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The leverage substitution

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Abstract This paper investigates the impact of a 2018 intervention by the European Securities and Markets Authority (ESMA), which limits the amount of leverage that retail investors can take on their trading activities. While the intervention successfully reduced leverage-usage, investors shifted their trading activities to riskier assets in the process, consistent with the idea that leverage-constrained investors substitute leverage with riskier securities. Thus, the intervention was not as effective as the reduction in leverage suggests.

Keywords Trading behavior; Risk-taking; Contracts for difference; Regulatory intervention.

JEL Classification G11, G40, G41.

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Risk is the salt and sugar of finance.

Carbo-Valverde et al. (2012)

1 Introduction

Effective August 1, 2018, the European Securities and Markets Authority (ESMA) introduced a temporary product intervention measure that included a new leverage constraint for all retail trading activities using contracts for differences (CFDs). The ESMA argues that these measures increase investor protection in the European Union by limiting the distribution of speculative products to retail clients. In this paper, I study the trading activities of retail investors around this intervention. Based on the argument that investors will find alternative paths to their preferred degree of risk-taking, I hypothesize that investors will shift their trading activities to riskier underlyings to obtain their desired risk levels—consistent with the idea of Frazzini and Pedersen (2014). The authors note that investors face heterogeneous leverage constraints. Investors who are constrained in the leverage that they can take may overweight risky securities instead of using leverage, while less-constrained investors overweight low-risk assets and possibly apply leverage (Frazzini and Pedersen, 2014). Such behavior may explain the "low-risk effect" that assets with low risk have high alpha (see, e.g., Black, 1972; Asness et al., 2020). In line with this hypothesis, my empirical observations indicate a shift toward riskier stocks in response to the new leverage constraint.

The basic idea of circumventing regulation is also related to the idea of "regulatory arbitrage" (Houston et al., 2012). Ongena et al. (2013) ask whether banks follow a deliberate risk-taking strategy in one market to compensate for the inability to take on risk in another market. In particular, stricter regulations in one market may yield more risk-taking in another (see also Bengui, 2014; Demyanyk and Loutskina, 2016), as banks may attempt to "make up" for the inability to engage in risk-taking in the first market. Alternatively, however, banks may export a conservative business model into other markets as a result of stricter regulations in one market (Ongena et al., 2013). Thus, the larger question is whether regulations eliminate excessive risk-taking or simply re(al)locate risk through actions by regulated entities.

While the evidence from the banking literature suggests a reallocation of risk (see, e.g., Carbo-Valverde et al., 2012; Demyanyk and Loutskina, 2016; Karolyi and Taboada, 2015; Scott Frame et al., 2020), the reaction of (retail) investors to stricter leverage constraints has been less studied. Frazzini and Pedersen (2014) do not have direct evidence of investors' (in)ability to employ leverage and consequently study investors in aggregate. Hitzemann et al. (2022) find supporting evidence that high-beta mutual funds experience larger inflows when leverage constraints tighten. The authors also find evidence that fees increase in a fund's beta. Investors demand leverage, and mutual funds adjust their asset management fees accordingly. Jylhä and Rintamäki (2021) find that closed-end funds with access to leverage that was constrained following the collapse of the market for auction rate securities in February 2008 purchased high-beta stocks following the collapse and sold significantly more low-beta stocks.

However, the reaction of retail investors to such a regulatory intervention remains an empirically open and important question. This question is particularly important considering the increasingly large share of retail trading volume in financial markets as part of the retail renaissance (Sambasivan, 2020; Rooney, 2020; Phillips and Lorenz, 2021; Ozik et al., 2021). In July and August 2020, the share of the retail volume in US equity markets was more than 25% (McCrank, 2021). Retail trading has also significantly increased in Europe, with the share of total trading carried out by retail investors more than doubling since 2019, albeit at a significantly lower level (from 2% to around 5%, Chatterjee, 2021). The intervention, together with individual investors' trading data, allows me to study how individual investors react to (new) constraints at the micro level.

Using leverage allows retail investors to take larger positions than they could afford with their own money and is a major catalyst of speculative trading (Heimer and Simsek, 2019). Trading with leverage has increased significantly in recent years (see, e.g., Wursthorn, 2020). In August 2021, investors in the US borrowed more than $900 billion for the first time. This amount represents growth of 41% over the previous year, 14% in 2021 alone (Financial Industry Regulatory Authority (FINRA), 2021). Ladley et al. (2020) argue that trading on margins is popular because it skews the distribution of returns and thereby provides lottery-like payoffs. Given the preference of investors for such payoffs (Gao and Lin, 2015; Kumar, 2009; Liu et al., 2022), the preference for trading on leverage is no surprise. By trading on leverage, investors significantly increase the volatility of their returns because very high positive and very low negative returns are more likely.

If we assume that investors deliberately take high levels of leverage—for example, that their risky behavior could reflect a "search for yield" (Rajan, 2006)—the intervention leads to too low risk exposure. As a result, retail investors may attempt to find other ways to achieve their desired level of risk-taking. I argue that one possible path to increased risk exposure is a shift to riskier underlyings and test the hypothesis that investors trade riskier assets following the 2018 ESMA intervention.

I use data from a trading platform (henceforth, the trading data) that allows its international customer base to trade CFDs on a wide variety of underlyings. Investors can trade, for example, CFDs on stocks, currency pairs, cryptocurrencies, commodities, or indices. While doing so, investors can specify the leverage of each position. Important for the analysis, the platform allows investors from various countries to trade CFDs, allowing me to investigate the trading activities of investors subject to regulatory intervention (treated investors) and those who are not (control investors) in the same trading environment (see also Heimer and Simsek, 2019).

The main analysis exploits a standard difference-in-differences (DID) analysis that compares the trading activities of treated investors to those of control investors around the intervention. I also estimate a setting that compares the trading activities of treated investors for whom the intervention was binding to treated investors who never made use of high levels of leverage. My results indicate that while—in line with the intention of the intervention—overall risk-taking decreased, investors found alternative approaches to obtaining high risk levels. In particular, I find that investors trade stocks with higher volatility and higher idiosyncratic volatility. Quantitatively, the effect amounts to approximately 7% of the average volatility of stocks that investors trade. Investors also trade cryptocurrencies more frequently. With respect to performance, my results are in line with the literature (Heimer and Simsek, 2019; Subrahmanyam et al., 2023; Eliner, 2022) and show that investors realize higher returns following the intervention, with lower variance in their returns.

To make the mechanism explicit and to underline the substitution channel, I use an instrumental variable (IV) approach. Whereas the DID coefficient estimates the total effect of the intervention on the outcome (i.e., the risk of the underlyings that investors trade), the IV assumes that the intervention affects the outcome only through the instrumented variable—change in leverage-usage—and thus isolates a "treatment of the successfully treated"-effect specifically for investors who face new binding constraints. In a cross-sectional setting, I focus on the change in risk-taking measures and find results in line with the DID approach, both qualitatively and quantitatively.

I also estimate the quantile treatment effect on the treated (QTT) following the approach of Callaway and Li (2019) to study the distributional impacts of the intervention. Treatment effects are heterogeneous, and investors who trade fairly risky stocks prior to the intervention show a more pronounced shift to even riskier underlyings. To further test the robustness of my findings, I use a matching approach and run a placebo analysis.

Then, I study the potential spillover effects between investors in the treatment and control groups. Potential "spillovers" or indirect effects in financial regulatory experiments, as highlighted by Boehmer et al. (2020), have thus far been studied only at the surface. Indirect effects relate to the *stable unit treatment value assumption* (SUTVA) of the Rubin causal model, which includes the condition that treating one subject does not affect other treated or control subjects (Atanasov and Black, 2016). Indirect effects in a DID may arise due to externalities through which the treatment influences the control group. For example, Ouimet and Tate (2020) show that the trading of peers influences other investors' trading. Thus, indirect effects in my setting could occur if the risk shifting of treated peers influences the risk-taking of control investors. While I find some evidence of a spillover effect, the estimates for the risk shift of treated investors to riskier underlyings remain almost unchanged.

Finally, I exploit observable investor traits, such as gender, age, and experience, to shed light on the cross-sectional differences in investors' trading activities around the intervention. I find that, in particular, investors who made use of high leverage prior to the intervention substitute more, providing additional support for the notion that risk-taking is premeditated rather than accidental. These investors also do not realize higher returns after the intervention. I find that, in particular, investors who took large amounts of leverage and realized returns in the bottom quartile prior to the intervention substitute significantly more. Young and short-term-oriented investors also substitute more. I do not find a more pronounced substitution for inexperienced investors who also do not reduce their leverage-usage quite as much and do not seem to particularly benefit from the intervention.

The paper contributes to a fast-growing body of literature that (mostly) studies the performance implications of leverage-usage (see, e.g., Barber et al., 2020; Heimer and Imas, 2022; Subrahmanyam et al., 2023; Eliner, 2022). Closely related to this paper, Heimer and Simsek (2019) study the 2010 regulation by the Commodity Futures Trading Commission (CFTC) in the US and show that, on average, investors realize better returns following the intervention. I extend their work and show that investors not only reduced their leverage-usage in response to the new regulation but also shifted their investment activities toward riskier underlyings in an effort to maintain their risk-taking. Therefore, I provide evidence that may plausibly be interpreted as causal evidence in support of the notion that retail investors prefer to hold assets with more volatility and expand the literature that has shown correlations between retail investor holdings and certain types of stocks (e.g., lottery-type stocks, Kumar, 2009).

The paper proceeds as follows. Section 2 describes the institutional background and the intervention. Section 3 discusses the related literature and develops the main hypothesis. I present the data, measures, and methods in Section 4. Section 5 investigates how investors shift their trading activities toward riskier underlyings. I provide cross-sectional analyses in Section 6. The last section concludes the paper.

2 The regulatory intervention on leverage constraints

A CFD is a financial contract with a price that equals that of the underlying security (see, e.g., Arnold et al., 2022; Brown et al., 2010, for more details). Two counterparties agree to replicate the price of the underlying security and settle the change in its price when the position closes. In contrast to futures contracts, a CFD has no explicit maturity date but can be closed out at any time at the prevailing market price that is equal to the price of the underlying. Importantly, CFDs allow investors to employ leverage very easily at the position level (see also Arnold et al., 2022).

As a majority of CFD traders lost money, effective on August 1, 2018, the ESMA introduced a temporary product intervention measure that included a new leverage constraint for all trading activities using CFDs. The ESMA's Board of Supervisors agreed on those measures on March 23, 2018, with the intention to limit the risk-taking of retail investors using CFDs. The ESMA is allowed to introduce such temporary interventions based on Article 40 of the Markets in Financial Instruments Directive (MiFIR) (Regulation (EU) No 600/2014). In particular, MiFIR gives the ESMA the power to introduce temporary intervention measures on a three-month basis. The product interventions are then reviewed and can be extended for an additional three months.

The intervention consisted of, among other provisions, new leverage limits on *opening* positions.[1] In particular, the intervention reduced the maximum leverage that investors are allowed to take on individual equities to 5:1, from a previous maximum of 10:1.[2] Given that the average leverage of investors in my sample prior to the intervention was considerably larger than 5, the new leverage constraint was likely binding for many investors subject to the regulation, and an adjustment of trading strategies had to occur.

In addition to new leverage constraints on individual equities, the intervention also included new leverage constraints of 30:1 for major currency pairs; 20:1 for nonmajor currency pairs, gold and major indices; 10:1 for commodities other than gold and nonmajor equity indices; and 2:1 for cryptocurrencies.

In its initial product intervention decision regarding CFDs, the ESMA indicated that these measures represented a necessary minimum level of protection for retail clients across the union, in addition to existing investor protection requirements (European Securities and Markets Authority, 2020).

Following three consecutive renewals, these temporary measures expired on July 31, 2019 (European Securities and Markets Authority, 2020). ESMA noted that "nearly all National Competent Authorities in the EU have now taken national product intervention measures in order to address, in a permanent way, the investor protection concerns arising from these products" (European Securities and Markets Authority, 2020, p. 3).

[1] Existing positions were not affected by the intervention and could continue to be held without additional restrictions.

[2] In comparison, the current regulation allows 2:1 leverage on long stock positions in the US.

Investors were first informed about the intervention by ESMA on March 27, 2018, when a press release summarized the agreements around the intervention.[3] The broker informed its clients first in June 2018 and then several times in the months that followed.

The regulation was also discussed on social media. Posts and discussions can be found on `forexfactory.com`, `reddit.com`, and other (national) discussion forums. A few early discussions took place immediately following the ESMA announcement; however, most activity is from late June 2018. Several of these discussions suggest that investors look for brokerage services (from abroad) that do not (have to) comply with the regulation. This provides initial anecdotal evidence that investors are looking for alternative paths to take risks and highlights the importance of focusing the analysis on investors who trade with the broker before and after the intervention.

3 Retail investors' usage of leverage

Investors can create CFD positions with various risk levels using a combination of risky assets and applying leverage. The total volatility of a position ($\sigma_{position}$) that an investor creates results from the volatility of the underlying (σ_{asset}) multiplied by the leverage applied:

$$\sigma_{position} = \sigma_{asset} \times \text{leverage}.$$

A growing body of literature documents investors' demand for leverage. Dam et al. (2023) focus on closed-end funds and show that investors are willing to pay a premium to obtain amplified risk exposure, even though leverage does not yield improved returns on investment. Frazzini and Pedersen (2021) study assets with embedded leverage and show that investors' high demand for these products drives up prices, leading to lower risk-adjusted returns.

However, not all investors can apply leverage in the same way (Frazzini and Pedersen, 2014). Investors face heterogeneous leverage constraints, and some only have limited access to leverage. As a result, these investors can only purchase risky securities to obtain a desired (high) risk level. In contrast, investors who have unlimited access to leverage have the

[3]See press release dated March 27, 2018: `https://www.esma.europa.eu/press-news/esma-news/esma-agrees-prohibit-binary-options-and-restrict-cfds-protect-retail-investors`.

option to either purchase less risky assets and apply leverage to their positions or purchase riskier assets and not apply leverage. Frazzini and Pedersen (2014) argue that unconstrained investors overweight low-risk assets and apply leverage. In accordance with this idea, Boguth and Simutin (2018) propose a theoretical model in which mutual funds shift to riskier assets when leverage constraints are binding. Hitzemann et al. (2022) and Jylhä and Rintamäki (2021) provide supporting evidence for this notion.

Dam et al. (2023) argue that—due to leverage constraints—investors may demand riskier securities to get closer to their preferred portfolios. Importantly, investors with leverage constraints may rationally demand riskier securities to get closer to an efficient portfolio or may act irrationally and demand riskier securities to satisfy their desire for lotteries (Dam et al., 2023; Frazzini and Pedersen, 2014; Kumar, 2009). In any case, investor behavior in line with "betting against beta" (Frazzini and Pedersen, 2014) may explain the "low-risk effect" that assets with low risk have high alpha (see, e.g., Black, 1972; Asness et al., 2020). Liu et al. (2018) demonstrate that beta is not the stock characteristic driving this "beta anomaly". They show that idiosyncratic volatility (IVOL) plays an important role in explaining this effect. Bali et al. (2017) show that investors' demand for lottery-type stocks is an important driver of the beta anomaly.

The ESMA intervention reduces the maximum amount of leverage that retail investors are able to apply. Thus, newly regulated investors can no longer achieve high risk levels with low-volatility assets. They can achieve high risk levels only by purchasing high-volatility underlyings. In other words, investors must move to riskier assets to obtain high volatility in their position. Based on this argument, I aim to test the following hypothesis:

H1: *Investors who are subject to new leverage constraints turn to riskier assets.*

Considering the evidence by Liu et al. (2018) and Bali et al. (2017) that the "low-risk effect" is driven by idiosyncratic rather than systematic risk, I additionally hypothesize the following:

H2a: *Investors who are subject to new leverage constraints turn to stocks with higher IVOL.*

H2b: *Investors who are subject to new leverage constraints turn to lottery-like stocks.*

4 Data, variables, and methodology

4.1 The trading platform

The increasing overlap between social media and financial markets has led to the emergence of new business models in recent years. Several online brokerage services combine their brokerage services with features of social networks and allow individuals to simultaneously manage their portfolios and exchange capital market information. Typical features enable investors to disclose and discuss their investment decisions with their peers (see, e.g., Heimer, 2016). Via a disclosure function, investors can share their trading decisions and outcomes with peers while observing the trading decisions and outcomes of their peers in large international networks. I use data from a trading platform provider that offers brokerage services to a large, international client base. The broker allows retail investors to trade CFDs on a large set of international blue chip stocks, FX rates, and cryptocurrencies. The data are similar to those used by Heimer and Simsek (2019) and Heimer et al. (2021).

4.2 Data

The data include the trades executed on the platform between March 2018 and December 2018. In this paper, I focus on stocks because the intervention has been particularly binding for stocks. I provide some supplementary evidence on cryptocurrencies, where the intervention has not been binding, on average. The data contain the exact timestamp of each trade, the specific underlying, an indicator for long or short positions, the execution price, the leverage, and the position size (in percent of the overall portfolio value). The broker quotes stock prices in USD irrespective of the currency in which the underlying trades; thus, the dataset shows all prices and trades in USD. It provides returns after adjusting for stock splits, dividends, and transaction costs.

In addition, the data contain several types of information on investors' demographics, their previous trading experience, and their planned trading horizons. The data are collected from a questionnaire issued by the broker upon account opening, which is inspired by the MiFID client profile review.

I carefully filter the data to ensure that the treatment group contains only investors subject to ESMA regulations, i.e., those from the European Union, and that the control group contains only investors who are not subject to such regulations.[4] The final dataset comprises a total of 49,696 investors, with 28,694 investors subject to the new regulation and 21,002 investors in the control group. These investors are responsible for a total of 2,097,456 transactions (2,068,578 round trips and 28,878 openings of a position) and trade more than 1,000 different stocks from various exchanges worldwide (i.e., Nasdaq, NYSE, LSE, Frankfurt Stock Exchange, Bolsa De Madrid, Borsa Italiana, Euronext Amsterdam, Euronext Brussels, Euronext Paris, Euronext Lisbon, Copenhagen Stock Exchange, Helsinki Stock Exchange, Oslo Stock Exchange, Stockholm Stock Exchange and others).

4.3 Variables

The broker allows investors to flexibly select the leverage for each individual CFD trade. If investors decide to take a leveraged position, they can choose between a leverage of 2:1, 5:1, or 10:1, depending on their regulatory environment. The choice of leverage does not affect the trading cost. Following the intervention, investors in the treatment group are able to select a leverage of only 2:1 or 5:1. The variable *leverage* denotes the leverage of a trade (see also, e.g., Arnold et al., 2022; Heimer and Simsek, 2019). Importantly, the broker allows its customers to exploit leverage without risking a loss of more than 100% and without the need for dynamic rebalancing.

I use different measures to capture investors' risk-taking beyond their leverage-usage. I quantify investor risk-taking via both the time-varying and the unconditional volatility of stocks in which they invest. I estimate the *volatility* of a stock using a GARCH(1,1) model based on daily log returns. To address the concern that the overall volatility of stock markets significantly increased in the last quarter of 2018 (see Figure 4 for an evolution of the CBOE

[4] The treatment group comprises the United Kingdom, Germany, France, Italy, Spain, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, Greece, Hungary, Ireland, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, and Sweden. The control group comprises, for example, Switzerland, Singapore, Australia, the United Arab Emirates, Malaysia, Mexico, Argentina, Bahrain, Bolivia, Brazil, the Cayman Islands, Chile, Colombia, the Dominican Republic, Ecuador, Gibraltar, Iceland, Israel, Kuwait, Liechtenstein, Norway, Oman, Peru, the Philippines, South Africa, South Korea, Taiwan, Thailand, the United States, Uruguay, and Vietnam.

Volatility Index, the VIX, and the average stock volatility of all stocks that investors traded during the sample period in 2018), I also estimate the unconditional standard deviation of stocks (*SD Stock*) using monthly returns between January 2015 and February 2018, that is, before the sample period begins. Next, I use the idiosyncratic volatility (*IVOL*), defined as the standard deviation of the residuals from rolling market-model regressions over the past 262 trading days. For each stock, I use the major stock market index of the country in which the stock is primarily listed. Following Kumar (2009), I define stocks with below-median prices, above-median idiosyncratic volatility, and above-median idiosyncratic skewness as *lottery-type* stocks.

In an additional analysis, I use the fraction of cryptocurrency trades as an additional measure of risk-taking (*Crypto*). While the intervention also limited the maximum leverage to be used on cryptocurrencies, this constraint was less binding, as the average leverage-usage in the data for trades on cryptocurrencies prior to the intervention amounts to only 1.008 (median 1, indicating no leverage-usage). Thus, the new constraints did not mitigate the risk-taking attractiveness of cryptocurrencies. Additionally, I directly exploit the volatility of the underlyings that investors trade, including cryptocurrencies. I estimate *SD Asset* using daily log returns between January 1, 2015, and February 28, 2018.

To quantify the aggregate effect of risk-taking, I use *leverage* $\times$ *volatility*, which is the simple product of the leverage of a particular trade and the volatility of the underlying stock. The measure is based on the notion that taking a certain leverage, for example, 2:1, doubles the price movements of the position relative to the price movements of the underlying stock.

As additional proxies for investors' trading activities, I use *trades*, which denotes the number of trades that an investor executes in a given month. *Investment* is the nominal amount of a trade, expressed as a fraction of the investor's total nominal amount of assets that s/he deposited with the broker. Unfortunately, I do not have access to the absolute nominal amounts of investors' positions.

Next, I use several measures to quantify investors' portfolio composition and risk. First, I account for investors' portfolio features using *No. stocks*, which denotes the number of different stocks in an investor's portfolio at a given point in time and the Herfindahl–Hirschman index (*HHI*) as a simple measure of diversification based on the sum of the squared portfolio weights (Dorn et al., 2008; Ivkovich et al., 2008; Bhattacharya et al., 2012). A larger value indicates a more concentrated portfolio.

I estimate the expected return of an investors' portfolio based on past returns of the stocks in the portfolio according to their portfolio weights (*investment*). Recall that the trade data include *investment*, measured as the trade amount's fraction of total assets deposited with the online broker, i.e., the portfolio weight of the trade. I adjust the investment for cash positions so that the weights of all of the positions sum to one. To account for the risk of an investor's portfolio, I estimate *portfolio risk* based on the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights. In addition, I estimate the unsystematic volatility of the portfolio based on the diagonal entries of the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights and the systematic risk based on the covariance of stocks in the portfolio.

I estimate investors' portfolio variables at the end of each trading day. If investors do not hold any stocks in their portfolio, the corresponding variable is missing, with *No. stocks* being the exception. This variable takes the value of 0 if investors do not hold any stocks in their portfolio at the end of a trading day. I aggregate the daily measures at the monthly level using simple averages.

Additionally, the individual investor data allow me to investigate the implications of investors' risk-taking—their objective trading performance. To measure trade profitability, I follow Arnold et al. (2022) and use the leveraged holding-period return on a given trade. *Profit* measures a trade's profitability, which is the return on investment net of transaction costs. Finally, *SD(profit)* denotes the standard deviation of the return on investment net of transaction costs in a given month.

4.4 Methodology

I use a standard DID estimation approach to analyze the marginal impact of the regulatory intervention on risk-taking. In particular, I compare the risk-taking of treated investors subject to the new regulation after August 1, 2018, (treatment group), with that of investors not subject to the regulatory intervention (control group), conditional on trading. In an alternative specification, I compare the risk-taking of treated investors for whom the intervention was binding, i.e., who used leverage larger than 5 prior to the intervention, with that of investors for whom the intervention was not binding because they did not use leverage above the new regulatory threshold prior to the intervention. I focus only on the risk-taking of new positions. Thus, the risk-taking measures for a given month include only those positions created in that month and not positions created in a previous month and that investors continue to hold.

First, using equally weighted averages, I aggregate the risk-taking measures for each investor in the period prior to the intervention (observation period). Similarly, using equally weighted averages, I aggregate the risk-taking measures for each investor in the period following the intervention (treatment period). In a robustness exercise, I use investment-weighted averages to account for the influence of the position on investors' overall risk exposure. I use the investment weight at the time the position is opened. Using data both before and after the treatment reduces the risk of bias due to imperfect randomization in the DID design (Atanasov and Black, 2016). To mitigate the concern that different "types" of investors in the treatment group begin trading with CFDs following the intervention (i.e., that new "risk-seeking" ESMA investors begin to trade risky underlyings and drive the change in risk-taking), I consider only those who execute at least one trade before and after the intervention. In addition, taking monthly averages before and after the intervention prevents the possibility that the estimates are affected by the weighting of traders and how much more or less they may trade after the leverage regulation.

Then, I calculate the difference between the risk-taking of the treated investors and that of the counterfactual investors during the observation period. I also measure the difference between the risk-taking of the treated investors and that of the counterfactual investors in the treatment period. The marginal impact of the regulatory intervention on risk-taking then corresponds to the difference between these two differences. Formally, I estimate the following equation:

$$\text{Risk-taking}_{it} = \alpha + \beta_1 \text{ ESMA}_i \times \text{post intervention}_t + \psi_i + \eta_t + \varepsilon_{it}, \tag{1}$$

where Risk-taking$_{it}$ denotes the risk-taking of investor i at time t (in months), measured using leverage, volatility, SD stock, IVOL, and lottery type. $ESMA$ is a dummy variable that takes the value of 1 for investors in the treatment group, and 0 otherwise; *post intervention* is a dummy variable that takes the value of 1 for the treatment period, and 0 otherwise. β_1 is the coefficient of interest that captures the impact of the regulatory intervention on the risk-taking measures. The specification includes investor fixed effects ψ_i to control for observed and unobserved heterogeneity across investors. I also incorporate time dummies η_t to account for aggregate time trends. Fixed effects can help address covariate imbalances between the treatment and control groups (Atanasov and Black, 2016; Dinc, 2005). The coefficients on $ESMA_i$ and *post intervention*$_t$ are absorbed in the investor- and time-fixed effects.

In addition to the risk-taking measures, I estimate equation (1) for the cryptocurrency and portfolio measures, and for the profitability measures, profit and SD(profit).

4.5 Summary statistics

Most investors in the sample are male and are between 25 and 44 years of age (see Table A.1 in the Appendix). The dataset contains both novices and experienced traders (Panel C of Table A.1). Investors are mostly focused on short- and medium-term trading horizons (Panel D of Table A.1).

Investors trade fairly frequently, with an average of 6.27 trades/month (see Table A.2 in the Appendix). However, the distribution is heavily skewed with a median of zero. Conditional on trading, approximately 10% of all CFD trades are on cryptocurrencies. Again, the distribution is heavily skewed, with the median investor not trading cryptocurrencies at all. Conditional on trading CFDs on stocks, investors take a fairly high amount of leverage with an average leverage of 6.1. They invest approximately 15.66% of their total account value in a single position and hold a position for, on average, almost 10 days. The median holding time, however, is less than two days, indicating many highly speculative short-term positions. At the same time, investors hold, on average, fewer than three stocks in their portfolio on any given day (conditional on holding at least one stock; not tabulated).[5] Thus, investors

[5]This observation is consistent with the overall empirical evidence that suggests that households are

seem to (mostly) focus on individual stocks. Consequently, I focus on individual positions in this paper. Nonetheless, I provide additional evidence on investors' portfolio risk. Of all CFD trades on stocks, approximately 13% are based on a lottery-type stock. The average trade provides a negative net return of -3.4%. The median holding-period return is positive at 0.81%.

Figure 1 focuses on the covariate balance between treated and control investors and shows the distribution of investors' risk-taking measures prior to the intervention. The figure shows common support for all variables. The surprising spikes that can be observed in the distribution of unconditional volatility occur because a few stocks, such as Facebook, Amazon, and Alphabet, are traded very heavily by the majority of the investors. The five most-traded stocks are Facebook, Amazon, Netflix, Tesla, and Alphabet.

— Place Figure 1 about here —

5 Risk-taking following the regulatory intervention

5.1 Leverage-usage

First, I shed light on the leverage-usage of investors around the intervention. Figure 2 visualizes the leverage-usage around the intervention, separately for treated and control investors. The average leverage-usage of treated investors prior to the intervention moves around slightly below 6.5 prior to the intervention. On August 1, 2018, the date of the intervention, the average leverage-usage decreases to approximately 4.6-4.7. The decline in leverage-usage is highly statistically significant. The figure also indicates that investors did not reduce their leverage-usage prior to the intervention, which is consistent with the broker implementing the constraint only on August 1, 2018, and investors being able to continue to hold positions with larger leverage that were opened prior to the intervention. The average leverage-usage of the control group does not show any meaningful variation around the time of the intervention. The fact that the average leverage-usage of the control investors prior to the intervention was slightly lower than the average leverage-usage of the treatment group

poorly diversified (see, e.g., Roussanov, 2010; Dorn and Huberman, 2010).

is not problematic. First, Panel a of Figure 1 shows that the distributions of the leverage-usage of the treatment and the control groups exhibit substantial overlap (common support). Second, the DID approach in equation (1) accounts for the pretreatment differences with the ESMA$_i$-coefficient or rather the investor-fixed effects ψ_i that subsume the ESMA$_i$-coefficient.

— Place Figure 2 about here —

Table 1 provides a formal test of the observation and reports the results from a DID analysis using equation (1) on leverage. As expected, investors who are affected by the intervention significantly reduce their leverage-usage on August 1, 2018, whereas investors who are not subject to the regulation do not. Quantitatively, the coefficient of -1.87 indicates an economically important reduction in leverage relative to that of the control group (Column 1). Investors in the treatment group reduced their leverage-usage from an average of 6.6 prior to the intervention to an average of 4.7 after the intervention. Compared to the overall mean of 6.1 and standard deviation of 2.6 (Table A.2), the coefficient corresponds to 31% of the mean and 72% of the standard deviation of investors' leverage.

In additional tests, I consider only ESMA investors who used a leverage of 10 at some point prior to the intervention to be treated. In other words, I consider only ESMA investors for whom the intervention was binding to be treated. I exclude ESMA investors who did not use such high leverage. Control investors are those who are not subject to the new ESMA regulations. In line with my expectations, the reduction in leverage is more pronounced in this setting (Column 2). Finally, I focus on the differences between ESMA investors for whom the intervention was binding ($binding = 1$) and those for whom the intervention was not binding ($binding = 0$).[6] I consider only ESMA investors for the analysis and compare binding versus nonbinding investors in the DID setting. The results summarized in Column 3 indicate that investors for whom the intervention was binding decrease their use of leverage to a significantly larger degree. This observation is intuitive and indicates that the ESMA intervention does not affect the use of leverage through channels other than the ban itself.

— Place Table 1 about here —

[6] Table A.3 in the Appendix provides summary statistics split by binding. ESMA investors for whom the intervention was binding are slightly more experienced, trade more actively, and appear more short-term oriented.

5.2 Risk measures of the underlyings

Next, I study the various risk-taking measures around the intervention and the potential substitution effect. Figure 3 visualizes the average conditional volatility (Panel a), unconditional volatility (Panel b), IVOL (Panel c), and lottery-type stocks (Panel d) around the intervention. For all of the measures, I observe clear parallel trends prior to the intervention. Starting in August 2018, the measures diverged, and treated investors, on average, began to take riskier underlyings.

— Place Figure 3 about here —

Panel a of Figure 3 also shows a significant increase in the group of control investors after October 2018. At first glance, this increase may appear rather puzzling. However, the overall market developments in the last quarter of 2018 provide a convincing explanation for the overall increase in conditional GARCH volatility. Panel a of Figure 4 shows the average conditional GARCH(1,1) volatility of all stocks that investors trade on the platform. Importantly, the figure provides an unweighted average across all stocks that investors trade at any point in time during the sample period, independent of whether and how frequently the particular stocks are traded in a given month. The average conditional volatility increases substantially starting in October 2018. Panel b of Figure 4 provides additional supporting evidence and shows the CBOE Volatility Index in 2018. Starting in October, the VIX increased significantly.

— Place Figure 4 about here —

To provide additional supporting evidence for the notion that an increase in market volatility explains the increase in the average conditional volatility, I study unconditional volatility in Panel b. Unconditional volatility is estimated using the period prior to March 2018 and, thus, does not account for the increase in volatility in the last quarter of 2018. The figure indicates an increase in risk-taking in the treatment group, whereas the risk-taking in the control group does not increase.

5.2.1 DID analysis

Table 2 analyses the risk-taking measures using the DID regression model (1). Panel A shows equally weighted risk-taking measures for investors' new positions in a given month. The table indicates a significant treatment effect for volatility, SD Stock, and IVOL in Columns 1 to 3. The coefficient on volatility in Column 1 is 0.007, with a t-statistic of 4.88. To put this into perspective, the coefficient amounts to 8.5% of the standard deviation of average stock volatility and, thus, is economically very meaningful. Columns 2 and 3 paint a similar picture. The coefficient on lottery type in Column 4 (0.01) is not statistically significant (t-statistic of 1.57).

— Place Table 2 about here —

Panel A additionally shows single-clustered standard errors at the investor level in square brackets to address the concern that the number of clusters at the monthly level may be too small. Standard errors decrease significantly, indicating that double-clustering standard errors is the more conservative approach here.[7] Therefore, and because of plausible correlation between observations, I focus on double-clustered standard errors where appropriate.

In Panel B, I consider only ESMA investors for whom the intervention was binding to be treated and again exclude ESMA investors who did not use such high leverage. Control investors are those not subject to the new ESMA regulations. In line with my expectations, the substitution effect is more pronounced in this setting.

Next, I focus on the comparison between ESMA investors for whom the intervention was binding and those for whom the intervention was not binding. I summarize the results in Panel C. In particular, investors for whom the intervention was binding substitute to riskier underlyings.

Panel D again uses the sample used in Panel A and additionally reports investment-weighted risk-taking measures for investors' new positions in a given month. The alternative weighting scheme produces similar results.

[7]Note that double-clustered standard errors are not always the more conservative option. In addition, multiway clustering following Cameron et al. (2011) may yield a non-definite variance matrix. This is generally not a problem since the matrix is forced to be semidefinite by setting negative eigenvalues to zero in these cases, and the variance estimator is asymptotically correct. However, in my setting, the number of clusters at the monthly level is small. Thus, I revert to single-clustered standard errors in these cases.

Finally, I address the concern that changes in market conditions affect investors differently from the treatment and control groups, and I add additional control variables to the model in Panel E. Investor reactions may differ, for example, because of home bias (Coval and Moskowitz, 1999). I include various stock markets' returns as country-specific time-varying factors. I include the stock market returns of most markets to which the broker gives its clients access. As the broker serves clients from countries who cannot trade stocks from their home country, I interact the market returns with the ESMA dummy.[8] The interaction of the index return with the treatment dummy enables me to control for potentially different responses to country-specific market conditions from investors in the treatment and control groups. As a result of the additional interaction terms in the model, multiway clustering following Cameron et al. (2011) yields a non-definite variance matrix. This can happen occasionally and is generally not a problem since the variance estimator is asymptotically correct. However, here the clustering factor has only few levels. As a result, I report single-clustered standard errors here. While the effect sizes are slightly different than those in Panel A, the overall conclusion remains the same: Treated investors move to riskier underlyings.

Overall, the evidence in Table 2 supports the notion that treated investors shift their trading activities toward riskier underlyings following the leverage intervention.

5.2.2 IV analysis

As noted above, the main advantage of studying individual trading data around the regulatory intervention is that it allows me to observe whether an investor's leverage constraint is binding. I exploit this opportunity in a cross-sectional instrumental variable estimation. Intuitively, an investor is constrained if s/he exploited leverage to a degree that is no longer available following the intervention. Those investors exhibit (unobservable) risk preferences that drive their preference for leverage; however, treated investors had the ability to apply leverage only prior to the intervention and consequently are constrained following the intervention. The IV assumes that the instrument—the regulatory intervention—affects the

[8]The model includes the following index returns, all interacted with the ESMA-dummy: NYSE Composite Index, FTSE 100 Index, Helsinki General Index (HEX), Madrid Stock Exchange Index, Hang Seng Index, Nikkei 225 Index, Swiss Market Index, Belgium General Index, CAC 40 Index, Deutscher Aktienindex (DAX) Index, Amsterdam AEX Index, OBX Index, OMX Copenhagen 20 Index, PSI 20 Index, Tadawul All Share Index, and OMX Stockholm 30 Index.

outcome—the risk-taking measure—only through the instrumented variable—reduction in the use of leverage. Thus, the effect estimated with the IV approach using the regulatory intervention as the instrument captures the change in risk-taking measures as a result of the reduction in leverage following the intervention—a "treatment of the successfully treated" effect. Thus, the IV approach enables me to isolate the substitution channel; i.e., investors substitute leverage with riskier underlyings.[9] Studying both the DID and the IV is also in line with the suggestion of Atanasov and Black (2016), who argue that "DID and shock-based IV are close cousins" (p. 283) and recommend that researchers use both approaches.

In general, instruments must fulfill two requirements. Instruments have to predict the actual "treatment." The ESMA intervention clearly predicts the change in leverage-usage for treated investors, particularly for investors who habitually took on leverage amounts that were above the new threshold. Second, instruments must not have a direct effect on the outcome of interest. Clearly, the intervention does not introduce any restrictions on the stocks or instruments that investors trade. Formally, I estimate the following regressions. For the first stage, I estimate

$$\Delta\text{Leverage}_i = \alpha + \beta_1 \text{intervention}_i + \sum_{ij} \beta_j \text{control}_{ij} + \varepsilon_i, \tag{2}$$

where ΔLeverage is the change in leverage-usage from July to August 2018 for investor i. The control variables include demographic information (age and gender) and previous trading characteristics (self-reported trading experience, self-reported trading horizon, previous leverage-usage, previous trading performance). Then, for the second stage, I estimate

$$\Delta\text{Risk-taking}_i = \alpha + \beta_1 \widehat{\Delta\text{Leverage}_i} + \sum_{ij} \beta_j \text{control}_{ij} + \varepsilon_i, \tag{3}$$

where $\Delta\text{Risk-taking}_i$ denotes the change in the various risk-taking measures for July to August 2018, and $\widehat{\Delta\text{Leverage}_i}$ is the fitted change in leverage-usage from equation (2). As the IV considers only the change in trading from July to August 2018, the analysis includes

[9] In contrast, the DID coefficient estimates the total effect of the intervention on the outcome but does not narrow the channel. Thus, I use what is commonly viewed as a drawback of IV estimation (i.e., that it is based on only the subset of investors who are affected by the instrument; see, e.g., Imbens and Angrist, 1994) as an advantage in isolating the channel.

only investors who trade in both months. As a result, and because of the required control variables, the sample is smaller than the DID sample.

Table 3 summarizes the results. Column 1 presents the first stage and shows that treated investors significantly reduced their leverage-usage around the intervention. The coefficient of -1.80 is almost identical to the coefficient of the DID estimation in Table 1 (-1.87). The F-statistic of the first-stage regression is satisfactory (Montiel Olea and Pflueger, 2013; Andrews et al., 2019).

— Place Table 3 about here —

Columns 2 to 5 show the second-stage results. Note that $\widehat{\Delta\text{Leverage}_i}$ takes negative values. Thus, negative coefficients indicate a larger increase in risk-taking measures for an increasing leverage reduction. These results are in line with the DID estimation and support the notion that investors substitute their risk-taking by moving toward riskier underlyings in response to having to reduce their use of leverage.

5.2.3 QTT estimation

In addition to studying the average treatment effect, understanding the distributional impacts of the intervention is helpful. As noted by Callaway and Li (2019), the treatment effects literature explicitly recognizes that the effect of a treatment can be heterogeneous across individuals (see also, e.g., Heckman et al., 1997). Does the intervention affect all treated investors similarly (i.e., through a homogeneous treatment effect), or is the risk-shifting particularly pronounced for investors who trade risky assets more or less often (i.e., through a heterogeneous treatment effect)? Investors who already trade fairly risky stocks may find it difficult to shift to even riskier underlyings. Moreover, investors who abstain from trading risky underlyings, perhaps due to their higher risk aversion, may not be willing to shift to riskier underlyings following the intervention.

I estimate the QTT following the approach by Callaway and Li (2019) to shed light on the distributional effects of the intervention.[10] Figure 5 visualizes the distributional

[10] Estimating the QTT requires several additional assumptions (see Callaway and Li, 2019): In particular, the approach requires the *Distributional Difference in Differences Assumption* and the *Copula Stability*

impacts of the intervention. Panel a shows the QTT for leverage. Mechanically, investors who took higher leverage prior to the intervention had to reduce their leverage to a larger degree. Panel b shows the QTT for conditional volatility. The treatment effect is clearly heterogeneous across investors, with investors who already trade riskier stocks prior to the intervention showing a more pronounced substitution effect. Investors in the lowest deciles do not substitute. Panel c shows unconditional volatility, and Panel d shows IVOL. The results are similar and show that in particular, those investors who trade stocks with high unconditional volatility and high IVOL prior to the intervention, respectively, substitute more. Panel e shows QTT for lottery-type stocks. The variable is based on an average of dummy variables that indicate a lottery-type stock trade. As the median investor in the dataset does not trade lottery-type stocks, the distribution of the variable is different from zero only for the upper part and does not allow a unique sorting for lower deciles. Consequently, I estimate the QTT only for the upper part of the distribution. The results indicate that particularly those investors in the highest deciles increase their trading in lottery-type stocks. Overall, the takeaway from studying the distributional effects of the intervention is the existence of heterogeneous treatment effects: Investors who make riskier trades prior to the intervention move to even riskier underlyings.

— Place Figure 5 about here —

5.2.4 Robustness analyses

Next, I summarize several additional tests to address potential identification issues affecting the DID analysis.

First, investors subject to ESMA regulation and those who are not may differ with respect to both observable and unobservable characteristics. Such differences raise the concern that the control group does not provide feasible controls for the DID analysis. I have already discussed the covariate balance in the sample in Figure 1, which indicates common support for all covariates. I now exploit the common support of investors by balancing the treatment

Assumption. The former requires full independence between the change in untreated potential outcomes over time and whether an individual is treated. The latter requires the (unknown) dependency structure between the change in untreated potential outcomes for the treatment group and the initial level of untreated potential outcomes for the treatment group to stay constant over time.

and control groups on covariates to ensure that the two groups are as similar as possible and use a combined DID/balancing design. Such a procedure increases the credibility of the inference (Atanasov and Black, 2016). I match the treated investors with the control investors using a nearest-neighbor matching routine with respect to trading activities prior to the intervention and standard controls for risk-taking. Finally, I estimate the DID equation (1) with the matched investors. The findings are robust to this approach (Table A.4 in the Appendix), and the coefficients are almost identical to those of the main analysis. In the matched data, I also find a significantly positive coefficient on *lottery type* (0.013, t-statistic of 2.01), which could be explained by the argument of Mitton and Vorkink (2007) that investors have heterogeneous preferences for skewness. As a result of the matching procedure, I now compare investors with similar trading activities (and thus similar preferences for skewness) to each other, whereas the DID analysis of the raw data may compare investors who have preferences for skewness to investors who do not.

To test the differences between the treatment and control groups, I estimate a logit model using $ESMA$ as the dependent variable. The explanatory variables are investors' age, gender, and past trading characteristics (trading intensity, average leverage, average holding period, average volatility of underlying stocks, average lottery type stocks, and average profitability). I repeat this procedure for the raw and the matched data. Then, I calculate the fitted values and the root mean squared error (RMSE) of the fitted values. A forecast with absolutely no explanatory power has an RMSE of .399 [median: .275] for the raw data (as the treatment and the control groups are of unequal size) and of .5 [median: .5] for the matched data. The distributions of the RMSEs are presented in Figure A.1 in the Appendix. The mean [median] RMSE is .395 [.295] for the raw data and .495 [.495] for the matched sample, which enables me to conclude that the treatment and control groups are already very similar in the raw data and that the matching procedure yields an even closer match.

Next, I run a placebo analysis. In particular, I create a random sample of pseudotreated investors. First, I randomly select a sample of 20,000 investors from the treatment group and 20,000 investors from the control group. Second, I randomly assign ESMA regulations to these 40,000 investors. Finally, I repeat the DID analysis and estimate equation (1). The results in Table A.5 in the Appendix show that the pseudotreated investors do not yield statistically significant results.

Overall, the additional tests support the results of the main analysis and the notion that investors move toward riskier underlyings in response to the intervention.

5.2.5 Trading of cryptocurrencies

I provide additional evidence in support of the hypothesis that investors shift to riskier underlyings and study the average trading activity in cryptocurrencies. In the dataset, even the 95th percentile of the unconditional volatility of stocks is smaller than the lowest unconditional volatility of cryptocurrencies. Thus, turning to cryptocurrencies may provide investors with alternative paths to volatility. I estimate equation (1) using *Crypto* as the dependent variable and report the results in Table 4. The coefficient indicates a significant increase in the use of cryptocurrencies following the intervention. The coefficient is 0.018 (t-statistic of 2.98). Economically, the coefficient amounts to 8.6% of the standard deviation of crypto, and this magnitude is the same as that of the coefficient in Column 1 of Table 2. In a similar fashion, I exploit the volatility of all assets, including cryptocurrencies, and report the results in Column 2. The coefficient of 0.026 (t-statistic of 4.21) is in line with the previous results and indicates a move toward riskier underlyings.

— Place Table 4 about here —

5.2.6 Spillover effects

Finally, I turn to the potential spillover effect of the intervention as a result of social connections among investors. Boehmer et al. (2020) highlight the importance of potential "spillovers" in financial regulatory experiments. As noted above, potential indirect treatment effects, or spillovers, relate to the SUTVA of the Rubin causal model (Rubin, 1980). The critical condition is that treating one individual does not affect other treated or control individuals (Atanasov and Black, 2016). As peers' trading may influence other investors' trading (see, e.g., Manski, 1993, 2013; Ouimet and Tate, 2020, among others), the risk-shifting of treated peers may influence the risk-taking of investors not directly affected by the intervention but rather in a "spillover" group via the network.

Han et al. (2022) build on the general idea that investors spend a substantial part of their leisure time discussing investments or sharing information about others' successes or failures in investing (Shiller, 1984) and show how risky investment strategies propagate through the population (see also Heimer and Simon, 2015). Similarly, various social interaction models support the argument that individuals within a peer group make more similar choices than do the general population (Bursztyn et al., 2014; Ouimet and Tate, 2020), either in an effort "to keep up with the Joneses" (Abel, 1990; Galí, 1994) or due to the exchange of information (Banerjee, 1992; Bikhchandani et al., 1998). Extremely high returns reported in social interactions are highly salient. As a result, investors may be attracted to volatile (and positively skewed) stocks by social interactions even if they do not have inherent preferences for such stocks (Han et al., 2022).[11] Consequently, trading strategies using highly risky underlyings may spread through the population and also affect investors who are not affected by the new leverage restrictions.

The scopic regime (Gemayel and Preda, 2018) of the trading platform provides a perfect environment for spillover effects. Investors can share their trading strategies on the trading platform (see also Heimer, 2016). In the following, I exploit the social features of the platform and investigate potential spillover effects. Specifically, the data allow me to identify social relations between investors that have formed on the trading platform and then investigate whether a social transmission of investment strategies via these connections occurs.

Social relations The dataset contains information on the social relations of investors on the trading platform. On the platform, investors can manually or automatically duplicate other investors' trades. While I do not include these "social" trades in the analysis, I exploit them to identify investors who have ties to one another.[12] Investors who duplicate the trades of other investors closely observe their trading activities (see also Pelster and

[11] Even as the intervention drastically reduces the leverage-usage for a subset of investors, resulting in a post-intervention distribution of the returns that is less skewed, investors may nonetheless be attracted to more volatile rather than less volatile stocks due to social interactions, as also argued by Han et al. (2022).

[12] I do not include these trades in the analysis because the decision to trade a particular underlying in this situation is distinctively different from independent individual trading decisions and more akin to trading based on financial advice or with a financial advisor (Hoechle et al., 2017). Nonetheless, social trades affect investors' overall portfolio risk. Given that investors hold, on average, very few individual stocks in their portfolio, I believe that it is reasonable to assume that they are more focused on stock-level positions and do not follow a portfolio approach.

Hofmann, 2018). Thus, these investors are more likely to take notice of a change in the trading strategies of their connected peers than are investors who do not duplicate trades of this peer. Importantly, the connection between investors is directed. While an investor who duplicates the trading activity of another investor closely monitors this investor, an investor who is duplicated does not necessarily pay attention to the trading activities of those duplicating their trades. Thus, I define investor A as having a relation with investor B if they duplicate at least one trade of investor B in the previous month. This procedure is similar to that of Pelster (2017) and leads to a total of 245,858 monthly connections between investors. Figure 7 visualizes the resulting network in August 2018, the month the intervention became effective.

— Place Figure 7 about here —

Spillover regression analysis Based on the resulting network, I define an investor as belonging to the "spillover group" when they have a direct relation to a treated investor. I study potential spillover effects in a variation of the DID (Butts, 2021; Clarke, 2017) in equation (1), where the variable *treatment group* is now defined as categorical and can take three values: treatment, spillover, and groups. In this instance, the control group contains only investors who are neither directly affected by the intervention, that is, subject to ESMA regulations, nor are they related to a treated investor. This definition of the spillover group assigns 5,779 investors from the control group to the spillover group. In addition to the *parallel changes in treatment and control* assumption, this analysis requires a *parallel changes in spillover and control* assumption (Butts, 2021; Clarke, 2017).

Identifying the correct peer group is crucial to the spillover analysis. Therefore, in an alternative specification, I define all investors who are not subject to ESMA regulation but at some point during the sample period engage in relations with other investors on the platform as part of the spillover group. The argument is that investors who, in general, are open to social interactions on the platform—as indicated by their relation to other investors on the platform—are more likely to study the trading activities of their peers than are investors who never engage in social interactions. As a result of this increased likelihood of observing other investors, they are also more likely to become aware of the shift toward riskier underlyings of their peers. This definition of the spillover group assigns 6,742 investors from the control group to the spillover group.

— Place Table 5 about here —

Table 5 summarizes the results of the spillover analysis. In Panel A, the spillover group is defined on direct relations to treated peers. Column 1 focuses on leverage-usage and shows that the general finding that treated investors reduce their leverage is robust to the alternative specification. The coefficient on $spillover \cdot post\ intervention$ is -0.08 (t-statistic of 1.99) and is thus very small compared to the direct effect $ESMA \cdot post\ intervention$. The remaining columns of Panel A of Table 5 focus on the substitution strategies. For all of the dependent variables, *volatility*, *SD Stock*, *IVOL*, and *lottery type*, I observe a significantly positive coefficient on the direct effect ($ESMA \cdot post\ intervention$). The effect sizes are similar to those of the main analysis. Turning to the indirect spillover effect ($Spillover \cdot post\ intervention$), I observe a coefficient of 0.002 for *volatility* (t-statistic of 1.70), of 0.007 for *SD Stock* (t-statistic of 1.88), and of 0.009 for *lottery type* (t-statistic of 1.98). For all three variables, the indirect effect is smaller than the direct effect. While the ratio of the spillover effect to the direct effect amounts to approximately 1/4 for volatility, this ratio is about 3/4 for lottery-type stocks. I do not find meaningful spillover effects for *IVOL*.

Panel B uses the alternative definition of the spillover group and shows similar results. The direct effects remain virtually the same. For the indirect effects, the coefficients are also almost identical. The t-statistics are slightly larger in this setting (*volatility*, 0.002, t-statistic of 2.13; *SD Stock*, 0.007, t-statistic of 2.01; *lottery type*, 0.01, t-statistic of 2.22).

Of course, an important question is why lottery-type stocks in particular are subject to such a pronounced spillover effect. Han et al. (2022) provide a possible explanation with their *social transmission bias*, which highlights how risky investment strategies propagate through the population. Consistent with the predictions of Han et al. (2022) that investors are drawn to lottery stocks as a result of social interactions, Bali et al. (2021) show that a higher intensity of social interactions contributes to stronger investor attraction to lottery stocks. More extensive social interactions can help increase investors' awareness of positively skewed assets through word-of-mouth communication (Bali et al., 2021). Based on this notion, an especially high spillover effect for lottery-type stocks seems plausible.

5.3 Investors' aggregate risk-taking

The observation that treated investors reduce their leverage-usage following the intervention but also shift their trading activities toward riskier underlyings raises the question of the aggregate effect of the intervention on investors' risk-taking. I use equation (1) and *leverage* $\times$ *volatility*, defined as the product of the leverage of a particular trade with the volatility of the underlying stock, to investigate the aggregate impact on risk-taking. Table 6 summarizes the results.

— Place Table 6 about here —

The treatment coefficient is negative (-0.18) and statistically significant with a t-statistic of 20.16, indicating that, on average, investors take less risky positions following the intervention. Considering the drastic decrease in investors' leverage-usage of -1.87, it is not surprising that the aggregate effect is indeed negative because investors would have to shift toward stocks that are 2.9 times as risky as the stocks that they traded prior to the intervention. Considering the average volatility of all of the stocks that investors in the sample traded during the sample period, such a shift could not even be achieved when moving from the 25% quantile (volatility of 0.07; see Table A.2 in the Appendix) to the 75% quantile (volatility of 0.13). Thus, the intervention was effective in the sense that the overall risk-taking of investors was reduced. Nonetheless, an evaluation of the intervention that neglects the shift toward riskier underlyings overestimates the effectiveness of the intervention. In Section 6, I shed additional light on specific groups of investors and study the risk-shifting behavior of, for example, investors who traded with particularly high leverage prior to the intervention, as these investors naturally had to reduce their leverage-usage to the largest extent (see also Panel D of Table 2 and the IV analysis in Section 5.2.2).

5.4 A portfolio perspective

One advantage of the individual trading data is that I also observe the portfolio of each investor at each point in time, which enables me to investigate the impact of the intervention on investors' portfolio composition. While investors may move to stocks with larger idiosyncratic risk, these risky positions may not increase investors' portfolio risk if they yield significant diversification benefits. Consequently, I study the impact of the intervention on investors' portfolio risk.

— Place Table 7 about here —

Table 7 summarizes the results of the analysis. Panel A studies the number of stocks in investors' portfolios and their HHI. The results indicate that, compared with those in the control group, treated investors do not increase the number of stocks in their portfolios or their portfolio diversification (as measured with the HHI). Instead, they hold slightly more concentrated portfolios following the intervention.

Panel B focuses on the expected portfolio return and the portfolio risk. Notably, the expected returns of the portfolios of treated investors do not change meaningful compared to those of control investors—on an economic scale. However, treated investors increase their portfolio risk (Column 2) by adding both systematic (Column 3) and idiosyncratic risk (Column 4). Thus, the portfolio analysis is in line with Table 2 and indicates a shift toward riskier underlyings that is not compensated by an additional diversification benefit.

Finally, Panel C studies the leveraged expected returns and risk measures, which is analogous to the analysis in Table 6. The results are also analogous to those in Table 6 and indicate an overall reduction in risk-taking and no change in expected return. Again, it is important to note that—while risk-taking decreases—the decrease is smaller than the reduction in leverage indicates due to the shift to riskier underlyings (see Panel B).

5.5 Trade profitability and holding times

As highlighted by, for example, Barber et al. (2020), Heimer and Imas (2022), and Subrahmanyam et al. (2023), leverage is associated with poor investment performance, particularly for less sophisticated investors.

Table 8 provides a performance analysis using the DID approach and equation (1). Following Arnold et al. (2022), I use the leveraged holding-period returns of investors' trades. Column 1 indicates a significant increase in profit of approximately 1.24 percentage points, which is economically quite important.

— Place Table 8 about here —

Given that leverage-usage is supposed to widen the profitability distribution by making larger positive and negative realizations more likely, I expect stricter regulatory boundaries to also reduce the variability of leveraged returns. In line with this notion, Column 2 indicates that SD(profit) is significantly smaller for treated investors after the intervention (-3.18, t-statistic of 12.97). This observation is underlined by a comparison of the profitability distributions of treated investors before and after the intervention (see Figure 6). Most notably, the distribution of returns after the intervention lacks a significant probability weight in the lower tail. In particular, losses larger than 60% appear to occur much less frequently following the intervention than they did before the intervention. I also observe significantly less distribution mass for reasonably large profits. In particular, profits between 20% and 50% are less frequent following the intervention.

— Place Figure 6 about here —

Inspired by the observation of Subrahmanyam et al. (2023) that the forced liquidation of positions contributes to investors' poor performance when trading on leverage, I examine average holding times before and after the intervention. Intuitively, more restrictive leverage constraints should reduce the number of positions that are forcibly closed, which should increase the average holding times of treated investors following the intervention. Table 9 provides evidence in support of this notion. On average, treated investors hold their positions 1.3 days longer than do control investors following the intervention.

— Place Table 9 about here —

6 The influence of investor characteristics

Risk-taking varies as a function of the characteristics of the decision maker (see, e.g., Arnold et al., 2022). Thus, to better understand the risk-shifting activities and their nature and to provide a deeper understanding of the main result, I now provide several cross-sectional analyses. To this end, I split the sample according to several investor characteristics. In particular, I introduce a difference-in-differences-in-differences (DDD) approach with interaction terms with variables related to investors' trading activities prior to the intervention, gender, age, and trading experience. Based on sample medians or 25% quantiles, I create dummy variables that split the sample into below- and above-threshold portions. Where medians are not appropriate, i.e., gender, I rely on the splits that directly result from the respective variable.

Intuitively, the leverage intervention should most affect investors who frequently made use of high leverage prior to the intervention (see also Section 5.2.3 and Figure 5, Panel a). Moreover, we would expect investors who have a particular preference for risky trading—as indicated by their high leverage-usage—to seek alternative paths to taking risky positions. Consequently, I begin by studying the influence of leverage-usage prior to the intervention and introduce a variable *high leverage* that takes a value of 1 for investors who took leverage in the top 25% quantile prior to the intervention, and 0 otherwise.[13] Panel A of Table 10 summarizes the results.

— Place Table 10 about here —

Consistent with intuition, I find that, in particular, investors who took high leverage prior to the intervention (a) reduce their leverage-usage to a larger degree and (b) substitute significantly more than do investors who used less leverage. In Column 1, not surprisingly, the coefficient on $ESMA \cdot post\ intervention \cdot high\ leverage$ is -2.72 and statistically highly significant, with a t-statistic of 47.8. Because the coefficient on $ESMA \cdot post\ intervention$ is also negative (-1.18) and highly significant, both treated high-leverage investors and those

[13]Note that the intuition of this approach is similar to Panel D of Table 2, the IV approach in Section 5.2.2, and the QTT estimation in Section 5.2.3. However, the quantile regression conditions on the dependent variable in the regression, while here, all estimates are "conditional" on leverage.

who are treated but used lower levels of leverage reduce their leverage by economically highly meaningful levels; however, high-leverage investors do so by more than three times as much (-1.18 vs. $-3.54 = -0.82 - 2.72$).

A similar picture emerges for the shift toward riskier underlyings (Column 2). The coefficient on $ESMA \cdot post\ intervention$ remains positive, indicating a general move toward riskier stocks by treated investors. In addition, the coefficient on $ESMA \cdot post\ intervention \cdot high\ leverage$ is positive and significant, indicating heavier substitution by high-leverage investors. Turning to performance implications, the results in Column 3 show that high-leverage users do not realize significantly larger returns following the intervention.

Investor skill is important when trading on leverage. Subrahmanyam et al. (2023) highlight that unskilled investors in particular suffer from poor performance due to their leverage-usage. In contrast, skilled investors benefit from leveraged positions because they are able to time the market.[14] Consequently, I analyze the influence of investor skill using average trading performance prior to the intervention as a proxy for skill. However, as the intervention addresses only leverage-usage, only low-skilled investors who took leverage above the new threshold should benefit from the intervention. In other words, the intervention should not improve the performance of low-skill investors who lost before the intervention, but not because of high leverage-usage position. Thus, I define investors who took the maximum leverage prior to the intervention and who realize an overall performance in the bottom 25% of returns to be low-profit investors and argue that these investors show poor trading skills. Panel B of Table 10 summarizes the results.

The results in Panel B largely mirror those in Panel A. In general, this is not surprising, as I observe an overlap of investors in the bottom 25% of returns and the top 25% of leverage users of 81%, and the analysis is also conditioned on a leverage-usage of 10 prior to the intervention. The coefficient on $ESMA \cdot post\ intervention \cdot low\ profit$ is smaller (-1.83) than the coefficient on $ESMA \cdot post\ intervention \cdot high\ leverage$; however, the substitution

[14] The reason behind this finding is that unskilled investors suffer from behavioral biases and a tendency toward gambling. Arnold et al. (2022) show that individual attention triggers induce investors to trade with higher leverage. Barber et al. (2020) show that overconfidence can explain the use of leverage, while Heimer and Imas (2022) find that having the option to use leverage exacerbates biases such as the disposition effect. Hence, leverage constraints can improve financial decision-making by reducing behavioral biases and thereby increasing investors' trading performance.

coefficients of the three-way interactions are similar in magnitude. With respect to trading performance, low-profit investors benefit from the intervention more than do other investors.

Moreover, gender and age have been documented to be significant determinants of risk-taking (He et al., 2008; Morin and Suarez, 1983; Powell and Ansic, 1997). Panel C of Table 10 summarizes the results on the influence of gender. Column 1 indicates that male investors are particularly affected by the intervention and reduce their leverage-usage accordingly. However, male investors do not substitute more. With respect to trading performance, I observe weak evidence that male investors realize larger returns following the intervention (Column 3, coefficient of 1.67, t-statistic of 1.75).

Next, I turn to the influence of investor age (Panel D). The baseline age group is $18-25$. Column 1 shows the change in leverage. The decrease in leverage-usage decreases monotonically with age. Younger investors (have to) reduce their leverage-usage to a larger extent than do older investors, and those in the age group > 65 reduce their leverage the least. A similar picture emerges for the move toward riskier underlyings. In particular, investors from the baseline age group $18-25$ trade more volatile stocks following the intervention (Column 2), whereas older investors substitute very little ($55-64$) or not at all (> 65). The analyses of the trading performance do not yield any clear-cut observations.

Experience has been documented to have large implications for investors' behavioral errors and trading tactics (Arnold et al., 2022; Feng and Seasholes, 2005; Kaustia and Knüpfer, 2008). Consequently, I study the impact of investors' experience, using two proxies for experience. First, I use self-reported trading experience. Second, I proxy "learning by trading" and use the number of trades before the intervention as a proxy of experience. Panels E and F of Table 10 summarize the results. Low-experience investors reduce their leverage to a lesser degree than do investors with more self-reported trading experience and more trading experience. Thus, the intervention does not appear to particularly benefit inexperienced investors.

Finally, I consider investors' (self-reported) trading horizons (Panel G). The baseline is a long-horizon investor. Column 1 indicates that short-horizon investors in particular reduce their leverage-usage following the intervention. These are also the investors who show a more pronounced shift to more volatile underlyings (Columns 2). Their profitability is not affected to a larger extent than that of long-term investors.

To summarize, the cross-sectional analyses indicate that young, risk-seeking, short-term-oriented, and poorly performing investors (have to) reduce their leverage-usage and respond to the intervention with a shift toward riskier underlyings. Inexperienced investors do not reduce their leverage-usage quite as much and do not benefit specifically. Overall, these findings could be interpreted as consistent with the notion that investors who purposefully take risky positions (i.e., short-term-oriented, risk-seeking investors) show a more focused move toward riskier underlyings.

7 Conclusion

This study presents novel evidence on the impact of a regulatory intervention intended to limit the risk-taking of retail investors based on a unique dataset of international trading records. As intended, the intervention reduced investors' average leverage-usage. However, my results also indicate that investors have shifted their trading activities toward riskier underlyings. In particular, compared to control investors who were not subject to the intervention, treated investors traded stocks with higher volatility, stocks with higher idiosyncratic volatility, and more cryptocurrencies following the intervention. Nonetheless, overall risk-taking is slightly lower following the intervention; that is, investors did not fully compensate for lower leverage-usage with their shift toward riskier assets. Considering the drastic decrease in leverage-usage due to the intervention, this is not particularly surprising since investors may have difficulties finding stocks that supply sufficient volatility. Nevertheless, neglecting the shift toward riskier underlyings results in overestimation of the effectiveness of the intervention.

I complete the picture with several refinements to my main result. Specifically, I show that particularly young, risk-seeking, short-term-oriented, and poorly performing investors reduce their leverage-usage and shift toward riskier underlyings following the intervention. Inexperienced investors, who do not reduce their leverage-usage quite as much, do not particularly benefit from the intervention.

Overall, the findings of the paper may be interpreted as plausibly causal evidence of investors having a preference for risky positions. As a result, they move toward riskier underlyings in an effort to compensate for the reduced availability of leverage. A detailed understanding of individual risk-taking is important for the study of choice under uncertainty and for a better comprehension of financial markets and financial stability (e.g., Charness and Sutter, 2012; Lian et al., 2018; Liu et al., 2010). This paper complements earlier studies that have shown correlations between retail investor holdings and certain types of stocks. My study also complements the banking literature on regulatory arbitrage and shows that the reallocation of risk-taking behavior is not only unique to financial institutions but also relevant when analyzing the effectiveness of regulatory interventions designed for retail investors.

Investors increasing their trading intensity in different underlyings can have implications for the market as well (Frazzini and Pedersen, 2014). As highlighted by Foucault et al. (2011); French and Roll (1986); Jones et al. (1994) and Avramov et al. (2006), among others, correlated trading can increase stock volatility and create return comovement (Kumar et al., 2016). Thus, when investors shift their trading activities to more volatile stocks, doing so may increase the volatility of the stocks even further. As the focus of this paper is on CFDs, which are traded over-the-counter (OTC), and CFD-traders, who trade with short-investment horizons and are most likely price-takers, I leave such an analysis to future research. However, even if the CFD traders used in the analysis may not be representative of the overall population of investors, the recent episode surrounding meme stocks and Reddit investors vividly highlights the potential impact of a group of nonrepresentative investors on financial markets.

In addition to moving to riskier underlyings, investors could also switch to different financial products that may be less regulated. For example, investors may decide to trade financial products with *embedded leverage* (for example, options, structured financial products, or leveraged exchange-traded funds) (Frazzini and Pedersen, 2021). Such products may be attractive for investors, as they provide access to leverage for investors who may be unable to use sufficient outright leverage (Frazzini and Pedersen, 2021). Unfortunately, the broker does not provide access to such instruments, and my dataset does not include such trades. Thus, I leave this analysis to future research.

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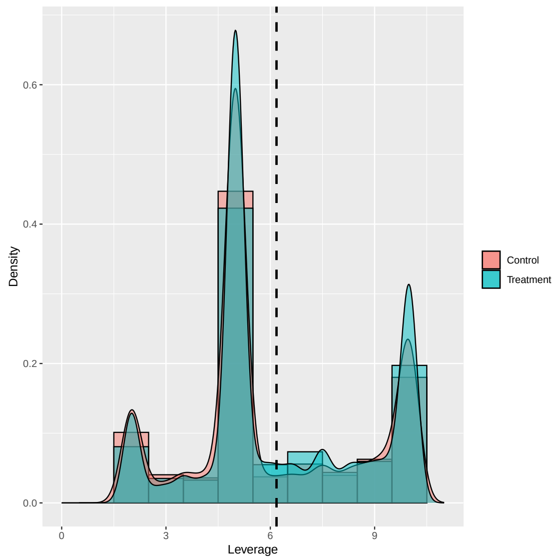
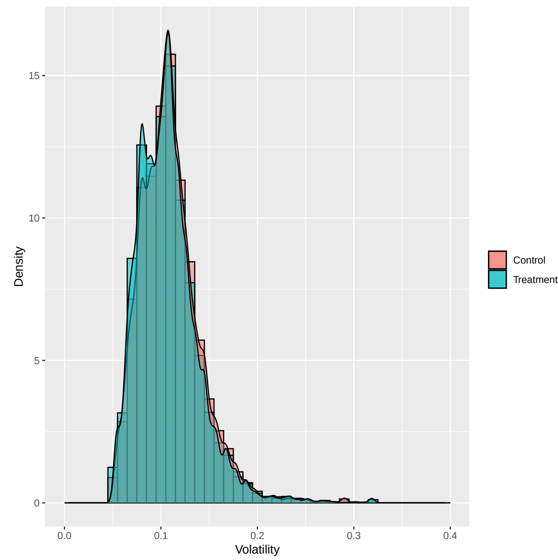
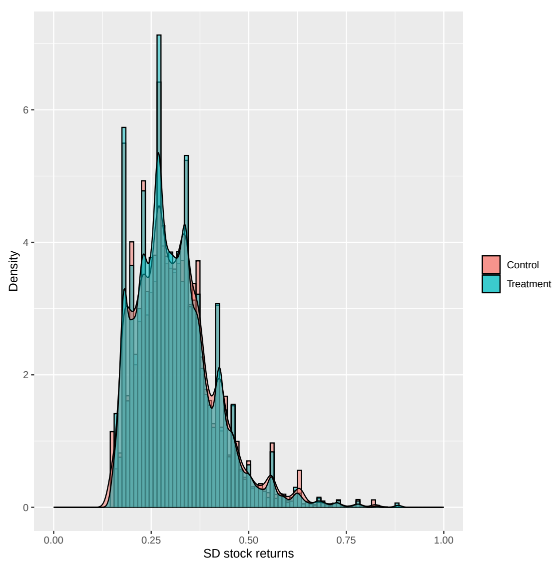


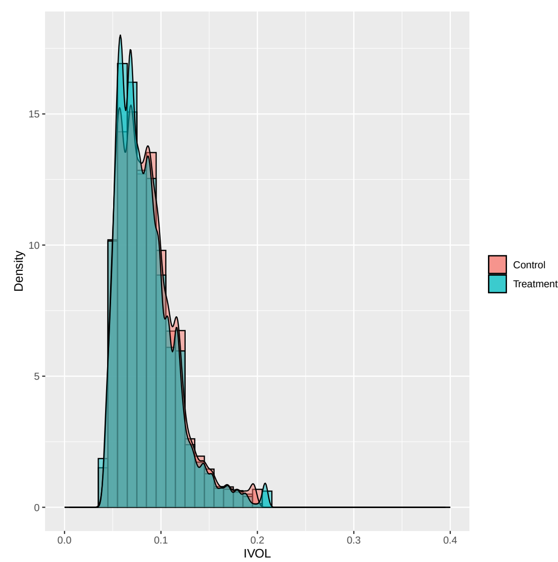
(a) Leverage



(b) Conditional volatility

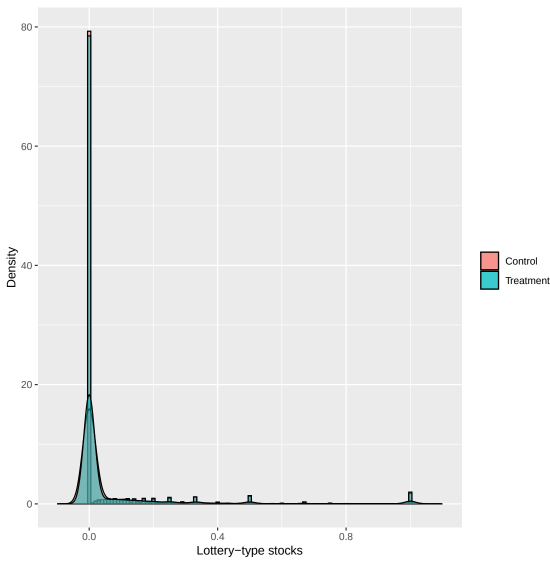


(c) Unconditional volatility

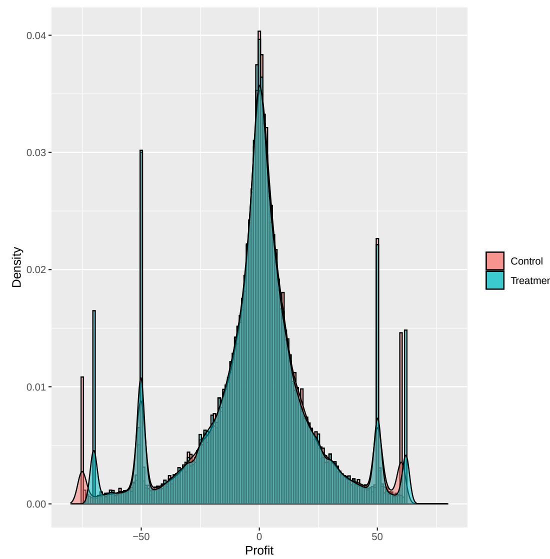


(d) IVOL

Figure 1: Distribution of trade characteristics, split by treatment group.



(e) Lottery-type stocks



(f) Profit

Figure 1: Distribution of trade characteristics, split by treatment group (cont.).
This figure presents the distributions of the average leverage-usage (Panel a), GARCH(1,1) volatility (Panel b), standard deviation (Panel c), idiosyncratic volatility (IVOL, Panel d), and lottery type based on Kumar (2009) (Panel e) of CFDs on stocks that investors trade prior to the leverage intervention at the investor-month level. Panel f shows the distribution of holding-period returns. The control group (red) comprises all investors who are not affected by the intervention. The treatment group comprises all investors subject to the intervention restricting the use of leverage on August 1, 2018. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

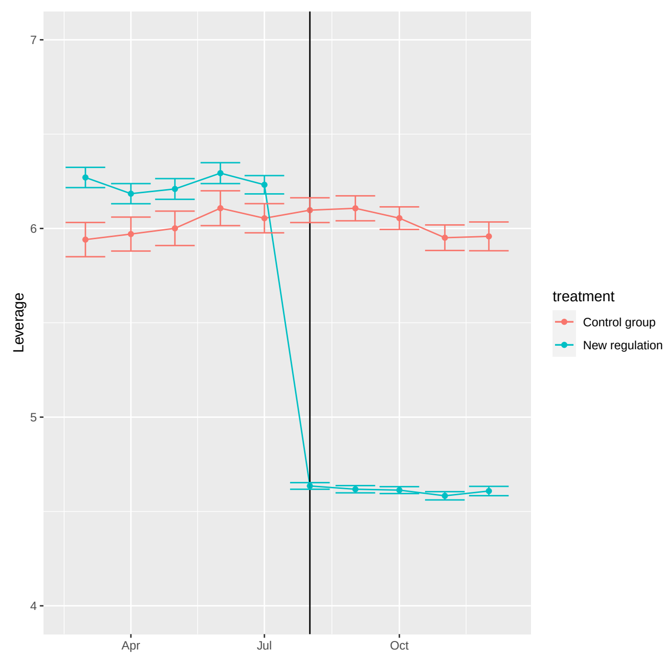
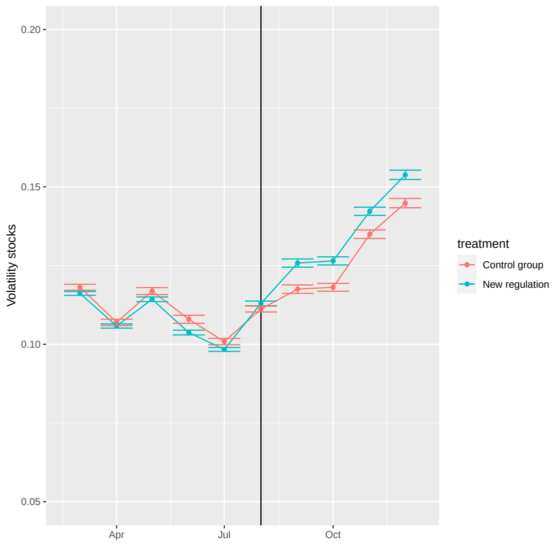
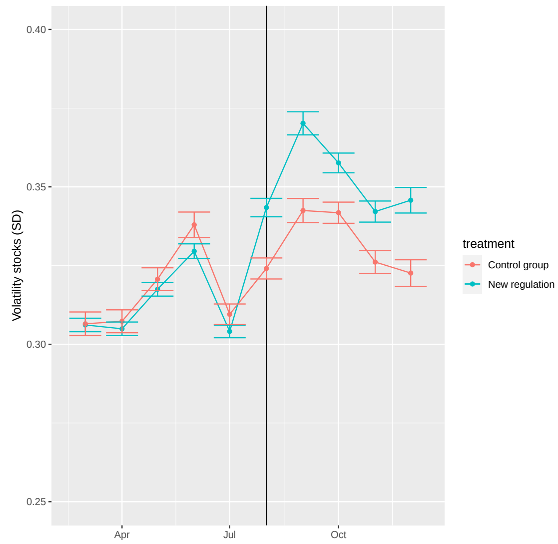


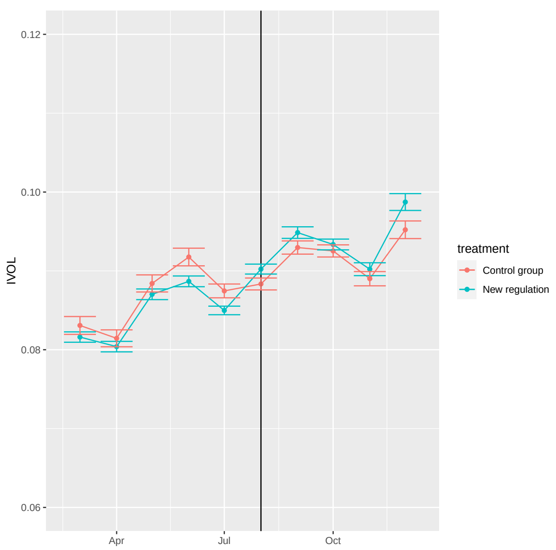
Figure 2: Leverage-usage around the regulatory intervention.
This figure presents the average use of leverage by investors around the leverage intervention. The control group (red) comprises all investors who are not affected by the intervention. The treatment group comprises all investors subject to the intervention restricting the use of leverage on August 1, 2018. The graph shows the average use of leverage of all CFD trades on stocks in a given month. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.



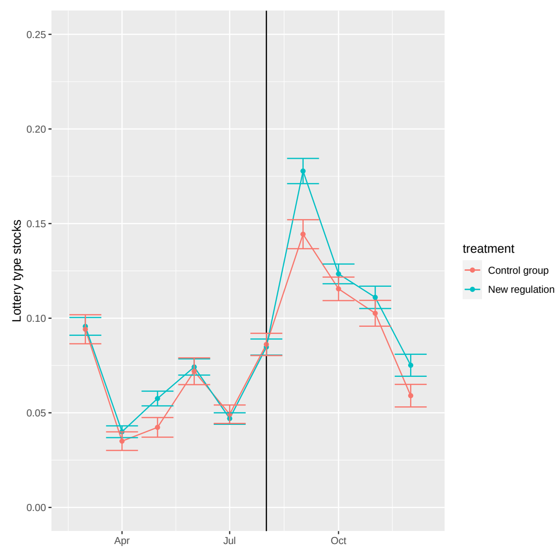
(a) Conditional volatility



(b) Unconditional volatility

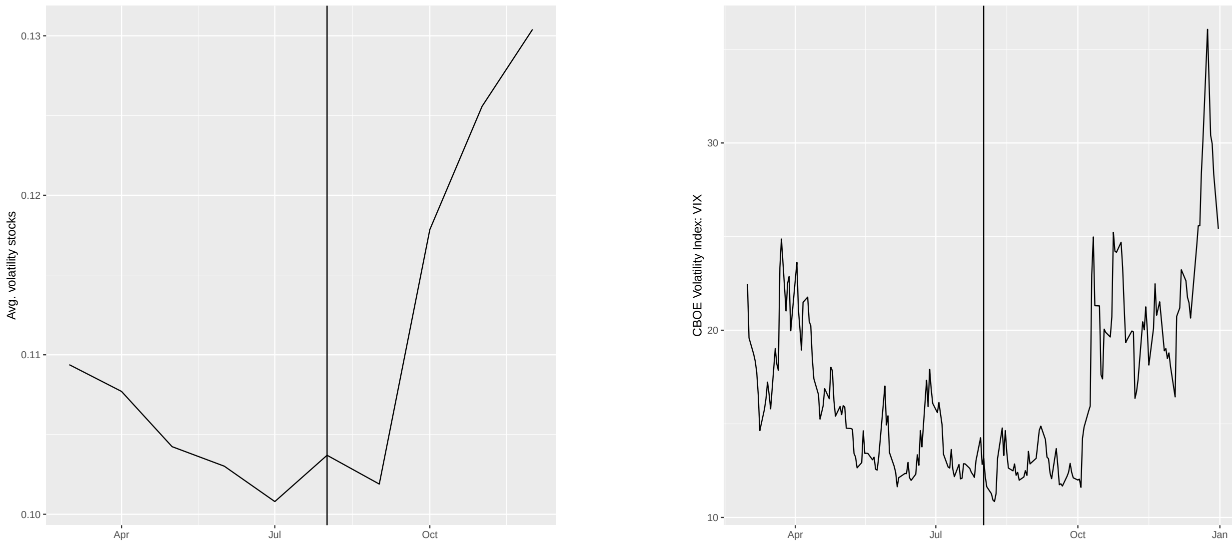


(c) IVOL



(d) Lottery-type stocks

Figure 3: Average risk of stocks traded around the regulatory intervention.
This figure presents the GARCH(1,1) volatility (Panel a), average standard deviation (Panel b), idiosyncratic volatility (IVOL, Panel c), and lottery type based on Kumar (2009) (Panel d) of CFDs on stocks that investors trade around the leverage intervention. The control group (red) comprises all investors who are not affected by the intervention. The treatment group comprises all investors subject to the intervention restricting the use of leverage on August 1, 2018. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

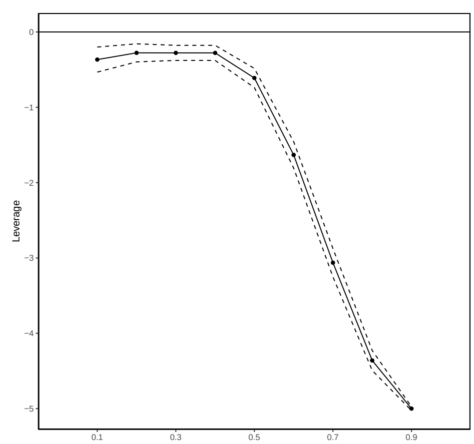


(a) Average stock volatility

(b) CBOE Volatility Index: VIX

Figure 4: Average market volatility in 2018.

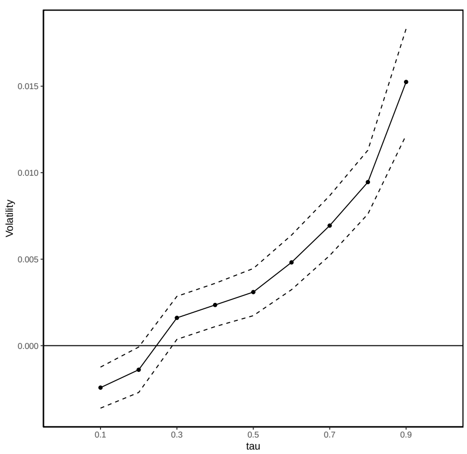
This figure presents the average GARCH(1,1) volatility (Panel a) of all stocks that investors can trade on the trading platform and displays the CBOE Volatility Index (VIX, Panel b).



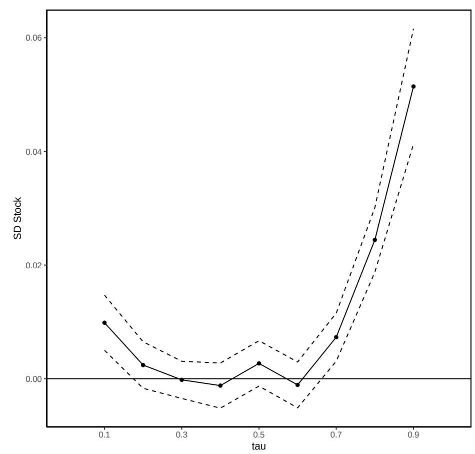
(a) Leverage

Figure 5: QTT estimates of the substitution effect around the regulatory intervention.

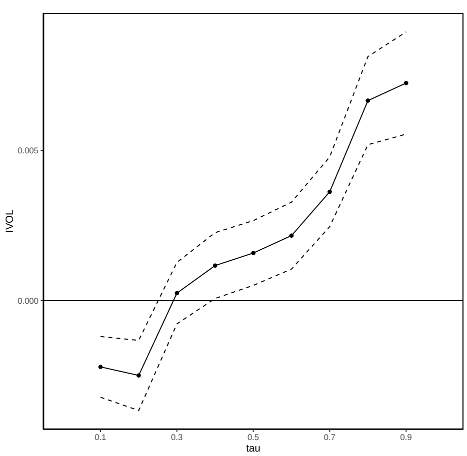
This figure presents QTT estimates of leverage (Panel a), the GARCH(1,1) volatility (Panel b), average standard deviation (SD Stock, Panel c), IVOL (Panel d), and lottery type (Panel e). QTT estimates are estimated using the procedure of Callaway and Li (2019). 95% pointwise confidence intervals are computed using a bootstrap procedure with 1000 iterations.



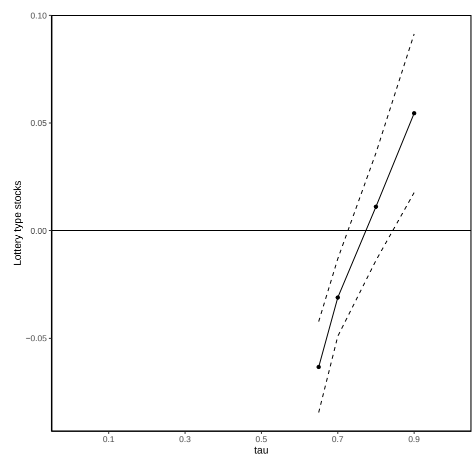
(b) Conditional GARCH volatility



(c) SD Stock



(d) IVOL



(e) Lottery-type stocks

Figure 5: QTT estimates of the substitution effect around the regulatory intervention (cont.).

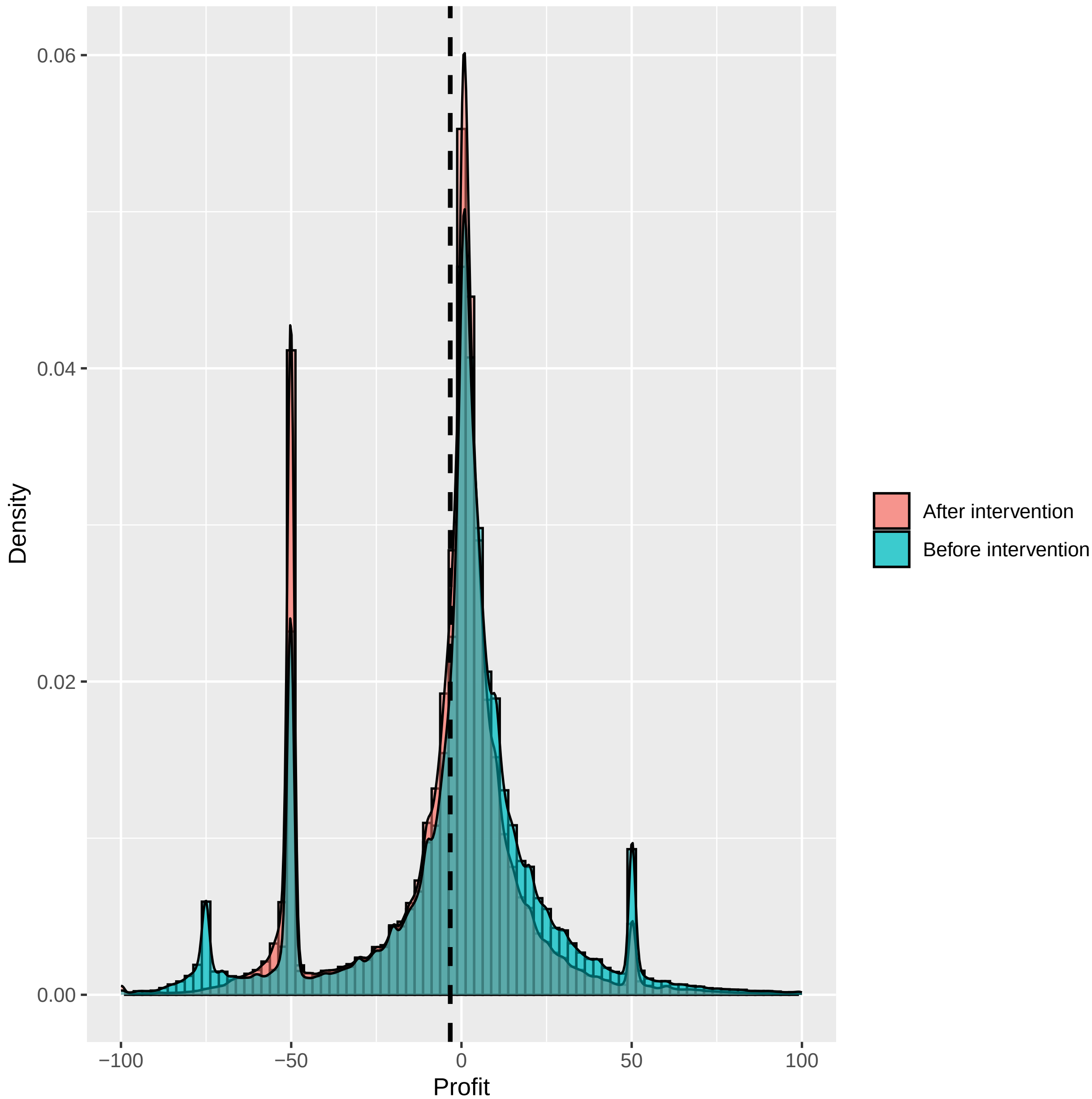


Figure 6: Distribution of holding-period returns of ESMA investors.
This figure presents the holding-period returns of individual positions that investors subject to the leverage intervention open before (green) and after (red) the intervention.

Figure 7: Network model of the trading platform based on trade data

The figure illustrates the network model of the trading platform based on the trade data. Each node represents an investor of the network. Two investors are connected by a directed edge if one investor manually or automatically duplicates trades from the other investor in August 2018.

Table 1: Leverage-usage following the intervention: Difference-in-differences analysis.

This table reports the results from a difference-in-differences regression analysis on the leverage-usage of trades that investors initiate in the trade data. Column 1 contains the full sample. Column 2 is restricted to investors who used a leverage of 10 at some point prior to the intervention (binding intervention). Column 3 is restricted to ESMA investors and compares investors who used a leverage of 10 at some point prior to the intervention to those who did not. *Leverage* denotes the average leverage employed for a trade. The leverage is aggregated at the monthly level using a simple average. *ESMA / Binding* is a dummy variable that takes a value of 1 for investors subject to the leverage intervention [Column 3: who used a leverage of 10 at some point prior to the intervention], and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are double-clustered at the individual investor level and over time using the method of Cameron et al. (2011) to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

	(1)	(2)	(3)
Sample	Main	Binding intervention	Binding vs. non-binding intervention
Dependent var.	Leverage	Leverage	Leverage
ESMA / Binding · post intervention	-1.866	-2.863	-2.694
	(-64.39)	(-58.34)	(-45.04)
Investor fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Obs.	209,671	154,873	138,857
Adj. R^2	0.60	0.63	0.64
No. investors	49,696	36,046	28,694
No. month	10	10	10

Table 2: Risk-taking following the intervention: Difference-in-differences analysis.

This table reports the results from a difference-in-differences regression analysis on various risk-taking measures of trades that investors initiate in the trade data. In Panel A, initiated trades are equally weighted at the investor level over a given month. Panel B is restricted to investors who used a leverage of 10 at some point prior to the intervention (binding intervention). Panel C is restricted to ESMA investors and compares investors who used a leverage of 10 at some point prior to the intervention to those who did not. In Panel D, initiated trades are investment-weighted at the investor level over a given month. Panel E uses equally weighted averages and additionally includes market returns of available markets interacted with $ESMA$. $Volatility$ denotes the conditional volatility of the traded stock, measured using a standard GARCH(1,1) model; *SD Stock* denotes the unconditional volatility of the traded stock; $IVOL$ denotes the idiosyncratic volatility of the traded stock, measured using rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks classified as lottery stocks according to Kumar (2009). All risk-taking measures are aggregated at the monthly level using averages. $ESMA$ is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *Binding* is a dummy variable that takes a value of 1 for investors who used a leverage of 10 at some point prior to the intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are double-clustered at the individual investor level and over time using the method of Cameron et al. (2011) to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. t-statistics based on single-clustered standard errors at the individual investor level are in brackets. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Table 2: Risk-taking following the intervention: Difference-in-differences analysis (cont.).

Dependent var.	(1) Volatility	(2) SD Stock	(3) IVOL	(4) Lottery type
Panel A: Equally weighted averages				
ESMA · post intervention	0.007	0.018	0.002	0.010
	(4.88)	(5.32)	(4.87)	(1.57)
	[16.13]	[13.19]	[6.08]	[4.50]
Obs.	$207,003$	$205,557$	$202,076$	$207,003$
Adj. R^2	0.43	0.41	0.44	0.24
No. investors	$49,448$	$49,254$	$48,806$	$49,448$
No. month	10	10	10	10
Panel B: Binding intervention				
ESMA · post intervention	0.010	0.026	0.003	0.018
	(5.60)	(6.71)	(7.72)	(2.02)
Num. obs.	$153,143$	$152,145$	$149,717$	$153,143$
Adj. R^2	0.44	0.41	0.44	0.24
No. investors	$35,893$	$35,760$	$35,467$	$35,893$
No. month	10	10	10	10
Panel C: Binding intervention vs. non-binding intervention				
Binding · post intervention	0.009	0.021	0.003	0.020
	(6.41)	(9.08)	(6.07)	(2.67)
Obs.	$137,218$	$136,347$	$133,754$	$137,218$
Adj. R^2 (full model)	0.42	0.38	0.43	0.22
No. investors	$28,591$	$28,525$	$28,330$	$28,591$
No. month	10	10	10	10
Panel D: Investment-weighted averages				
ESMA · post intervention	0.007	0.018	0.002	0.010
	(4.78)	(5.25)	(4.62)	(1.52)
Obs.	$207,003$	$205,557$	$202,076$	$207,003$
Adj. R^2	0.43	0.40	0.43	0.24
No. investors	$49,448$	$49,254$	$48,806$	$49,448$
No. month	10	10	10	10
Panel E: Market return controls				
ESMA · post intervention	0.006	0.014	0.001	0.040
	[5.82]	[4.36]	[1.45]	[6.57]
Market returns · ESMA	Yes	Yes	Yes	Yes
Obs.	$207,003$	$205,557$	$202,076$	$207,003$
Adj. R^2	0.43	0.41	0.44	0.24
No. investors	$49,448$	$49,254$	$48,806$	$49,448$
No. month	10	10	10	10
All panels:				
Investor fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes

Table 3: Risk-taking following the intervention: Instrumental variable analysis.

This table reports the results from a cross-sectional instrumental variable regression analysis on various risk-taking measures of trades that investors initiate in the trade data. Δ denotes the change in the respective trading characteristic from July to August 2018. $\widehat{\Delta \text{Leverage}}$ denotes the fitted values of the change in the average leverage employed for a trade from the first stage. *Volatility* denotes the conditional volatility of the traded stock, measured using a standard GARCH(1,1) model; *SD Stock* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured using rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks classified as lottery stocks according to Kumar (2009). All risk-taking measures are aggregated at the monthly level using averages. *ESMA* is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise. Control variables include demographics (age and gender) and previous trading characteristics (self-reported trading experience, self-reported trading horizon, previous leverage-usage, previous trading performance). Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

	(1)	(2)	(3)	(4)	(5)
	First stage	Second stage			
	ΔLeverage	ΔVolatility	ΔSD Stock	ΔIVOL	ΔLottery type
(Intercept)	0.505	0.019	0.043	0.012	0.032
	(5.72)	(10.78)	(6.59)	(6.97)	(2.88)
$\widehat{\Delta \text{Leverage}}$		-0.002	-0.011	-0.003	-0.001
		(-4.67)	(-8.52)	(-8.63)	(-0.45)
ESMA	-1.800				
	(-53.48)				
Controls	Yes	Yes	Yes	Yes	Yes
F-test	318.13				
p-value (F-test)	0.00				
Obs.	13,329	12,995	12,848	12,975	12,995
Adj. R^2	0.39	0.01	0.01	0.01	0.00

Table 4: Cryptocurrency trading following the intervention: Difference-in-differences analysis.

This table reports the results from a difference-in-differences regression analysis on investors' cryptocurrency trading. *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; and *SD Asset* denotes the average unconditional volatility of all traded underlyings, including cryptocurrencies. The risk-taking measures are aggregated at the monthly level using averages. $ESMA$ is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. t-statistics based on single-clustered standard errors at the individual investor level are in brackets. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Dependent var.	(1) Crypto	(2) SD Asset
ESMA · post intervention	0.018	0.026
	(2.98)	(4.21)
Investor fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Obs.	209,671	208,022
Adj. R^2	0.59	0.60
No. investors	49,696	49,482
No. month	10	10

Table 5: Spillover effects in risk-taking following the intervention: Difference-in-differences analysis.

This table reports the results from a difference-in-differences regression analysis on various risk-taking measures of trades that investors initiate in the trade data focusing on spillover effects. In Panel A, an investor is part of the spillover group if they are not subject to ESMA regulation but have a direct relation to another investor who is subject to ESMA regulation. In Panel B, an investor is part of the spillover group if they are not subject to ESMA regulation but has at least one direct relation to any other investor. *Leverage* denotes the average leverage employed for a trade; *Volatility* denotes the conditional volatility of the traded stock, measured using a standard GARCH(1,1) model; *SD Stock* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured using rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks classified as lottery stocks according to Kumar (2009). All risk-taking measures are aggregated at the monthly level using averages. In Panel a, *Spillover* denotes a dummy variable that takes a value of 1 for investors who have a relationship to at least one investor who is subject to the leverage intervention, and 0 otherwise; in Panel b, *Spillover* denotes a dummy variable that takes a value of 1 for investors who have a relationship to at least one other investor, and 0 otherwise; *ESMA* is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are clustered at the individual investor level; *t*-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Panel A: Direct relation to ESMA investor					
	(1)	(2)	(3)	(4)	(5)
Dependent var.	Leverage	Volatility	SD Stock	IVOL	Lottery type
Spillover	−0.015	0.001	0.007	0.001	0.001
	(−0.34)	(1.33)	(2.20)	(1.03)	(0.16)
Spillover · post intervention	−0.082	0.002	0.007	0.000	0.009
	(−1.99)	(1.70)	(1.88)	(0.04)	(1.98)
ESMA · post intervention	−1.883	0.008	0.026	0.002	0.012
	(−83.34)	(15.67)	(12.85)	(5.56)	(4.89)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	209,671	207,003	205,557	202,076	207,003
Adj. R^2	0.60	0.43	0.41	0.44	0.24
No. investors	49,696	49,448	49,254	48,806	49,448
No. month	10	10	10	10	10
Panel B: Any relation to other investors					
	(1)	(2)	(3)	(4)	(5)
Dependent var.	Leverage	Volatility	SD Stock	IVOL	Lottery type
Spillover	−0.033	0.001	0.008	0.001	−0.000
	(−0.81)	(1.26)	(2.34)	(1.30)	(−0.05)
Spillover · post intervention	−0.068	0.002	0.007	0.000	0.010
	(−1.74)	(2.13)	(2.01)	(0.51)	(2.22)
ESMA · post intervention	−1.883	0.008	0.026	0.002	0.013
	(−82.35)	(15.70)	(12.81)	(5.66)	(5.01)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	209,671	207,003	205,557	202,076	207,003
Adj. R^2	0.60	0.43	0.41	0.44	0.24
No. investors	49,696	49,448	49,254	48,806	49,448
No. month	10	10	10	10	10

Table 6: Risk-taking following the intervention: Difference-in-differences analysis.

This table reports the results from a difference-in-differences regression analysis on the aggregate risk-taking of trades that investors initiate in the trade data. $Leverage \times Volatility$ denotes the product leverage $\times$ volatility for each trade aggregated at the monthly level using a simple average. $ESMA$ is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

	(1)
Dependent var.	Leverage $\times$ volatility
ESMA $\cdot$ post intervention	-0.183
	(-20.16)
Investor fixed effects	Yes
Time fixed effects	Yes
Obs.	$207,003$
Adj. R^2	0.52
No. investors	$49,448$
No. month	10

Table 7: Portfolio risk following the intervention: Difference-in-differences analysis.

This table reports the results from a difference-in-differences regression analysis on the portfolio risk of investors. *No. stocks* denotes the number of different stocks in an investor's portfolio; *HHI* denotes the Herfindahl–Hirschman index as a measure of diversification conditional on investors holding at least one stock in their portfolio; *Expected return* denotes the expected portfolio return based on past stocks returns of the stocks in the portfolio according to their portfolio weights; *PF risk* denotes the volatility of the portfolio estimated based on the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights; *PF cov* denotes the systematic volatility of the portfolio estimated based on the covariance entries of the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights; *PF var* denotes the unsystematic volatility of the portfolio estimated based on the variance entries of the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights; *ESMA* is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; *t*-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Panel A: Portfolio composition				
	(1)	(2)		
Dependent var.	No. stocks	HHI		
ESMA · post intervention	−1.713	0.014		
	(−1.81)	(5.52)		
Obs.	496,960	400,497		
Adj. R^2	0.83	0.78		
No. investors	49,696	49,602		
No. month	10	10		
Panel B: Portfolio expected returns and risk				
	(1)	(2)	(3)	(4)
Dependent var.	Expected return	PF risk	PF cov	PF var
ESMA · post intervention	0.000	0.046	0.008	0.044
	(5.59)	(5.19)	(3.02)	(5.26)
Obs.	400,135	352,039	352,064	352,039
Adj. R^2	0.70	0.75	0.80	0.74
No. investors	49,601	47,739	47,741	47,739
No. month	10	10	10	10
Panel C: Leveraged Portfolio expected returns and risk				
	(1)	(2)	(3)	(4)
Dependent var.	Expected return	PF risk	PF cov	PF var
ESMA · post intervention	0.000	−0.426	−0.017	−0.417
	(1.41)	(−15.45)	(−7.87)	(−15.20)
Obs.	400,135	352,039	352,064	352,039
Adj. R^2	0.52	0.68	0.61	0.68
No. investors	49,601	47,739	47,741	47,739
No. month	10	10	10	10
All panels:				
Investor fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes

Table 8: CFD leverage intervention and average trading performance.

This table reports the results from a difference-in-differences regression analysis on the average performance of trades that investors initiate in the trade data. $Profit$ denotes the average leveraged holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average leveraged holding-period returns in a given month. $ESMA$ is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise; *Holding period* denotes the average holding period in days. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Dependent var.	(1) Profit	(2) SD(profit)
ESMA · post intervention	1.236	−3.183
	(3.38)	(−12.97)
Holding period	−0.046	0.155
	(−0.78)	(10.72)
Investor fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Obs.	206,288	153,027
Adj. R^2	0.15	0.28
No. investors	49,251	41,992
No. month	10	10

Table 9: Holding times following the intervention: Difference-in-differences analysis.

This table reports the results from a difference-in-differences regression analysis on the holding periods of trades that investors initiate in the trade data. *Holding period* measures the time span between the opening and closing of a position in days; $ESMA$ is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Dependent var.	(1) Holding period
ESMA · post intervention	1.307
	(4.30)
Investor fixed effects	Yes
Time fixed effects	Yes
Obs.	206,288
Adj. R^2	0.44
No. investors	49,251
No. month	10

Table 10: Regression results focusing on investors' characteristics.

This table reports the results from a difference-in-differences regression analysis on investors' leverage-usage, risk-taking, and profitability measures focusing on investors' characteristics prior to the intervention. Investor characteristics are high leverage (Panel A, top quartile leverage-usage), low profitability (Panel B, maximum leverage of 10 prior to the intervention and bottom quartile realized profitability), gender (Panel C, male investors), age (Panel D), low experience (Panel E, below median trading experience, self-assessment), low trading experience (Panel F, bottom quartile number of total trades prior to the intervention), and trading horizon (Panel G). *Leverage* denotes the average leverage employed for a trade; $Volatility$ denotes the conditional volatility of the traded stock, measured with a standard GARCH(1,1) model; $Profit$ denotes the average holding-period return in a given month. The trading measures are aggregated at the monthly level using averages. $ESMA$ is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise; $High\ leverage$ is a dummy variable that takes a value of 1 for investors whose leverage-usage was in the top quartile prior to the intervention, and 0 otherwise; *Low* $profit$ is a dummy variable that takes a value of 1 for investors who used a maximum leverage of 10 prior to the intervention and who realized profitability in the bottom quartile prior to the intervention, and 0 otherwise; $Male$ is a dummy variable that takes a value of 1 for investors who are male, and 0 otherwise; $25 - 34$ and similar variables are dummy variables that take a value of 1 for investors who are 25-34 years of age or in other age groups, and 0 otherwise; *Low experience* is a dummy variable that takes a value of 1 for investors with below median trading experience (self-assessment) (Panel E) [for investors whose total number of trades prior to the intervention is in the bottom quartile, Panel F], and 0 otherwise; $Medium\ horizon$ is a dummy variable that takes a value of 1 for investors who indicate that they follow a medium-horizon investment strategy (self-assessment), and 0 otherwise; *Long horizon* is a dummy variable that takes a value of 1 for investors who indicate that they follow a long-horizon investment strategy (self-assessment), and 0 otherwise; Standard errors are double-clustered at the individual investor level and over time; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

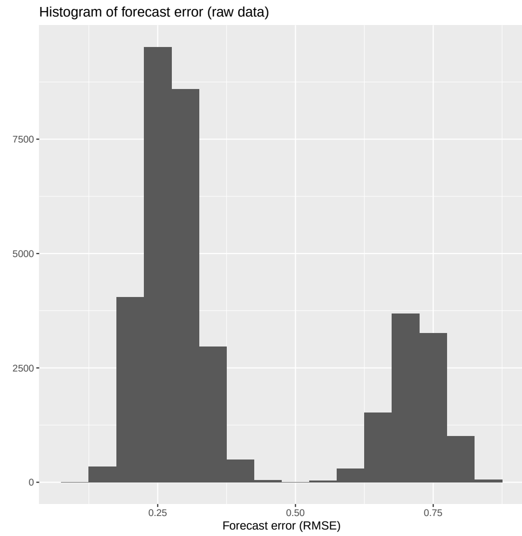
Table 10: Regression results focusing on investors' characteristics (cont.).

Investor characteristic	Panel A: High leverage investors			Panel B: Low profitability investors		
	(1)	(2)	(3)	(1)	(2)	(3)
Dependent var.	Leverage	Volatility	Profit	Leverage	Volatility	Profit
ESMA · post intervention	−1.184	0.006	0.788	−0.964	0.005	−0.216
	(−42.13)	(4.71)	(1.89)	(−35.76)	(4.13)	(−0.60)
Post intervention · high leverage	−0.820	0.004	2.314			
	(−11.13)	(3.52)	(1.83)			
ESMA · post intervention · high leverage	−2.719	0.006	1.431			
	(−47.76)	(3.86)	(1.37)			
Post intervention · low profit				−0.196	0.005	6.745
				(−2.26)	(4.40)	(5.29)
ESMA · post intervention · low profit				−1.834	0.004	1.473
				(−41.04)	(4.14)	(2.40)
Obs.	188,163	185,698	185,532	199,799	197,190	196,686
Adj. R^2	0.70	0.41	0.15	0.64	0.43	0.16
No. investors	37,517	37,366	37,471	44,223	44,004	43,927
No. month	10	10	10	10	10	10

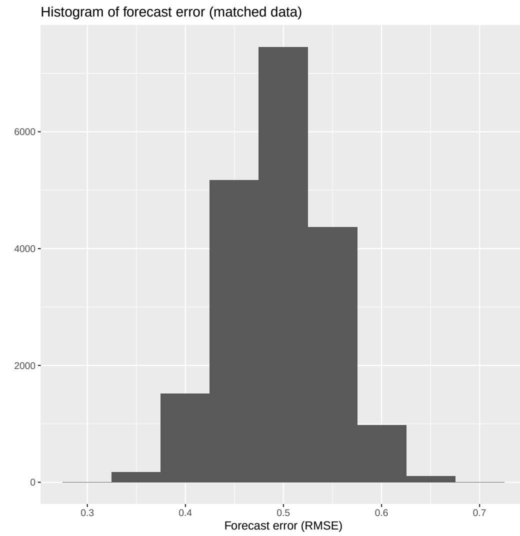
Investor characteristic	Panel C: Gender			Panel D: Age		
	(1)	(2)	(3)	(1)	(2)	(3)
Dependent var.	Leverage	Volatility	Profit	Leverage	Volatility	Profit
ESMA · post intervention	−1.387	0.005	−0.401	−2.297	0.022	−0.098
	(−20.94)	(2.52)	(−0.51)	(−25.50)	(3.83)	(−0.06)
Post intervention · male	0.107	0.002	1.361			
	(1.74)	(1.54)	(1.51)			
ESMA · post intervention · male	−0.517	0.002	1.665			
	(−6.49)	(1.66)	(1.75)			
Post intervention · 25-34				0.009	−0.005	−1.402
				(0.09)	(−2.14)	(−0.68)
Post intervention · 35-44				−0.034	−0.006	−0.237
				(−0.35)	(−2.84)	(−0.19)
Post intervention · 45-54				−0.001	−0.009	−0.808
				(−0.02)	(−3.87)	(−0.50)
Post intervention · 55-64				−0.106	−0.008	−0.134
				(−1.07)	(−3.61)	(−0.07)
Post intervention · >65				0.082	−0.007	0.826
				(0.78)	(−2.30)	(0.29)
ESMA · post intervention · 25-34				0.219	−0.012	1.067
				(2.02)	(−3.27)	(0.50)
ESMA · post intervention · 35-44				0.378	−0.016	0.943
				(3.58)	(−3.09)	(0.58)
ESMA · post intervention · 45-54				0.539	−0.015	2.223
				(5.31)	(−3.03)	(0.85)
ESMA · post intervention · 55-64				0.943	−0.018	1.356
				(8.41)	(−3.29)	(0.54)
ESMA · post intervention · >65				1.212	−0.022	0.270
				(9.35)	(−3.10)	(0.08)
Obs.	209,662	206,994	206,279	208,633	205,981	205,273
Adj. R^2	0.60	0.43	0.15	0.60	0.43	0.15
No. investors	49,692	49,444	49,247	49,499	49,252	49,057
No. month	10	10	10	10	10	10
All panels:						
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Regression results focusing on investors' characteristics (cont.).

Investor characteristic	**Panel E: Self-reported experience**			**Panel F: Trading experience**		
Dependent var.	(1) Leverage	(2) Volatility	(3) Profit	(1) Leverage	(2) Volatility	(3) Profit
ESMA · post intervention	−1.927	0.007	1.232	−1.869	0.007	1.203
	(−60.55)	(4.67)	(2.82)	(−64.88)	(4.88)	(3.10)
Post intervention · low experience	−0.006	0.000	−2.937	0.457	0.009	−1.234
	(−0.15)	(0.33)	(−4.83)	(3.28)	(2.00)	(−0.41)
ESMA · post intervention · low experience	0.217	0.001	0.153	0.863	−0.005	−6.680
	(4.85)	(0.76)	(0.28)	(5.11)	(−1.02)	(−1.72)
Obs.	209,588	206,920	206,206	209,671	207,003	206,288
Adj. R^2	0.60	0.43	0.15	0.60	0.43	0.15
No. investors	49,679	49,431	49,235	49,696	49,448	49,251
No. month	10	10	10	10	10	10
Investor characteristic	**Panel G: Trading horizon**					
Dependent var.	(1) Leverage	(2) Volatility	(3) Profit			
ESMA · post intervention	−1.903	0.004	1.270			
	(−29.20)	(2.29)	(1.10)			
Post intervention · medium horizon	−0.088	−0.002	1.925			
	(−1.57)	(−1.35)	(1.91)			
Post intervention · short horizon	0.067	0.002	3.902			
	(0.89)	(1.15)	(2.67)			
ESMA · post intervention · medium horizon	0.119	0.003	−0.006			
	(1.65)	(1.91)	(−0.01)			
ESMA · post intervention · short horizon	−0.336	0.006	0.035			
	(−3.85)	(2.47)	(0.03)			
Obs.	156,449	154,335	153,865			
Adj. R^2	0.61	0.44	0.15			
No. investors	36,194	36,005	35,867			
No. month	10	10	10			
All panels:						
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes



(a) Raw data



(b) Matched data

Figure A.1: Forecast error of matched sample

This figure presents the distribution of the forecast error of fitted values of a logit model that attempts to forecast the traders that are subject to ESMA regulation. The dependent variable of the model is a dummy variable that takes a value of 1 if the investor is subject to ESMA regulation, and 0 otherwise. Explanatory variables are investors' age, gender, and trading characteristics prior to the intervention (trading intensity, avg. leverage, avg. holding period, and avg. profitability). A forecast with absolutely no explanatory power has a root mean squared error (RMSE) of .399 [median: 0.275] for the raw data and of .5 [median: 0.5] for the matched data.

Table A.1: Summary statistics of investor information.

Panel A reports the ESMA regulation distribution of the investors in our dataset. Panel B reports the gender and age distributions of the investors in our dataset. Panel C reports investors' self-reported trading experience. Panel D reports investors' self-reported trading horizon. The remaining investors did not provide the corresponding information. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Panel A: Treatment characteristics								
	ESMA regulation							
	Yes	No						
Total	28,694	21,002						
Panel B: Demographic characteristics								
	Gender		Age					
	Female	Male	18-24	25-34	35-44	45-54	55-64	$\geq$65
Total	4,000	45,692	2,369	17,446	16,950	8,292	3,439	1,003
Panel C: Investors' trading experience								
	None	Less than one year	One year	One to three years	More than three years	Missing		
Percent	29.4%	24.4%	2.4%	27.3%	16.5%	0.02%		
Panel D: Trading horizon								
	long	medium	short					
Total	4,955	21,038	10,201					

Table A.2: Summary statistics of the trade and stock data.

The table shows summary statistics of the trade data (Panel A) and the stock characteristics (Panel B). *Trades/month* denotes the average number of CFD trades on stocks per investor-month; *Crypto* measures the fraction of positions that investors open in CFDs on cryptocurrencies in a given month, conditional on trading; *Leverage* denotes the leverage employed for a trade; *Investment* is measured as the trade amount's fraction of total assets deposited with the online broker; *Lottery type* is a dummy variable that takes a value of 1 for trades in stocks classified as lottery stocks according to Kumar (2009) using rolling-window regressions over the last 130 days (half year), and 0 otherwise; *Holding period* measures the timespan between the opening and closing of a position in days; *Profit* denotes the percentage return on investment on a closed position; *Volatility* is measured using a standard GARCH(1,1) model; *Stock SD* is measured as the standard deviation of a stock's return between January 2, 2015, and February 28, 2018; and *IVOL* (idiosyncratic volatility) is measured using rolling-window regressions over the last 262 days (one year). The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Panel A: Trade data						
	Investor-months / Obs.	Mean	SD	P25	P50	P75
Trades/month	496,960	6.27	13.79	0	0	5
Crypto	209,671	0.10	0.20	0	0	0.1
Leverage	2,097,456	6.11	2.63	5	5	10
Investment	2,097,456	15.66	23.16	1.94	6.82	17.41
Lottery type	2,039,276	0.13	0.33	0	0	0
Holding period	2,068,578	9.77	30.09	0.08	1.81	7.22
Profit	2,068,578	−3.42	32.20	−11.55	0.81	8.82
Panel B: Stock data						
	Obs.	Mean	SD	P25	P50	P75
Volatility	32,704	0.11	0.09	0.07	0.09	0.13
SD Stock	32,065	0.33	0.24	0.19	0.26	0.39
IVOL	19,502	0.08	0.04	0.05	0.07	0.10

Table A.3: Summary statistics of treated investors split by leverage-usage prior to the intervention.

The table shows summary statistics of treated investors split by their leverage-usage prior to the intervention. *Binding intervention* denotes investors who made use of a leverage of 10 prior to the intervention, *Non-binding intervention* denotes investors who never made use of a leverage of 10 prior to the intervention. $Male$ is a dummy variable that takes a value of 1 for male investors, and 0 otherwise; *Age* denotes the average age of investors in years; *Experience* denotes investors self-reported trading experience; $Short-term$ denotes the fraction of investors who report to follow a short-term trading horizon; $Trades/month$ denotes the average number of CFD trades on stocks per investor-month; *Crypto* measures the fraction of positions that investors open in CFDs on cryptocurrencies in a given month, conditional on trading; *Leverage* denotes the leverage employed for a trade; $Investment$ is measured as the trade amount's fraction of total assets deposited with the online broker; *Lottery type* is a dummy variable that takes a value of 1 for trades in stocks classified as lottery stocks according to Kumar (2009) using rolling-window regressions over the last 130 days (half year), and 0 otherwise; $Holding\ period$ measures the timespan between the opening and closing of a position in days; $Profit$ denotes the percentage return on investment on a closed position. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Panel A: Investor demographics				
	Male	Age	Experience	Short-term
Binding intervention	0.94	34.25	1.26	0.28
Non-binding intervention	0.92	36.62	1.18	0.24

Panel B: Trade data						
	Investor-months / Obs.	Mean	SD	P25	P50	P75
Binding intervention						
Trades/month	150,440	9.84	17.32	0	2	10
Crypto	84,059	0.10	0.20	0.00	0.00	0.11
Leverage	973,800	6.16	2.53	5	5	10
Investment	973,800	15.59	23.42	2.07	6.46	16.66
Lottery type	948,495	0.13	0.34	0	0	0
Holding period	963,674	8.55	26.76	0.08	1.12	6.94
Profit	963,674	−3.09	30.96	−10.37	0.91	8.65
Non-binding intervention						
Trades/month	136,500	4.39	10.97	0	0	3
Crypto	54,798	0.12	0.22	0.00	0.00	0.14
Leverage	355,567	4.39	1.209	5	5	5
Investment	355,567	15.25	21.89	2.19	7.52	17.08
Lottery	345,300	0.11	0.310	0	0	0
Holding period	348,004	14.26	38.30	0.11	2.88	12.23
Profit	348,004	−3.83	28.79	−10.10	0.42	7.47

Table A.4: Difference-in-differences analysis: Matched data.

This table reports the results from a difference-in-differences regression analysis on various risk-taking measures of trades that investors initiate in the trade data using a matched dataset. *Leverage* denotes the average leverage employed for a trade; *Volatility* denotes the conditional volatility of the traded stock, measured using a standard GARCH(1,1) model; *SD Stock* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured using rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks classified as lottery stocks according to Kumar (2009). All trading measures are aggregated at the monthly level using averages. *ESMA* is a dummy variable that takes a value of 1 for investors subject to the leverage intervention, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. I obtain the control group from all investors who are not subject to ESMA regulation ("comparable investors") with a nearest-neighbor matching routine. I match investors from the treatment group with investors from the group of comparable investors based on their gender, age, previous trading intensity, average usage of leverage, average holding periods, average volatility of underlying stocks, average lottery-type stocks, and average profitability prior to the intervention. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Dependent var.	(1) Leverage	(2) Volatility	(3) SD Stock	(4) IVOL	(5) Lottery type
ESMA · post intervention	−1.81	0.008	0.019	0.002	0.013
	(−55.00)	(4.96)	(5.37)	(4.34)	(2.01)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	101,445	100,438	99,833	98,601	100,438
Adj. R^2	0.64	0.41	0.39	0.44	0.21
No. investors	19,780	19,780	19,766	19,723	19,780
No. month	10	10	10	10	10

Table A.5: Difference-in-differences analysis: Pseudotreated investors.

This table reports the results from a pseudo difference-in-differences regression analysis on various risk-taking measures of trades that investors initiate in the trade data. First, I randomly draw a sample of 20,000 investors from the treatment group, and 20,000 investors from the control group. Then, I randomly assign ESMA regulation to these investors. Finally, I repeat the main difference-in-differences regression analysis. All risk-taking measures are aggregated at the monthly level using averages. *Leverage* denotes the average leverage employed for a trade; $Volatility$ denotes the conditional volatility of the traded stock, measured using a standard GARCH(1,1) model; *SD Stock* denotes the unconditional volatility of the traded stock; $IVOL$ denotes the idiosyncratic volatility of the traded stock, measured using rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks classified as lottery stocks according to Kumar (2009). $ESMA$ is a dummy variable that takes a value of 1 for investors who are randomly assigned to the treatment group, and 0 otherwise; *post intervention* is a dummy variable that takes a value of 1 after August 1, 2018, and 0 otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation; t-statistics are in parentheses. The data are from an online trading platform and contain all trades on the platform between March 1, 2018, and December 31, 2018.

Dependent var.	(1) Leverage	(2) Volatility	(3) SD Stock	(4) IVOL	(5) Lottery type
"*ESMA*" · post intervention	0.007	0.000	0.001	−0.000	0.002
	(0.28)	(0.13)	(0.45)	(−0.40)	(0.86)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	164,013	161,910	160,776	158,083	161,910
Adj. R^2	0.57	0.43	0.41	0.44	0.25
No. investors	40,000	39,801	39,631	39,254	39,801
No. month	10	10	10	10	10