# Information Processing Skills of Short Sellers: Empirical Evidence from the Covid-19 Pandemic

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**January 2021**

We aim to answer if superior performance by short sellers' is generated by processing public information rather than by exploiting private information. To achieve this, we analyze if short sellers with healthcare expertise outperform in short selling of non-healthcare stocks compared to those with no healthcare expertise. Since we expect that any short sellers' private information about healthcare stocks is unlikely to be material for non-healthcare stocks, we conclude that any observed outperformance in non-healthcare stocks is more likely caused by processing public information. As an identification strategy, we interpret the outbreak of the Covid-19 pandemic as a treatment to short sellers with healthcare expertise. Our measures of healthcare expertise are based on pre-Covid-19 performance related to either holding or covering a short position in healthcare stocks. Using a unique German sample of daily short selling data, we find that treated short positions identified by general shorting (covering) outperformance are associated with lower 10-day CARs for non-healthcare stocks by an economically significant magnitude of 4.3 percent (7.2 percent). Robustness test rule out that our results are also driven by the use of private information or non information-based trading advantages such as better funding or lending ability of observed short sellers.

Keywords: short sales; healthcare; Covid-19, information processing skills; private information

JEL classification code: G14, G23

We thank Jean-Gabriel Cousin, Gael Imad'Eddine, and Martin Ruckes, and participants of the Research Seminar 2020 at the University of Lille for helpful comments and discussions.

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## 1. Introduction

The literature provides overwhelming evidence that short sellers are informed and sophisticated traders with an information advantage over other market participants (e.g., Asquith, Pathak, and Ritter (2005); Boehmer, Jones, Wu and Zhang (2020); Boehmer, Jones, and Zhang (2008); Desai, Ramesh, Thiagarajan, and Balachandran (2002); Diether, Lee, and Werner (2009)). But how do they obtain their information advantage? Whereas there are some empirical indications for the use of private information for informed short selling (e.g., Boehmer, Jones, Wu, and Zhang (2020); Christophe, Ferri, and Angel (2004); Karpoff and Lou (2010)), Engelberg, Reed, and Ringgenberg (2012), for instance, document that short seller's information advantage is determined by their superior skills to process public information.

Our paper aims to provide empirical evidence for this information processing argument and applies a difference-in-differences approach by interpreting the exogenous shock event of the Covid-19 pandemic in 2020 as treatment to short sellers with healthcare expertise. If short sellers with healthcare expertise (treatment group) outperform a control group of other short sellers without healthcare-specific trading skills in short selling non-healthcare stocks after the outbreak of the Covid-19 pandemic, we interpret this finding as empirical evidence that this outperformance is likely caused by public information processing skills of treated short sellers rather than their use of private information on healthcare stocks because private information on healthcare stocks is less likely applicable in superior trading of non-healthcare stocks. As outcome of superior information processing skills we regard better predictions of the pandemic's impact on non-healthcare firms' stock performance because of two reasons. First, we expect that healthcare expertise leads to more timely acquisition of publicly-available but hard-to-find pandemic-related information. Second, we assume that healthcare expertise enables a more accurate understanding and subsequent prediction of the dissemination and health impact of Covid-19 to anticipate more precisely customer behavior changes and governmental measures such as lockdowns, shutdowns, stay-at-home orders, and travel restrictions.

We use the Covid-19 pandemic in our analysis as an appropriate identification strategy of public information processing skills as source of short sellers' information advantage for several reasons. First, it is exogenous by nature so no short sellers have anticipated it. More precisely, healthcare expertise is unlikely to enable them to anticipate it so the group assignment is uncorrelated with this treatment event. Second, the newness of the Covid-19 disease makes it rather unlikely that private information on healthcare stocks helps anticipate the availability of a vaccine or any medical treatment against Covid-19 shortly after its outbreak so that we assume that outperformance of short sellers with healthcare expertise is not driven by such private information. Third, since we rely on timely disclosed public information in our study, Covid-19 caused skyrocketing volatility and higher short selling constraints through stock recalls by selling long investors and withdrawals in short sellers' funds likely prevent uninformed short sellers from immediate imitating informed short sellers' trading so that we are more able to measure the outcome of informed short sales in our empirical setting.[1]

For our analysis, we build a sample of daily publicly disclosed short sales in Germany before and during the pandemic. In a first step, using a multivariate regression model, we assign healthcare expertise to short sellers that outperform in holding short positions or, alternatively, in covering short positions both in healthcare stocks over the course of seven years reasonably earlier before the outbreak of Cocid-19. In our subsequent main analysis, we date the outbreak event of the Covid-19 pandemic on January 3, 2020 and find that after this date non-healthcare stocks perform worse if their short sellers possess healthcare expertise based on holding short positions or covering them. Since we assume that those outperforming short sellers use more likely public information on Covid-19 for their trades, we interpret this finding as empirical evidence that their information advantage stems from superior information processing skills rather than the use of private information on specific stocks. We find that the value of healthcare expertise is also economically significant: in the case of, for instance, the 10-day cumulative abnormal returns, short sellers with healthcare expertise outperform their control group post-shock by 4.3 percent when using the general shorting performance, and by 7.2 percent when applying the covering performance to identify healthcare expertise. Consistently, we find qualitatively similar outperformances for 5-day and 20-day CAR windows.

We choose German data in our study for several reasons: First, in Germany as in all other EU-member states, short sellers are obliged to disclose changes to their short holdings in listed firms if they exceed 0.5 percent of shares outstanding (e.g., Jan et al. (2019)). Combining these public disclosures with stock data, the high level of detail in our sample allows us to track every position individually

[1] Jank, Roling, and Smajlbegovic (2019) show that short sellers that trade below the public disclosure threshold of 0.5 percent of stocks shorted outperform above-this-threshold short sellers. They argue that disclosure might deter short selling because others might react to them timely potentially causing lower profits.

throughout the complete sample period from Nov. 1, 2012, through June 30, 2020. Second, Germany has an internationally relevant and sufficiently large publicly-listed healthcare industry. Third, Germany is the only Euro-zone country with developed financial markets that refrains from issuing a ban on short sales during Covid-19. Fourth, even if the UK stock market is larger than the German stock market, we expect that Brexit-induced market volatility and information flow makes it difficult to apply a shock event-based treatment model.

As a first robustness test, we also run our regressions with a sample also including and one only including healthcare stocks. Our results hold for the sample including all industries that shows that our analysis without healthcare stocks does not suffer from a selection bias. In the case of a sample containing solely healthcare stocks, we find no relation of treated short positions to performance that supports our assumption that private information on healthcare stocks such as information on the development of a vaccine or medical treatment against Covid-19 provides no additional information advantage in trading during the Covod-19 pandemic. In addition, we find statistically significant evidence that during the pandemic healthcare expertise is related to higher outperformance in short selling of non-healthcare stocks compared to short selling of healthcare stocks.

In addition, one major concern might be that outperformance of short sellers with healthcare expertise is also driven by factors other than our suggested information-based trading advantage through healthcare expertise during the Covid-19 pandemic. Alternative sources of such outperformance might be the ability to secure funding by short sellers' own investors during pandemic-caused financial market turmoil when fund investors tend to withdraw money, or the ability to locate stocks for borrowing in those volatile pandemic times when stock lenders tend to recall lent-out stocks to trade themselves. To rule out such non information-based trading advantages as alternative explanations for our findings, we conduct several empirical tests.

First, we examine if the outperformance of healthcare expertise short sellers is caused solely by general short selling skills that we expect to stem from the ability to secure funding and locate stocks more likely than the ability to acquire and process information. Applying a measure of general shorting skills, we are not able to replicate our results so that our assumptions are not weakened by alternative explanations such as non information-based skills.

Second, we apply an alternative measure of healthcare expertise that is based on short sellers' fraction of long positions in healthcare stocks retrieved from 13F filings with the SEC. Then, we obtain qualitatively the same results. Since this measure is unrelated to technical short selling abilities such as locating stocks, this finding does not support such an alternative explanation.

Third, we retrieve stock lending data from IHS Markit to include lending fee, active utilization, and short selling risk calculated according to Engelberg, Reed, and Ringgenberg (2018) to control for short selling constraints. Again, our findings remain robust to their inclusion so that non informational trading advantages are not supported to drive our results.

Our paper contributes to several strands of the short sale literature. Our findings extend the understanding about the sources of short sellers' information advantage contributing to studies that assign such advantage to the use of private information (e.g., Christophe et al. (2004); Karpoff and Lou (2010)) or public information processing (e.g., Kandel and Pearson (1995); Engelberg et al. (2012)). To our knowledge, we are the first to document a causal relationship for superior information processing skills being a driver for short selling outperformance.

Our additional analysis with 13F data to identify industry-specific trading expertise contributes to the literature on investor skills beyond the narrower view on short sellers (e.g., Kacperczyk and Seru (2007), Cremers and Petajisto (2009), Baker et al. (2010)).

Moreover, our studies contribute to literature on institutional investors during economic crises (e.g., Kacperczyk, Van Nieuwerburgh, and Laura Veldkamp (2011)), in particular during the Covid-19 pandemic (e.g., Pástor and Vorsatz (2020)).

Regarding methodology, we use the Covid-19 outbreak as appropriate identification strategy and thus add to other studies using Covid-19-induced governmental measures for similar identification and difference-in-differences approaches (e.g., Heggeness (2020); Coibion, Gorodnichenko, and Weber (2020); Betcherman et al. (2020); Giommoni and Loumeau (2020)). Most related to our idea that the Covid-19 outbreak is linked to an information advantage for trading and is used for an identification strategy, Henry, Plesko, and Rason (2020) document that insiders of U.S. firms with operations in China trade more frequently early after the Covid-19 outbreak that they attribute to their early access to information on Covid-19 compared to their U.S. counterparts without Chinese operations.

The remainder of this paper is structured as follows: Section 2 provides a literature review and develops the hypothesis. Section 3 describes the data and the empirical strategy. Section 4 presents summary statistics and main results. Section 5 includes various robustness tests. Concluding comments are provided in Section 6.

## 2. Related Literature and Hypothesis

### 2.1 Related Literature

Short Sellers are generally perceived to be informed and sophisticated traders because a wide range of researchers show that short selling predicts future stock returns (e.g., Asquith et al. (2005); Boehmer et al. (2008); Desai et al. (2002); Diether et al. (2009)). Theoretical models suggest they trade on private information, thereby revealing parts of their information to uninformed investors or copycat traders, and eventually this mechanism causes the information to be incorporated into stock prices (Glosten and Milgrom (1985); Kyle (1985)). Empirical studies find that short selling indeed aids the process of price discovery and improves market efficiency (Aitken et al. (1998), Boehmer and Wu (2013)).

Considerable efforts have been devoted to understanding short sellers' information advantage throughout the last decades. Overvaluation is regularly ascribed as the main motivation for short sellers. Studies find that short sellers have private information about earnings and fundamentals (Boehmer et al. (2020)), and trade on temporary deviation from those fundamentals (Diether et al. (2009)). They are adept at identifying stock-specific overvaluations and avoid shorting undervalued stocks (Boehmer, Huszar, and Jordan (2010)). There are, however, other motivations such as tax, hedging and arbitrage, of which arbitrage seems to be the most prevalent (Brent et al. (1990); Asquith et al. (2005)). The informational content of short sales depends on the underlying motivation, as, for example, arbitrage and hedging trades exert comparably weaker negative impact on stock prices (Aitken et al. (1998)). Moreover, different trader characteristics are associated with different degrees of informational content. Boehmer et al. (2008) show that among individual, institutional and proprietary traders, nonprogram institutional traders' positions are most negatively associated with future stock returns.

Building on the question whether active fund management adds value to investors, a wide body of literature examines if active fund managers possess skills. While the average mutual fund does not outperform passive investment strategies net of fees, many studies find that a small subgroup of mutual funds persistently outperforms (e.g., Kacperczyk and Seru (2007); Cremers and Petajisto (2009); Baker et al. (2010)). Findings are similar for hedge funds in the way that only a subset of traders persistently outperforms (Jagannathan, Malakhov and Novikov (2010); Grinblatt et al.

(2020)). However, there is strong consensus that short sellers, on average, have an information advantage over other market participants (Asquith et al. (2005); Boehmer et al. (2020); Boehmer et al. (2008); Desai et al. (2002); Diether et al. (2009)).

When asking where the advantage stems from, prevalent explanations are the use of private information or superior processing skills of public information (e.g., Kandel and Pearson (1995)). Agarwal et al. (2013) use quarterly hedge funds' 13F filings to demonstrate outperformance in confidential holdings, suggesting the use of private information. Moreover, managers with a lower reliance on public information perform better than their peers (Kacperczyk and Seru (2007)), and short sellers are shown to trade before the public revelation of financial misrepresentation (Karpoff and Lout (2010)).

On the contrary, Engelberg et al. (2012) examine short sales around news event and find no evidence in favor of private information. They do, however, find evidence for better pulblic information processing skills as short sellers increase trading directly after the publication of news. A skilled information processor converts new public data into valuable trading information, e.g., by analyzing corporate news (Engelberg (2008)). Boehmer et al. (2020) find empirical evidence for short sellers' trading on public superior processed as well as private information. In addition, they document that the information advantage more likely stems from the use of private information.

### 2.2 Hypothesis

Following literature consensus, informed short sellers obtain superior performance through the use of private information or superior public information processing skills. As outlined above, only few studies address the question as to what extent outperformance stems from either of these sources, as they are difficult to distinguish under normal market conditions.

Contributing to this question, we aim to exploit the unique market conditions during the Covid-19 pandemic to disentangle public information processing skills from private information. The pandemic constitutes a large exogeneous shock to global financial markets that alters market conditions. Since the Covid-19 pandemic is a healthcare crisis by nature, we argue that healthcare-related information which is used to be industry-specific becomes value-relevant for all industries: Firm-specific information (i.e., private information) becomes subordinate to pandemic information that shows global impact and becomes promptly publicly available. Kacperczyk et al. (2011) argue that aggregate payoff shocks are more volatile, and the price of risk is increased during downturns. Following this, we assume acquiring and processing information about the aggregate impact of a pandemic shock to be more valuable than doing so for micro-level (i.e., firm-level) information: Acquisition of firm-specific information loses its relevance as markets are driven by Covid-19 news which are publicly available in a timely manner due to the global communication infrastructure and public and press interest. Furthermore, we argue that private information value is low in times of the pandemic indicated by the fact that firms' management themselves are not able to assess the impact of Covid-19 as documented by the numerous withdrawals of earnings guidance.[2] So, we expect that short sellers that are experienced in the healthcare industry (henceforth denoted as expertise traders) have an edge over their peers, as the Covid-19 shock enables them to use their industry-specific trading expertise for market-general trading.[3]

In terms of aggregate information processing most relevant for the market level, expertise traders possess knowledge about models of infectious diseases and their applications (e.g., Anderson R.M., Anderson B. and Might (1992); Hethcote (2000); Kermack and McKendrick (1927)), enabling them to forecast global contagion. They can assess probability and severity of lockdowns, shutdowns, stay-at-home orders, and other governmental measures. On the firm level, they are advantaged at assessing winners[4] and losers[5] of Covid-19, or finding resilient and vulnerable geographical regions in regard to their healthcare infrastructure[6], ultimately affecting the workforce of local companies and consumer demand. One might argue that the act of acquiring aggregate healthcare information is the same for expertise and non-expertise short sellers as they belong to the most informed and

[2] For an overview of withdrawals, see Ashwell, Ben (2020): How Covid-19 is affecting earnings guidance and dividend payments, URL: https://www.irmagazine.com/reporting/how-covid-19-affecting-earnings-guidance-and-dividend-payments, [Oct 31, 2020]

[3] This wording is similar to the terms specific and general human capital in the personnel and labor economics literature.

[4] One example of a Covid-19 winner is HelloFresh AG, a Germany-based company that provides online food services. Driven by increased business during the lockdown period, HelloFresh customer demand more than doubled over the course of the pandemic. Expertise traders might have advantages at assessing the duration and severity of lockdowns.

[5] An example of a Covid-19 loser is TUI AG, a multinational travel and tourism company headquartered in Germany. Lockdowns and travel restriction pose a severe limitation to business activities. Expertise traders might have advantages at assessing the pandemic situation at major destinations and itineraries.

[6] The Spanish healthcare system, for instance, is generally perceived to be of high quality. Nevertheless, Spain became the worst hit European country regarding confirmed infected patients and ranks top three for deaths in Europe (as of Oct. 31, 2020. Reported by John Hopkins University). Expertise traders might have advantages at assessing the pandemic development in Spain which ultimately impacts firms that draw workforce from Spanish regions or engage in business activities with such firms.

sophisticated traders, but nevertheless we expect the pace differs: the processing for non-expertise traders takes longer, but they might achieve the same trading-relevant information in the end.

Which short sellers then possess healthcare expertise? Prior studies define mutual fund or hedge fund manager skills as the ability to persistently generate alpha over a longer time period, e.g., 3 years, 5 years, or even 10 years (e.g., Cremers and Petajisto (2009); Grinblatt et al. (2020), Jagannathan et al. (2010); Baker et al. (2010)). We follow the literature and define healthcare expertise as industry-specific, persistent outperformance in healthcare stocks pre-Covid-19. Thus, we identify the outperforming short sellers pre-Covid-19 and assess their performance during the Covid-19 pandemic. As outlined above, since we assume that private information on healthcare stocks is unlikely material to improve short selling performance in non-healthcare stocks, only information processing skills remain as potential source of information advantage of healthcare expertise in trading non-healthcare stocks. Since we argue that Covid-19 related information is public by nature and can be processed better by healthcare expertise traders, we suggest that short sellers with healthcare expertise profit from superior Covid-19-related public information processing when trading non-healthcare stocks because for those stocks Covid-19 information is also highly relevant. This reasoning leads to our main hypothesis:

> *Healthcare expertise is associated with superior short selling performance in non-healthcare stocks during the Covid-19 pandemic.*

## 3. Methodology

### 3.1 Sample Construction

We use German data on publicly disclosed short positions as provided by the German Federal Financial Supervisory Authority[7] (BaFin) from Nov. 1, 2012, through June 30, 2020. Changes in short positions must be disclosed via the Federal Gazette (Bundesanzeiger). We use these disclosures to construct a panel of daily short positions in German stocks, including stocks from direct neighboring countries for which the main trading venue lies within Germany.[8]

[7] In German: Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin)
[8] List of stocks and short sellers are tabulated in Appendix A1.

Starting Nov. 1, 2012, the BaFin implements a two-tier transparency system for disclosing net short positions in stocks exceeding a certain threshold, as constituted by the EU Short Selling Regulation.[9] A first notification to the BaFin must be made by 3:30 p.m. on the following trading day if the net short position exceeds 0.2 percent of a firm's issued shares, and subsequently for each additional 0.1 percent.[10] Upon exceeding 0.5 percent, short sellers are also required to publicly disclose those short positions in the Federal Gazette. Position changes in between two thresholds (e.g., between 0.5 percent and 0.6 percent) are not subject to disclosure. The regulation applies to all issues for which the main trading venue lies within the EU and includes information on position size, stock issuer, ISIN and the name of the investor.[11]

After the outbreak of the Covid-19 pandemic, six EU member states issued a ban on short selling beginning in late April.[12] With Germany and UK not participating in a ban, short selling in UK financial markets might be related to Brexit-induced information. Thus, we argue that Germany is the only country within the EU that provides high-quality daily data on short selling during the pandemic, has developed financial markets, and has a significant healthcare industry with international relevance. Thus, we observe only German data in our study.

Due to the disclosure threshold, we do not observe the exact day of the opening or covering of short positions. Instead, we observe the first day on which the aggregate short position initially surpasses the reporting limit (henceforth opening), the day on which the position declines below the reporting limit (henceforth covering), and changes in between both dates if they exceed another 0.1 percent threshold. As a consequence, a short seller might build up a position before we are able to observe an opening, and keep a position below the threshold after we observe a covering. Consequently, our sample only accounts for positions that are publicly observable, and we are not able to correctly

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[9] See Article 5(1) and 5(2), and Article 6(1) and 6(2) of *Council Regulation (EU) No 236/2012 of 14 March 2012 of the European Parliament and of the Council on short selling and certain aspects of credit default swaps [2012] OJ L86/1.*

[10] On Mar. 16, 2020, the European Securities and Markets Authority (ESMA) adopted a decision to lower the initial reporting threshold to 0.1 percent instead of 0.2 percent. See *European Securities and Markets Authority Decision (EU) No 2020/525 of 16 March 2020 to require natural or legal persons who have net short positions to temporarily lower the notification thresholds of net short positions in relation to the issued shares capital of companies whose shares are admitted to trading on a regulated market above a certain threshold to notify the competent authorities in accordance with point (a) of Article 28(1) of Regulation (EU) No 236/2012 of the European Parliament and of the Council [2020] OJ L116/5.*

[11] Investors can be both natural and legal persons.

[12] Austria, Belgium, France, Greece, Spain and Italy issued a temporary ban on short selling, starting on Mar. 17 or 18, 2020.

estimate the returns of the entire short position. Jank et al. (2019) use confidential data on short positions below the disclosure threshold to provide insights on the behavior and performance of secretive short sellers.

We build two disjunct data samples: First, we create a larger sample prior to the pandemic (henceforth Training Set[13]) which we use to estimate persistent outperformance in trading healthcare stocks, i.e., healthcare expertise. Second, we create a 1-year sample around the Covid-19 shock (henceforth Covid Set[14]) to apply a difference-in-differences approach, including 6 months of data in the pre-Covid-19 and post-Covid-19 period each. Midnight on June 30, 2019, constitutes the separating date between both sets. The Training Set then covers Nov. 1, 2012, through June 30, 2019, whereas the Covid Set covers Jul. 1, 2019, through June 30, 2020.

In total, our complete sample comprises 266 different short sellers and 214 different stocks in total, including a range of well-known brokers and hedge funds like J.P. Morgan or Renaissance Technologies. Of that, 136 short sellers and 146 stocks show at least one active short position during Covid-19. Throughout the complete sample period, stocks and short sellers appear in 1497 unique combinations,[15] of which the Covid Set covers 38%. Overall, short sellers file 22,313 disclosures in the Training Set and 4,853 in the Covid Set, resulting in 232,757 and 53,010 days with active short positions, respectively.

We use industry classifications from Capital IQ to label each stock as healthcare or non-healthcare. If a business is too diversified or allocates only few resources to healthcare-related activities, we cannot be certain whether traders execute their short sales due to healthcare-related information. Therefore, a stock is classified as healthcare only if most of the firm's business engages in healthcare activities.

We complement our data with stock-level information from the Capital IQ database (e.g., market capitalization, spread, turnover, volatility) and daily abnormal returns. Following prior literature, we implement a conservative approach and assume that sophisticated traders exercise their trades near market close (Jank et al. (2019)). Hence, we estimate returns based on the stock's daily adjusted close price in excess of the dividend-adjusted German Prime All Share Index. This accounts

[13] Referred to as Estimation Window in Event Study Terminology
[14] Referred to as Observation Window in Event Study Terminology
[15] In some cases, a combination of a short seller and stock appears multiple times. This is due to entities that trade an issue through different investment vehicles at the same time. Common examples for distinguishable multi-vehicle entities are Blackrock, Marshall Wace, and Citadel.

for the circumstance that only the aggregate short position at the end of the day (midnight) must be disclosed and intraday changes in position size are generally unobservable. Furthermore, we control for aggregate short interest in a stock using all simultaneously disclosed short positions from the Federal Gazette.

### 3.2 Empirical Strategy

*Training Set: Determining health expertise*

Following our hypothesis, we aim to identify a group of short sellers that possess healthcare expertise before the pandemic outbreak. As stated above, expertise refers to the ability to generate persistent abnormal returns in a specific industry (i.e., industry-specific skill). Thus, we estimate the following fixed-effects panel regression model in our Training Set for each short seller *j* individually:

$$Abnormal\ Returns_{i,t} = \alpha_t + \beta_0\left(Position_{i,t}\ x\ Healthcare_j\right) + \gamma_{i,t}X_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t}\ ,$$

where the dependent variable is the 10-day abnormal return in excess of the German Prime All Share Index.[16] $X_{i,t}$ denotes control variables on the firm level *i*.[17] $\delta_i$ denotes fixed effects on the firm level. $\theta_t$ denotes time fixed effects.

First, we examine the impact of the individual position size on 10-day abnormal returns (henceforth Shorting Expertise). $Position_{i,t}\ x\ Healthcare_i$ denotes the interaction term of individual position size and healthcare stock classification, and the corresponding coefficient is used as the expertise measure. The literature consensus states that a high degree of short selling predicts lower future returns (e.g., Asquith et al. (2005); Boehmer et al. (2008)). Hence, the coefficient is expected to be negatively linked to abnormal returns (i.e., negative coefficient for larger short selling performance) if a short seller is truly skilled. The measure accounts for the overall short selling performance, but we cannot assess if the traders are adept at timing their trades.

We use a variety of stock-specific and trade-specific controls in our models. In particular, we control for position size and opening days; in the spirit of Boehmer et al. (2018), we include coverings days and prior day short interest as reported in the Federal Gazette. Moreover, we include market capitalization (denoted as *MarketCap*), market-to-book ratio, the logarithm of the average prior 5-day

[16] All stock returns here and forthcoming are winsorized at the 1 and 99 level.
[17] On a short seller level, it is difficult to observe specific characteristics, e.g., assets under management or portfolio turnover, since most traders inherent a secretive behavior and data availability on the long side of trades is not as good as on the short side.

spread plus one, the logarithm of the 3-month volatility plus one, the 1-year beta and the average 5-day turnover. Also, 5-day prior abnormal returns are used to control for momentum effects.[18]

As a second measure to identify healtcare expertise, we implement a measure based on covering of short positions that reflects more precisely timing ability (henceforth Covering Expertise) inspired by Boehmer et al. (2018) as follows:

$$Abnormal\ Returns_{i,t} = \alpha_t + \beta_0\left(Cover_{i,t}\ x\ Healthcare_j\right) + \gamma_{i,t}X_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t}$$

Boehmer et al. (2018) shed light on the price movement around covering dates and find positive stock returns on the exact day of covering, although partially reverting over the course of the next 7 days due to market impact reversal. Their evidence suggests that some short sellers exhibit timing in covering shorts. Likewise, we examine abnormal returns around coverings in healthcare stocks and expect positive returns post-covering if traders are truly skilled. By using 10-day abnormal returns we ensure that a technical price run-up, induced by the market impact of large buy orders, has already reverted by the time we take measure. This way we account for the information-driven impact of coverings. $Cover_{i,t}\ x\ Healthcare_i$ denotes the interaction term of covering days and healthcare stock classification, and $\beta_0$ then constitutes our expertise measure.

The samples are reduced to active short positions to reduce noise. Consequently, we apply the models for all 266 short seller and retrieve a list of statistically significant interaction coefficients at the five percent level. Traders are assigned to the healthcare expertise group or control group depending on their measure's association with 10-day abnormal returns and if their corresponding coefficients are statistically significant at the five percent level. Then, we assign short sellers to the healthcare expertise group if the measure for Shorting Expertise (Covering Expertise) is negative (positive).

For those coefficients that are statistically insignificant, or if we lack short disclosures in healthcare stocks, we cannot assume a group assignment due to the disclosure threshold of 0.5 percent in a firm's outstanding shares. Jank et al. (2019) use confidential data provided by the BaFin to show how secretive short sellers consistently refrain from crossing the reporting threshold. So even if we do not observe traders' individual positions in some cases, they might still have a smaller active short position and exert unobservable expertise.[19]

[18] An overview of the variables can be found in Appendix A2.
[19] Example regressions for the expertise measurement are reported in Appendix A3.

*Covid-Set: difference-in-differences approach*

Subsequently, we examine the expertise traders' performance post-shock in market-general trading. A naive approach suggests examining the difference in 10-day abnormal returns in non-healthcare stocks for the pre-Covid-19 and post-Covid-19 period. This method, however, captures the entire effect of the Covid-19 pandemic. To isolate the higher value of healthcare expertise, we propose a difference-in-differences approach. Specifically, the expertise group is affected the Covid-19 shock and the shock of elevated expertise value, whereas the control group is exposed to the Covid-19 shock only. If returns are driven by processing of public information, we expect the expertise group to outperform the control group in trading non-healthcare stocks post-Covid-19.

$$Effect\ of\ HC\ Leverage\ = \left(\bar{\alpha}^{post}_{HC\ Value} - \bar{\alpha}^{post}_{HC\ no\ Value}\ \mid\ E = 1\right),$$

To account for the Covid-19 shock, we need to know how the expertise group would have performed given there was no higher value added for healthcare expertise ($\bar{\alpha}^{post}_{HC\ no\ Value}$) . The delta to the observed performance ($\bar{\alpha}^{post}_{HC\ Value}$) then precisely represents the isolated effect of healthcare expertise on performance. However, $\bar{\alpha}^{post}_{HC\ no\ value}$ is unobservable by design. $E$ denotes the expertise group.

Instead, the difference-in-differences approach circumvents unobservable outcomes by imposing parallel trends. That is, had the trading advantage of healthcare expertise not happened, both groups would have shown the same change in average performance. We thus use the observed change in the control group to estimate the unobserved change in the expertise group as follows:

$$Effect\ of\ Healthcare\ Expertise = (\ \bar{\alpha}^{post}_{Exp} - \bar{\alpha}^{pre}_{Exp}\ ) - (\ \bar{\alpha}^{post}_{Control} - \bar{\alpha}^{pre}_{Control}\ ),$$

where $\bar{\alpha}^{post}_{Exp}$ and $\bar{\alpha}^{pre}_{Exp}$ denote the expertise group's average investment performance after and before the shock, respectively. Vice versa, $\bar{\alpha}^{post}_{Control}$ and $\bar{\alpha}^{pre}_{Control}$ denote the control group's average investment performance before and after the shock.

*Covid Set: regression model*

Identically to our Training Set estimations, 10-day abnormal returns are used as dependent variable in the difference-in-differences approach. We argue that a 10-day return window is sufficiently short to capture relevant information in efficient financial markets, and sufficiently long not to be biased by the market impact of large orders.[20]

To apply the difference-in-differences approach, we specify our fixed effects panel regression model as follows:

$$Abnormal\ Returns_{i,j,t} = \alpha_t + \beta_0\left(Covic_t\ x\ Expertise_j\right) + \beta_1 Covid_t + \gamma_{i,j,t} X_{i,j,t} + \delta_{i,j} + \theta_t + \varepsilon_{i,j,t}$$

We implement a dummy variable $Covid_t$ for the post-Covid period and the interaction term $Covic_t\ x\ Expertise_j$ captures the effect of Covid-19 on expertise traders after the shock. The Covid Set ranges from Jul. 1, 2019, through June 30, 2020, and both the pre-Covid-19 and post-Covid-19 period represent a 6-month interval around our suggested shock date on January 3, 2020.

*When does the pandemic shock take place?*

The choice of shock date is critical. On January 3, 2020, the AAAS[21] is the first association to feature a scientific article about the pandemic on ScienceMag.org[22], thereby providing public and easily accessible information on the virus. Hence, we argue that short sellers possess knowledge about Covid-19 by January 3, 2020. Considering major indices movements, another approach suggests Saturday, Feb. 22, 2020, as shock date. On that day Italy reported the first European Covid-19 casualty,[23] followed by severe declines in global financial markets after the weekend. We refrain from using this shock date as it represents the point in time that the entirety of non-sophisticated traders is unanimously informed about the virus. Alike, we also refrain from using the WHO's declaration of the pandemic outbreak[24] as it is too late to capture relevant effects.[25]

[20] We also test 5-day and 20-day abnormal returns and obtain qualitatively the same results.

[21] American Association for the Advancement of Science

[22] Normile, Dennis (2020): Novel human virus? Pneumonia cases linked to seafood market in China stir concern; URL: https://www.sciencemag.org/news/2020/01/novel-human-virus-pneumonia-cases-linked-seafood-market-china-stir-concern [Oct 31, 2020].

[23] See Mackenzie, James (2020): First Italien patient dies of coronavirus: Ansa news agency; URL: https://www.reuters.com/article/us-china-health-italy-death/first-italian-patient-dies-of-coronavirus-ansa-news-agency-idUKKBN20F2W5 [Oct 31, 2020].

[24] See Farge, Emma, and Michael Shields (2020): World Health Organization calls coronavirus outbreak 'pandemic' for first time; URL: https://www.reuters.com/article/us-health-coronavirus-who-idUSKBN20Y2OI [Oct 31, 2020].

[25] Henry at al. (2020) choose January 19, 2020 as the starting point of the Covid-19 period when the first trading is after the US has begun screening travelers from the Chinese city Wuhan.

Finally, can the shock occur prior to January 3, 2020? We do not have plausible evidence on public information on the pandemic before our main shock date, however, short sellers might possess indications about Covid-19 at an earlier point in time. In this case, our empirical results would be weakened in statistical significance rendering our result more conservative.

*Identifying assumptions*

For identification, the parallel trends assumption represents a necessary condition. We assume parallel trends as

$$\mathbb{E}\left[\bar{\alpha}_{HC\ no\ Value}^{post} - \bar{\alpha}_{pre\ Shock}^{pre} \mid E = 1\right] = \mathbb{E}\left[\bar{\alpha}_{HC\ no\ Value}^{post} - \bar{\alpha}_{pre\ Shock}^{pre} \mid E = 0\ \right],$$

where E = 1 denotes the expertise group and E = 0 denotes the control group. This equation imposes the same difference in average investment performance for both groups from pre-Covid-19 to post-Covid-19 had there been no leverage of healthcare expertise. However, $\bar{\alpha}_{HC\ no\ Value}^{post}$ is an unobserved counterfactual and therewith parallel post-trends are an assumption by design. Instead, we test for parallel pre-trends to ascertain the validity of our difference-in-differences model. Healthcare stocks are excluded from the test as intuition suggests they enable healthcare expertise traders to achieve systematic outperformance. This, however, prevents us from examining the effect of processing skills on market-general trading.

Appendix A4 reports the outcome of our test for parallel pre-trends. Using the 6-month period before the Covid-19 outbreak to identify short-run parallel trends, we find statistically insignificant differences in monthly performance after controlling for group-specific trends. We therefore fail to reject parallel pre-trends (see Kahn and Lang (2019); Roth (2018)). Furthermore, both groups show similar associations with control variables and we assume the groups to be equally affected by other exogeneous forces post-Covid-19 (see Dimick and Ryan (2014), Ryan et al. (2015)).

## 4. Empirical Results

### 4.1. Descriptive Statistics

Figure 1 shows the time trend of disclosed shorting activity in the Covid Set. On any given day, an average of 191 positions are public as reported by the Federal Gazette. These positions account for an average aggregate value EUR 52,590 million in short sales. Noticeably, Graph A reveals interesting changes in shorting activity. Firstly, the total number of short positions that are public stays within a narrow corridor between 230 and 196 active disclosures, suggesting there is a rather stable group of traders that consistently cross the reporting threshold (see Jank et al. (2019)). Secondly, starting in mid-October, the total value shorted shows a run-up until the crash in March without noteworthy increases in nominal positions. This spread is related to a simultaneous run-up in stock prices and increasing short interest. At peak, traders hold EUR 66,398 million in public short sales. Lastly, when the downward price movements commence in mid-March, active short positions increase and decrease inverse to market returns, but only as the markets already plunge, suggesting short sellers capitalize on the momentum.

Graph B underlines March as the busiest month for short sellers. We observe an average of 41 openings and coverings each month except March, which shows twice the activity. Both the day with the most openings and the day with the most coverings take place during March.[26]

Detailed summary statistics are reported in Table 2. We report statistics both with (A) and without (B) healthcare stocks, but we do find not a significant difference in magnitudes for any of the variables. To classify the characteristics of the Covid Set, we refer to related studies by Jank et al. (2019) who use the same disclosure mechanism in a sample with German stocks. Levels in short interest and marker capitalization are very similar, however, spread is only one half to one fourth of the levels observed by Jank et al. (2019), suggesting enhanced liquidity during Covid-19 markets. Overall, statistical characteristics are in similar ranges. When comparing to Boehmer et al. (2018) who use disclosure rules on Japanese markets to assess covering trades, characteristics differ to a greater extent, i.e., market capitalization, market to book, and aggregate short interest is lower for Japanese stocks. The difference in short interest is likely due to the sample construction by Boehmer et al. (2018) including all listed stocks, whereas we only examine stocks that have at least one active short position. The differences in the remaining variables pertain to the lower threshold of 0.25 percent for public disclosure in Japan, making more stocks eligible for the list of stocks with publicly held short positions, and there are more small firms than large firms. The disparity suggests that lowering the threshold forces more public short disclosures for mid or small caps, ultimately reducing the average and median market capitalization of shorted stock.

As expected, we observe a negative mean and median for abnormal returns, except for the 20-day median. Excluding healthcare stocks yields even lower returns which coincides with the intuition that healthcare stocks might not be as affected by the crisis as other firms might be. When disaggregating summary statistics (reported in Table 2) into pre-Covid-19 and post-Covid-19 intervals, we

[26] Maximum openings (16) on March 9. Maximum coverings (9) on March 24.

find that mean and median returns are invariably positive prior to Covid-19 and negative afterwards. Interestingly, the level of aggregate short interest is rather stable which coincides with the observed narrow corridor of nominal public disclosures.[27] We observe slightly greater averages for market capitalization which might be due to more short selling in large firms, volatility and spread increase post-Covid-19.

[27] See Figure 1. Active disclosures are between 196 and 230 at any given point.

### 4.2 Main Results

Table 3 displays the results of our difference-in-differences estimation. The interaction terms for Shorting Expertise represent statistically significant alphas of -2.0 percent, -4.3 percent, and -7.7 percent for 5-day, 10-day, and 20-day stock returns, respectively. They reflect the average alpha of expertise traders over their non-expertise control group during the pandemic indicating that the expertise group indeed exhibits superior performance. Moreover, from 5-day to 10-day returns and from 10-day to 20-day returns, the alpha grows 109 percent and 81 percent, respectively. This co-efficient growth indicates that outperformance is persistent within our measured return windows, and expertise traders increase their alpha as their holding periods lengthen. It seems the effect is more pronounced for the 5-day to 10-day transition and shows deceleration for longer return-win-dows.

Specifications (4)-(6) show the regression results for Covering Expertise. Consistent with the results for Shorting Expertise, we find significant alphas of -2.6 percent, -5.9 percent, and -10.8 percent for 5-day, 10-day and 20-day returns, respectively.

Consistent with our hypothesis, our findings indicate that expertise traders possess superior pro-cessing skills in Covid-19 markets, as healthcare information is then also relevant for non-healthcare stocks. Taken together, since short sellers devote their resources to processing Covid-19 infor-mation, the expertise traders have an edge through their superior processing skills of healthcare-related information, and ultimately generate alpha over their control group with no healthcare ex-pertise in market-general trading.

The coefficients on the *Covid* variable in specifications (1)-(6) reflect the expected mean change in returns from pre- to post-shock for the control group. There are only statistically significant coeffi-cients for the Covering Expertise that are positive indicating a worse short selling performance by non-expertise short sellers post-Covid-19.

## 5. Robustness Tests

### 5.1 Alternative Explanation: private Information on healthcare stocks

One concern with our analysis might be that our results suffer from a selection bias because we only look at non-healthcare stocks. Even though we do this on purpose to rule out private information-based Covid-19 treatment effects, we also run our main regression with a larger sample including healthcare stocks and obtain the same qualitive results as shown in Table 4.

If we run our regressions on a sample only containing healthcare stocks, we do not estimate any relation of treated short positions to abnormal returns. Tests for differences in coefficients also reveal that our effect is more pronounced for non-healthcare stocks. If the use of private information were also an alternative source of short sale outperformance, we would expect to see a treatment effect of Covid-19 on healthcare stocks as well. Since we do not observe this, we regard this as support for our public information processing assumption behind the treatment effect.

### 5.2 Alternative explanation: non information-based trading advantage

One major concern might be that outperformance of short sellers with healthcare expertise is also driven by factors other than our suggested information-based trading advantage. Alternative sources of such outperformance might be the ability to secure funding by short sellers' own investors during pandemic-caused financial market turmoil when fund investors tend to withdraw money, or the ability to locate stocks for borrowing in those volatile pandemic times when stock lenders tend to recall lent-out stocks to trade themselves. To rule out such non information-based trading advantages as alternative explanations for our findings, we conduct several empirical tests.

*General shorting skills*

First, we examine if the outperformance of healthcare expertise short sellers is driven only by general short selling skills that we expect to be highly correlated with the ability to secure funding and locate stocks. So, we re-estimate *Expertise* in the regression for the Training Set without the Interaction with the *Healthcare*. Consistent with our previous applied methodology, we assign short sellers to the expertise group according to the coefficients on *Position* and *Covering* for Shorting Expertise and Covering Expertise, respectively. Applying those new measured expertise assignments to our regressions of the Covid Set (exhibited in Table 5), we obtain no statistically significant findings. So, we conclude that general shorting skills do not drive our results so that our information-based trading advantage is not weakened.

*Healthcare expertise based on long positions*

To further support that our treatment group is influenced solely by information-related to Covid-19 through processing skills, we identify healthcare expertise if short sellers' long positions in healthcare stocks according to their 13F filings with the SEC is above the median of the sample average over two years preceding the Covid Set. Since this approach is not based on short selling performance and we assume that long investing is not necessarily correlated short selling performance, we assume that this approach rules out the impact of non information-based trading advantages regarding short selling.

As exhibited in Table 6, we find qualitatively the same results as found with our short selling data-based measures of healthcare expertise so that our results hold even if we rule out a important fraction of non information-based trading advantages.

We do not take this measure as our main measure although we would get more observations because long positions are less costly than short positions so that internal incentives to invest in expertise for those long positions is lower than for short positions that might question the value of the expertise measured. In addition, long positions might be matched to unobserved short selling activity that would also question our information-based treatment effect assumption. Moreover, quarterly reporting of long positions is too infrequent to measure expertise that is used for much shorter investment horizons in the case of short selling.

*Stock lending data*

For further support our assumption that information drives the treatment effect, we also control for short selling conditions and constraints as potential alternative driver of non information-based trading advantages. So, we include lending fee and active utilization that we retrieve on a daily basis from IHS Markit. In addition, we include short selling risk calculated according to Engelberg et al. (2018). As shown in Table 7, our results remain qualitatively the same that indicates that our results are not driven by an important fraction of non information-based trading advantages.

## 6. Conclusion

We use public German data on daily short sales before and during the Covid-19 pandemic to isolate the processing skills of healthcare expertise traders from the use of private information and assess if better information processing through healthcare expertise is associated with superior returns.

Consistent with our hypothesis, we find overwhelming evidence that healthcare expertise causes market-wide outperformance in the Covid-19 pandemic. We argue that short sellers shift their resources to gather and process aggregate pandemic-induced information and private, firm-specific information becomes subordinate in the fast-moving and volatile Covid-19 markets. The formerly industry-specific healthcare expertise then enables expertise traders to outperform. Hence, our findings are in line with the studies by Engelberg et al. (2018) and provide causal evidence that processing skills are a main driver of returns. Overall, we offer new insights into the success of short sales. We show that superior processing skills is a driver of performance, and to our knowledge, we are the first to document a causal relationship for this.

Our research is relevant to market participants and researchers to understand the competitive edge of some short sellers and the origin of their success. Form the regulators' point of view, our results support that short sellers might be good information processors and therefore are important for improving market efficiency by using public (legal) information (e.g., Saffi and Sigurdsson (2011)). We also document how industry-specific expertise becomes general expertise under certain conditions that provides a new perspective on labor economics' notion of specific human capital.

Traders show varying motivations for short selling, such as hedging, arbitrage, tax reasons or overvaluation. It would be interesting for future research to differentiate expertise traders across their investment strategies for further insights. Moreover, our data is limited to the Federal Gazette publications, but as the BaFin confidentially collects short positions below that threshold, we suggest that future researchers with access investigate if secretive expertise traders exert even better information processing, and if the disclosure rules constitute a binding short constraint that impairs expertise trader performance. It might also be fruitful to examine if the outperformance of expertise traders repeats in the second wave of Covid-19 where short selling constraints rise again. If the outperformance does not repeat, it is more likely evidence for our suggested information-based trading advantage that other short sellers then also experience when have invested in healthcare expertise on their own.

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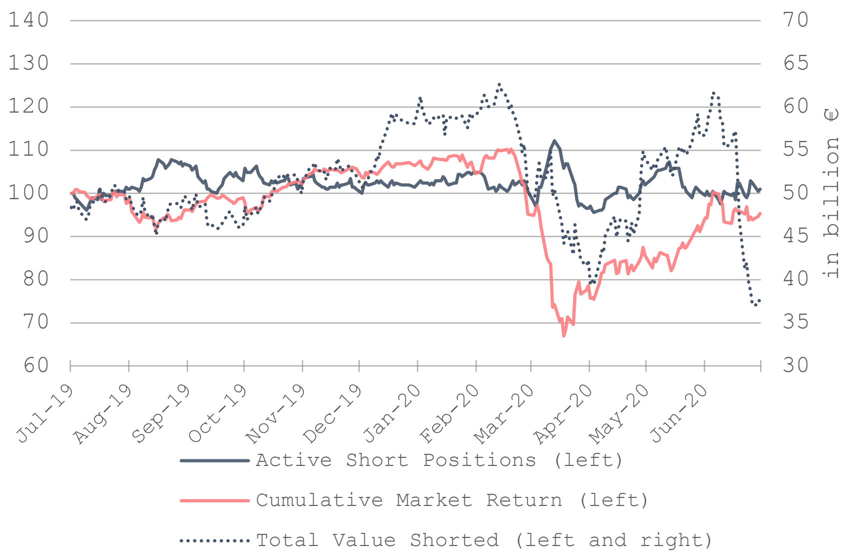
Figure 1

## Timeline of Active Short Positions, Total Value Shorted and Market Returns

Graph A in Figure 1 shows the time series of publicly disclosed short positions compared to the market benchmark. All time series variables are relative to their respective level on Jul. 1, 2019 (left axis). *ActiveShortPositions* denote the nominal amount of positions that simultaneously exceed the reporting threshold. *TotalValueShorted* denotes the aggregate value of all public short positions (absolute values on right axis). *CumulativeMarketReturn* is based on the German Prime All Share Index.

**Graph A. Relative Amount of Shorts Positions, their Aggregate Value, and Market Returns**




**Graph B. Monthly Openings and Coverings**

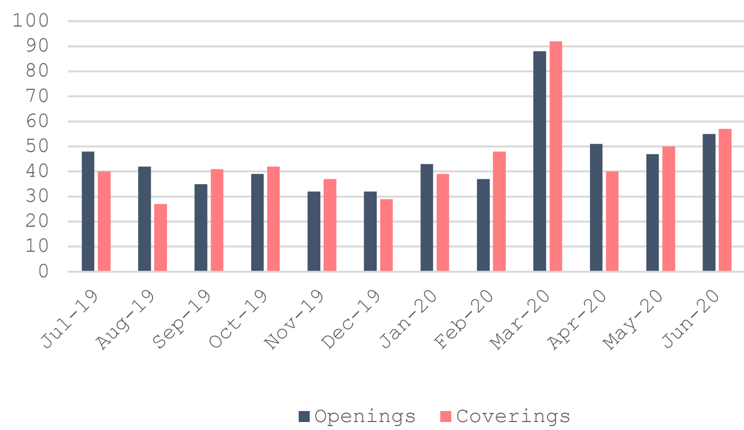



Table 1

## Descriptive Statistics of Publicly Disclosed Short Positions from BaFin amid the Covid-19 pandemic from Jul. 2019 to June 2020 (Covid Set)

Table 1 reports detailed summary statistics on the Covid Set with (A) and without healthcare stocks (B), active short positions only. *Ln ShortInterest$_{-1}$* is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover$_{[-5,-1]}$* is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread$_{-1}$* is the prior day difference of bid and ask divided by their average. *Momentum$_{[-5,-1]}$* is the cumulative abnormal return of the five preceding trading days. *Ln Indicative Fee* is the annualized indicative lending fee for a stock. *Rebate Rate* is the annualized rebate rate. *Short Risk* is the natural logarithm of 1-year lending fee volatility. *Ln Active Utilization* is the percentage of shares out on loan relative to available shares for lending. Returns are in excess of the German Prime All Share daily returns.

**A: Corona Set**

| Variable | N | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| *BaFin* | | | | | | |
| Ln Short Interest$_{-1}$ | 52,675 | 1.09 | 1.24 | 0.97 | -0.76 | 2.80 |
| Short Interest$_{-1}$ | 52,805 | 4.36 | 3.46 | 3.41 | 0.00 | 16.39 |
| Position Size | 53,010 | 1.03 | 0.75 | 0.78 | 0.01 | 9.80 |
| *Capital IQ* | | | | | | |
| Ln MarketCap | 53,010 | 7.47 | 7.48 | 1.18 | 0.67 | 11.7 |
| MarketCap | 53,010 | 3,573 | 1,768 | 5,986 | 1.96 | 120,000 |
| Market-To-Book | 52,566 | 1.60 | 1.18 | 1.09 | 0.63 | 11.78 |
| Ln Spread$_{[-5,-1]}$ | 52,802 | -1.51 | -1.65 | 0.89 | -4.15 | 1.74 |
| Spread$_{[-5,-1]}$ | 52,802 | 0.34 | 0.19 | 0.38 | 0.02 | 5.68 |
| Turnover$_{[-5,-1]}$ | 51,752 | 0.62 | 0.39 | 1.40 | 0.00 | 36.43 |
| Ln Volatility | 52,822 | 0.93 | 0.93 | 0.42 | -0.50 | 3.02 |
| Volatilty | 52,822 | 2.76 | 2.54 | 1.15 | 0.60 | 20.40 |
| Beta 1-Year | 52,934 | 1.34 | 1.29 | 0.72 | -1.24 | 3.57 |
| Momentum$_{[-5,-1]}$ | 52,967 | -0.06 | -0.08 | 5.80 | -19.02 | 17.51 |
| *Markit IHS* | | | | | | |
| Ln Indicative Fee | 40,881 | 0.55 | 0.24 | 1.28 | -1.01 | 3.15 |
| Indicative Fee | 40,881 | 3.98 | 1.27 | 5.42 | 0.36 | 23.38 |
| Rebate Rate | 40,881 | -2.79 | -0.48 | 5.62 | -22.66 | 1.92 |
| Short Risk | 52,492 | 3.55 | 3.65 | 1.65 | 0.01 | 7.49 |
| Ln Active Utilization | 40,895 | 3.32 | 3.68 | 1.26 | -1.07 | 4.61 |
| Active Utilization | 40,895 | 47.27 | 39.79 | 36.17 | 0.34 | 100.00 |
| Abn. Returns 5-days | 53,010 | 0.02 | -0.02 | 5.95 | -19.02 | 17.51 |
| Abn. Returns 10-days | 53,010 | 0.03 | -0.07 | 8.53 | -27.15 | 23.64 |
| Abn. Returns 20-days | 53,010 | -0.01 | 0.10 | 12.04 | -36.00 | 34.41 |

**B: Corona Set without Healthcare Stocks**

| Variable | N | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| *BaFin* | | | | | | |
| Position Size | 48,309 | 1.03 | 0.76 | 0.01 | 0.75 | 9.80 |
| Ln Short Interest$_{-1}$ | 47,998 | 1.07 | 0.95 | -0.76 | 1.21 | 2.80 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Short Interest$_{-1}$ | 48,120 | 4.25 | 3.36 | 0.00 | 3.33 | 16.39 |
| | | | | | | |
| *Capital IQ* | | | | | | |
| Ln MarketCap | 48,309 | 7.43 | 1.19 | 0.67 | 7.38 | 11.7 |
| MarketCap | 48,309 | 3,451 | 5,633 | 2 | 1,605.49 | 120,000 |
| Market-To-Book | 47,979 | 1.49 | 0.96 | 0.63 | 1.16 | 11.78 |
| Ln Spread$_{[-5,-1]}$ | 48,117 | -1.48 | 0.89 | -4.15 | -1.60 | 1.74 |
| Spread$_{[-5,-1]}$ | 48,117 | 0.35 | 0.38 | 0.02 | 0.20 | 5.68 |
| Turnover$_{[-5,-1]}$ | 47,182 | 0.63 | 1.46 | 0.00 | 0.38 | 36.43 |
| Ln Volatility | 48,121 | 0.94 | 0.43 | -0.50 | 0.94 | 3.02 |
| Volatility | 48,121 | 2.80 | 1.18 | 0.60 | 2.56 | 20.40 |
| Beta 1-Year | 48,309 | 1.35 | 0.74 | -1.24 | 1.31 | 3.57 |
| Momentum$_{[-5,-1]}$ | 48,269 | -0.07 | 5.82 | -19.02 | -0.10 | 17.51 |
| | | | | | | |
| *Markit IHS* | | | | | | |
| Ln Indicative Fee | 37,235 | 0.58 | 1.29 | -1.01 | 0.29 | 3.15 |
| Indicative Fee | 37,235 | 4.13 | 5.56 | 0.36 | 1.34 | 23.38 |
| Rebate Rate | 37,235 | 2.94 | 5.76 | -1.92 | 0.48 | 22.66 |
| Short Risk | 47,806 | 3.64 | 1.62 | 0.01 | 3.69 | 7.49 |
| Ln Active Utilization | 37,241 | 3.34 | 1.26 | -1.07 | 3.73 | 4.61 |
| Active Utilization | 37,241 | 47.80 | 35.87 | 0.34 | 41.48 | 100.00 |
| | | | | | | |
| Abn. Returns 5-days | 48,309 | -0.01 | 6.03 | -19.02 | -0.05 | 17.51 |
| Abn. Returns 10-days | 48,309 | -0.05 | 8.65 | -27.15 | -0.10 | 23.64 |
| Abn. Returns 20-days | 48,309 | -0.16 | 12.20 | -36.00 | 0.07 | 34.41 |

Table 2

## Descriptive Statistics of Publicly Disclosed Short Positions Pre- and Post-Covid (Covid Set)

Table 2 reports detailed summary statistics for the Covid Set (active Positions only, without healthcare stocks) for the pre-Covid and post-Covid sample window. *Ln ShortInterest$_{-1}$* is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover$_{[-5,-1]}$* is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread$_{-1}$* is the prior day difference of bid and ask divided by their average. *Momentum$_{[-5,-1]}$* is the cumulative abnormal return of the five preceding trading days. *Ln Indicative Fee* is the annualized indicative lending fee for a stock. *Rebate Rate* is the annualized rebate rate. *Short Risk* is the natural logarithm of 1-year lending fee volatility. *Ln Active Utilization* is the percentage of shares out on loan relative to available shares for lending. Returns are in excess of the German Prime All Share daily returns.

| | Pre Covid | | Post Covid | |
|---|---|---|---|---|
| **Variable** | **Mean** | **Median** | **Mean** | **Median** |
| *BaFin* | | | | |
| Ln Short Interest$_{-1}$ | 1.11 | 1.24 | 1.07 | 1.28 |
| Short Interest$_{-1}$ | 4.33 | 3.44 | 4.4 | 3.59 |
| Position Size | 1.04 | 0.77 | 1.02 | 0.73 |
| *Capital IQ* | | | | |
| Ln MarketCap | 7.45 | 7.45 | 7.5 | 7.51 |
| MarketCap | 3,461 | 1,717 | 3,688 | 1,819.02 |
| Market-To-Book | 1.55 | 1.19 | 1.64 | 0.96 |
| Ln Spread$_{[-5,-1]}$ | -1.64 | -1.81 | -1.38 | -1.45 |
| Spread$_{[-5,-1]}$ | 0.3 | 0.16 | 0.38 | 0.24 |
| Turnover$_{[-5,-1]}$ | 0.45 | 0.32 | 0.79 | 0.47 |
| Ln Vola 6 months | 0.78 | 0.83 | 1.09 | 1.11 |
| Vola 6 months | 2.32 | 2.28 | 3.21 | 2.35 |
| Beta 1-Year | 1.48 | 1.49 | 1.19 | 0.77 |
| Momentum$_{[-5,-1]}$ | -0.05 | -0.09 | -0.07 | -0.07 |
| *Markit IHS* | | | | |
| Ln Indicative Fee | 0.42 | 0.02 | 0.62 | -0.62 |
| Indicative Fee | 3.42 | 1.02 | 4.3 | 1.56 |
| Rebate Rate | -1.35 | 1 | -3.64 | -0.96 |
| Short Risk | 3.46 | 3.57 | 3.65 | 3.76 |
| Ln Active Utilization | 3.15 | 3.46 | 3.43 | 3.9 |
| Active Utilization | 41.67 | 31.72 | 50.59 | 49.57 |
| Abn. Returns 5-days | 0.11 | 0.06 | -0.06 | -0.12 |
| Abn. Returns 10-days | 0.14 | -0.01 | -0.09 | -0.22 |
| Abn. Returns 20-days | 0.26 | 0.31 | -0.29 | -0.08 |

# Table 3
## Main Results

In Table 3, we report the Difference-in-Differences estimation for healthcare expertise traders and non-expertise traders using the Covid Set (active positions, without healthcare stocks). Group affiliation is determined via Shorting Expertise or Covering Expertise from the Training Set. *Covid X Expertise* and *Covid* denote the variables of interest for the Difference-in-Differences estimation. *Covid* is a dummy variable that equals 1 if the date is later or equal to Jan. 3, 2020. *Covid X Expertise* is the interaction term of *Covid* and the *Expertise* dummy. *Ln ShortInterest*$_{-1}$ is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover*$_{[-5,-1]}$ is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread*$_{-1}$ is the prior day difference of bid and ask divided by their average. *Momentum*$_{[-5,-1]}$ is the cumulative abnormal return of the five preceding trading days. Stock-level data is based on Capital IQ. Returns are in excess of the German Prime All Share daily returns. We include time-fixed and firm-short-seller fixed effects. All Standard errors are clustered robust at the firm-short-seller level and reported in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

| | **Shorting Expertise** | | | **Covering Expertise** | | |
|---|---|---|---|---|---|---|
| | Abnormal Returns | | | Abnormal Returns | | |
| Variables | 5 days | 10 days | 20 days | 5 days | 10 days | 20 days |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Covid x Expertise** | **-2.040**** | **-4.268**** | **-7.746***** | **-3.355***** | **-7.163***** | **-13.159***** |
| | (0.814) | (1.628) | (2.718) | (0.900) | (1.852) | (3.355) |
| Covid | 0.091 | 1.080 | 2.517 | 2.196** | 5.686*** | 12.205*** |
| | (0.935) | (1.063) | (1.631) | (1.000) | (1.591) | (2.915) |
| Ln Short Interest$_{-1}$ | 2.004*** | 3.800*** | 6.522*** | 1.074** | 2.024** | 3.397* |
| | (0.592) | (1.135) | (1.978) | (0.455) | (0.906) | (1.748) |
| Position Size | -0.085 | -0.036 | -0.185 | 0.165 | 0.308 | 0.773 |
| | (0.469) | (0.893) | (1.466) | (0.318) | (0.652) | (1.170) |
| Opening | -0.382 | -0.675 | 0.952 | 0.047 | 0.299 | 2.483** |
| | (0.801) | (0.995) | (1.374) | (0.740) | (0.934) | (1.130) |
| Covering | 0.452 | 1.075 | 1.610* | 0.836* | 1.135* | 1.180 |
| | (0.686) | (0.672) | (0.878) | (0.464) | (0.581) | (0.790) |
| Ln MarketCap | -4.265*** | -10.083*** | -20.069*** | -4.545*** | -10.926*** | -22.563*** |
| | (0.847) | (1.627) | (2.686) | (0.908) | (1.622) | (2.685) |
| Market-To-Book | 0.922* | 1.839* | 5.113*** | 1.020** | 2.002* | 5.898** |
| | (0.514) | (1.001) | (1.850) | (0.507) | (1.167) | (2.379) |
| Ln Spread$_{[-5,-1]}$ | -0.278 | -1.571** | -3.827*** | -0.262 | -1.323* | -2.679** |
| | (0.472) | (0.781) | (1.204) | (0.432) | (0.754) | (1.128) |
| Turnover$_{[-5,-1]}$ | -0.025 | -0.327 | -0.864** | -0.142 | -0.446* | -1.287*** |
| | (0.194) | (0.231) | (0.389) | (0.182) | (0.238) | (0.358) |
| Ln Vola 6m | 0.713 | 1.057 | 1.126 | 1.538 | 2.925 | 3.844 |
| | (1.381) | (2.701) | (4.370) | (1.193) | (2.320) | (3.734) |
| Beta 1 year | -0.408 | -1.078 | -2.189 | -0.091 | -0.690 | -1.621 |
| | (0.390) | (0.807) | (1.431) | (0.380) | (0.743) | (1.305) |
| Momentum$_{[-5,-1]}$ | 0.007 | 0.016 | 0.035* | 0.005 | 0.001 | 0.012 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.010) | (0.015) | (0.018) | (0.007) | (0.010) | (0.014) |
| Constant | 29.364*** | 69.688*** | 136.931*** | 31.079*** | 75.846*** | 156.835*** |
| | (6.202) | (12.132) | (19.942) | (6.779) | (12.100) | (19.973) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Short Seller - Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,560 | 8,560 | 8,560 | 12,939 | 12,939 | 12,939 |
| R-squared | 0.037 | 0.074 | 0.146 | 0.038 | 0.076 | 0.148 |

# Table 4

## Robustness: Healthcare Stocks

In Table 4, we vary the main analysis by including or excluding healthcare stocks in the Covid Set. Group affiliation is determined via Shorting Expertise or Covering Expertise from the Training Set. *Covid X Expertise* and *Covid* denote the variables of interest for the Difference-in-Differences estimation. *Covid* is a dummy variable that equals 1 if the date is later or equal to Jan. 3, 2020. *Covid X Expertise* is the interaction term of *Covid* and the *Expertise* dummy. *Ln ShortInterest*$_{-1}$ is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover*$_{[-5,-1]}$ is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread*$_{-1}$ is the prior day difference of bid and ask divided by their average. *Momentum*$_{[-5,-1]}$ is the cumulative abnormal return of the five preceding trading days. Stock-level data is based on Capital IQ. Returns are in excess of the German Prime All Share daily returns. We include time-fixed and firm-short-seller fixed effects. All Standard errors are clustered robust at the firm-short-seller level and reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

**A: Shorting Expertise**

| Variables | No Healthcare | Only Healthcare | Full Sample | Difference | Difference | Difference |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) - (3) | (2) - (3) | (1) - (2) |
| **Covid x Expertise** | **-4.268**** | **0.380** | **-4.153***** | **-0.115** | **4.533*** | **-4.648**** |
| | (1.628) | (1.599) | (1.506) | **(0.850)** | **(0.0523)** | **(0.0354)** |
| Covid | 1.080 | 1.520 | 1.012 | | | |
| | (1.063) | (3.314) | (1.080) | | | |
| Constant | 69.688*** | 133.275*** | 67.335*** | | | |
| | (12.132) | (20.777) | (11.889) | | | |
| Controls | Yes | Yes | Yes | | | |
| Time FE | Yes | Yes | Yes | | | |
| Short Seller - Stock FE | Yes | Yes | Yes | | | |
| Observations | 8,560 | 1,015 | 9,575 | | | |
| R-squared | 0.074 | 0.278 | 0.069 | | | |

**B. Covering Expertise**

| Variables | No Healthcare | Only Healthcare | Full Sample | Difference | Difference | Difference |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) - (3) | (2) - (3) | (1) - (2) |
| **Covid x Expertise** | **-7.163***** | **-4.551** | **-7.046***** | **-0.117** | **2.495** | **-2.612** |
| | (1.852) | (2.287) | (1.719) | **(0.6934)** | **(0.3396)** | **(0.3454)** |
| Covid | 5.686*** | 3.120 | 5.408*** | | | |
| | (1.591) | (4.513) | (1.541) | | | |

| | | | |
|---|---|---|---|
| Constant | 75.846*** | 172.833*** | 77.713*** |
| | (12.100) | (39.229) | (11.704) |
| Controls | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Short Seller - Stock FE | Yes | Yes | Yes |
| Observations | 12,939 | 719 | 13,658 |
| R-squared | 0.076 | 0.313 | 0.070 |

## Table 5

# **Robustness: General Shorting Skills**

In Table 5, we report outcomes of robustness tests using General Shorting Skills, i.e., Shorting Expertise and Covering Expertise from short selling of all stocks instead of only healthcare stocks, in the Covid Set (active positions, without healthcare stocks). *Covid X Expertise* and *Covid* denote the variables of interest for the Difference-in-Differences estimation. *Covid* is a dummy variable that equals 1 if the date is later or equal to Jan. 3, 2020. *Covid X Expertise* is the interaction term of *Covid* and the *Expertise* dummy. *Ln ShortInterest*$_{-1}$ is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover*$_{[-5,-1]}$ is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread*$_{-1}$ is the prior day difference of bid and ask divided by their average. *Momentum*$_{[-5,-1]}$ is the cumulative abnormal return of the five preceding trading days. Stock-level data is based on Capital IQ. Returns are in excess of the German Prime All Share daily returns. We include time-fixed and firm-short-seller fixed effects. All Standard errors are clustered robust at the firm-short-seller level and reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

| Variables | **Shortin Expertise** | **Covering Expertise** |
|---|---|---|
| | (1) | (2) |
| **Covid x Expertise** | **3.339*** | **-0.238** |
| | (1.690) | (1.432) |
| Covid | -0.850 | -0.079 |
| | (1.324) | (0.954) |
| Ln Short Interest$_{-1}$ | 0.802 | -1.024 |
| | (0.879) | (0.693) |
| Position Size | -0.739 | 3.582*** |
| | (1.951) | (0.757) |
| Opening | -2.790 | -0.899 |
| | (1.924) | (1.144) |
| Covering | 0.616 | 1.622** |
| | (1.610) | (0.671) |
| Ln MarketCap | -11.473*** | -15.344*** |
| | (2.695) | (2.313) |
| Market-To-Book | -0.794 | 1.735 |
| | (1.908) | (2.043) |
| Ln Spread$_{[-5,-1]}$ | -0.595 | -0.408 |
| | (0.844) | (0.828) |
| Turnover$_{[-5,-1]}$ | -0.636** | -0.447 |
| | (0.265) | (0.402) |
| Ln Vola 6m | -2.804 | -3.993 |
| | (2.769) | (2.567) |
| Beta 1 year | -0.037 | -0.374 |
| | (1.374) | (1.143) |
| Momentum$_{[-5,-1]}$ | 0.005 | 0.009 |
| | (0.016) | (0.015) |

| | | |
|---|---|---|
| Constant | 85.768*** | 114.072*** |
| | (17.911) | (15.907) |
| Time FE | Yes | Yes |
| Short Seller - Stock FE | Yes | Yes |
| Observations | 7,650 | 9,421 |
| R-squared | 0.069 | 0.093 |

Table 6

## Robustness: Alternative 13F Healthcare Expertise

In Table 6, we report outcomes of robustness tests using 13F filings as alternative measure for healthcare expertise. We compute the percentage of 13F portfolios allocated to healthcare stocks using data from IHS Markit. Short sellers are denoted as expertise traders in specification (1) if their healthcare allocation exceeds the median of all 13F allocations. *Covid X Expertise* and *Covid* denote the variables of interest for the Difference-in-Differences estimation. *Covid* is a dummy variable that equals 1 if the date is later or equal to Jan. 3, 2020. *Covid X Expertise* is the interaction term of *Covid* and the *Expertise* dummy. *Ln ShortInterest*$_{-1}$ is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover*$_{[-5,-1]}$ is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread*$_{-1}$ is the prior day difference of bid and ask divided by their average. *Momentum*$_{[-5,-1]}$ is the cumulative abnormal return of the five preceding trading days. Stock-level data is based on Capital IQ. Returns are in excess of the German Prime All Share daily returns. We include time-fixed and firm-short-seller fixed effects. All Standard errors are clustered robust at the firm-short-seller level and reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

| Variables | Full Sample | < $Q_{0.25}$ | $Q_{0.25}$-$Q_{0.5}$ | $Q_{0.5}$-$_{0.75}$ | > $Q_{0.75}$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Covid x Expertise** | **-2.024**** | **0.002** | **3.260**** | **-1.761**** | **-0.680** |
| | (0.889) | (0.821) | (1.343) | (0.758) | (0.756) |
| Covid | 2.454*** | 1.029** | 0.506 | 1.570*** | 1.178** |
| | (0.737) | (0.460) | (0.507) | (0.480) | (0.487) |
| Ln Short Interest$_{-1}$ | 1.339*** | 1.450*** | 1.282*** | 1.330*** | 1.464*** |
| | (0.468) | (0.463) | (0.467) | (0.465) | (0.464) |
| Position Size | 0.540 | 0.613 | 0.481 | 0.629 | 0.587 |
| | (0.495) | (0.521) | (0.484) | (0.518) | (0.523) |
| Opening | -0.385 | -0.351 | -0.410 | -0.345 | -0.357 |
| | (0.538) | (0.540) | (0.540) | (0.538) | (0.540) |
| Covering | 1.056** | 1.105** | 1.037** | 1.072** | 1.104** |
| | (0.434) | (0.438) | (0.438) | (0.436) | (0.439) |
| Ln MarketCap | -8.649*** | -8.371*** | -8.533*** | -8.532*** | -8.335*** |
| | (0.896) | (0.892) | (0.905) | (0.889) | (0.887) |
| Market-To-Book | 0.308 | 0.224 | 0.114 | 0.332 | 0.182 |
| | (0.845) | (0.833) | (0.824) | (0.856) | (0.829) |
| Ln Spread$_{[-5,-1]}$ | -0.462 | -0.486 | -0.480 | -0.449 | -0.480 |
| | (0.378) | (0.382) | (0.375) | (0.375) | (0.379) |
| Turnover$_{[-5,-1]}$ | -0.350*** | -0.341*** | -0.355*** | -0.345*** | -0.339*** |
| | (0.112) | (0.113) | (0.112) | (0.112) | (0.113) |
| Ln Volatility | 0.891 | 1.059 | 1.037 | 0.974 | 1.042 |
| | (1.119) | (1.143) | (1.121) | (1.120) | (1.152) |
| Beta 1 year | -1.030*** | -0.990*** | -1.074*** | -0.928** | -1.002*** |
| | (0.379) | (0.375) | (0.380) | (0.377) | (0.376) |
| Momentum$_{[-5,-1]}$ | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Constant | 62.371*** | 60.029*** | 61.846*** | 61.173*** | 59.878*** |
| | (6.475) | (6.578) | (6.498) | (6.407) | (6.516) |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Short Seller - Stock FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 46,519 | 46,519 | 46,519 | 46,519 | 46,519 |
| R-squared | 0.050 | 0.048 | 0.052 | 0.050 | 0.049 |

## Table 7

# **Stock Lending Data**

In specification (1) and (2) of Table 7, we report probit regressions on variables denoting short selling constraints. Specifications (3) and (4) use 10-day abnormal returns as dependent variable. *Covid* is a dummy variable that equals 1 if the date is after or equal to Jan. 3, 2020. *Ln Indicative Fee* is the annualized indicative lending fee for a stock. *Short Risk* is the natural logarithm of 1-year lending fee volatility. *Ln Active Utilization* is the percentage of shares out on loan relative to available shares for lending. *Ln ShortInterest*$_{-1}$ is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover*$_{[-5,-1]}$ is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread*$_{-1}$ is the prior day difference of bid and ask divided by their average. *Momentum*$_{[-5,-1]}$ is the cumulative abnormal return of the five preceding trading days. Stock-level data is based on Capital IQ. Returns are in excess of the German Prime All Share daily returns. We include time-fixed and firm-short-seller fixed effects. All Standard errors are clustered robust at the firm-short-seller level and reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

| Variables | Shorting Expertise | Covering Expertise |
|---|---|---|
| | (1) | (2) |
| Covid x Expertise | -3.816* | -5.898** |
| | (2.100) | (2.261) |
| Covid | 0.844 | 4.636*** |
| | (1.150) | (1.768) |
| Ln Indicative Fee | 0.738 | -1.454* |
| | (0.861) | (0.834) |
| Short Risk | -0.877 | 0.190 |
| | (0.796) | (0.565) |
| Ln Active Utilization | -0.345 | 0.438 |
| | (0.342) | (0.490) |
| Ln Short Interest$_{-1}$ | 4.103*** | 2.303** |
| | (1.268) | (1.042) |
| Position Size | 0.055 | -0.146 |
| | (0.850) | (0.693) |
| Opening | -0.597 | 0.415 |
| | (1.159) | (1.073) |
| Covering | 1.121 | 0.682 |
| | (0.773) | (0.692) |
| Ln MarketCap | -10.775*** | -12.029*** |
| | (1.890) | (1.898) |
| Market-To-Book | 1.431* | 2.007 |
| | (0.858) | (1.363) |
| Ln Spread$_{[-5,-1]}$ | -1.831** | -1.144 |
| | (0.837) | (0.903) |
| Turnover$_{[-5,-1]}$ | -0.350 | -0.486* |
| | (0.308) | (0.272) |
| Ln Volatility | 1.137 | 2.516 |
| | (2.882) | (2.411) |
| Beta 1-Year | -1.939** | -1.372 |

| | | |
|---|---|---|
| | (0.745) | (0.852) |
| $Momentum_{[-5,-1]}$ | 0.031* | 0.008 |
| | (0.017) | (0.013) |
| Constant | 79.341*** | 84.954*** |
| | (15.067) | (13.958) |
| Time FE | Yes | Yes |
| Firm FE | | |
| Short Seller - Firm FE | Yes | Yes |
| Observations | 6,463 | 9,617 |
| R-squared | 0.081 | 0.074 |

## Appendix A1

### Table A1

**Overview of stocks and short sellers**

Table A1 provides a comprehensive list of (1) stocks, (2) short sellers and (3) an overview over the most active short sellers in the Covid Set. ACTIVE DAYS denotes the nominal number of days on which a short position is publicly disclosed (>0.5%). AVG POSITION SIZE is the average over the days on which a position is public, relative to shares outstanding.

**(1) Stocks**

| | | |
|---|---|---|
| 1&1 Drillisch AG | ENCAVIS AG | PATRIZIA AG |
| Aareal Bank AG | Evonik Industries AG | ProSiebenSat.1 Media SE |
| adidas AG | Evotec AG | publity AG |
| ADLER Real Estate AG | Fielmann AG | PUMA SE |
| ADVA Optical Networking SE | flatex AG | QIAGEN |
| AIXTRON SE | Fraport AG | QSC AG |
| Allianz SE | freenet AG | Rheinmetall AG |
| alstria office REIT-AG | Fresenius SE & Co. KGaA | RIB Software SE |
| AROUNDTOWN | GEA Group AG | RTL GROUP SA |
| Aumann AG | Gerresheimer AG | RWE AG |
| AURELIUS SE | Gerry Weber International AG | S&T AG |
| Aurubis AG | GFT Technologies AG | SAF HOLLAND |
| BASF SE | GRENKE AG | Salzgitter AG |
| BAUER AG | HAMBORNER REIT AG | SAP SE |
| Bayer AG | Hamburger Hafen und Logistik | Sartorius AG |
| Bayerische Motoren Werke AG | HeidelbergCement AG | Schaeffler AG |
| Bechtle AG | Heidelberger Druckmaschinen | Scout24 AG |
| Befesa | HELLA GmbH & Co. KGaA | SGL Carbon SE |

| | | |
|---|---|---|
| Beiersdorf AG | HelloFresh SE | SHOP APOTHEKE EUROPE |
| Bertrandt AG | Henkel AG & Co. KGaA | Siemens AG |
| Bilfinger SE | HOCHTIEF AG | Siltronic AG |
| Borussia Dortmund | HUGO BOSS AG | Sixt SE |
| Brenntag AG | Infineon Technologies AG | SLM Solutions Group AG |
| CANCOM SE | Instone Real Estate Group AG | SMA Solar Technology AG |
| Carl Zeiss Meditec AG | ISRA VISION AG | SNP Schneider SE |
| CECONOMY AG | JOST Werke AG | Software AG |
| COMMERZBANK AG | Jungheinrich AG | Stabilus AG |
| Continental AG | K+S AG | Steinhoff International |
| Core State Capital Holding SA | KION GROUP AG | Ströer SE |
| Covestro AG | Klöckner & Co SE | Südzucker AG |
| CTS Eventim AG & Co. KGaA | Knorr-Bremse AG | TAG Immobilien AG |
| CYAN AG | Koenig & Bauer AG | TeamViewer AG |
| Daimler AG | KRONES AG | technotrans SE |
| Delivery Hero SE | LANXESS AG | Tele Columbus AG |
| DEUTSCHE BANK AG | LEG Immobilien AG | Telefónica Deutschland Holding AG |
| Deutsche Börse AG | Leifheit AG | thyssenkrupp AG |
| Deutsche EuroShop AG | LEONI AG | TOM TAILOR Holding AG |
| Deutsche Lufthansa AG | LPKF Laser & Electronics AG | TUI AG |
| Deutsche Pfandbriefbank AG | Medigene AG | Uniper SE |
| Deutsche Post AG | MERCK KgaA | United Internet AG |
| Deutsche Telekom AG | METRO AG | va-Q-tec AG |
| Deutsche Wohnen SE | MorphoSys AG | VARTA AG |
| DEUTZ AG | MTU Aero Engines AG | Voltabox AG |
| Dialog Semiconductor | Munich Re | Wacker Chemie AG |
| DIC Asset AG | Nemetschek SE | Wacker Neuson SE |
| Drägerwerk AG & Co. KGaA | New Work SE | WashTec AG |
| Dürr AG | Nordex SE | Wirecard AG |
| E.ON SE | NORMA Group SE | Zalando SE |
| ElringKlinger AG | OSRAM Licht AG | zooplus AG |

**(2) Short Sellers**

| | | |
|---|---|---|
| Adage Capital Mgmt | FourWorld Capital Mgmt | Park West Asset Mgmt |
| Adehi Capital | GF Trading | PDT Partners |
| AHL Partners | Gladstone Capital Mgmt | Pelham Capital |
| AKO Capital | GLG Partners | Petrus Advisers |
| Albar Capital | GMT Capital Corp | Pictet Asset Mgmt |
| Amia Capital | Greenvale Capital | Point72 Asset Mgmt |
| Anchorage Capital Master Offshore | GSA Capital Partners | Polar Capital |
| AQR Capital Mgmt | Half Sky Capital (UK) | Polygon Global Partners |
| Arrowstreet Capital | Harbor Spring Capital | Portsea Asset Mgmt |
| Atom Investors | HBK Investments | PSquared Asset Mgmt |

| | | |
|---|---|---|
| Balyasny Asset Mgmt | Helikon Investments | Public Equity Partners Mgmt |
| BlackRock | Henderson Global Investors | Qube Research & Technologies |
| Bloom Tree Partners | Highbridge Capital Mgmt | Renaissance Technologies |
| BlueCrest Capital Mgmt | Immersion Capital | Rye Bay Capital |
| BlueMountain Capital Mgmt | Jericho Capital Asset Mgmt | Samlyn Capital |
| BNP PARIBAS | JPMorgan Asset Mgmt (UK) | Sand Grove Capital Mgmt |
| BODENHOLM CAPITAL | Kairos | Sandbar Asset Mgmt |
| Bridgewater Associates | Kintbury Capital | Sanditon Asset Mgmt |
| Bybrook Capital | Kontiki Capital Mgmt (HK) | Scopia Capital Mgmt |
| Caledonia (Private) Investments | Kuvari Partners | Sculptor Capital Mgmt Europe |
| Canada Pension Plan Inv Board | Lakewood Capital Mgmt | Slate Path Capital |
| CapeView Capital | Lancaster Investment Mgmt | Soros Fund Mgmt |
| Capital Fund Mgmt | Lansdowne Partners (UK) | Squarepoint Ops |
| Caxton Associates | Lazard Asset Mgmt | Susquehanna International |
| Citadel | Leucadia Investment Mgmt | Sylebra Capital |
| Coatue Mgmt | LMR Partners | Systematica Investments |
| Coltrane Asset Mgmt | Lone Pine Capital | TCI Fund Mgmt |
| Connor Clark & Lunn Inv Mgmt | Makuria Inv Mgmt (UK) | Thames River Capital |
| Covalis Capital | Maple Rock Capital Partners | Think Investments |
| CPMG | Maplelane Capital | Third Point |
| CQS (UK) | Marshall Wace | Thunderbird Partners |
| Credit Suisse International | Maverick Capital | Tiger Global Mgmt |
| D. E. Shaw & Co. | MEAG MUNICH ERGO | Tower House Partners |
| Darsana Capital Partners | Melqart Asset Mgmt (UK) | TT International |
| Davidson Kempner | Melvin Capital Mgmt | Two Creeks Capital Mgmt |
| DNB Asset Mgmt | Merian Global Investors (UK) | Tybourne Equity |
| Duquesne Family Office | Meritage Group | UBS Asset Mgmt |
| Eleva Capital SAS | Millennium | Valiant Capital Mgmt |
| Elliott Investment Mgmt | Muddy Waters Capital | Viking Global Investors |
| Eminence Capital | Naya Capital Mgmt UK | Voleon Capital Mgmt |
| ENA Investment Capital | No Street | Wellington Mgmt Company |
| Engadine Partners | Numeric Investors | Whale Rock Capital Mgmt |
| Ennismore Fund Mgmt | Oceanwood Capital Mgmt | Whitebox Advisors |
| EXANE ASSET MGMT | Odey Asset Mgmt | Winton Capital Mgmt |
| ExodusPoint Capital Mgmt | Otus Capital Mgmt | WorldQuant |
| Fosse Capital Partners | Paloma Partners Mgmt | Zimmer Partners |

| **(3) Short Sellers** | **Active Days** | **Avg Position Size** |
|---|---|---|
| Marshall Wace | 4182 | 0.96 |
| BlackRock | 3876 | 1.23 |
| AQR Capital Mgmt | 2944 | 1.25 |
| Citadel | 2810 | 1.24 |
| Canada Pension Plan Investment Board | 1917 | 0.83 |

| | | |
|---|---|---|
| Millennium | 1571 | 0.64 |
| Ennismore Fund Management | 1290 | 1.25 |
| GLG Partners | 1213 | 0.91 |
| JPMorgan Asset Management | 1114 | 0.85 |

## Appendix A2

Table 2

### Variables and Basic Fixed effects Panel Regression Model

In Table A2, we report the basic structure of our fixed-effects panel regression model, used in both the Training Set and the Corona Set. The same structure applies for each analysis. We adjust the Variable of Interest for different interaction terms, depending on the purpose. An example for the application of this model to estimate a short seller's expertise can be found in Appendix C.

| **Variables** | |
|---|---|
| Abnormal Returns | 5-day, 10-day or 20-day abnormal returns in excess of the German Prime All Share Index, based on dividend-adjusted close prices, winsorized at the 1 and 99 level |
| Covid x Healthcare Expertise | Interaction term and Variable of Interest |
| Covid Dummy | Denotes the post-shock period, starting from Jan. 3 |
| Healthcare Expertise Dummy | Denotes whether a short seller has healthcare expertise |
| Healthcare Dummy | Denotes whether a stock is classified as healthcare |
| Position Size | Individual position size as % of shares outstanding |
| Opening Dummy | Denotes the exact day of short position opening |
| Covering Dummy | Denotes the exact day of short position covering |
| Short Interest$_{-1}$ | Prior day aggregate net short positions as % of shares outstanding |
| Ln MarketCap | Natural Logarithm of same day market capitalization |
| Market-To-Book | (MarketCap +Total Assets – Book Value of Common Equity) over Total Assets |
| Ln Spread$_{[-5,-1]}$ | Natural Logarithm of 5 to 1-day prior average bid-ask spread |
| Turnover$_{[-5,-1]}$ | 5 to 1-day prior average turnover relative to WASO |
| Ln Volatility | Natural Logarithm of 6-month average volatility |
| Beta | 1-year beta |
| Momentum$_{[-5,-1]}$ | 5 to 1-day prior cumulative abnormal returns |
| Indicative Fee | Indicative Lending Fee p.a. |
| Rebate Rate | Rebate Rates p.a. |
| Short Risk | Natural logarithm of 1-year volatility of Indicative Fee |
| Active Utilization | Percentage of Shares on Loan relative to Available Shares for lending |

## Appendix A3

### Exemplary Expertise Measurement in Training Set

Table A3 displays an example of expertise measurement for the short seller Millennium Management in the Training Set. The Shorting Expertise variable *Position x Healthcare* is an interaction term of the position size and healthcare stock classification. The Covering Expertise variable *Covering x Healthcare* is an interaction term of a dummy for covering days and healthcare stock classification. *Ln ShortInterest*$_{-1}$ is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover*$_{[-5,-1]}$ is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread*$_{-1}$ is the prior day difference of bid and ask divided by their average. *Momentum*$_{[-5,-1]}$ is the cumulative abnormal return of the five preceding trading days. Stock-level data is based on Capital IQ. Returns are in excess of the German Prime All Share daily returns. We include time-fixed and firm-short-seller fixed effects. All Standard errors are clustered robust at the firm-short-seller level and reported in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

| | **Shorting Expertise** | **Covering Expertise** |
|---|---|---|
| Variables | Abnormal Returns 10 days | Abnormal Returns 10 days |
| **Position x Healthcare** | **-4.829*** ** | |
| | **-1.516** | |
| **Covering x Healthcare** | | **7.105*** ** |
| | | **-2.480** |
| Ln Short Interest$_{-1}$ | 0.149 | 0.136 |
| | (0.206) | (0.210) |
| Position Size | -1.002 | -2.822** |
| | (1.237) | (1.244) |
| Opening | -0.149 | -0.280 |
| | (0.424) | (0.405) |
| Covering | -0.473 | -0.980 |
| | (0.655) | (0.671) |
| Ln MarketCap | 8.103* | 8.951* |
| | (4.292) | (4.739) |
| Market-To-Book | 0.447 | 0.356 |
| | (1.040) | (1.030) |
| Ln Spread$_{[-5,-1]}$ | 2.346** | 2.239* |
| | (1.117) | (1.121) |
| Turnover$_{[-5,-1]}$ | -0.010 | -0.037 |
| | (0.769) | (0.773) |
| Ln Volatility | -20.512*** | -21.592*** |
| | (6.414) | (7.011) |
| Beta 1-Year | -0.538 | -0.650 |
| | (0.744) | (0.710) |
| Momentum$_{[-5,-1]}$ | -0.164*** | -0.160*** |
| | (0.027) | (0.027) |

| | | |
|---|---|---|
| Constant | -7.711<br>(17.350) | -9.339<br>(18.467) |
| Time FE | Yes | Yes |
| Short Seller - Stock FE | Yes | Yes |
| Observations | 3,980 | 3,980 |
| R-squared | 0.2233 | 0.2198 |
| **Short Seller** | **Millennium Management** | **Millennium Management** |
| **Classification** | **Expertise Group** | **Expertise Group** |

## Appendix A4

Table A4

**Test for Parallel Pre-Trends (Covid Set)**

In Table A4, we test for monthly parallel pre-trends in the Covid Set. Pre-Trends are indicated by the monthly interaction with the *Expertise* variable. Expertise Group Affiliation is determined via Shorting Expertise or Covering Expertise from the Training Set. *Ln ShortInterest*$_{-1}$ is the aggregate of all public short positions relative to shares outstanding. *Position Size* is the size of individual short positions relative to shares outstanding. *Opening* and *Covering* are dummy variables for days with openings and coverings. *Ln MarketCap* is the natural logarithm of market capitalization in EUR millions. *Market-To-Book* is defined in Table 2. *Ln Volatility* is the 6-month volatility. *Beta 1-Year* is the 1-year rolling beta to its closest benchmark. *Turnover*$_{[-5,-1]}$ is the average turnover of the five preceding trading days, relative to shares outstanding. *Ln Spread*$_{-1}$ is the prior day difference of bid and ask divided by their average. *Momentum*$_{[-5,-1]}$ is the cumulative abnormal return of the five preceding trading days. Stock-level data is based on Capital IQ. Returns are in excess of the German Prime All Share daily returns. We include time-fixed and firm-short-seller fixed effects. All Standard errors are clustered robust at the firm-short-seller level and reported in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

| | **Shorting Expertise** | **Covering Expertise** |
|---|---|---|
| Variables | Abnormal Returns 10 days | Abnormal Returns 10 days |
| July x Expertise | 2.182 | -0.230 |
| | (2.643) | (1.492) |
| August x Expertise | 2.905 | 2.715 |
| | (2.707) | (2.350) |
| September x Expertise | 1.510 | 1.795 |
| | (2.433) | (2.043) |
| October x Expertise | 6.038** | 6.919*** |
| | (2.419) | (1.791) |
| November x Expertise | 4.362* | 2.211 |
| | (2.469) | (1.604) |
| Ln Short Interest$_{-1}$ | 3.964*** | 1.937** |
| | (1.163) | (0.935) |
| Position Size | -0.018 | 0.615 |
| | (0.921) | (0.708) |
| Opening | -0.690 | 0.368 |
| | (1.006) | (0.916) |
| Covering | 1.078 | 1.184** |
| | (0.664) | (0.590) |
| Ln MarketCap | -10.065*** | -12.042*** |
| | (1.585) | (1.648) |
| Market-To-Book | 1.625 | 1.884** |
| | (1.019) | (0.952) |

| | | |
|---|---|---|
| Ln Spread$_{[-5,-1]}$ | -1.553* | -1.256* |
| | (0.816) | (0.736) |
| Turnover$_{[-5,-1]}$ | -0.347 | -0.495** |
| | (0.234) | (0.243) |
| Ln Volatility | 0.975 | 2.924 |
| | (2.689) | (2.289) |
| Beta 1-Year | -1.115 | -0.717 |
| | (0.824) | (0.788) |
| Momentum$_{[-5,-1]}$ | 0.015 | 0.002 |
| | (0.015) | (0.010) |
| Constant | 85.768*** | 114.072*** |
| | (17.911) | (15.907) |
| Post-Shock Interactions | Yes | Yes |
| Time FE | Yes | Yes |
| Short Seller - Stock FE | Yes | Yes |
| Observations | 8,560 | 12,939 |
| R-squared | 0.082 | 0.096 |