Essays on the Behavior and Performance of Retail Investors

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Essays on the Behavior and Performance of Retail Investors

A dissertation presented by

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ABSTRACT

In recent years, retail trading in stocks, cryptocurrencies and other assets has become significantly more popular, and since the onset of the Covid-19 pandemic and the shift to a work-from-home regime, it has in many ways become a mainstream activity. In this dissertation, I utilize a proprietary dataset obtained from an international broker to produce new insights about the behavior and performance of this important group of traders.

In the first essay, I study the use of leverage by retail traders. Utilizing a major regulatory intervention that limited the amount of leverage that retail brokers may offer on certain financial derivatives, I deploy a difference-in-differences research design and report that leverage is highly detrimental to the wealth of retail traders. I further show that overconfidence and an insufficient understanding of leverage are important contributors to this result. These findings portray a situation in which retail traders make a financial mistake that is so extreme that it may justify a regulatory intervention even in the absence of an apparent market failure.

In the second essay, I investigate the implications of the recent shift to a work-from-home regime on retail trading. Exploiting the changes in work-from-home policies within and across countries, I demonstrate that, upon working from home, retail traders pay more attention to their brokerage accounts, trade more and perform better. These findings not only illustrate important changes in the behavior of retail traders but also provide causal support for the literature aiming to link traders' attention to their performance.

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CHAPTER 1

Introduction

Over the past two decades, retail trading in financial markets has been completely transformed. Technological innovations have shifted trading activities to online platforms, which enable a very simple and seamless way of trading, and new fintech brokers have removed many barriers to entry, such as high account minimums, and made trading accessible to a new and generally younger set of clients. Recently, the shift of many brokers to zero-commission stock trading for retail clients and, most importantly, the Covid-19 pandemic, with its associated lockdowns and workplace closures, have drawn more and more individuals to engage in trading activities. Nonetheless, most of what we know about the behavior and performance of retail traders stems from a series of papers that utilized trading data from the early 1990s.[1] For illustration purposes, during that time period, most trades were initiated by calling one's broker over the phone.

Throughout my doctoral studies at Harvard Business School, I have dedicated my research to studying the behavior and performance of retail traders in this new world. Utilizing a proprietary—and recent—dataset obtained from an international broker, I attempted to study aspects of retail trading that have gained importance in recent years. In this dissertation, I have chosen to include two of my essays, which I believe to be especially timely.

In the first essay, included in the second chapter of this dissertation, I explore the use of leverage by retail traders. Recently, the use of leverage by retail traders has significantly grown. In fact, in a recent survey by Yahoo Finance and the Harris Poll, 43% of retail traders said that

[1] The following papers provide good summaries of this literature: Barber and Odean (2013), Barberis (2018), Beshears et al. (2018) and Guiso and Sodini (2013).

they use margin, options or both, with the percentage going up to 67% for younger traders aged 18–34.[2] Using a major regulatory intervention that restricted the amount of leverage offered on a unique financial derivative in Europe, I employ a difference-in-differences research design and demonstrate that leverage significantly hinders the trading performance of retail traders. I further provide evidence that ignorance with respect to the implications of leverage and overconfidence serve as important contributors to the suboptimal use of leverage by individuals. These findings not only extend our understanding of the behavior of retail traders but also provide an example of a situation in which gross financial mistakes by consumers may warrant a regulatory intervention even in the absence of an apparent market failure.

In the second essay, presented in the third chapter of this dissertation, I investigate how the recent shift to a work-from-home regime during the Covid-19 pandemic affected the trading behavior and performance of retail traders. Utilizing the global nature of the broker, I exploit the variation in work-from-home policies, both within each country over time and across countries during specific points in time, and find evidence that retail traders who work from home pay more attention to their brokerage accounts, trade more and perform better. Otherwise, they continue to trade in a relatively similar manner. As many leading firms are expected to maintain a work-from-home regime in the long term, at least in a partial or hybrid way, these findings highlight important changes in the behavior of retail traders that may endure into the future. Furthermore, the plausibly exogenous nature of the government-mandated work-from-home restrictions during the pandemic may allow for a causal interpretation of the positive relationship between time, attention and performance, which prior literature has not been able to ascertain.

[2] https://theharrispoll.com/briefs/portfolio-strategy-shifts-during-covid-19/.

CHAPTER 2

Less Can Be More: A Test Case for Restrictions in the Retail Trading Market

2.1 Introduction

In recent years, meaningful financial and technological innovations have completely transformed the realm of retail trading. Trading platforms have become more accessible, with lower barriers to entry; trades have become easier and cheaper to execute, culminating in a recent shift to zero-commission stock-trading; and novel and innovative financial instruments, which have historically not been available to a retail clientele, are now being offered to individual traders. These new opportunities, however, may in certain cases be detrimental to the wealth of retail traders. Some traders, for example, may not be sufficiently informed or may lack the necessary intellectual capacity to assess and understand these opportunities. Other traders, for some other reason, may not make decisions that maximize their utility under a rational utility model (Campbell 2016, Campbell et al. 2011). As a result, regulatory restrictions on certain offerings to retail traders are continuously being considered and, in certain cases, implemented.

In this essay, we focus on the use of leverage by retail traders as a test case for the suitability of certain financial products for this type of traders. Indeed, leverage has many benefits for retail traders, such as the ability to earn superior returns or access to investments that they would otherwise not be able to afford. However, leverage also entails many risks. If these risks are not properly accounted for by retail traders, then they may suffer significant detriment. Indeed, this is what we find. In a nutshell, we document that the use of leverage significantly impedes the trading performance of retail traders, causing them not only to underperform the market but also to earn negative absolute returns and lose money.

To assess the use of leverage by retail traders, we utilize the unique setting of retail trading in contracts for difference (CFDs). A CFD is a derivative that mimics the performance of an underlying asset so that the profit or loss of the trader is calculated based on the change that occurs between the price of the asset at the opening of the trade and the price of the asset at the closing of the trade. Ignoring microstructure frictions and fees, traders should reach the same result in a CFD trade as if they had bought and sold the underlying asset itself. CFDs provide an ideal setting in which to investigate the effects of leverage for retail traders for two reasons. First, in CFD trading, leverage is deployed by the trader at the specific trade level, as opposed to regular margin accounts that do not assign the borrowed funds to specific trades. Therefore, we are able to directly compare trades that are made by the same trader with different amounts of leverage. In fact, because many CFD traders are day traders, we are able to use highly focused fixed effects to create relatively accurate comparisons. For example, in certain specifications, we include user-day-asset fixed effects so that each trade is compared to other trades executed by the same trader, in the same asset, on the same day. Second, in 2018, following evidence that CFD trading is associated with significant losses, the European Securities and Markets Authority (ESMA) limited the amount of leverage that retail brokerage firms can offer on CFDs. This significant regulatory restriction serves as an exogenous intervention in the use of leverage by retail traders and therefore invites a causal analysis.

We obtain a proprietary dataset from a global broker, which operates a trading platform for retail traders. As of January 2022, the broker had more than 27 million registered users in over 140 countries.[3] While the broker offers regular stock, exchange-traded fund (ETF) and cryptocurrency

[3] The number of registered users is the number of users who have signed up to the broker's platform since its inception. The number of active users with funded accounts at any point in time is significantly smaller.

trading, it utilizes CFDs to support trading in foreign currency pairs and commodities, to allow an easy and simple way to open short positions, and primarily to enable the use of leverage, with available leverage ratios ranging from 2:1 to 400:1, depending on the specific asset.

Using this dataset and the unique characteristics of our setting, we conduct our analysis in three parts. First, we employ robust fixed effect specifications and document a strong, seemingly causal, negative relationship between leverage and trade-level returns. In the tightest specification, with user-day-asset fixed effects, leverage gradually reduces trade-level returns, from a reduction of 1.9 basis points in trades with a leverage level of 2:1 to a reduction of 7.6 basis points in trades with a leverage level of 400:1, compared to non-leveraged trades. We further find that these negative effects cross asset classes and are evident in individual stock, stock index, foreign currency, commodity and cryptocurrency trading.

Second, we utilize ESMA's regulatory intervention to compare traders' performance before and after the implementation of leverage limitations. As the broker's global clientele includes residents of countries in the European Economic Area (EEA), who were subject to ESMA's intervention, alongside residents of other countries who were not, the intervention creates a classic setting for a difference-in-differences research design. We find that ESMA's leverage constraints improved trading performance by 5.2 basis points in monthly portfolio returns and 1.3 basis points in trade-level returns. We further show that the improvement spans across all of the asset classes that were affected by the regulation and that the improvement can primarily be explained by a reduction in the transaction costs associated with leverage.

Finally, given the evidence on retail traders' sub-optimal use of leverage, we suggest and test two potential reasons that may cause individuals to deviate from a model of rational choice and use leverage to their detriment. The first is ignorance with respect to the characteristics and risks of leveraged trading. Using users' responses to know-your-customer questions, we show that many of the leverage users in our sample incorrectly answer a one-question quiz that tests their understanding of leverage, have preferences that do not correspond with the use of leverage, or have insufficient trading experience or financial knowledge to engage in this type of trading. Utilizing a difference-in-difference-in-differences (triple-difference) design, we further show that the implementation of leverage constraints had a greater effect on the trading performance of leverage-ignorant traders than on the trading performance of non-leverage-ignorant traders.

The second explanation that we suggest is overconfidence. In the user onboarding process, the broker uniquely warns users against depositing more than 10% of their net worth in their trading account. Nonetheless, some users decide to ignore this warning. We posit that these users are overconfident and find that the leverage users in our sample are generally more overconfident than the non-leverage users. Furthermore, utilizing a triple-difference regression specification in the period surrounding ESMA's intervention, we report that overconfident traders exhibited a greater improvement in trading performance after the implementation of leverage constraints than did non-overconfident traders.

This essay is part of the large body of literature on consumer financial regulation. Where the classic literature in this field has justified regulatory interventions with arguments relating to standard market failures, such as externalities and information asymmetries, a new strand of literature has advocated for a more paternalistic approach. According to this new literature, certain biases or financial mistakes of consumers may be sufficient to justify regulatory interventions (Campbell 2016, Campbell et al. 2011). In this essay, we discuss one example of such financial mistakes—the excessive use of leverage in trading—and provide evidence on the effectiveness of a major regulatory intervention that limited the use of leverage by retail traders. We further show that individuals may not understand the risks associated with leveraged trading or may suffer from behavioral biases, such as overconfidence, that interact with leverage to their detriment. According to the new approach in the literature, these reasons may be sufficient to justify a regulatory intervention, even in the absence of an apparent market failure. Indeed, in justifying its regulatory intervention, ESMA focused primarily on the concern that retail traders do not adequately understand the risks associated with leveraged trading and not on a market failure (ESMA 2018a).

This essay also contributes to the general literature on the behavior and performance of retail traders. This literature has generally found that the average individual underperforms in stock trading, concluding that "individuals lose from trade" (Barber et al. 2009a, Barber and Odean 2000, Grinblatt and Keloharju 2000, Hvidkajer 2008, Odean 1999).[4] This is especially true for net returns, after transaction costs (e.g., fees, commissions and bid-ask spreads), but there is also ample evidence that suggests that this is true for gross returns. In trying to explain the poor performance of retail traders, the literature has suggested several behavioral explanations, including cognitive limitations (Grinblatt et al. 2012, Korniotis and Kumar 2013), lack of attention (Gargano and Rossi 2018), overconfidence (Barber and Odean 2001, Grinblatt and Keloharju 2009), the disposition effect (Grinblatt and Keloharju 2001b, Odean 1998a, Shefrin and Statman 1985), sensation seeking (Dorn et al. 2015, Dorn and Sengmueller 2009, Grinblatt and Keloharju 2009) and preferences for skewness (Barberis et al. 2006, Mitton and Vorknik 2007, Kumar 2009). In this study, we document that leverage significantly exacerbates individuals' losses from trading. In fact, in prior studies, retail traders did not actually lose money. Rather, these traders underperformed relative to a market benchmark. In years in which the stock market performed well, most of these traders

[4] Nonetheless, the literature has also found that retail trading positively predicts short-run returns in the United States (Kaniel et al. 2008, 2012, Barber et al. 2009b, Kelley and Tetlock 2013, 2017). In Barber et al. (2021), the authors attempt to reconcile this seemingly contradictory evidence.

probably made money, albeit not as much as they could have potentially made by investing in the market portfolio, through a total market index fund, for example.[5] However, we find that leverage negatively affects the trading performance of individuals in such an extreme manner that traders who use significant amounts of leverage not only underperform but also earn negative absolute returns. We further show that an insufficient understanding of what using leverage means, as well as overconfidence, may explain, at least in part, why retail traders use leverage to their detriment.

Recently, three other papers have also explored the use of leverage by retail traders. Heimer and Simsek (2019) focus on the retail foreign exchange market and investigate the effects of leverage restrictions that were imposed by the Commodity Futures Trading Commission (CFTC) in 2010. Their main finding is that the restrictions reduced trading volume. They further provide some evidence that the restrictions improved trading performance, especially for users in the highest quintile of leverage use. Using the same setting, Heimer and Imas (2022) show that leverage constraints can be effective in reducing the disposition effect in the retail foreign exchange market. They hypothesize that leverage enables traders to make new trades, while refraining from closing current losing ones, thereby exacerbating the disposition effect. Our study complements these two papers. First, we extend the investigation of leverage use beyond the foreign exchange market and document that leverage is even more detrimental to the wealth of retail traders in other markets, and especially in stock and cryptocurrency trading. While the foreign currency market is a relatively niche market for the average retail trader, participation in the stock or cryptocurrency markets is significantly more common. Second, we report that

[5] Odean (1999) makes exactly this point: “In aggregate the investors in this study make trading choices which lead to below-market returns. This does not mean these investors lose money. 1987 through 1993 were good years to be in the stock market and most of these investors are probably happy that they were.” Indeed, in the past 70 years (1950–2019), the annual returns of the S&P 500, possibly the most widely used proxy for the market portfolio, have been positive in 79% of the years (55 years), with double digit profits in 61% of the years (43 years), suggesting that individuals have generally benefitted from stock trading.

ignorance with respect to the meaning of leverage, as well as overconfidence, may explain these poor results. The exacerbation of the disposition effect in leveraged trades, as suggested by Heimer and Imas (2022), is another potential explanation.

In the third paper on retail leverage use, Barber et al. (2020) use survey data from the Financial Industry Regulatory Authority (FINRA) to show that margin traders tend to be more overconfident than cash traders. Subsequently, using trading data, they document that margin traders trade more, speculate more and have worse stock selection ability than cash traders. Nonetheless, because their trading data do not include a measure of overconfidence, Barber et al. (2020) are not able to directly link overconfidence, leverage use and poor trading performance. We fill this gap by providing robust causal evidence on the negative effects of the interaction between overconfidence and leverage on trading performance.

The remainder of this essay is organized as follows. Section 2.2 provides background on CFDs and on ESMA's regulatory intervention. Section 2.3 describes the data and our research design and presents summary statistics. Section 2.4 explores the relationship between leverage and trading performance and the effects of implementing ESMA's leverage restrictions. Section 2.5 discusses the roles of ignorance with respect to what leverage means and of overconfidence. Section 2.6 concludes.

2.2 Background: Contracts for Difference and Regulatory Interventions

Contracts for difference (CFDs) are cash-settled derivative contracts that mirror the performance of an underlying asset, giving their holder exposure to fluctuations in the price of the asset. They can reference a wide range of assets, from stocks, exchange-traded funds and indices, to foreign currency pairs,[6] commodities and cryptocurrencies. Some of these assets, especially commodities and assets in foreign markets, are not easily available to retail traders otherwise. Additionally, because they are cash-settled, CFDs enable flexible contract sizes so that there is no need to purchase an asset in whole units, as well as allow for a simple and cheap way to make short trades without needing to borrow the asset. The key feature of CFDs, however, is that they are often traded on margin, or leveraged. While leverage levels differ between different brokerage firms and across the variety of underlying assets, levels of up to 500:1 have been quite common. In some countries, extreme leverage levels of up to 2000:1 have been observed.[7] At a leverage level of 500:1, for example, traders could open a trade with a notional value of $100,000 by committing only $200 of their own funds. At the milder leverage level of 10:1, traders would need to commit $10,000 of their own money in order to open a $100,000 trade.

In a series of surveys conducted by national securities regulators around the world, it has been found that approximately 70%–80% of retail CFD accounts lose money. Appendix A provides a brief summary of these surveys. As a result, these leveraged products have been the subject of much debate, and many countries eventually decided to impose leverage restrictions on CFD trading. Asian regulators were the first to act. In 2003, the Securities and Futures Commission

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[6] In the context of foreign currency (FX) trading, these contracts are referred to as rolling spot forex contracts, but for all practical purposes they are the same as other CFDs.

[7] See reports by the Board of the International Organization of Securities Commissions (IOSCO) for a detailed review: IOSCO 2016, IOSCO 2018a, IOSCO 2018b.

of Hong Kong (SFC) imposed leverage restrictions of 20:1 on foreign exchange transactions,[8] and in 2006, the Monetary Authority of Singapore (MAS) enacted leverage caps that ranged from 5:1 to 50:1, based on the type of the underlying asset.[9] South Korea and Japan also implemented similar limitations.[10] Subsequently, in 2010, the US CFTC imposed margin requirements on retail foreign exchange brokers, limiting the amount of permissible leverage to 50:1 for major currency pairs and 20:1 for all other currency pairs.[11] In the following years, several additional countries, such as Belgium, Canada, Israel, Malta, Poland, Russia and Turkey also implemented leverage restrictions on CFD trading.[12] A few other countries, such as Cyprus, France, Germany and Spain, did not explicitly limit the amount of permissible leverage but, instead, imposed various other

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[8] Code of Conduct for Persons Licensed by or Registered with the Securities and Futures Commission (2003). The Code also set a maintenance margin requirement of 3% (i.e., 33:1). These leverage restrictions apply only to foreign currency trading. CFDs referencing other underlying assets are prohibited.

[9] Securities and Futures (Financial and Margin Requirements for Holders of Capital Markets Services Licenses) (Amendment No. 2) Regulations 2006. These requirements were tightened further in a 2018 amendment, Securities and Futures (Financial and Margin Requirements for Holders of Capital Markets Services Licenses) (Amendment) Regulations 2018, which also granted more flexibility in loosening the leverage restrictions when a guaranteed stop-loss is applied to a trade.

[10] In Japan, a 2009 amendment to the Cabinet Office Ordinance on Financial Instruments Business, etc., set leverage restrictions ranging from 5:1 to 50:1, based on the underlying asset. In South Korea, leverage limits were first introduced in 2005, as part of the Forward Trade Regulation, and then tightened to 20:1 in 2009 (FX Margin Trade Analysis and Policy Improvement) and to 10:1 in 2011 (FX Margin Market Stabilization Plan).

[11] Regulation of Off-Exchange Retail Foreign Exchange Transactions and Intermediaries, 75 F.R. § 55410 (2010). Even prior to this regulation, the National Futures Association (NFA), an industry-wide, self-regulatory organization for the US derivatives industry, imposed leverage restrictions on the foreign currency offerings of its members. The NFA rules were initially adopted in 2003 and amended several times throughout the years, mostly with regard to the rules' exemptions. At the time of the CFTC's regulation, the NFA's leverage restrictions were 100:1 on major currency pairs and 25:1 on non-major currency pairs.

[12] For example, in Turkey, the Capital Markets Board of Turkey (CMB) imposed a leverage limit of 100:1 on all leveraged transactions contracted by retail investors in 2013 and further reduced the leverage limit to 10:1 in 2017. In Poland, the Komisja Nadzoru Finansowego (KNF) implemented a maximum leverage limit of 100:1 on retail CFD products in 2015. Similarly, in Malta, the Malta Financial Services Authority (MFSA) imposed the following leverage limits for CFD products in 2017: 50:1 for retail clients and 100:1 for retail clients who elect to be treated as professional clients. In Belgium, the Financial Services and Markets Authority (FSMA) introduced a complete and total ban on the distribution of CFDs and rolling spot foreign currency contracts via electronic trading platforms in 2016. In Israel, a 2014 ordinance imposed leverage limits ranging from 100:1 to 20:1, based on the type of the underlying asset. Similar limitations have also been adopted in Canada and Russia.

restrictions on CFD trading, and many other countries issued detailed warnings to retail traders without imposing specific restrictions.[13]

Finally, in May 2018, the European Securities and Markets Authority (ESMA) issued—for the first time since it was granted the authority to do so in the European Union's MiFIR legislation[14]—a product intervention measure imposing leverage restrictions on CFD trading. Specifically, ESMA implemented the following leverage limits: 30:1 for major currency pairs; 20:1 for other currency pairs, major equity indices and gold; 10:1 for other equity indices and commodities; 5:1 for individual stocks; and 2:1 for cryptocurrencies. Appendix B provides a detailed description of these constraints. Concurrently, ESMA also imposed a margin close-out rule, requiring CFD providers to close-out a retail client's position at 50% of the initial margin, and a negative balance protection rule, preventing retail client accounts from reaching a negative balance.[15] These measures came into force on August 1, 2018 for a period of three months and were then renewed an additional three times, finally expiring on July 31, 2019.[16] During this one-year time period, however, almost all of the countries in the European Economic Area[17] adopted national intervention measures that were typically very similar to those of ESMA.[18]

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[13] ESMA 2018a provides a partial summary of these measures.

[14] Regulation (EU) 600/2014 Markets in Financial Instruments (MiFIR) (2014). Under this legislation, ESMA was given the power to temporarily prohibit or restrict the marketing, distribution and sale of any financial instrument giving rise to serious concerns regarding investor protection, the orderly functioning and integrity of financial markets or commodities markets, or the stability of the whole or part of the financial system.

[15] ESMA further imposed certain restrictions on CFD marketing techniques and a standardized risk warning.

[16] ESMA 2018a is the initial decision. ESMA 2018b, 2019a and 2019b are the extensions.

[17] The European Economic Area (EEA) includes the 27 member states of the European Union (EU), as well as Iceland, Liechtenstein and Norway. The United Kingdom, which was still part of the EU until January 31, 2020, was also subject to ESMA's intervention.

[18] https://www.esma.europa.eu/policy-activities/mifid-ii-and-investor-protection/product-intervention.

2.3 Research Design

2.3.1 Data

We use proprietary data obtained from an international broker. The broker allows its users to trade 2,500 assets in various asset classes, including stocks in twenty exchanges around the world, foreign currencies, commodities and cryptocurrencies. Trades in foreign currencies, commodities and certain indices, as well as all short or leveraged trades, are conducted via CFDs. Importantly, the use of CFDs is seamless to the trader. Upon initiating a stock trade, for example, the trader may choose the level of leverage to apply to the trade. If no leverage is applied, then the trade is executed as a regular stock trade. If leverage is applied, or if the trader opens a short position, the trade is executed as a CFD trade.

The data include the broker's full trading records from January 1, 2012 to March 31, 2021, at both the individual trade level and the portfolio level, as well as information on trader characteristics.[19] The trade-level data include the following information for each trade: the name of the asset, the exact date-time the trade was executed, the execution price, the function of the trade (open/close), the direction of the position (long/short), the leverage applied to the position, the percentage of equity that was invested in the position at open and the net return on the position at close. The portfolio-level data include a returns file with portfolio-level returns calculated at different horizons, as well as a daily snapshot of the portfolio of each user with the name of the asset, the current percentage of equity that is invested in the position and the current (paper) net return on the position. The trader characteristics data include information on each user's country of residence, gender and age group, as well as answers to know-your-customer (KYC) questions

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[19] We describe only the parts of the data that are utilized in this essay. The data include many additional datasets, which are not used in this essay.

that each user needs to answer upon opening the account and at certain time intervals after that. These questions ask about prior trading experience, knowledge in trading, preferred trading strategy, primary purpose of trading, attitude towards risk, preferred trading frequency, net annual income, total cash and liquid assets, sources of income, occupation and more. Additionally, one of these questions aims to objectively assess the trader's understanding of leveraged trading ("appropriateness test").

2.3.2 Identification Strategy #1: Trade-Level Fixed Effects

2.3.2.1 Methodology Rationale

Our analyses are based on two complementary identification strategies. Our first strategy is applied at the trade level and utilizes two important features of the broker and the traders in our sample: the ability to employ leverage at the individual trade level, as opposed to regular margin accounts in which funds are borrowed at the account level; and the day trading nature of many of the broker's users. Taken together, these features allow us to run a series of trade-level regression models with extremely focused fixed effect groups. Certain specifications include, for example, user-day-asset fixed effects so that each trade is compared to other trades executed by the same user, in the same asset, on the same day. Formally, we deploy the following regression specification:

$$(2.1)\ R_{i,j,t} = \sum_{k=1}^{10} \beta_k \, Leverage_{i,j,t} + \beta_{11} Short_{i,j,t} + FE\ Group_{i,j,t} + \varepsilon_{i,j,t}.$$

$R_{i,j,t}$ is the net return generated on a specific trade *i*, executed by trader *j*, on day *t*.[20] $Leverage_{i,j,t}$ is a series of ten indicator variables, representing ten possible leverage levels,

[20] Throughout the trade-level analyses in this essay, except those presented in Table 2.7, we use net returns as calculated by the broker and displayed to the users. Appendix C describes this calculation in detail, as well as the other

ranging from 2:1 to 400:1. For each trade i, executed by trader j, on day t, one indicator variable, representing the leverage level of the trade, equals one, and the remaining indicator variables equal zero. The reference level of no leverage is omitted. $Short_{i,j,t}$ is an indicator variable that equals one for a short position and zero for a long position. $FE\ Group_{i,j,t}$ is one of six possible fixed effect groups. While the tightest specification with user-day-asset fixed effects essentially compares identical trades, it uses only a small part of the available data to calculate the coefficient estimates. This is because the deployment of tighter fixed effect groups includes more groups without sufficient within-group variation, and these groups do not affect the calculation of the coefficient estimates.[21] We therefore also display results for specifications with looser fixed effect groups: user-day-asset class, user-month-asset, user-month-asset class, country-day-asset and country-day-asset class, in which a greater portion of the observations is utilized,[22] as well as results for a specification with separate user, day and asset fixed effects.

2.3.2.2 Sample Construction and Trade-Level Summary Statistics

The fixed effect analyses are conducted on the full sample of trades between January 1, 2012 and March 31, 2021. Table 2.1 presents trade-level summary statistics for the full period.

return calculations used in this essay.

[21] In order to affect the calculation of the coefficient estimates, an observation must meet two criteria. First, it must not be a singleton, i.e., the fixed effect group in which it is included must have at least two observations. Second, there needs to be variation in the level of at least one regressor across the observations in the fixed effect group. If a certain group has several observations, but all of these observations have the same values for all of the regressors, then there is no variation to exploit in this group, and these observations will not affect the calculation of the coefficient estimates. As the specification gets tighter, there are more groups with singletons and more groups without sufficient variation in the level of the regressors.

[22] A related problem is the calculation of the standard errors. Generally, while some observations may not affect the calculation of the coefficient estimates, they do affect the calculation of the standard errors. Nonetheless, as all of our fixed effect regressions include standard errors that are double-clustered by trader and calendar-day, and as the fixed effect groups are nested within these clusters, the standard errors are adjusted in a manner that solves this problem.

Table 2.1. Trade-Level Summary Statistics

This table reports trade-level summary statistics. These are presented for the full sample of round-trip trades, as well as separately for each asset class and for each year. The return distribution is calculated on net trade-level returns, with the exact calculation described in Appendix C. The mean and standard deviation are calculated after winsorization at the 0.01% and 99.99% levels. The three rightmost columns display, respectively, the percentage of trades with a positive net return, the percentage of trades with any leverage and the percentage of trades with high leverage. High leverage is defined as a level of leverage that exceeds ESMA's restrictions, as detailed in Appendix B.

		Net Return Distribution									
	N	5th Pct	25th Pct	Med	75th Pct	95th Pct	Mean	SD	% Pos	% Lev	% High Lev
Full Sample	217,116,401	-0.517	-0.046	0.009	0.071	0.417	-0.0004	0.377	59.87	68.00	35.58
By Asset Class											
Stock	61,118,700	-0.422	-0.025	0.006	0.057	0.356	0.023	0.310	61.15	39.02	5.68
ETF	2,340,351	-0.160	-0.009	0.002	0.023	0.156	0.004	0.167	60.96	10.46	0.49
CFD Index	34,801,527	-0.500	-0.029	0.008	0.049	0.250	-0.010	0.236	62.61	99.46	44.19
Currency	49,942,848	-0.992	-0.081	0.020	0.103	0.503	-0.027	0.432	61.16	99.62	79.08
Commodity	35,926,050	-0.560	-0.097	0.011	0.083	0.458	-0.032	0.351	58.21	98.88	52.14
Crypto	32,986,925	-0.500	-0.058	0.005	0.075	0.500	0.039	0.527	54.39	11.05	0.50
By Year											
2012	6,039,600	-1.000	-0.164	0.030	0.137	0.618	-0.052	0.482	60.93	99.92	95.35
2013	9,722,537	-1.000	-0.097	0.040	0.150	0.676	-0.024	0.504	65.84	97.52	93.56
2014	8,112,998	-1.000	-0.100	0.033	0.138	0.610	-0.028	0.597	63.51	95.11	92.10
2015	9,088,140	-0.994	-0.085	0.020	0.106	0.502	-0.021	0.435	61.28	98.04	83.73
2016	8,870,484	-0.720	-0.061	0.015	0.085	0.480	-0.021	0.371	63.21	97.68	74.24
2017	16,378,750	-0.560	-0.058	0.014	0.100	0.508	0.027	0.496	60.14	65.17	49.52
2018	25,059,541	-0.746	-0.121	0.004	0.068	0.392	-0.053	0.368	52.91	76.05	49.03
2019	21,431,428	-0.503	-0.045	0.009	0.062	0.356	-0.0004	0.376	59.54	79.71	26.67
2020	74,461,836	-0.498	-0.032	0.007	0.057	0.355	0.018	0.352	60.60	62.59	15.90
2021 (Q1)	37,951,087	-0.303	-0.030	0.006	0.049	0.288	0.017	0.251	59.51	35.32	7.32

68% of the trades in our sample used some amount of leverage, with more than 52% of these trades (35.6% of total trades) using high leverage. High leverage is defined as a level of leverage that exceeds ESMA's restrictions, as detailed in Appendix B. The median trade had a positive net return of 0.9 basis points but a negative mean return of 0.4 basis points. Leverage was primarily used in foreign currency, commodity and stock index trades, and less in individual stock, exchange-traded fund and cryptocurrency trades. This result is at least partly due to the leverage offerings of the broker. For cryptocurrency trades, the broker has not offered high leverage since mid-2017, and for individual stock and exchange-traded fund trades, only one level of high leverage is offered (10:1). For the other asset classes, the available leverage options are greater. It is also noteworthy that the use of leverage has declined since 2017. In 2017 and early 2018, this was primarily due to the large number of non-leveraged cryptocurrency trades conducted by the broker's users, and since mid-2018, ESMA's leverage constraints were the primary mitigating factor.

To reach our final sample, we remove trades in exchange-traded funds (ETFs). While the broker applies the same leverage restrictions to ETFs as it does to stocks, ETFs reference other asset classes, such as indices or commodities, which have higher leverage limits. It is therefore difficult to classify ETFs to an appropriate category of leverage use. In some analyses, we further remove cryptocurrency trades, for which the broker voluntarily implemented leverage restrictions.

2.3.3 Identification Strategy #2: Difference-in-Differences

2.3.3.1 Methodology Rationale

Our second and primary identification strategy is based on a difference-in-differences design utilizing ESMA's regulatory intervention. The broker serves its users around the world through several subsidiaries on a cross-border basis. Except for a few negligible instances, residents of countries in the European Economic Area (EEA) are registered in an EEA subsidiary, and residents of countries outside of the EEA are registered in a non-EEA subsidiary. Furthermore, due to the cross-border model, the broker is generally not affected by the local regulations of its users' home countries; rather, each subsidiary is subject only to the local regulatory regime of the jurisdiction in which it is licensed. At the time of ESMA's intervention, the subsidiaries that were not subject to ESMA's regulations were also not subject to any alternative leverage restrictions. Therefore, while users who resided in the EEA ("EEA traders") were affected by the new leverage constraints, users who resided outside of the EEA ("non-EEA traders") were generally not. This creates a clear distinction between a treatment group and a control group, laying the groundwork for a difference-in-differences analysis.[23]

Figure 2.1, Panel A presents the monthly proportions of highly leveraged trades conducted by EEA and non-EEA traders during the three-year period of 2017–2019. A highly leveraged trade is defined as a trade with a level of leverage that exceeds ESMA's restrictions. Figure 2.1, Panel B presents the monthly proportions of traders who made at least one highly leveraged trade during the month. Overall, the rates moved together for EEA and non-EEA traders during the 19 months that preceded the intervention. However, after the intervention, on August 1, 2018, the use of high leverage by EEA traders converged to zero.

The meaningful changes in the use of high leverage in the pre-intervention period, by both EEA and non-EEA traders, can be explained by changes in the proportion of cryptocurrency trades. For these trades, the broker already set a maximum leverage level of 2:1 in mid-2017 so that traders were not able to conduct highly leveraged cryptocurrency trades even before ESMA's intervention. Therefore, in periods in which traders made more cryptocurrency trades, the use of high leverage declined and vice versa. Figure 1.1, Panels C and D, present the monthly proportions of highly leveraged trades and of traders who made at least one such highly leveraged trade, respectively, after excluding cryptocurrency trades. While both EEA and non-EEA traders exhibited similar patterns of high leverage use prior to ESMA's intervention, the patterns clearly diverged after the intervention.[24]

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[23] While ESMA's regulatory intervention included a few other measures alongside the leverage restrictions, these should only minimally affect our difference-in-differences analysis. Specifically, the broker already applied negative balance protection to all of its retail users before the regulatory intervention, and the new reduction in the margin close-out rule from 100% to 50% was simultaneously implemented by the broker in all of its accounts at the intervention date, including accounts of users who resided in countries outside of the EEA.

[24] Non-EEA traders also exhibited a certain decline in the use of high leverage following the intervention Such decrease may potentially be attributed to improved awareness to the risks of high leverage following ESMA's

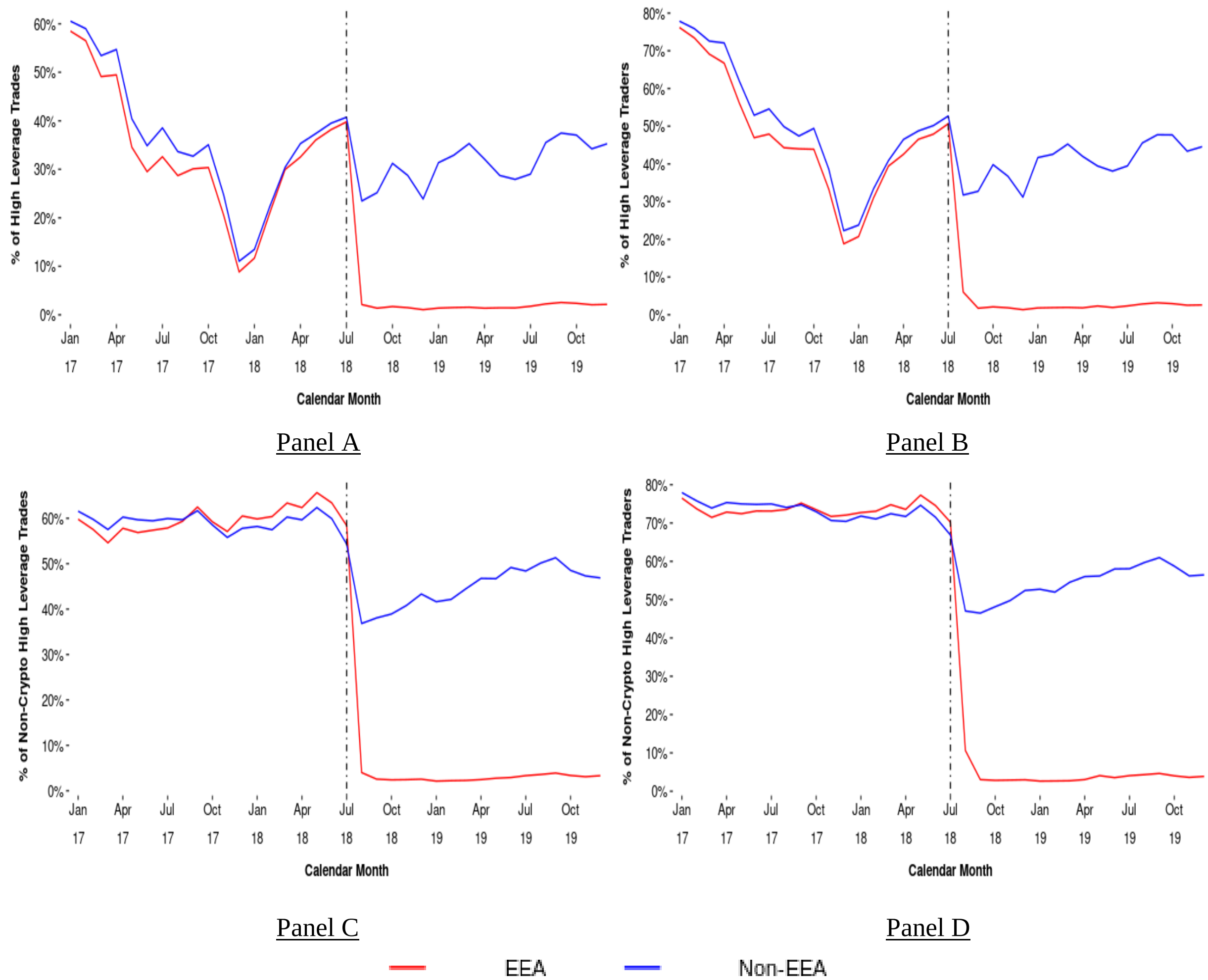

Figure 2.1. The Use of High Leverage by EEA and Non-EEA Traders

This figure illustrates the use of high leverage by traders in the three-year period between January 2017 and December 2019. The results are presented separately for residents of EEA countries and residents of non-EEA countries. Panel A presents the monthly percentages of highly leveraged trades. A highly leveraged trade is defined as a trade with a leverage level that exceeds ESMA's restrictions, as detailed in Appendix B. Panel B displays the monthly percentages of users who made at least one highly leveraged trade during the month. Panels C and D repeat the trade- and user-level analyses, respectively, after excluding cryptocurrency trades.

2.3.3.2 Sample Construction

Some of our difference-in-differences analyses are conducted at the monthly portfolio level, while others are conducted at the trade level. Both types of analyses are limited to the twelve-

intervention, to the increased risk of an automatic margin close-out at high leverage levels following the reduction of the close-out limit from 100% to 50%, to peer effects or to the accidental registration of certain non-EEA users in EEA-based subsidiaries.

month period surrounding ESMA’s regulatory intervention, from February 1, 2018 to January 31, 2019. This is intended to limit the effects of other events that may have affected trading behavior and performance. We further remove cryptocurrency trades in our trade-level analyses, and traders who made only cryptocurrency trades during the period in our portfolio-level analyses, as these trades and traders were not affected by the intervention. Finally, in the monthly sample, we also remove months that are more than sixty days after the trader’s last new opening trade, in order to focus on active traders, as well as users from countries with fewer than fifty unique users, as these users may not have been properly allocated by the broker to EEA and non-EEA subsidiaries.

2.3.3.3 Treatment and Control Groups and User-Level Summary Statistics

Table 2.2, Panel A, presents user-level summary statistics for EEA and non-EEA traders who opened at least one new position in the six-month period preceding ESMA’s intervention. Non-EEA traders include more women, are more experienced, have more trading knowledge, trade more and have a greater tendency to trade stock indices. Most of the other differences, even those that are statistically significant, are relatively small in terms of economic significance.

Table 2.2. User-Level Summary Statistics for EEA and Non-EEA Traders

This table reports summary statistics for residents of EEA countries and residents of non-EEA countries who were active on the broker's platform during the six-month period before ESMA's regulatory intervention. The displayed trading characteristics are calculated during this period only. Panel A presents the results for the full sample of traders. Panel B displays the results for a matched sample of EEA and non-EEA traders. For continuous and binary variables, a t-test is used to compare means. For categorical variables with more than one category, a chi-square test is used to compare distributions. *High-Leverage Trader* and the six *Asset Class Trader* variables are defined as traders who made at least one such trade during the period. A highly leveraged trade is defined as a trade with a leverage level that exceeds ESMA's restrictions, as detailed in Appendix B.

	Panel A—Full Sample			**Panel B—Matched Sample**		
	EEA Traders	Non-EEA Traders	χ^2 or t-statistic (p-value)	EEA Traders	Non-EEA Traders	χ^2 or t statistic (p-value)
Number of Traders	91,326	40,500	-	40,466	40,466	-
Personal Characteristics						
Female, %	0.075	0.096	t = 11.89 (p < 0.01)	0.096	0.097	t = 0.44 (p = 0.66)
Age Range, %						
18–24	0.134	0.081	χ^2 = 1834.5 (p < 0.01)	0.080	0.081	χ^2 = 4.3 (p = 0.51)
25–34	0.356	0.429		0.427	0.429	
35–44	0.276	0.319		0.320	0.321	
45–54	0.152	0.119		0.119	0.119	
55–64	0.063	0.041		0.043	0.041	
≥ 65	0.020	0.011		0.010	0.011	
Know Your Customer Responses						
Trading Experience, %						
< 1 year	0.666	0.590	χ^2 = 698.6 (p < 0.01)	0.588	0.590	χ^2 = 0.5 (p = 0.77)
1–3 years	0.195	0.241		0.243	0.241	
> 3 years	0.140	0.170		0.169	0.170	
Trading Knowledge, %						
No Financial Knowledge	0.587	0.439	χ^2 = 2515.3 (p < 0.01)	0.440	0.439	χ^2 = 0.6 (p = 0.91)
Financial Degree or Trading Courses	0.354	0.483		0.482	0.483	
Professional Certificate or Work Experience	0.037	0.046		0.046	0.046	
Both	0.021	0.032		0.031	0.032	
Purpose of Trading, %						
Short-Term Returns	0.254	0.248	χ^2 = 11.2 (p = 0.01)	0.248	0.248	χ^2 = 0.0 (p = 1.00)
Additional Revenues	0.525	0.522		0.522	0.522	
Future Planning (Kids/Retirement)	0.146	0.150		0.151	0.150	
Saving for Home	0.076	0.079		0.079	0.079	
Risk Appetite, %						
Gain 5% / Lose -3%	0.039	0.048	χ^2 = 223.3 (p < 0.01)	0.048	0.048	χ^2 = 1.0 (p = 0.91)
Gain 10% / Lose -6%	0.075	0.061		0.061	0.061	
Gain 20% / Lose -12%	0.228	0.212		0.214	0.212	
Gain 40% / Lose -24%	0.340	0.333		0.335	0.333	
Gain 80% / Lose -48%	0.318	0.345		0.342	0.345	

Table 2.2. User-Level Summary Statistics for EEA and Non-EEA Traders (Continued)

	Panel A—Full Sample			Panel B—Matched Sample		
	EEA Traders	Non-EEA Traders	χ^2 or t-statistic (p-value)	EEA Traders	Non-EEA Traders	χ^2 or t statistic (p-value)
Trading Characteristics (February–July 2018)						
Monthly Average # of Trades	20.832	21.788	t = 3.39 (p < 0.01)	21.397	21.683	t = 0.85 (p = 0.40)
Monthly Average # of Unique Assets	3.489	3.469	t = 0.88 (p = 0.38)	3.465	3.470	t = 0.16 (p = 0.87)
Mean % of Short Trades	0.208	0.226	t = 12.67 (p < 0.01)	0.225	0.226	t = 0.89 (p = 0.38)
Mean % of Leveraged Trades	0.712	0.708	t = 2.21 (p = 0.03)	0.703	0.707	t = 1.63 (p = 0.10)
High Leverage Trader (≥1 Trade), %	0.748	0.732	t = 6.02 (p < 0.01)	0.732	0.731	t = 0.29 (p = 0.77)
Asset Classes Traded, %						
One	0.223	0.251	χ^2 = 203.8 (p < 0.01)	0.251	0.251	χ^2 = 3.7 (p = 0.59)
Two	0.329	0.328		0.326	0.327	
Three	0.203	0.204		0.201	0.204	
Four	0.140	0.131		0.135	0.131	
Five	0.090	0.073		0.073	0.073	
Six	0.014	0.014		0.014	0.014	
Stock Trader (≥ 1 Trade), %	0.634	0.621	t = 4.56 (p < 0.01)	0.625	0.621	t = 1.11 (p = 0.27)
Currency Trader (≥ 1 Trade), %	0.399	0.425	t = 8.99 (p < 0.01)	0.424	0.425	t = 0.21 (p = 0.84)
Commodity Trader (≥ 1 Trade), %	0.525	0.517	t = 2.88 (p < 0.01)	0.516	0.517	t = 0.15 (p = 0.88)
Index Trader (≥ 1 Trade), %	0.320	0.228	t = 35.49 (p < 0.01)	0.226	0.228	t = 0.55 (p = 0.59)
ETF Trader (≥ 1 Trade), %	0.044	0.052	t = 6.45 (p < 0.01)	0.052	0.052	t = 0.27 (p = 0.79)
Crypto Trader (≥ 1 Trade), %	0.666	0.647	t = 6.73 (p < 0.01)	0.651	0.647	t = 1.08 (p = 0.28)

Despite these differences between our treatment and control groups, the parallel trends assumption that stands at the basis of the difference-in-differences design remains valid. Figure 2.2 displays the average monthly portfolio returns of the EEA and non-EEA traders in our sample. While the monthly portfolio returns of EEA and non-EEA traders are similar in both the levels and the trends prior to the regulatory intervention, a clear gap forms after the intervention. Furthermore, even in the post-intervention period, the monthly portfolio returns of EEA and non-EEA traders continue to move in parallel.

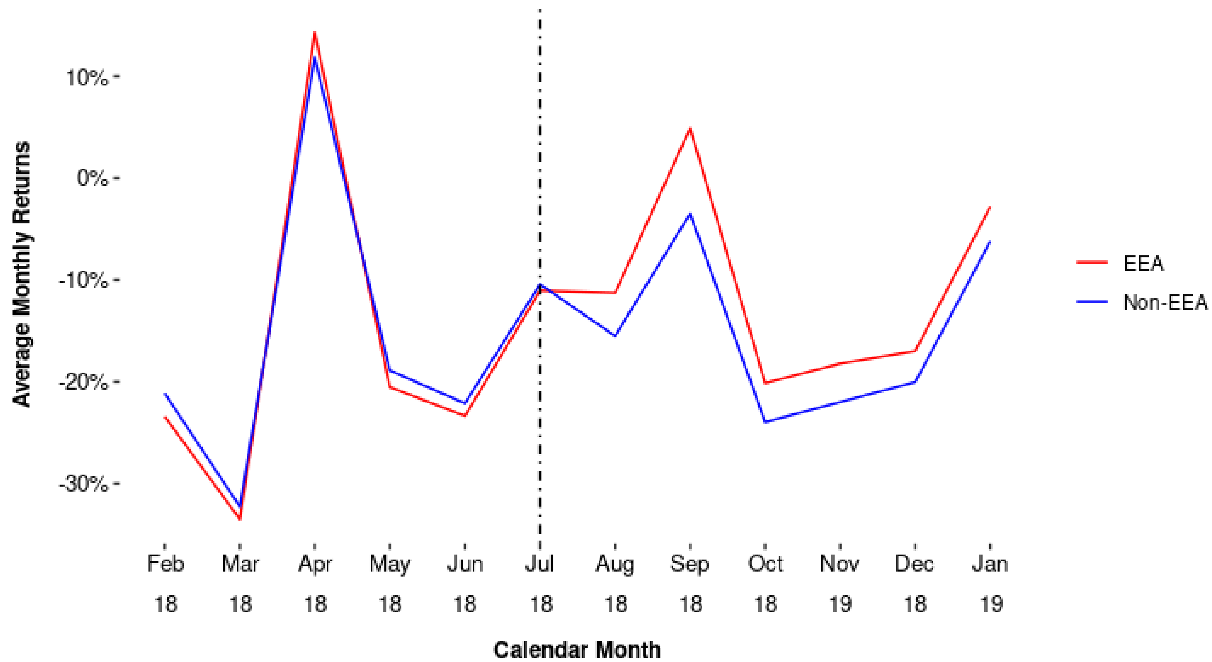

Figure 2.2. Average Monthly Portfolio Returns of EEA and Non-EEA Traders

This figure compares the average monthly portfolio returns of traders who were residents of EEA countries and traders who were not residents of EEA countries during the twelve-month period surrounding the implementation of ESMA's leverage constraints on August 1, 2018. The exact calculation of monthly portfolio returns is described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels.

Nonetheless, in our analyses, we take several measures to ensure the validity of the parallel trends assumption. First, all of the difference-in-differences specifications include trader fixed effects, which capture the time-invariant differences between traders. Second, some of our analyses are conducted on a matched sample. Specifically, we employ a nearest neighbor 1:1 propensity score model to match EEA traders to non-EEA traders based on the characteristics displayed in Table 2.2. Because we have more EEA traders than non-EEA traders, the matching procedure reduces the number of treatment observations, but the matched groups are similar in all observable aspects. Table 2.2, Panel B presents summary statistics for the matched groups.

2.4 The Effect of Leverage on Trading Performance

2.4.1 Fixed Effect Regression Analysis

We begin our analysis by exploring the effects of leverage on trade-level returns using our first identification strategy. We run a series of robust fixed effect regression models in the form of equation (2.1) on the full sample of trades, after excluding ETF trades. Standard errors are double-clustered by trader and calendar-day.

Table 2.3, Panel A presents the results. Across all columns, the per-trade returns consistently decrease with increasing levels of leverage. Based on the results of the tightest specification, presented in column (1), a leverage level of 2:1 reduces per-trade returns by 1.9 basis points and a leverage level of 400:1 reduces per-trade returns by 7.6 basis points, compared to trades without any leverage. The additional robust fixed effect specifications, presented in columns (2)–(6), display a similar trend, although the coefficient estimates are generally larger. In column (7), we forego our robust specifications for a model with separate user, day and asset fixed effects, and report similar results. Overall, across all specifications, we document compelling evidence for a negative relationship between leverage and trading performance. Given the robustness of our fixed effect groups, this relationship is seemingly causal.

A shortcoming of our analysis is that the broker offers different leverage levels for different asset classes so that the coefficient for each level of leverage is affected by a different set of assets. Additionally, in certain asset classes, some level of leverage is almost always used, and thus the reference category of no leverage may be negligible (see Table 2.1). Therefore, we repeat our fixed effect analysis but replace the leverage indicator variables in equation (2.1) with one indicator variable that depicts a high level of leverage that exceeds ESMA's restrictions. As these restrictions were determined based on an analysis of the volatility of the underlying assets, the definition of high leverage should be relatively comparable across asset classes. The results are reported in Table 2.3, Panel B. We find that high leverage reduces trade-level returns by 1.0 to 2.6 basis points, depending on the specification, confirming that leverage hinders trading performance.

Table 2.3. Leverage and Trade-Level Returns

This table reports the results of fixed effect regression specifications exploring the relationship between leverage and trading performance. The sample includes all of the trades made by the users of the broker between January 1, 2012 and March 31, 2021. Exchange-trade-fund (ETF) trades are excluded. The dependent variable is net trade-level returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels separately for each leverage level. In Panel A, the variables of *2:1* to *400:1* are indicator variables depicting the trade's level of leverage. The reference group of no leverage is excluded. In Panel B, the variable *High Leverage* is an indicator variable that equals one for a level of leverage that exceeds ESMA's restrictions, as detailed in Appendix B. In both panels, *Short* is an indicator variable that equals one for short positions and zero for long positions. Each column includes a different type of fixed effect groups, with column (1) including the tightest groups. Standard errors are double-clustered by trader and calendar-day. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2:1	-0.019***	-0.027***	-0.016***	-0.030***	-0.051***	-0.052***	-0.029***
	(-7.614)	(-14.787)	(-4.564)	(-11.787)	(-18.653)	(-20.399)	(-10.632)
5:1	-0.022***	-0.030***	-0.015***	-0.031***	-0.039***	-0.041***	-0.026***
	(-6.874)	(-12.421)	(-4.072)	(-10.940)	(-15.196)	(-16.582)	(-10.882)
10:1	-0.024***	-0.034***	-0.023***	-0.040***	-0.046***	-0.050***	-0.025***
	(-7.421)	(-14.224)	(-6.329)	(-14.325)	(-18.134)	(-20.278)	(-8.645)
20:1	-0.028***	-0.033***	-0.027***	-0.039***	-0.054***	-0.050***	-0.038***
	(-8.923)	(-13.447)	(-7.237)	(-13.925)	(-21.480)	(-21.483)	(-14.369)
25:1	-0.026***	-0.035***	-0.030***	-0.045***	-0.052***	-0.052***	-0.032***
	(-8.515)	(-14.341)	(-8.479)	(-15.942)	(-20.834)	(-21.988)	(-8.714)
30:1	-0.031***	-0.038***	-0.034***	-0.047***	-0.060***	-0.058***	-0.043***
	(-9.841)	(-15.671)	(-9.069)	(-16.493)	(-23.610)	(-24.566)	(-15.518)
50:1	-0.032***	-0.039***	-0.039***	-0.051***	-0.064***	-0.061***	-0.038***
	(-10.418)	(-15.987)	(-10.689)	(-18.121)	(-25.462)	(-26.265)	(-10.725)
100:1	-0.042***	-0.049***	-0.057***	-0.069***	-0.077***	-0.073***	-0.054***
	(-13.100)	(-18.749)	(-15.516)	(-23.958)	(-30.254)	(-30.887)	(-15.318)
200:1	-0.055***	-0.066***	-0.073***	-0.090***	-0.099***	-0.095***	-0.073***
	(-16.657)	(-24.467)	(-19.227)	(-29.659)	(-37.273)	(-38.020)	(-19.797)
400:1	-0.076***	-0.091***	-0.113***	-0.129***	-0.129***	-0.123***	-0.104***
	(-22.100)	(-31.999)	(-29.061)	(-41.807)	(-44.188)	(-44.839)	(-27.592)
Short	-0.004**	-0.006***	-0.008***	-0.010***	-0.017***	-0.016***	-0.016***
	(-2.211)	(-3.569)	(-3.916)	(-4.911)	(-7.225)	(-7.017)	(-7.015)
Fixed Effects	User-Day-Asset	User-Day-Asset Class	User-Month-Asset	User-Month-Asset Class	Country-Day-Asset	Country-Day-Asset Class	User + Day + Asset
N	214,776,050	214,776,050	214,776,050	214,776,050	214,776,050	214,776,050	214,776,050
Adj. R^2	0.502	0.408	0.309	0.233	0.097	0.048	0.090

Table 2.3. Leverage and Trade-Level Returns (Continued)

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Leverage	-0.010***	-0.012***	-0.017***	-0.019***	-0.026***	-0.025***	-0.015***
	(-8.948)	(-14.370)	(-21.276)	(-25.061)	(-40.365)	(-37.942)	(-8.528)
Short	-0.004**	-0.006***	-0.008***	-0.010***	-0.019***	-0.019***	-0.017***
	(-2.252)	(-3.743)	(-4.003)	(-5.189)	(-8.020)	(-8.140)	(-7.457)
Fixed Effects	User-Day-Asset	User-Day-Asset Class	User-Month-Asset	User-Month-Asset Class	Country-Day-Asset	Country-Day-Asset Class	User + Day + Asset
N	214,776,050	214,776,050	214,776,050	214,776,050	214,776,050	214,776,050	214,776,050
Adj. R^2	0.501	0.408	0.309	0.232	0.095	0.046	0.089

2.4.2 Difference-in-Differences Analysis

After establishing the negative relationship between leverage and trading performance, we turn to our difference-in-differences analysis. Figure 1.2, described above, provides initial evidence on the negative effects of leverage and on the effectiveness of ESMA's intervention in mitigating these effects. However, to formalize our analysis, we focus on the twelve-month period surrounding the intervention and run the following regression specification:

$$(2.2)\ R_{i,t} = \sum_{k} \beta_k\, EEA_i \times Month_{t=k} + \lambda_i + \delta_t + \varepsilon_{i,j,t}.$$

$R_{i,t}$ is the monthly portfolio return of trader *i* in month *t*. EEA_i is an indicator variable that is equal to one if the trader is a resident of an EEA country that is subject to ESMA's intervention, and to zero otherwise. $Month_t$ is a set of indicator variables depicting the specific calendar-month. The three months k = [-6,-4] are excluded and serve as the reference period. λ_i and δ_t are trader and calendar-month fixed effects, respectively. Standard errors are double-clustered by trader and calendar-month.[25]

[25] All of the analyses in this essay use double-clustered standard errors by user and time. When the time dimension is based on a month and the sample period includes the year surrounding ESMA's intervention, there are only twelve time clusters. In such situations, the use of double-clustered standard errors is debatable (Petersen 2009). Therefore, in all of these analyses, we verify that the results remain statistically significant when clustering only at the user level.

Figure 2.3 displays the results as point estimates with 95% confidence intervals. Following the regulatory intervention, the average monthly portfolio returns of EEA traders increased by approximately 5.0 basis points per month, with an even higher increase for the second month after the intervention. The improvement persists throughout the entire post-intervention period. In addition, Figure 2.3 provides further confirmation of the validity of the parallel trends assumption, as the difference in returns between EEA and non-EEA traders is not statistically different from zero in the three months leading up to the intervention, and is relatively constant in the post-intervention period.

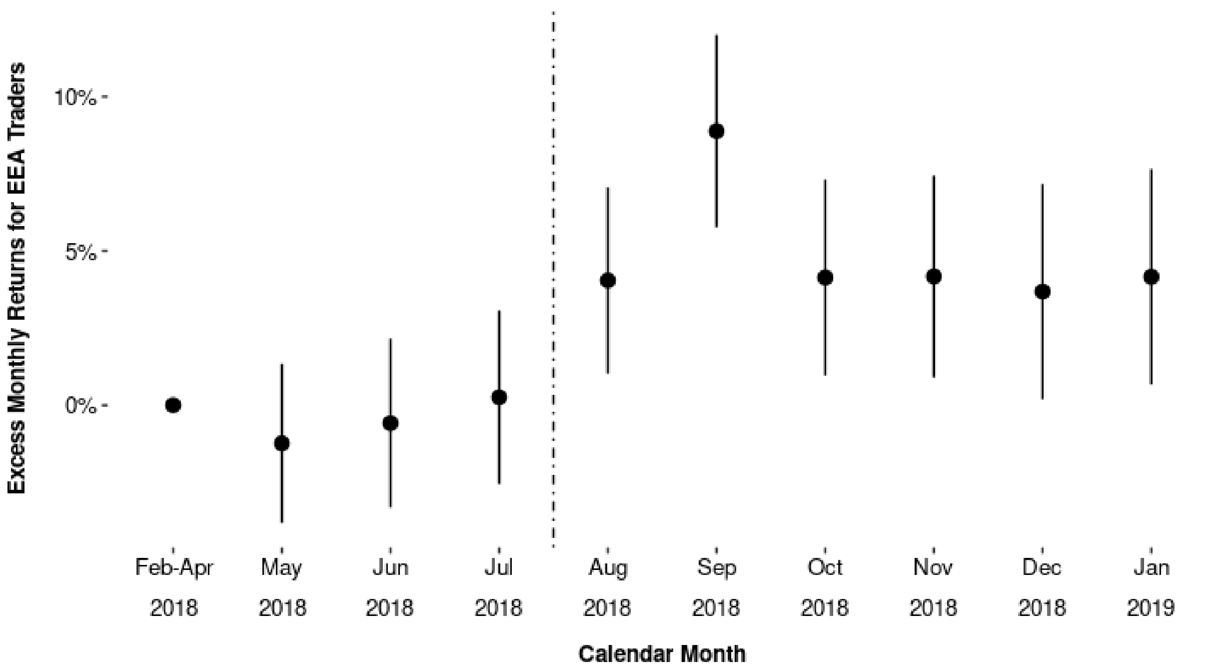

Figure 2.3. A Dynamic Analysis of the Impact of Leverage Limits on Monthly Portfolio Returns

This figure illustrates the results of a dynamic difference-in-differences regression specification of the form: $R_{i,t} = \sum_k \beta_k \, EEA_i \times Month_{t=k} + \lambda_i + \delta_t + \varepsilon_{i,j,t}$, exploring the effects of ESMA's intervention on trading performance. The sample is restricted to the twelve-month period surrounding the intervention, which was implemented on August 1, 2018. The dependent variable is monthly portfolio returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels. *EEA* is an indicator variable that is equal to one for residents of EEA countries, and to zero otherwise. *Month* is a set of indicator variables depicting the specific calendar-month. The three months of February–April 2018 are excluded and serve as the reference period. λ_i and δ_t are trader and calendar-month fixed effects, respectively. Standard errors are double-clustered by trader and calendar-month. Results are presented as point-estimates with 95% confidence intervals.

In Table 2.4, we replace our dynamic difference-in-differences specification with a static one. Specifically, we substitute the monthly indicator variables in equation (2.2) with one indicator variable ($Post_t$) that is equal to one for the months following ESMA's regulatory intervention, and to zero otherwise.[26] Column (1) displays the results for the full sample, and column (2) displays the results for a matched sample of EEA and non-EEA traders. The results in both columns are practically identical, confirming that the implementation of leverage restrictions improved the monthly portfolio returns of EEA traders by approximately 5.0 basis points.

Table 2.4. A Static Analysis of the Impact of Leverage Limits on Monthly Portfolio Returns

This table reports the results of difference-in-differences regression specifications exploring the effects of ESMA's regulatory intervention on trading performance. The dependent variable is monthly portfolio returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels. *EEA Trader* is an indicator variable that is equal to one for residents of EEA countries, who were subject to the leverage restrictions, and to zero otherwise. *Post* is an indicator variable that equals one for the period following the implementation of ESMA's leverage restrictions on August 1, 2018, and zero otherwise. *Austrian Trader* is an indicator variable that equals one for Austrian traders and zero for Swiss traders. *High-Leverage Trader* is an indicator variable that is equal to one for traders who made at least one highly leveraged trade in the pre-intervention period, and to zero otherwise. A highly leveraged trade is defined as a trade with a leverage level that exceeds ESMA's restrictions, as detailed in Appendix B. Column (1) presents the results for the full sample of EEA and non-EEA traders who meet the inclusion criteria. Column (2) displays the results for a matched sample of EEA and non-EEA traders. Column (3) focuses on a sample that includes only traders from Austria and Switzerland. Column (4) estimates the specification on a sample of EEA traders only. Column (5) includes a sample of traders who made only cryptocurrency trades during the twelve months surrounding the intervention. Standard errors are double-clustered by trader and calendar-month. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Matched Sample	Austria and Switzerland Sample	EEA Sample	Cryptocurrency Sample
EEA Trader x Post	0.052***	0.053***			0.010
	(4.471)	(4.275)			(1.464)
Austria Trader x Post			0.028***		
			(3.506)		
High-Leverage Trader x Post				0.072**	
				(2.512)	
Trader FE	X	X	X	X	X
Month FE	X	X	X	X	X
N	841,039	465,546	37,992	514,289	643,341
Adj. R^2	0.227	0.224	0.277	0.250	0.729

[26] This specification takes the following form: $R_{i,t} = \beta_1 ESMA_i \times Post_t + \lambda_i + \delta_t + \varepsilon_{i,j,t}$.

To further ensure the robustness of our results, we use alternative treatment and control groups in columns (3)–(4). In column (3), we focus specifically on Switzerland and Austria and compare the monthly portfolio returns of the traders residing in these countries. Switzerland and Austria are similar countries in many ways. They not only share a border and have a similar population size (8.5–9 million people as of 2019) but are also similar in various other factors, including primary language (German), primary religion (Christianity) and legal origin (German) (Laporta et al. 1998). Nevertheless, Austria is part of the EEA and was affected by ESMA's regulatory intervention, while Switzerland is not part of the EEA and was therefore not affected by the intervention. In column (4), we focus solely on users located in the EEA who were subject to ESMA's intervention and compare traders who made at least one highly leveraged trade that exceeded ESMA's restrictions in the pre-intervention period to traders who did not. Generally, only traders with a history of high leverage use should have been affected by the regulatory intervention. Overall, the results in both columns support those of our main specifications, pointing to an improvement in trading performance after ESMA's intervention. Finally, in column (5), we perform a placebo test. We create a sample of users who made only cryptocurrency trades during the twelve-month period surrounding ESMA's intervention. Since the broker already voluntarily limited the amount of leverage available in cryptocurrency trades in 2017, these users should not have experienced any change on August 1, 2018, and indeed we do not find any improvement in the performance of EEA cryptocurrency traders compared to non-EEA cryptocurrency traders.

Overall, the results of this section provide strong evidence to support the conclusion that leverage is detrimental to the wealth of retail traders and that ESMA's leverage constraints were successful in improving trading performance.

2.4.3 Leverage and Trading Performance by Asset Class

The broker offers its users the ability to trade assets in six asset classes: individual stocks, ETFs, stock indices, foreign currency pairs, commodities and cryptocurrencies. In this section, we test whether the effects of leverage vary across the different asset classes offered by the broker. ETFs are excluded from our analyses.

In Table 2.5, we report the results of separate fixed effect regression models for each asset class. Our main independent variable is an indicator variable that depicts a high level of leverage that exceeds ESMA's restrictions. For the sake of brevity, we report the results of specifications with user-day fixed effects. The specifications with the other fixed effect groups, as well as the specifications depicting different levels of leverage, are relegated to Appendix D. Across all asset classes, we document a strong negative relationship between the use of high levels of leverage and trade-level returns, suggesting that the use of leverage can be detrimental to the average retail trader in any type of trade.

Table 2.5. Leverage and Trade-Level Returns by Asset Class

This table reports the results of fixed effect regression specifications exploring the relationship between leverage and trading performance for different asset classes. The sample includes all of the trades made by the users of the broker between January 1, 2012 and March 31, 2021. Exchange-traded fund (ETF) trades are excluded. The dependent variable is net trade-level returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels separately for each leverage level. The variable *High Leverage* is an indicator variable that equals one for a level of leverage that exceeds ESMA's restrictions, as detailed in Appendix B. *Short* is an indicator variable that equals one for short positions and zero for long positions. Standard errors are double-clustered by trader and calendar-day. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	(1) Stocks	(2) Indices	(3) Currencies	(4) Commodities	(5) Cryptocurrencies
High Leverage	-0.014*** (-5.350)	-0.002** (-2.132)	-0.010*** (-15.351)	-0.018*** (-6.696)	-0.066** (-2.362)
Short	-0.021*** (-6.757)	-0.004 (-1.547)	-0.002 (-0.871)	-0.004 (-1.045)	-0.042*** (-8.948)
Fixed Effects	User-Day	User-Day	User-Day	User-Day	User-Day
N	61,118,700	34,801,527	49,942,848	35,926,050	32,986,925
Adj. R^2	0.424	0.311	0.221	0.282	0.593

In Table 2.6, we explore the effects of ESMA's leverage restrictions for each asset class separately. We stratify the sample of trades opened during the twelve-month period surrounding the intervention by asset class and apply a trade-level difference-in-differences regression model for each asset class separately. As this analysis is applied at the trade-level, we include trader, asset and calendar-day fixed effects.

Table 2.6. The Impact of Leverage Constraints on Trade-Level Returns by Asset Class

This table reports the results of difference-in-differences regression specifications exploring the effects of ESMA's regulatory intervention on trading performance for different asset classes. The sample includes all of the trades made by the users of the broker in the twelve-month period surrounding ESMA's intervention (February 1, 2018–January 31, 2019). Exchange-traded fund (ETF) trades are excluded. The dependent variable is net trade-level returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels. *EEA Trader* is an indicator variable that is equal to one for residents of EEA countries, who were subject to the leverage restrictions, and to zero otherwise. *Post* is an indicator variable that equals one for the period following the implementation of ESMA's leverage restrictions on August 1, 2018, and zero otherwise. *Short* is an indicator variable that equals one for short positions and zero for long positions. Column (1) presents the results for the full sample of trades, excluding cryptocurrency trades. Columns (2)–(6) display the results for specific asset classes. Standard errors are double-clustered by trader and calendar-day. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	(1) Full w/o Cryptocurrencies	(2) Stocks	(3) Indices	(4) Currencies	(5) Commodities	(6) Cryptocurrencies
EEA Trader x Post	0.013*** (7.754)	0.008*** (3.233)	0.008*** (3.270)	0.014*** (3.626)	0.029*** (7.700)	0.004 (0.683)
Short	0.010* (1.840)	-0.006 (-0.811)	0.004 (0.649)	0.022*** (3.158)	0.010 (0.916)	-0.019* (-1.699)
Trader FE	X	X	X	X	X	X
Asset FE	X	X	X	X	X	X
Day FE	X	X	X	X	X	X
N	18,485,457	4,066,128	5,180,187	4,260,007	4,979,135	3,774,948
Adj. R^2	0.032	0.099	0.031	0.032	0.042	0.333

Column (1) presents the results for the full sample of trades excluding cryptocurrency trades (and ETFs), and columns (2)–(5) display the results separately for stocks, indices, currencies and commodities. Column (6) reports the results for cryptocurrencies and serves as a placebo test. Overall, the leverage constraints had a positive effect on trading performance for all of the asset classes that were affected by the regulation. The effects were larger for currency and commodity trades, for which leverage levels were reduced in a more significant way in comparison to the leverage offerings in the pre-intervention period. Cryptocurrency trades, which were not affected by the intervention, do not display any change in performance.

2.4.4 Leverage and Transaction Costs

Our analyses thus far, at both the trade and portfolio levels, have focused on net returns. Nonetheless, the most meaningful effect of leverage on trading performance may potentially be the exacerbation of transaction costs. In this section, we embark on an exercise to determine how much of the documented improvement in trading performance that followed the implementation of ESMA's leverage constraints can be attributed to a reduction in transaction costs versus other factors.

Most providers of leveraged CFDs, including the broker, charge two main types of fees: bid-ask fees and overnight fees. The bid-ask fee is a mark-up that is added to the bid and ask prices of the asset, effectively widening the bid-ask spread on the trade. The overnight fee is the interest or funding fee that is charged on leveraged or short trades. These costs are calculated on the full notional value of the trade and therefore increase with increasing levels of leverage.

In Table 2.7, we report the results of trade level difference-in-differences specifications, in which we vary the dependent variable across different types of returns on the spectrum between net returns and gross returns. We exclude from our sample trades in assets that are denominated in any currency other than USD to neutralize the effects of currency conversions. Column (1) presents the results for trade-level returns that are displayed to the users by the broker. These returns are net of bid-ask fees but not of overnight fees. Additionally, these returns account for position top-ups, which are additional amounts that are added to a position after it is opened, in the case of a margin call, for example, effectively reducing the leverage on the trade. In the remaining columns, we ignore position top-ups and assume that the round-trip trade maintained the same level of leverage from open to close. In column (2), we display the results for returns after bid-ask fees but before overnight fees. In column (3), we report the results for net returns after all types of fees. Finally, in column (4), we show the results for gross returns. The exact calculations of the different types of returns and the data used for these calculations are described in Appendix C.

Table 2.7. Leverage and Transaction Costs

This table reports the results of difference-in-differences regression specifications exploring the effects of ESMA's regulatory intervention on trading performance for net and gross returns. The sample includes all of the trades made by the users of the broker in the twelve-month period surrounding ESMA's intervention (February 1, 2018–January 31, 2019). Exchange-traded fund (ETF) trades and trades in assets that are not denominated in USD are excluded. The dependent variable is trade-level returns, where the type of return varies across the different columns. Column (1) presents the results for net returns that are provided by the broker. These account for bid-ask fees but not for overnight fees. They further account for position top-ups, which are ignored in the remaining columns. Column (2) displays the results for returns after bid-ask fees but before overnight fees. Column (3) displays the results for net returns after bid-ask fees and overnight fees. Column (4) reports the results for gross returns. The exact return calculations are described in Appendix C. All returns are winsorized at the 0.01% and 99.99% levels. *EEA Trader* is an indicator variable that is equal to one for residents of EEA countries, who were subject to the leverage restrictions, and to zero otherwise. *Post* is an indicator variable that equals one for the period following the implementation of ESMA's leverage restrictions on August 1, 2018, and zero otherwise. *Short* is an indicator variable that equals one for short positions and zero for long positions. Standard errors are double-clustered by trader and calendar-day. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	(1) Broker Returns	(2) Returns w/o Overnight Fees	(3) Net Returns	(4) Gross Returns
EEA Trader x Post	0.016***	0.028***	0.030***	0.012***
	(8.784)	(10.059)	(10.407)	(4.480)
Short	0.012*	0.020**	0.023**	0.021**
	(1.655)	(2.193)	(2.412)	(2.259)
Trader FE	X	X	X	X
Asset FE	X	X	X	X
Day FE	X	X	X	X
N	13,475,317	13,475,317	13,475,317	13,475,317
Adj. R^2	0.035	0.030	0.031	0.025

The results in Table 2.7 suggest that transaction costs are the main channel through which leverage hinders trading performance and that the implementation of leverage constraints improved trading performance primarily by reducing these costs. While net per-trade returns, ignoring position top-ups, improved by 3.0 basis points after ESMA's intervention (column 3), gross per-trade returns improved by 1.2 basis points (column 4). Nonetheless, the improvement in gross returns is large. This improvement may have several explanations. First, in CFDs and other leveraged products, leverage not only multiplies the broker's fees but also the market-based bid-ask spread itself. At high levels of leverage, this may be meaningful even for very liquid assets. Second, leverage restrictions may reduce the probability of margin close-outs. To limit their risk, brokers are typically entitled to unilaterally close users' trades if their net equity falls below a pre-specified percentage of their initial margin. While this feature protects traders by reducing the probability that they lose more money than they had put into their account, its combination with high leverage, which makes trades extremely sensitive to small fluctuations in the price of the underlying asset, increases the probability of trades being closed at a loss due to normal intra-day volatility (regardless of whether the trade would have made a positive return at the end of the intended investment period). Finally, leverage restrictions may further limit the effects of "slippage" and "gapping,"[27] as well as the effects of currency conversion when the account is denominated in a different currency than the traded asset.

[27] "Slippage" refers to a situation where the trade is executed at a different price than the quoted price. This may occur, for example, when there is a lack of liquidity in the market for the asset. "Gapping" is a special situation that may lead to "slippage." In "gapping," the market price of the asset moves in large and discrete steps, skipping all of the price points in between. It may occur, for example, after the publication of significant economic data or following major economic events.

2.5 Why Do Retail Traders Use Leverage to Their Detriment?

The results of the previous section demonstrate that the deployment of leverage negatively affects the trading performance of retail traders and that the implementation of leverage constraints is effective in improving their performance. Given these results, a natural question is why individuals use leverage to their detriment. In this section, we propose and test two potential explanations: ignorance with respect to the meaning of leverage and overconfidence. We begin by documenting the prevalence of leverage-ignorant and overconfident traders in our sample and then proceed to examining how these explanations interact with leverage to affect trading performance.

2.5.1 Do Leverage Users Understand Leverage?

An important concept in behavioral finance is that of bounded rationality. According to this framework, people may attempt to act rationally and optimize their utility, but they are confined by limitations on their mental processing capacity. These limitations can be purely cognitive limitations (i.e., IQ; Grinblatt et al. 2012, Korniotis and Kumar 2013), attention limitations (Barber and Odean 2008, DellaVigna and Pollet 2009, Gargano and Rossi 2018, Hirshleifer et al. 2009) or other information processing limitations that may cause investors to misunderstand certain aspects of trading, such as inflation (Modilgiani and Cohn 1979), dividends (Hartzmark and Solomon 2018) or proportional thinking (Shue and Townsend 2021). Therefore, if retail investors do not fully understand the nuances of leveraged trading, or are otherwise unable to adjust for them, they may use leverage inappropriately and to their detriment.

We begin our analysis by exploring the alignment between the preferences of the leverage users in our sample and the act of using leverage. We split the sample of users who made at least one new trade in the six-month period preceding ESMA's regulatory intervention into three groups by leverage use: "Not High-Leverage Traders," who did not make even one highly leveraged trade during the period; “Mild High-Leverage Traders,” who traded with high leverage in less than 50% of their trades; and “Extreme High-Leverage Traders,” who traded with high leverage in more than 50% of their trades. We then compare the distribution of several know-your-customer questions that should be associated with the use of leverage across these groups.

The results are presented in Table 2.8, Panel A. While there is some evidence that traders who use high leverage are more risk-seeking, focus more on short-term trading goals and prefer shorter holding periods, the percentage of leverage users who have misaligned preferences is large. For example, 32.4% of the “Extreme High-Leverage Traders” are willing to risk only 12% of their invested capital. Similarly, 20.4% of the traders in this group list a long-term goal, such as saving for a home or future planning (for kids or retirement), as their main purpose of trading, and 57.5% state that they intend to keep their positions open for at least several weeks. These preferences are not compatible with the characteristics of leveraged trading and with the risks that are associated with using leverage.

Similarly, in Table 2.8, Panel B, we further explore the distribution of users’ responses to the know-your-customer questions on trading experience and trading knowledge. While the users in both leverage groups are on average slightly more experienced and knowledgeable than users who do not use high leverage at all, the large majority of users in these groups still self-report that they have no trading experience or financial knowledge.

Table 2.8. Leverage Alignment, Leverage Ignorance and Overconfidence

This table reports the distribution of certain leverage-related know-your-customer questions, as well as of proxies for leverage-ignorance and overconfidence, across three groups: "Not High-Leverage Traders" are users who did not make even one highly leveraged trade during the period, "Mild High-Leverage Traders" are users who traded with high leverage in less than 50% of their trades, and "Extreme High-Leverage Traders" are users who traded with high leverage in more than 50% of their trades. The statistics are reported for users who were active on the broker's platform during the six-month period before ESMA's regulatory intervention. For continuous and binary variables, a t-test is used to compare means. For categorical variables with more than one category, a chi-square test is used to compare distributions. The comparisons are presented for all column-pairs.

	Not High-Leverage Traders	**Mild High-Leverage Traders**	**Extreme High-Leverage Traders**	**χ^2 or t-statistic (p-value)**
Number of Traders	33,911	26,501	71,414	-
Panel A—Trader Alignment				
Risk Appetite, %				
Gain 5% / Lose -3%	0.036	0.037	0.046	$\chi^2_{1,2}$ = 35.7 (p < 0.01) $\chi^2_{1,3}$ = 482.4 (p < 0.01) $\chi^2_{2,3}$ = 194.5 (p < 0.01)
Gain 10% / Lose -6%	0.075	0.071	0.069	
Gain 20% / Lose -12%	0.246	0.232	0.209	
Gain 40% / Lose -24%	0.353	0.349	0.327	
Gain 80% / Lose -48%	0.290	0.311	0.349	
Purpose of Trading, %				
Short-Term Returns	0.225	0.236	0.271	$\chi^2_{1,2}$ = 25.7 (p < 0.01) $\chi^2_{1,3}$ = 549.1 (p < 0.01) $\chi^2_{2,3}$ = 246.6 (p < 0.01)
Additional Revenues	0.522	0.524	0.525	
Future Planning (Kids/Retirement)	0.176	0.161	0.128	
Saving for Home	0.077	0.078	0.076	
Trading Duration, %				
Short (up to 24 Hours)	0.201	0.243	0.425	$\chi^2_{1,2}$ = 256.6 (p < 0.01) $\chi^2_{1,3}$ = 5124.4 (p < 0.01) $\chi^2_{2,3}$ = 2551.9 (p < 0.01)
Medium (Weeks to Several Months)	0.541	0.551	0.446	
Long (More than Several Months)	0.258	0.206	0.129	
Panel B—Experience and Knowledge				
Trading Experience, %				
< 1 year	0.662	0.617	0.642	$\chi^2_{1,2}$ = 126.0 (p < 0.01) $\chi^2_{1,3}$ = 8717.6 (p < 0.01) $\chi^2_{2,3}$ = 9763.7 (p < 0.01)
1–3 years	0.201	0.230	0.205	
> 3 years	0.137	0.153	0.153	
Trading Knowledge, %				
No Financial Knowledge	0.561	0.542	0.532	$\chi^2_{1,2}$ = 24.9 (p < 0.01) $\chi^2_{1,3}$ = 82.0 (p < 0.01) $\chi^2_{2,3}$ = 8.5 (p = 0.04)
Financial Degree or Trading Courses	0.377	0.392	0.403	
Professional Certificate or Work Experience	0.039	0.041	0.040	
Both	0.022	0.025	0.025	
Panel C—Understanding Leverage				
Appropriateness Test, %				
Correct Answer	0.494	0.500	0.462	$t_{1,2}$ = 1.33 (p = 0.18) $t_{1,3}$ = 8.64 (p < 0.01) $t_{2,3}$ = 9.50 (p < 0.01)
Panel D—Overconfidence				
Amount in Trading Account, %				
> 10% of Net Worth	0.216	0.275	0.264	$t_{1,2}$ = 16.74 (p < 0.01) $t_{1,3}$ = 17.21 (p < 0.01) $t_{2,3}$ = 3.57 (p < 0.01)

Finally, in Table 2.8, Panel C, we report the distribution of users' responses to a short one-question quiz administered by the broker ("appropriateness test"), which directly tests for an understanding of leveraged trading. Appendix E presents examples of two variations of this quiz. The quiz is extremely simple, and traders with a very minimal understanding of leverage should not answer it incorrectly. Nonetheless, across all groups, no more than 50% of the users answer this question correctly, with the percentage significantly decreasing to 46.2% in the group of "Extreme High- Leverage Traders" who use high leverage the most.

Overall, the statistics presented in this section thus far suggest that many of the traders who utilize leverage in their trading are ignorant about its implications.

2.5.2 Are Leverage Users Overconfident?

A large body of literature in psychology has shown that people tend to be overconfident, either with respect to the precision of their information and judgments ("miscalibration" or "overprecision"; Alpert and Raiffa 1982), their own ability ("overestimation"; Campbell et al. 2004) or their ability relative to others ("overplacement" or the "better than average" effect; Svenson 1981).[28] Based on this literature, several papers have developed theoretical models of overconfident traders (Benos 1998, Caballé and Sákovics 2003, Gervais and Odean 2001, Hong et al. 2006, Kyle and Wang 1997, Odean 1998b, Scheinkman and Xiong 2003). In these models, the overconfident trader typically puts excessive weight on the information content of certain public signals or on their own private signal. Alternatively, the trader can downplay or dismiss the information content of other investors' private signals ("dismissiveness"; Eyster et al. 2019). A natural prediction of these models is that overconfident traders trade more and underperform, and

[28] See Moore and Healy (2008) for a discussion of this literature.

indeed, various empirical studies have found evidence to support this relationship (Barber and Odean 2000, Barber and Odean 2001, Dorn and Huberman 2005, Grinblatt and Keloharju 2009). An intuitive extension of this behavior would be that overconfident traders use excessive amounts of leverage to their detriment. Barber et al. 2020 propose a theoretical model to support this prediction. In a nutshell, their model predicts that overconfident traders believe that their signals are more precise than they actually are and, consequently, use more leverage to support larger trade sizes. Because the overconfident traders have misinterpreted the precision of their signals, they eventually underperform.

To create our measure of overconfidence, we combine traders' answers to the know-your customer questions on net annual income, total cash and liquid assets and the amount that they intend to deposit in their trading account. As part of the users' onboarding process, the broker strongly recommends that users not deposit more than 10% of their net worth (defined as the higher of net annual income and total cash and liquid assets) in their trading account, and if they mark that they intend to do so, a clear warning is presented advising against this decision. Therefore, we posit that traders who disregard this warning and still intend to deposit more than 10% of their net worth are potentially overconfident. Indeed, some of these traders may certainly be appropriately confident, but given the poor trading results of the leverage users in our sample, we believe that these traders are more likely to be—on average—overconfident.

Table 2.8, Panel D, displays the distribution of our overconfidence proxy across the three groups of leverage use. Overall, high-leverage users are more overconfident than non-high-leverage users, with 26.4% and 27.5% of "Extreme High-Leverage Traders" and "Mild High-Leverage Traders," respectively, self-reporting that they intend to deposit more than 10% of their net worth in their trading account, compared to 21.6% of "Not High-Leverage Traders."

2.5.3 Leverage Ignorance, Overconfidence and Trading Performance

After establishing that many of the users in our sample, including users who deploy large amounts of leverage, are ignorant with respect to the implications of leverage and/or overconfident with respect to their trading abilities, we explore how these explanations interact with the use of leverage to affect trading performance. We focus on the twelve-month period surrounding ESMA's intervention and augment our difference-in-differences specification to create a difference-in-difference-in-differences, or triple-difference, equation of the form:[29]

$$(2.3)\ R_{i,t} = \beta_1 EEA_i \times Post_t + \beta_2 Biased_i \times Post_t + \beta_3 EEA_i \times Biased_i \times Post_t + \lambda_i + \delta_t + \varepsilon_{i,j,t}.$$

$R_{i,t}$ is the monthly portfolio return of trader *i* in month *t*. $Biased_i$ is an indicator variable that equals one for leverage-ignorant traders, who answer the appropriateness test incorrectly, or for overconfident traders, who deposit more than 10% of their net worth in their trading account. The other variables are as previously defined. The coefficient β_1 captures the effect of ESMA's intervention on the monthly portfolio returns of non-leverage-ignorant or non-overconfident traders, as relevant, and the coefficient β_3 captures the change in this effect for leverage-ignorant or overconfident traders.

Table 2.9 reports the results. Column (1) displays the results for leverage-ignorant traders and column (4) presents the results for overconfident traders. The results suggest that while non-ignorant traders exhibited an improvement of approximately 4.7 basis points in their monthly portfolio returns after the regulatory intervention, ignorant traders exhibited an additional improvement of 1.9 basis points. Similarly, while non-overconfident traders exhibited an

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[29] The main effects, as well as the interaction term $EEA_i \times Biased_i$, are nested within the trader and calendar-month fixed effects and are therefore suppressed.

improvement of 4.8 basis points, the improvement for overconfident traders was greater by 2.8 basis points. For ease of interpretation, columns (2)–(3) present the results of regular difference-in-differences specifications applied on separate sub-samples of leverage-ignorant and non-leverage-ignorant traders, and columns (5)–(6) present the results for such specification applied on separate sub-samples of overconfident and non-overconfident traders. Overall, these results confirm that leverage has a greater adverse effect for leverage-ignorant and overconfident traders, and thus these traders benefited more from the implementation of ESMA's leverage limitations.

Table 2.9. Leverage Ignorance, Overconfidence and Trading Performance

This table reports the results of regression specifications exploring the effects of ESMA's regulatory intervention on trading performance for leverage-ignorant vs. non-leverage-ignorant and overconfident vs. non-overconfident traders. The dependent variable is monthly portfolio returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels. *EEA Trader* is an indicator variable that is equal to one for residents of EEA countries, who were subject to the leverage restrictions, and to zero otherwise. *Post* is an indicator variable that equals one for the period following the implementation of ESMA's leverage restrictions on August 1, 2018, and zero otherwise. *Ignorant Trader* is an indicator variable that is equal to one for leverage-ignorant traders, who fail the appropriateness test, and to zero otherwise. *Overconfident Trader* is an indicator variable that equals one for overconfident traders, who deposited more than 10% of their net worth in their trading account, and zero otherwise. Columns (1) and (4) present the results of difference-in-difference-in-differences (triple-difference) regression specifications on the full sample. The remaining columns display the results of regular difference-in-differences regression specifications on different sub-samples of traders. Standard errors are double-clustered by trader and calendar-month. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	Leverage Ignorance			Overconfidence		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Ignorant Traders	Non-Ignorant Traders	Full Sample	Overconfident Traders	Non-Overconfident Traders
EEA Trader x Post	0.047*** (3.855)	0.065*** (4.941)	0.046*** (3.848)	0.048*** (4.610)	0.075*** (4.450)	0.048*** (4.639)
Ignorant Trader x Post	-0.011** (-2.305)					
Ignorant Trader x EEA Trader x Post	0.019*** (4.558)					
Overconfident Trader x Post				0.000 (-0.010)		
Overconfident Trader x EEA Trader x Post				0.028*** (3.157)		
Trader FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
N	723,333	369,570	353,763	841,021	234,659	606,362
Adj. R^2	0.299	0.294	0.305	0.294	0.316	0.285

2.6 Conclusion

Leverage is detrimental to the wealth of retail traders. When retail traders use high amounts of leverage, they not only underperform relative to a market benchmark but also earn negative absolute returns and lose money. In this essay, we document the adverse effects of leverage on trading performance and show that a regulatory intervention that restricted the amount of leverage available to retail traders was successful in improving trading performance. We further provide evidence that ignorance with respect to what leverage entails and overconfidence contribute to the poor use of leverage by individuals. These lessons are especially important given a recent surge in the use of leverage by retail traders. In a survey conducted by Yahoo Finance and the Harris Poll at the end of 2020, it was found that 43% of retail traders in the United States use margin, options or both, with the percentage increasing to 67% for younger traders aged 18–34, such as the ones captured in this study.[30] The results of this survey are further supported by the significant rise in the debit balances in margin accounts of FINRA members' customers, which reached an all-time high of above $900 billion at the end of 2021,[31] and by the concurrent increase in the net flows to leveraged and inverse ETFs.[32]

This study provides an important case study for a new type of regulatory intervention that does not rely on a classic market failure justification but, rather, on a more paternalistic motivation of protecting consumers from making financial mistakes (Campbell et al. 2011, Campbell 2016). According to this rationale, which was at the heart of ESMA's intervention, there may be instances in which consumers make financial mistakes that are so extreme or that cause so much detriment

[30] https://theharrispoll.com/briefs/portfolio-strategy-shifts-during-covid-19/.

[31] https://www.finra.org/investors/learn-to-invest/advanced-investing/margin-statistics.

[32] https://www.wsj.com/articles/investors-pile-into-risky-etfs-during-wild-market-rally-11606665600.

that they may warrant a regulatory intervention even when there is no apparent market failure. Indeed, our study confirms that ESMA's intervention was able to reduce retail trader detriment. Nonetheless, this study does not claim that the imposition of leverage constraints is the most appropriate solution. Such constraints are an extreme measure, and alternative measures, such as extensive onboarding exams for users who wish to use leverage, may potentially be equally or even more effective. Additionally, this study does not try to conduct a complete welfare analysis, nor a complete cost-benefit analysis. It focuses only on the side of retail traders, with the goal of documenting the negative effects that leverage has on this important group of traders.

CHAPTER 3

Trading from Home: On the Implications of Time Constraints for Retail Investors

3.1 Introduction

Recent years have seen a surge of trading activity by retail investors, and in many ways retail trading has become a mainstream activity. This phenomenon, which was initially spurred by the proliferation of online trading platforms that made trading easily accessible and further fueled by the introduction of zero-commission stock trading, peaked during the coronavirus (Covid-19) pandemic. In fact, during many days in 2020 and 2021, retail trading accounted for as much as 20–25% of the trading volume on stock market exchanges in the United States, more than doubling the comparative percentages in previous years.[33]

At first glance, the significant increase in retail trading volume during one of the largest crises that the world has ever known may seem puzzling in light of the evidence of increasing individual risk aversion during times of calamity. Guiso et al. (2018), for example, found that during the 2008 financial crisis individual investors in Italy were more risk-averse and, in turn, more likely to divest their stock holdings. Similarly, in a lab setting, Cohn et al. (2015) documented increased levels of risk aversion among individuals who were faced with a financial bust scenario. In a related stream of literature, several papers have documented that that the risk appetite of retail investors is inversely related to terrorist activity. These papers have shown that terrorist attacks are followed by an increase in aggregate flows to “safe” government bond mutual funds at the expense of “risky” equity mutual funds (Wang and Young 2020), by a reduction in retail trading volume (Levy and Galili 2006) and by an increase in retail stock selling (Burch et al. 2016).

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[33] https://www.bnymellonwealth.com/articles/strategy/the-rise-of-retail-traders.jsp; https://www.bloomberg.com/news/articles/2021-07-06/record-everything-in-u-s-stock-market-including-retail-froth.

Nonetheless, some research has found evidence to the contrary. For example, Barrot et al. (2016) showed that during the 2008 financial crisis retail investors in France increased their direct stock holdings (albeit selling their mutual funds), concluding that the risk-bearing capacity of retail investors increases during periods of ambiguity. Similarly, Weber et al. (2013) surveyed customers of a UK-based online broker during the 2008 financial crisis and found that self-reported risk attitudes remained relatively stable, despite allocations to risky assets decreasing.

In any case, regardless of the effects of uncertainty on the risk tolerance of individual investors, retail trading volume may have increased during the Covid-19 pandemic due to entirely other reasons. One potential explanation may be investor beliefs about potential returns. As opposed to the market decline of the 2008 financial crisis that occurred over an extended period of time (Anand et al. 2013), the Covid-19 market crash was large and immediate (Mazur et al. 2021), creating a unique opportunity for investors who believed in their ability to generate positive returns to enter the market (Ortmann et al. 2020). Another potential explanation may be the distribution of funds via stimulus checks and economic support plans, which may have been used by certain individuals to fund trading accounts (Divakaruni and Zimmerman 2021). The most compelling potential explanation, however, is related to work-from-home restrictions and lockdowns. According to this explanation, work-from-home mandates may have increased retail trading volume if individuals had more free time and decided to direct this additional time to trading activities (Guzman et al. 2021, Ozik et al. 2021, Priem 2021).

In this essay, we aim to explore the effects of working from home on the trading behavior of retail investors. As many leading companies have recently announced that they will permanently shift to a full or partial work-from-home model even after the end of the pandemic,[34] understanding

[34] https://www.cnbc.com/2022/04/13/10-companies-that-switched-to-permanent-hybrid-or-remote-work-and-hiring-

the effects of work-from-home policies on retail trading may be of immediate importance. This is especially true given the potential economic effects of changes in retail trading activity on aggregate market outcomes, such as prices and liquidity (Barber et al. 2009b, Barber et al. 2021b, Barrot et al. 2016, Bohmer 2021, Dorn et al. 2008, Han and Kumar 2013, Hvidkjaer 2008, Kaniel et al. 2008, Kaniel et al. 2012, Kelley and Tetlock 2013, Kelley and Tetlcok 2017).

Moreover, the sudden shift to a work-from-home regime during the pandemic provides a unique opportunity to study the relationship between time constraints and retail investor behavior. An important concept in behavioral finance is that of bounded rationality. According to this framework, people may attempt to act rationally and optimize their utility, but they can only do so within the limitations of their mental processing capacity (Barberis 2018). These processing limitations can be purely cognitive or intellectual limitations (Grinblatt et al. 2012), but they can also be limitations on time and attention. In line with this framework, prior literature has shown, for example, that there is a greater post-earnings announcement drift when a firm announces earnings on a Friday, when investors are presumed to be less attentive (DellaVigna and Pollet 2009). Subsequently, several papers have tried to explore the effects of attention on the trading behavior and performance of retail investors. Due to data limitations, most of this literature has used indirect aggregate measures of attention, such as trading volume (Gervais et al. 2001), price limits (Li and Yu 2012, Seasholes and Wu 2007), Google search volume (Andrei and Hasler 2015, Da et al. 2011), news coverage (Engelberg et al. 2012, Engelberg and Parsons 2011, Yuan 2015) and advertising spending (Lou 2014), but some recent literature has been able to measure investor attention directly. For example, utilizing data on the logins of retail investors to their brokerage accounts, Gargano and Rossi (2018) find a positive relationship between retail investor attention

right-now.html; https://www.forbes.com/sites/kristinstoller/2021/01/31/never-want-to-go-back-to-the-office-heres-where-you-should-work/.

and performance, and Dierick et al. (2019) document that more attentive retail investors are less prone to the disposition effect. Nonetheless, due to the strong correlation between attention and skill, or between attention and market-wide events (Karlsson et al. 2009, Sicherman et al. 2016), this literature has focused on documenting associations and refrained from making any causal statement. The unique setting in which work-from-home mandates were unilaterally imposed by governments creates a potentially exogenous change in people's time constraints that would allow us to make a causal statement about the effects of time and attention on trading behavior and performance.

Our analysis utilizes two unique datasets. The first dataset comes from an international discount broker with a client profile akin to that of Robinhood and includes detailed trading information at the individual level. As of January 2022, the broker had a total of 27 million registered users in over 140 countries.[35] The second dataset is the Oxford Covid-19 Government Response Tracker, which provides a daily time series of policy measures that governments have taken in response to the Covid-19 pandemic, including work-from-home policies. In combining these datasets, we are able to exploit the variation in work-from-home policies both within each country during our sample period and across countries during specific points in time, while controlling for the unique characteristics of each individual trader or trade, as relevant.

We begin our analysis by exploring the relationship between working from home and the attention that investors devote to their trading accounts. While we do not directly observe the amount of time that investors spend on their accounts, we do observe their reactions to messages and notifications sent by the broker. We find that the probability that investors pay attention to

[35] The amount of registered users represents the total amount of users that have signed up to the trading platform since its inception in 2007. The number of funded accounts in January 2022 is approximately 10% of the number of registered users.

these messages increases by 1.5 basis points in days in which they work from home and that the daily percentage of messages that they pay attention to increases by 0.8 basis points. We further show that on work-from-home days the minimal amount of time that it takes investors to pay attention to messages is reduced by 4.1 basis points. Finally, we report that, upon working from home, the probability that investors make a trade that is related to a message in the following 24 hours increases by 0.5 basis points. Overall, our evidence suggests that investors pay more attention to their brokerage accounts when they work from home.

We continue our analysis by asking if and how the additional time and attention that investors devote to their brokerage accounts affect their trading activities. We find that individuals trade more when they work from home. On average, retail investors make 4.4% more trades per week in weeks in which they work from home. In our main analysis, we ignore work-from-home recommendations and focus on work-from-home mandates. If we account for work-from-home recommendations, the increase in trading activity ranges from 2.6% in weeks with work-from-home recommendations to 10.8% in weeks with the most severe work-from-home restrictions. These differences are potentially the result of an increase in the amount of people who actually worked from home in weeks in which governments imposed severe work-from-home restrictions compared to weeks in which governments only suggested that people work from home. Therefore, 2.6% and 10.8% can be viewed as lower and upper bounds, respectively, for the effects of working from home on the number of weekly trades.

Nonetheless, despite the significant increase in individuals' trading intensity when working from home, we find only limited evidence that individuals change the types of trades that they make. Specifically, we report that, upon working from home, retail investors are more prone to day trading but otherwise continue to invest in the same asset classes—whether they be equities, currencies, commodities or cryptocurrencies—and to maintain similar ratios of long vs. short and leveraged vs. unleveraged positions.

Subsequently, we explore whether the additional time and attention that retail investors devote to their trading accounts when they work from home affect their well-documented tendencies to open positions in assets that have recently caught their attention ("attention-induced trading"; Barber et al. 2021a, Barber and Odean 2007, Odean 1999) or in assets that they are familiar with ("familiarity bias"; Benartzi 2001, French and Poterba 1991, Grinblatt and Keloharju 2001, Huberman 2001). We find that, upon working from home, retail investors increase their reliance on news to facilitate trades. Specifically, the conditional probability of opening a position after a day with extreme abnormal news increases by 0.2 basis points, which is equivalent to a relative increase of 4.07% compared to the mean. We further show that on work-from-home days retail investors are less prone to familiarity bias, with the conditional probability of trading an asset that is tied to the investor's home country going down by approximately 1.0 basis point. Otherwise, however, retail investors do not change their decision making process, as they continue to rely on our additional proxies for attention-grabbing events, such as extreme absolute returns, extreme abnormal trading volume and extreme abnormal social media volume, in a similar manner.

Finally, we test whether working from home affects investors' performance. Using several methods for calculating market-adjusted returns, we find that retail investors improve their trade-level performance by at least 0.1 basis points when they work from home. This is equivalent to an increase of at least 12.5% compared to the mean market-adjusted return. We conclude that the increase in retail investors' performance is caused by the additional attention that they devote to their brokerage accounts when they work from home, suggesting that time constraints have a meaningful hindering effect on retail investors' performance.

The rest of this essay is organized as follows. Section 3.2 describes the data, the work-from-home variables and our identification strategy. This section also presents summary statistics. Section 3.3 explores the impact of working from home on investor attention. Section 3.4 investigates the effects of working from home on trading behavior. Section 3.5 studies the implications of working from home for trading performance. Section 3.6 concludes.

3.2 Research Design

3.2.1 Data

Our analyses combine proprietary brokerage data with data on Covid-19 and work-from-home mandates. Our brokerage data are obtained from a discount broker that operates a global online trading platform for retail investors. The trading platform gives investors the ability to trade a wide variety of assets, including individual stocks, indices and exchange-traded funds (ETFs) from twenty exchanges around the world, as well as foreign currency pairs, commodities and cryptocurrencies. The platform further provides a simple and seamless way to open short positions and the ability to flexibly deploy leverage at the individual trade level.

The broker's data include the full log of trades executed on its trading platform during the period between January 1, 2012 and March 31, 2021. For each trade, the data include: the name of the traded asset, the exact timestamp of the trade, the execution price, the direction of the trade (open/close), the direction of the overall position (long/short), the leverage ratio applied to the position at open, the percentage of the user's equity that was invested in the position at open and, for closing trades, the net return on the round-trip trade. In addition, the data also include several auxiliary datasets.[36] First, for each user, the data include verified demographic information on age,

[36] We describe only the parts of the data that are utilized in this essay. The data include several additional datasets, which we do not use in this essay.

gender and country of residence, as well as self-reported responses to know-your-customer questions on prior trading experience, trading education, preferred trading strategy, primary purpose of trading, attitude towards risk, preferred trading frequency, net annual income, total cash and liquid assets, sources of income, occupation and more. Second, the data include information on messages and notifications that are sent by the broker to its clients and on clients' reactions to these messages. For each message, we observe the exact timestamp of the message, the number of recipients to whom the message was sent, and a series of variables that describe the content of the message. For each recipient of the message, we further observe the number of minutes after the message was sent that the user reacted to it, if at all, in each of the following ways: clicking on a push message, opening an in-app notification, opening a browser-based notification or reaching the unique page of the asset on the trading platform. Finally, the data also include a daily time series of open, close, minimum and maximum prices for each of the assets offered on the platform.

For work-from-home and other Covid-19-related information, we use data from the Oxford Covid-19 Government Response Tracker (OxCGRT) (Hale et al. 2021). The data cover more than 180 countries and include information at the country-day level on policy measures that governments have taken in response to the Covid-19 pandemic. The tracked measures include containment and closure policies, such as school closures, work-from-home mandates, stay-at-home requirements and travel restrictions, as well as economic policies regarding income support and debt relief, and health systems policies on testing, vaccination, facial coverings and more. The data further include daily statistics on the number of reported Covid-19 cases and Covid-19 deaths in each country.

In addition, we augment our brokerage and work-from-home data with information from the International Country Risk Guide (ICRG), published by The PRS Group, on the monthly political, economic and financial risk of each country. The political risk rating aims to assess the political stability of a country and aggregates a total of twelve measures, including measures of government stability, corruption, law and order, and internal and external conflicts. The economic risk rating provides a means of assessing a country's economic strengths and weaknesses and is based on gross domestic product (GDP) estimates, inflation estimates, the central government's budget and more. Finally, the financial risk rating measures a country's ability to pay off its obligations by aggregating factors such as foreign debt, foreign debt service and exchange rate stability. The advantages of the ICRG data for our purposes, in comparison to other macro-level data sources, are its breadth of coverage, with data on 141 countries, and the relatively high frequency of the data, which is updated monthly.

Finally, in some of our analyses we also utilize data from several additional sources. First, we acquire news coverage data on stocks from the FinSentS Web News Sentiment database, published by Inoftrie.[37] The data analyzes the content of thousands of news websites and media sources from around the world and provides news information on over 49,000 global equities. Second, we receive data from a provider that scraped posts and comments from one of the leading social media forums on stock trading, Reddit's WallStreetBets (r/WSB).[38] Third, we collect price data from CRSP and Compustat to support and verify the platform's price data for individual stocks and ETFs. We further use Compustat to determine the location of each firm's headquarters and country of incorporation, as well as the dates of earnings announcements.

[37] We access the data via the Nasdaq Data Link.

[38] r/WSB has several sub-forums on which its users can communicate. Our data includes posts and comments from two of these sub-forums labeled as "Tomorrow's Moves" and "Daily Discussion." The "Tomorrow's Moves" thread includes users' comments on their trading strategies and expectations for the next trading day, while the "Daily Discussion" thread includes users' comments on the current trading session.

3.2.2 Sample and Summary Statistics

We limit our sample to the period between January 1, 2019 and March 31, 2021, providing approximately one year of data before Covid-19 was first detected in Wuhan, China in December 2019, and approximately one year of data after Covid-19 was declared a global pandemic by the World Health Organization in early March 2020 and work-from-home restrictions began to be issued by governments. We further remove users who opened fewer than ten new positions during our sample period, users from countries in which the broker had fewer than 100 unique users during our sample period and users from countries that do not match to our additional data sources.

Table 3.1 presents summary statistics for the retail investors in our sample. Column (1) displays summary statistics for the full sample, while columns (2)–(3) display these statistics separately for users who joined the broker prior to March 1, 2020 ("existing pre-Covid users") and users who joined the broker from March 1, 2020 onwards ("new Covid users"). Column (4) presents the results of a comparison between columns (2) and (3). In Panel A, we report basic user demographics and the distribution of responses to several know-your-customer questions.[39] The broker's users are primarily male and relatively young, with 81.1% of the users being under the age of 45. However, the percentage of female users and the average age of the users have increased following the onset of Covid-19. A large portion of the users do not have prior trading experience, with 37.2% of the users stating that they have not traded stocks or ETFs in the previous year and 44.8% stating that they have not traded cryptocurrencies. The users who join the platform beginning on March 1, 2020 have significantly less experience trading both types of assets. Nonetheless, the broker's users tend to be relatively risk-seeking, with 62% of the users stating

[39] For the sake of brevity, we include summary statistics only for a few know-your-customer questions. We relegate to Appendix F information on additional know-your-customer questions.

that they are willing to risk at least 24% of their capital for the opportunity to gain a return of at least 40%. 72.3% of the users further state that they are trading to achieve short-term goals, such as short-term returns or additional revenues, as opposed to long-term goals that include future planning for kids or retirement and saving for a home. However, the new Covid users tend to lean slightly more towards long-term goals compared to the existing pre-Covid users. Finally, 91.9% of our sample has an annual income of up to $200,000, with 66.6% having an annual income of less than $50,000.

In Panel B, we report summary statistics for the trading behavior of the users in our sample. The average user makes at least one trade (either opening a position or closing a position) in 55.3% of the weeks. Conditional on trading, the average user makes 14.5 trades per week. New users who joined the platform beginning on March 1, 2020 trade more, both in terms of the fraction of trading weeks and in terms of the number of trades in trading weeks.[40] Of the trades that open a new position each week, an average of 10.7% open short positions and an average of 29.5% open a leveraged position. However, new users are significantly less engaged in short trading and leveraged trading. Finally, over 60% of the users in our sample trade across at least two asset classes, with 85.6% of the users opening at least one equity position and 82.5% of the users opening at least one cryptocurrency positon. Existing pre-Covid users are more inclined than new users to trade in foreign currencies and commodities.

[40] It is, however, important to note that part of the difference may be explained by increased trading activity in the first few weeks after users join the platform as they begin building their portfolio.

Table 3.1. Summary Statistics

This table reports summary statistics for the users in our sample. Column (1) presents statistics for the full sample of users. Column (2) displays statistics for users who joined the broker prior to March 1, 2020, and column (3) displays statistics for users who joined the broker beginning on March 1, 2020. Column (4) presents the results of a comparison between columns (2) and (3). For continuous and binary variables, a t-test is used to compare means. For categorical variables with more than one category, a chi-square test is used to compare distributions.

	Full Sample	**Existing Users**	**New Covid Users**	**χ^2 or t-statistic (p-value)**
N	963,805	327,670	636,135	-
Panel A—User Demographics & Know Your Customer Responses				
Female, %	0.117	0.087	0.133	t = 71.45 ($p < 0.01$)
Age Range, %				
18–24	0.142	0.090	0.168	χ^2 = 17784 ($p < 0.01$)
25–34	0.396	0.367	0.411	
35–44	0.273	0.313	0.253	
45–54	0.129	0.153	0.116	
55–64	0.049	0.061	0.043	
≥ 65	0.011	0.016	0.009	
Trading Experience in Past Year—Stocks and ETFs, %				
0 times	0.372	0.290	0.399	χ^2 = 10559 ($p < 0.01$)
1–10 times	0.312	0.313	0.312	
10–20 times	0.123	0.144	0.117	
≥ 20 times	0.192	0.253	0.173	
Trading Experience in Past Year—Cryptocurrencies, %				
0 times	0.448	0.278	0.503	χ^2 = 37044 ($p < 0.01$)
1–10 times	0.322	0.364	0.308	
10–20 times	0.105	0.153	0.089	
≥ 20 times	0.125	0.205	0.100	
Preferred Risk-Reward Scenario, %				
Gain 5% / Lose -3%	0.033	0.038	0.031	χ^2 = 1670 ($p < 0.01$)
Gain 10% / Lose -6%	0.087	0.081	0.090	
Gain 20% / Lose -12%	0.259	0.243	0.267	
Gain 40% / Lose -24%	0.343	0.341	0.344	
Gain 80% / Lose -48%	0.277	0.297	0.267	
Primary Purpose of Trading, %				
Short-Term Returns	0.199	0.203	0.197	χ^2 = 1850.7 ($p < 0.01$)
Additional Revenues	0.524	0.547	0.512	
Future Planning (for Kids/Retirement)	0.200	0.180	0.210	
Saving for Home	0.077	0.070	0.080	
Net Annual Income (USD), %				
< 10K	0.190	0.180	0.196	χ^2 = 3534.4 ($p < 0.01$)
10–50K	0.476	0.477	0.475	
50–200K	0.253	0.273	0.242	
200–500K	0.030	0.031	0.030	
500K–1M	0.016	0.017	0.016	
≥ 1M	0.035	0.022	0.041	

Table 3.1. Summary Statistics (Continued)

	Full Sample	Existing Users	New Covid Users	χ^2 or t-statistic (p-value)
Panel B—Trading Characteristics				
% of Weeks with Trades, Mean (SD)	0.553 (0.298)	0.365 (0.272)	0.650 (0.262)	t = 493.92 (p < 0.01)
Weekly Number of Trades, Mean (SD)	14.515 (26.440)	12.901 (23.304)	15.347 (27.882)	t = 45.57 (p < 0.01)
% of Short Trades per Week, Mean (SD)	0.107 (0.167)	0.165 (0.196)	0.077 (0.141)	t = 228.03 (p < 0.01)
% of Leveraged Trades per Week, Mean (SD)	0.295 (0.360)	0.464 (0.385)	0.208 (0.313)	t = 329.10 (p < 0.01)
% of Users by Number of Traded Asset Classes				
One	0.200	0.162	0.221	χ^2 = 45766 (p < 0.01)
Two	0.401	0.305	0.451	
Three	0.252	0.301	0.227	
Four	0.145	0.232	0.101	
% of Users Who Trade in Each Asset Class				
Equity Trader	0.856	0.823	0.873	t = 49.58 (p < 0.01)
Currency Trader	0.219	0.336	0.159	t = 54.43 (p < 0.01)
Commodity Trader	0.430	0.582	0.352	t = 86.29 (p < 0.01)
Cryptocurrency Trader	0.825	0.843	0.815	t = 63.08 (p < 0.01)

3.2.3 Variable Definitions and Methodology

The OxCGRT data provide a daily "work closure" categorical variable that can take one of four possible values: 0 for days in which there are no work-from-home measures in place; 1 for days in which work-from-home is recommended or there are significant alterations in the way that businesses operate; 2 for days in which work-from-home is required for some sectors or categories of workers; and 3 for days in which work-from-home is mandated for all but essential workers. Because there may be significant variation in Covid-19 policies between different cities or regions, the work-from-home categorical variable is coded to represent the most stringent policy that is in place within a country, and an indicator variable is used to differentiate between general policies that apply to the entire country and targeted polices that apply to a specific city or region.

In our analyses, we define work-from-home in one of two ways. In our main specifications, we define work-from-home days as days in which work-from-home is mandated for all workers, either as a general country-wide policy or as a targeted region-specific policy, as well as days in which work-from-home is required for some sectors or categories of workers as a general country-wide policy. In alternative specifications, we create four work-from-home categories, declining in their level of stringency: Level 1 for general policies requiring work-from-home for all workers; Level 2 for general policies requiring work-from-home for some workers, as well as targeted policies requiring work-from-home for all workers; Level 3 for general policies recommending work-from-home, as well as targeted policies requiring work-from home for some workers; and Level 4 for targeted policies recommending work-from-home, as well as no work-from-home limitations whatsoever. Appendix G describes the creation of these variables.

Using these work-from-home definitions, we employ an identification strategy that is akin to a difference-in-differences design. Specifically, we utilize the variation in work-from-home policies, both within each country during our sample period and across countries during specific points in time, to tease out the effects of work-from-home mandates. However, as opposed to a classic difference-in-differences design where treatment occurs at a specific point in time for each unit of observation (even if this point of time varies across observations) and remains constant thereafter, our analysis allows for individuals to shift in and out of a work-from-home status. Formally, our core analyses are based on the following regression specification:

$$(3.1)\ Y_{i,t} = \beta_1 Work_{j,t} + \beta_2 EconRisk_{j,t} + \beta_3 FinRisk_{j,t} + \beta_4 PolRisk_{j,t} + \beta_5 NewCases_{j,t} + \beta_6 NewDeaths_{j,t} + \lambda_i + \delta_t + \varepsilon_{i,t}.$$

$Work_{j,t}$ indicates the work-from-home status in country *j* at time *t*. It is either our primary work-from-home binary measure or our alternative work-from-home categorical measure, coded as a series of three binary variables indicating the stringency level of the work-from-home mandate. $EconRisk_{j,t}$, $FinRisk_{j,t}$, $PolRisk_{j,t}$ are the ICRG measures of the economic, financial and political risks of country j at time t, standardized from 1 to 100.[41] $NewCases_{j,t}$ and $NewDeaths_{j,t}$ are, respectively, the numbers of new Covid-19 cases and deaths per 100,000 people in country *j* during time *t*. λ_i and δ_t are investor and time fixed-effects, respectively. In some of our analyses equation (3.1) is applied at the weekly level, in some of our analyses it is applied at the daily level, and in some of our analyses it is applied at the trade level. Standard errors are double-clustered by investor and the relevant time period.[42]

3.3 Work-from-Home and Attention

We begin our analysis by exploring the effects of working from home on investor attention. We measure investors' attention using their reactions to messages and notifications sent by the broker. We aggregate the sample of all of the messages and notifications that were received by investors[43] to the daily level and create four measures of attention: an indicator variable that is equal to one if the investor opened at least one message during the day; the percentage of messages that were opened by the investor during the day out of all of the messages received; the log value

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[41] The original ICRG political risk factor runs from 1 to 100, while the economic and financial risk factors run from 1 to 50. We multiply the latter two risk factors by two to create comparable measures. Additionally, as the ICRG risk factors are updated on a calendar-month basis, in our weekly analyses we calculate the weighted average of the scores in weeks that cross two months, based on the number of days in the relevant week that are part of each month.

[42] As work-from-home mandates are implemented at the country level, double-clustering by time and individual investor might overstate statistical significance. The most conservative approach would be to double-cluster by time and country. This approach accounts for correlation between the residuals of individuals in the same country across the full sample period. In unreported sensitivity analyses, we find that with the exception of the results regarding extreme last-day abnormal news volume (Table 3.7, column 4), exchange-based measures of familiarity bias (Table 3.8, columns 1–2), within-broker market-adjusted returns (Table 3.9, Panel A, columns 1–3) and unleveraged within-broker market-adjusted returns (Table 3.9, Panel B, columns 1–3), our results remain statistically significant, albeit at reduced significance levels. A somewhat less conservative approach, although still highly conservative, would be to double-cluster by time and country-occupation. This approach accounts for correlation between the residuals of individuals in both the same country and the same occupation across the full sample period. Using this approach, all of our results remain statistically significant and the significance levels are generally unchanged.

[43] Within our sample period, we further limit our analysis to messages that were received between each investor's first and last activities on the platform. Messages that were received after an investor's last activity are ignored.

of the minimal number of minutes that it took the investor to open a message during the day, conditional on opening at least one message; and an indicator variable that equals one if the investor traded at least one of the assets that they received messages about during the next 24 hours.

Using these measures, we estimate equation (3.1) at the investor-day level. Table 3.2, Panel A displays the results. Columns (1)–(4) include the results for our main work-from-home-definition. We find that, during days in which work-from-home mandates are in place, investors pay more attention to their brokerage accounts. Specifically, in columns (1) and (2), we show that during work-from-home days, the probability that an investor opens a message from the broker increases by 1.5 basis points and that the percentage of messages that an investor opens increases by 0.8 basis points. These effects are significant, given that the investors in our sample react to at least one message in only 28.17% of the days and open an average of 11.32% of the messages received per day. Similarly, in column (3), we document that the minimal amount of time that it takes an investor to open a message decreases by 4.1 basis points. Finally, in column (4), we report that the probability that an investor trades based on a message sent by the broker increases by 0.05 basis points, which corresponds to a relative increase of 7.4% compared to the mean of 6.7%.

Columns (5)–(8) present the results for our alternative work-from-home measures. Across all columns, we see that the effects increase with the stringency of the work-from-home mandate. This can potentially be explained by the additional people who shift to a work-from-home regime as the restrictions become more comprehensive. In other words, some people work from home when it is only recommended, additional people work from home when it is required for some sectors or categories of workers, and most people work from home when it is mandated for all but essential workers. As a result, the documented effect increases with the stringency of the measure.

Table 3.2. The Impact of Work-from-Home on Investor Attention

This table reports the results of regression specifications exploring the effects of working from home on the attention that investors devote to their brokerage accounts. Investors' attention is proxied by investors' reactions to messages and notifications that are sent by the broker. The analyses are conducted at the daily frequency, and the dependent variable is one of four proxies: *Is React?* is an indicator variable that is equal to one if the investor opened at least one message during the day; *React %* is the percentage of messages that were opened by the investor during the day out of all of the messages received; *React Time* is the log value of the minimal number of minutes that it took the investor to open a message during the day, conditional on opening at least one message; and *Is Trade?* is an indicator variable that equals one if the investor traded at least one of the assets that they received messages about during the next 24 hours. Panel A reports our main set of results. *WFH* is an indicator variable that is equal to one when a work-from-home mandate is in place in the investor's country of residence. *Full WFH*, *Part WFH* and *Rec WFH* differentiate between different levels of work-from-home mandates and decline in their level of stringency. The definitions of the different work-from-home variables are described in Appendix G. *Econ Risk*, *Fin Risk* and *Pol Risk* are the ICRG measures of the economic, financial and political risks of the investor's country of residence, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new daily Covid-19 cases and deaths, respectively, per 100,000 people in the investors' country of residence. In Panel B, we include the interaction between *WFH* and *Unemployed*, where *Unemployed* is an indicator variable that is equal to one for investors who self-report that they are unemployed, retired or students. In all specifications, standard errors are double-clustered by investor and date. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

Panel A

	(1) Is React?	(2) React %	(3) React Time	(4) Is Trade?	(5) Is React?	(6) React %	(7) React Time	(8) Is Trade?
WFH	0.015***	0.008***	-0.041***	0.005***				
	(13.131)	(16.646)	(-6.805)	(10.910)				
Full WFH					0.046***	0.018***	-0.094***	0.016***
					(15.294)	(17.382)	(-6.093)	(13.726)
Part WFH					0.024***	0.011***	-0.063***	0.006***
					(10.346)	(13.039)	(-5.586)	(7.053)
Rec WFH					0.013***	0.004***	-0.030**	0.002**
					(5.205)	(4.504)	(-2.502)	(2.118)
Econ Risk	0.001***	0.000***	0.000	0.000***	0.000***	0.000***	0.000	0.000*
	(4.062)	(3.915)	(-0.207)	(2.702)	(3.310)	(3.041)	(0.243)	(1.880)
Fin Risk	0.000	0.000**	0.003**	0.000**	0.000	0.000***	0.003	0.000***
	(-0.103)	(2.575)	(2.008)	(2.020)	(1.544)	(3.909)	(1.605)	(3.439)
Pol Risk	0.002***	0.001***	-0.003***	0.001***	0.002***	0.000***	-0.003**	0.000***
	(7.937)	(4.944)	(-2.624)	(4.557)	(6.323)	(3.517)	(-2.107)	(2.827)
New Cases	0.000***	0.000	0.000	0.000*	0.000***	0.000*	0.000	0.000***
	(3.334)	(0.384)	(-1.084)	(1.926)	(4.839)	(1.743)	(-1.472)	(3.306)
New Deaths	0.014***	0.006***	-0.029***	0.007***	0.006***	0.003***	-0.018**	0.004***
	(7.966)	(9.551)	(-3.533)	(8.241)	(3.423)	(5.195)	(-2.167)	(4.364)
Trader FE	X	X	X	X	X	X	X	X
Day FE	X	X	X	X	X	X	X	X
N	198,400,929	198,400,929	55,894,638	198,400,929	198,400,929	198,400,929	55,894,638	198,400,929
Adj. R^2	0.292	0.274	0.187	0.129	0.293	0.274	0.187	0.129

Table 3.2. The Impact of Work-from-Home on Investor Attention (Continued)

Panel B	(1) Is React?	(2) React %	(3) React Time	(4) Is Trade?
WFH	0.018***	0.009***	-0.049***	0.006***
	(15.048)	(18.832)	(-7.843)	(12.594)
WFH x Unemployed	-0.018***	-0.008***	0.043***	-0.005***
	(-13.291)	(-14.111)	(8.072)	(-10.898)
Econ Risk	0.001***	0.000***	0.000	0.000***
	(4.023)	(3.861)	(-0.184)	(2.675)
Fin Risk	0.000	0.000**	0.003**	0.000**
	(-0.178)	(2.488)	(2.028)	(1.969)
Pol Risk	0.002***	0.001***	-0.003***	0.001***
	(7.978)	(4.987)	(-2.639)	(4.586)
New Cases	0.000***	0.000	0.000	0.000*
	(3.314)	(0.347)	(-1.066)	(1.911)
New Deaths	0.014***	0.006***	-0.029***	0.007***
	(7.976)	(9.566)	(-3.542)	(8.239)
Trader FE	X	X	X	X
Day FE	X	X	X	X
N	198,394,078	198,394,078	55,891,437	198,394,078
Adj. R^2	0.293	0.274	0.187	0.129

A potential concern with our results may be that of omitted variable bias—namely that work-from-home mandates are correlated with our proxies of investor attention in ways that are unrelated to the additional time that investors presumably have when they work from home. We respond to this concern in several ways. First, by including both investor and time fixed effects in all of our specifications, any alternative explanation would have to correspond to the variation both within and across investors. Second, the gradual increase in our results for the alternative work-from-home measures provides strong evidence in support of a direct and causal link between working from home and investor attention. Third, in Table 3.2, Panel B, we add to equation (3.1) an interaction term between working from home and the employment status of the investor. We define unemployed investors as individuals who self-report that they are unemployed, retired or students. As unemployed investors should be less affected by work-from-home mandates, we expect the coefficient on the interaction term to be negative in columns (1), (2) and (4) and positive in column (3). This is indeed what we find.

3.4 Work-from-Home and Trading

3.4.1 Trading Intensity

After establishing that retail investors pay more attention to their brokerage accounts when working from home, we explore whether such additional attention translates to changes in their trading behavior. We begin by testing the effects of work-from-home mandates on weekly trading intensity. We do so by aggregating our trading data to the weekly level, and applying equation (3.1) at the investor-week level.[44] In our main specifications, the indicator variable $Work_{j,t}$ is equal to one if our primary work-from-home measure was equal to one on at least one day during the week. In the specifications that use our alternative work-from-home definition, the weekly work-from-home status is defined by the most stringent policy in place during the week.

The results are displayed in Table 3.3. Columns (1)–(3) present our main set of results. In column (1), we focus on the unconditional number of trades. The dependent variable is the natural log of the total number of trades made by investor *i* in week *t*, and the sample includes all of the weeks between the investor's first and last activities on the platform, including weeks in which no trades were made. In column (2), we continue to use the full sample and utilize a linear probability model in which the dependent variable is equal to one if at least one trade was made during the week. In column (3), we restrict our sample to weeks in which at least one trade was made and include the log number of trades as the dependent variable.

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[44] We conduct these sets of analyses at the weekly level for two reasons. First, because different asset classes have different trading days, the trading activity on different days of the week may not be comparable, and it may further be difficult to define the set of relevant trading days for traders of different asset classes. For example, while stocks on US stock exchanges are traded Monday through Friday, cryptocurrencies are traded throughout the entire week. By aggregating to the weekly level, we create comparable units of time both within investors and across investors. Second, many investors do not trade every day. Therefore, in our unconditional analyses, which are not limited to time periods in which the investor made at least one trade, a daily time interval may inflate the amount of zeroes in the dependent variable, skewing our data and potentially violating the normal distribution assumption of the linear regression model. A weekly time interval significantly reduces the amount of these zeroes.

Table 3.3. The Impact of Work-from-Home on Trading Intensity

This table reports the results of regression specifications that investigate the effects of working from home on trading intensity. The analyses are conducted at the weekly frequency, and the dependent variable is one of two variables: *Trade #* is the natural log of the total number of trades made by the investor during the week, and *Is Trade?* is an indicator variable that equals one if at least one trade was made by the investor during the week. *WFH* is an indicator variable that is equal to one if a work-from-home mandate was in place in the investor's country of residence for at least one day during the week. *Full WFH*, *Part WFH* and *Rec WFH* differentiate between different levels of work-from-home mandates and decline in their level of stringency. The definitions of the different work-from-home variables are described in Appendix G. *Unemployed* is an indicator variable that is equal to one for investors who self-report that they are unemployed, retired or students. *Econ Risk*, *Fin Risk* and *Pol Risk* are the ICRG measures of the economic, financial and political risks of the investor's country of residence, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new weekly Covid-19 cases and deaths, respectively, per 100,000 people in the investors' country of residence. In columns that utilize the full sample, the sample includes all of the weeks between the investor's first and last activities on the platform, including weeks in which no trades were made. In columns that utilize the trading sample, we restrict our sample to weeks in which at least one trade was made. In all specifications, standard errors are double-clustered by investor and week. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	(1) Trade #	(2) Is Trade?	(3) Trade #	(4) Trade #	(5) Is Trade?	(6) Trade #	(7) Trade #	(8) Is Trade?	(9) Trade #
WFH	0.044*** (9.399)	0.019*** (9.797)	0.041*** (8.398)				0.054*** (11.260)	0.024*** (11.497)	0.051*** (10.033)
Full WFH				0.108*** (8.582)	0.043*** (7.773)	0.098*** (9.607)			
Part WFH				0.063*** (7.468)	0.027*** (7.362)	0.046*** (6.334)			
Rec WFH				0.026*** (2.815)	0.011*** (2.691)	0.011 (1.429)			
WFH x Unemployed							-0.054*** (-8.115)	-0.024*** (-8.814)	-0.053*** (-7.452)
Econ Risk	0.000 (-0.062)	0.000 (0.316)	0.000 (0.237)	0.000 (-0.647)	0.000 (-0.151)	0.000 (-0.696)	0.000 (-0.092)	0.000 (0.284)	0.000 (0.215)
Fin Risk	0.002** (2.359)	0.001** (2.015)	-0.001 (-0.945)	0.003*** (3.306)	0.001*** (2.879)	0.000 (0.104)	0.002** (2.291)	0.001* (1.946)	-0.001 (-0.995)
Pol Risk	0.003** (2.290)	0.001** (2.249)	0.002 (1.373)	0.002 (1.589)	0.001* (1.708)	0.000 (0.305)	0.003** (2.338)	0.001** (2.302)	0.002 (1.393)
New Cases	0.000 (-0.196)	0.000 (0.096)	0.000 (-0.767)	0.000 (0.572)	0.000 (0.795)	0.000 (0.192)	0.000 (-0.210)	0.000 (0.084)	0.000 (-0.785)
New Deaths	0.012*** (6.915)	0.005*** (6.066)	0.013*** (9.288)	0.009*** (5.801)	0.003*** (5.320)	0.009*** (6.775)	0.012*** (6.955)	0.005*** (6.110)	0.013*** (9.306)
Trader FE	X	X	X	X	X	X	X	X	X
Week FE	X	X	X	X	X	X	X	X	X
Sample	Full	Full	Trading	Full	Full	Trading	Full	Full	Trading
N	41,034,806	41,034,806	16,071,264	41,034,806	41,034,806	16,071,264	41,033,236	41,033,236	16,070,393
Adj. R^2	0.437	0.324	0.427	0.437	0.324	0.427	0.437	0.324	0.427

We find that investors trade more in weeks in which they work from home, increasing their total number of trades by 4.4% (column 1). This increase can be attributed to increases in both the extensive and intensive margins. Specifically, we document an increase in both the fraction of weeks in which people trade, with a 1.9% increase in the probability of making at least one trade during the week (column 2), and a 4.1% increase in the number of trades made during weeks in which at least one trade is made (column 3).

In columns (4)–(6), we repeat our analysis with the alternative work-from-home definition. Across all columns, we document a gradual increase in trading intensity as the stringency of the work-from-home mandate increases, presumably because the number of people who actually work from home increases as well. Finally, in columns (7)–(9), we interact the work-from-home variable with an indicator variable that equals one for unemployed investors. The coefficient on the interaction term is negative, confirming that the effect of work-from-home mandates is reduced for unemployed investors. Taken together, columns (4)–(9) provide strong evidence to support the conclusion that our results are driven by the relaxation of time constraints when working from home and not by other factors that may be associated with work-from-home mandates.

According to the summary statistics, presented in Table 3.1, new investors who joined the broker after the onset of Covid-19 trade more than its pre-existing users. Therefore, in Table 3.4, we verify that our results are not concentrated in new investors. We divide the sample to investors who joined the platform before March 1, 2020 and investors who joined the platform from March 1, 2020 onwards and run our regression specifications separately for each sample. Overall, while the coefficients are higher for new investors, work-from-home mandates increased the trading intensity for both types of users.

Table 3.4. The Impact of Work-from-Home on Trading Intensity by User Tenure

This table reports the results of regression specifications that explore the effects of working from home on trading intensity, separately for users who joined the platform before March 1, 2020 (columns 1–3) and beginning on March 1, 2020 (columns 4–6). The analyses are conducted at the weekly frequency, and the dependent variable is one of two variables: *Trade #* is the natural log of the total number of trades made by the investor during the week, and *Is Trade?* is an indicator variable that equals one if at least one trade was made by the investor during the week. *WFH* is an indicator variable that is equal to one if a work-from-home mandate was in place in the investor's country of residence for at least one day during the week. The definition of the work-from-home variable is described in Appendix G. *Econ Risk*, *Fin Risk* and *Pol Risk* are the ICRG measures of the economic, financial and political risks of the investor's country of residence, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new weekly Covid-19 cases and deaths, respectively, per 100,000 people in the investors' country of residence. In columns that utilize the full sample, the sample includes all of the weeks between the investor's first and last activities on the platform, including weeks in which no trades were made. In columns that utilize the trading sample, we restrict our sample to weeks in which at least one trade was made. In all specifications, standard errors are double-clustered by investor and week. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	Existing Pre-Covid Users			New Covid Users		
	(1)	(2)	(3)	(4)	(5)	(6)
	Trade #	Is Trade?	Trade #	Trade #	Is Trade?	Trade #
WFH	0.029***	0.014***	0.027***	0.051***	0.019***	0.043***
	(7.041)	(8.295)	(5.988)	(7.145)	(6.889)	(6.511)
Econ Risk	-0.001	0.000	-0.001	0.000	0.000	0.001
	(-1.453)	(-0.606)	(-1.186)	(0.929)	(0.098)	(1.509)
Fin Risk	0.003***	0.001**	0.001	-0.007***	-0.002**	-0.009***
	(2.906)	(2.103)	(0.662)	(-3.079)	(-2.168)	(-4.304)
Pol Risk	0.003**	0.001**	0.002	-0.004	-0.002*	-0.002
	(2.159)	(2.340)	(1.424)	(-1.522)	(-1.976)	(-1.186)
New Cases	0.000	0.000	0.000	0.000*	0.000	0.000
	(0.967)	(1.201)	(0.104)	(-1.737)	(-1.351)	(-1.491)
New Deaths	0.009***	0.004***	0.012***	0.016***	0.006***	0.013***
	(5.708)	(4.846)	(8.664)	(7.507)	(7.638)	(7.251)
Trader FE	X	X	X	X	X	X
Week FE	X	X	X	X	X	X
Sample	Full	Full	Trading	Full	Full	Trading
N	27,892,338	27,892,338	8,666,466	13,142,468	13,142,468	7,404,798
Adj. R^2	0.386	0.292	0.412	0.455	0.282	0.446

3.4.2 Trading Characteristics

We continue our analysis by testing whether the increase in trading intensity is also followed by a change in trading characteristics. Since most of the decisions regarding these characteristics are made by investors at the time in which they open the position, we focus in this section only on opening trades. We further limit our sample to weeks in which at least one such trade was made.

Table 3.5. The Impact of Work-from-Home on Asset Class Composition

This table reports the results of regression specifications investigating the effects of working from home on the asset classes that retail investors trade in. The analyses are conducted at the weekly frequency on a sample that includes only weeks in which the investor opened at least one new position. The dependent variable is one of two types of variables: *New Trade #* is the natural log of the total number of new positions opened by the investor during the week in the specific asset class, and *New Trade %* is the ratio of the number of new positions opened in the specific asset class to the total number of new positions opened during the week. *WFH* is an indicator variable that is equal to one if a work-from-home mandate was in place in the investor's country of residence for at least one day during the week. The definition of the work-from-home variable is described in Appendix G. *Econ Risk*, *Fin Risk* and *Pol Risk* are the ICRG measures of the economic, financial and political risks of the investor's country of residence, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new weekly Covid-19 cases and deaths, respectively, per 100,000 people in the investors' country of residence. In all specifications, standard errors are double-clustered by investor and week. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	New Trade #				New Trade %			
	(1) Equity	(2) Currency	(3) Commodity	(4) Crypto	(5) Equity	(6) Currency	(7) Commodity	(8) Crypto
WFH	0.019***	0.006***	0.015***	0.013***	-0.002	0.000	0.000	0.001
	(4.550)	(4.463)	(4.831)	(4.393)	(-1.079)	(0.882)	(-0.237)	(0.871)
Econ Risk	-0.001***	0.000***	0.000	0.000	-0.001***	0.000***	0.000**	0.000**
	(-3.245)	(4.785)	(0.399)	(1.150)	(-4.538)	(4.726)	(2.447)	(2.213)
Fin Risk	0.004***	-0.002***	-0.003***	0.001**	0.001***	-0.001***	-0.001***	0.000
	(3.659)	(-4.229)	(-5.007)	(2.249)	(4.575)	(-4.268)	(-4.908)	(0.222)
Pol Risk	0.001	-0.002***	0.003***	-0.001	0.000	-0.001***	0.002***	0.000
	(1.255)	(-5.347)	(4.316)	(-0.831)	(-0.441)	(-6.509)	(7.065)	(-1.100)
New Cases	0.000	0.000	0.000**	0.000	0.000	0.000	0.000	0.000**
	(-0.929)	(0.817)	(-2.353)	(0.235)	(-1.381)	(1.546)	(-1.498)	(2.114)
New Deaths	0.006***	0.001***	0.006***	0.003***	0.000	0.000**	0.001***	-0.001***
	(7.606)	(3.654)	(8.807)	(3.310)	(0.849)	(-2.088)	(4.727)	(-2.908)
Trader FE	X	X	X	X	X	X	X	X
Week FE	X	X	X	X	X	X	X	X
N	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842
Adj. R^2	0.517	0.538	0.484	0.503	0.573	0.585	0.493	0.591

In Table 3.5, we test whether the documented increase in trading intensity spans across all of the main asset classes in our data, and whether the asset class composition of investors' trades changes when they work from home. Columns (1)–(4) display the results of specifications in which the dependent variable is the log number of opening trades conducted in each of the asset classes, and columns (5)–(8) present the results of specifications in which the dependent variable is the ratio of the number of opening trades in each asset class to the total number of opening trades in all asset classes. We find that in weeks in which investors worked from home, they traded more in all of the available asset classes. However, overall, the weekly ratio of trades attributed to each of the asset classes did not change in work-from-home weeks.

Table 3.6. The Impact of Work-from-Home on Trading Characteristics

This table reports the results of regression specifications that explore the effects of working from home on several characteristics of the positions that retail investors open. The analyses are conducted at the weekly frequency on a sample that includes only weeks in which the investor opened at least one new position. The dependent variable is one of two types of variables: A # variable (columns 1–2, 4–6 and 7–8) is the natural log of the number of new positions with the specific characteristic opened by the investor during the week, and a % variable (columns 3, 6 and 9) is the ratio of the number of new positions opened with the specific characteristic to the total number of new positions opened during the week. *WFH* is an indicator variable that is equal to one if a work-from-home mandate was in place in the investor's country of residence for at least one day during the week. The definition of the work-from-home variable is described in Appendix G. *Econ Risk*, *Fin Risk* and *Pol Risk* are monthly ICRG measures of the economic, financial and political risks of the investor's country of residency, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new weekly Covid-19 cases and deaths per 100,000 people in the investors' country of residence. In all specifications, standard errors are double-clustered by investor and week. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	Direction of Position			Use of Leverage			Duration of Position		
	(1) Short #	(2) Long #	(3) Short %	(4) Leverage #	(5) No Leverage #	(6) Leverage %	(7) Day Trade #	(8) No Day Trade #	(9) Day Trade %
WFH	0.017***	0.031***	0.000	0.021***	0.022***	-0.002	0.029***	0.023***	0.005***
	(6.208)	(7.637)	(0.396)	(5.802)	(5.648)	(-1.361)	(7.566)	(8.663)	(4.501)
Econ Risk	0.000	0.000	0.000	0.000	-0.001**	0.000***	0.000	0.000	0.000
	(-0.102)	(-1.141)	(1.486)	(0.427)	(-2.582)	(3.380)	(-0.195)	(-1.204)	(1.301)
Fin Risk	-0.004***	0.002**	-0.001***	-0.005***	0.006***	-0.003***	-0.004***	0.003***	-0.002***
	(-4.365)	(2.143)	(-5.339)	(-4.825)	(5.974)	(-7.140)	(-4.553)	(3.790)	(-7.822)
Pol Risk	0.002*	0.001	0.000	0.004***	-0.003***	0.002***	0.002*	0.000	0.001***
	(1.935)	(0.843)	(0.660)	(4.128)	(-2.851)	(5.756)	(1.831)	(-0.150)	(2.756)
New Cases	0.000**	0.000*	0.000***	0.000	0.000**	0.000**	0.000	0.000	0.000
	(2.112)	(-1.870)	(3.453)	(0.065)	(-2.090)	(2.068)	(-0.712)	(-0.884)	(-0.443)
New Deaths	0.002***	0.011***	-0.001**	0.008***	0.005***	0.001**	0.009***	0.006***	0.002***
	(3.884)	(10.375)	(-2.590)	(9.825)	(6.142)	(2.176)	(9.394)	(9.399)	(7.143)
Trader FE	X	X	X	X	X	X	X	X	X
Week FE	X	X	X	X	X	X	X	X	X
N	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842	14,475,842
Adj. R^2	0.478	0.405	0.393	0.586	0.543	0.668	0.474	0.397	0.423

In Table 3.6, we test the effect of working from home on several other trading characteristics, namely: the use of short positions, the use of leverage and the duration of trades. In columns (1)–(3), we focus on the decision to open a long vs. a short position, and in columns (4)–(6), we focus on the decision to apply leverage to the trade. We document that investors made more trades across all trade types (columns 1–2 and 4–5), but do not find any change in the ratio of each of these trade types to the total number of opening trades. In columns (7)–(9), we focus on the duration of the positions and test whether investors tend to make more day trades when they work from home. We document increases in both day trades and non-day trades but further find that the ratio of day trades to total trades increases by 0.5 basis points. As the percentage of day trades in our sample is 22.4%, this increase translates to a relative increase of approximately 2.23%. Investors therefore not only trade more when they work from home, but are also more inclined to day trading.

3.4.3 Attention-Induced Trading

In Tables 3.2–3.6, we document that while investors pay more attention to their brokerage accounts and trade more on days in which they work from home, the composition and characteristics of their trades exhibit only a limited change. In this section we test whether working from home changes the decision making process of retail investors.

Upon opening new positions, investors face a difficult search problem, with thousands of potential assets to choose from, and therefore tend to trade more heavily in assets that have recently caught their attention (Barber et al. 2021a, Barber and Odean 2008, Odean 1999). In Table 3.7, we explore whether working from home affects the tendency of retail investors to engage in such attention-induced trading and rely on attention-grabbing events as trading facilitators. On the one hand, if people have more time when they work from home and, in turn, pay more attention to their brokerage accounts, as we document in Table 3.2, they may spend more time researching the assets that they invest in and have less of a need to rely on attention-grabbing events. On the other hand, however, upon working from home, retail investors may be even more susceptible to attention-induced trading if they simply use the additional time that they have to pay more attention to attention-grabbing events.

Table 3.7. The Impact of Work-from-Home on Attention-Induced Trading

This table reports the results of regression specifications that investigate the effects of working from home on retail investors' tendency to make attention-induced trades. The analyses are conducted via linear probability models at the trade level, and the sample is limited to trades that open a new position in individual stocks that are traded on US stock exchanges. The dependent variable is an indicator variable that equals one in cases where the trade can be deemed an attention-induced trade by one of the following proxies: extreme last-day absolute returns (column 1), extreme last-day abnormal trading volume (column 2), last-day earnings announcement (column 3), extreme last-day abnormal news volume (column 4) and extreme abnormal social media volume (column 5). Appendix H includes a detailed description of the formation of these proxies. *WFH* is an indicator variable that is equal to one if a work-from-home mandate was in place in the investor's country of residence. The definition of the work-from-home variable is described in Appendix G. *Econ Risk*, *Fin Risk* and *Pol Risk* are the ICRG measures of the economic, financial and political risks of the investor's country of residence, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new daily Covid-19 cases and deaths, respectively, per 100,000 people in the investors' country of residence. In all specifications, standard errors are double-clustered by investor and date. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	(1) Extreme Absolute Returns	(2) Extreme Trading Volume	(3) Earnings Announcements	(4) Extreme News Volume	(5) Extreme Social Media Volume
WFH	0.001	0.000	0.000	0.002***	0.002
	(0.811)	(-0.225)	(-0.674)	(2.771)	(1.517)
Econ Risk	0.000	0.000***	0.000	0.000	0.000
	(1.217)	(-2.749)	(0.652)	(0.361)	(-1.416)
Fin Risk	-0.001***	0.000	0.000**	0.000	0.000
	(-2.970)	(-0.030)	(2.200)	(-0.607)	(0.114)
Pol Risk	0.000	0.001**	0.000	0.000	0.001
	(0.217)	(2.136)	(1.245)	(0.398)	(1.497)
New Cases	0.000**	0.000***	0.000*	0.000**	0.000*
	(-2.227)	(-2.747)	(1.819)	(-2.185)	(-1.817)
New Deaths	0.005***	0.013***	-0.002***	0.006**	0.006***
	(2.766)	(5.749)	(-3.317)	(2.301)	(2.762)
Trader FE	X	X	X	X	X
Day FE	X	X	X	X	X
N	48,788,540	48,479,167	48,304,818	39,013,102	49,835,356
Adj. R^2	0.184	0.130	0.101	0.169	0.148

In our analysis, we limit our sample to trades that open a new position in individual stocks that are traded on US stock exchanges and run a series of trade-level linear probability models in the form of equation (3.1). The dependent variable in these specifications is an indicator variable that equals one in cases where the trade can be deemed an attention-induced trade. In line with prior literature, we create five proxies of attention-grabbing events: extreme last-day absolute returns, extreme last-day abnormal trading volume, last-day earnings announcement, extreme last-day abnormal news volume and extreme abnormal social media volume. We relegate to Appendix

H the detailed description of the formation of these proxies and proceed to present the results of this analysis.

We find limited evidence of a change in individuals' attention-induced trading when they work from home. Conditional on trading, the probabilities that retail investors' trades are induced by extreme absolute returns (column 1), extreme abnormal trading volume (column 2), earnings announcements (column 3) or extreme abnormal social media volume (column 5) remain unchanged. Nonetheless, when people work from home, the conditional probability of making a trade after a day with extreme abnormal news volume increases by 0.2 basis points (column 4). As only 4.91% of the trades in our sample follow a day with extreme abnormal news volume, this can be interpreted as a relative increase of approximately 4.07%.

Importantly, our results do not suggest that news coverage impacts investors' trades more than other attention-grabbing sources but, rather, only that investors increase their reliance on media sources when working from home. In fact, in a related paper, we show that the effect of traditional media on trading is smaller than that of social media (Eliner and Kobilov 2022). Therefore, upon working from home, retail investors continue to rely on most attention-grabbing events in the same manner that they typically do, but they also increase their reliance on news articles, potentially because they have more time to follow such news.

3.4.4 Familiarity Bias

A related concept is the well-documented phenomenon of familiarity or home bias. According to this bias, people tend to invest in stocks that they are familiar with, such as the stock of their own employer (Benartzi 2001, Mitchell and Utkus 2003, Poterba 2003), stocks of firms headquartered in their own country (French and Poterba 1991, Cooper and Kaplanis 1994, Tesar and Werner 1995) and stocks of domestic companies with headquarters in geographic proximity to their residence (Grinblatt and Keloharju 2001a, Huberman 2001, Ivkovic and Weisbenner 2005). Presumably, people who work from home may have more time to research their investments, giving them the ability to learn about new assets and deviate from familiarity-based investing. On the other hand, however, people who work from home may simply make more trades in assets that they are familiar with. We explore these conjectures in Table 3.8.

Table 3.8. The Impact of Work-from-Home on Familiarity Bias

This table reports the results of regression specifications exploring the effects of working from home on investors' tendency to familiarity or home bias. The analyses are conducted via linear probability models at the trade level. The dependent variable is an indicator variable that equals one in cases where the trade can be deemed local or familiar. In column (1), we limit our sample to stock or exchange-traded fund trades made by investors who reside in a country with a local stock exchange that is exhibited on the platform, and define a familiar asset as an asset that is traded on the local stock exchange in the investor's country of residence. In column (2), we limit our sample to trades in individual stocks and keep the same familiarity definition. In columns (3) and (4), our sample includes trades in individual stocks made by investors who reside in a country with at least one locally headquartered (column 3) or incorporated (column 4) firm whose stock is available for trading on the platform, and we define a familiar asset as a stock of a firm that is headquartered or incorporated, as relevant, in the investor's country of residence. *WFH* is an indicator variable that is equal to one if a work-from-home mandate was in place in the investor's country of residence. The definition of the work-from-home variable is described in Appendix G. *Econ Risk*, *Fin Risk* and *Pol Risk* are the ICRG measures of the economic, financial and political risks of the investor's country of residence, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new daily Covid-19 cases and deaths, respectively, per 100,000 people in the investors' country of residence. In all specifications, standard errors are double-clustered by investor and date. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

	(1) Local Exchange	(2) Local Exchange	(3) Local Firm Headquarters	(4) Local Firm Incorporation
WFH	-0.008***	-0.008***	-0.010***	-0.011***
	(-3.649)	(-3.562)	(-5.831)	(-5.801)
Econ Risk	-0.001***	-0.001***	-0.001***	-0.001***
	(-9.855)	(-9.785)	(-15.234)	(-15.570)
Fin Risk	0.000	0.000	0.004***	0.004***
	(0.608)	(0.588)	(9.602)	(10.381)
Pol Risk	-0.005***	-0.005***	-0.004***	-0.004***
	(-7.327)	(-7.076)	(-10.010)	(-8.183)
New Cases	0.000**	0.000**	0.000	0.000
	(2.103)	(2.136)	(1.277)	(-0.056)
New Deaths	-0.009***	-0.009***	-0.011***	-0.011***
	(-4.887)	(-4.841)	(-7.165)	(-7.098)
Trader FE	X	X	X	X
Day FE	X	X	X	X
Sample	Stocks & ETFs	Stocks	Stocks	Stocks
N	34,911,369	33,476,236	48,922,856	44,075,244
Adj. R^2	0.278	0.283	0.273	0.271

Because the broker's users span over 140 countries and because the broker offers these users the ability to trade stocks with a great geographical dispersion, both in terms of the locations of the exchanges and in terms of the locations of companies' headquarters or incorporation, we evaluate familiarity bias using geographically-based definitions. Our regression specifications are trade-level linear probability models, similar to those used in Table 3.7, in which the dependent variable is an indicator variable depicting trades in assets that are geographically local. In column (1), we define a local asset as an individual stock or exchange-traded fund that is traded on the local stock exchange in the investor's country of residence, and in column (2), we repeat the analysis but focus only on individual stocks. In column (3) and (4), we continue to focus only on individual stocks and define a stock as local if it is headquartered or incorporated, respectively, in the same country as the investor. In each specification, we limit our sample to investors who reside in a country with at least one local firm.[45] Across all columns, we document a consistent reduction of approximately 1.0 basis point in the conditional probability of trading a local asset, suggesting that the additional time that investors presumably have when they work from home allows them to explore and invest in assets that they are less familiar with.

3.5 **Work-from-Home and Trading Performance**

Our results thus far suggest that investors pay more attention to their brokerage accounts and trade more when they work from home. Additionally, upon working from home, investors are more inclined to day trading and to trading based on news, and less subject to home bias. Other aspects of their trading behavior remain largely unchanged.

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[45] In columns (1) and (2), our sample is limited to investors who reside in a country with a local stock exchange that is exhibited on the platform. In columns (3) and (4), our sample includes only investors from countries with locally headquartered or incorporated firms, respectively, whose stocks are available for trading on the platform.

Table 3.9. The Impact of Work-from-Home on Trade-Level Performance

This table reports the results of regression specifications exploring the effects of working from home on investors' trade-level performance. In Panel A, the dependent variable is market-adjusted returns, in which the benchmark portfolio is leveraged at the same level as the trade. In Panel B, the dependent variable is unleveraged market-adjusted returns, in which the returns on the trade are calculated under the assumption that no leverage was applied to the trade. In both panels, the market-adjusted returns in columns (1)–(3) are calculated using an equally-weighted portfolio of all of the assets in the same asset class as the traded asset that are available for trading on the platform. In columns (4)–(6), the market-adjusted returns are calculated using benchmark indices. Specifically, equity trades are adjusted by the returns on the MSCI World Index, currency trades are adjusted by the returns on a short position in the USD Index, commodity trades are adjusted by the returns on the S&P GSCI Index, and cryptocurrency trades are adjusted by the returns on the S&P Cryptocurrency Broad Digital Market Index. *WFH* is an indicator variable that is equal to one if a work-from-home mandate was in place in the investor's country of residence. The definition of the work-from-home variable is described in Appendix G. *Short Position* is an indicator variable that is equal to one for a short position and to zero for a long position. *Leveraged Position* is an indicator variable that equals one when leverage was applied to the position. *Trade Size* is a proxy for the size of the trade, equal to the percentage of realized equity that was invested in the position. *Log # of Holding Days* is the natural log of the number of days between the opening and closing of a position. *Econ Risk*, *Fin Risk* and *Pol Risk* are the ICRG measures of the economic, financial and political risks of the investor's country of residence, standardized from 1 to 100. *New Cases* and *New Deaths* are the numbers of new daily Covid-19 cases and deaths, respectively, per 100,000 people in the investors' country of residence. In all specifications, standard errors are double-clustered by investor and date. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

Panel A	Within-Broker Market-Adjusted Returns			Index-Based Market-Adjusted Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
WFH	0.0010**	0.0010**	0.0009**	0.0021***	0.0018***	0.0017***
	(2.4888)	(2.3618)	(2.2605)	(4.4395)	(4.0022)	(3.9198)
Short Position		-0.0050*	-0.0066**		-0.0061***	-0.0070***
		(-1.8809)	(-2.4431)		(-2.5820)	(-2.9397)
Leveraged Position		-0.0360***	-0.0304***		-0.0372***	-0.0392***
		(-23.7740)	(-19.1551)		(-22.6191)	(-21.4622)
Trade Size		0.0070***	0.0021***		0.0031***	-0.0028***
		(9.7141)	(2.9247)		(3.8632)	(-3.5146)
Log # of Holding Days		-0.0063***	-0.0042***		-0.0163***	-0.0146***
		(-5.1366)	(-3.0229)		(-10.0641)	(-8.3402)
Econ Risk	0.0000	0.0000	-0.0000	0.0001***	0.0001***	0.0001***
	(0.1596)	(0.2747)	(-0.2222)	(3.3968)	(3.3917)	(3.4761)
Fin Risk	-0.0000	-0.0000	0.0001	-0.0004**	-0.0004*	-0.0003
	(-0.1392)	(-0.0677)	(0.6095)	(-2.3589)	(-1.8876)	(-1.3499)
Pol Risk	-0.0001	-0.0000	-0.0001	0.0002	0.0002	0.0001
	(-0.6402)	(-0.2516)	(-0.9945)	(1.1941)	(1.3833)	(0.6950)
New Cases	0.0000**	0.0000***	0.0000***	0.0000*	0.0000**	0.0000**
	(2.4165)	(2.5879)	(2.5952)	(1.9287)	(2.0056)	(2.4329)
New Deaths	-0.0002	-0.0004	-0.0005	0.0015***	0.0011*	0.0009
	(-0.4320)	(-0.6776)	(-0.9828)	(2.6314)	(1.9251)	(1.5697)
Trader FE	X	X	X	X	X	X
Day FE	X	X	X	X	X	X
Asset FE			X			X
N	130,309,265	130,309,265	130,309,265	130,309,265	130,309,265	130,309,265
Adj. R^2	0.050	0.051	0.061	0.055	0.057	0.069

Table 3.9. The Impact of Work-from-Home on Trade-Level Performance (Continued)

Panel B	Unleveraged Within-Broker Market-Adjusted Returns			Unleveraged Index-Based Market-Adjusted Returns		
	(4)	(4)	(4)	(4)	(5)	(6)
WFH	0.0006**	0.0007**	0.0006**	0.0015***	0.0014***	0.0013***
	(2.3455)	(2.5071)	(2.5637)	(4.4390)	(4.0788)	(4.1022)
Short Position		-0.0026***	-0.0039***		-0.0032***	-0.0033***
		(-5.7564)	(-8.3736)		(-6.4032)	(-6.7473)
Leveraged Position		-0.0110***	-0.0099***		-0.0131***	-0.0158***
		(-9.3887)	(-14.1964)		(-10.8370)	(-21.3157)
Trade Size		0.0014***	-0.0023***		-0.0022***	-0.0062***
		(3.1259)	(-5.4794)		(-4.1590)	(-11.6117)
Log # of Holding Days		0.0015	0.0038***		-0.0097***	-0.0080***
		(1.5410)	(3.4067)		(-7.2118)	(-5.4277)
Econ Risk	-0.0000	-0.0000	-0.0000*	0.0001***	0.0001***	0.0001***
	(-0.9201)	(-0.8027)	(-1.7670)	(3.5525)	(3.4891)	(3.4423)
Fin Risk	-0.0001	-0.0001	0.0000	-0.0005***	-0.0004***	-0.0003**
	(-0.4650)	(-0.6716)	(0.3212)	(-3.4630)	(-3.0062)	(-2.2436)
Pol Risk	-0.0001*	-0.0001	-0.0002**	0.0001	0.0001	0.0000
	(-1.6827)	(-1.3341)	(-2.2172)	(1.1434)	(1.1203)	(0.4574)
New Cases	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(2.7642)	(2.9152)	(3.2709)	(2.8663)	(2.8856)	(3.5890)
New Deaths	0.0002	0.0002	0.0000	0.0017***	0.0014***	0.0012**
	(0.3845)	(0.4725)	(0.0871)	(3.3565)	(2.8518)	(2.4191)
Trader FE	X	X	X	X	X	X
Day FE	X	X	X	X	X	X
Asset FE			X			X
N	130,309,265	130,309,265	130,309,265	130,309,265	130,309,265	130,309,265
Adj. R^2	0.109	0.109	0.132	0.116	0.118	0.143

In Table 3.9, Panel A, we explore the effect of working from home on trading performance. We apply equation (3.1) at the trade level and include the market-adjusted returns on the trade as the dependent variable. In columns (1)–(3), the comparable market returns are calculated based on an equally-weighted portfolio of all of the assets in the same asset class as the traded asset that are available for trading on the platform ("within-broker market-adjusted returns"). In columns (4)–(6), the benchmark market returns are calculated using a set of widely-acceptable asset-class specific indices ("index-based market-adjusted returns"). Equity trades are adjusted by the returns on the MSCI World Index,[46] currency trades are adjusted by the returns on a short position in the

[46] Since the broker enables investors to trade equities on 20 stock exchanges around the world, we use the returns on

USD Index,[47] commodity trades are adjusted by the returns on the S&P GSCI Index, and cryptocurrency trades are adjusted by the returns on the S&P Cryptocurrency Broad Digital Market Index. Across all columns, the benchmark portfolio is leveraged at the same level as the trade, in order to neutralize the effects of leverage in our calculations.[48]

In columns (1) and (4), we include only the control variables that are included in equation (3.1). In columns (2) and (5), we augment the regression specification with several additional control variables that capture the specific characteristics of the trade: an indicator variable for whether the position was a short position, an indicator variable for whether leverage was applied to the position, the size of the trade proxied by the percentage of realized equity that was invested in the position, and the log of the holding period measured as the number of days between the opening and closing of a position. In columns (3) and (6), we also add asset fixed effects. Across all columns, we find that working from home improves retail investors' market-adjusted trade-level returns. In the columns that use within-broker market-adjusted returns, the increase is approximately 0.1 basis points, and in the columns that use index-based market-adjusted returns, the increase is about 0.2 basis points. As the average (median) market-adjusted return per-trade in our sample ranges from -0.8 to -1.1 (0.18 to 0.23) basis points, depending on the adjustment methodology, the economic magnitude of the improvement is large.

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the MSCI World Index, which captures large and mid-cap representation in 23 developed markets. Nonetheless, our results are robust to using the returns on country-specific indices, based on the country in which the stock is traded, as well as to using the returns on the S&P 500 for all equities.

[47] All of the trades on the platform are converted from and to USD, and most of the currency trades directly include the USD as one side of the currency pair. Therefore, a long position in most currency pairs is equivalent to a bet against the USD, similar to a short position in the USD Index.

[48] To calculate the benchmark portfolio returns, we use the average of the closing price on the day before the position was opened and the closing price at the end of the day in which the position was opened as the opening price of the benchmark portfolio. We use a similar average for the closing price of the benchmark portfolio. In addition, the returns of intraday trades are included in the analyses in raw form. The exclusion of all intraday trades increases the size of the work-from-home coefficients.

In Table 3.9, Panel B, we repeat the analysis for unleveraged market-adjusted returns to better capture the market-timing performance of investors. The magnitudes of the coefficients on the work-from-home indicator variable are smaller on an absolute basis, as may be expected, but compared to the means (medians) of 0.3 and -0.1 (0.02 and 0.02) basis points, the relative magnitudes of the coefficients actually increase compared to the leveraged analysis. These results suggest that, upon working from home, retail traders have better market timing.

3.6 Conclusion

The Covid-19 pandemic has had profound implications for capital markets in general and for retail investors specifically. In this study, we explore the effects of one of the important economic changes facilitated by the Covid-19 pandemic—the shift to a work-from-home regime—on the behavior and performance of retail investors.

We find that when people work from home, they pay more attention to their brokerage accounts and trade more. They further increase their tendency to day trade. Nonetheless, the types of trades that individuals make, in terms of the asset classes that they trade in, the amount of leverage that they use and their use of short positions, remain similar when they work from home. We further show that working from home has only a limited effect on the asset-picking process of individual investors. Individual investors generally continue to rely on attention-grabbing events in a similar manner when they open new positions but do increase their reliance on news and media sources. Individual investors are further less inclined to familiarity or home bias, opening more positions in foreign assets. Finally, we find that working from home improves the trade-level performance of retail investors. We suggest that investors have better market timing when they work from home and presumably have more time.

The results of this study not only speak to the effects of the important economic trend of working from home, which is expected to continue in the long term, but also provide novel evidence on the implications of time constraints on the trading behavior and performance of retail investors. Specifically, using government-mandated work-from-home restrictions as a plausibly-exogenous change to individuals' time constraints, we document that such relaxation of time constraints increases investors' attention and improves trading performance. In doing so, we provide causal support to prior studies, such as Gargano and Rossi (2018), that have documented a positive association between attention and performance.

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APPENDICES

Appendix A. Summary of Surveys Conducted by National Regulatory Authorities

This table summarizes the results of several surveys that were conducted by national regulators with respect to the performance of Contract for Difference (CFD) accounts.

Country	Regulator	Time Period	Sample Size	% of Losing Accounts	Average Loss Per Account
Australia	Australian Securities & Investments Commission	Any 12-month period between 1/1/2016 and 6/30/2017	57 CFD providers	72% when trading CFDs, 63% when trading FX	-
Croatia	Hrvatska agencija za nadzor financijskih uskuga (HANFA)	January–September 2016	267 clients at one CFD provider	-	EUR 2,239 (EUR 3,812 for losing accounts only)*
Cyprus	Cyprus Securities and Exchange Commission (CySEC)	1/1/2017–8/31/2017	290,000 clients at 18 CFD providers	76%	EUR 1,600
France	Autorité des marchés financiers (AMF)	4-year period from 2009 to 2013	-	89%	EUR 10,887 (Median: EUR 1,843)
Ireland	Central Bank of Ireland (CBI)	2013–2014	-	75%	EUR 6,900
		2015–2016	-	74%	EUR 2,700
Italy	Commisione Nazionale per le Società e la Borsa (CONSOB)	2014–2015	One CFD provider	78% when trading CFDs, 75% when trading FX	EUR 2,800
		2016	5 Italian branches of CFD providers	83%	EUR 7,000
Luxembourg	Commission de Surveillance du Secteur Financier (CSSF)	- (Reported in September 2017)	2 CFD providers	-	EUR 4,500 at one provider, EUR 1,700 at second provider
Norway	Finanstilsynet	12- or 24-month period from January 2014	1000 clients at 6 CFD providers	82%	EUR 29,000

Country	Regulator	Time Period	Sample Size	% of Losing Accounts	Average Loss Per Account
Poland	Komisja Nadzoru Finansowego (KNF)	2012	-	81%	-
		2013	-	81%	-
		2014	-	80%	-
		2015	-	82%	-
		2016	130,399 clients (38,691 active) at 10 CFD providers	79%	PLN 10,060
		2017	177,883 clients (40,209 active) at 7 CFD providers	80%	PLN 12,156
Portugal	Comissão do Mercado de Valores Mobiliários (CMVM)	2016	-	-	Total loss of EUR 66.8 M on notional value of EUR 44,700 M
		2017	-	-	Total loss of EUR 44.7 M on notional value of EUR 44,200 M
Spain	Comisión Nacional del Mercado de Valores (CNMV)	21-month period between early 2015 and late 2016	-	82%	EUR 4,700
United Kingdom	Financial Conduct Authority (FCA)	2014	8 CFD providers	82%	GBP 2,200
		12-month period during 2016–2017	CFD providers with advisory and discretionary services	76%	GBP 4,100 (GBP 9,000 for losing accounts only)

* HANFA reported total client retail losses of EUR 1,017,900 and total retail client gains of EUR 420,000. We divided these numbers by the size of the sample (267).

Appendix B. ESMA's Leverage Restrictions

This table describes the leverage restrictions imposed by ESMA on August 1, 2018 (ESMA 2018a).

Type of Underlying Asset	Details	Mandatory Initial Margin
Major Currency Pairs	Currency pair composed of any two of the following currencies: US Dollar, Euro, Japanese Yen, Pound Sterling, Canadian Dollar or Swiss Franc	30:1
Other Currency Pairs	Any currency pair that is composed of at least one non-major currency	20:1
Major Equity Indices	Any of the following: Financial Times Stock Exchange 100 (FTSE 100), Cotation Assistée en Continu 40 (CAC 40), Deutsche Bourse AG German Stock 30 (DAX 30), Dow Jones Industrial Average, Standard & Poors 500 (S&P 500), Nasdaq Composite, Nasdaq 100, Nikkei 225, Standard & Poors/Australian Securities Exchange 200 (S&P/ASX 200), Euro Stoxx 50	
Gold		
Other Equity Indices	Any non-major equity index	10:1
Other Commodities	Any commodity other than gold	
Individual Shares	-	5:1
Any Unlisted Asset	-	
Cryptocurrencies	-	2:1

Appendix C. Return Calculations

This table displays the formulas used to calculate the different types of returns used in chapter 2 of this dissertation.

Monthly Portfolio Returns	Used in	Figure 2.2; Figure 2.3; Table 2.4; Table 2.9	
	Calculation Formula	$\frac{(End\ Equity + Monthly\ Withdrawls) - (Beg\ Equity + Monthly\ Deposits)}{Beg\ Equity + Monthly\ Deposits}$	
	Explanation	Calculated as the change in equity during a given month, adjusted for monthly deposits and withdrawals.	
	Data	Returns are calculated by the broker and included in a file of portfolio returns.	
Broker Provided Returns	Used in	Table 2.1; Table 2.3; Table 2.5; Table 2.6; Table 2.7—Column 1	
	Calculation Formula	Long	$\frac{\#\ of\ Units \times (USD\ Close\ Price - USD\ Open\ Price)}{Total\ Sum\ Invested\ by\ Customer} = \frac{\#\ of\ Units \times (USD\ Close\ Price - USD\ Open\ Price)}{\left(\frac{\#\ of\ Units \times USD\ Open\ Price}{Leverage\ Level} + Any\ "top - up"\ sums\ added\right)}$
		Short	$\frac{\#\ of\ Units \times (USD\ Open\ Price - USD\ Close\ Price)}{Total\ Sum\ Invested\ by\ Customer} = \frac{\#\ of\ Units \times (USD\ Close\ Price - USD\ Open\ Price)}{\left(\frac{\#\ of\ Units \times USD\ Open\ Price}{Leverage\ Level} + Any\ "top - up"\ sums\ added\right)}$
	Explanation	1. Prices are execution prices, including fees incorporated in the bid-ask spread. 2. Prices are converted to USD at the time of purchase/sale and include fees incorporated in conversion rates. 3. Returns are calculated on the total invested sum, including “top-up” amounts. These are amounts that are added to a trade after open, such as in the case of a margin call, and that effectively reduce the leverage level of the trade.	
	Data	Returns are calculated by the broker and included in the trade-level data file.	
Trade-Level Returns w/o Overnight Fees	Used in	Table 2.7—Column 2	
	Calculation Formula	Long	$\frac{\#\ of\ Units \times (Close\ Price - Open\ Price)}{\left(\frac{\#\ of\ Units \times Open\ Price}{Leverage\ Level}\right)} = \frac{(Close\ Price - Open\ Price)}{Open\ Price} \times Leverage\ Level$
		Short	$\frac{\#\ of\ Units \times (Open\ Price - Close\ Price)}{\left(\frac{\#\ of\ Units \times Open\ Price}{Leverage\ Level}\right)} = \frac{(Open\ Price - Close\ Price)}{Open\ Price} \times Leverage\ Level$
	Explanation	Prices are base currency execution prices, including fees incorporated in the bid-ask spread.	
	Data	Open and close prices are included in the trade-level data file provided by the broker.	
Net Trade-Level Returns	Used In	Table 2.7—Column 3	
	Calculation Formula	Long	$\frac{\#\ of\ Units \times (Close\ Price - Open\ Price - Overnight\ Fees)}{\left(\frac{\#\ of\ Units \times Open\ Price}{Leverage\ Level}\right)} = \frac{(Close\ Price - Open\ Price - Overnight\ Fees)}{Open\ Price} \times Leverage\ Level$ $where\ Overnight\ Fees = Daily\ Overnight\ Fees \times Overnight\ Days$
		Short	$\frac{\#\ of\ Units \times (Open\ Price - Close\ Price - Overnight\ Fees)}{\left(\frac{\#\ of\ Units \times Open\ Price}{Leverage\ Level}\right)} =$

			$\frac{(Open\ Price - Close\ Price - Overnight\ Fees)}{Open\ Price} \times Leverage\ Level$ $where\ Overnight\ Fees = Daily\ Overnight\ Fees \times Overnight\ Days$
	Explanation		1. Prices are base currency execution prices, including fees incorporated in the bid-ask spread. 2. For individual stocks, ETFs and stock indices, daily overnight fees are calculated using the broker's actual overnight fee formulas. For individual stocks and ETFs, the annual overnight interest rate is 6.4% above the one-month USD Libor rate for long positions and 2.9% above the one-month USD Libor rate for short positions. For indices, the annual overnight interest rate is 3% plus the one-month USD Libor rate for long positions and 3% minus the one-month USD Libor rate for short positions. For commodities and foreign currencies, a 2.5% annual interest rate is assumed. For cryptocurrencies, a 12.5% annual interest rate is assumed. 3. Overnight days are the number of times a position is held over 00:00 ET. Weekends are three overnight days and are charged on Wednesday or Friday, depending on the asset.
	Data		Open and close prices, as well as trade execution timestamps, which are used to calculate the number of overnight days, are included in the trade-level data file provided by the broker. Data on overnight fees were taken from the broker's website. For commodities, foreign currencies and cryptocurrencies, the overnight fee assumptions are based on the assumptions made by ESMA (ESMA 2018c).
Gross Trade-Level Returns	Used in	Table 2.7—Column 4	
	Calculation Formula	Long	$\frac{\#\ of\ Units \times (Adj\ Close\ Price - Open\ Price)}{\left(\frac{\#\ of\ Units \times Open\ Price}{Leverage\ Level}\right)} =$ $\frac{(Adj\ Close\ Price - Open\ Price)}{Open\ Price} \times Leverage\ Level$ $where\ Adj\ Close\ Price = \frac{Close\ Price + Open\ Price \times \frac{Per\ Fee}{2}}{1 - \frac{Per\ Fee}{2}}$ $or\ Close\ Price + Pip\ Fee$
		Short	$\frac{\#\ of\ Units \times (Open\ Price - Adj\ Close\ Price)}{\left(\frac{\#\ of\ Units \times Open\ Price}{Leverage\ Level}\right)} =$ $\frac{(Open\ Price - Adj\ Close\ Price)}{Open\ Price} \times Leverage\ Level$ $where\ Adj\ Close\ Price = \frac{Close\ Price - Open\ Price \times \frac{Per\ Fee}{2}}{1 + \frac{Per\ Fee}{2}}$ $or\ Close\ Price - Pip\ Fee$
	Explanation		1. Adjusted prices are base currency execution prices, after adding back fees incorporated in the bid-ask spread. 2. The bid-ask fee adjustment formula depends on the type of the spread, which can be either in the form of a percentage or in the form of a pip. For individual stocks and ETFs, the broker charged a bid-ask fee of 0.09% on each side of the bid-ask spread during the relevant period. For indices, foreign currencies and commodities, the bid-ask fee is given in the form of an asset-specific pip, and for cryptocurrencies the bid-ask fee is given in the form of an asset-specific percentage. 3. All fees are calculated at the close of the position.
	Data		Open and close prices are included in the trade-level data file provided by the broker. Data on fees were taken from the broker's website.

Appendix D. Leverage and Trade-Level Returns by Asset Class—Detailed Results

Table D.1

This table reports the detailed results of fixed effect regression specifications exploring the relationship between leverage and trading performance for different asset classes. The sample includes all of the trades made by the users of the broker between January 1, 2012 and March 31, 2021. Exchange-traded fund (ETF) trades are excluded. The dependent variable is net trade-level returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels separately for each leverage level. The variable *High Leverage* is an indicator variable that equals one for a level of leverage that exceeds ESMA's restrictions, as detailed in Appendix B. *Short* is an indicator variable that equals one for short positions and zero for long positions. Each column includes a different type of fixed effect groups, with column (1) including the tightest groups. Standard errors are double-clustered by trader and calendar-day. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

Panel A—Stocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Leverage	-0.014***	-0.014***	-0.016***	-0.020***	-0.025***	-0.021***	-0.020***
	(-6.326)	(-5.350)	(-6.280)	(-7.065)	(-8.662)	(-8.335)	(-5.921)
Short	-0.010***	-0.021***	-0.022***	-0.028***	-0.053***	-0.050***	-0.040***
	(-3.485)	(-6.757)	(-5.742)	(-7.281)	(-9.845)	(-10.380)	(-8.664)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	61,118,700	61,118,700	61,118,700	61,118,700	61,118,700	61,118,700	61,118,700
Adj. R^2	0.666	0.424	0.368	0.200	0.145	0.036	0.099

Panel B—Indices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Leverage	-0.001	-0.002**	-0.008***	-0.009***	-0.008***	-0.008***	-0.009***
	(-0.482)	(-2.132)	(-8.347)	(-9.934)	(-11.843)	(-11.280)	(-14.034)
Short	-0.003	-0.004	-0.006**	-0.006**	-0.009***	-0.009***	-0.009***
	(-1.191)	(-1.547)	(-2.216)	(-2.396)	(-2.776)	(-2.811)	(-3.069)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	34,801,527	34,801,527	34,801,527	34,801,527	34,801,527	34,801,527	34,801,527
Adj. R^2	0.351	0.311	0.102	0.079	0.075	0.034	0.032

Panel C—Currencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Leverage	-0.011***	-0.010***	-0.015***	-0.016***	-0.028***	-0.027***	-0.017***
	(-10.474)	(-15.351)	(-16.969)	(-23.273)	(-37.264)	(-35.567)	(-22.386)
Short	-0.001	-0.002	-0.001	-0.002	0.000	0.001	-0.001
	(-0.514)	(-0.871)	(-0.465)	(-0.830)	(0.077)	(0.235)	(-0.377)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	49,942,848	49,942,848	49,942,848	49,942,848	49,942,848	49,942,848	49,942,848
Adj. R^2	0.265	0.221	0.081	0.068	0.037	0.016	0.033

Panel D—Commodities	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Leverage	-0.018***	-0.018***	-0.028***	-0.028***	-0.039***	-0.037***	-0.035***
	(-4.561)	(-6.696)	(-12.498)	(-14.895)	(-29.544)	(-27.711)	(-25.760)
Short	-0.003	-0.004	-0.006	-0.006	-0.008*	-0.007	-0.008*
	(-0.728)	(-1.045)	(-1.387)	(-1.599)	(-1.666)	(-1.463)	(-1.834)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	35,926,050	35,926,050	35,926,050	35,926,050	35,926,050	35,926,050	35,926,050
Adj. R^2	0.315	0.282	0.098	0.081	0.072	0.038	0.039

Panel E—Cryptocurrencies	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Leverage	-0.030***	-0.042***	-0.016**	-0.032***	-0.086***	-0.090***	-0.075***
	(-4.958)	(-8.082)	(-2.249)	(-5.061)	(-15.587)	(-17.145)	(-14.868)
Short	-0.033***	-0.041***	-0.048***	-0.053***	-0.108***	-0.110***	-0.088***
	(-7.294)	(-8.816)	(-9.945)	(-10.367)	(-15.776)	(-15.688)	(-16.661)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	32,986,925	32,986,925	32,986,925	32,986,925	32,986,925	32,986,925	32,986,925
Adj. R^2	0.799	0.593	0.638	0.466	0.152	0.078	0.231

Table D.2

This table reports the detailed results of fixed effect regression specifications exploring the relationship between leverage and trading performance for different asset classes. The sample includes all of the trades made by the users of the broker between January 1, 2012 and March 31, 2021. Exchange-traded fund (ETF) trades are excluded. The dependent variable is net trade-level returns, with the exact calculation described in Appendix C. Returns are winsorized at the 0.01% and 99.99% levels separately for each leverage level. The variables of *2:1* to *400:1* are indicator variables depicting the trade's level of leverage. The reference group of no leverage is excluded. *Short* is an indicator variable that equals one for short positions and zero for long positions. Each column includes a different type of fixed effect groups, with column (1) including the tightest groups. Standard errors are double-clustered by trader and calendar-day. T-statistics are reported in parentheses, and *, ** and *** denote statistical significance at the 10%, 5% and 1%, respectively.

Panel A—Stocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2:1	-0.012***	-0.024***	-0.014***	-0.030***	-0.019***	-0.026***	-0.023***
	(-6.110)	(-12.842)	(-3.157)	(-10.225)	(-8.524)	(-11.031)	(-10.424)
5:1	-0.022***	-0.028***	-0.014***	-0.029***	-0.031***	-0.033***	-0.026***
	(-5.251)	(-10.263)	(-2.831)	(-8.713)	(-10.116)	(-11.349)	(-9.033)
10:1	-0.032***	-0.039***	-0.027***	-0.045***	-0.045***	-0.045***	-0.041***
	(-7.481)	(-10.877)	(-5.162)	(-11.085)	(-11.704)	(-13.084)	(-10.611)
20:1	-0.051***	-0.053***	-0.065***	-0.069***	-0.070***	-0.052***	-0.064***
	(-7.326)	(-7.529)	(-7.528)	(-8.583)	(-9.630)	(-7.026)	(-6.540)
Short	-0.010***	-0.018***	-0.021***	-0.025***	-0.046***	-0.041***	-0.037***
	(-3.307)	(-5.980)	(-5.520)	(-6.373)	(-8.109)	(-7.792)	(-7.661)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	61,118,700	61,118,700	61,118,700	61,118,700	61,118,700	61,118,700	61,118,700
Adj. R^2	0.666	0.424	0.368	0.200	0.146	0.037	0.100

Panel B—Indices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2:1	-0.001**	-0.001**	-0.001**	-0.001*	-0.002***	-0.002***	-0.002***
	(-1.982)	(-1.984)	(-1.981)	(-1.849)	(-3.150)	(-3.467)	(-3.368)
5:1	-0.002***	-0.002***	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***
	(-2.628)	(-2.869)	(-3.039)	(-3.262)	(-3.806)	(-3.466)	(-5.152)
10:1	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.006***	-0.006***
	(-3.674)	(-4.210)	(-3.766)	(-4.763)	(-5.954)	(-6.651)	(-6.818)
20:1	-0.005***	-0.005***	-0.007***	-0.007***	-0.009***	-0.009***	-0.010***
	(-4.605)	(-4.911)	(-5.866)	(-6.046)	(-10.680)	(-10.473)	(-10.560)
25:1	-0.002	-0.003**	-0.008***	-0.008***	-0.007***	-0.007***	-0.010***
	(-1.382)	(-2.163)	(-4.737)	(-4.926)	(-5.622)	(-5.757)	(-7.499)
30:1	-0.007***	-0.007***	-0.010***	-0.011***	-0.008***	-0.007***	-0.013***
	(-4.462)	(-4.731)	(-6.478)	(-7.280)	(-6.286)	(-5.928)	(-10.263)
50:1	-0.005***	-0.007***	-0.013***	-0.014***	-0.012***	-0.011***	-0.015***
	(-2.782)	(-4.330)	(-7.882)	(-8.866)	(-12.043)	(-11.904)	(-13.263)
100:1	-0.004**	-0.008***	-0.022***	-0.025***	-0.020***	-0.019***	-0.026***
	(-2.412)	(-4.769)	(-12.979)	(-14.786)	(-18.257)	(-18.368)	(-20.885)
Short	-0.003	-0.004	-0.006**	-0.006**	-0.009***	-0.009***	-0.009***
	(-1.189)	(-1.543)	(-2.207)	(-2.383)	(-2.748)	(-2.774)	(-3.051)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	34,801,527	34,801,527	34,801,527	34,801,527	34,801,527	34,801,527	34,801,527
Adj. R^2	0.351	0.311	0.102	0.079	0.076	0.034	0.032

Panel C—Currencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2:1	-0.003	-0.001	-0.001	0.000	-0.001	-0.003**	0.004
	(-0.498)	(-0.343)	(-0.286)	(0.008)	(-0.587)	(-2.047)	(1.532)
5:1	0.001	0.000	0.000	0.000	-0.001	-0.004***	0.002
	(0.356)	(-0.310)	(0.189)	(-0.013)	(-1.407)	(-3.829)	(0.985)
10:1	0.002	-0.002	0.001	-0.002	-0.002**	-0.006***	-0.001
	(0.852)	(-1.116)	(0.364)	(-1.390)	(-2.331)	(-6.145)	(-0.357)
20:1	-0.004	-0.006***	-0.004***	-0.008***	-0.009***	-0.012***	-0.005***
	(-1.578)	(-3.437)	(-2.622)	(-5.661)	(-6.072)	(-8.582)	(-2.746)
25:1	-0.002	-0.003*	-0.004**	-0.005***	-0.001	-0.002*	-0.004**
	(-0.978)	(-1.768)	(-2.568)	(-3.354)	(-0.623)	(-1.804)	(-1.999)
30:1	-0.004	-0.005***	-0.007***	-0.007***	-0.014***	-0.013***	-0.007***
	(-1.619)	(-2.972)	(-4.001)	(-4.989)	(-9.856)	(-9.833)	(-3.862)
50:1	-0.005**	-0.006***	-0.007***	-0.008***	-0.010***	-0.011***	-0.008***
	(-2.454)	(-3.720)	(-4.069)	(-5.768)	(-8.434)	(-9.381)	(-4.384)
100:1	-0.012***	-0.014***	-0.016***	-0.019***	-0.016***	-0.015***	-0.016***
	(-4.811)	(-7.329)	(-8.422)	(-12.356)	(-12.920)	(-13.029)	(-9.274)
200:1	-0.025***	-0.031***	-0.035***	-0.042***	-0.043***	-0.043***	-0.040***
	(-10.199)	(-15.734)	(-16.039)	(-22.605)	(-30.779)	(-30.902)	(-20.128)
400:1	-0.047***	-0.056***	-0.075***	-0.082***	-0.073***	-0.071***	-0.074***
	(-17.572)	(-25.808)	(-33.402)	(-42.212)	(-42.685)	(-41.955)	(-33.715)
Short	-0.001	-0.002	-0.001	-0.002	0.001	0.002	-0.001
	(-0.498)	(-0.836)	(-0.429)	(-0.765)	(0.279)	(0.502)	(-0.287)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	49,942,848	49,942,848	49,942,848	49,942,848	49,942,848	49,942,848	49,942,848
Adj. R^2	0.266	0.221	0.082	0.070	0.040	0.018	0.035

Panel D—Commodities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2:1	-0.023*	-0.020**	-0.023***	-0.021***	-0.016**	-0.017**	-0.017***
	(-1.952)	(-2.086)	(-3.278)	(-3.401)	(-2.223)	(-2.551)	(-2.726)
5:1	-0.025**	-0.023**	-0.026***	-0.025***	-0.022***	-0.023***	-0.024***
	(-2.212)	(-2.557)	(-3.555)	(-3.831)	(-3.341)	(-3.661)	(-3.847)
10:1	-0.028***	-0.029***	-0.036***	-0.037***	-0.031***	-0.035***	-0.033***
	(-2.598)	(-3.545)	(-5.252)	(-6.203)	(-4.819)	(-5.701)	(-5.600)
20:1	-0.036***	-0.024***	-0.039***	-0.030***	-0.044***	-0.028***	-0.050***
	(-4.378)	(-3.135)	(-5.967)	(-5.370)	(-7.583)	(-4.901)	(-8.930)
25:1	-0.035***	-0.034***	-0.046***	-0.044***	-0.046***	-0.044***	-0.050***
	(-4.155)	(-4.726)	(-7.621)	(-8.162)	(-7.639)	(-7.465)	(-8.905)
30:1	-0.042***	-0.043***	-0.053***	-0.056***	-0.053***	-0.054***	-0.062***
	(-6.046)	(-6.911)	(-9.378)	(-10.900)	(-9.170)	(-9.518)	(-11.451)
50:1	-0.048***	-0.041***	-0.063***	-0.056***	-0.064***	-0.056***	-0.067***
	(-6.290)	(-6.046)	(-10.877)	(-10.637)	(-10.978)	(-9.915)	(-12.507)
100:1	-0.070***	-0.061***	-0.100***	-0.089***	-0.094***	-0.084***	-0.101***
	(-8.703)	(-8.393)	(-16.435)	(-16.006)	(-15.291)	(-14.117)	(-17.954)
Short	-0.003	-0.004	-0.005	-0.006	-0.007	-0.006	-0.007*
	(-0.703)	(-1.005)	(-1.316)	(-1.507)	(-1.461)	(-1.242)	(-1.683)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	35,926,050	35,926,050	35,926,050	35,926,050	35,926,050	35,926,050	35,926,050
Adj. R^2	0.315	0.282	0.099	0.082	0.073	0.039	0.041

Panel E—Cryptocurrencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2:1	-0.031***	-0.041***	-0.018**	-0.030***	-0.087***	-0.088***	-0.073***
	(-5.044)	(-7.623)	(-2.466)	(-4.587)	(-15.598)	(-16.342)	(-14.047)
5:1	-0.004	-0.092***	0.037***	-0.112***	-0.037***	-0.202***	-0.179***
	(-0.330)	(-3.368)	(2.758)	(-4.979)	(-3.513)	(-9.366)	(-8.322)
Short	-0.033***	-0.041***	-0.048***	-0.053***	-0.108***	-0.110***	-0.088***
	(-7.293)	(-8.811)	(-9.941)	(-10.357)	(-15.774)	(-15.678)	(-16.655)
Fixed Effects	User-Day-Asset	User-Day	User-Month-Asset	User-Month	Country-Day-Asset	Country-Day	User + Day + Asset
N	32,986,925	32,986,925	32,986,925	32,986,925	32,986,925	32,986,925	32,986,925
Adj. R^2	0.799	0.593	0.638	0.466	0.152	0.079	0.231

Appendix E. Appropriateness Test

This figure presents two variations of the appropriateness test administered by the broker.

Trading Knowledge Assessment

We would like to assess your level of knowledge of complex derivatives and trading with leverage.

Please mark all the correct statements:

1. Opening a trade with $100 and a leverage of 50 will equate to a $5000 investment.
2. If the equity in your account falls below the required margin, a “margin call” will liquidate your trades.
3. If the price of Google stock on NASDAQ goes up, the price of your CFD in Google will go down.
4. My open positions will automatically close out when my stopped loss is triggered.

Trading Knowledge Assessment

We would like to assess your level of knowledge of complex derivatives and trading with leverage.

Please mark the correct statement:

1. If the equity in your account falls below the required margin, a “margin call” will not liquidate your trades.
2. Opening a trade with $100 and 20X leverage will equate to a $2000 investment.
3. If the price of Google stock on NASDAQ goes up, the price of your CFD in Google will go down.
4. My open positions will remain open when the stop loss is triggered.

Appendix F. Additional Summary Statistics

This table reports additional summary statistics for the users in our sample. Column (1) presents statistics for the full sample of users. Column (2) displays statistics for users who joined the broker prior to March 1, 2020, and column (3) displays statistics for users who joined the broker beginning on March 1, 2020. Column (4) presents the results of a comparison between columns (2) and (3). For continuous and binary variables, a t-test is used to compare means. For categorical variables with more than one category, a chi-square test is used to compare distributions.

	Full Sample	**Existing Users**	**New Covid Users**	**χ^2 or t-statistic (p-value)**
N	963,805	327,670	636,135	-
Trading Experience in Past Year—Leveraged Trading, %				
0 times	0.467	0.357	0.503	χ^2 = 20777 ($p < 0.01$)
1–10 times	0.322	0.329	0.319	
10–20 times	0.088	0.117	0.078	
≥ 20 times	0.123	0.197	0.099	
Trading Education, %				
No Financial Education	0.412	0.451	0.392	χ^2 = 3366.9 ($p < 0.01$)
Financial Degree	0.157	0.159	0.155	
Work Experience or Professional Certificate	0.111	0.103	0.116	
Trading Courses	0.411	0.378	0.428	
Trading Strategy (Duration), %				
Short (up to 24 Hours)	0.192	0.222	0.174	χ^2 = 2885.9 ($p < 0.01$)
Medium (Few Weeks to Several Months)	0.530	0.515	0.538	
Long (More than Several Months to Years)	0.279	0.262	0.288	
Trading Interests (Asset Classes), %				
Stocks	0.849	0.743	0.905	χ^2 = 8799.7 ($p < 0.01$)
Indices	0.408	0.403	0.410	
Currencies	0.437	0.466	0.421	
Commodities	0.518	0.515	0.520	
Cryptocurrencies	0.707	0.752	0.683	
Main Sources of Income, %				
Employment	0.783	0.800	0.773	χ^2 = 9799.8 ($p < 0.01$)
Savings	0.345	0.267	0.384	
Investments	0.165	0.148	0.173	
Family Support	0.044	0.031	0.051	
Inheritance	0.027	0.023	0.030	
Other	0.053	0.041	0.059	
Total Cash and Liquid Assets (USD), %				
< 10K	0.430	0.435	0.428	χ^2 = 2331.2 ($p < 0.01$)
10–50K	0.311	0.311	0.311	
50–200K	0.145	0.153	0.141	
200–500K	0.047	0.046	0.047	
500K–1M	0.024	0.025	0.024	
≥ 1M	0.043	0.029	0.050	
Expected Annual Deposits in Trading Account (USD), %				
< 1K	0.328	0.324	0.330	χ^2 = 614.69 ($p < 0.01$)
1–5K	0.281	0.275	0.284	
5–20K	0.270	0.270	0.271	
20–50K	0.078	0.083	0.075	
50–200K	0.033	0.037	0.031	
≥ 200K	0.010	0.012	0.009	

Appendix G. Work-from-Home Variable Definitions

This table describes the construction of the work-from-home variables used in chapter 3 of this dissertation.

<table>
<tr><th>OxCGRT Work-from-Home Categorical Variable</th><th>OxCGRT Indicator for General or Targeted Policy</th><th>Primary Work-from-Home Binary Variable</th><th>Alternative Work-from-Home Categorical Variable</th></tr>
<tr><td rowspan="2">Require closing or work-from-home for all but essential workplaces</td><td>Policy applied across the whole country</td><td rowspan="3">Yes</td><td>Level 1</td></tr>
<tr><td>Policy targeted to a specific geographical region</td><td rowspan="2">Level 2</td></tr>
<tr><td rowspan="2">Require closing or work-from-home for some categories of workers</td><td>Policy applied across the whole country</td></tr>
<tr><td>Policy targeted to a specific geographical region</td><td rowspan="4">No</td><td rowspan="2">Level 3</td></tr>
<tr><td rowspan="2">Recommend closing or work-from-home / All businesses open with alterations resulting in significant differences compared to pre-Covid-19 operation</td><td>Policy applied across the whole country</td></tr>
<tr><td>Policy targeted to a specific geographical region</td><td rowspan="2">Level 4</td></tr>
<tr><td>No measures</td><td>-</td></tr>
</table>

Appendix H. Attention-Grabbing Variable Definitions

This table describes the construction of the attention-grabbing variables used in Table 3.7.

Variable	**Dataset used to create variable**	**Definition**
Extreme Last-Day Absolute Returns	CRSP	Indicator variable that equals one if the absolute value of returns (CRSP: Holding Period Return—RET) on day *t-1* is ranked in the top quintile (20%).
Extreme Last-Day Abnormal Trading Volume	CRSP	Indicator variable that equals one if the abnormal trading volume for the stock on day *t-1* is ranked in the top quintile (20%) of the abnormal trading volume for all stocks that day. Abnormal trading volume is the trading volume on day *t-1* divided by the average trading volume during the previous 42 trading days with a five-day gap (i.e., between *t-6* to *t-48*). Trading volume is the total number of shares of a stock that were sold on a certain day (CRSP: Share Volume—VOL).
Last-Day Earnings Announcement	Compustat	Indicator variable that equals one if the firm had an earnings announcement on day *t-1* (Compustat: Report Date of Quarterly Earnings – RDQ).
Extreme Last-Day Abnormal News Volume	FinSentS Web News Sentiment database (published by Inoftrie)	Indicator variable that equals one if the abnormal news volume for the stock on day *t-1* is ranked in the top quintile (20%) of the abnormal news volume for all stocks that day. Abnormal news volume is the news volume on day *t-1* divided by the average news volume during the previous 42 trading days with a five-day gap (i.e., between *t-6* to *t-48*). News volume is the total number of news articles on a certain day.
Extreme Abnormal Social Media Volume	Reddit's WallStreetBets	Indicator variable that equals one if the abnormal social media volume for the stock on day *t* is ranked in the top quintile (20%) of the respective social media volume for all stocks that day. Abnormal social media volume is the social media volume on day *t* divided by the average social media volume during the previous 42 trading days with a five-day gap (i.e., between *t-5* to *t-47*). Social media volume is the total number of comments in the "Tomorrow's Moves" and "Daily Discussion" sub-forums on Reddit's WallStreetBets (r/WSB). The number of comments for day *t* include all of the comments that were posted after the markets closed on day *t-1* and before the markets closed on day *t*.