bid-ask spreads). To test these predictions, we rely on three unique data sets that we describe in this section.

3.1. Transaction-level data from a sample of retail forex accounts

A potential challenge to studying trading activity in the retail forex market is that there is no centralized data repository in the retail segment of the forex market. Related to this challenge, the few data sets that have been used by academics come from just a single brokerage (e.g., Ben-David, Birru, and Prokopenya, 2018).

To overcome this data limitation, the trade- and portfolio-level data used in this paper's analysis were compiled by a social networking website that, for privacy purposes, we call myForexBook. Registering with myForexBook—which is free—requires a trader to have an open account on one of 70 retail-specific forex brokerages (by the time of the CFTC regulation, around 45 brokerages had partnered with myForexBook and allowed traders to use the service). After registering, myForexBook can access the trader's complete trading records at these brokerages, even some trades made before joining the social network. New trades are executed on a trader's brokerage, but they are simultaneously recorded by the myForexBook database and are time-stamped to the second. Hence, an advantage of the data is that there are no concerns about reporting bias. There are 8,735 traders in the database and approximately 5.5 million trades that execute between early 2009 and April 2012.

The account level-data identify traders' location. They provide the domestic currency—as revealed by a link to a domestic bank account—for 68% of traders in the sample. Also, upon joining the social network, traders are surveyed and asked to identify whether they are from one of the following locations: United States, Europe, or Asia-Pacific.[8] Ninety-eight percent of traders responded to the survey. Traders provide honest answers to the survey. Ninety-seven percent of respondents that say they are from the U.S. have USD-denominated accounts and the matching rate is similar for European respondents.[9]

The transaction data include many details per-trade. They include the currency pair, direction, size of the trade, open and close execution prices, and the second that trades execute. They also include daily account balances and deposits/withdraws, which allow us to calculate traders' portfolio returns.

3.1.1. Representativeness of the transaction-level data

Traders that use myForexBook are plausibly representative of traders in this market (see Appendix Section A.3 for a detailed discussion). First, we compare myForexBook traders to a second account-level data set—a year's worth of transactions on one of the world's largest forex brokerages (Appendix Table A.2). Both myForexBook traders and traders from this comparison data set have worse returns when they trade with leverage, which suggests that the relationship of interest between leverage and traders' returns is unlikely to be biased by sample selection. Second, trading volume in the myForexBook data set strongly covaries (a Pearson's correlation coefficient equal to 41%) with reductions in brokerages' aggregate retail forex obligations, using data from CFTC reports that we describe later in this section (Appendix Figure A.1). This provides evidence that, though myForexBook traders self-select into a social networking environment, these traders are a fair representation of the typical retail forex trader.

We are also confident that lessons from our tests on the leverage of retail forex traders extend to retail traders more broadly. Not only is the worldwide market for retail forex large, but the structure of the market is increasingly similar to modern-day active retail trading in equities markets. Both markets are primarily served by online brokerages, and are increasingly accessible to clients that do not have much initial capital and are seeking low, or even zero-commissions (e.g., Robinhood Markets, Inc.). More concretely, Heimer (2016) provides evidence that the behaviors of myForexBook traders are similar to the behaviors of retail stock traders on a large discount brokerage that has been extensively studied by the finance literature (Barber and Odean, 2000).

3.1.2. Data trimming

We estimate the effect of the leverage restriction policy (as well as its announcement) on trader-level outcomes using standard difference-in-difference regressions that compare a treatment group of trades affected by the regulations to a control group of unaffected trades, before and after the CFTC regulations. There are a few potential shortcomings of any difference-in-difference design, and these shortcomings guide how we conduct the following data trimming.

First, we restrict the sample to traders who reside in the United States or Europe according to the survey, because European traders are presumably the closest available control group of unregulated traders. European and

[8] The trader's brokerage provides the base currency for five of the traders that did not respond to the survey. These five traders are included in the analysis.

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

U.S. traders tend to trade the same assets (most frequently the EUR/USD). They face similar market conditions, because the European and U.S. markets overlap within a given day. Second, we limit the sample window to the 12 months that surround the leverage regulations. And, in robustness tests (reported in the Appendix), we confine the tests' sample to the narrow 3-month window around the regulations. We do this, because a longer sample window also risks exposing the difference-in-difference estimates to shocks that are unrelated to the leverage regulations, as well as to changes over time in traders' behavior, e.g., existing studies document that some learn to become better traders, see Seru et al. (2010), Linnainmaa (2011).

These data trimmings make the sample window around the October 2010 leverage-constraint run from May 2010 to April 2011. This sample has 15,125 trader-month observations made by 2,672 traders, and 1,193 of these traders come from the U.S. and 1,479 are from Europe. To estimate the impact of the CFTC's announcement in January 2010 of its intent to regulate forex leverage, we create a second sample that goes from August 2009 to July 2010, and includes 13,833 trader-month observations. A few factors contribute to the imbalance of the panel. The median trader in our data set has four months of trading data. The attrition rate is due partly to natural trader attrition rates, such as trading losses, and partly to the growth and decline of the myForexBook social network during this period (for about half of the traders in our data, we only have their trading records that come from after the trader joins the social network).

3.1.3. Are U.S. and European traders comparable?

European traders are a suitable control group to estimate the effect of the leverage-constraint on U.S. traders. Not only do they tend to trade similar assets and their trading hours overlap, but we find evidence that they have similar personal characteristics and trading behaviors.

Table 1, Panel A presents difference-in-means tests for personal characteristics of the traders. When setting up a profile at myForexBook, traders are asked to provide their years of trading experience, trading style, and age. Traders from the U.S. and Europe are similarly experienced with most having 0–1 or 1–3 years of experience, with 20% having 3–5 or greater than five years of experience. U.S. and European traders use the same trading styles—around 65% use technical trading strategies. U.S. traders are about as old as Europeans—they average 37-years-old. Panel A further shows that U.S. and European traders have similar trading habits. Using observations from the pre-leverage-constraint sample period (May 1 to October 17, 2010), treatment and control traders have executed over 300 trades on average, six to seven trades per day on days that they trade, trade over eight distinct currency pairs, and use more than 50:1 leverage on an average of between 15% to 20% of trades. We also use a probit model to test whether these characteristics predict the propensity to be a U.S. trader. The regression's pseudo-R^2 is small (0.006). This suggests that whether a trader is in the control or treatment group is as good as random with respect to trader characteristics—characteristics that could be relevant to the relationship between leverage and trading outcomes.

Finally, we find that U.S. and European traders' activities move in concert prior to the regulation. We calculate daily changes in average trading activities for the U.S. and European samples by taking log-first differences. The correlation coefficient of daily changes in average trading volume in returns is 59%, the number of trades is 62%, and daily returns is 44% (Table 1, Panel B). The tight time-series correlation in trading outcomes prior to the regulation provides initial evidence that there are common trends between treatment and control groups, which is a crucial identifying assumption for our difference-in-difference tests that follow.

3.2. Data on the characteristics of forex brokerage firms

To estimate the effect of the leverage restriction policy on broker-level outcomes, we develop a panel data set of the characteristics of brokerage firms that are regulated by the CFTC. Since 2002, the CFTC has collected on a monthly basis select financial information from futures commissions merchants (FCMs). The 2010 CFTC regulations created a new category of CFTC registrant called retail foreign exchange dealers (RFEDs). RFEDs are brokerages that "exercise discretionary trading authority or operate pools with respect to retail forex," and they were "required to register, either as introducing brokers, commodity trading advisers, commodity pool operators ... or as associated persons of such entities."[10] FCMs and RFEDs are required to maintain net capital of $20 million plus 5% of the amount of liabilities to retail forex customers in excess of $10 million.

Our panel data set includes a large selection of brokerages that were required to report their net operating capital. The data go back to 2002. They include 124 brokerages at the time of the October 2010 leverage restriction. Owing to the new reporting requirements established in 2010, we can also classify many of these brokerages as serving the retail forex market. The data begin including brokerages' total retail forex obligations starting in November 2010, the month after the CFTC regulations. We classify 24 brokerages as being a retail forex brokerage, because they have nonzero obligations in the year following the start of the reporting requirement. Notably, our brokerage panel data are unbalanced, because new brokerages can enter the market, brokerages can exit, or merge with other entities. But, we have a sufficiently large enough sample to estimate panel regressions on brokerage outcomes.

3.3. Forex price quotes from the interbank market

Our final set of predictions concerns the effect of the policy on market-level outcomes, in particular, the bid-ask spreads. The myForexBook data set does not contain data on spreads, just the trade's execution prices. To analyze bid-ask spreads, we incorporate data on market prices in the interbank market, presumably the market's national best bid and offer (NBBO).

We use a proprietary database provided by Tick Data, which records intra-second forex quotes by approximately 80 banks that are active in wholesale forex markets. Tick Data offers their data product to investors that want to test trading strategies. The Tick Data data set contains roughly one-third of the banks typically used by retail brokers. However, the data set also contains banks quoting less competitive prices. We match each myForexBook transaction to the most competitive price—i.e., the highest bid or lowest ask price—in that second from the Tick Data data set. We can match roughly two-thirds of trades to the exact second, but our analysis also considers the sensitivity to the nearest match.

We use the Tick Data pricing series to formally construct a measure of the spread charged by a retail broker relative to the spreads observed in the interbank market. We focus on this relative measure, because it enables us to control for many factors (such as time-varying uncertainty) that might affect the bid-ask spreads in practice for reasons outside our model. Because the retail market is a small fraction of the forex market, local changes in the retail market would arguably affect the local spreads without impacting the interbank spreads. Our measure of relative spreads is designed to pick up these local effects.

Specifically, for a transaction that was opened at time t and closed at a later time t', we define the broker's *relative bid-ask spread* as,

$$S_t = \left(\frac{P_t^{\text{broker}} - P_t^{\text{interbank ask}}}{P_t^{\text{interbank ask}}} + \frac{P_{t'}^{\text{interbank bid}} - P_{t'}^{\text{broker}}}{P_{t'}^{\text{interbank bid}}} \right)$$

[10] CFTC Release: pr5883-10. August 30, 2010.

if the transaction is long, and,

$$S_t = \left(\frac{P_t^{\text{interbank bid}} - P_t^{\text{broker}}}{P_t^{\text{interbank bid}}} + \frac{P_{t'}^{\text{broker}} - P_{t'}^{\text{interbank ask}}}{P_{t'}^{\text{interbank ask}}} \right)$$

if the transaction is short. The measure, S_t, can be thought of as the additional spread the customer pays, as a fraction of the price, compared to trading directly in the interbank market. Notably, the average value of S_t is slightly negative. Although this might sound surprising, it can be understood by the fact that, as in our theoretical model, retail forex brokerages tend to use their own inventory (rather than the interbank market) to fill traders' orders. Hence, there is no strong reason for the spread in the retail market to be greater than in the interbank market—the spread in each market depends on its own characteristics (such as the degree of adverse selection).

4. The leverage-constraint policy, trading volume, and returns

4.1. Trading volume

We estimate the effect of the constraint on trading volume using difference-in-difference regressions of the form:

$$\log(\text{trading volume})_{it} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post constraint}_t + \varepsilon_{it}. \tag{1}$$

Trading volume is the dollar value of positions taken by trader *i* in month *t*. *US trader* equals one if the trader is from the U.S., and zero if they are from Europe. *Post constraint* equals one in the months following October 2010 (the month at which the policy was implemented), zero otherwise. All of our specifications include trader and calendar month fixed effects, γ_i and γ_t, respectively. Trader fixed effects account for idiosyncratic differences across traders that could affect trading volume, such as the amount of capital in a traders' brokerage account. The interaction of *US trader* and *post constraint*, β_1, estimates the average treatment effect of the CFTC regulation on the outcome variable. We calculate double-clustered standard errors that account for correlated residuals by month and trader.

We find that the leverage-constraint lowers average trading volume by around 23% (regression summary statistics are in Table 2 and regression results are in Table 3). The estimate of β_1 equals -0.27 in Table 3 and the estimate is statistically significant at the 1% level when we use trader and month fixed effects (FE) (Column 1). This estimate translates to about a 23% reduction in trading volume.[11] The coefficient estimate is -0.20 and statistically significant at the 5% level when the regression uses brokerage-month fixed effects (Column 2). Brokerage-month fixed effects flexibly control for differences in aggregate trading volume across brokerages over time. This accounts for possible differences in the growth of trading records in the myForexBook database that are the result of the social network's partnering with these brokerages at different times during the sample period. Though we expect the leverage-constraint to primarily affect the extensive margin of trading volume, because the constraint caps the size of traders' positions, we also test the constraint's effect on the log number of trades per month (Columns 3 and 4). We estimate that the constraint lowers the amount of trading by approximately 10% (β_1 equals -0.11 and is statistically significant at the 1% level). In Column 4, when we use brokerage-month fixed effects, the estimate of the constraint on trading frequency equals approximately -0.07, but the effect is not statistically different from zero.

Though a 23% reduction in trading volume is large by most standards, we also communicate the economic magnitudes of the leverage-constraint's effect by examining simple trading statistics before and after the regula-

[11] The estimate of β_1 comes from a log-level regression, and so a percentage change in the dependent variable equals $100 \cdot (e^{\beta} - 1)$.

tion. Prior to the leverage-constraint, the median volume of trading per trader-month is 138,474 USD for our sample of U.S. traders. Median trading volume falls to 104,000 USD per trader-month after the constraint, a decline of 25%.

4.1.1. Testing for common trends

We provide evidence that supports the assumption of parallel trends for the difference-in-differences tests. Fig. 1 presents an event study plot of the effect of the CFTC regulation on trading volume. It uses the following regression

$$\log(\text{trading volume})_{it} = \gamma_i + \gamma_t + \sum_{k=T-l}^{T+l} \beta_{1k} \text{US trader}_i \times I_{T+k=t} + \varepsilon_{it} \tag{2}$$

where I is a set of indicator variables for k weeks surrounding the regulation that occurred in period T. Therefore, β_k for $k = \{-T,...,T\}$ is the sequence of treatment effects, and hence maps out the impulse response. For the months prior to the regulation, β_{1k} tends to be close to zero, indicating that there are common trends between U.S. and European traders' trading volume. The coefficient estimate drops sharply to less than -0.25 immediately after the regulation. The difference stays large and negative until February 2011, at which point the effect stays negative, but is relatively small.

4.1.2. Robustness to alternative treatment and control groups

Because not all traders apply much leverage to their trades, the CFTC regulation could affect U.S. trading outcomes for reasons other than their use of leverage. If enhanced leverage is the cause of the reduction in trading volume, then the regulation would have the strongest effect on traders that use a lot of leverage, because they would be more sensitive to the intended effect of the regulation.

Panel B of Table 3 uses the following regression to test the leverage-constraint's effect on high-leverage traders:

$$\log(\text{trading volume})_{it} = \gamma_i + \gamma_t + \beta_1 \text{high leverage trader}_i \times \text{post constraint}_t + \beta_2 \text{controls}_{it} + \varepsilon_{it}. \tag{3}$$

We calculate the average amount of leverage traders use on their trades prior to the regulation. We then set *high leverage trader* equal to one for traders that are above the median in average leverage-use, zero otherwise. The coefficient β_1 estimates how the reduced availability of leverage affects the performance of traders predisposed to using leverage.

Indeed, we find that the leverage-constraint reduces the trading volume of traders that use more leverage. Using the same four regression specifications as Panel A, the estimate of β_1 approximately equals -0.35 when the dependent variable is log trading volume (statistically significant at the 1% level) and -0.16 when it is the log number of trades per month (statistically significant at the 5% level). These estimates suggest the leverage-constraint reduces trading volume by 30% and the number of trades by 15%.

4.1.3. The effect of the announcement of leverage regulation

While the leverage-constraint significantly reduced trading volume, warnings of the risks of trading with leverage could also be an effective way to discourage unprofitable speculation. On January 20, 2010, the CFTC announced its intent to restrict leverage to 10:1. The following regressions test whether warnings such as these can affect traders' demand:

$$\log(\text{trading volume})_{it} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post announcement}_t + \varepsilon_{it}. \tag{4}$$

This difference-in-differences regression is analogous to Eq. (1), and includes similar data trimming to restrict the sample to the one-year window around the announcement (August 2009 to July 2010). In this regression, the variable *post announcement* equals one if the month is after January 2010.

We do not find evidence that the announcement affects trading volume. Using the same fixed effects and controls as Panels A and B, the estimate of β_1 in Panel C equals 0.15 when the dependent variable is the logarithm of trading volume and between 0.04 to 0.10 for the logarithm of the number of trades. These coefficients are not statistically different from zero, and they are also roughly half as large in absolute value as the corresponding coefficients that estimate the effect of the actual leverage-constraint.

One plausible alternative reason why the CFTC announcement would not have affected trading volume would be that traders were unaware of it. Contrary to this explanation, the CFTC's announcement received considerable attention. Google search volume for the term "forex leverage" spiked in the week of the announcement and reached a two-year peak (Appendix Fig. A.2). Therefore, though traders knew that they were likely to have less access to leverage, the announcement did not significantly affect traders' demand.

4.2. Traders' portfolio returns

We further test the leverage regulation's effect on traders' returns. We use traders' account balances to calculate monthly returns, excluding account deposits. We then form five portfolios by sorting traders by their average leverage use in the prior month.[12]

First, we find that the use of leverage is negatively correlated with traders' returns. Fig. 2 presents a bar graph that separates the portfolio sorts by pre- and post-legislation, and by U.S. and European traders. Across all combinations of period and trader location, the highest-quintile-of-leverage portfolio has worse returns than the lowest-quintile-of-leverage portfolio. For example, prior to the leverage-constraint, the U.S. traders' high-leverage portfolio loses 44%, while the low-leverage portfolio loses 3%.[13] Therefore, the return difference between the high- and low-leverage portfolios, which we refer to as the *high-minus-low return*, is 41 percentage points per month.

Second, and more importantly, the leverage-constraint curtails traders' losses (see Table 4, Panel A). Before the leverage-constraint, the average U.S. portfolio loses 17%, whereas after the constraint it loses only 10%. To estimate the treatment effect on the average return, we also control for changes in European traders' portfolio return. The European traders' average portfolio loses 15% before the constraint and 12% after the constraint. Comparing the gains in performance for U.S. traders to that of European traders, our findings imply that the leverage-constraint increases the average portfolio return by five percentage points (i.e., $(\bar{R}_{US,post} - \bar{R}_{US,pre})$ minus $(\bar{R}_{EUR,post} - \bar{R}_{EUR,pre})$ equals 0.05, where $\bar{R}$ is the average portfolio return).

Third, as one would expect from a causal mechanism, the effect of the leverage-constraint is considerably stronger for traders that use high leverage. In particular, the policy substantially improves the return of the high-leverage portfolio without having a significant effect on the return of the low-leverage portfolio. Therefore, it also mitigates the relative underperformance of the high-leverage portfolio. After the leverage-constraint, the U.S. traders' *high-minus-low return* is 18%, compared to 41% before the constraint. So, the constraint improves the

[12] Traders' returns are equal-weighted in these portfolios. When we value-weight the portfolios based on the size of traders' accounts, the portfolio sorts become considerably noisy. This is because there are several traders with substantially larger account balances than the rest of the sample and their returns constitute almost all of the weight within a given quintile.

[13] Though these are large monthly losses, the size of these losses is not unusual relative to findings in existing studies of active retail traders. For example, Barber et al. (2014) study 15 years of retail investing in Taiwan. They find that some traders lose 29 basis points (bps) per day (after fees), which translates to monthly losses equal to approximately 9%. Hence, it would take just 5:1 leverage—which is significantly less than the amount used by our traders (e.g., close to 20% of positions use at least 50:1 leverage prior to the leverage-constraint)—for these Taiwanese traders to match the worst monthly performance in our data.

relative return of the high-leverage portfolio by 23 percentage points. As before, we also control for changes in European traders' portfolio returns. The European traders' high-leverage portfolio performs higher by 6 percentage points after the constraint compared to before. This implies that the leverage-constraint increases the *high-minus-low return* by 18 percentage points (i.e., $(\bar{R}_{US,post} - \bar{R}_{US,pre})$ minus $(\bar{R}_{EUR,post} - \bar{R}_{EUR,pre})$ equals 0.18, where $\bar{R}$ is the *high-minus-low return*). We interpret this as the main treatment effect of the regulation. Because, prior to the policy, the average high-leverage U.S. trader loses 44% per month, our estimate suggests that the leverage-constraint policy mitigates these traders' losses by about 40%.

One concern is that changes in traders' expected return might reflect changes in their loading on well-known pricing factors that generate a risk premium. To address this concern, we construct portfolio alphas after regressing the portfolio returns on a carry-trade factor—the pricing factor that is presumably most relevant to the traders we study.[14] We then repeat our analysis using portfolio alphas as opposed to raw returns and find that the results are largely unchanged.[15] For instance, the effect of the policy on the difference between the alphas of the high- and low-leverage portfolio, *high-minus-low alpha*, is 19 percentage points—similar to the effect we find on *high-minus-low return*. This difference is statistically significant. Using a χ^2 test from a seemingly unrelated regressions estimation to compare the differences in high-minus-low alphas, the p-value for the null hypothesis that $(\alpha_{US,post} - \alpha_{US,pre})$ minus $(\alpha_{EUR,post} - \alpha_{EUR,pre})$ equals zero is approximately 1%.[16]

Consistent with our previous findings that the announcement of regulation does not significantly affect trading volume, we do not find strong evidence that the announcement affects traders' returns. Table 4, Panel B, presents portfolio returns for U.S. and European traders before and after the leverage announcement. Similar to our findings in Panel A, the average portfolio underperforms between 15 and 20 percentage points, and the high-leverage portfolio underperforms between 30 and 40 percentage points worse than the low-leverage portfolio. However, the portfolio returns do not significantly change after the announcement date (for the *high-minus-low portfolio*, $(\bar{R}_{US,post} - \bar{R}_{US,pre})$ minus $(\bar{R}_{EUR,post} - \bar{R}_{EUR,pre})$ equals -0.02 and is statistically insignificant).

4.2.1. Back-of-the-envelope calculations for gross (pre-fee) portfolio returns

We provide evidence that most of the improvement in U.S. traders' net performance is due to the trading costs associated with more trading volume prior to the constraint (see Appendix A.5). Because trading costs come from paying the spread on each transaction, our data do not directly provide us with the costs of trading. However, we know from historical sources that the typical brokerage would have charged between 2 to 5 pips per trade, where a pip is equal to one-hundredth of one percent. When we assume that traders were charged 2 pips, we can attribute approximately 60% of traders' losses to transaction costs (i.e., prior to the constraint, the U.S. traders' high-leverage portfolio return equals -0.44 net and -0.17 gross). When we assume 3 to 4 pips, the difference between the gross returns of the high-leverage and the low-leverage portfolios is small and not statistically different from zero. When

[14] International pricing factors are provided to us by Brusa et al. (2014). Brusa et al. (2014) show that three factors can price global equity returns: a world market equity portfolio, a dollar factor (the investor borrows in the U.S. and invests in a basket of international currencies), and a carry-trade factor. Because of the short time frame of our sample, a multivariable regression that includes all three factors is considerably noisy, and so we focus specifically on the carry-trade factor.

[15] It is worth emphasizing that these alphas do not necessarily reflect pricing anomalies since they correspond to portfolio returns after trading costs (aggregated over many positions). For instance, one could not simply reverse the positions in these portfolios and obtain the minus of these alphas—this would generate a very different return that would depend on the gross returns as well as trading costs.

[16] A related concern is that while the leverage-constraint improves traders' portfolio return on average, it might also increase the volatility of their portfolios, which would generate a counteracting effect on their welfare. In unreported results, we analyze the effect of the policy on traders' portfolio volatility, calculated for each trader-month as the standard deviation of traders' daily portfolio returns over the month. We find mixed evidence that seems to point toward the constraint lowering portfolio volatility. Our model also predicts that the policy should reduce portfolio volatility (see Section 2.2 and the Internet Appendix).

we assume 5 pips, the high-leverage traders' portfolio actually has better gross performance than the low-leverage traders.

4.2.2. Effect on trade-level returns

As a robustness check, we also investigate the effect of the leverage-constraint policy on the (after-fee) return on each trade. Similar to our portfolio-level results, we find that the policy substantially reduces average per-trade losses (see Appendix A.6). There are several ways in which these tests at the trade-level support our portfolio-level findings that the leverage-constraint lessens traders' underperformance. First, these tests allow us to use trader fixed effects to control for unobserved heterogeneity in trader ability. These regressions also control for relevant characteristics of each trade, such as the currency pair or the holding period, which give us confidence that our findings are attributed to the leverage-constraint, and not to other time-varying changes in investors' behavior. Second, trade-level regressions give us the ability to test whether U.S. and European traders have common trends in their trading returns prior to the regulation, and indeed they do whether we define time-trends in calendar-time or trade-time.

5. The leverage-constraint's effect on brokerages

Section 4 shows that the leverage-constraint reduces trading volume and traders' net returns. Our model in Section 2.2 suggests that the decline in trading volume also reduces the revenues for brokerages that intermediate trades in this market. We expect the decline in revenue to be reflected in the financial accounts of the brokerages, and to reduce their capital in excess of the regulatory requirements. Therefore, we explore the effect of the regulation on the brokerages by estimating the following regression,

$$\log(\text{excess capital})_{bt} = \gamma_b + \gamma_t + \beta_1 \text{FX broker}_b \times \text{post constraint}_t + \text{controls}_{bt} + \varepsilon_{bt} \quad (5)$$

where b is a broker and t is a month. *FX broker* equals one if the brokerage has retail forex obligations, and zero if it does not. *Post constraint* equals one if month t comes after October 2010, and zero otherwise. The coefficient β_1 is an estimate of the average treatment effect of the reduction in leverage on brokerage excess capital. For these tests, we restrict the sample to May 2010 to April 2011 to allow an equal amount of time before and after the constraint was imposed, and to let the policy's effect accrue over time. Summary statistics for these regression variables are presented in Table 5. We calculate double-clustered standard errors that allow for correlated residuals across time and brokerage.

The leverage-constraint leads to approximately a 25% reduction in brokerage's excess capital, according to the tests in Table 6, Panel A. All of our estimates of Eq. (5) include brokerage and month fixed effects, and Columns 2 and 4 control for the brokerage's net capital requirement in month t. Columns 3 and 4 apply weights to balance the average size of control and treatment brokerage. The weights are calculated using the method developed by Hainmueller (2012).[17] We apply these weights to refine our estimates, because brokerages with FX obligations tend to be smaller than those without. The estimate of β_1 equals approximately -0.28 when the sample is not balanced by broker size and -0.31 when it is. In all cases, the coefficient estimate is statistically significant at the 5% level.

[17] Hainmueller (2012) develops a procedure to balance covariates in observational studies with binary treatments. The procedure uses maximum entropy to reweight control and treatment groups. In Hainmueller's (2012) words, this nonparametric balancing procedure "exactly adjusts inequalities in representation with respect to first, second, and possibly higher moments of the covariate distribution." In our case, it re-balances the control group, brokerages without forex obligations, so that the first three moments of its distribution—mean, standard deviation, and skewness—match that of the treatment group, brokerages without forex obligations. In the finance literature, this procedure has also been used by Hartzmark (2014).

We find evidence of common trends prior to the leverage-constraint between brokerages with and brokerages without forex obligations. Fig. 3 presents an event study plot of the following regression

$$\log(\text{excess captal})_{bt} = \gamma_b + \gamma_t + \sum_{j=-6}^{7} \beta_j \text{FX broker}_b \times I_{T+j=t} + \varepsilon_{bt} \tag{6}$$

where $I_{T+j=t}$ is a set of indicator variables for the sequence of months that surround the leverage-constraint. From February 2010 (the month after the CFTC's initial announcement) through August 2010, the estimates of I are close to zero, which suggests parallel trends. The estimate of I falls to approximately -0.2 in September and then to approximately -0.4 starting in December 2010, and thereafter. That the treatment effect of the leverage regulation starts in September, the month prior to the compliance date of the leverage-constraint, we attribute to some brokerages enforcing the constraint after the final rules were outlined (September 10), but before the mandated compliance date (October 18). Furthermore, the policy has a larger effect on brokerages that allow traders substantial amounts of leverage (see Appendix Table A.7).[18] This is precisely the group of brokerages that would be more sensitive to the policy, furthering our confidence that we identify the leverage-constraint's effect.

The reduction in brokerages' excess capital is likely caused by the loss of revenue from intermediating retail trading, as a result of the restrictions on providing leverage. This is evidenced by the reduction in trading volume and retail trader losses documented in Section 4. However, an alternative story is that these brokerage firms were less able to receive external financing because the regulations weakened their projected value.

Two additional tests provide evidence that the reduction in brokerage capital is the result of less internally generated revenues. First, we find that the leverage-constraint has a stronger effect on small brokerage firms. Table 6, Panel B sorts the sample of firms into above and below median brokerage capital (using the median of the sample of brokerage firms with retail forex obligation as the dividing point). The coefficient estimate is approximately -0.5 for below median brokerages Columns 1 and 2) and -0.1 for above median brokerages (Columns 3 and 4). These small brokerage firms are presumably less able to raise external capital, or to make up for the loss of revenues by reallocating internal firm resources toward other markets. Second, the January 2010 CFTC announcement of leverage regulations did not strongly affect brokerage capital. According to regression estimates in Panel C, the treatment effect of the announcement is small (approximately -0.045) and not statistically different from zero. If the leverage-constraint caused reductions in brokerage capital through a channel of decreased external financing, then we would expect the CFTC announcement to have an effect, because the announcement would have lowered the projected revenues of these brokerage firms.

Furthermore, we consider whether the reduction in brokerage firms' capital is also caused by the leverage-constraints' effect on client retention and acquisition. The CFTC brokerage data include information on client flows, and so we use the myForexBook account-level data set to estimate trader entry and exit from the forex market. Appendix Section A.8 describes our approach.[19] We find that, after controlling for time-trends in the myForexBook data, the CFTC regulation reduces trader exits, which is consistent with Section 4's result that traders lose less money as a result of the leverage-constraint. But, the leverage-constraint reduces the entry rate of new traders by more than the exit rate, causing an approximately 1% reduction in the number of clients per brokerage,

[18] Note, we sort brokerages into high- versus low-leverage by searching web archives, the details of which we discuss in the Appendix. We are unable to sort the brokerages using our trading data, because the brokerages in the myForexBook data set and those in the CFTC data set do not always overlap.

[19] Though the results on trader entry and exit corroborate our findings that the constraint lowered trading volume, we encourage readers to carefully consider our tests and our estimates. This is because we have to estimate traders' entry and exit into the forex market using empirical proxies, and because some entry and exit could be mismeasured due to the fact that the account-level data come from an online social network that does not provide us information on account openings and closings at traders' brokerages.

per month. This suggests that the leverage-constraint lessened the appeal of forex trading, which also contributes to the reduction in brokerages' revenues.

Finally, we conjecture that the reduction in revenues caused by the leverage-constraint precipitated significant changes in the structure of the brokerage market. Fig. 4 plots a time series of brokerages' retail forex obligations. When the CFTC's reporting requirements began in November 2010, there were around 25 brokerages and these brokerages had a wide range of sizes. Today, only four brokerages registered with the CFTC have retail forex obligations and these four are among the market's largest brokerages.

6. The leverage-constraint and relative bid-ask spreads

So far, the leverage-constraint reduces the trading volume and traders' losses, and thereby weakens the brokerages. As our stylized model illustrates, the policy can also affect the bid-ask spreads by changing the informativeness of traders' orders. Moreover, adding realistic financial frictions (which we abstracted away from) could also generate effects on bid-ask spreads. For instance, if the brokerages need some of their own capital to intermediate positions, then a reduction in their revenues and capital can further reduce market liquidity and increase the bid-ask spreads (Brunnermeier and Pedersen, 2008; Gromb and Vayanos, 2010). We therefore assess whether the regulation caused brokers' bid-ask spreads to rise.

We focus on local liquidity in the retail market, measured as the bid-ask spreads charged by the brokerages relative to the interbank market. This is the appropriate measure for our analysis because the foreign exchange market is very large, and the retail segment of the market is significantly smaller. Thus, the CFTC leverage regulation undoubtedly had no effect on global currency prices or liquidity in the interbank market, and measuring the spreads relative to this market enables us to control for many factors. We construct this relative spread measure using a data series we estimate from our interbank data merged with myForexBook transactions (see Section 3 for details and Table 7 for summary statistics).

We test the effect of the leverage policy on the relative bid-ask spreads by estimating the following difference-in-differences regression

$$\text{relative bid-ask spread}_{jit} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post constraint}_t + \beta_2 \text{controls}_{jit} + \varepsilon_{jit} \tag{7}$$

where j is a trade executed by trader i. We estimate this regression at the trade-level and include daily fixed effects (γ_t) in all of the regressions.[20] The coefficient β_1 on the interaction between *US trader* and *post constraint* is an estimate of the constraint's effect on local bid-ask spreads.[21] Furthermore, due to the imperfect matching between myForexBook transactions and interbank price quotes, Table 8 presents results for trades that we can match to the exact second (Columns 1 and 2), as well as for the full sample of trades while controlling for the distance of the match (Columns 3 and 4).

The leverage-constraint does not have a strong effect on the relative bid-ask spreads at these brokerages. The estimate of β_1 equals -0.011 when we can match myForexBook trades to Tick Data prices precisely to the second and it equals -0.014 when we control for the distance of the match, neither of which are statistically different from zero. Columns 2 and 4 interact *US trader* with leads and lags around the month of the leverage-constraint. We

[20] For regressions that test Eq. (7), we winsorize the dependent variable *relative bid-ask spread* at the 1% level.

[21] In alternative, but unreported tests, we replace *US trader* with an indicator variable for the share of U.S. traders in the myForexBook database that use a given brokerage. The idea behind these tests is that a given brokerage might not charge different prices to U.S. versus European traders even after the leverage-constraint. However, we would expect brokerages that predominately have U.S. clientele to be more strongly affected by the leverage regulations, and the regulations would affect all traders on the brokerage. The results of these tests are not noticeably different than our findings in Table 8.

do not find that the leverage-constraint affects bid-ask spreads at different leads and lags around the regulation. Likewise, similar to the results on trading activity and brokerage capital, we do not find any evidence that the January 2010 CFTC announcement of the leverage restriction affects brokerages' bid-ask spreads (see Panel B).

Recall that our model predicts an increase (resp. decrease) in bid-ask spreads if and only if the leverage-constraint policy increases (resp. decreases) traders' average information. Hence, the zero effect on bid-ask spreads can be reconciled with our model as long as the policy does not substantially change traders' average information. In Section 4, we present back-of-the-envelope calculations on gross returns (which provides a measure of traders' information) that suggests this might be the case. Specifically, with our preferred measure of trading costs, our analysis suggests the policy does not substantially change traders' gross returns. Put differently, the brokerages seem to face a similar degree of adverse selection before and after the leverage-constraint policy, which provides an explanation for why they do not change their bid-ask spreads.

7. Conclusion

This paper asks whether retail traders' leverage should be limited by empirically analyzing a unique policy intervention that restricted the provision of leverage to U.S. retail traders of foreign exchange. Using three data sets—a large transaction level-data set, panel data on brokerages regulated by the CFTC, and a data set of inter-bank prices—and a difference-in-difference empirical strategy, we find that the policy reduces trading volume, increases traders' net returns, and lowers brokerages' excess capital. Yet, the policy has no discernible effect on the relative bid-ask prices charged by these brokerages. We reconcile these findings with a model in which traders with heterogeneous and dogmatic beliefs take speculative positions, and a competitive brokerage sector intermediates these trades subject to technological and informational costs. From the lens of the model, these empirical results suggest that the leverage-constraint policy generates a sizable improvement in belief-neutral welfare, by economizing on productive resources used to intermediate speculation, while having no adverse effect on market liquidity. Put differently, our analysis suggests leverage is attractive to speculative traders who do not necessarily contribute to market quality. By providing leverage to these traders, financial intermediaries exacerbate speculation, which increases trading volume and their intermediation revenues, but at the expense of traders' profits and social welfare.

Our analysis is largely agnostic about the behavioral distortions that induce retail traders to speculate. This is because, as our model illustrates, our results apply for a large class of behavioral distortions that ultimately translate into dogmatic beliefs and trade. That said, the most parsimonious explanation for our findings is an overconfidence bias. Leverage would be particularly attractive to overconfident speculators with precise beliefs about asset payoffs. While some behavioral distortions sometimes struggle to explain asset market participation in the first place, e.g., Cumulative Prospect Theory, Barberis and Xiong (2009), overconfident investors' attraction to markets with high-leverage can explain why the retail traders we study choose to join this market, why they are more likely to leave the market when leverage is taken away, and why they are undeterred by the CFTC's announcement of leverage regulations. Furthermore, a robust empirical finance literature documents that overconfident individual investors have high trading volume, and because these traders pay more in transaction costs, they have poor net returns (e.g., Barber and Odean, 2000). Indeed, our results on retail forex traders' leverage use (and the associated transaction costs) mirror the literature's findings.

Obviously, our motivating model is too stylized to capture all potential reasons for trade in the forex market. For instance, some traders could be trading to hedge their background risks, as in Simsek (2013b). Others might be enjoying the sensation from trading. If we were to model these other motives for trade, leverage would improve social welfare through these channels. In an empirical analysis, it is impossible to capture all possible reasons for trade. We view our analysis as capturing a key driving force for trade in the foreign exchange market (monetary pursuits from speculation). Our empirical results suggest that through this channel the leverage-constraint policy has a large positive impact on social welfare. This can also be viewed as setting a (very high) threshold that other rationales for trade would have to exceed to overturn our qualitative conclusion that the leverage restriction policy improves social welfare.

Our results also shed some light on the extraordinary growth of the financial services sector in the last decades (although this growth is also driven by many other factors, which we haven't touched upon in our analysis). We present evidence that suggests the growth of the foreign exchange brokerage market has been socially excessive, and that a leverage-constraint policy is an effective tool to reduce this excess. To the extent that our results apply in other markets, leverage (that finances speculation) could have contributed to inefficient growth also elsewhere in the financial sector. More broadly, recent decades have seen a considerable increase in trading volume, and some of this volume has arguably been speculative, as evidenced by the recent trading frenzies in the Chinese stock market and cryptocurrencies. Our results suggest that speculative trading volume could have inefficiently increased the size of the financial sector, and policies that target speculative trading could deal with this inefficiency without having adverse effects on market liquidity. We leave the analysis of other markets and other anti-speculation policies (such as financial transaction taxes) to future work.

References

Adrian, T., Shin, H. S., 2010. Liquidity and leverage. Journal of Financial Intermediation 19, 418–437.

Bailey, M. C., Dávila, E., Kuchler, T., Stroebel, J., 2018. House price beliefs and mortgage leverage choice. Review of Economic Studies Forthcoming.

Barber, B. M., Lee, Y.-T., Liu, Y.-J., Odean, T., 2014. The cross-section of speculator skill: Evidence from day trading. Journal of Financial Markets 18, 1–24.

Barber, B. M., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance 55, 773–806.

Barber, B. M., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. The Quarterly Journal of Economics 116, 261–292.

Barber, B. M., Odean, T., Zhu, N., 2008. Do retail trades move markets? The Review of Financial Studies 22, 151–186.

Barberis, N., Xiong, W., 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. The Journal of Finance 64, 751–784.

Barrot, J.-N., Kaniel, R., Sraer, D., 2016. Are retail traders compensated for providing liquidity? Journal of Financial Economics 120, 146–168.

Ben-David, I., 2018. High leverage and willingness to pay: Evidence from the residential housing market. Real Estate Economics Forthcoming.

Ben-David, I., Birru, J., Prokopenya, V., 2018. Uninformative feedback and risk taking: Evidence from retail forex trading. Review of Finance Forthcoming.

Ben-David, I., Birru, J., Rossi, A., 2017. Industry familiarity and trading: Evidence from the personal portfolios of industry insiders. Journal of Financial Economics Forthcoming.

Berkman, H., Koch, P. D., Westerholm, P. J., 2014. Informed trading through the accounts of children. The Journal of Finance 69, 363–404.

Bertrand, M., Morse, A., 2011. Information disclosure, cognitive biases, and payday borrowing. The Journal of Finance 66, 1865–1893.

Black, F., 1986. Noise. The Journal of Finance 41, 528–543.

Brunnermeier, M. K., Pedersen, L. H., 2008. Market liquidity and funding liquidity. The Review of Financial Studies 22, 2201–2238.

Brunnermeier, M. K., Simsek, A., Xiong, W., 2014. A welfare criterion for models with distorted beliefs. The Quarterly Journal of Economics 129, 1753–1797.

Brusa, F., Ramadorai, T., Verdelhan, A., 2014. The international CAPM redux. Unpublished working paper, Temple University .

Campbell, J. Y., Jackson, H. E., Madrian, B. C., Tufano, P., 2011. Consumer financial protection. Journal of Economic Perspectives 25, 91–114.

Cao, D., 2017. Speculation and financial wealth distribution under belief heterogeneity. The Economic Journal 128, 2258–2281.

Carlin, B. I., 2009. Strategic price complexity in retail financial markets. Journal of Financial Economics 91, 278–287.

Dorn, D., Huberman, G., Sengmueller, P., 2008. Correlated trading and returns. The Journal of Finance 63, 885–920.

Favara, G., Imbs, J., 2015. Credit supply and the price of housing. American Economic Review 105, 958–992.

Fostel, A., Geanakoplos, J., 2008. Leverage cycles and the anxious economy. The American Economic Review 98, 1211–1244.

Foucault, T., Sraer, D., Thesmar, D. J., 2011. Individual investors and volatility. The Journal of Finance 66, 1369–1406.

Gabaix, X., Laibson, D., 2006. Shrouded attributes, consumer myopia, and information suppression in competitive markets. The Quarterly Journal of Economics 121, 505–540.

Garleanu, N., Pedersen, L. H., 2011. Margin-based asset pricing and deviations from the law of one price. The Review of Financial Studies 24, 1980–2022.

Geanakoplos, J., 2003. Liquidity, default, and crashes: Endogenous contracts in general equilibrium. In: Dewatripont, M., Hansen, L., Turnovsky, S. (eds.), *Advances in Economics and Econometrics: Theory and Applications*, Eighth World Congress, Cambridge University Press, New York, vol. 2, pp. 170–205.

Geanakoplos, J., 2010. The leverage cycle. NBER Macroeconomics Annual 24, 1–65.

Gervais, S., Odean, T., 2001. Learning to be overconfident. Review of Financial Studies 14, 1–27.

Gilboa, I., Samuelson, L., Schmeidler, D., 2014. No-betting-pareto dominance. Econometrica 82, 1405–1442.

Glosten, L. R., Milgrom, P. R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 14, 71–100.

Greenwood, R., Scharfstein, D., 2013. The growth of finance. The Journal of Economic Perspectives 27, 3–28.

Grinblatt, M., Keloharju, M., 2009. Sensation seeking, overconfidence, and trading activity. Journal of Finance 64, 549–578.

Gromb, D., Vayanos, D., 2010. A model of financial market liquidity based on intermediary capital. Journal of the European Economic Association 8, 456–466.

Grossman, S. J., Stiglitz, J. E., 1980. On the impossibility of informationally efficient markets. The American Economic Review 70, 393–408.

Gurun, U. G., Matvos, G., Seru, A., 2016. Advertising expensive mortgages. The Journal of Finance 71, 2371–2416.

Hainmueller, J., 2012. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. Political Analysis 20, 25–46.

Hardouvelis, G. A., Peristiani, S., 1992. Margin requirements, speculative trading, and stock price fluctuations: The case of Japan. The Quarterly Journal of Economics 107, 1333–1370.

Hartzmark, S. M., 2014. The worst, the best, ignoring all the rest: The rank effect and trading behavior. The Review of Financial Studies 28, 1024–1059.

Haughwout, A., Lee, D., Tracy, J., van der Klaauw, W., 2011. Real estate investors, the leverage cycle, and the housing market crisis. Federal Reserve Bank of New York Staff Reports No.514.

Heimer, R. Z., 2016. Peer pressure: Social interaction and the disposition effect. The Review of Financial Studies 29, 3177–3209.

Kahraman, B., Tookes, H. E., 2017. Trader leverage and liquidity. Journal of Finance 72, 1567–1610.

Kaniel, R., Liu, S., Saar, G., Titman, S., 2012. Individual investor trading and return patterns around earnings announcements. The Journal of Finance 67, 639–680.

Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. Journal of Finance 63, 273–310.

Kelley, E. K., Tetlock, P. C., 2013. How wise are crowds? Insights from retail orders and stock returns. The Journal of Finance 68, 1229–1265.

King, M. R., Osler, C. L., Rime, D., 2013. The market microstructure approach to foreign exchange: Looking back and looking forward. Journal of International Money and Finance 38, 95–119.

King, M. R., Rime, D., 2010. The $4 trillion question: what explains FX growth since the 2007 survey? BIS Quarterly Review December 2010, 27–42.

Kumar, A., 2009. Who gambles in the stock market? Journal of Finance 64, 1889–1933.

Kupiec, P. H., 1989. Initial margin requirements and stock returns volatility: Another look. Journal of Financial Services Research 3, 287–301.

Kyle, A. S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Linnainmaa, J. T., 2011. Why do (some) households trade so much? Review of Financial Studies 24, 1630–1666.

Mancini, L., Ranaldo, A., Wrampelmeyer, J., 2013. Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. The Journal of Finance 68, 1805–1841.

Odean, T., 1998. Volume, volatility, price, and profit when all traders are above average. The Journal of Finance 53, 1887–1934.

Posner, E. A., Weyl, E. G., 2013. An FDA for financial innovation: Applying the insurable interest doctrine to 21st century financial markets. Northwestern University Law Review 107, 1307–1485.

Schwert, G. W., 1989. Margin requirements and stock volatility. Journal of Financial Services Research 3, 153–164.

Seguin, P. J., Jarrell, G. A., 1993. The irrelevance of margin: Evidence from the crash of '87. The Journal of Finance 48, 1457–1473.

Seru, A., Shumway, T., Stoffman, N., 2010. Learning by trading. Review of Financial Studies 23, 705–739.

Shleifer, A., Summers, L. H., 1990. The noise trader approach to finance. The Journal of Economic Perspectives 4, 19–33.

Simsek, A., 2013a. Belief disagreements and collateral constraints. Econometrica 81, 1–53.

Simsek, A., 2013b. Speculation and risk sharing with new financial assets. Quarterly Journal of Economics 128, 1365–1396.

Stiglitz, J. E., 1989. Using tax policy to curb speculative short-term trading. Journal of Financial Services Research 3, 101–115.

Summers, L. H., Summers, V. P., 1989. When financial markets work too well: a cautious case for a securities transactions tax. Journal of Financial Services Research 3, 261–286.

Thaler, R. H., Benartzi, S., 2004. Save more tomorrow: Using behavioral economics to increase employee saving. Journal of Political Economy 112, S164–S187.

Wang, Y., 2015. Why can margin requirements increase volatility and benefit margin constrained investors? Review of Finance 20, 1449–1485.

Zingales, L., 2015. Presidential address: Does finance benefit society? The Journal of Finance 70, 1327–1363.

Table 1
A comparison balancing test.
This table compares traders in the myForexBook data set from the United States to traders from Europe. Panel A includes a comparison of means. Panel B presents Pearson's correlation coefficients from daily fluctuations in aggregate trading activity between U.S. and European traders (weekends excluded). Daily fluctuations equal $log\left(\bar{y}_{t,i}/\bar{y}_{t-1,i}\right)$ where $\bar{y}$ is the average by day t, and i indexes U.S. versus European traders. The sample window for these tests is the period immediately preceding the CFTC leverage-constraint – May 1 to October 17, 2010.

Panel A: Difference in means between U.S. and European traders

	US	*EUR*	t-stat[a]
Personal characteristics			
Trading experience (years)			
0 - 1	0.29	0.31	*1.17*
1 - 3	0.45	0.44	*0.40*
3 - 5	0.10	0.10	*0.25*
5 +	0.15	0.14	*0.76*
Trading approach			
Technical	0.65	0.66	*0.66*
Fundamentals	0.046	0.053	*0.78*
News	0.024	0.020	*0.70*
Not specific	0.23	0.22	*0.62*
Momentum	0.053	0.048	*0.57*
Age	37.4	37.4	*0.09*
Trading characteristics			
Trades per account	364.6	307.3	*0.68*
Trades per account/day, if ≥ 1 trade in day	6.59	7.03	*0.60*
Distinct currency pairs traded at least once	8.46	8.17	*1.15*
Fraction trades w/ leverage > 50:1	0.16	0.19	*2.67*
Number of traders	1,193	1,479	

[a] test of equality of means between *US* and *EUR*

Panel B: Correlation of aggregate daily trading for U.S. versus Europeans

	Corr. coef.
Trading volume (USD)	0.59
Number of trades	0.62
Returns	0.44

Table 2

Summary statistics from traders' accounts.

This table presents summary statistics from the myForexBook account-level database trimmed according to the criteria described in Section 3. The sample includes trades executed by U.S. and European retail forex traders. *US trader* equals one if the trader is located in the U.S. and equal to zero if located in Europe. *Post constraint* equals one if the month comes after October 2010, the month in which brokerages needed to comply with CFTC regulations limiting the leverage available to U.S retail forex traders at 50:1, zero otherwise. *Post announcement* equals one if the trade was opened after the CFTC's announcement in the Federal Registrar in January 2010 of their intent to restrict traders' leverage to 10:1, zero otherwise. *High-leverage trader* equals one if the traders' average leverage use prior to the leverage-constraint is above the median of all traders in the sample. Monthly *portfolio returns* are calculated using the account's balances at the beginning and end of the month, excluding deposits.

Panel A: Sample window around leverage-constraint (May 2010 - April 2011)

Variable	Mean	Std dev	5%	10%	25%	50%	75%	90%	95%
Log trading volume (USD)	11.7	2.65	7.14	8.29	10.00	11.8	13.5	14.8	15.7
Log number of trades	3.31	1.62	0	1.10	2.20	3.43	4.44	5.28	5.81
Portfolio return	-0.19	0.90	-1.42	-1.00	-0.34	-0.0092	0.020	0.23	0.70
US trader (= 1)	0.46								
Post constraint (= 1)	0.54								
High-leverage trader (= 1)	0.55								
Trader-month observations	15,125								

Panel B: Sample window around regulation announcement (August 2009 - July 2010)

Variable	Mean	Std dev	5%	10%	25%	50%	75%	90%	95%
Log trading volume (USD)	11.9	2.46	7.67	8.85	10.3	12.1	13.6	15.0	15.8
Log number of trades	3.31	1.55	0.69	1.10	2.30	3.47	4.42	5.16	5.62
Portfolio return	-0.31	1.05	-1.98	-1.22	-0.74	-0.046	0.013	0.26	0.89
US trader (= 1)	0.47								
Post announcement (= 1)	0.69								
Trader-month observations	13,833								

Table 3

Leverage constraints and trading volume.

This table uses account level data from the myForexBook data set collapsed to the level of trader-month. It reports ordinary least squares estimates of the regression

$$\log(\text{volume})_{it} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post constraint}_t + \varepsilon_{it},$$

where i is a trader and t is a month. *Trading volume* is the USD value of the assets traded. *US trader* equals one if the trader is from the U.S. and equal to zero if they are from Europe. *Post constraint* equals one in months starting in November 2010, and zero otherwise. The sample period in Panel A and Panel B is May 2010 to April 2011 The sample period in Panel C is August 2009 to July 2010. Standard errors are double-clustered by trader and month, and *, **, and *** denote significance at the $p < 0.1$, $p < 0.05$ and $p < 0.01$ levels, respectively.

Panel A: The October 2010 leverage constraint and trading volume

Dep var:	Log trading volume		Log number of trades	
	(1a)	(2a)	(3a)	(4a)
US trader (=1) × Post constraint (=1)	-0.265***	-0.200**	-0.108*	-0.0685
	(0.094)	(0.097)	(0.062)	(0.065)
Trader FE	x	x	x	x
Month FE	x		x	
Brokerage-month FE		x		x
Trader-month observations	15,125	15,016	15,156	15,047
R^2	0.72	0.73	0.61	0.61

Panel B: Alternative treatment and control groups – high- vs. low-leverage traders

Dep var:	Log trading volume		Log number of trades	
	(1b)	(2b)	(3b)	(4b)
High leverage trader (=1) × Post constraint (=1)	-0.365***	-0.340***	-0.155**	-0.154**
	(0.094)	(0.096)	(0.062)	(0.063)
Trader FE	x	x	x	x
Month FE	x		x	
Brokerage-month FE		x		x
Trader-month observations	15,125	15,016	15,156	15,047
R^2	0.72	0.73	0.61	0.61

Panel C: The January 2010 announcement of leverage regulation

Dep var:	Log trading volume		Log number of trades	
	(1c)	(2c)	(3c)	(4c)
US trader (=1) × Post announcement (=1)	0.148	0.153	0.0433	0.0998
	(0.10)	(0.12)	(0.075)	(0.080)
Trader FE	x	x	x	x
Month FE	x		x	
Brokerage-month FE		x		x
Trader-month observations	13,833	13,741	13,861	13,767
R^2	0.70	0.71	0.55	0.57

Table 4

Leverage constraints and traders' portfolio returns.

This table reports portfolio returns of traders in the myForexBook database. Monthly returns are calculated using the account's balances at the beginning and end of the month, excluding deposits. We sort traders monthly by the average amount of leverage the trader uses in $t-1$. We calculate one-factor alphas by regressing the return difference between the high- and low-leverage portfolios (*high-minus-low return*) on the carry-trade factor described in Brusa et al. (2014). To calculate statistical differences between pre- and post-constraint portfolios, we use seemingly unrelated regressions (joint equation regressions) to conduct χ^2 tests on the regression alphas; the table presents p-values for the null hypothesis that the difference in alphas is equal to zero. Stars *, **, and *** denote significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Sample window around leverage-constraint (May 2010 - April 2011)

	US traders				European traders				Local ave. treatment effect ($US_{post} - US_{pre}$) minus ...
	Pre-constraint	Post-constraint	Post minus pre	t-stat	Pre-constraint	Post-constraint	Post minus pre	t-stat	... ($EUR_{post} - EUR_{pre}$)
Sample average	-0.174	-0.095	0.079***	[4.46]	-0.149	-0.119	0.030	[1.53]	0.05
Leverage quintile									
High	-0.444	-0.195	0.249***	[4.02]	-0.340	-0.285	0.055	[0.87]	0.19
4	-0.229	-0.142	0.086**	[2.18]	-0.205	-0.176	0.029	[0.64]	0.06
3	-0.094	-0.079	0.014	[0.44]	-0.134	-0.055	0.079**	[2.18]	-0.06
2	-0.086	-0.041	0.045*	[1.64]	-0.058	-0.056	0.003	[0.09]	0.04
Low	-0.032	-0.020	0.012	[0.46]	-0.021	-0.024	-0.003	[0.09]	0.01
High minus low	-0.412***	-0.175***	0.237		-0.319***	-0.261***	0.058		0.18
	[5.75]	[4.07]	–		[6.84]	[4.35]	–		
1-Factor alpha	-0.434***	-0.196***	0.237***		-0.298***	-0.255***	0.043		0.19**
	[30.02]	[3.64]	χ^2 *p-val* < 0.00		[3.70]	[9.76]	χ^2 *p-val* = 0.62		χ^2 *p-value* = 0.01

Panel B: Sample window around regulation announcement (August 2009 - July 2010)

	US traders				European traders				Local ave. treatment effect ($US_{post} - US_{pre}$) minus ...
	Pre-announce	Post-announce	Post minus pre	t-stat	Pre-announce	Post-announce	Post minus pre	t-stat	... ($EUR_{post} - EUR_{pre}$)
Sample average	-0.145	-0.169	-0.023	[0.83]	-0.193	-0.213	-0.020	[0.66]	0.00
Leverage quintile									
High	-0.392	-0.458	-0.066	[0.66]	-0.420	-0.518	-0.098	[0.97]	0.03
4	-0.224	-0.192	0.032	[0.50]	-0.355	-0.265	0.090	[1.16]	-0.06
3	-0.018	-0.078	-0.060	[1.19]	-0.153	-0.180	-0.027	[0.52]	-0.03
2	-0.044	-0.071	-0.027	[0.83]	-0.049	-0.064	-0.015	[0.36]	-0.01
Low	-0.057	-0.066	-0.009	[0.21]	0.012	-0.051	-0.063	[1.41]	0.05
High minus low	-0.335***	-0.392***	-0.057		-0.432***	-0.467***	-0.035		-0.02
	[3.05]	[3.80]	–		[5.07]	[5.57]	–		
1-Factor alpha	-0.349***	-0.414***	-0.066*		-0.662***	-0.459***	0.203		-0.27*
	[4.01]	[4.12]	χ^2 *p-val* = 0.06		[8.40]	[5.00]	χ^2 *p-val* = 0.49		χ^2 *p-val*= 0.05

Table 5

Summary statistics on retail forex brokerages.

The data comes from monthly reports to the CFTC. The CFTC requires futures commission merchants and retail foreign exchange dealers to file monthly financial reports with the CFTC's Division of Swap Dealer and Intermediary Oversight. The CFTC collects data on brokerage excess capital and net capital requirements for the entire sample. They begin collecting data on retail forex obligations in November 2010. *Net capital requirement* is set as a minimum of $1,000,000 or some greater amount as determined under CFTC Regulation 1.17(a). *FX broker* equals one if the broker has retail forex obligations greater than zero post-November 2010, and zero otherwise. *Post constraint* equals one starting in November, 2010, the date by which brokerages needed to comply with CFTC regulation limiting the leverage available to U.S retail forex traders at 50:1, zero otherwise. *Post announcement* equals one starting in February 2010, following the CFTC's announcement in the Federal Registrar of their intent to restrict traders' leverage to 10:1, zero otherwise.

Panel A: Sample window around leverage-constraint (May 2010 - April 2011)

Variable	Broker-month obs.	Mean	Std dev	5%	10%	25%	50%	75%	90%	95%
Log excess net capital	1,505	17.4	2.88	13.2	13.6	15.1	17.3	19.5	21.3	22.6
Log net capital requirement	1,505	16.1	2.27	13.8	13.8	13.8	16.0	17.5	19.8	20.6
FX broker (=1)	1,505	0.16								
Post constraint (=1)	1,505	0.50								
Log retail forex obligations if FX broker = 1	117	16.5	1.79	14.1	14.2	15.0	16.9	17.5	18.8	18.8

Panel B: Sample window around regulation announcement (August 2009 - July 2010)

Variable	Broker-month obs.	Mean	Std dev	5%	10%	25%	50%	75%	90%	95%
Log excess net capital	1,571	17.2	2.98	12.7	13.3	14.9	17.0	19.4	21.2	22.6
Log net capital requirement	1,573	15.8	2.37	13.1	13.1	13.8	15.6	17.2	19.2	20.5
FX broker (=1)	1,573	0.14								
Post announcement (=1)	1,573	0.49								
Log retail forex obligations	no data prior to November 2010									

Table 6
The effect of the leverage-constraint and announcement on brokerage excess capital.
This table reports OLS estimates of the regression

$$\log(\text{excess capital})_{bt} = \gamma_b + \gamma_t + \beta_1 \text{FX broker}_b \times \text{post constraint}_t + \varepsilon_{bt},$$

where b is a broker and t is a month. The data come from monthly CFTC Futures Commission Merchants Financial Reports. Excess capital is the capital in excess of the regulatory requirement, for each brokerage in the CFTC data set. *FX broker* equals one if the brokerage has any retail forex obligations after they were required to report these obligations starting in November 2010. *Post constraint* equals one in months starting in November 2010, and zero otherwise. *Post announcement* equals one in months starting in February 2010, and zero otherwise. Using the non-parametric, entropy balancing procedure designed by Hainmueller (2012), some regressions weight observations so that the control group's mean, standard deviation, and skewness match that of the set of the FX brokers in the pre-constraint period. The sample period is May 2010 to April 2011 in Panels A and B , and is August 2009 to July 2010 in Panel C. Standard errors are double-clustered by broker and month, and *, **, and *** denote significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Panel A: The October 2010 leverage constraint's effect on brokerage capital

Dep var: Log excess capital	(1a)	(2a)	(3a)	(4a)
FX broker (=1) × Post constraint (=1)	-0.276**	-0.289**	-0.312**	-0.313**
	(0.12)	(0.14)	(0.13)	(0.13)
Log net capital requirement		-0.207		-0.00912
		(0.17)		(0.19)
Brokerage FE	x	x	x	x
Month FE	x	x	x	x
Sample balanced by broker size	no	no	yes	yes
Brokerage-month observations	1,503	1,503	1,456	1,456
R^2	0.99	0.99	0.97	0.97

Panel B: The leverage constraint, brokerage capital sorted by broker size

Sample: Broker size ...	Below median		Above median	
Dep var: Log excess capital	(1b)	(2b)	(3b)	(4b)
FX broker (=1) × Post constraint (=1)	-0.495**	-0.548*	-0.100	-0.100
	(0.23)	(0.29)	(0.092)	(0.093)
Log net capital requirement		-0.367		-0.00250
		(0.27)		(0.057)
Brokerage FE	x	x	x	x
Month FE	x	x	x	x
Brokerage-month observations	635	635	821	821
R^2	0.86	0.88	0.98	0.98

Panel C: The January 2010 announcement of leverage regulation

Dep var: Log excess capital	(1c)	(2c)	(3c)	(4c)
FX broker (=1) × Post announcement (=1)	-0.0542	-0.0456	-0.0418	-0.0463
	(0.11)	(0.11)	(0.12)	(0.11)
Log net capital requirement		0.0284		-0.0146
		(0.081)		(0.086)
Brokerage FE	x	x	x	x
Month FE	x	x	x	x
Sample balanced by broker size	no	no	yes	yes
Brokerage-month observations	1,570	1,570	1,542	1,542
R^2	0.98	0.98	0.98	0.98

Table 7

Summary statistics on relative bid-ask spreads.

This table presents summary statistics from the myForexBook account-level database trimmed according to the criteria described in Section 3. The sample includes trades executed by U.S. and European retail forex traders. *US trader* equals one if the trade is executed by a trader located in the U.S. and equal to zero if located in Europe. *Post constraint* equals one if the trade was opened after October 18, 2010, the date by which brokerages needed to comply with CFTC regulations limiting the leverage available to U.S retail forex traders at 50:1, zero otherwise. *Post announcement* equals one if the trade was opened after the CFTC's announcement in the Federal Registrar on January 13, 2010 of their intent to restrict traders' leverage to 10:1, zero otherwise. The trade's *relative bid-ask spread* is defined as: relative bid-ask spread$_{jit}$ = $\left(\frac{P^{\text{broker}}_{jit} - P^{\text{interbank ask}}_{t}}{P^{\text{interbank ask}}_{t}} + \frac{P^{\text{interbank bid}}_{t'} - P^{\text{broker}}_{jit'}}{P^{\text{interbank bid}}_{t'}}\right)$ if the transaction is long, and relative bid-ask spread$_{jit}$ = $\left(\frac{P^{\text{interbank bid}}_{t} - P^{\text{broker}}_{jit}}{P^{\text{interbank bid}}_{t}} + \frac{P^{\text{broker}}_{jit'} - P^{\text{interbank ask}}_{t'}}{P^{\text{interbank ask}}_{t'}}\right)$ if the transaction is short, where j is a trader, i is a trade, and t is the second the trade is opened. To calculate *relative bid-ask spread*, we match traders' transactions in the myForexBook data with the closest (in time) quoted price in Tick Data - a data set of interbank foreign exchange quotes.

Panel A: Sample window around leverage-constraint (May 1, 2010 - April 30, 2011)

Variable	Mean	Std dev	5%	10%	25%	50%	75%	90%	95%
Relative bid-ask spreads	-0.00035	0.31	-0.49	-0.32	-0.14	-0.022	0.12	0.36	0.57
US trader (= 1)	0.47								
post constraint (= 1)	0.47								
Number of trades	1,444,159								

Panel B: Sample window around regulation announcement (August 1, 2009 - July 31, 2010)

Variable	Mean	Std dev	5%	10%	25%	50%	75%	90%	95%
Relative bid-ask spreads	0.0021	0.31	-0.49	-0.32	-0.13	-0.021	0.11	0.36	0.57
US trader (= 1)	0.48								
Post announcement (= 1)	0.69								
Number of trades	1,140,274								

Table 8
The effect of the leverage-constraint on brokers' relative bid-ask spreads.
This table reports OLS estimates of the following regression:

$$\text{relative bid-ask spread}_{jit} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post constraint}_t + \beta_2 \text{trade}_{jit} + \varepsilon_{jit}$$

where i is a trader, j is a trade, and t is a day (trades are recorded by the second). The dependent variable is relative bid-ask spread$_{jit}$ = $\left(\frac{P^{\text{broker}}_{jit} - P^{\text{interbank ask}}_{t}}{P^{\text{interbank ask}}_{t}} + \frac{P^{\text{interbank bid}}_{t'} - P^{\text{broker}}_{jit'}}{P^{\text{interbank bid}}_{t'}}\right)$ if the transaction is long, and relative bid-ask spread$_{jit}$ = $\left(\frac{P^{\text{interbank bid}}_{t} - P^{\text{broker}}_{jit}}{P^{\text{interbank bid}}_{t}} + \frac{P^{\text{broker}}_{jit'} - P^{\text{interbank ask}}_{t'}}{P^{\text{interbank ask}}_{t'}}\right)$ if the transaction is short. *US trader* equals one if the trade is executed by a trader located in the U.S. and equal to zero if located in Europe. To calculate *relative bid-ask spread*, we match traders' transactions in the myForexBook data with the closest (in time) quoted price in Tick Data - a data set of inter-bank foreign exchange quotes. Columns 1 and 2 include trades that we can match perfectly to the second, while Columns 3 and 4 include all trades that we can match and the regression controls for the match distance (in seconds). *Post constraint* equals one if the trade was opened after October 18, 2010, the date by which brokerages needed to comply with CFTC regulation limiting the leverage available to U.S retail forex traders at 50:1, zero otherwise. *Post announcement* equals one if the trade was opened after the CFTC's announcement in the Federal Registrar on January 13, 2010 of their intent to restrict trader leverage to 10:1, zero otherwise. In Panel A, the sample period is from May 1, 2010 to April 30, 2011. In Panel B, the sample period is from August 1, 2009 to July 31, 2010. Standard errors are double-clustered by day and trader, and *, **, and *** denote significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: The October 2010 leverage constraint and relative bid-ask spreads

Dep var: Relative bid-ask spreads	(1a)	(2a)	(3a)	(4a)
US trader (=1) × Post constraint (=1)	-0.0105	0.00559	-0.0138	0.00145
	(0.0080)	(0.053)	(0.0085)	(5.10)
US trader (=1) × ...				
... Ind[May 2010 - Jul 2010]		0.0256		0.0263
		(0.17)		(3.71)
... Ind[Aug 2010 - Sep 2010]		0.00851		0.0113
		(1.24)		(0.91)
... Ind[Nov 2010 - Dec 2010]		-0.00606		-0.00692
		(0.0056)		(0.0048)
... Ind[Jan 2011 - Feb 2011]		-0.0103*		-0.00732
		(0.0062)		(0.0050)
... Ind[Mar 2011 - Apr 2011]		-0.00247		0.00307
		(0.0070)		(0.0077)
Trader FE	x	x	x	x
Day FE	x	x	x	x
Bid-ask quotes matched perfectly to trades	yes	yes	no	no
Controls for match distance in log(seconds)	no	no	yes	yes
Number of trades	920,573	920,573	1,444,159	1,444,159
R^2	0.016	0.016	0.015	0.015

Panel B: The January 2010 regulation announcement and relative bid-ask spreads

Dep var: Relative bid-ask spreads	(1b)	(2b)	(3b)	(4b)
US trader (=1) × Post announcement (=1)	-0.00940	0.00789	-0.00586	0.0110
	(0.013)	(6.16)	(0.0099)	(0.33)
US trader (=1) × ...				
... Ind[Aug 2009 - Oct 2009]		-0.0118		-0.00869
		(6.96)		(2.42)
... Ind[Nov 2009 - Dec 2009]		-0.0141		-0.0105
		(1.67)		(1.01)
... Ind[Feb 2010 - Mar 2010]		-0.0235		-0.0200
		(0.015)		(0.013)
... Ind[Apr 2010 - May 2009]		-0.0227		-0.0217
		(0.019)		(0.017)
... Ind[Jun 2009 - Jul 2009]		-0.0586		-0.0535
		(0.040)		(0.036)
Trader FE	x	x	x	x
Day FE	x	x	x	x
Bid-ask quotes matched perfectly to trades	yes	yes	no	no
Controls for match distance in log(seconds)	no	no	yes	yes
Number of trades	644,755	644,755	1,140,274	1,140,274
R^2	0.017	0.018	0.013	0.013

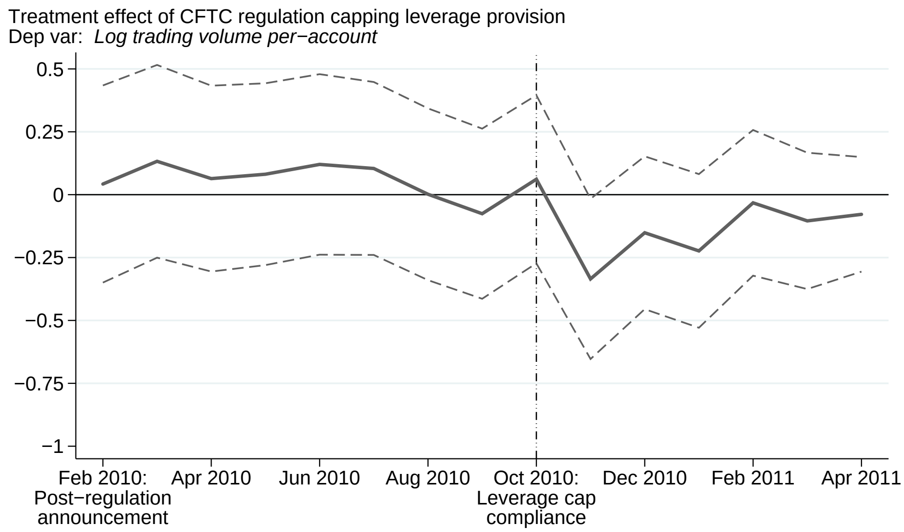


Fig. 1. Impulse response of treatment effect on trading volume. This table reports ordinary least squares estimates of the following regression:

$$\log(\text{trading volume})_{it} = \gamma_i + \gamma_t + \sum_{k=T-l}^{T+l} \beta_{1k} \text{US trader}_i \times I_{T+k=t} + \varepsilon_{it}$$

where i is a trader and t is a month. The dependent variable is *log(trading volume),* which is the natural logarithm of total monthly trading volume in USD. *US trader* equals one if the trader is located in the U.S. and equal to zero if located in Europe. T is the date of the regulation, i.e., October 2010. $I_{T+j=t}$ is an indicator variable for months surrounding the regulation. Therefore, β_j for $j = \{-T, ..., T\}$ is the sequence of treatment effects, and hence maps out the impulse response. Standard errors are double-clustered by day and trader, and the dashed lines are 95% confidence intervals around the point estimate of β_j.

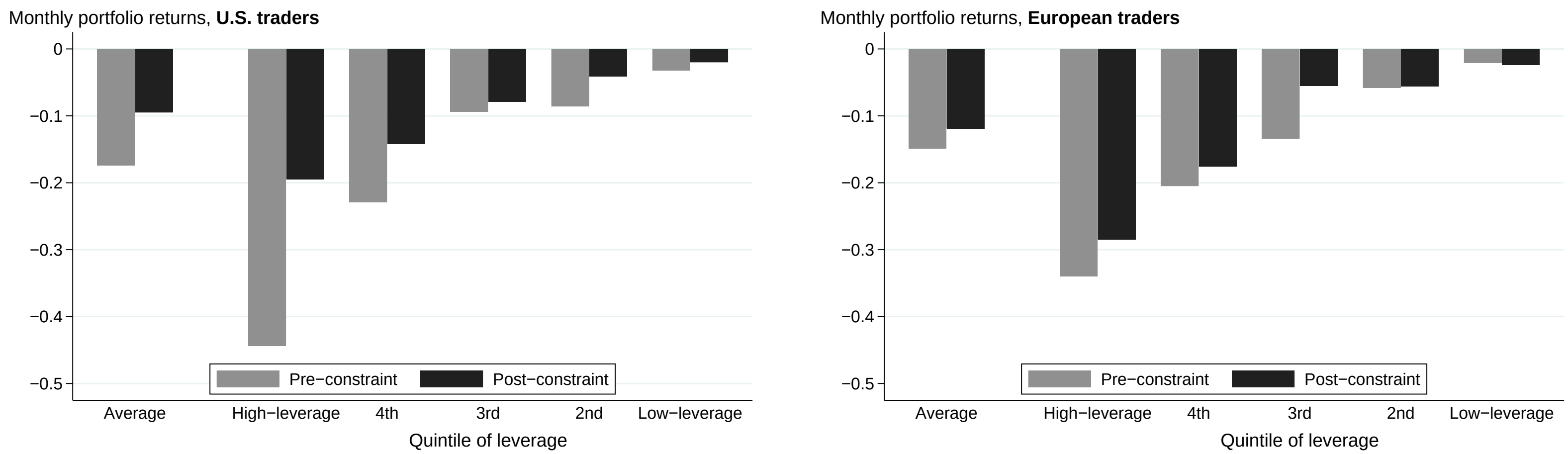


Fig. 2. Leverage constraints and portfolio returns. This table reports average portfolio returns of traders in the myForexBook database. Monthly returns are calculated using the account's balances at the beginning and end of the month, excluding deposits. We sort traders monthly by the average amount of leverage the trader uses in $t-1$.

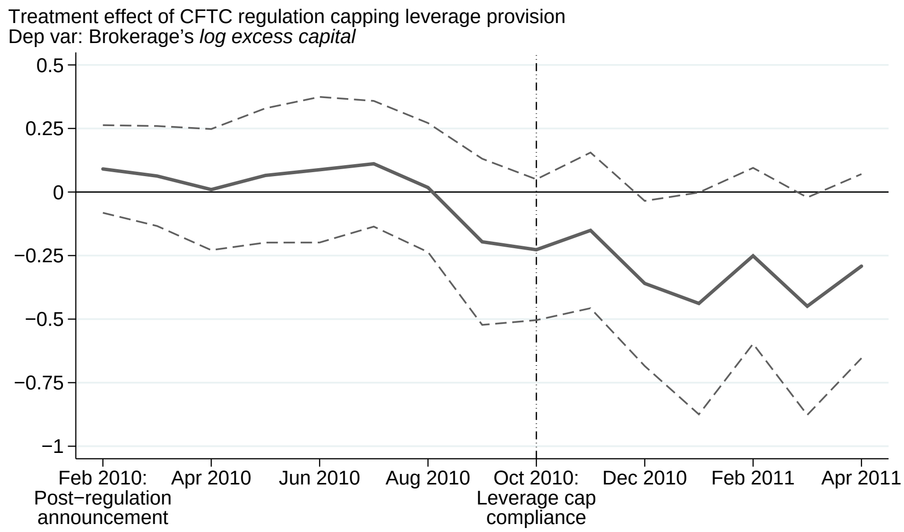


Fig. 3. Impulse response of treatment effect on brokerage excess capital. This table reports ordinary least squares estimates of the following regression:

$$\log(\text{excess captal})_{bt} = \gamma_b + \gamma_t + \sum_{j=-6}^{7} \beta_j \text{FX broker}_b \times I_{T+j=t} + \varepsilon_{bt},$$

where b is a broker and t is a month. The dependent variable is the logarithm of the brokerages' excess capital, recorded by the CFTC. *FX broker* equals one if the brokerage has any retail forex obligations after they were required to report these obligations starting in November 2010. T is the date of the regulation, i.e., October 18, 2010. $I_{T+j=t}$ is an indicator variable for months surrounding the regulation. Therefore, β_j for $j = \{-T, ..., T\}$ is the sequence of treatment effects, and hence maps out the impulse response. Standard errors are double-clustered by month and broker, and the dashed lines are 95% confidence intervals around the point estimate of β_j.

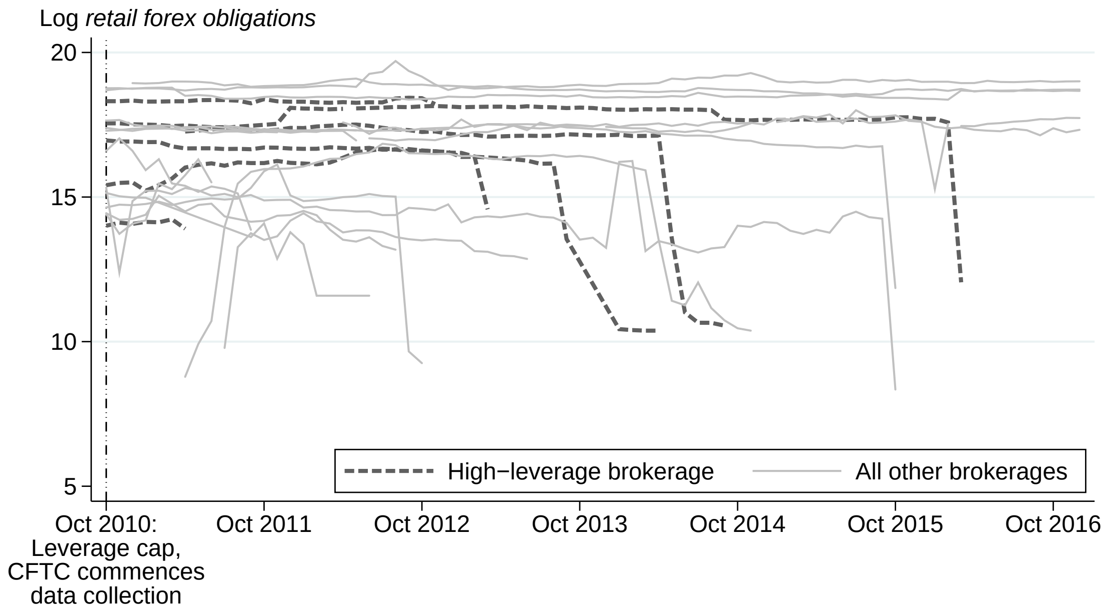


Fig. 4. Brokerages' retail forex obligations. This figure presents each brokerage's retail foreign exchange obligations. Obligations are equal to the total amount of funds at a brokerage that would be obtained by combining all money, securities, and property deposited by a retail forex customer into a retail forex account or accounts, adjusted for the realized and unrealized net profit or loss. The CFTC began requiring this reporting in November 2010. We manually classify brokerages as *high-leverage* if they were advertised as offering traders at least 400:1 leverage per-trade around the time of the November 2010 CFTC regulation. To generate this classification, we searched Internet archives. Most of the brokerages were listed on the website www.100forexbrokers.com, which provides a directory of forex brokerages and their characteristics.

Appendix to:

Should Retail Investors' Leverage Be Limited?

(intended for online publication)

Appendix A.1: Currency Pairs Affected by the CFTC Regulation

Table A.1
The CFTC regulation and Leverage-Constraints across Currency Pairs
Description: This table lists the currency pairs affected by the CFTC trading rule restricting the amount of leverage at 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	

Appendix A.2: A Stylized Model of the Retail Forex Market

In this appendix, we present a stylized model that motivates our empirical analysis and enables us to evaluate social welfare. We first describe the environment and characterize the equilibrium together with various variables of interest. We then analyze how the leverage-constraint policy affects the equilibrium variables as well as social welfare.

Environment and equilibrium

Agents, information structure, and beliefs.. Consider an economy with a single consumption good (which will be referred to as a dollar) and a single trading period. There is a risk-free asset with gross return normalized to one. There is also a single risky asset (a currency). In the interbank market, the asset currently trades at an exogenous market price normalized to one, $p_0 = 1$. At the next period, the asset will trade at price, p_1, which is a random variable. The objective distribution of the asset price change (that will be reflected in our empirical analysis) is given by $p_1 - 1 \sim N\left(\mu_s^{true}, \sigma^2\right)$. Here, $s \in S$ denotes an aggregate state realized at the beginning of date 0. We let q_s denote the ex-ante probability of the aggregate state (according to each agent) and assume $\sum_s q_s \mu_s^{true} = 0$ so that the price is a martingale under the objective belief.

There are traders, denoted by $i \in I$, that take optimal positions in the asset that will be described below. For simplicity, we normalize the mass of traders to one so that the aggregate and the per-trader outcomes are the same. Traders have dogmatic beliefs and do not learn from prices (formally, traders know each others' beliefs and agree to disagree). Traders' beliefs can also depend on the aggregate state $s \in S$. Specifically, trader i believes the price change is distributed according to, $p_1 - 1 \sim N\left(\mu_s^i, \sigma^2\right)$. Since the objective belief is unique, the heterogeneity in traders' beliefs can be thought of as capturing various behavioral distortions (which we leave unmodeled for simplicity). On the other hand, the dependence of traders' beliefs on the aggregate state allows traders also to be somewhat informed. In particular, to the extent that a trader's belief and the objective belief (μ_s^i and μ_s^{true}) are positively correlated, the trader's positions will tend to generate positive expected return before transaction costs, which we refer to as "information."

Trader i also starts with initial initial wealth given by, n_0^i, and has CARA preferences with coefficient of absolute risk aversion, γ^i. The type of trader i is given by the parameters, $\left(\gamma^i, n_0^i, \mu_s^i\right)$. We let $dF_s\left(\gamma^i, n_0^i, \mu_s^i\right)$ denote the joint distribution function over trader types conditional on the aggregate state. We can be quite general about the shape of this distribution except for a technical condition that we note below. All agents know and agree upon the type distribution, $dF_s\left(\gamma^i, n_0^i, \mu^i\right)$, as well as the probability of aggregate states, $\left(q_s\right)_s$. Their disagreements concern he asset's expected payoff.

There is also a competitive retail brokerage sector that provides intermediation services. Consider a single (representative) broker. For simplicity, the broker is risk neutral and she has the objective belief about the asset payoff. In particular, she believes the price change is distributed according to $p_1 - 1 \sim N\left(\mu_s^{true}, \sigma^2\right)$ conditional on the aggregate state $s \in S$. However, the broker does not observe the aggregate state, and it sets bid and ask prices at the beginning of the period before she can observe endogenous signals about the aggregate state (such as aggregate trading volume). Since traders' beliefs depends on the aggregate state, this might put the broker at an informational disadvantage relative to traders. As in Glosten and Milgrom (1985), the broker will set bid and ask prices that take into account the information content of traders' orders. For simplicity, we assume the broker sets a single bid price and a single ask price, p_0^{bid} and p_0^{ask}, and stands ready to fill sell and buy orders linearly at these prices regardless of the size of the order.[22] We will make assumptions so that, similar to Glosten and Milgrom (1985), the equilibrium bid price will be lower than the ex-ante objective value of the broker (normalized to one) which in turn will be lower than the equilibrium ask price, $p_0^{bid} < 1 < p_0^{ask}$.

Traders' optimal positions.. Trader i takes the bid and ask prices as given and decides to take a long or short position in the risky asset denoted by x_s^i. She invests her residual wealth in the risk-free asset. She can also use leverage on long or short positions without any additional fees but that might be subject to a regulatory limit. Specifically, we require the position (evaluated at the market value) to satisfy, $\left|x_s^i\right| \leq \bar{l} n^i$ where $\bar{l}$ is an exogenous leverage limit

[22] In general, the size of the order can also contain some information about the aggregate state (e.g., larger orders might be associated with better information), and the broker might want to set size-dependent prices that reflect this information. Modeling this feature explicitly could generate additional interesting predictions but it wouldn't change our qualitative conclusions. We therefore restrict attention to linear prices and simplify the analysis.

set by regulation. We also allow for the case $\bar{l} = \infty$, which corresponds to the equilibrium without leverage restriction.[23] The trader's portfolio problem can be written as,

$$\max_{x_s^i \in \left[-\bar{l} n_0^i, \bar{l} n_0^i\right]} E_s^i \left[-\exp\left(n_1^i\right)\right] \text{ where } n_1^i = \begin{cases} n_0^i + x_s^i \left(p_1 - p_0^{ask}\right) & \text{if } x_s^i > 0 \\ n_0^i + x_s^i \left(p_1 - p_0^{bid}\right) & \text{if } x_s^i < 0 \end{cases} \tag{8}$$

In view of the CARA-Normal setup, the trader's optimal position (conditional on the aggregate state realization) is given by,

$$x_s^i = \begin{cases} \min\left(\frac{\mu_s^i - p_0^{ask}}{\gamma^i \sigma^2}, \bar{l} n_0^i\right), & \text{if } \mu_s^i > p_0^{ask} \\ 0, & \text{if } \mu_s^i \in \left(p_0^{bid}, p_0^{ask}\right) \\ \max\left(-\bar{l} n_0^i, \frac{\mu_s^i - p_0^{bid}}{\gamma^i \sigma^2}\right), & \text{if } \mu_s^i < p_0^{bid} \end{cases}. \tag{9}$$

The broker's problem and bid-ask spreads.. The broker is subject to two types of costs. First, as we already mentioned, the broker can be subject to informational costs since traders might on average have some information. The broker takes the opposite side of traders' (possibly informed) positions, and keeps the positions on its balance sheet, which exposes it to potential losses.[24] Second, the broker also incurs technological costs that capture the infrastructure and the employees utilized to facilitate intermediation. For simplicity, we assume these costs grow linearly in the size of traders' positions: specifically, intermediating each unit of long or short position costs the broker $c > 0$ additional dollars. Using these assumptions, the broker's expected certainty equivalent wealth (under its objective belief) conditional on the aggregate state is given by,

$$CE_s^b = \begin{array}{l} \int_{i, x_s^i > 0} -x_s^i \left(E_s^{true}\left[p_1\right] - \left(p_0^{ask} - c\right)\right) dF_s\left(\gamma^i, n_0^i, \mu_s^i\right) \\ + \int_{i, x_s^i < 0} -x_s^i \left(E_s^{true}\left[p_1\right] - \left(p_0^{bid} + c\right)\right) dF_s\left(\gamma^i, n_0^i, \mu_s^i\right) \end{array}. \tag{10}$$

We assume there are a large number of identical brokers that compete a la Bertrand to set bid and ask prices, p_0^{bid} and p_0^{ask}. Competition drives down the broker's expected profit from both buy and sell orders to zero, that is,

$$\sum_{s \in S} q_s \int_{i, x_s^i < 0} -x_s^i \left(E_s^{true}\left[p_1\right] - \left(p_0^{ask} - c\right)\right) dF_s\left(\gamma^i, n_0^i, \mu_s^i\right) = 0,$$
$$\text{and } \sum_{s \in S} q_s \int_{i, x_s^i < 0} -x_s^i \left(E_s^{true}\left[p_1\right] - \left(p_0^{bid} + c\right)\right) dF_s\left(\gamma^i, n_0^i, \mu_s^i\right) = 0.$$

This also implies that the broker's total expected profit is zero, $\sum_{s \in S} q_s CE_s^b = 0$. After rearranging these expressions and using $E_s^{true}\left[p_1\right] = 1 + \mu_s^{true}$, we obtain,

$$p_0^{ask} = 1 + m^{long} + c \text{ and } p_0^{bid} = 1 - m^{short} - c \tag{11}$$

where

$$m^{long} = \frac{E\left[x_s^i \mu_s^{true} | x^i > 0\right]}{E\left[x_s^i | x_s^i > 0\right]} \text{ and } m^{short} = \frac{E\left[x_s^i \mu_s^{true} | x_s^i < 0\right]}{E\left[-x_s^i | x_s^i < 0\right]}. \tag{12}$$

Here, the expectation operator $E[\cdot]$ is taken with respect to the distributions dF_s and q_s (on which there is no disagreement). The terms m^{long} and m^{short} reflect traders' average information: their expected profit per unit position on respectively long and short trades. In particular, m^{long} is positive if the traders on average purchase the asset when it has a positive expected return. Likewise, m^{short} is positive if the traders' on average sell the asset when it has a negative expected return.

[23] In practice, there might also be endogenous restrictions on the leverage ratio as in Geanakoplos (2009) or Simsek (2013). We abstract away from these endogenous leverage limits since they do not affect our qualitative results.

[24] One could wonder whether the broker could avoid this outcome by outlaying the position immediately to the interbank market. Our empirical analysis shows that the bid-ask spreads in the interbank market are on average very similar to the bid-ask spreads in the retail market. This means that outlaying the position to the interbank market is on average not profitable, arguably because similar intermediation costs also apply in the interbank market.

Eq. (11) says that, similar to Glosten and Milgrom (1985), the broker takes into account the information content in buy and sell orders. If m^{long} is positive, then the broker that receives a buy order faces adverse selection. In equilibrium, it increases the ask price so as to break even (otherwise, it would consistently lose money). Symmetrically, if m^{long} is negative, then the broker faces an advantageous selection and lowers its ask price (due to competitive pressure) while still breaking even. Similar considerations explain the relationship between traders' market-timing profit on the short trades, m^{short}, and the broker's bid price.

Definition of equilibrium.. The equilibrium in this model is a collection, $\left(\left(p_0^{ask}, p_0^{bid}\right), \left(\left(x_s^i\right)_{i\in I}\right)_{s\in S}\right)$, such that the positions satisfy (9) given the bid-ask prices, and the bid-ask prices satisfy (11) given the positions and the cumulative distribution function $F_s\left(\gamma^i, n_0^i, \mu_s^i\right)$. We assume there exists a unique equilibrium that also satisfies the inequality, $p_0^{bid} < 1 < p_0^{ask}$ (the bid price is lower than the ex-ante expected payoff which is lower than the ask price). This would be the case under a mild technical assumption on the distribution F_s.[25]

Trading volume.. We next characterize traders' expected profit as well as their expected utility and the social welfare. As we will see, trading volume plays a central role in these characterizations. Therefore, we define the long, the short, and the total trading volume as respectively,

$$\begin{aligned}
V^{long} &= E\left[x_s^i | x_s^i > 0\right]\left\{\sum_{s\in S} q_s \int_{i.x_s^i>0} dF_s\left(\gamma^i, n_0^i, \mu_s^i\right)\right\} \qquad (13)\\
V^{short} &= E\left[-x_s^i | x_s^i < 0\right]\left\{\sum_{s\in S} q_s \int_{i.x_s^i<0} dF_s\left(\gamma^i, n_0^i, \mu_s^i\right)\right\}\\
\text{and} \qquad V &= V^{long} + V^{short}.
\end{aligned}$$

Here, the terms in set brackets capture the fraction of traders that take respectively long or short positions.[26] The expressions illustrate that the trading volume reflects the fraction of long or short trades as well as the expected size of each trade.

Traders' expected profit.. Under the objective distribution, trader i's expected profit is given by, $\sum_{s\in S} q_s x_s^i \left(E_s^{true}\left[p_1\right] - p_0^{ask}\right)$, if he takes a long position, and a similar expression if he takes a short position. Aggregating these positions, traders' overall expected profit is given by,

$$\Pi = \begin{array}{c} \sum_{s\in S} q_s \int_{i,x_s^i>0} x_s^i \left(E_s^{true}\left[p_1\right] - p_0^{ask}\right) dF_s\left(\gamma^i, n_0^i, \mu_s^i\right) \\ +\sum_{s\in S} q_s \int_{i,x_s^i<0} x_s^i \left(E_s^{true}\left[p_1\right] - p_0^{bid}\right) dF_s\left(\gamma^i, n_0^i, \mu_s^i\right) \end{array}.$$

After substituting $E_s^{true}\left[p_1\right] = 1 + \mu_s^{true}$, together with the definitions of the volume and market-timing profit in Eqs. (12) and (13), we can further rewrite this as,

$$\Pi = V^{long}\left(1 + m^{long} - p_0^{ask}\right) + V^{short}\left(p_0^{bid} - \left(1 - m^{short}\right)\right) \qquad (14)$$

The intuition behind this expression is that the typical long position pays $1 + m^{long}$ and costs the ask price, p_0^{ask}. Likewise, the typical short position pays the bid price, p_0^{bid}, and it costs $1 - m^{short}$. The expression illustrates that the traders' expected profit is increasing in their average information and decreasing in the bid-ask spreads.

In equilibrium, the bid and ask prices are given by Eq. (11). Substituting this into Eq. (14), traders' expected profit in equilibrium is given by,

$$\Pi = -cV^{long} - cV^{short} = -cV. \qquad (15)$$

[25] To illustrate this, suppose $F_s\left(\gamma^i, n^i, \mu_s^i\right)$ is independent of s. In this case, traders' positions contain no information about the aggregate state, the information terms drop out of (11). Then, there exists a unique equilibrium which also satisfies the inequality, $p_0^{bid} < 1 < p_0^{ask}$ (since $c > 0$). By a continuity argument, there exists a unique equilibrium that satisfies the same inequality as long as the dependence of the distribution $F_s\left(\gamma^i, n^i, \mu_s^i\right)$ on the aggregate state s is sufficiently small. We could parameterize this dependence and formalize the assumption but this is not necessary for our purposes.

[26] These two fractions do not necessarily sum to one since there are also traders that take a zero position (see Eq. (9)).

That is, the equilibrium profit depends negatively on the trading volume. Intuitively, since the competitive broker breaks even, the technological intermediation costs are ultimately passed through to traders via bid-ask spreads. The more traders trade, the more they incur these costs. Perhaps more surprisingly, traders' average information does not affect their equilibrium profit. The intuition is that the market maker sets bid and ask prices to neutralize information. For instance, if the traders' average information improves, then the market maker widens the bid-ask spreads (otherwise, it would consistently make losses and go out of business). Once the broker adjusts, the improved information does not affect traders' profits but it is reflected in bid and ask prices.

The broker's expected revenue and size.. Recall that the broker breaks even in equilibrium. In particular, its expected intermediation revenues are equal to the technological intermediation costs, cV. Recall that we view these costs as capturing the infrastructure and the labor the brokerage employees. Hence, the brokerage's intermediation revenues and size depend positively on the trading volume.

Belief-neutral social welfare.. We next characterize the social welfare in equilibrium. Since there are heterogeneous beliefs about the asset payoff, the social welfare will generally depend on the belief used to calculate agents' utilities. The standard Pareto welfare criterion would correspond to maximizing each agent's utility under her own belief. However, it is unclear whether perceived gains from speculation should be counted towards social welfare since they capture a collective form of irrationality: while all agents believe they have the correct belief, at most one of them could be right.

An alternative is to evaluate investors' beliefs under the objective belief distribution (which in this model corresponds to the broker's belief distribution). While appropriate, this approach faces a challenge in practice: The planner might not know who has the correct belief. Following Brunnermeier et al. (2014), we instead assume the planner evaluates the welfare under a fixed belief h, but she also makes the welfare comparisons robust to the choice of the belief. Specifically, we allow h to be an arbitrary convex combination of the traders' beliefs or the broker's (objective) belief.

We also focus on a utilitarian social planner that maximizes the sum of agents' certainty-equivalent wealth,

$$W^h = \sum_{s \in S} q_s \left(CE_s^{b,h} + \int_i CE_s^{i,h} dF_s \left(\gamma^i, n_0^i, \mu_s^i \right) \right). \tag{16}$$

Here, $CE_s^{b,h}$ denotes the broker's certainty-equivalent payoff and $CE_s^{i,h}$ denotes trader i's certainty-equivalent payoff conditional on the aggregate state. In view of the CARA-Normal setting, restricting attention to traders' certainty-equivalent payoffs is without loss of generality. Assigning all traders as well as the broker the same Pareto weight is slightly more restrictive but it provides a natural benchmark.[27]

Combining Eqs. (9) and (8), trader i's certainty-equivalent payoff under belief h can be calculated as,

$$CE_s^{i,h} = n_0^i + \begin{cases} x_s^i \left(E_s^h [p_1] - p_0^{ask} \right) - \frac{1}{2} \gamma^i \left(x_s^i \right)^2 \sigma^2, & \text{if } \mu_s^i > p_0^{ask} \\ 0 & \text{if } \mu_s^i \in \left(p_0^{bid}, p_0^{ask} \right) \\ x_s^i \left(E^h [p_1] - p_0^{bid} \right) - \frac{1}{2} \gamma^i \left(x_s^i \right)^2 \sigma^2, & \text{if } \mu_s^i < p_0^{bid} \end{cases}. \tag{17}$$

Thus, traders' certainty-equivalent payoff reflects their expected profits under belief h as well as their risk aversion and portfolio variance. Likewise, the broker's certainty-equivalent payoff under belief h can be calculated as,

$$CE_s^{b,h} = \begin{array}{l} \int_{i, x_s^i > 0} -x_s^i \left(E_s^h [p_1] - \left(p_0^{ask} - c \right) \right) dF_s \left(\gamma^i, n_0^i, \mu_s^i \right) \\ + \int_{i, x_s^i < 0} -x_s^i \left(E_s^h [p_1] - \left(p_0^{ask} - c \right) \right) dF_s \left(\gamma^i, n_0^i, \mu_s^i \right) \end{array}. \tag{18}$$

This is similar to Eq. (10) with the difference that the expected asset payoff is calculated according to a general belief h (which is not necessarily the true belief).

[27] In fact, this assumption is also without loss of generality as long as we allow the planner to do one-time ex-ante transfers among the agents. In this case, an allocation x that leads to greater utilitarian welfare, W^h, than another allocation y can be also made to Pareto dominate the allocation y (under belief h) after combining it with appropriate ex-ante transfers.

Combining Eqs. (16), (17), and (18), we can calculate the social welfare as,

$$\begin{aligned} W^h &= -cV + \sum_{s\in S} q_s \int_i \left(n_0^i - \frac{1}{2}\gamma^i \left(x_s^i\right)^2 \sigma^2 \right) dF_s\left(\gamma^i, n_0^i, \mu_s^i\right) \\ &= E\left[n_0^i\right] - cV - \frac{1}{2} E\left[\gamma^i \left(x_s^i\right)^2 \sigma^2\right]. \end{aligned} \tag{19}$$

Here, the expectation operators in the second line are taken with respect to the distributions dF_s and q_s (on which there is no disagreement). Hence, Eq. (19) illustrates that the welfare does not depend on the belief h used for the calculation (i.e., the expected price, $E_s^h\left[p_1\right]$, drops out of the welfare calculations). This is because, under any fixed belief h, the expected gain of an agent is the expected loss of another agent. This captures the idea that speculation transfers wealth among agents without creating social value. Once properly accounted for, these transfers do not affect social welfare.[28] As in Brunnermeier et al. (2014), the planner can evaluate the effect of speculation on social welfare without taking a stand on whose belief is correct. We refer to $W \equiv W^h$ as the belief-neutral welfare.

Eq. (19) also illustrates that the belief-neutral welfare is decreasing in the expected intermediation costs, $-Vc$, as well as their expected (risk-aversion weighted) portfolio variance, $E\left[\gamma^i \left(x^i\right)^2 \sigma^2\right]$. Intuitively, every intermediated position requires technological costs, which reduces social welfare as the resources or people used for intermediation could also be used elsewhere. These costs are naturally increasing in trading volume. In addition, to the extent that speculation induces investors to take riskier positions, the resulting portfolio risks also reduce social welfare.

Comparative statics of the leverage-constraint policy

We next characterize the effect of the leverage restriction policy on the equilibrium variables. It is useful to break this exercise into two steps: a partial equilibrium exercise in which brokers' bid-ask spread remain at their pre-policy levels, and a general equilibrium exercise in which the spreads also adjust. In practice, brokers are unlikely to change their spreads in the very short run (which we view as a month or so) due to inertia or optimization frictions.[29] Hence, we view our short-run empirical results as testing the partial equilibrium predictions. In the longer run (which we view as several months), brokers would arguably adjust their bid-ask spreads to their new equilibrium levels. Thus, we view our longer-run empirical results as testing the general equilibrium predictions. We denote the partial equilibrium with hatted variables, and the general equilibrium (after the policy change) with starred variables.

Partial equilibrium effects on trading volume.. Before the leverage-constraint policy, traders' positions are given by Eq. (9) with $\bar{l} = \infty$ and the volume is given by Eq. (13). Now suppose the leverage-constraint policy is imposed. In partial equilibrium, traders' positions are still given by Eq. (9) but with a finite $\bar{l}$ (but still evaluated at the same bid and ask prices). That is, we have,

$$\begin{cases} \hat{x}_s^i = \bar{l} n_0^i < x_s^i, & \text{if } x_s^i = \frac{\mu_s^i - p_0^{ask}}{\gamma^i \sigma^2} > \bar{l} n_0^i \\ \hat{x}_s^i = -\bar{l} n_0^i > -x_s^i, & \text{if } x_s^i = \frac{\mu_s^i - p_0^{bid}}{\gamma^i \sigma^2} < \bar{l} n_0^i \end{cases}.$$

In particular, the long and short positions that violate the leverage-constraint are downscaled to satisfy the leverage-constraint. Thus, the expected size of the long and short positions both decline. By Eq. (13), the trading volumes decline, that is,

$$\hat{V}^{long} \leq V^{long}, \hat{V}^{short} \leq V^{short} \text{ and } \hat{V} \leq V.$$

Partial equilibrium effects on portfolio risks.. In partial equilibrium, the average portfolio risks decline, $E\left[\gamma^i \left(\hat{x}_s^i\right)^2 \sigma^2\right] \leq E\left[\gamma^i \left(x_s^i\right)^2 \sigma^2\right]$, since the risky positions that violate the leverage-constraint are reduced, $\hat{x}_s^i \leq x_s^i$.

[28] Likewise, the bid and ask prices, p_0^{ask} and p_0^{bid}, do not affect social welfare since they represent transfers between the traders and the brokers. In particular, Eq. (19) would apply not only with the equilibrium bid and ask prices given by Eq. (11)—which ensure that brokers break even, but also with other bid and ask prices that might generate net profits or net losses for the brokers.

[29] Since the leverage-constraint changes the set of trades the broker intermediates, it might take a while for the broker to figure out its overall profits and losses in this new market, and to adjust its bid-ask spreads appropriately.

Partial equilibrium effects on traders' expected profit.. In partial equilibrium, Eq. (14) still applies and implies that traders' expected profit becomes,

$$\hat{\Pi} = \hat{V}^{long}\left(1 + \hat{m}^{long} - p_0^{ask}\right) + \hat{V}^{short}\left(p_0^{bid} - \left(1 - \hat{m}^{short}\right)\right).$$

However, the bid-ask spreads are still at their old equilibrium levels,

$$p_0^{ask} = 1 + m^{long} + c \text{ and } p_0^{bid} = 1 - m^{short} - c.$$

Combining these expressions with Eq. (15), which applies before the policy, we obtain,

$$\hat{\Pi} - \Pi = -c\left(\hat{V} - V\right) + \hat{V}^{long}\left(\hat{m}^{long} - m^{long}\right) + \hat{V}^{short}\left(\hat{m}^{short} - m^{short}\right).$$

Here, the first term captures the effect of the constraint via trading volume. Since $\hat{V} \le V$, the leverage-constraint tends to improve traders' profits through its effect on volume. The second and the third terms capture the effect via changes in average information. To the extent that the leveraged positions are associated with a different level of information than other positions, then the policy would also affect traders' (partial equilibrium) profit by improving or worsening their average information.

General equilibrium effects on bid-ask spreads.. In general equilibrium, bid and ask prices adjust to neutralize the changes in traders' average information. More specifically, Eq. (11) implies,

$$p_0^{ask,*} - p_0^{ask} = m^{long,*} - m^{long} \text{ and } p_0^{bid} - p_0^{bid,*} = m^{short,*} - m^{short}.$$

Recall also that the equilibrium level of the bid and ask prices are determined as a fixed point. Under the regularity assumptions we made (that ensure unique equilibrium), the signs of the price changes are determined by the sign of the partial equilibrium change in average information, respectively, $\hat{m}^{long} - m^{long}$ and $\hat{m}^{short} - m^{short}$. Hence, the model predicts that the bid-ask spreads should eventually increase (resp. decrease) if the policy increases (resp. decreases) the average information in traders' orders.

Note also that, once the bid-ask spreads adjust, traders' payoffs are given by Eq. (15), and the effect of the policy on these payoffs is given by, $M^* - M = -c(V^* - V)$. In general equilibrium, the leverage-constraint policy affects traders' payoffs only by its effect on trading volume.

General equilibrium effects on the broker... Recall that, in general equilibrium, the broker's revenue and its size are determined by the technological intermediation costs, cV. Hence, by lowering the trading volume, the leverage-constraint policy lowersthe revenue as well as the size of the brokerage sector.

Effects on social welfare.. Before the leverage-constraint policy, the belief-neutral social welfare is given by Eq. (19). After the policy, the social welfare is given by the same expression but evaluated with the partial equilibrium (hatted) variables or the general equilibrium (starred) variables. In particular, the welfare effect of the policy is characterized by its effect on trading volume and average portfolio risks. Recall that in partial equilibrium, the model predicts that the policy reduces the trading volume as well as average portfolio risks. Hence, the model also predicts that the policy improves belief-neutral social welfare in partial equilibrium. This prediction also applies in general equilibrium as long as the endogenous price response is not strong to overturn the sign of the partial equilibrium effects on trading volume and portfolio risks.

In our empirical analysis, we find that the policy substantially reduces the trading volume in the short run as well as in the longer run (see Section 4.1). In unreported results, we also analyze the effect on the volatility of traders' portfolio returns, and find mixed evidence that seems to point toward the policy lowering portfolio volatility (see Footnote 15 in Section 4.2). Hence, from the lens of this model, our empirical evidence suggests that the leverage-constraint policy improves social welfare.

Obviously, our model is too stylized to capture all potential reasons for trade in the forex market. For instance, some traders could be trading to hedge their background risks, as in Simsek (2013a). Others might be enjoying the sensation from trading. If we were to model these other motives for trade, they would show up as additional terms in Eq. (19). Moreover, restricting leverage (and trade) would typically tend to lower social welfare through these terms. In an empirical analysis, it is impossible to capture all possible reasons for trade. We view our analysis as capturing a key driving force for trade (monetary pursuits from speculation). Our empirical analysis suggests that through this channel the leverage restriction policy had a large positive impact on social welfare. This can also be viewed as setting a (very high) threshold that other rationales for trade would have to exceed to overturn our qualitative conclusion that the leverage restriction policy improved social welfare.

Finally, recall that according to our welfare criterion the bid and ask prices do not matter for the social welfare. This is because they represent transfers among investors, which is ignored by a utilitarian planner that uses a single belief and puts equal weight on all agents (see also Footnote 28).[30] While this provides a reasonable benchmark, one could imagine reasons for why the social planner might also care about bid-ask spreads. For instance, suppose some traders are trading for non-speculative reasons, e.g., to hedge their background risks. Higher bid-ask spreads would reduce these traders' welfare. To the extent that the planner overweights such traders' welfare (and underweights the welfare of the "speculative" traders), then higher bid-ask spreads could also lower social welfare. More generally, bid-ask spreads reflect market quality, which the planner might care about in addition to social welfare.

As we noted, our theoretical analysis suggests the policy increases the bid-ask spreads over the longer run if and only if it improves traders' average information. In our empirical analysis, we find no significant effect on bid-ask spreads. We also find (in back-of-the-envelope calculations) that the policy does not substantially change traders' gross returns, which provides a measure of their average information. Hence, the zero result on bid-ask spreads can also be reconciled with our model, and it suggests that the leverage-constraint policy does not have an adverse effect on social welfare through bid-ask spreads.

[30] This is also why the social welfare is characterized by the same equation (19) in partial as well as general equilibrium, even though the corresponding equilibrium allocations differ in terms of the bid and ask prices.

Appendix A.3: Evidence on the Representativeness of the myForexBook Data

This section provides evidence that the trade level data from myForexBook provides a good representation of the population of retail forex traders. The myForexBook web platform provides a social networking environment for traders who have accounts with at least one of around fifty partnering brokerages. Because traders choose to use the myForexBook platform, these traders could be unrepresentative of the overall population.

We first compare the myForexBook traders' performance to that of the population of traders on the brokerage eToro, one of the market's largest off-exchange brokerages. The eToro data includes all transactions between June 2, 2013, and July 14, 2014.[31] The data include over 11 million transactions from retail traders located in nearly 200 countries and independent territories.

Our analysis is specifically interested in how the availability of leverage affects traders' wealth. Though our eToro sample comes from a time period different than the myForexBook data, eToro traders also have worse returns on positions that use more leverage (A.2, columns 3 and 4). On average, they lose between 65 and 75% ROI per trade for every additional 100 units of leverage. myForexBook traders during our main sample window lose around 28% per trade for every 100 unit increase in leverage. These results are consistent with the myForexBook data being plausibly representative of how traders in the market respond to having less leverage.

Table A.2
Correlation Between Leverage and Trader Returns Across Different Data Sets
Description: This table reports OLS estimates of the following regression:

$$\text{ROI}_{jit} = \gamma_i + \gamma_t + \beta_1 \text{leverage}_{jit} + \varepsilon_{jit}$$

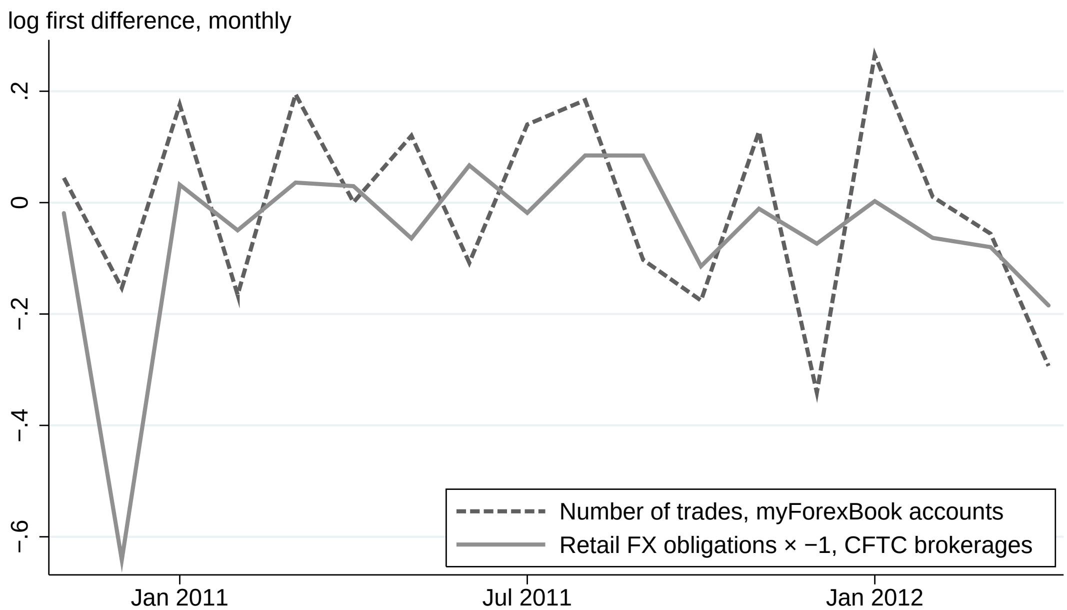
where i is a trader, j is a trade, and t is a day (trades are recorded by the second). The dependent variable is *ROI,* which is per-trade return on investment. Columns (1) and (2) use the myForexBook sample that is used throughout the paper. Columns (3) and (4) use the entire population of trades on eToro between June 2, 2013 and July 14, 2014. Standard errors are double-clustered by day and trader, and *, **, and *** denote significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

data set:	myForexBook		eToro (June 2013 - July 2014)	
dep var: ROI	(1)	(2)	(3)	(4)
leverage / 100	-0.281**	-0.278**	-0.660***	-0.744***
	(0.12)	(0.12)	(0.16)	(0.13)
trader FE	x	x	x	x
day FE		x		x
Number of trades	270,051	270,051	11,580,789	11,580,789
R^2	0.038	0.040	0.079	0.082

We also find that the myForexBook data is similar to the CFTC data (the brokerages in the CFTC reports account for about 95% of the U.S. market for retail forex). We calculate the total number of trades per month in the myForexBook data and take the log first difference. We also take the log first difference of aggregate retail foreign exchange obligations in the CFTC reports. We multiply the forex obligations time series by negative one, because we would expect the brokerage's obligations to decrease when there is more trading; on average, traders lose money when they trade, which would reduce the value of the traders' accounts (lower the brokerages' obligations). These series overlap from November 2011 to April 2012. The Pearson's correlation coefficient between these series is 0.41, which suggests a reasonably strong correlation between the myForexBook and CFTC data sets. Figure A.1 plots these times series.

[31] The data come from the brokerage, eToro. Per our NDA, eToro maintains the right to approve the use of the company's name in the description of the data prior to any publication.

Fig. A.1. Correlation Between the myForexBook Data and the CFTC Brokerage Reports
Description: This figure plots time series of the number of trades in the myForexBook data set and retail foreign exchange obligations for brokerages in the CFTC reports. The time series are transformed to the logarithm of monthly first differences. Retail forex obligations are multiplied by negative one.

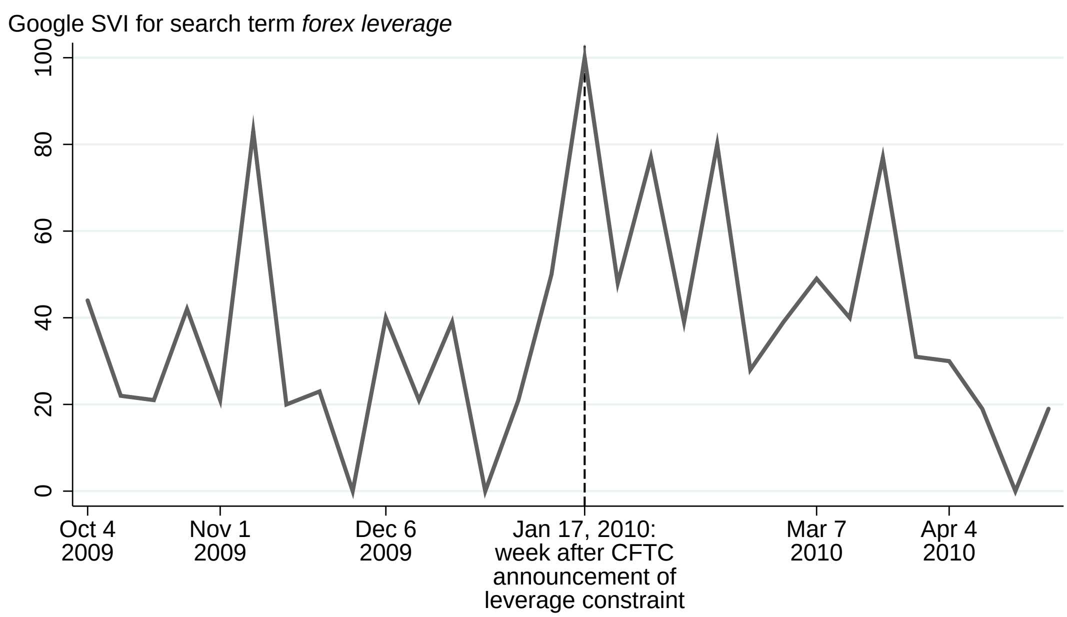


Appendix A.4: Awareness of the CFTC Regulation Announcement

On January 13, 2010, the CFTC announced in the Federal Registrar their intent to restrict foreign exchange dealers' provision of leverage at 10:1. Our analysis shows that this announcement did not affect trader returns, brokerage capital, or the spreads charged by forex brokerages. One plausible explanation for these results is that the announcement could have gone unnoticed by traders, and therefore did not significantly affect trader behavior.

Figure A.2 plots the time series of Google search volume index (SVI) for the search term "forex leverage." Google SVI is often used by the literature to measure attention. There is a substantial increase in attention on forex leverage that occurs as a result of the CFTC's announcement, which is consistent with traders being aware that they were going to have less available leverage.

Fig. A.2. Attention on the CFTC Announcement of Leverage Regulation
Description: This figure plots a time series of U.S. Google search volume index (SVI) for the search term "forex leverage." Google SVI is the ratio of searches for a particular term to the total number of Google searches, normalized on a scale from 0 to 100. The data is at a weekly frequency.



Appendix A.5: Trading Costs and Traders' Gross Returns

Section presents traders' net portfolio returns. Table A.3 presents estimates of traders' gross portfolio returns. To make these back-of-the-envelope estimates, we have to make assumptions about the transaction costs paid by retail forex traders. Trading costs come from traders paying the bid-ask spread on each transaction (to our knowledge, no brokerages charge fixed per-fee costs presently, or during the period of our study). Unfortunately, our transaction-level data set does not tell us the spreads paid by traders, and the amount of trading we observe is too thin to estimate spreads by matching buy to sell orders (for example, many studies use trade and quote database (TAQ) quotes to estimate spreads).

Therefore, our approach is to make assumptions about average spreads and then apply these assumptions to traders' net portfolio returns. Specifically, we believe that average spreads paid are between 3 to 4 pips, where a pip is one one-hundredth of one percent (for example, it would cost three to four dollars to execute the modal trade in our data ($1,000)). We come to this conclusion by noting that most brokerages advertise spreads that are as low as 1 to 2 pips. This headline number is presumably in reference to the most liquid currency pair, the EUR/USD, but other currency pairs cost more to trade. Spreads can also change depending on market conditions: spreads increase by as much as 10 times during episodes of high volatility (see for example, the live spreads presented by the brokerage Oanda: www.oanda.com/forex-trading/markets/recent). Additionally, price slippage would increase the spreads traders actually pay, and the National Futures Association (NFA) found that, during the period we study, at least a few brokerages had computer systems designed to take advantage of slippage (reference). Finally, in support of our assumption that transactions cost an average of 3 to 4 pips, MarketWatch's May 2011 review comparing retail forex brokerages writes that the only brokerage to offer fixed spreads was FX Solutions, which offered 3 pips per EUR/USD transaction (reference).

Under these assumptions, when traders are charged 2 pips per trade, transaction costs explain about 60% of high-leverage traders' about transaction costs (e.g., prior to the leverage-constraint high-leverage traders lose 44% on net and 18% gross). The high-leverage traders still perform worse than low-leverage traders, but not by nearly as much as the difference in their net returns. If we assume that traders are charged 3 to 4 pips per trade, there would be no difference between high- and low-leverage traders gross returns.

Table A.3

Back-of-the-envelope Calculation of Trading Costs' Effect on Gross Returns

Description: This table extends the results on traders' portfolio returns presented in Table 4. Monthly returns are calculated using the account's balances at the beginning and end of the month, excluding deposits. The columns in this table present gross returns calculated after adjusting net returns by the assumed amount of transaction costs paid by traders. Transaction costs in retail forex are the spreads paid by traders. We assume that average spreads during the period we study fell within a range of 2 to 5 pips, where a pip is one one-hundredth of one percent. Stars *, **, and *** denote significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

U.S. Traders' Portfolio Returns

			gross returns							
assumed per-trade spreads:	net returns (from Table 4)		2 pips		3 pips		4 pips		5 pips	
pre- or post-constraint:	pre-	post-	pre-	post-	pre-	post-	pre-	post-	pre-	post-
sample average	-0.174	-0.095	-0.063	-0.026	-0.007	0.008	0.043	0.040	0.102	0.074
leverage quintile										
high	-0.444	-0.195	-0.176	-0.061	-0.028	0.002	0.092	0.060	0.246	0.122
low	-0.032	-0.020	-0.002	-0.004	0.012	0.008	0.025	0.020	0.038	0.033
high minus low	**-0.412*** **	**-0.175*** **	**-0.174*** **	**-0.058***	**-0.040**	**-0.006**	**0.067**	**0.040**	**0.207** **	**0.089**
	(5.75)	(4.07)	(3.43)	(1.86)	(0.71)	(0.19)	(0.97)	(0.90)	(2.42)	(1.54)

Appendix A.6: Trade-level Returns

This section shows that the leverage-constraint improves traders' returns using tests at the trade-level. These tests look exclusively at the narrow window around the dates of the leverage-constraint (the sample window September 1, 2010 - December 1, 2010) and the regulation's announcement (December 1, 2009 - March 1, 2010). Table A.4 presents summary statistics for trade-level outcomes in this window. Table A.5 uses difference-in-difference regressions to show that the leverage-constraint reduces per-trade losses by about 20 percentage points. A.3 and A.4 plot the impulse-response of the treatment effect of the leverage-constraint in calendar-time and trade-time, respectively. These tests show that the U.S. treatment group and European control group have common trends prior to the regulation. A.5 presents placebo tests for false dates of the regulation. These tests produce few false positive results, indicating that our tests are unlikely to suffer from Type I error. Table A.6 shows that the CFTC's regulation announcement does not significantly affect trade-level outcomes.

Table A.4
Trade-level summary statistics
Description: This table presents summary statistics from the myForexBook account-level database trimmed according to the criteria described in Section 3. The sample includes trades executed by U.S. and European retail forex traders. Return on investment (*roi*) for long (short) positions equals the difference between the nominal value of the currency pair when the position is closed (opened) and when it is opened (closed), divided by the trader's dollar stake in the trade. *Post constraint* equals one if the trade was opened after October 18, 2010, the date by which brokerages needed to comply with CFTC regulation limiting the leverage available to U.S retail forex traders at 50:1, zero otherwise. *Post announcement* equals one if the trade was opened after the CFTC's announcement in the Federal Registrar on January 13, 2010 of their intent to restrict traders' leverage to 10:1, zero otherwise. *High leverage trader* equals one if trader i uses at least 50:1 leverage on at least one trade prior to the CFTC regulation, zero otherwise. *Holding period* is the length of time in hours between when the position is opened and when it is closed.

Panel A: ***sample window around leverage-constraint (Sep 1 - Dec 1, 2010)***

variable	mean	std dev	median	10^{th} %tile	90^{th} %tile
Dependent variables					
Return on investment (ROI)	-0.26	4.81	0.016	-2.33	1.79
trade uses leverage > 50:1 (= 1)	0.084				
Treatment variables					
US trader (= 1)	0.45				
Post constraint (= 1)	0.48				
High leverage trader (= 1)	0.49				
Additional Controls					
log trade size (USD)	0.57	2.24	0.69	-2.30	3.04
log holding period (hours)	0.16	2.43	0.073	-2.93	3.39
Number of trades	270,595				

Panel B: ***sample window around regulation announcement (Dec 1, 2009 - Mar 1, 2010)***

variable	mean	std dev	median	10^{th} %tile	90^{th} %tile
Dependent variables					
Return on investment (ROI)	-0.22	3.93	0.087	-3.21	2.44
trade uses leverage > 10:1 (= 1)	0.42				
Treatment variables					
US trader (= 1)	0.48				
Post announcement (= 1)	0.59				
High leverage trader (= 1)	0.63				
Additional Controls					
log trade size (USD)	1.41	1.83	1.61	0	3.40
log holding period (hours)	0.041	2.50	-0.083	-2.99	3.18
Number of trades	167,035				

Table A.5
Leverage-Constraints and Trade-Level Outcomes
Description: This table reports OLS estimates of the following regression:

$$Y_{jit} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post constraint}_t + \beta_2 \text{trade}_{jit} + \varepsilon_{jit}$$

where i is a trader, j is a trade, and t is the day trades are opened (execution of trades are recorded at the second). In **Panel A**, the dependent variable is *trade uses leverage > 50:1*, which equals one if the trade uses at least 50:1 leverage. In **Panels B** and **C**, the dependent variable is *ROI,* which is per-trade return on investment. *US trader* equals one if the trade is executed by a trader located in the U.S. and equal to zero if located in Europe. *Post constraint* equals one if the trade was opened after October 18, 2010, the date by which brokerages needed to comply with CFTC regulation limiting the leverage available to U.S retail forex traders at 50:1, zero otherwise. *High leverage trader* equals one if trader i uses at least 50:1 leverage on at least one trade prior to the CFTC regulation, zero otherwise. The sample period is from September 1 to December 1, 2010. Standard errors are double-clustered by day and trader, and *, **, and *** denote significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: ***The Binding Effect of the October 2010 Leverage-Constraint on Trading***

dep var: trade uses leverage > 50:1 (=1)	(1a)	(2a)	(3a)	(4a)
US trader (=1) × post constraint (=1)	-0.0491**	-0.0523**	-0.0520**	-0.0520**
	(0.022)	(0.021)	(0.021)	(0.021)
log(trade size)			0.0148***	0.0145***
			(0.0043)	(0.0043)
log(holding period)				-0.00138**
				(0.00058)
trader FE	x	x	x	x
day FE	x	x	x	x
broker-pair FE		x	x	x
Number of trades	270,595	270,541	270,541	270,541
R^2	0.51	0.53	0.54	0.54

Panel B: ***Oct 2010 Leverage-Constraint & Performance, Euro Traders Control Group***

dep var: per-trade ROI	(1b)	(2b)	(3b)	(4b)
US trader (=1) × post constraint (=1)	0.191**	0.207**	0.204**	0.204**
	(0.094)	(0.098)	(0.098)	(0.099)
log(trade size)			-0.110***	-0.124***
			(0.024)	(0.025)
log(holding period)				-0.0649***
				(0.017)
trader FE	x	x	x	x
day FE	x	x	x	x
currency risk-free rate differential	x	x	x	x
std dev of trader's weekly returns	x	x	x	x
broker-pair FE		x	x	x
Number of trades	270,595	270,541	270,541	270,541
R^2	0.037	0.041	0.042	0.042

Panel C: ***Constraint and Performance; Alt. Control Group – High- vs. Low-Leverage Traders***

dep var: per-trade ROI	(1c)	(2c)	(3c)	(4c)
high leverage trader (=1) × post constraint (=1)	0.237**	0.252***	0.247***	0.253***
	(0.098)	(0.093)	(0.094)	(0.093)
log(trade size)			-0.110***	-0.124***
			(0.024)	(0.025)
log(holding period)				-0.0652***
				(0.016)
trader FE	x	x	x	x
day FE	x	x	x	x
currency risk-free rate differential	x	x	x	x
std dev of trader's weekly returns	x	x	x	x
broker-pair FE		x	x	x
Number of trades	270,595	270,541	270,541	270,541
R^2	0.037	0.041	0.042	0.042

Fig. A.3. Impulse Response of Treatment Effect on Per-Trade Returns
Description: This table reports OLS estimates of the following regression:

$$\mathrm{ROI}_{jit} = \gamma_i + \gamma_t + \sum_{k=T-l}^{T+l} \beta_{1k} \mathrm{US\ trader}_i \times I_{T+k=t} + \varepsilon_{jit}$$

where i is a trader, j is a trade, and t is a week (trades are recorded by the second). The dependent variable is *ROI,* which is per-trade return on investment. *US trader* equals one if the trade is executed by a trader located in the U.S. and equal to zero if located in Europe. T is the date of the regulation, i.e. October 18, 2010. $I_{T+j=t}$ is an indicator variable for weeks surrounding the regulation. Therefore, β_j for $j = \{-T, ..., T\}$ is the sequence of treatment effects, and hence maps out the impulse response. Standard errors are double-clustered by day and trader, and the dashed lines are 95% confidence intervals around the point estimate of β_j.

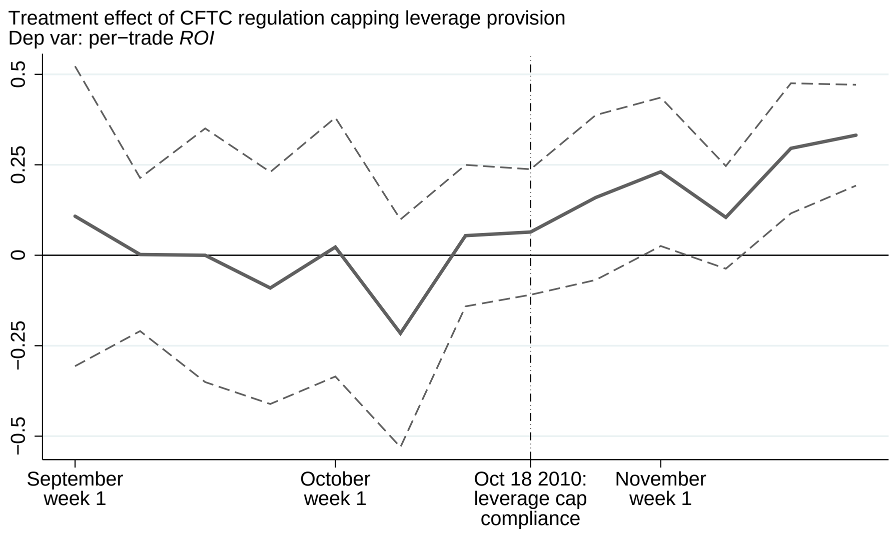


Fig. A.4. Impulse Response of Leverage-Constraint on Per-Trade Returns Using Trade-time
Description: This table reports OLS estimates of the following regression:

$$\text{ROI}_{jit} = \gamma_i + \gamma_t + \sum_{k=T-l}^{T+l} \beta_{1k} \text{US trader}_i \times I_{T+k=t} + \varepsilon_{jit}$$

where i is a trader, j is a trade, and t is a week (trades are recorded by the second). The dependent variable is *ROI,* which is per-trade return on investment. *US trader* equals one if the trade is executed by a trader located in the U.S. and equal to zero if located in Europe. T is the date of the regulation, i.e. October 18, 2010. $I_{T+j=t}$ is an indicator variable for weeks surrounding the regulation. Therefore, β_j for $j = \{-T, ..., T\}$ is the sequence of treatment effects, and hence maps out the impulse response. We sort trades into quartiles, within a trader's account, according to their distance from the leverage-constraint. The omitted coefficient is the interaction between *US trader* and the indicator for the fourth quartile in distance prior to the leverage-constraint. We restrict this sample to traders that use greater than 50:1 leverage on at least one trade prior to the leverage-constraint. Standard errors are double-clustered by day and trader, and the dashed lines are 95% confidence intervals around the point estimate of β_j.

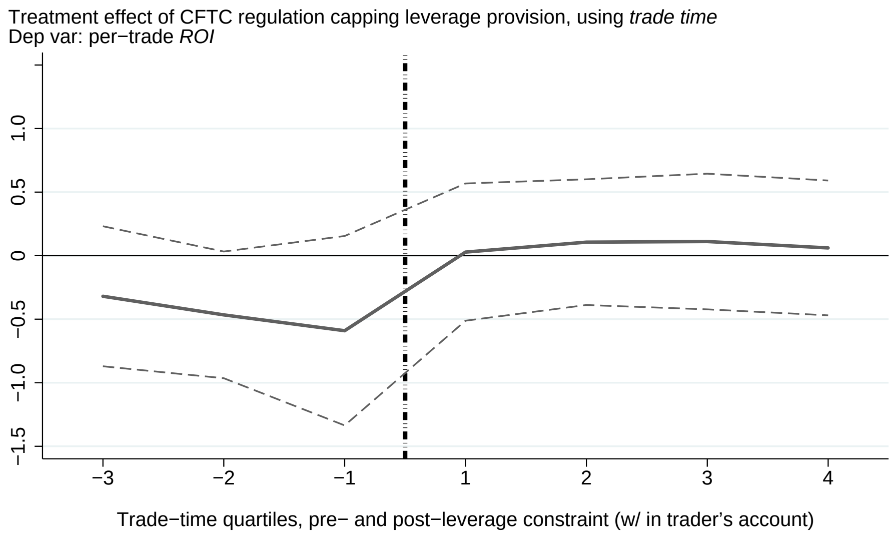
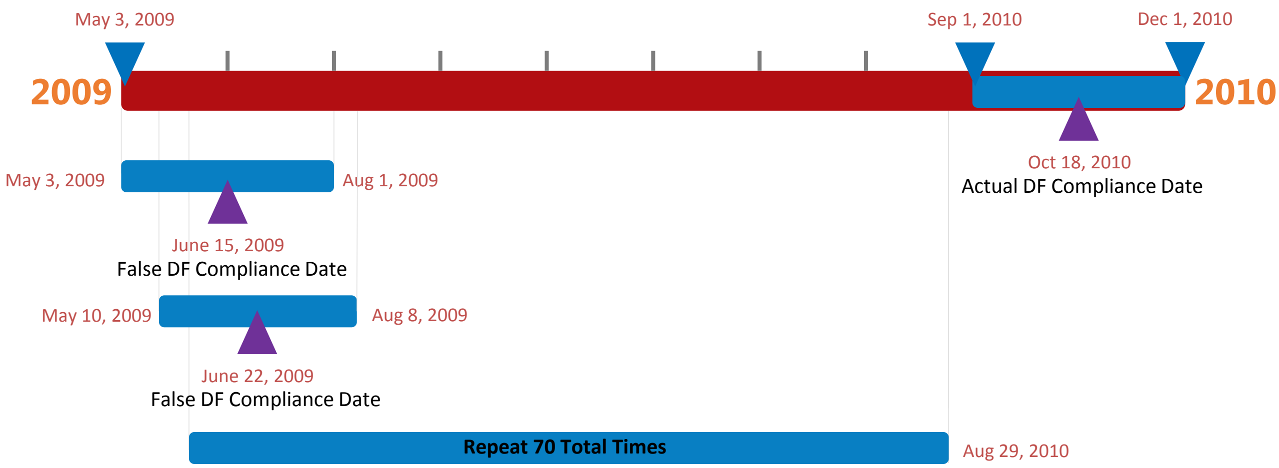


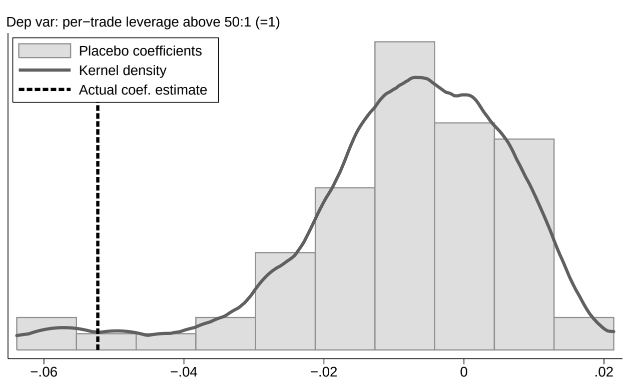
Fig. A.5. Placebo test for the effect of the leverage-constraint
Description, Panel A: This figure illustrates the placebo exercise described in Section **??** and below.



Description, Panel B: This figure plots kernel density estimates using the Epanechnikov kernel function and a histogram of β_1's from a series of placebo tests for the effect of the CFTC regulation on trading outcomes. We run the following regression 70 times

$$Y_{jit} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post constraint}_t + \beta_2 \text{trade}_{jit} + \varepsilon_{jit}$$

collecting the coefficient, β_1 after each iteration. For each iteration, we change the date of *post constraint*, starting from Sunday, May 3, 2009 rolling forward a week at a time until Aug 29, 2010. Prior to each iteration, we trim the sample using the procedure described in Section 3. This restricts the sample to include only traders that execute trades before and after the false date for *post constraint*.



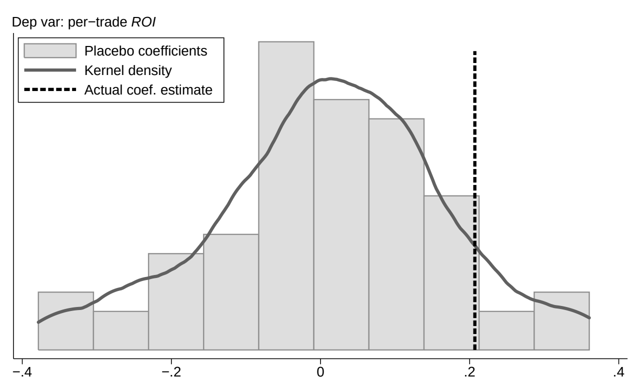


Table A.6
The Announcement of Regulation and Trade-Level Outcomes
Description: This table reports OLS estimates of the following regression:

$$Y_{jit} = \gamma_i + \gamma_t + \beta_1 \text{US trader}_i \times \text{post announcement}_t + \beta_2 \text{trade}_{jit} + \varepsilon_{jit}$$

where i is a trader, j is a trade, and t is a day (trades are recorded by the second). In **Panel A**, the dependent variable is *trade uses leverage > 50:1*, which equals one if the trade uses at least 10:1 leverage. In **Panels B** and **C**, the dependent variable is *ROI,* which is per-trade return on investment. *US trader* equals one if the trade is executed by a trader located in the U.S. and equal to zero if located in Europe. *Post announcement* equals one if the trade was opened after the CFTC's announcement in the Federal Registrar on January 13, 2010 of their intent to restrict traders' leverage to 10:1, zero otherwise. *High leverage trader* equals one if trader i uses at least 50:1 leverage on at least one trade prior to the CFTC regulation, zero otherwise. The sample period is from December 1, 2009 to March 1, 2010. Standard errors are double-clustered by day and trader, and *, **, and *** denote significance levels $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: ***The January 2010 Regulation Announcement and High-Leverage Trading***

dep var: trade uses leverage > 10:1 (=1)	(1a)	(2a)	(3a)	(4a)
US trader (=1) × post announcement (=1)	0.0443	0.0169	0.0205	0.0203
	(0.033)	(0.030)	(0.026)	(0.026)
log(trade size)			0.144***	0.143***
			(0.017)	(0.017)
log(holding period)				-0.00299
				(0.0023)
trader FE	x	x	x	x
day FE	x	x	x	x
broker-pair FE		x	x	x
Number of trades	167,035	166,985	166,985	166,985
R^2	0.54	0.56	0.61	0.61

Panel B: ***The Regulation Announcement and Performance, using Euro control group***

dep var: per-trade ROI	(1b)	(2b)	(3b)	(4b)
US trader (=1) × post announcement (=1)	0.00425	-0.0125	-0.0152	-0.0236
	(0.075)	(0.079)	(0.078)	(0.081)
log(trade size)			-0.0649	-0.0946*
			(0.047)	(0.048)
log(holding period)				-0.103***
				(0.017)
trader FE	x	x	x	x
day FE	x	x	x	x
currency risk-free rate differential	x	x	x	x
std dev of trader's weekly returns	x	x	x	x
broker-pair FE		x	x	x
Number of trades	167,035	166,985	166,985	166,985
R^2	0.053	0.057	0.057	0.060

Panel C: ***Performance; Alternative Control Group – High- vs. Low-Leverage Traders***

dep var: per-trade ROI	(1c)	(2c)	(3c)	(4c)
high leverage trader (=1) × post announcement (=1)	-0.0544	-0.0696	-0.0763	-0.0665
	(0.072)	(0.075)	(0.075)	(0.076)
log(trade size)			-0.0655	-0.0950*
			(0.047)	(0.048)
log(holding period)				-0.103***
				(0.017)
trader FE	x	x	x	x
day FE	x	x	x	x
currency risk-free rate differential	x	x	x	x
std dev of trader's weekly returns	x	x	x	x
broker-pair FE		x	x	x
Number of trades	167,035	166,985	166,985	166,985
R^2	0.053	0.057	0.057	0.060

Appendix A.7: Alternative Treatment Groups for Tests of Brokerage Capital

Table 6 shows that the CFTC regulation reducing the provision of leverage to retail traders reduced the amount of capital held by brokerages. The table establishes this finding by comparing CFTC-regulated brokerages that have retail forex obligations to those that do not. However, a plausible concern with this test is that – despite having similar trends prior to the regulation – brokerages without forex obligations are different in unobservable ways, and are therefore not suitable to be a control group. Brokerages with and without forex brokerages could diverge following the regulation because of factors that are unrelated to the leverage restrictions. We address this concern by showing that the regulation has the strongest effect on brokerages that provided more leverage to traders prior to the regulation.

To do so, the following variation on Table 6 sorts brokerages into the amount of leverage they offer traders. We define brokerages as *high leverage* (*low leverage)* if they were providing traders with above (less than) 400:1 leverage around the time of the October 2010 CFTC regulation. We assign brokerages to these classifications by manually searching internet archives, and most of the brokerages were listed on the website: www.100forexbrokers.com.[32] We choose 400:1 leverage as a cutoff, because the website specifies 400:1 as the minimum for a broker's inclusion in their list of "high leverage brokers". Seven brokerages classify as *high leverage* and sixteen as *low leverage.*

Columns (1) and (2) of Table A.7 run difference-in-difference regressions that compare *high leverage* brokerages against brokerages without forex obligations. Columns (3) and (4) use *low leverage* brokerages. The dependent variable is log brokerage excess capital. The point estimate on the difference-in-difference coefficient is between -0.36 and -0.51 for the *high leverage* brokerages and -0.19 to 0.23 for *low leverage* brokerages. These estimates are close to being significant at the 10% level. The lack of statistical significance is presumably due to having few brokerages with forex obligations after conducting the sample splits. Regardless, the effect of the constraint is larger for brokerages that provide more leverage, consistent with the CFTC regulation affecting brokerage excess capital through its effect on retail trader leverage.

Table A.7
Leverage-Constraints and the Excess Capital of High-Leverage-Brokerages
Description: This table reports OLS estimates of the regression

$$\log(\text{excess capital})_{bt} = \gamma_b + \gamma_t + \beta_1 \text{FX broker}_b \times \text{post constraint}_t + \varepsilon_{bt},$$

where b is a broker and t is a month. The data comes from monthly CFTC Futures Commission Merchants Financial Reports. Excess capital is the capital in excess of the regulatory requirement, for each brokerage in the CFTC data set. *FX broker* equals one if the brokerage has any retail forex obligations after they were required to report these obligations starting in November 2010. *Post constraint* equals one in months starting in November 2010, and zero otherwise. Appendix 7 describes how FX brokerages are sorted into high- and low-leverage. Standard errors are double-clustered by broker and month, and *, ** and *** denote significance at the $p < 0.1$, $p < 0.05$ and $p < 0.01$ levels, respectively.

dep var: brokerage excess capital	(1)*	(2)*	(3)†	(4)†
FX broker high leverage (=1) × post constraint (=1)	-0.367	-0.512		
	(0.29)	(0.36)		
FX broker low leverage (=1) × post constraint (=1)			-0.234**	-0.190
			(0.12)	(0.13)
log net capital requirement		-0.274		-0.292
		(0.17)		(0.18)
brokerage FE	x	x	x	x
month FE	x	x	x	x
N (broker-month)	1,332	1,332	1,427	1,427
Number of high (or low) leverage brokers	7	7	16	16
R^2	0.99	0.99	0.99	0.99

* sample includes high-leverage FX brokerages and CFTC regulated brokerages w/ no-FX obligations

† sample includes low-leverage FX brokerages and CFTC regulated brokerages w/ no-FX obligations

[32] An alternative approach to this classification would be to assign brokerages to *high leverage* or *low leverage* using the amount of leverage used by traders in the myForexBook data set. However, there are only seven brokerages that are common to the CFTC's data set and the myForexBook data set.

Appendix A.8: Trader Flows

This section tests for the effect of the leverage-constraint on the entry and exit rates of traders into the retail forex market. Unfortunately, the CFTC brokerage reports do not list the number of trader accounts. So, we use the myForexBook account-level data set to approximate account flows. We define trader entry as the first month a trader is in the data. We define trader exit as the last month that they trade. We then collapse the indicators for trader entry and exit to the brokerage-month-location level, where location is either traders from the U.S. or from Europe.

Table A.8 presents difference-in-differences regressions that compare the number of new (or exiting) U.S. traders to European traders, as a result of the leverage-constraint. The logarithm of new traders is the dependent variable in columns (1) and (2), and the logarithm of exiting traders is the dependent variable in columns (3) and (4). The coefficient of interest is the interaction of *post constraint* and *US traders* – an indicator that equals one if the traders come from the U.S. and zero if they come from Europe. The regressions include month, brokerage, and trader location fixed effects. Columns (2) and (4) have brokerage fixed effects interacted with a time trend, which accounts for the possibility that the growth and exit rates of new traders can vary by brokerage. This also helps control for the unconditional growth rate of the membership of the myForexBook website during this period (the website started in 2009 and its population grew to a peak of around 10,000 traders by the middle of 2011).

The leverage-constraint caused a reduction in trader inflows for new U.S. traders. The constraint reduced trader outflows, but the estimate is not statistically distinguishable from zero. Moreover, the reduction in inflows of U.S. traders is larger than the reduction in outflows. The difference-in-difference coefficient for trader inflows is -0.118, and the sample average of monthly inflows is 1.21, which suggests a 0.118 / 1.21 = 9.8% reduction in inflows. Using the same calculation, the reduction in outflows is 8.5%. Furthermore, columns (2) and (4) use distributed lags around the regulation date to test for pre-trends. The effect of inflows is close to zero before the regulation, but the coefficient falls to around -0.1 persistently thereafter. On the other hand, the effect on outflows is noisy around the regulation date.

Table A.8
The Effect of the Leverage Regulation on Trader Flows
Description: This table uses account level data from the myForexBook data set collapsed to observations at the level of brokerage, month, and the geography of traders within the brokerage. It reports OLS estimates of the regression

$$\log(\text{number of traders})_{bgt} = \gamma_b + \gamma_g + \gamma_t + \beta_1 \text{US flows}_g \times \text{post constraint}_t + \varepsilon_{bgt},$$

where b is a broker, g is trader geography (either U.S. or Europe), and t is a month. *US flows* equals one if the number of traders are from the U.S. and equal to zero if they are from Europe. *Post constraint* equals one in months starting in November 2010, and zero otherwise. The sample period is May 2010 to April 2011 Standard errors are double-clustered by broker and month, and *, ** and *** denote significance at the $p < 0.1$, $p < 0.05$ and $p < 0.01$ levels, respectively.

	trader inflows		**trader outflows**	
dep var:	log(# new traders + 1)		log(# exiting traders + 1)	
	(1)	(2)	(3)	(4)
US flows (=1) × post constraint (=1)	-0.118*		-0.134	
	(0.065)		(0.080)	
US flows (=1) × Sept 2010 (=1)		0.0160		-0.0459
		(0.072)		(0.042)
US flows (=1) × Oct 2010 (=1)		-0.0122		0.111***
		(0.14)		(0.019)
US flows (=1) × Nov 2010 (=1)		-0.101		0.0258
		(0.066)		(0.072)
US flows (=1) × Dec 2010 (=1)		-0.141***		0.136
		(0.044)		(0.090)
US flows (=1) × Jan 2011 (=1)		-0.104		-0.0699***
		(0.061)		(0.0063)
month FE	x	x	x	x
US flows FE	x	x	x	x
brokerage FE	x		x	
time trend × broker FE		x		x
mean of dependent variable	1.21	1.48	1.57	1.81
Broker-month-trading region obs.	393	286	345	260
R^2	0.75	0.87	0.78	0.84