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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) limiting the amount of leverage that investors can take on their trading activities. While it successfully reduced the leverage-usage, investors shifted their trading activities to riskier assets in the process, consistent with the idea that leverage-constraint investors substitute leverage with riskier securities. Thus, the intervention was not as effective as the reduction in leverage suggests. Consistent with the notion that risky investment strategies spread through the population, I find some evidence of a spillover effect to investors who are not affected by the regulatory intervention.

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 trading activities using contracts for differences (CFDs). The ESMA argues that these measures increase retail investor protections 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 optimal 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) that investors who are constrained in their leverage-usage substitute leverage with risky securities. In line with the hypothesis, my empirical observations indicate a shift toward riskier stocks and cryptocurrencies in response to the new leverage constraint.

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). Frazzini and Pedersen (2014) provide supporting evidence for this notion. They identify investors who are likely to be relatively constrained and unconstrained, but highlight an important challenge doing so: "Whether an investor's constraint is binding depends both on the investor's ability to apply leverage and on its unobservable risk aversion" (Frazzini and Pedersen, 2014, p. 19). While Frazzini and Pedersen (2014) do not have direct evidence of investors' (in)ability to employ leverage and consequently study investors on aggregate, the intervention together with individual investors' trading data allow me to study how individual investors react to (new) constraints on the micro-level. Thereby, I provide evidence that may plausibly be interpreted as causal evidence in support of the notion that retail investors have a preference 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 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 strategy of risk-taking in one market to make up for the inability to take on risk in another market. In particular, stricter regulation in one market may yield more risk-taking in another (see also Bengui, 2014; Demyanyk and Loutskina, 2016) as banks may try to "make up" for the inability to engage in risk-taking in the first market. Alternatively, however, banks may also export a conservative business model into other markets as a result of stricter regulation 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 regulations intended to curb their risk-taking has—to the best of my knowledge—not previously been analyzed. Instead, the literature largely focuses on the performance implications of such interventions. Thus, the reaction of retail investors to such a regulatory intervention remains an empirically open and important question. This question is particularly important considering the large share of retail trading volume in financial markets. In July and August 2020, the share of retail volume in US equity markets amounted to more than 25% (McCrank, 2021). Even more extreme, in Asia, individual investors often account for more than 80% of trading volume (Osipovich, 2020).

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 had borrowed over $900 billion for the first time. This is a 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 margin 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, 2014; Kumar, 2009; Liu et al., 2021), 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.

Citing retail investor protection as an important goal of the intervention indicates that regulators—at least to some extent—perceive retail investor risk-taking to be unintentional. If, on the other hand, we assume that investors deliberately take specific levels of leverage—for example, risky behavior could reflect a "search for yield" (Rajan, 2006)—and in full awareness of the consequences, the intervention will lead to too low risk exposure. As a result, we would expect investors to find other ways to achieve their desired level of risk-taking (see, e.g., Frazzini and Pedersen, 2014). In this paper, 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 who are subject to the 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. My results indicate that while—in line with the intention of the intervention—overall risk-taking decreased, investors found alternative approaches to obtain their desired 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—which are perceived to be rather risky (Pelster et al., 2019)—more frequently. With respect to performance, my results are in line with the literature (Heimer and Simsek, 2019; Subrahmanyam et al., 2021) and show that investors realize higher returns following the intervention, with lower levels of 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—the 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 by 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 make use of a matching approach and run a placebo analysis.

Then, I exploit observable investor traits such as their gender, age, or experience to shed light on the cross-sectional differences in investors' trading activities around the intervention. I find that investors who made use of high levels of leverage prior to the intervention in particular substitute more, providing additional support for the notion that the risk-taking is premeditated and not accidental. These investors also do not realize higher returns after the intervention. In line with the recent literature on the performance implications of trading on leverage, I find that investors who realized returns in the bottom quartile prior to the intervention particularly had to reduce their leverage to a larger degree. These investors substitute significantly more, and do not benefit from less volatile returns. Young and short-term-oriented investors also substitute more. I also find some evidence for a more pronounced substitution for male investors. I do not find a more pronounced substitution for inexperienced investors, who also do not reduce their leverage-usage quite as much.

Finally, I carefully study potential spillover effects between investors in the treatment group and investors in the control group. The analysis of potential "spillovers" or indirect effects in financial regulatory experiments, as highlighted by Boehmer et al. (2020), has 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.

Han et al. (2021) build on the general idea that investors spend a substantial part of their leisure time discussing investments, or sharing information about others' success or failures in investing (Shiller, 1984), and show how risky investment strategies propagate through the population (see also Heimer and Simon, 2015). Based on this notion, it is reasonable to assume that a shift toward riskier underlyings may also affect investors who are not affected by the new leverage restrictions. My data provide a perfect laboratory to study spillover effects because investors can share their trading strategies on the trading platform (see also Heimer, 2016). Based on investors' social relations on the trading platform, I identify a spillover group of investors with relations with treated investors. Using a variation of the DID-approach (Butts, 2021; Clarke, 2017), I investigate the risk-taking of the spillover group and also find some evidence of a shift to riskier stocks in the spillover group. The effect size of the spillover group amounts to approximately 20-25% of the effect size of the treatment group, while the control group (i.e., investors who do not have relations with treated investors) does not show a shift toward riskier underlyings.

The paper contributes to a fast-growing literature that (mostly) studies the performance implications of leverage-usage (see, e.g., Barber et al., 2020; Heimer and Imas, 2021; Subrahmanyam et al., 2021). Most 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 build on their findings and additionally show that investors turn to higher-risk underlyings in response to the intervention. This finding has important implications, as it indicates that evaluations of the intervention that focus only on the leverage-usage of investors will overestimate the effectiveness of the intervention. Instead, I highlight that such evaluations have to consider the full picture of investors' risk-taking to account for risk-taking through alternative channels.

The paper proceeds as follows. I discuss the literature on the usage of leverage by retail investors in Section 2. Section 3 describes the institutional background and the intervention. I present the data, measures, and methods in Section 4. Section 5 presents summary statistics. Section 6 investigates how investors shift their trading activities toward riskier underlyings. I provide cross-sectional analyses in Section 7 and analyze spillover effects in Section 8. The last section concludes the paper.

2 Retail investors' usage of leverage

The analysis of the usage of leverage at the individual level has received increasing attention in recent years. Most closely related to this paper, Heimer and Simsek (2019) evaluate the effects of a 2010 regulation by the CFTC that restricts leverage-usage in the US retail foreign exchange market. In general, the 2010 US intervention is very similar to the 2018 ESMA intervention. Heimer and Simsek (2019) show that high-risk investors in particular realize smaller losses as a result of the regulation. However, although the trading volume is reduced by 23% and the losses of high-leverage traders are reduced by approximately 40%, the authors cannot find any effect on market liquidity. Specifically, the relative bid-ask prices charged by three analyzed brokerage services remain the same. I extend the work of Heimer and Simsek (2019) and show that investors not only reduced their leverage-usage in response to the new regulation, but that investors also shifted their investment activities toward riskier underlyings in an effort to maintain their levels of risk-taking, and that there are some indications of a shift toward riskier underlyings by investors who were not directly affected by the intervention in the sense of a spillover effect.

Several recent studies focus on the performance implications of trading on leverage using account-level data. Subrahmanyam et al. (2021) argue that regulatory constraints on leverage do not affect all traders similarly. In particular, the performance of unskilled investors improves, while the performance of skilled investors and institutions deteriorates. The reason behind this finding is that unskilled investors suffer from behavioral biases and a tendency toward gambling. Using higher leverage increases their losses from these behaviors, in particular as a result of margin calls and the forced liquidation of positions by brokerage firms. In contrast, skilled investors are able to time the market and consequently increase their profits when trading on leverage. In a closely related work, Kim et al. (2021) find that the propensity to experience a margin call when trading on margin decreases with investors' literacy. The authors also note that literate investors are less likely to trade on margin—in line with Warren Buffet's quote on leverage "If you're smart you don't need it and if you're dumb you don't want to use it." Ladley et al. (2020) also find that investors who trade on margin consistently underperform and realize losses. Additionally, related studies show that using leveraged products is (also) associated with poor investment performance, both for institutional (DeVault et al., 2021) and for retail investors (D'Hondt et al., 2021).

Focusing on the mechanisms that lead to lower performance, leverage has been associated with several well-known behavioral biases. 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 usage of leverage, while Heimer and Imas (2021) find that having the option to use leverage exacerbates biases such as the disposition effect. Barber et al. (2020) and Heimer and Imas (2021) also find that leverage consequently leads to worse performance. Hence, leverage constraints can improve financial decision-making by reducing behavioral biases, and thereby increase investors' trading performance.

Also related to this study, several recent contributions analyze the use of leverage on the housing market. For example, Bailey et al. (2018b) show an important relation between individuals' beliefs and their leverage choices. Interestingly, more pessimistic homebuyers choose higher leverage, in particular when default costs are low or house prices are expected to fall, on average. In a related work, Ben-David (2019) finds that in particular (unsophisticated) homebuyers who overpay use higher leverage.

Finally, this paper is related to studies on the effectiveness of regulatory interventions to protect retail investors in general (see, for example, Firth, 2020). In this strand of literature, for example, Agarwal et al. (2014) study the effectiveness of the 2009 Credit Card

Accountability Responsibility and Disclosure (CARD) Act. The authors find that the regulations saved consumers approximately $11.9 billion per year, where consumers with low credit scores particularly benefited from the new limits on credit card fees.

3 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 very easily employ leverage at the position level (see also Arnold et al., 2022).

As a majority of CFD traders lose money, effective 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 reviewed and can be extended for a further 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. Given that the average leverage of investors in my sample prior to the intervention was significantly 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 take place. Such high

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

leverage-usage is consistent with other studies. For example, Arnold et al. (2022) report an average amount of leverage of approximately 6.1 in their sample of stock-CFD traders. In comparison, the current regulation allows 2:1 leverage on long stock positions in the US.

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 were 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).

4 Data, variables, and methodology

4.1 The trading platform

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) or Heimer et al. (2021). The data were obtained under a nondisclosure agreement with a financial institution.

4.2 Data

The data comprise all trades executed on the platform between March 2018 and December 2018. I focus on stocks in this paper, because the intervention has been binding in particular for stocks. I provide some supplementary evidence on cryptocurrencies, where the intervention has not been binding, on average. However, cryptocurrencies are perceived to be rather risky (Pelster et al., 2019) and may provide investors alternative paths to volatility. 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. The broker quotes the 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. Transaction costs are moderate and charged via the spread when investors close a position. The choice of leverage does not affect the transaction cost.

In addition, the data contain several types of information on investors' demographics, information on their previous trading experience, and on 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 only contains investors who are subject to ESMA regulations, i.e., those from the European Union, and the control group only contains investors who are not subject to such regulations.[2] The final dataset comprises a total of 49,696 investors, with 28,694 investors subject to the new regulation,

[2]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, United Arab Emirates, Malaysia, Mexico, Argentina, Bahrain, Bolivia, Brazil, Cayman Islands, Chile, Colombia, Dominican Republic, Ecuador, Gibraltar, Iceland, Israel, Kuwait, Liechtenstein, Norway, Oman, Peru, Philippines, South Africa, South Korea, Taiwan, Thailand, United States, Uruguay, and Vietnam.

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., from 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, or Stockholm Stock Exchange and others).

4.3 Variables

The broker allows investors to flexibly select the leverage for each individual trade. If investors decide to take a levered position, they can choose between a leverage of 2:1, 5:1, or 10:1, depending on their regulatory environment. Following the intervention, investors in the treatment group are only able to select a leverage of 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 take leverage without risking a loss of more than 100% and without a need for dynamic rebalancing.

I use five 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 Volatility Index, the VIX, and the average stock volatility of all stocks that investors trade during the sample period in 2018), I also estimate the unconditional standard deviation of stocks (*stock SD*) 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 last 262 trading days. For each stock, I use the major stock market index of the country in which the stock is primarily listed. I use a stock's volatility and idiosyncratic volatility based on the argument that the "low-risk effect" is driven by idiosyncratic, and not systematic risk (Bali et al., 2017; Liu et al., 2018). Following Kumar (2009), I define stocks with below-median prices, above-median idiosyncratic volatility, and above-median idiosyncratic skewness as *lottery-type* stocks. Finally, I make use of the fraction of cryptocurrency trades as an additional measure for risk-taking, as these are perceived to be rather risky (Pelster et al., 2019). 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 constraints did not mitigate the risk-taking-attractiveness of cryptocurrencies.

To quantify an aggregate effect of risk-taking, I use *leverage* $\times$ *volatility*, which is the simple product of the leverage of a particular trade with the volatility of the underlying stock. The measure is based on the notion that taking a leverage of, 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 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 she deposited with the broker. Unfortunately, I do not have access to the absolute nominal amounts of investors' positions.

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 levered 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 who are subject to the new regulation after August 1, 2018, (treatment group) with that of investors who are not subject to the regulatory intervention (control group), conditional on trading. I only focus on the risk-taking of new positions. Thus, the risk-taking measures for a given month only include those positions that were created in that month, but not positions that were created in a previous month and that investors continue to hold.

First, I aggregate the risk-taking measures for each investor in the time period prior to the intervention (observation period) using equally-weighted averages. Similarly, I aggregate the risk-taking measures for each investor in the time period following the intervention (treatment period) using equally-weighted averages. 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 of the opening of the position. Using data both before and after treatment reduces the risk of bias due to imperfect randomization in the DID design (Atanasov and Black, 2016). I only include investors who execute at least one trade before and after the intervention in the analysis to mitigate the concern that different "types" of investors begin trading with CFDs following the intervention in the treatment group. In addition, taking averages before and after the intervention prevents 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:

$$\begin{aligned} \text{Risk-taking}_{it} = \alpha + \beta_1 \text{ ESMA}_i \times \text{post intervention}_t + \beta_2 \text{ ESMA}_i \\ + \beta_3 \text{ post intervention}_t + \psi_i + \eta_t + \varepsilon_{it}, \quad (1) \end{aligned}$$

where Risk-taking_{it} denotes the risk-taking of investor i at time t, measured with the leverage, volatility, stock SD, IVOL, lottery type, and crypto. $ESMA$ is a dummy variable that takes a value of 1 for investors in the treatment group, and 0 otherwise; *post intervention* is a dummy variable that takes a 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 to address covariate imbalance 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. I double-cluster standard errors using the method of Cameron et al. (2011).

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

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 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 15.6% 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, less than three stocks in their portfolio on any given day (conditional on holding at least one stock; not tabulated).[3] Based on these insights, I conclude that investors (mostly) do not consider their overall portfolios but rather focus on individual stocks. Consequently, I focus on individual positions in this paper. Of all CFD trades on stocks, 12.6% 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

[3] This observation is consistent with the overall empirical evidence that suggests that households are poorly diversified (see, e.g., Roussanov, 2010).

at 0.806%.

Figure 1 focuses on 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 the unconditional volatility occur because a few stocks such as Facebook, Amazon, or 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 —

6 Risk-taking following the regulatory intervention

I start the main analysis by reporting the impact of the regulatory intervention in August 2018 on the trading strategies of investors—separately for investors who are subject to the intervention and those who are not subject to the intervention—in a standard DID setting. As the brokerage service serves an international customer base, a large number of customers were not affected by the intervention.

6.1 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 is moving around slightly below 6.5 prior to the intervention. On August 1, 2018, the date of the intervention, the average leverage-usage dropped to approximately 4.6-4.7. The decline in leverage-usage is highly statistically significant. The figure also indicates that investors did not anticipate the regulation reducing their access to leverage and did not adjust their behavior prior to the intervention, which is consistent with the broker only implementing the constraint on August 1, 2018. 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 is not problematic. First, Panel a of Figure 1 shows that the distributions of the leverage-usage of the treatment and the control group 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. The table 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, while investors who are not subject to the regulation do not. Quantitatively, the coefficient of −1.8665 indicates an economically important reduction in leverage relative to the control group. Investors in the treatment group reduce 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 6.106 and standard deviation of 2.632 (Table A.2), the coefficient corresponds to 31% of the mean and 71% of the standard deviation of investors' leverage.

— Place Table 1 about here —

6.2 Measures of stock risk

Next, I study the various risk-taking measures around the intervention and a 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 measures, I observe clear parallel trends prior to the intervention. Starting in August 2018, the measures diverge, and treated investors, on average, begin to take higher risks.

— Place Figure 3 about here —

Panel a of Figure 3 also shows a significant increase in the group of control investors following October 2018. At first glance, this increase may seem rather puzzling. However, the overall market developments in the last quarter of 2018 provide a convincing explanation for the overall increase in the 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 significantly increases 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 the increase in market volatility explains the increase in the average conditional volatility, I study the unconditional volatility in Panel b. The unconditional volatility is estimated using the period prior to March 2018 and therefore 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, while the risk-taking in the control group does not increase.

6.2.1 DID analysis

Table 2 analyzes 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, stock SD, and IVOL in Columns 1 to 3. The coefficient on volatility in Column 1 amounts to 0.0073 with a t-statistic of 4.87. To place this into perspective, the coefficient amounts to 8.6% 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 (0.0103) is not statistically significant (t-statistic of 1.5655).

— Place Table 2 about here —

In Column 5, I provide additional evidence in support of the hypothesis and study the average trading activity in cryptocurrencies, which are perceived to be rather risky. The coefficient indicates a significant increase in the usage of cryptocurrencies following the intervention. The coefficient amounts to 0.0176 (t-statistic of 2.9831). Economically, the coefficient amounts to 8.6% of the standard deviation of crypto, and this magnitude is the same as to the magnitude of the coefficient in Column 1.

Panel B additionally reports investment-weighted risk-taking measures for investors' new positions in a given month. The alternative weighting-scheme produces almost identical results.

Finally, I address the concern that changes in market conditions affect investors from the treatment and control groups differently and add additional control variables to the model in Panel C. Investors reactions may differ, for example, because of the 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 the 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.[4] The interaction of the index return with the treatment dummy allows me to control for potentially different responses from investors in the treatment and control groups to country-specific market conditions. While the effect sizes are slightly different than in Panel A, the overall conclusion remains the same: Treated investor move to riskier underlyings.

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

6.2.2 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 an (unobservable) degree of risk

[4]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.

aversion that drives their preference for leverage; however, treated investors only had the ability to apply leverage prior to the intervention and consequently are constrained following the intervention. The IV assumes that the instrument, the regulatory intervention, affects the outcome, the risk-taking measure, only through the instrumented variable, the reduction in leverage-usage. Thus, the effect estimated with the IV approach using the regulatory intervention as the instrument captures the change in the 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 allows me to isolate the substitution channel, i.e., investors substitute leverage with riskier underlyings.[5]

In general, instruments have to 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 those investors who habitually took leverage amounts that were above the new threshold. Second, instruments must not have a direct effect on the outcome of interest. Obviously, 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 of investor i. 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). 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

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

the IV only considers the change in trading from July to August 2018, the analysis only includes investors who trade in both months. As a result, and because of the required control variables, the sample is smaller than the DID sample, where the restriction is that investors trade within the five months prior to the intervention, and the five months following the intervention.

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 -1.8002 is almost identical to the coefficient of the DID estimation in Table 1 (-1.8665). 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 6 show the second-stage results. Note that $\widehat{\Delta \text{Leverage}_i}$ takes negative values. Thus, negative coefficients indicate a larger increase in the risk-taking measures for an increasing leverage reduction. The 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 leverage-usage.

6.2.3 QTT estimation

In addition to studying the average treatment effect, it is helpful to understand the distributional impacts of the intervention. 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., a homogeneous treatment effect), or is the risk-shifting particularly pronounced for investors who trade risky assets more or less often (i.e., a heterogeneous treatment effect)? Investors who already trade fairly risky stocks may find it difficult to shift to even riskier underlyings. At the same time, 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.[6] Figure 5 visualizes the distributional impacts of the intervention. Panel a shows the QTT for leverage. Mechanically, investors who took higher levels of leverage prior to the intervention had to reduce their leverage to a larger degree. Panel b shows the QTT for the 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 the unconditional volatility, Panel d IVOL. The results are similar and show that particularly 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, Panel f for crypto. Both of these variables are based on an average of dummy-variables that indicate a lottery-type stock or a cryptocurrency trade. As the median investor in the dataset does neither trade lottery-type stocks nor cryptocurrencies, the distribution of both variables 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 investors in the highest deciles increase their trading in lottery-type stocks and cryptocurrencies, respectively. Overall, the takeaway from studying distributional effects of the intervention indicates heterogeneous treatment effects: Investors who trade riskier prior to the intervention move to even riskier underlyings.

— Place Figure 5 about here —

6.2.4 Robustness analyses

Finally, I summarize some additional tests to address potential identification issues affecting the DID analysis. Investors who are subject to ESMA regulation and those who are not may differ with respect to both observable and unobservable characteristics. Such differences raise

[6] Estimating the QTT requires several additional assumptions (see Callaway and Li, 2019): In particular, it requires the *Distributional Difference in Differences Assumption* and the *Copula Stability Assumption*. The former requires full independence between the change in untreated potential outcomes over time and whether or not 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.

the concern that the control group does not provide feasible control for the DID analysis. I already discussed the covariate balance in the sample in Figure 1, which does indicate common support on all covariates. I now exploit the common support of investors by balancing the treatment and control groups on covariates to ensure that the two groups are as similar as possible and make use of 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 by using a nearest-neighbor matching routine with respect to their trading activities prior to the intervention and standard controls for risk-taking. Finally, I estimate DID equation (1) with the matched investors. The findings are robust to this approach (Table A.3 in the Appendix), and the coefficients are almost identical to the main analysis. In the matched data, I also find a significantly positive coefficient on *lottery type* (0.0136, t-statistic of 2.0131). This can potentially be explained with 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, while the DID analysis on the raw data may potentially 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 with $ESMA$ as the dependent variable. Explanatory variables are investors' age, gender, and past trading characteristics (trading intensity, avg. leverage, avg. holding period, avg. volatility of underlying stocks, avg. lottery type stocks, and avg. 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 a RMSE of .3991 [median: .2754] 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 .3945 [.2954] for the raw data and .4947 [.4948] for the matched sample, which allows 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.

Finally, 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 regulation to these 40,000 investors. Finally, I repeat the DID analysis and estimate equation (1). The results in Table A.4 in the Appendix show that pseudotreated investors do not yield statistically significant results.

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

6.3 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 4 summarizes the results.

— Place Table 4 about here —

The treatment coefficient is negative (-0.1830) and statistically significant with a t-statistic of 20.1333, indicating that, on average, investors take less risky positions following the intervention. Considering the drastic decrease in investors' leverage-usage of -1.8665, 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 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 0.065, see Table A.2 in the Appendix) to the 75% quantile (volatility of 0.132). 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 7, I will 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 the IV analysis in Section 6.2.2).

6.4 Trade profitability and holding times

As highlighted by, for example, Barber et al. (2020), Heimer and Imas (2021), and Subrahmanyam et al. (2021), leverage is associated with poor investment performance, particularly for less sophisticated investors.

Table 5 provides a performance analysis using the DID approach and equation (1). Following Arnold et al. (2022), I use the levered 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 5 about here —

Given that leverage-usage is supposed to widen the profitability distribution by making larger positive and negative realizations more likely, I expect the stricter regulatory boundaries to also reduce the variability of returns. In line with this notion, Column 2 indicates that SD(profit) is significantly smaller for treated investors after the intervention (-3.1980, t-statistic of 13.1096). 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% seem 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. (2021) that 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 6 provides evidence in support of this notion. On average, treated investors hold their positions 1.3 days longer than control investors following the intervention.

— Place Table 6 about here —

7 The influence of investor characteristics

It is well known that 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 along 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, their gender, age, or trading experience. Based on sample medians or 25% quantiles, I create dummy variables that split the sample into a below- and an above-threshold portion. 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 6.2.3 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 take 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.[7] Table 7 summarizes the results.

— Place Table 7 about here —

[7]Note that the intuition of this approach is similar to the IV approach in Section 6.2.2 and the QTT estimation in Section 6.2.3. However, the quantile regression conditions on the dependent variable in the regression, while here all estimates are "conditional" on leverage.

Consistent with intuition, I find that investors who took high levels of leverage prior to the intervention in particular (a) reduce their leverage-usage to a larger degree and (b) substitute significantly more than investors who used less leverage. In Column 1, not surprisingly, the coefficient on $ESMA \cdot$ *post intervention* $\cdot$ *high leverage* amounts to -2.7115 and is statistically highly significant with a t-statistic of 48.8. Because the coefficient on $ESMA \cdot$ *post intervention* is also negative (-1.2767) and highly significant, this indicates that both treated high-leverage investors and those who are treated but used lower levels of leverage reduce their leverage by economically highly meaningful levels, but high-leverage investors did so by more than three times as much (-1.2767 vs. $-3.6134 = -0.9019 - 2.7115$).

A similar picture emerges for the shift toward riskier underlyings (Columns 2-6). The coefficients on $ESMA \cdot$ *post intervention* remain positive, indicating a general move toward riskier stocks by treated investors. In addition, the coefficients on $ESMA \cdot$ *post intervention* $\cdot$ *high leverage* are positive and significant (with *lottery type* being the lone exception) indicating heavier substitution by high-leverage investors. Turning toward performance implications, the results in Columns 8 and 9 show that high-leverage users, despite significantly reducing the standard deviation of their profitability, do not realize significantly larger returns following the intervention.

Investors' skill is important when trading on leverage. Subrahmanyam et al. (2021) highlight that unskilled investors particularly suffer from poor performance due to their leverage-usage. In contrast, skilled investors benefit from levered positions because they are able to time the market. Consequently, I analyze the influence of investors' skill, using their average trading performance prior to the intervention as a proxy for skill. In particular, I define investors 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. Table 8 summarizes the results.

— Place Table 8 about here —

The results in Table 8 largely mirror those in Table 7. 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 82%. The coefficient on $ESMA \cdot$ *post intervention* $\cdot$ $low\ profit$ is smaller (-0.6503) than the coefficient on $ESMA \cdot post\ intervention \cdot high\ leverage$, but the substitution coefficients of the three-way interactions are of similar magnitude. In this setting, the coefficient on the three-way interaction for *lottery type* is also significant. With respect to trading performance, low-profit investors benefit from the intervention more than other investors in terms of higher average holding-period returns, but not in terms of a lower variation of those returns.

Next, 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). Table 9 summarizes the results on the influence of gender. Column 1 indicates that male investors were particularly affected by the intervention and reduced their leverage-usage accordingly. Columns 2 and 3 provide some (weak) evidence in favor of a more pronounced risk-shifting for male investors (t-statistics are at the 10%-significance level). Overall, male investors reduce their aggregate risk-taking to a larger degree than female investors (Column 7). With respect to trading performance, I observe that male investors realize larger returns following the intervention (Column 8, coefficient of 1.6618, t-statistic of 1.7408). The reduction in return variability (Column 9) is not particularly pronounced for male investors.

— Place Table 9 about here —

Next, I turn to the influence of investors' age. The results are summarized in Table 10. The baseline age group is $18 - 25$. Column 1 shows the change in leverage. The decrease in leverage-usage decreases monotonically in age. Younger investors (have to) reduce their leverage-usage to a larger extent than older investors, and those in 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 (Columns 2 and 3), while older investors substitute very little $(55 - 64)$ or not at all (> 65). Columns 4 and 5 focusing on $IVOL$ and *lottery type* do not show any clear patterns. The move toward cryptocurrencies (Column 6) seems to be driven by investors from age group $35-44$. The analyses on the aggregate risk-taking and the trading performance also do not yield any clear-cut observations.

— Place Table 10 about here —

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 their self-reported trading experience. Table 11 summarizes the results. The results show that low-experience investors reduce their leverage to a lesser degree than investors with more self-reported trading experience. In line with this observation—also considering that the low-experience investors overall do not seem to shift toward riskier underlyings more often (the exception is the positive coefficient in Column 3, *stock SD*)—the aggregate risk-taking of these investors declines by significantly less than those of more experienced investors (Column 7), and the variability of their trading performance is reduced to a smaller extent (Column 9). Thus, the intervention does not seem to particularly benefit inexperienced investors.

— Place Table 11 about here —

Finally, I consider investors' (self-reported) trading horizons. The baseline is a long-horizon investor, and the results are summarized in Table 12. 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 and 3). While the analyses on $IVOL$, *lottery type*, and *crypto* do not provide interesting findings, the analysis on investors' aggregate risk-taking (Column 7) shows that medium-horizon investors reduce their risk-taking to a lesser extent than long-term investors and that short-horizon investors do so to the same extent as long-term investors. Given that I observe the largest reduction in leverage-usage for short-horizon investors, this is at least somewhat surprising because it indicates that short-term investors are able to successfully substitute the additional reduction in leverage by moving to even more volatile stocks.

— Place Table 12 about here —

To summarize, the cross-sectional analyses indicate that particularly young, risk-seeking, short-term-oriented, and poor-performing investors (have to) reduce their leverage-usage and respond to the intervention with a shift toward riskier underlyings. I find some evidence for a more pronounced substitution for male investors, who also reduce their leverage-usage to a larger degree, but not for inexperienced investors, who also do not reduce their leverage-usage quite as much. Overall, these findings could be interpreted as being 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.

8 Spillover effects

Finally, I turn to a 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 the trading of peers 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 who are not directly affected by the intervention, but in a "spillover" group—via the network. Various models of social interactions argue that individuals within a peer group make more similar choices than 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, and 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., 2021).[8] Consequently, trading strategies using highly risky underlyings may spread through the population.

Due to the scopic regime (Gemayel and Preda, 2018) of the trading platform, the dataset is well-suited to study the impact of social interactions on investors' risk-taking, in particular in a setting with an exogenous shock. The data allow me to identify social relations between investors that have formed on the trading platform, and then investigate whether a social

[8] Even as the intervention drastically reduces the leverage-usage for a subset of investors resulting in a distribution of the returns after the intervention 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. (2021).

transmission of investment strategies via these connections takes place. Thus, the data allow me to study the implications of peers' decisions for investors' risk-taking. In the following, I investigate the impact of social connections on the risk-taking behavior of investors in the context of the intervention and answer the following question: Do investors adjust their trading strategies and risk-taking in response to the regulatory-induced trading-strategy adjustments of their peers?

By answering this question, the paper also contributes to a growing literature that studies the existence of peer effects on risk-taking in laboratory experiments (Trautmann and Vieider, 2012; Cooper and Rege, 2011; Bougheas et al., 2013; Schwerter, 2021; Krull et al., 2021) or in the real world (Hong et al., 2004; Ivkovic and Weisbenner, 2007; Hvide and Östberg, 2015). The main message of this literature is that social comparisons influence portfolio choices (Bault et al., 2008; Dijk et al., 2014; Fafchamps et al., 2015; Frydman, 2015, 2016; Kirchler et al., 2012; Linde and Sonnemans, 2012; Schwerter, 2021).[9] Typically, the research on peer effects proxies for social relations using a common place of residence (i.e., measured with postal codes) (Hong et al., 2004; Ivkovic and Weisbenner, 2007; Brown et al., 2008; Kaustia and Knüpfer, 2012; Kalda, 2019), a common workplace (Hvide and Östberg, 2015; Kalda, 2019; Ouimet and Tate, 2020), or the *average* connectedness of individuals in a specific region on Facebook (Bailey et al., 2018a; Bali et al., 2021). One potential limitation of such proxies is that few individuals assigned to a particular peer group may actually exchange information or know each other. In addition, such peer groups are exposed to the same local shocks. In contrast to this literature, I exploit explicit social network data that allow me to identify individual investors who interacted via the network.

8.1 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 trades of other investors. While I do not include these "social" trades in the analysis, I exploit them to identify investors

[9] Note that Corazzini and Greiner (2007) do not find an effect of peer information on risk-taking in their study, thereby contrasting with the vast evidence in this strand of the literature.

who have ties to one another.[10] Investors who duplicate trades of other investors will closely observe their trading activities (see also Pelster and Hofmann, 2018). Thus, these investors will be more likely to take notice of a change in the trading strategies of their connected peer than 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 will closely monitor 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 to have a relation with investor B if they duplicate at least one trade of investor B in the previous month. This procedure is similar to Pelster (2017) or Deng et al. (2021) and leads to a total of 245,858 monthly connections between investors. Figure 7 visualizes the resulting network in August 2018, the month of the intervention being effective.

— Place Figure 7 about here —

8.2 Spillover regression analysis

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

Obviously, identifying the correct peer group is crucial to the spillover analysis. Therefore, in a robustness exercise, I define all investors who are not subject to ESMA regulation, but at

[10] 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, the social trades affect investors' overall portfolio risk. Given that investors hold, on average, only 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.

some point during the sample period engage in relations with other investors on the platform to be 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 compared to 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.

In general, the main challenge when studying peer effects is to address the obvious endogeneity concern. The endogeneity concern arises because individuals may simply be exposed to the same shock or trade on the same information (Manski, 1993). Investors may also choose their peer group based on their intended trading activities and may change their peer group when they plan to change their trading strategy, before implementing the new (more risky) trading strategy. Then, changes in investors' risk-taking may not be attributable to adjustments in the trading strategies of their peer group, but the choice of the peer group could be explained by the planned risk-taking. As a result, the observed commonalities may not be driven by peer effects.

However, the regulatory intervention introduces an exogenous shock to some investors that allows me to overcome this endogeneity concern inherent in the analysis of peer effects. The intervention requires treated investors to adjust their trading strategies, and allows me to study how these adjustments spill over to the trading strategies of their peers. Thus, the regulatory shock that influences some investors, but not others,[11] provides an ideal playing field to shed new light on potential peer effects.

— Place Table 13 about here —

Table 13 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 -0.0847 (t-statistic

[11] In other words, in my setting, individuals are not exposed to the same shock.

of 2.0208) and thus very small compared to the direct effect $ESMA \cdot post\ intervention$. The remaining columns of Panel A of Table 13 focus on the substitution strategies. For all dependent variables, *volatility*, *stock SD*, $IVOL$, *lottery type*, and *crypto*, I observe a significantly positive coefficient on the direct effect ($ESMA{\cdot}post\ intervention$). Turning to the indirect spillover effect, I find a borderline significant spillover ($Spillover \cdot post\ intervention$, at the 10%-level) for *volatility* (0.0017, t-statistic of 1.7575), *stock SD* (0.0076, t-statistic of 1.8256), and *lottery type* (0.0097, t-statistic of 1.7890). 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 less than 1/4 for volatility, this ratio is more than 3/4 for lottery-type stocks. I do not find meaningful spillover effects for $IVOL$ and *crypto*.

Panel B makes use of the alternative definition of the spillover group and shows similar results. The direct effects remain virtually the same. For the indirect effects, coefficients are also almost identical. t-statistics are larger in this setting, indicating significance at the 5%-level for *volatility* (0.0019, t-statistic of 2.2145), *stock SD* (0.0076, t-statistic of 2.0407), and *lottery type* (0.0103, t-statistic of 2.2754).

Interestingly, the spillover analysis shows a positive coefficient on $ESMA{\cdot}post\ intervention$ for a move toward lottery-type stocks (Panel A: coefficient of 0.0126, t-statistic of 1.8865; Panel B: coefficient of 0.0131, t-statistic of 5.1736), whereas the main analysis in Table 2 did not (coefficient of 0.0103, t-statistic of 1.5655). The reason may be the relatively large spillover effect for lottery-type stocks. In the main analysis, this spillover group is part of the control group—as the investors in the group are not directly affected by the intervention. Consequently, the difference between the treatment and control groups is slightly less pronounced, and the variation in the control group is larger—some investors in the group move to lottery-type stocks due to the spillover effect, while others do not. Of course, an important question is why lottery-type stocks in particular are subject to such a pronounced spillover effect. Han et al. (2021) provide a possible explanation with their *social transmission bias* that highlights how risky investment strategies propagate through the population. Consistent with the predictions of Han et al. (2021) 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 for lottery-type stocks seems plausible. Overall, the results in this section underline the conclusion of Bali et al. (2021) that the role of social networks in financial markets is complex and nuanced.

9 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 shifted their trading activities toward riskier underlyings. In particular, treated investors traded stocks with higher volatility and higher idiosyncratic volatility, and more cryptocurrencies (that are perceived to be rather risky) following the intervention relative to control investors who were not subject to the intervention. Nonetheless, the overall risk-taking is slightly lower following the intervention. That is, investors did not fully compensate for the 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 enough volatility. Nevertheless, neglecting the shift toward riskier underlyings overestimates the effectiveness of the intervention.

I complete the picture with several refinements of my main result. Specifically, I show that particularly young, risk-seeking, short-term-oriented, and poor-performing investors reduce their leverage-usage and shift toward riskier underlyings following the intervention. The results also provide some evidence for a more pronounced substitution for male investors. Inexperienced investors, who also do not reduce their leverage-usage quite as much, do not particularly move to riskier underlyings.

Overall, the findings of the paper may be interpreted as plausibly causal evidence of investors taking risky positions on purpose, and not accidentally. 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 a better comprehension of financial markets and financial stability (e.g., Charness and Sutter, 2012; Lian et al., 2018; Liu et al., 2010). The paper complements earlier studies that have shown correlations between retail investor holdings and certain types of stocks. My study also complements research from the banking literature on regulatory arbitrage and shows that the reallocation of risk-taking behavior is not unique to financial institutions, but also relevant when analyzing the effectiveness of regulatory interventions designed for retail investors.

In addition, the paper contributes to the existing literature on social finance (Kuchler and Stroebel, 2021) by documenting some spillover effects of investors' adjustments of their trading strategies in response to a regulatory intervention via a social network. Thus, the paper provides some evidence for an immediate implication of investors' decisions: their decisions may carry over to other investors. Given the increasing importance of social media on financial markets—see, for example, the recent hype surrounding "meme stocks" driven by "Reddit" retail investors (Costola et al., 2021; Hasso et al., 2021; Yahya and Chiu, 2022), which underlines the important implications that social interactions of retail investors can have for the performance of investors and capital market equilibria—a better understanding of the transmission of trading strategies through social networks is crucial.

Investors increasing their trading intensity in different underlyings can potentially have implications for the market as well (Frazzini and Pedersen, 2014). As highlighted by French and Roll (1986); Jones et al. (1994) or Avramov et al. (2006), among others, trading can increase stock volatility. Thus, when investors shift their trading activities to more volatile stocks, this may potentially 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 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 impact that a group of non-representative investors can have on financial markets.

Besides 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 enough 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 the analysis to future research.

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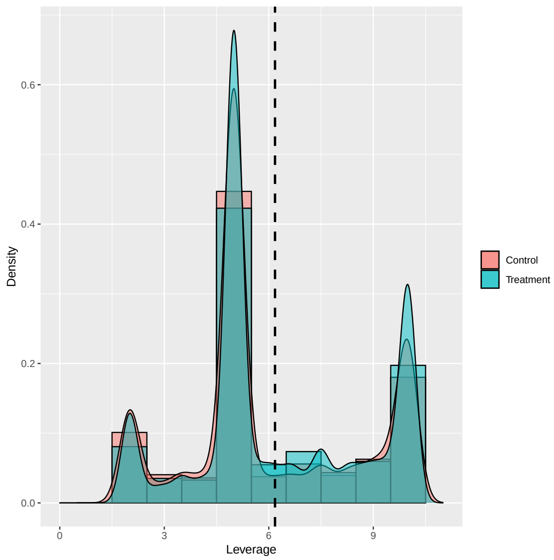
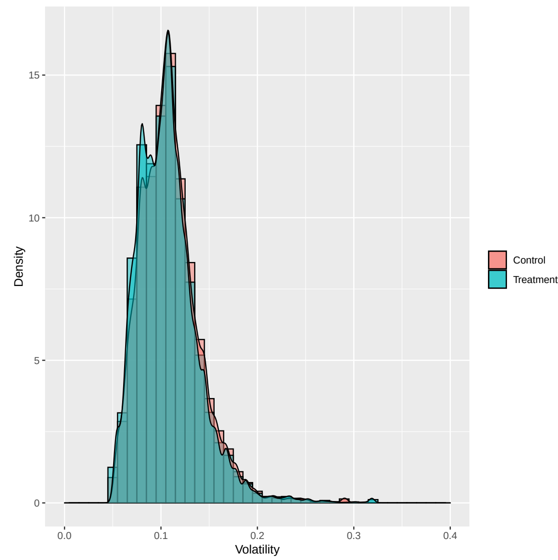
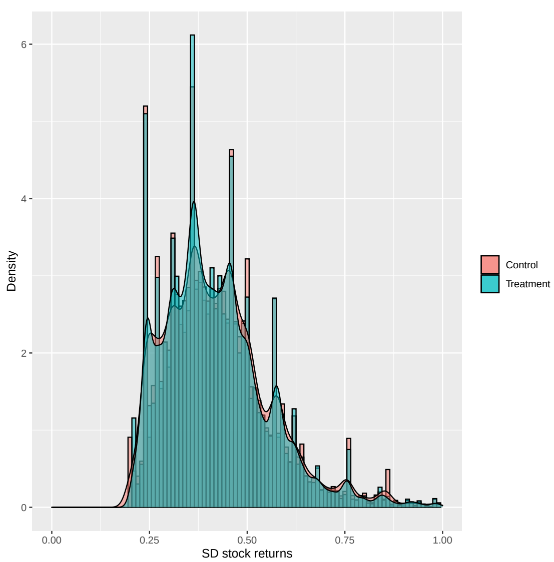


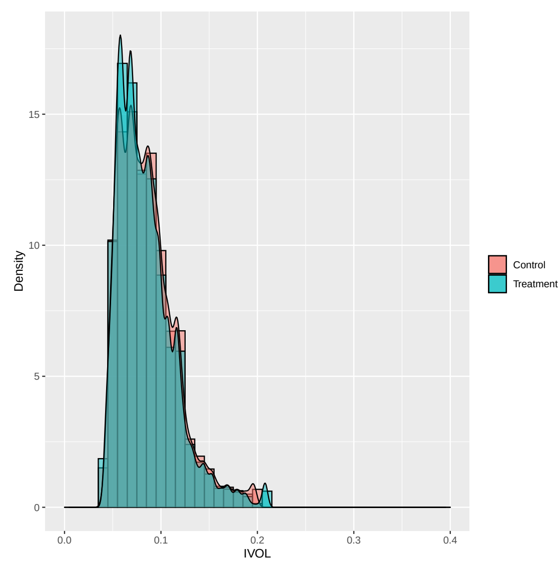
(a) Leverage



(b) Conditional volatility

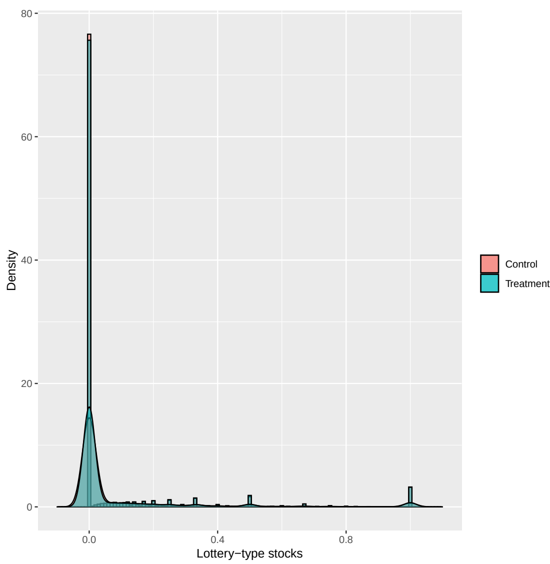


(c) Unconditional volatility

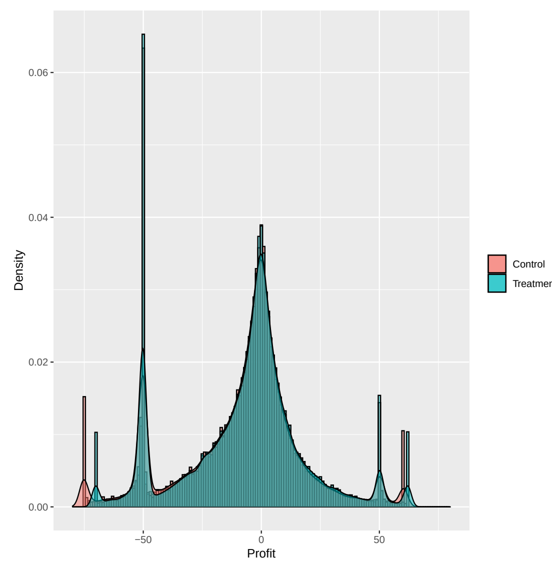


(d) IVOL

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 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. 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 who are subject to the intervention restricting the usage 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.

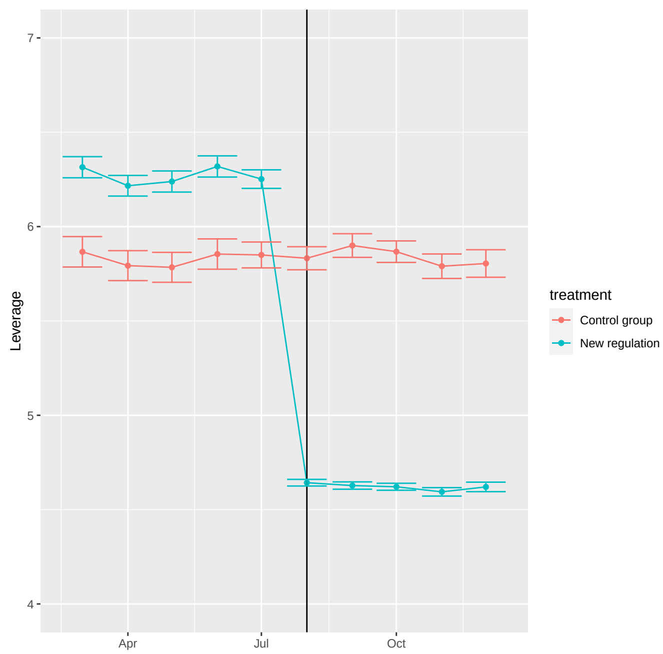
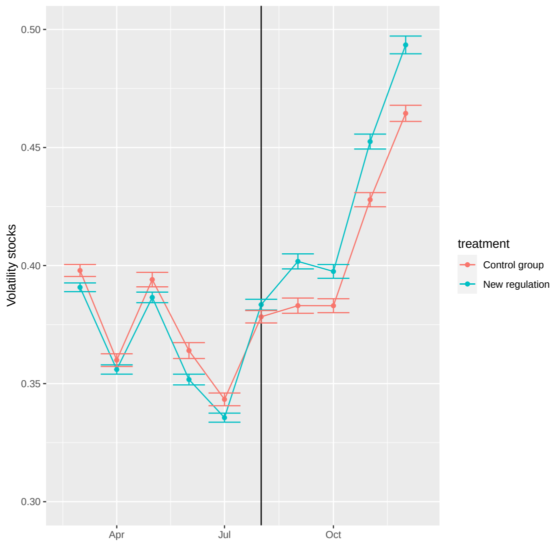
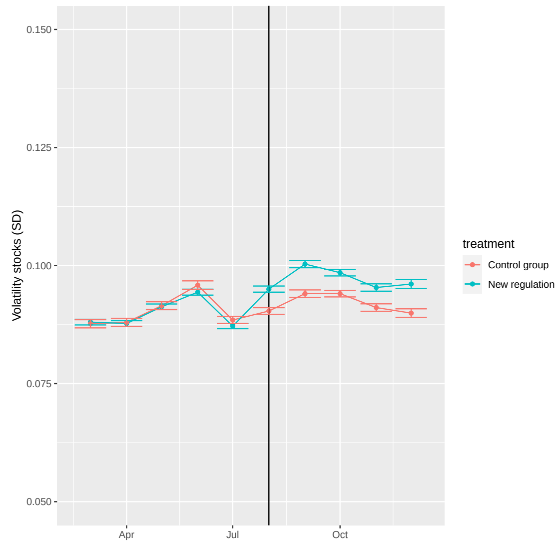


Figure 2: Leverage-usage around the regulatory intervention.

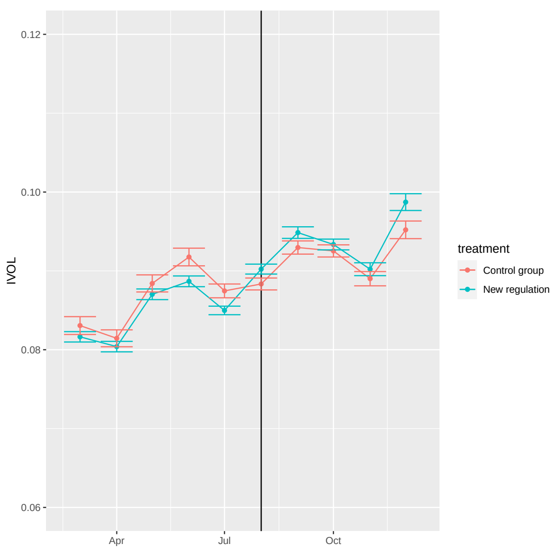
This figure presents the average usage of leverage by investors around the leverage intervention. The control group (red) comprises all investors who are not affected by the intervention. The treatment group comprises all investors who are subject to the intervention restricting the usage of leverage on August 1, 2018. The graph shows the average usage 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.



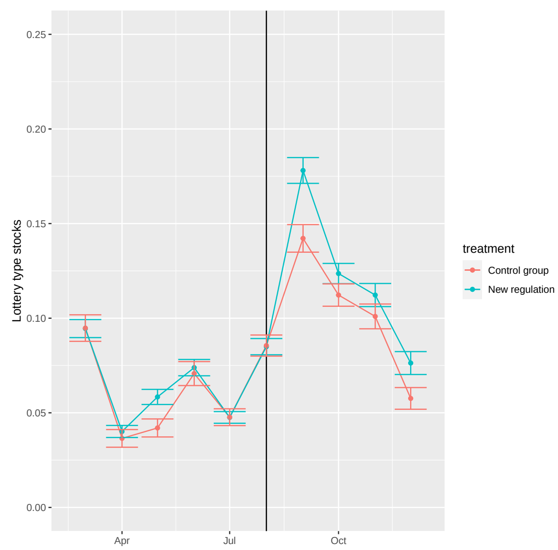
(a) Conditional volatility



(b) Unconditional volatility

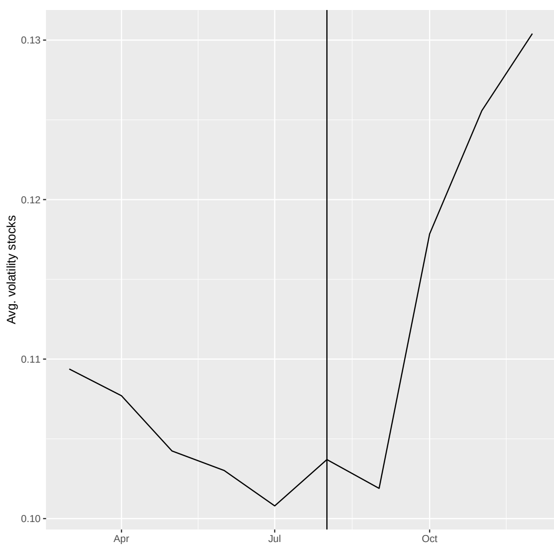


(c) IVOL

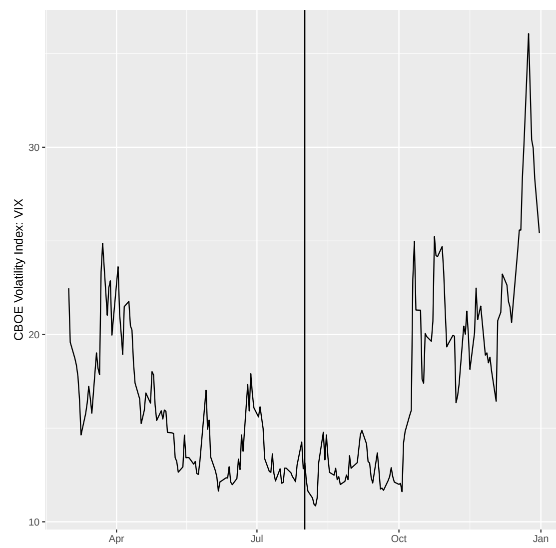


(d) Lottery-type stocks

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 who are subject to the intervention restricting the usage 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.

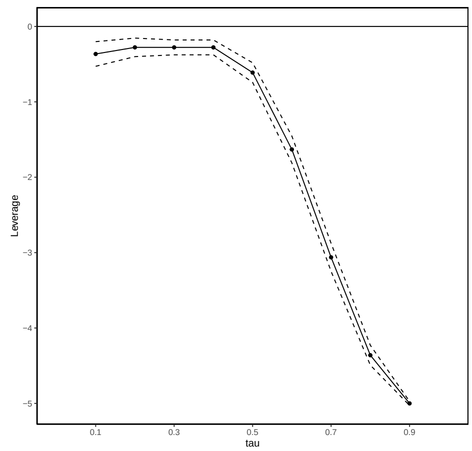


(a) Average stock volatility

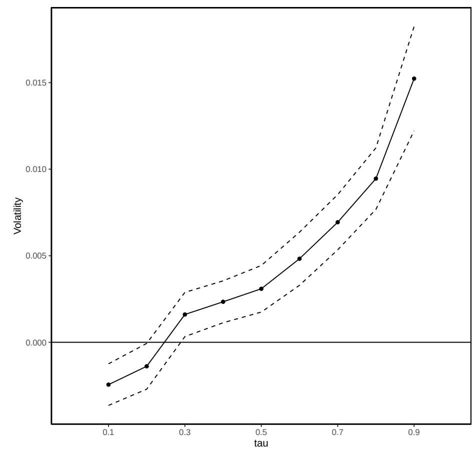


(b) CBOE Volatility Index: VIX

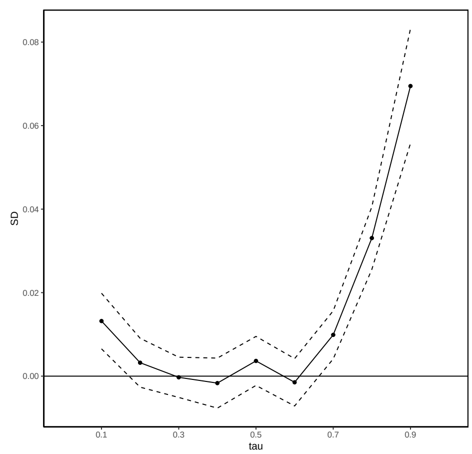
Figure 4: Average market volatility in 2018.
This figure presents the average GARCH(1,1) volatility (Panel a) of all stocks that investors can trade on the trading platform and the CBOE Volatility Index (VIX, Panel b).



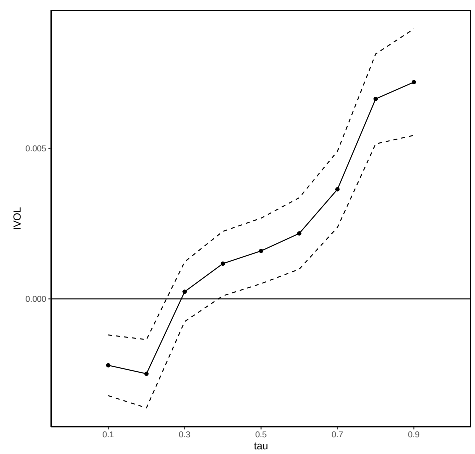
(a) Leverage



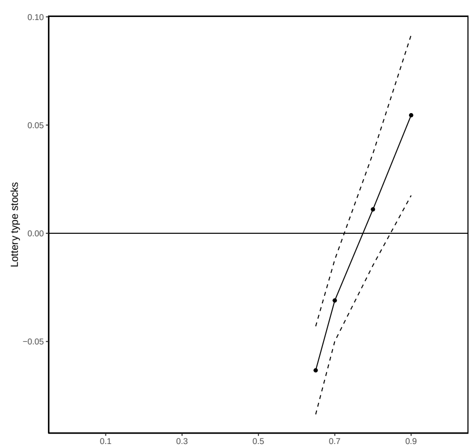
(b) Conditional volatility



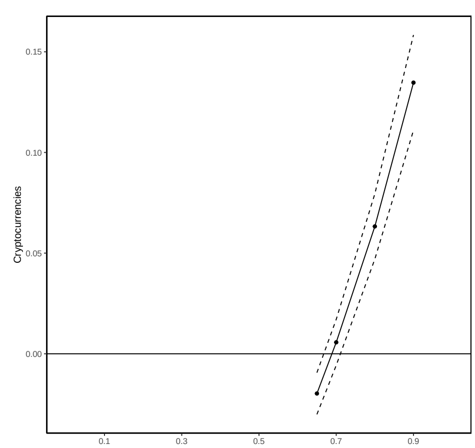
(c) Unconditional volatility



(d) IVOL



(e) Lottery-type stocks



(f) Cryptocurrencies

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 (Panel c), IVOL (Panel d), lottery type (Panel e), and crypto (Panel f). QTT estimates are estimated using the produce of Callaway and Li (2019). 95% pointwise confidence intervals are computed using a bootstrap procedure with 1000 iterations.

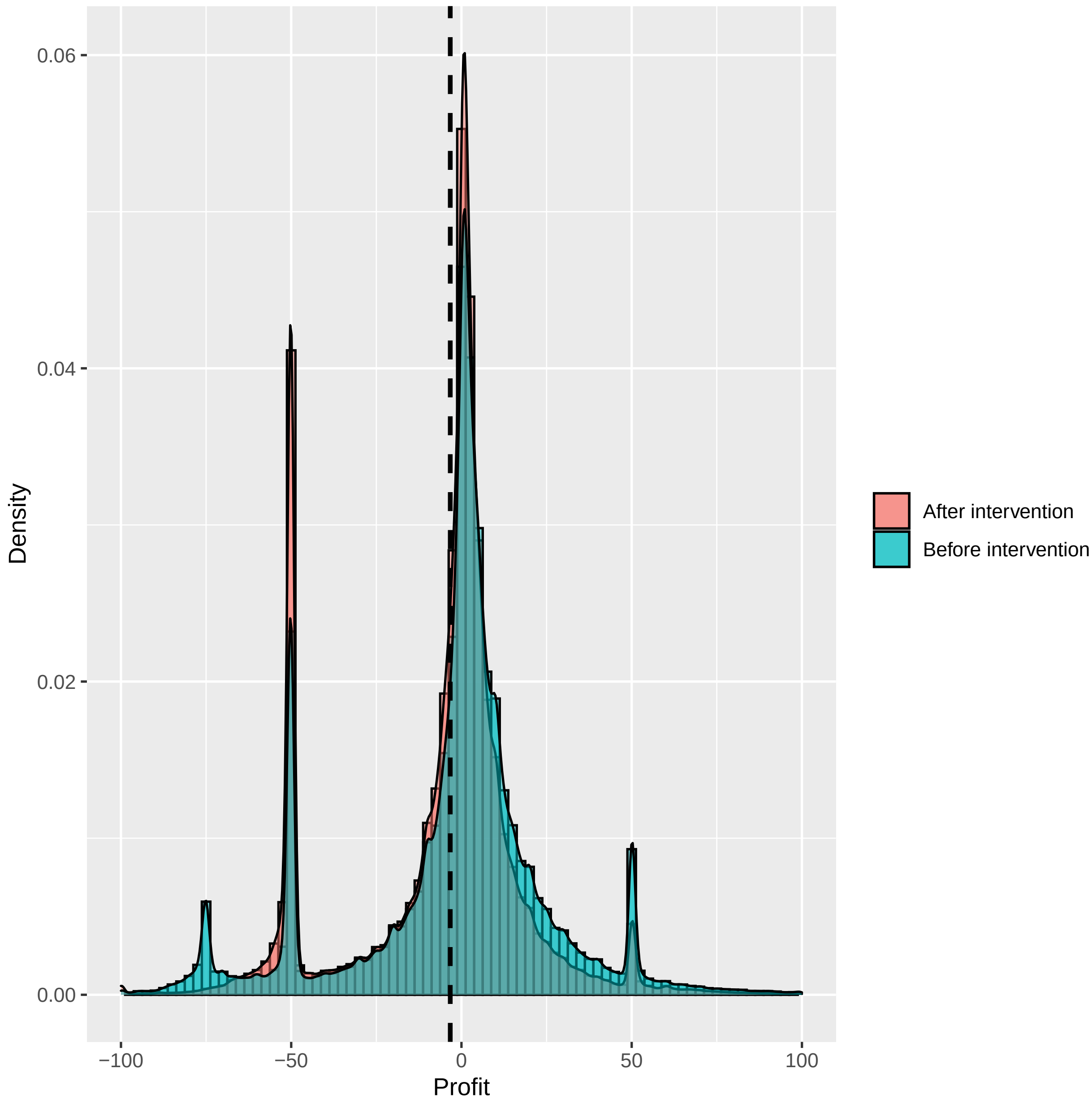


Figure 6: Distribution of holding-period returns of ESMA investors.
This figure presents the holding-period returns of individual positions that investors who are subject to the leverage intervention open before (green) and after (red) the intervention.

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 the 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. *Leverage* denotes the average leverage employed for a trade. The leverage is aggregated at the monthly level using a simple average. $ESMA$ is a dummy variable that takes a value of 1 for investors who are 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
ESMA · post intervention	-1.8665
	(-64.3186)
Investor fixed effects	Yes
Time fixed effects	Yes
Obs.	$209,671$
Adj. R^2	0.6008
No. investors	$49,696$
No. month	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. In Panel B, initiated trades are investment-weighted at the investor-level over a given month. Panel C 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 with a standard GARCH(1,1) model; *stock SD* denotes the unconditional volatility of the traded stock; $IVOL$ denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month. 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 who are 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) Volatility	(2) stock SD	(3) IVOL	(4) Lottery type	(5) Crypto
Panel A: Equally-weighted averages					
ESMA · post intervention	0.0073	0.0243	0.0019	0.0103	0.0176
	(4.8700)	(5.3072)	(4.8382)	(1.5655)	(2.9831)
Obs.	207,003	205,557	202,076	207,003	209,671
Adj. R^2	0.4321	0.4079	0.4398	0.2404	0.4674
No. investors	49,448	49,254	48,806	49,448	49,696
No. month	10	10	10	10	10
Panel B: Investment-weighted averages					
ESMA · post intervention	0.0072	0.0246	0.0019	0.0101	0.0176
	(4.7742)	(5.2656)	(4.6562)	(1.5307)	(2.9831)
Obs.	207,003	205,557	202,076	207,003	209,671
Adj. R^2	0.4281	0.4019	0.4344	0.2357	0.4674
No. investors	49,448	49,254	48,806	49,448	49,696
No. month	10	10	10	10	10
Panel C: Market return controls					
ESMA · post intervention	0.0060	0.0181	0.0011	0.0397	0.0433
	(4.3071)	(3.2756)	(1.9028)	(10.1404)	(10.5716)
Market returns · ESMA	Yes	Yes	Yes	Yes	Yes
Obs.	207,003	205,557	202,076	207,003	209,671
Adj. R^2	0.4325	0.4083	0.4399	0.2408	0.4684
No. investors	49,448	49,254	48,806	49,448	49,696
No. month	10	10	10	10	10
All panels:					
Investor fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	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 with a standard GARCH(1,1) model; *stock SD* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month. 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 who are 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)	(6)
	First stage			Second stage		
	ΔLeverage	ΔVolatility	Δstock SD	ΔIVOL	ΔLottery type	ΔCrypto
(Intercept)	0.5052	0.0194	0.0581	0.0053	0.0315	0.0136
	(5.7150)	(10.7752)	(6.5864)	(3.6936)	(2.8832)	(1.5005)
$\widehat{\Delta \text{Leverage}}$		−0.0017	−0.0148	−0.0012	−0.0010	−0.0105
		(−4.6721)	(−8.5240)	(−4.2150)	(−0.4465)	(−5.6429)
ESMA	−1.8002					
	(−53.4774)					
Controls	Yes	Yes	Yes	Yes	Yes	Yes
F-test	318.1333					
p-value (F-test)	0.0000					
Obs.	13,329	12,995	12,848	12,655	12,995	13,329
Adj. R^2	0.3927	0.0130	0.0088	0.0016	0.0006	0.0018

Table 4: 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 who are 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) Leverage $\times$ volatility
ESMA $\cdot$ post intervention	-0.1830
	(-20.1333)
Investor fixed effects	Yes
Time fixed effects	Yes
Obs.	$207,003$
Adj. R^2	0.5234
No. investors	$49,448$
No. month	10

Table 5: 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 levered holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average levered holding-period returns in a given month. $ESMA$ is a dummy variable that takes a value of 1 for investors who are 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 $\cdot$ post intervention	1.2365	-3.1980
	(3.3752)	(-13.1096)
Holding period	-0.0463	0.1588
	(-0.7818)	(10.5544)
Investor fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Obs.	$206,288$	$152,647$
Adj. R^2	0.1497	0.2829
No. investors	$49,251$	$41,860$
No. month	10	10

Table 6: 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 who are 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	1.2838
	(4.2607)
Investor fixed effects	Yes
Time fixed effects	Yes
Obs.	206,288
Adj. R^2	0.4364
No. investors	49,251
No. month	10

Table 7: The leverage intervention: Regression results focusing on investors' leverage-usage.

This table reports the results from a difference-in-difference-in-differences regression analysis on investors' leverage-usage and various risk-taking and profitability measures focusing on investors' leverage-usage prior to the intervention. *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; *stock SD* denotes the unconditional volatility of the traded stock; $IVOL$ denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; $Leverage \times Volatility$ denotes the average of the product leverage $\times$ volatility for each trade; $Profit$ denotes the average holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average holding-period returns in a given month; all trading measures are aggregated at the monthly level using averages. *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; $ESMA$ is a dummy variable that takes a value of 1 for investors who are 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var.	Leverage	Volatility	stock SD	IVOL	Lottery type	Crypto	Leverage × volatility	Profit	SD(profit)
ESMA · post intervention	−1.2767	0.0061	0.0197	0.0015	0.0092	0.0151	−0.1216	0.8872	−2.1188
	(−45.9511)	(4.7377)	(5.1658)	(3.8062)	(1.6907)	(2.7574)	(−22.1057)	(2.1591)	(−8.0169)
Post intervention · high leverage	−0.9019	0.0044	0.0159	0.0023	0.0167	0.0231	−0.0379	2.2519	−0.6696
	(−12.4666)	(3.7300)	(4.0278)	(3.0504)	(2.9322)	(2.8866)	(−2.1843)	(1.7573)	(−0.9981)
ESMA · post intervention · high leverage	−2.7115	0.0055	0.0214	0.0020	0.0047	0.0105	−0.2809	1.2217	−3.9549
	(−48.8210)	(3.6701)	(3.4687)	(2.3756)	(0.6735)	(2.0852)	(−15.5842)	(1.2459)	(−8.4065)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	186,994	184,543	183,320	180,544	184,543	186,994	184,543	184,428	138,078
Adj. R^2	0.6913	0.4109	0.3861	0.4320	0.2169	0.4631	0.5381	0.1453	0.2703
No. investors	36,826	36,681	36,605	36,479	36,681	36,826	36,681	36,811	33,323
No. month	10	10	10	10	10	10	10	10	10

Table 8: The leverage intervention: Regression results focusing on investors' profitability.

This table reports the results from a difference-in-difference-in-differences regression analysis on investors' leverage-usage and various risk-taking and profitability measures focusing on investors' profitability prior to the intervention. *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; *stock SD* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; $Leverage \times Volatility$ denotes the average of the product leverage $\times$ volatility for each trade; *Profit* denotes the average holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average holding-period returns in a given month; all trading measures are aggregated at the monthly level using averages. *Low profit* is a dummy variable that takes a value of 1 for investors who realized profitability in the bottom quartile prior to the intervention, and 0 otherwise; *ESMA* is a dummy variable that takes a value of 1 for investors who are 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var.	Leverage	Volatility	stock SD	IVOL	Lottery type	Crypto	Leverage $\times$ volatility	Profit	SD(profit)
ESMA · post intervention	−1.4138	0.0037	0.0111	0.0002	0.0026	0.0053	−0.1401	−0.1631	−2.6067
	(−42.5525)	(3.3654)	(2.2482)	(0.3749)	(0.4334)	(1.0194)	(−17.6881)	(−0.3005)	(−5.7712)
Post intervention · low profit	−0.0271	0.0028	0.0046	−0.0001	0.0053	−0.0127	0.0249	9.5745	0.0349
	(−0.8173)	(3.6769)	(1.4486)	(−0.1837)	(0.7371)	(−1.2921)	(3.2649)	(8.4414)	(0.0603)
ESMA · post intervention · low profit	−0.6503	0.0051	0.0188	0.0024	0.0108	0.0183	−0.0629	1.4097	−0.5350
	(−16.9945)	(3.8344)	(5.0829)	(4.1085)	(2.1508)	(3.7338)	(−7.3204)	(2.0781)	(−0.8210)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	199,799	197,190	195,815	192,556	197,190	199,799	197,190	196,686	145,481
Adj. R^2	0.6047	0.4274	0.4025	0.4387	0.2360	0.4680	0.5180	0.1639	0.2703
No. investors	44,223	44,004	43,843	43,492	44,004	44,223	44,004	43,927	37,700
No. month	10	10	10	10	10	10	10	10	10

Table 9: The leverage intervention: Regression results focusing on investors' gender.

This table reports the results from a difference-in-difference-in-differences regression analysis on investors' leverage-usage and various risk-taking and profitability measures focusing on investors' gender. *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; *stock SD* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; $Leverage \times Volatility$ denotes the average of the product leverage × volatility for each trade; *Profit* denotes the average holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average holding-period returns in a given month; all trading measures are aggregated at the monthly level using averages. *Male* is a dummy variable that takes a value of 1 for investors who are male, and 0 otherwise; *ESMA* is a dummy variable that takes a value of 1 for investors who are 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var.	Leverage	Volatility	stock SD	IVOL	Lottery type	Crypto	Leverage × volatility	Profit	SD(profit)
ESMA · post intervention	−1.3873	0.0049	0.0148	0.0014	0.0114	0.0229	−0.1361	−0.3965	−2.2971
	(−20.9488)	(2.5255)	(2.5507)	(1.4174)	(1.4301)	(2.0404)	(−9.9563)	(−0.5026)	(−3.5113)
Post intervention · male	0.1061	0.0018	0.0026	0.0010	0.0077	0.0116	0.0291	1.3725	−0.1890
	(1.7364)	(1.5493)	(0.6537)	(1.3556)	(1.3091)	(2.0037)	(2.3610)	(1.5251)	(−0.3691)
ESMA · post intervention · male	−0.5166	0.0025	0.0102	0.0005	−0.0014	−0.0060	−0.0509	1.6618	−0.7376
	(−6.4863)	(1.6639)	(1.6572)	(0.4381)	(−0.1597)	(−0.6767)	(−3.6928)	(1.7408)	(−1.1152)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	209,662	206,994	205,548	202,067	206,994	209,662	206,994	206,279	152,641
Adj. R^2	0.6012	0.4322	0.4080	0.4398	0.2404	0.4675	0.5234	0.1490	0.2704
No. investors	49,692	49,444	49,250	48,802	49,444	49,692	49,444	49,247	41,857
No. month	10	10	10	10	10	10	10	10	10

Table 10: The leverage intervention: Regression results focusing on investors' age.

This table reports the results from a difference-in-difference-in-differences regression analysis on investors' leverage-usage and various risk-taking and profitability measures focusing on investors' age. $Leverage$ 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; *stock SD* denotes the unconditional volatility of the traded stock; $IVOL$ denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); $Crypto$ denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; $Leverage \times Volatility$ denotes the average of the product leverage $\times$ volatility for each trade; $Profit$ denotes the average holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average holding-period returns in a given month; all trading measures are aggregated at the monthly level using averages. $25-34$ 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; $ESMA$ is a dummy variable that takes a value of 1 for investors who are 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var.	Leverage	Volatility	stock SD	IVOL	Lottery type	Crypto	Leverage × volatility	Profit	SD(profit)
ESMA · post intervention	−2.2986	0.0217	0.1050	0.0047	0.0398	0.0015	−0.1575	−0.0793	−0.8808
	(−25.6014)	(3.8151)	(5.6945)	(2.1890)	(1.4592)	(0.1529)	(−5.1145)	(−0.0455)	(−0.6134)
Post intervention · 25-34	0.0068	−0.0048	−0.0164	−0.0040	0.0034	−0.0061	−0.0428	−1.3921	−0.0275
	(0.0731)	(−2.1526)	(−1.8692)	(−2.7163)	(0.3656)	(−0.6377)	(−2.5162)	(−0.6795)	(−0.0175)
Post intervention · 35-44	−0.0348	−0.0060	−0.0229	−0.0048	−0.0059	−0.0121	−0.0541	−0.2237	0.2816
	(−0.3535)	(−2.8564)	(−2.6095)	(−3.2188)	(−0.5291)	(−1.1469)	(−3.2530)	(−0.1762)	(0.2128)
Post intervention · 45-54	−0.0021	−0.0088	−0.0276	−0.0058	−0.0071	−0.0106	−0.0647	−0.8056	−1.1368
	(−0.0244)	(−3.8816)	(−2.9680)	(−3.8544)	(−0.6996)	(−1.0914)	(−3.5383)	(−0.4995)	(−0.9274)
Post intervention · 55-64	−0.1055	−0.0081	−0.0178	−0.0054	−0.0047	−0.0195	−0.0760	−0.1713	−1.0462
	(−1.0734)	(−3.6334)	(−1.7476)	(−3.2299)	(−0.4427)	(−1.4307)	(−4.5864)	(−0.0906)	(−0.6245)
Post intervention · >65	0.0816	−0.0072	−0.0260	−0.0079	0.0017	−0.0082	−0.0637	0.8317	−2.4157
	(0.7764)	(−2.3332)	(−2.1047)	(−3.8806)	(0.1029)	(−0.4861)	(−3.1449)	(0.2919)	(−1.5713)
ESMA · post intervention · 25-34	0.2211	−0.0118	−0.0695	−0.0026	−0.0333	0.0147	−0.0344	1.0491	−2.3846
	(2.0517)	(−3.2554)	(−5.5221)	(−1.5209)	(−1.7442)	(1.3379)	(−1.5527)	(0.4898)	(−1.3648)
ESMA · post intervention · 35-44	0.3789	−0.0162	−0.0892	−0.0028	−0.0262	0.0223	−0.0435	0.9192	−3.2485
	(3.6031)	(−3.0804)	(−4.8822)	(−1.3019)	(−1.0040)	(2.0664)	(−1.4479)	(0.5632)	(−2.1685)
ESMA · post intervention · 45-54	0.5396	−0.0151	−0.0873	−0.0026	−0.0263	0.0137	−0.0181	2.2000	−0.7179
	(5.3377)	(−3.0143)	(−4.9980)	(−1.1487)	(−1.1042)	(1.4037)	(−0.6085)	(0.8399)	(−0.4445)
ESMA · post intervention · 55-64	0.9442	−0.0175	−0.0986	−0.0040	−0.0404	0.0186	0.0211	1.3838	−1.0627
	(8.4451)	(−3.2698)	(−5.4133)	(−1.5633)	(−1.4933)	(1.3583)	(0.6902)	(0.5535)	(−0.5498)
ESMA · post intervention · >65	1.2119	−0.0219	−0.1038	−0.0026	−0.0481	0.0004	0.0451	0.2509	1.6429
	(9.3099)	(−3.0903)	(−4.9779)	(−1.0716)	(−1.3981)	(0.0288)	(1.2334)	(0.0771)	(0.8231)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	208,633	205,981	204,542	201,076	205,981	208,633	205,981	205,273	151,861
Adj. R^2	0.6030	0.4343	0.4114	0.4402	0.2404	0.4677	0.5238	0.1489	0.2698
No. investors	49,499	49,252	49,059	48,613	49,252	49,499	49,252	49,057	41,688
No. month	10	10	10	10	10	10	10	10	10

Table 11: The leverage intervention: Regression results focusing on investors' experience.

This table reports the results from a difference-in-difference-in-differences regression analysis on investors' leverage-usage and various risk-taking and profitability measures focusing on investors' experience. *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; *stock SD* denotes the unconditional volatility of the traded stock; $IVOL$ denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; $Leverage \times Volatility$ denotes the average of the product leverage × volatility for each trade; $Profit$ denotes the average holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average holding-period returns in a given month; all trading measures are aggregated at the monthly level using averages. *Low experience* is a dummy variable that takes a value of 1 for investors with below median trading experience (self-assessment), and 0 otherwise; $ESMA$ is a dummy variable that takes a value of 1 for investors who are 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var.	Leverage	Volatility	stock SD	IVOL	Lottery type	Crypto	Leverage × volatility	Profit	SD(profit)
ESMA · post intervention	−1.9278	0.0070	0.0212	0.0018	0.0096	0.0190	−0.1925	1.2364	−3.3720
	(−60.3387)	(4.6587)	(5.1187)	(4.7190)	(1.4046)	(3.0174)	(−20.1125)	(2.8312)	(−12.0594)
Post intervention · low experience	−0.0080	0.0003	0.0005	0.0007	−0.0058	−0.0104	0.0021	−2.9396	−0.8629
	(−0.1944)	(0.3087)	(0.1406)	(1.2707)	(−1.3135)	(−2.8021)	(0.2660)	(−4.8352)	(−1.9640)
ESMA · post intervention · low experience	0.2192	0.0008	0.0113	0.0004	0.0031	−0.0040	0.0338	0.1434	1.5622
	(4.9193)	(0.7756)	(2.0109)	(0.4289)	(0.7278)	(−1.0306)	(4.2916)	(0.2618)	(3.1123)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	209,588	206,920	205,475	201,996	206,920	209,588	206,920	206,206	152,586
Adj. R^2	0.6011	0.4320	0.4080	0.4397	0.2404	0.4677	0.5237	0.1495	0.2700
No. investors	49,679	49,431	49,237	48,789	49,431	49,679	49,431	49,235	41,847
No. month	10	10	10	10	10	10	10	10	10

Table 12: The leverage intervention: Regression results focusing on investors' trading horizon.

This table reports the results from a difference-in-difference-in-differences regression analysis on investors' leverage-usage and various risk-taking and profitability measures focusing on investors' trading horizon. *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; *stock SD* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; $Leverage \times Volatility$ denotes the average of the product leverage × volatility for each trade; *Profit* denotes the average holding-period return in a given month; $SD(profit)$ denotes the standard deviation of average holding-period returns in a given month; all trading measures are aggregated at the monthly level using averages. *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; *ESMA* is a dummy variable that takes a value of 1 for investors who are 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var.	Leverage	Volatility	stock SD	IVOL	Lottery type	Crypto	Leverage × volatility	Profit	SD(profit)
ESMA · post intervention	−1.9022	0.0038	0.0060	0.0010	−0.0001	0.0253	−0.2063	1.2929	−2.8370
	(−29.2890)	(2.2929)	(1.2469)	(1.0072)	(−0.0136)	(2.5031)	(−18.0473)	(1.1211)	(−2.5225)
Post intervention · medium horizon	−0.0868	−0.0015	−0.0064	−0.0007	−0.0135	0.0035	−0.0165	1.9660	1.1287
	(−1.5508)	(−1.3402)	(−1.2997)	(−0.7806)	(−2.2074)	(0.4693)	(−1.7424)	(1.9551)	(0.9245)
Post intervention · short horizon	0.0680	0.0016	0.0047	0.0018	−0.0001	0.0107	0.0239	3.9179	2.0206
	(0.9001)	(1.1796)	(0.7922)	(1.5486)	(−0.0211)	(1.2161)	(1.9166)	(2.6854)	(1.6283)
ESMA · post intervention · medium horizon	0.1178	0.0027	0.0131	0.0007	0.0123	−0.0047	0.0263	−0.0312	−0.7039
	(1.6432)	(1.8973)	(2.3246)	(0.5363)	(1.6949)	(−0.5873)	(2.4172)	(−0.0264)	(−0.5736)
ESMA · post intervention · short horizon	−0.3371	0.0061	0.0298	0.0013	0.0111	−0.0147	−0.0046	0.0192	−0.1116
	(−3.8665)	(2.4461)	(2.8715)	(0.8052)	(1.1864)	(−1.5084)	(−0.2787)	(0.0139)	(−0.0857)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	156,449	154,335	153,285	150,677	154,335	156,449	154,335	153,865	114,605
Adj. R^2	0.6130	0.4357	0.4125	0.4430	0.2392	0.4796	0.5355	0.1494	0.2765
No. investors	36,194	36,005	35,880	35,527	36,005	36,194	36,005	35,867	30,517
No. month	10	10	10	10	10	10	10	10	10

Table 13: Spillover effects in risk-taking following the intervention: Difference-in-differences analysis.

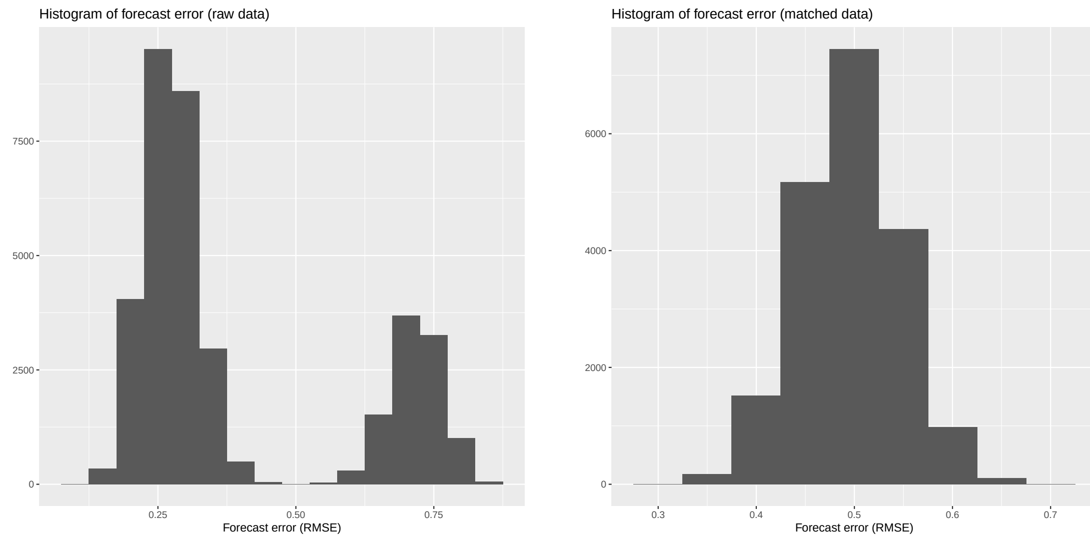
This table reports the results from a difference-in-differences regression analysis on various risk-taking measures of trades that investors initiate in the trade data focusing on spillover effects. In Panel A, an investor is part of the spillover group if they are not subject to ESMA regulation, but 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 with a standard GARCH(1,1) model; *stock SD* denotes the unconditional volatility of the traded stock; $IVOL$ denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month; all trading 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 who are 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: Direct relation to ESMA investor

Dependent var.	(1) Leverage	(2) Volatility	(3) stock SD	(4) IVOL	(5) Lottery type	(6) Crypto
Spillover	−0.0155	0.0011	0.0075	0.0007	0.0008	0.0013
	(−0.3526)	(0.9748)	(1.4005)	(0.8219)	(0.2078)	(0.2795)
Spillover · post intervention	−0.0847	0.0017	0.0076	0.0002	0.0097	−0.0088
	(−2.0208)	(1.7575)	(1.8256)	(0.2509)	(1.7890)	(−1.1938)
ESMA · post intervention	−1.8854	0.0077	0.0262	0.0019	0.0126	0.0156
	(−60.0664)	(4.9449)	(5.7856)	(4.4646)	(1.8865)	(2.3913)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	210,537	207,860	206,403	202,904	207,860	210,537
Adj. R^2	0.6014	0.4325	0.4083	0.4400	0.2416	0.4684
No. investors	49,696	49,448	49,254	48,806	49,448	49,696
No. month	10	10	10	10	10	10

Panel B: Any relation to other investors

Dependent var.	(1) Leverage	(2) Volatility	(3) stock SD	(4) IVOL	(5) Lottery type	(6) Crypto
Spillover	−0.0340	0.0010	0.0078	0.0008	−0.0001	−0.0000
	(−0.8270)	(1.2742)	(2.3453)	(1.3573)	(−0.0244)	(−0.0058)
Spillover · post intervention	−0.0707	0.0019	0.0076	0.0004	0.0103	−0.0071
	(−1.8086)	(2.2617)	(2.1919)	(0.6682)	(2.2754)	(−1.8911)
ESMA · post intervention	−1.8850	0.0078	0.0265	0.0020	0.0131	0.0157
	(−82.2493)	(15.8080)	(12.9708)	(5.7061)	(5.1736)	(7.9385)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	210,537	207,860	206,403	202,904	207,860	210,537
Adj. R^2	0.6014	0.4325	0.4083	0.4400	0.2416	0.4684
No. investors	49,696	49,448	49,254	48,806	49,448	49,696
No. month	10	10	10	10	10	10



(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 tries to forecast which traders 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 .3991 [median: 0.2754] 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%	16.45%	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 that are 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 with 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; *IVOL* (idiosyncratic volatility) is measured with 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	6.274	13.787	0	0	5
Crypto	209,671	0.104	0.203	0	0	0.1
Leverage	2,097,456	6.106	2.632	5	5	10
Investment	2,097,456	15.661	23.155	1.940	6.820	17.410
Lottery type	2,039,276	0.126	0.332	0.000	0.000	0.000
Holding period	2,068,578	9.770	30.085	0.082	1.812	7.216
Profit	2,068,578	−3.420	32.203	−11.546	0.806	8.824
Panel B: Stock data						
	Obs.	Mean	SD	P25	P50	P75
Volatility	32,704	0.112	0.086	0.065	0.090	0.132
Stock SD	31,992	0.447	0.318	0.260	0.355	0.526
IVOL	19,502	0.081	0.043	0.053	0.070	0.097

Table A.3: Matched data: 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 using a matched dataset. *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; *stock SD* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month. All trading measures are aggregated at the monthly level using averages. *ESMA* is a dummy variable that takes a value of 1 for investors who are 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) stock SD	(4) IVOL	(5) Lottery type	(6) Crypto
ESMA · post intervention	-1.8165	0.0077	0.0263	0.0020	0.0136	0.0177
	(-55.9957)	(4.9251)	(5.3372)	(4.2797)	(2.0131)	(2.9303)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	101,840	100,827	100,222	98,981	100,827	101,840
Adj. R^2	0.6425	0.4103	0.3888	0.4363	0.2138	0.4580
No. investors	19,780	19,780	19,766	19,723	19,780	19,780
No. month	10	10	10	10	10	10

Table A.4: Pseudo-treated investors: Difference-in-differences analysis.

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 with a standard GARCH(1,1) model; *stock SD* denotes the unconditional volatility of the traded stock; *IVOL* denotes the idiosyncratic volatility of the traded stock, measured with rolling-window regressions over the last 262 days (one year); *Lottery type* denotes stocks that are classified as lottery stocks according to Kumar (2009); *Crypto* denotes the fraction of trades initiated in cryptocurrencies relative to all trades initiated in a given month. *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) stock SD	(4) IVOL	(5) Lottery type	(6) Crypto
"*ESMA*" · post intervention	0.0069	0.0001	0.0010	−0.0001	0.0022	−0.0002
	(0.2756)	(0.1257)	(0.4452)	(−0.4010)	(0.8618)	(−0.0986)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	164,013	161,910	160,776	158,083	161,910	164,013
Adj. R^2	0.5728	0.4342	0.4123	0.4442	0.2481	0.4671
No. investors	40,000	39,801	39,631	39,254	39,801	40,000
No. month	10	10	10	10	10	10