CENTER FOR TAX AND ACCOUNTING RESEARCH

TAXATION, ACCOUNTING, AND FINANCE

TAF WORKING PAPER

No. 54 / April 2020

Ortmann, Regina / Pelster, Matthias /
Wengerek, Sascha Tobias

Covid-19 and Investor Behavior

Paderborn University
www.taf-wps.cetar.org

COVID-19 and investor behavior*

Regina Ortmann† Matthias Pelster‡ Sascha Tobias Wengerek§

April 2020

Abstract How do retail investors respond to the outbreak of COVID-19? We use transaction-level trading data to show that investors significantly increase their trading activities as the COVID-19 pandemic unfolds, both at the extensive and at the intensive margin. The average weekly trading intensity increases by 13.9% as the number of COVID-19 cases doubles. The increase in trading is especially pronounced for male and older investors, and affects stock and index trading. Following the 9.99%-drop of the Dow Jones Industrial Average on March 12, investors significantly reduce the usage of leverage across all asset classes.

Keywords: Trading Behavior; Risk-Taking; Pandemic; COVID-19

JEL Classification: G10, G11, G12, G40, G41.

*Data were obtained under a non-disclosure agreement with a financial institution. We thank our data provider for use and explanations of their data. We thank Thomas Müller for outstanding research support. Any errors, misrepresentations, and omissions are our own.

†Paderborn University. Warburger Str. 100, 33098 Paderborn, Germany, Phone: +49 (5251) 60-1780, e-mail: *regina.ortmann@upb.de.*

‡Paderborn University. Warburger Str. 100, 33098 Paderborn, Germany, Phone: +49 (5251) 60-3766, e-mail: *matthias.pelster@upb.de.*

§Paderborn University. Warburger Str. 100, 33098 Paderborn, Germany, Phone: +49 (5251) 60-5559, e-mail: *sascha.tobias.wengerek@upb.de.*

1 Introduction

The novel coronavirus has led to unprecedented repercussions on daily life and the economy. The efforts to contain the virus have led to a temporary lockdown of almost all major economies worldwide. While the aggregate effect of the pandemic on the stock market (Baker et al., 2020a; Ramelli and Wagner, 2020) and the spending behavior of households (Baker et al., 2020b) have been documented, little is known about the behavior of retail investors during such a turbulent time. It is, however, important to investigate the behavior of investors in these unprecedented conditions at the micro-level to allow for a better understanding of aggregate market outcomes. In this paper, we explore how retail investors respond to the outbreak of COVID-19. We investigate how a pandemic influences trading patterns and financial risk-taking based on a large sample of trading records of retail investors.

We use three arguments to express contrasting expectations about investor behavior during the COVID-19 outbreak. *First*, the outbreak of the pandemic is in many regards comparable to terrorist attacks: it is an exogenous shock, that has drastic consequences on everyday life, raises public fear, and causes great (economic) uncertainty. Investor behavior in the aftermath of terrorist activity is associated with more risk averse choices, such as a reduced trading intensity and a reduced flow to risky assets (Levy and Galili, 2006; Luo et al., 2020; Wang and Young, 2020). In line with the results of the terrorism literature, but against the background of the outbreak of COVID-19, Bu et al. (2020) survey Chinese students in Wuhan and find substantially lower general preferences for risk. Thus, investors may reduce their trading activities and risk-taking as a result of increased public fear and uncertainty during the COVID-19 outbreak.

Second, in line with this increased uncertainty, press articles, media reports, and expert opinions display a torn image of the future economic development and, thus, of optimal investment and portfolio strategies. The outbreak of COVID-19 has led to significant financial market declines around the world. Some commentators argue that, whereas previous recessions predominantly rooted in complex dysfunctions of markets, the origin of the recent economic downturn is quite special and lies in an "artificial" lockdown of economies. For example, statements of U.S. president Donald Trump give raise for a simple and optimistic assessment of the future development of markets. In March, Trump confidently proclaimed that there will be a V-shaped recovery of the U.S. economy that will quickly return to its former state of robust health, once the pandemic passes (Lachman, 2020). In line with this positive assessment, Hanspal et al. (2020) report that U.S. households expect a faster recovery of the stock market relative to previous crashes. Investors may thus assess the economic situation during and in the aftermath of the lockdown as easily ascertainable and clearly predictable. Accordingly, they may consider the economic lockdown as a favorable opportunity to enter the market. At the same time, however, experts and media echo growing scepticism over what Trump has said would be a quick economic rebound after the pandemic. For example, Janet Yellen expressed that it is common for economic growth after a crisis to remain on a lower track for years, not months (Lee, 2020). Considering these different opinions, the trading activities of market participants is highly unclear.

Third, the efforts to contain the outbreak of the pandemic have led to lockdowns or at least severe restrictions on public life, causing social isolation and boredom. The lockdown comes along with reduced opportunities for leisure activities and forces many residents to reduce their social contacts, to pause their work, and to stay at home. Given that the previous evidence in the finance literature suggests that (some) individual investors treat trading as a fun and exciting activity (Dorn and Sengmueller, 2009; Dorn et al., 2015; Gao and Lin, 2015; Kumar, 2009), others may join. In a broader scheme, boredom is found to be an important factor in the development of gambling behavior (e.g. Carroll and Huxley, 1994; Clarke et al., 2007; Coman et al., 1997; Hing and Breen, 2001; McNeilly and Burke, 2000; Williams and Hinton, 2006). Several studies indicate that boredom, loneliness, and isolation are among the primary motivators for engaging in gambling activity (e.g. Smith and Preston, 1984). Thus, people may join financial markets and increase their trading activities to fight their boredom and loneliness. Against the backdrop of these inconclusive expectations, it is highly interesting to investigate investors' trading activities during the outbreak of a pandemic.

Our paper contributes to a rapidly growing body of work studying the implications of the COVID-19 pandemic on various economic variables. Baker et al. (2020b) investigate U.S. household consumption behaviors during the COVID-19 pandemic. The authors find a sharp increase in overall spending activities ("stockpiling") as COVID-19 cases began to increase in the U.S. As the virus spread and more "stay at home" and "shelter in place" orders were imposed, households cut their overall spending dramatically. Hanspal et al. (2020) analyze the impact of COVID-19 pandemic on U.S. households' income, wealth, consumption activities, and expectations about the recovery. A substantial part of the population suffers wealth and income shocks; however, the magnitude depends on households' income and wealth distributions, age, and education levels. Households that are more exposed to losses are more likely to decrease their total expenditures and to increase their expectations regarding debt holdings, retirement age, and working hours. The authors find that, in comparison to previous crashes, U.S. households expect a faster recovery of the stock market. Bu et al. (2020) study the risk-taking behavior of Chinese students before and after the outbreak of COVID-19. They find lower preferences for risk during the continuing spread of COVID-19. Individuals that are more exposed to COVID-19 consequences display a decreased willingness to take risky investments, lower optimism, and lower perceived individual control and more pessimistic beliefs on the economy. Gormsen and Koijen (2020) use aggregate equity market and dividend futures data to study investors' expectations about economic growth in response to the COVID-19 pandemic and subsequent policy responses. The authors report that news about stimulus programs have boosted the market and long-term growth, but did not improve short-term growth expectations.

The outbreak of COVID-19 in 2020 has also led to unprecedented disturbances on financial markets (Baker et al., 2020a). Baker et al. (2020a) report 18 jumps in the U.S. stock market during 22 trading days between February 24 and March 24, 2020. In comparison, in the 120 years before, none of the more than 1,100 jumps has been attributed to infectious disease outbreaks or policy responses to such outbreaks (Baker et al., 2020a).

Ramelli and Wagner (2020) show clear cross-sectional differences in stock price movements during the outbreak of the pandemic, driven by corporate debt and liquidity, while Yan et al. (2020) analyze potential effects of the outbreak on the economy and propose investment strategies to profit of the affected markets.

The remainder of our paper proceeds as follows. The next section presents our data and methodology. Section 3 presents the results. We discuss our results in Section 4.

2 Data and methodology

We use transactional-level brokerage data from a UK-based discount broker that offers an online trading platform to retail investors. The broker allows its clients to trade stocks (*stocks*) and contracts for difference (CFD) on stock market indizes (*index*), cryptocurrencies (*crypto*), commodities (*gold*)[1], foreign exchange rates, and single name stocks (*CFD_stock*). Our data sample contains all trades that the investors executed with the broker between August 1, 2019 and April 17, 2020. The majority of transactions in our data is based on indizes (∼24%), followed by cryptocurrencies (∼20%), CFDs on single name stocks (∼19%), and single name stocks (∼15%). The data contain the exact timestamp and instrument of the trade, an indicator for long or short positions, the executed rate, the leverage, and the investment. The dataset quotes all trades in USD irrespective of the currency in which the underlying instrument trades and comprises net returns of closed positions after adjusting for stock splits, dividends, and transaction costs. In total, the dataset contains 45,003,637 transactions executed by 456,365 investors.

Additionally, the dataset includes the deposits to and withdrawals from the brokerage accounts that investors initiate. The data also contain information on push notifications that the broker sends to investors to alert them of volatility events (see Arnold et al., 2019). Lastly, the dataset comprises basic demographic information, such as age and gender.

[1] We exclude CFDs on oil from our analysis due to a large number of potential confounding effects, such as the debate on production quantities between Russia and Saudi, and restrict commodities to gold as a safe-haven instrument.

We obtain data on the number of cases and deaths due to COVID-19 from the European Centre for Disease Prevention and Control. In addition, we hand collect information on lockdowns and other restrictions on public life.

Formally, we study the relation between the outbreak of COVID-19 and investors' trading activities using an OLS regression analysis. We use several variables to proxy investors' trading activities. *Trading intensity* denotes the number of trades in a given week. The variable takes a value of zero for investors who do not trade in a given week. *Leverage*, a pure measure of risk-taking, denotes the leverage employed for a trade. *Short sale* is a dummy variable that takes a value of one, if a trade establishes a short position, and zero otherwise. We restrict the analysis on leverage and short sale to trades that open a new position. We aggregate the trading data at the weekly level using averages and totals.

Net deposits denotes the number of deposits minus the number of withdrawals on a given day. *First deposits* denotes the number of deposits by investors who opened a new account, on a given day. Finally, (broker-specific) buy-sell imbalances for long and short positions on day t are given by

$$BSI_t = \frac{NB_t - NS_t}{NB_t + NS_t},$$

where NB_t denotes the number of long positions on day t and NS_t denotes the number of short positions on day t.

We use three (sets of) explanatory variables to capture the outbreak of the pandemic, based on the large number of events that are relevant to investors during the COVID-19 outbreak (Baker et al., 2020a). *COVID-19 cases* denotes the logarithm of the number of corona cases plus one. We believe that this variable serves as the best proxy to capture the outbreak of the disease. *Dow drop* is a dummy variable that takes a value of one on March 13, the day after one day the Dow fell a record 2,352.60 points (9.99%) to close at 21,200.62, and zero otherwise. We select March 13 to create the dummy variable instead of the first drop of the Dow on Monday, March 9, when the Dow fell 7.79% based on the observation that investors risk-taking experiences a large change after the second drop of the Dow. Third, we use three dummy variables to define various stages of the outbreak. First, *Jan. 23 - Feb. 22* marks the time period from the lockdown in China to the lockdown in Italy; second, *Feb. 23 - Mar. 22* marks the time period from the lockdown in Italy to the lockdown in United Kingdom; third, *Mar. 23 - Apr. 17* marks the time period from the lockdown in United Kingdom to the end of our sample period. We select these dates based on the following arguments: At the latest when China ordered the lockdown, investors will have started to understand the importance of the disease, as this lockdown affected supply chains in Europe and other parts of the world. Second, when Italy ordered the lockdown in February, the disease had become a pandemic that reached Europe. When the United Kingdom ordered the lockdown in March, a large part of countries across the world had already issued lockdowns or severe restrictions on public life.

Our specification includes investor fixed effects to control for observed and unobserved heterogeneity across investors such as their gender, age, or wealth. We also include a full set of asset class dummies to control for different trading behaviors across asset classes. *Male* is a dummy variable that takes a value of one if the investor is male, and zero otherwise. *18-24* [*25-34*, ...] is a dummy variable that takes a value of one if the investor is between 18 and 24 [25 and 34, ...] years of age, and zero otherwise. Lastly, we control for push notifications before investors' trades. Arnold et al. (2019) show that such push notifications increase risk-taking and trading within a 24-hour time period.[2] *Push* is a dummy variable that takes a value of one, if the investor receives a push notification referring to the underlying of the trade within 24 hours before executing a trade.[3]

[2]We can confirm their findings in our sample and observe a significantly higher leverage-usage and trading intensity in the stock referred to in the push notifications within a 24-hour period.

[3]Approximately one percent of trades in our dataset are executed within 24 hours after the investor received a push notification on the underlying referred to in the notification.

3 Results

We present the evolution of investors' trading activities in Figure 1.[4] We observe a significant increase in index trading, mostly between February 23 and March 23, which decreases again after March 23. In a similar manner, but less pronounced, we observe a continuous increase in stock trading, followed by a decline after March 23. CFD trading shows several spikes over the course of the pandemic. Crypto trading shows a distinct spike following the drop of the Dow Jones on March 12. Figure 2 indicates that investors do not only increase their average trading intensities, but at the same time the number of investors who execute trades increases. Panel (b) of Figure 1 shows a decline in leverage-usage across asset classes between February 23 and March 23, that is most pronounced following the drop of the Dow Jones. Panel (c) shows an increase in short-selling using CFDs, but no clear trend across other asset classes.

Table 1 presents our main results. Panel A studies the trading intensity of investors. Model 1 shows a 13.9% increase in the average weekly trading intensity as the number of COVID-19 cases doubles, which is economically quite meaningful. The increase in trading is mainly driven by male investors (Model 4) and by older investors (Model 5). Model 2 shows that the trading intensity increased by 222% following the 9.99% drop of the Dow on March 12, which is largely driven by the spike in cryptocurrency trading (untabulated). Finally, in line with Figure 1, Model 3 shows that the largest increase in trading is observed during the period from Feb. 23 to March 22. In Panel B of Table 1, we show that the increase in trading is driven by increased stock and index trading, while CFDs on stocks, cryptocurrencies, and gold are less affected by the outbreak. Panel C indicates that the increase in trading is also prevalent for new created positions in stocks and indizes.

Table 2 shows that investors also, on average, add additional funds to their trading accounts. The number of net deposits increases by 751 (Model 1) as the cases number doubles. Figure 3 visualizes the abnormal increase in net deposits as the pandemic unfolds

[4]Figure A.1 in the Appendix shows the aggregate abnormal trading volume over time.

(Panel a). The increase in fund-flow is driven by both new and established investors (Table 2, Models 2 and 3; Figure 3, Panel b). Thus, investors increase their trading activities not only at the intensive but also at the extensive margin.[5]

Panels D and E of Table 1 show the results on leverage-usage during the outbreak of COVID-19. We show a large decline in leverage-usage across all genders and age groups. The largest decline can be observed following the Dow drop on March 12. As a response, investors reduced their average leverage-usage by 172 percentage points. In line with this sharp decline in leverage-usage, we find that investors, on average, use 299 percentage points less leverage during the time period of March 23 to April 17.

Panels F and G of Table 1 show that investors increase their propensity to take short positions during the outbreak of the pandemic by, on average, 2% of their propensity to engage in short positions before the outbreak of the disease. Model 3 indicates that investors particularly increase their short selling propensity during the more recent time periods. Model 5 shows that especially younger investors increase their short selling activities. Panel G shows that investors increase short selling across all asset classes.

Lastly, Figure 4 presents buy-sell imbalances over time. While investors, on average, take long stock positions, and this tendency increases during the outbreak of the pandemic, buy-sell imbalances for index positions and gold move around zero, indicating neutral positions, on average. Cryptocurrencies show two spikes towards long positions around February 23 and March 23. CFD positions overall show strong variation during the outbreak, with more short positions until March 23, and a tendency towards long positions afterwards.

4 Discussion

We find that investors increase their trading activities as the COVID-19 pandemic unfolds, both at the extensive and at the intensive margin. The number of investors who first open

[5]Figure A.2 in the appendix indicates that established and new investors show similar trading patterns over the outbreak of the virus.

an account with the broker increases, while at the same time established investors increase their average trading activities. Investors, on average, significantly increase their trading intensities. The average weekly trading intensity increases by 13.9% as the number of COVID-19 cases doubles. In particular, investors open more stock and index positions, but do not move to safe-haven (gold) or particularly "risky" (CFDs, cryptocurrencies) investments. The increase in trading is especially pronounced for male and older investors, and largest during the period from February 23 to March 22. Investors also marginally increase their tendency to engage in short selling.

Our results indicate that, in line with the torn image that press articles, media reports, and expert opinions paint these days, investors' trading activities are also not clear-cut. Our findings stand in contrast to investors' reactions to other shocks that increase uncertainty such as terrorist attacks, which are associated with reduced flows to risky asset classes (Wang and Young, 2020). While investors increase their trading intensity, we nonetheless show that investors act more cautiously following the drop of the Dow Jones on March 12. Following the 9.99%-drop of the Dow, investors significantly reduce their leverage-usage across all asset classes, which is in line with the notion that investors make more risk-averse choices due to public fear (Levy and Galili, 2006; Luo et al., 2020; Wang and Young, 2020). Considering that buy-sell imbalances in index positions are close to zero, approximately half of all new index positions are short positions, and some investors take long stock positions while others short single name stocks using CFDs underscores that investors have different expectations, in line with the torn picture experts and media outlets paint. Investors who take long stock or index positions may buy into the narrative of the fast economic recovery once the pandemic passes (Hanspal et al., 2020), and believe that the lockdown offers a favorable opportunity to enter the stock market, while those taking short positions may hold the opinion that this narrative is too optimistic.

Our results do not offer support for the notion that "stay at home" and "shelter in place" orders as well as closed sports betting markets and fewer other forms of entertainment, such as eating out (Baker et al., 2020b), could lead people to seek pastimes in financial markets. By the time lockdowns are in place almost everywhere, the trading activity of investors in our sample already starts to decline. We can, however, not rule out that some investors simply trade to fight their boredom.

A caveat of our analysis is that investors in our dataset may not be representative for the average household. Investors likely select a brokerage service based on their preferences. Notwithstanding this limitation, we believe that our study provide important insights into the trading activities of retail investors during the outbreak of a pandemic. Our study provides initial insights that may inform future research that attempts to explore this topic further.

References

Arnold, Marc, Matthias Pelster, and Marti G. Subrahmanyam, 2019, Attention triggers and investors' risk taking, *Working Paper* .

Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle Kost, Marco Sammon, and Tasaneeya Viratyosin, 2020a, The unprecedented stock market reaction to covid-19, *Working Paper* .

Baker, Scott R, R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis, 2020b, How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic, Working Paper 26949, National Bureau of Economic Research.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *The Review of Financial Studies* 21, 785–818.

Bu, Di, Tobin Hanspal, Yin Liao, and Yong Liu, 2020, Risk taking during a global crisis: Evidence from wuhan, *Working Paper* .

Carroll, Douglas, and Justine A. A. Huxley, 1994, Cognitive, dispositional, and psychophysiological correlates of dependent slot machine gambling in young people, *Journal of Applied Social Psychology* 12, 1070–1083.

Clarke, Dave, Samson Tse, Max Abbott, Sonia Townsend, Pefi Kingi, and Wiremu Manaia, 2007, Reasons forstarting and continuing gambling in a mixed ethnic communicty sample of pathological and nonproblem gamblers, *International Gambling Studies* 7, 299–313.

Coman, Greg J., Graham D. Burrows, and Barry J. Evans, 1997, Stress and anxiety as factors in the onset of problem gambling: Implications for treatment, *Stress Medicine* 13, 235–244.

Dorn, Anne Jones, Daniel Dorn, and Paul Sengmueller, 2015, Trading as gambling, *Management Science* 61, 2376–2393.

Dorn, Daniel, and Paul Sengmueller, 2009, Trading as entertainment?, *Management Science* 55, 591–603.

Gao, Xiaohui, and Tse-Chun Lin, 2015, Do individual investors treat trading as a fun and exciting gambling activity? evidence from repeated natural experiments, *The Review of Financial Studies* 28, 2128–2166.

Gormsen, Niels Joachim, and Ralph SJ Koijen, 2020, Coronavirus: Impact on stock prices and growth expectations, Working Paper 2020-22, University of Chicago.

Hanspal, Tobin, Annika Weber, and Johannes Wohlfart, 2020, Income and wealth shocks and expectations during the covid-19 pandemic, Working Paper 13/20, University of Copenhagen.

Hing, Nerilee, and Helen Breen, 2001, Profiling lady luck: An empirical study of gambling and problemgambling amongst female club members, *Journal of Gambling Studies* 17, 47–49.

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

Lachman, Desmond, 2020, Trump's v-shaped economic recovery delusion, *The Hill* 03/24/2020.

Lee, Don, 2020, Coronavirus recession now expected to be deeper and longer, *Los Angeles Times* 04/01/2020.

Levy, Ori, and Itai Galili, 2006, Terror and trade of individual investors, *The Journal of Socio-Economics* 35, 980 – 991.

Luo, Yue, Yangyang Chen, and Ji-Chai Lin, 2020, Do terrorist attacks make inventors more risk taking?, *Working Paper* .

McNeilly, Dennis P., and William J. Burke, 2000, Late life gambling: The attitudes and behaviours of older adults, *Journal of Gambling Studies* 16, 393–415.

Ramelli, Stefano, and Alexander F. Wagner, 2020, Feverish stock price reactions to covid-19, Working Paper 20-12, University of Zurich.

Smith, Ronald W., and Frederick W. Preston, 1984, Vocabularies of motives for gambling behavior, *Sociological Perspectives* 27, 325–348.

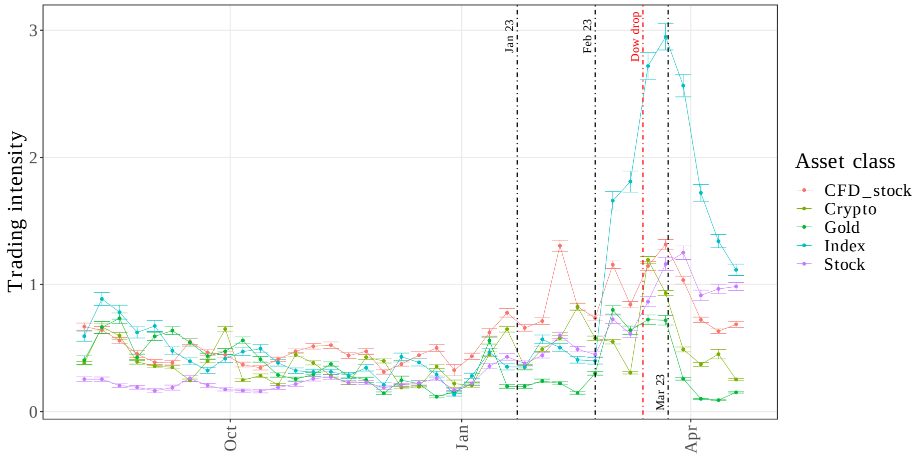
Wang, Albert Y., and Michael Young, 2020, Terrorist attacks and investor risk preference: Evidence from mutual fund flows, *Journal of Financial Economics* in press.

Williams, DJ, and Mary Liz Hinton, 2006, Leisure experience: Prison culture, or victimization? sex offenders report on prison gambling, *Victims and Offenders* 1, 175–192.

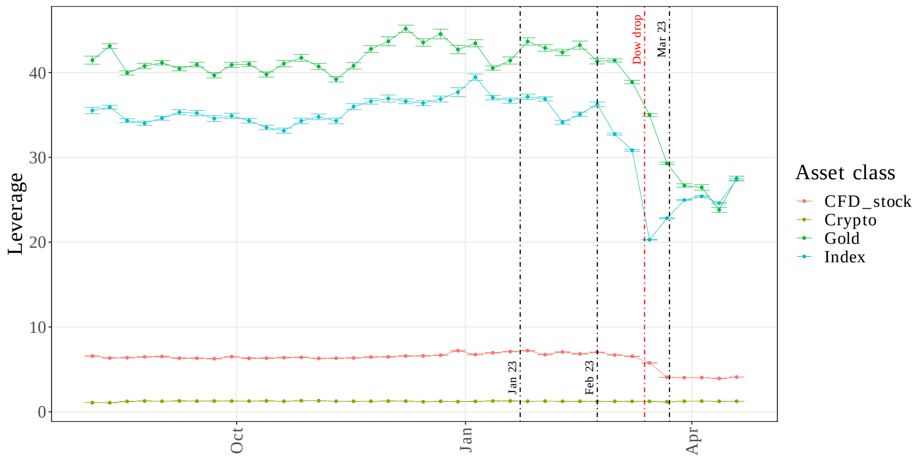
Yan, Heather, Andy Tu, Logan Stuart, and Qingquan Zhang, 2020, Analysis of the effect of covid-19 on the stock market andpotential investing strategies, *Working Paper* .

Figure 1: Trading activities over time

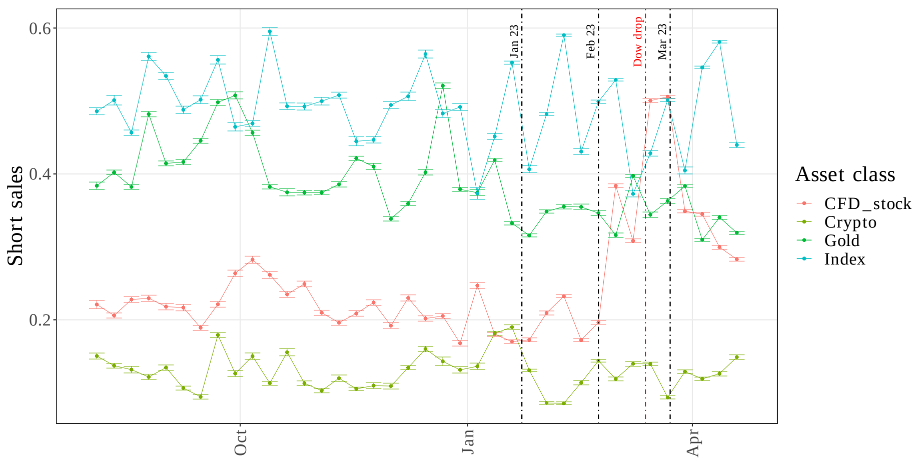
This figure presents the trading intensity, leverage-usage, and short sale propensity over time (with 99% confidence intervals).



(a) Trading intensity



(b) Leverage



(c) Short sales

Figure 2: Number of active investors

This figure presents the number of active investors over time.

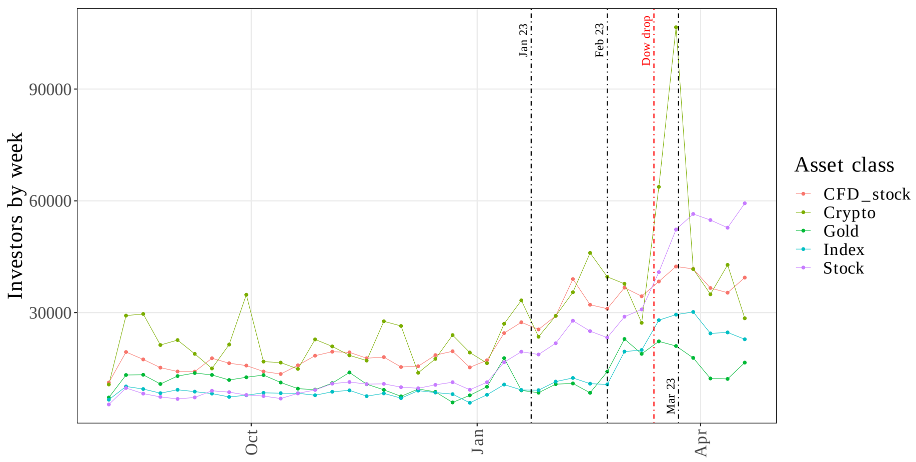
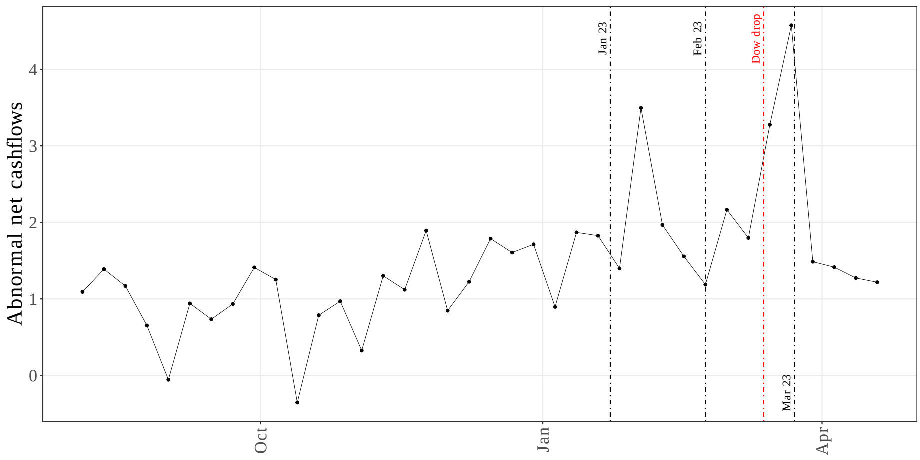
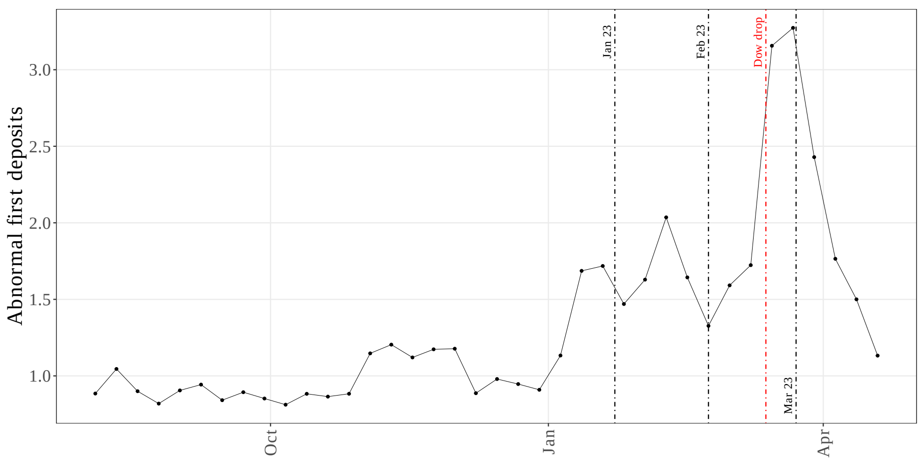


Figure 3: Abnormal account deposits

This figure presents abnormal net cashflows and abnormal first deposits over time. We define abnormal cashflows and first deposits as the net cashflows and first deposits divided by their rolling averages of the last six months, respectively.



(a) Abnormal net cashflows



(b) Abnormal first deposits

Figure 4: Buy-sell imbalances during the COVID-19 outbreak

This figure presents the buy-sell imbalances over time.

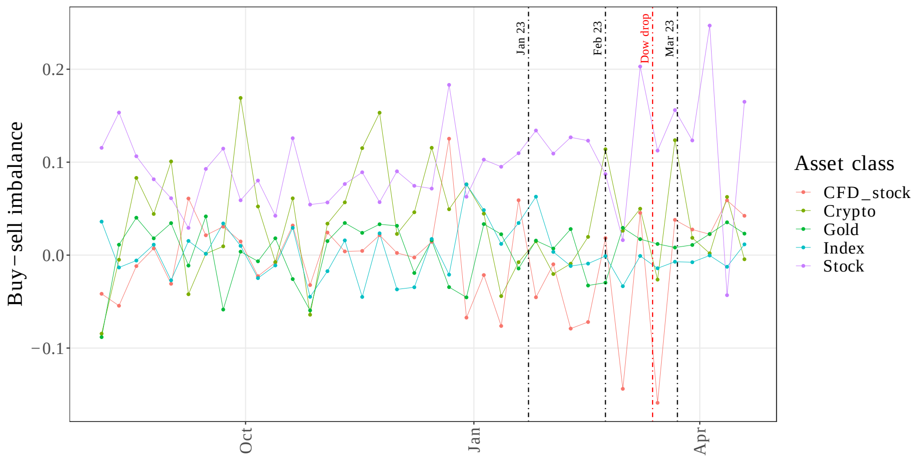


Figure A.1: Abnormal trading volume during the COVID-19 outbreak

This figure presents the abnormal trading volume over time. We follow Barber and Odean (2008) and define broker-specific abnormal trading volume on day t, AV_t as

$$AV_t = \frac{V_t}{\bar{V}_t},$$

where V_t denotes the trading volume on day t and $\bar{V}_t$ denotes the average trading volume of the last six months with the broker.

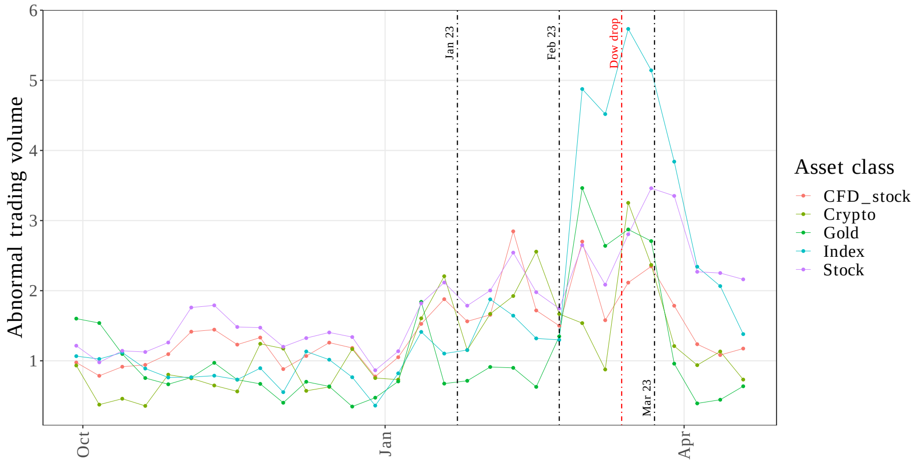


Table 1: Regression results: Trading activities

This table reports results from an OLS regression on the trading activities of investors in our trade data. Standard errors are double-clustered at the individual investor level and over time; *t*-statistics are in parentheses. The data are from a discount brokerage firm.

Panel A: Trading intensity					
	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable	Trading intensity	Trading intensity	Trading intensity	Trading intensity	Trading intensity
COVID-19 cases	0.2220			0.1202	0.2129
	(2.3004)			(1.5625)	(2.2849)
Dow drop		3.5557			
		(11.4704)			
Jan. 23 - Feb. 22			0.2763		
			(1.1377)		
Feb. 23 - Mar. 22			2.7410		
			(3.3521)		
Mar. 23 - Apr. 17			0.6378		
			(1.2035)		
Cases · male				0.1130	
				(4.0556)	
Cases · 18-24					−0.1714
					(−3.4184)
Cases · 25-34					−0.0150
					(−0.4196)
Cases · 35-44					0.0542
					(1.4619)
Cases · 45-54					0.0950
					(2.4387)
Cases · 55-64					0.0475
					(1.3193)
Push message control	Yes	Yes	Yes	Yes	Yes
Asset class dummy	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	14,113,014	14,525,010	14,525,010	14,088,650	14,072,248
Adj. R^2	0.36	0.37	0.37	0.36	0.36
Panel B: Trading intensity by asset classes					
	Model 1	Model 2	Model 3	Model 4	Model 5
Sample	Stocks	CFD_stock	Index	Crypto	Gold
COVID-19 cases	0.0363	0.0142	0.1813	−0.0008	−0.0165
	(5.1362)	(0.9807)	(4.0297)	(−0.0463)	(−1.4860)
Push message control	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	14,113,014	14,113,014	14,113,014	14,113,014	14,113,014
Adj. R^2	0.37	0.34	0.30	0.27	0.23
Panel C: Trading intensity (new positions) by asset classes					
	Model 1	Model 2	Model 3	Model 4	Model 5
Sample	Stocks	CFD_stock	Index	Crypto	Gold
COVID-19 cases	0.0195	0.0068	0.0910	−0.0028	−0.0083
	(5.1803)	(0.9776)	(4.0396)	(−0.3065)	(−1.4974)
Push message control	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	14,113,011	14,113,011	14,113,011	14,113,011	14,113,011
Adj. R^2	0.37	0.33	0.30	0.28	0.23

Table 1: Regression results: Trading activities (cont.)

Panel D: Leverage					
	Model 1	Model 2	Model 3	Model 4	Model 5
Dep. var.	Leverage	Leverage	Leverage	Leverage	Leverage
COVID-19 cases	−0.3019			−0.3155	−0.2406
	(−8.3412)			(−5.8471)	(−4.0663)
Dow drop		−1.7197			
		(−6.9803)			
Jan. 23 - Feb. 22			0.4080		
			(2.0808)		
Feb. 23 - Mar. 22			−1.0652		
			(−1.4160)		
Mar. 23 - Apr. 17			−2.9917		
			(−8.9368)		
Cases · male				0.0146	
				(0.3624)	
Cases · 18-24					0.0033
					(0.0484)
Cases · 25-34					−0.0970
					(−1.5689)
Cases · 35-44					−0.0963
					(−1.6319)
Cases · 45-54					−0.0114
					(−0.1945)
Cases · 55-64					0.0040
					(0.0639)
Push message control	Yes	Yes	Yes	Yes	Yes
Asset class dummy	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	4,771,217	4,946,112	4,946,112	4,767,966	4,758,012
Adj. R^2	0.64	0.64	0.64	0.64	0.64

Panel E: Leverage by asset classes				
	Model 1	Model 2	Model 3	Model 4
Dep. var.	Leverage	Leverage	Leverage	Leverage
Sample	CFD_stock	Index	Crypto	Gold
COVID-19 cases	−0.1530	−0.5289	0.0045	−0.5121
	(−11.5243)	(−12.9833)	(2.7170)	(−7.3752)
Push message control	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes
Obs.	1,040,042	650,338	1,174,571	591,974
Adj. R^2	0.64	0.76	0.55	0.79

Table 1: Regression results: Trading activities (cont.)

Panel F: Short sales					
	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable	Short sales	Short sales	Short sales	Short sales	Short sales
COVID-19 cases	0.0056			0.0055	0.0028
	(7.3213)			(5.5340)	(3.3955)
Dow drop		0.0158			
		(2.5069)			
Jan. 23 - Feb. 22			−0.0004		
			(−0.0798)		
Feb. 23 - Mar. 22			0.0315		
			(3.5548)		
Mar. 23 - Apr. 17			0.0364		
			(6.9650)		
Cases · male				0.0000	
				(0.1031)	
Cases · 18-24					0.0061
					(4.4759)
Cases · 25-34					0.0044
					(5.4906)
Cases · 35-44					0.0020
					(2.9686)
Cases · 45-54					0.0010
					(1.4507)
Cases · 55-64					−0.0002
					(−0.2507)
Push message control	Yes	Yes	Yes	Yes	Yes
Asset class dummy	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	4,771,217	4,946,112	4,946,112	4,767,966	4,758,012
Adj. R^2	0.15	0.15	0.15	0.15	0.15

Panel G: Short sales by asset classes				
	Model 1	Model 2	Model 3	Model 4
Dependent variable	Short sales	Short sales	Short sales	Short sales
Sample	CFD_stock	Index	Crypto	Gold
COVID-19 cases	0.0112	0.0033	0.0039	0.0041
	(5.2606)	(2.9362)	(4.5214)	(1.9366)
Push message control	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes
Obs.	1,047,042	650,338	1,174,571	591,974
Adj. R^2	0.15	0.04	0.09	0.08

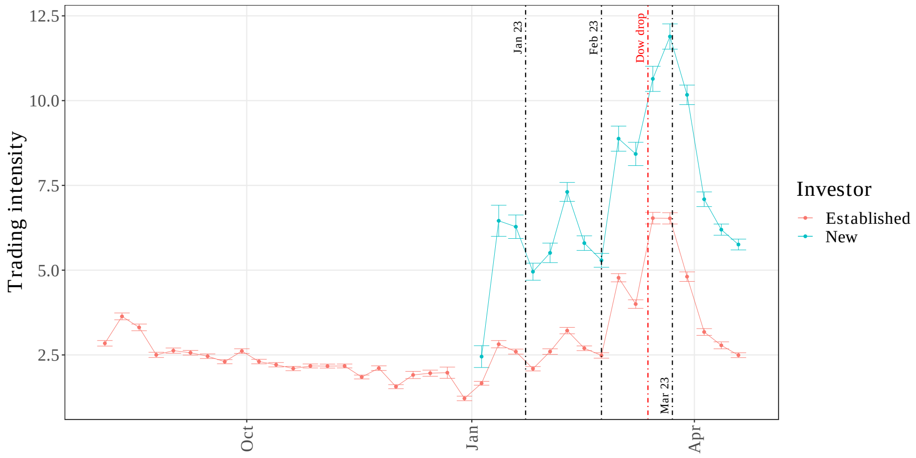
Table 2: Regression results: Account deposits

This table reports results from an OLS regression on the deposits and withdrawals that investors in our sample initiate. Standard errors are robust; *t*-statistics are in parentheses. The data are from a discount brokerage firm.

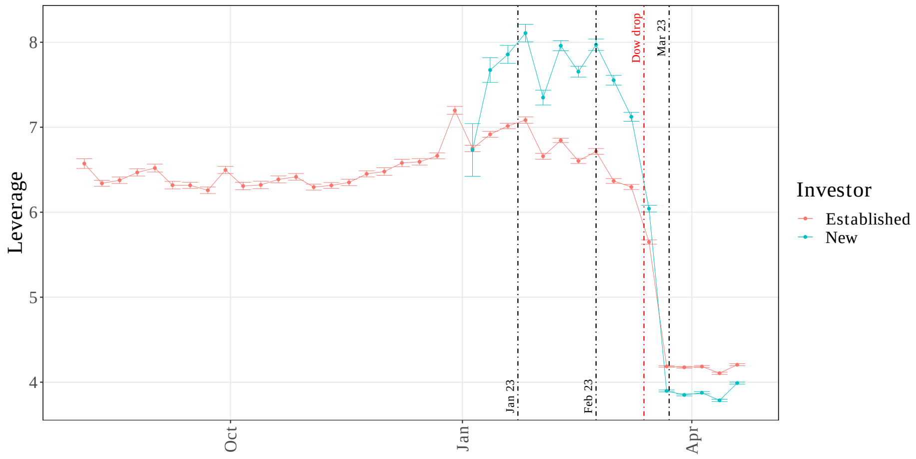
	Model 1	Model 2	Model 3
Dependent variable	Net deposits	First deposits	Net deposits
Sample	Full sample	New investors	Established investors
COVID-19 cases	751.3926	153.6394	290.7064
	(5.7601)	(13.6475)	(2.5400)
Obs.	261	261	261
Adj. R^2	0.17	0.60	0.04

Figure A.2: Trading differences between established and new investors

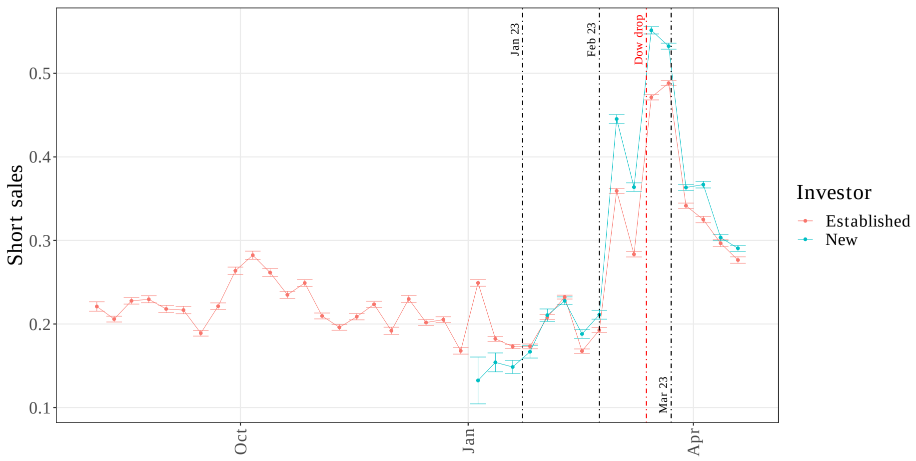
This figure presents the trading intensity, leverage-usage, and short sale propensity over time (with 99% confidence intervals), separately for investors who already traded in 2019 and for investors who started their trading activities in 2020.



(a) Trading intensity



(b) Leverage



(c) Short sales

Table A.1: Regression results: Buy-sell imbalances

This table reports results from an OLS regression on the buy-sell imbalances of the trades that investors execute with the broker. Standard errors are robust; t-statistics are in parentheses. The data are from a discount brokerage firm.

Panel A: COVID-19 cases						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Sample	Full sample	Stocks	Index	CFD_stock	Gold	Crypto
(Intercept)	0.0392	0.0883	0.0030	0.0005	0.0027	0.0420
	(6.6026)	(9.9580)	(0.4532)	(0.0528)	(0.2578)	(4.1970)
COVID-19 cases	0.0013	0.0033	−0.0006	−0.0020	0.0010	−0.0015
	(1.1269)	(1.0929)	(−0.7201)	(−0.9595)	(0.6540)	(−0.7712)
Obs.	261	197	223	205	223	261
R^2	0.0049	0.0131	0.0014	0.0040	0.0014	0.0023
Panel B: Dow drop						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Sample	Full sample	Stocks	Index	CFD_stock	Gold	Crypto
(Intercept)	0.0412	0.0983	0.0013	−0.0064	0.0057	0.0348
	(9.2828)	(11.1840)	(0.2753)	(−0.6972)	(0.7511)	(4.5540)
Dow drop	0.5050	(omitted)	−0.0483	0.1991	0.0110	0.7167
	(113.7420)		(−10.0074)	(21.5844)	(1.4536)	(93.7970)
Obs.	261	197	223	205	223	261
R^2	0.1612	0.0000	0.0020	0.0111	0.0000	0.1156
Panel C: Time period dummies						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Sample	Full sample	Stocks	Index	CFD_stock	Gold	Crypto
(Intercept)	0.0394	0.0881	0.0030	−0.0026	0.0047	0.0397
	(6.8349)	(10.9603)	(0.4722)	(−0.2624)	(0.4859)	(4.2425)
Jan. 23 - Feb. 22	0.0051	0.0234	−0.0076	−0.0367	−0.0116	−0.0137
	(0.4471)	(1.6721)	(−0.5773)	(−0.8921)	(−0.6285)	(−0.6508)
Feb. 23 - Mar. 22	0.0139	0.0684	−0.0102	−0.0267	0.0076	0.0094
	(0.6627)	(3.2012)	(−1.1767)	(−0.5861)	(0.5856)	(0.2228)
Mar. 23 - Apr. 17	0.0220	0.0298	−0.0028	0.0418	0.0216	−0.0185
	(1.6966)	(0.4164)	(−0.3467)	(2.6243)	(0.9203)	(−0.7049)
Obs.	261	197	223	205	223	261
R^2	0.0077	0.0255	0.0023	0.0192	0.0043	0.0029