The impact of the 2020 short selling bans

Abstract

At the height of the COVID-19 related market stress in March 2020, six European countries coordinated to impose market-wide short selling bans. Complementing existing literature in three ways, the analysis uses regulatory data on share trading volumes and short positions to assess the link between the bans and market fragmentation, and extend the analysis to the sectors most affected by the market stress. Based on a difference-in-difference approach and consistent with prior theoretical and empirical work, our estimation confirms that the 2020 short selling bans are associated with a deterioration in liquidity, volatility and volumes, with persistent liquidity effects. However, the bans did neither support nor harm the prices of banned shares over the enactment period. The deterioration of liquidity appears more pronounced for large-cap stocks, highly fragmented stocks, and stocks with listed derivatives – pointing towards stronger effects for shares deemed as liquid. Sectoral effects are observed for the stocks most affected by the market stress, namely the healthcare and the consumer cyclical sectors. Shares that were already shorted before the bans saw an expected stronger increase of their illiquidity, but a volatility decrease under the bans, signalling a more difficult price discovery process.

JEL Classifications: D02, G01, G12, G14, G18, G28

Keywords: short selling, market quality, financial crisis, COVID-19, liquidity, regulation impact, short selling ban

1 Introduction

As a result of the COVID-19 pandemic, financial markets have been hit by an external shock of unprecedented size in 2020. During the initial stage of the crisis in 1Q20, markets experienced one of the fastest declines in recent history, including surges in volatility and liquidity contractions (Chart 2 and 3 in Appendix 1), testing the resilience of market infrastructures and financial institutions. The STOXX Europe 600 index recorded a peak-to-trough fall of -35.5% in February and March 2020. As investor sentiment and equity market performance turned negative, short selling activity - a widespread phenomenon during market downturns - increased from late February 2020, reflecting investors' pessimism (Chart 1 in Appendix 1).

Consequently and in accordance with the European short selling regulation[1], the European Securities and Markets Authority temporarily lowered the reporting threshold for net short positions (NSPs) from 0.2% to 0.1%[2] to improve the monitoring of such positions, and four National Competent Authorities (NCAs) imposed one-day short selling bans on selected stocks.[3] In total, six European NCAs (Austria, Belgium, France, Greece, Italy, Spain) coordinated to impose for the first time a long-term exchange-wide short selling ban on their markets, to mitigate the effects of adverse developments, which started on 18 March 2020 and were lifted on 18 May 2020 as market conditions improved.[4]

The paper proposes an impact analysis on the effects of the short selling bans adopted during the first wave of the COVID-19 pandemic in 2020, with the aim to assess their effects on market quality, looking at liquidity, volumes, returns, and volatility indicators, as well as the possibility of a displacement effect between countries which had introduced short selling bans and countries which had not done so. Consistent with Siciliano and Ventoruzzo (2020), we believe that multi-country evidence, rather than individual country data, should be less affected by idiosyncratic effects arising from other country-specific policy interventions that occurred

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[1] Articles 20 and 23 of Regulation (EU) No 236/2012 (SSR) set out the framework under which NCAs may prohibit or restrict short-selling practice, making use of two different types of restrictions i.e., long-term and short-term bans. While the short-term ban aims at preventing a disorderly decline in the price of the instrument, the long-term ban aims at mitigating the effects of adverse developments which constitute a serious threat to financial stability or can undermine market confidence.

[2] The notification threshold set out in Article 5(2) of SSR provides that any individual or legal entity holding a net short position equal to or greater than 0.2% of the capital of a company, whose shares are admitted to trading on a Union trading venue, shall notify their position to competent authorities within one trading day. This decision was renewed three time in the course of 2020 and followed by an ESMA Opinion to the European Commission in May 2021, recommending lowering the notification threshold to 0.1% on a permanent basis. In January 2022, the Commission Delegated Regulation amending Article 5(2) SSR set the threshold permanently at 0.1 %.

[3] On 13 March 2020, Italy and Spain banned short selling on 85 and 69 stocks, respectively; on 17 March 2020, while Spain issued a long-term ban, Belgium, France, and Italy banned short selling for 17, 92 and 20 shares, respectively. Subsequently, in addition to Spain, on 18 March Belgium, France, Italy, Austria and Greece also issued long-term bans which lasted, taking into account the renewals, until 18 May 2020.

[4] The initial market impact of the COVID-19 crisis waned in 2Q20, with equity markets rapidly recovering. The April 2020 monthly equity performance was close to an historic high, with a further increase observed in May 2020. Massive policy responses – containment, fiscal, monetary and regulatory – in Europe and globally helped mitigating the economic impact of the pandemic.

during the crisis period. Thus, the analysis is conducted at the European level, taking into account all European Economic Area (EEA) countries as well as the UK[5], relying on a difference-in-difference design combined with matching techniques, in order to isolate the cross-sectional effects of the bans[6], similarly to Beber et al. (2018).

The paper complements existing literature in three ways: first, the analysis is enhanced by the use of regulatory data on trading volumes and net short positions, allowing a detailed analysis of the link between the bans and market fragmentation, as well as their impact on shorted shares. Lastly, given that the COVID-19 related market stress affected a large number of economic sectors, the proposed sectoral analysis is extended to the sectors that were most affected by the market stress, a broader perimeter than the traditional focus of short selling impact analyses on the financial sector.

Consistent with prior theoretical and empirical work, the 2020 short selling bans are associated with a liquidity deterioration, measured by significantly higher bid-ask spreads (+8% for stocks in banned jurisdictions during the restriction, compared to the control group) and Amihud illiquidity values (+5.8%), while the effects on abnormal returns do not appear significant. The bans also had the effect of decreasing the volumes traded (-14.9%), as well as the volatility of the shares traded under the ban (-8.4%).

To check whether the effects of the bans were long-lasting, in an alternative regression framework we find that liquidity was impacted by the bans after they were lifted (significant higher bid-ask spreads and illiquidity indicator). Similarly, volatility and volumes continued to be lower in the months following the ban lift compared to the ex-ante period, and abnormal returns are slightly lower.

Furthermore, separating our dataset by stock characteristics to estimate whether the bans had differentiated effects, we observe that their negative impact on liquidity is more pronounced for stocks with a large market capitalisation than for smaller capitalisation. Taking into account the level of fragmentation of those shares, a significant discrepancy is observed between shares with low trading fragmentation, for which liquidity slightly improved and volumes were unaffected, and highly fragmented shares, for which a major deterioration of liquidity and a decrease in volumes is observed under the bans. Additionally, since these bans were the first to explicitly extend the ban not only to shares, but also to their derivatives, the regression is extended to assess if the impact is different for shares that have derivatives or not, assuming

[5] The dataset covers the 30 members of the European Economic Area (EEA) and the UK. Since the data used in the analysis are encompassing the years 2019 and 2020, i.e. before the end of the Brexit transition period, and the amount of trading activities in the UK allow for increasing accuracy of the analysis during the matching process, the UK shares are included in the dataset in the control group of the matching process and in the regressions.

[6] However, the implementation of the ban was not an exogenous event, since six NCAs decided to put in place a short selling ban, while the other EEA countries decided not to implement such constraint, a policy decision based on their assessment of the effect of a ban as well as the market integrity level nationally. This has an impact on the results.

no difference between the sub-samples. The results show that the bans had a stronger impact on the liquidity of the stocks with listed derivatives, with an additional decrease of volumes traded and increasing volatility.

To assess whether sectoral dynamics influenced the effects of the bans, we performed the same analysis focusing on sectors that were especially hit during the COVID-19 crisis. In contrast to other analyses done on previous crises of a financial nature (like Beber et al. 2018), financial sector stocks did not seem to be particularly affected by the bans, which may be explained by the fact that the COVID-19 market stress impacted both the financial sector and the real economy from the outset. The stocks that were at the heart of the crisis, namely from the healthcare sector, saw an important increase in their volatility, volumes as well as a surge in their liquidity, suggesting that information revelation was high for them, while shares under the bans from the consumer cyclical sector saw a deterioration of their liquidity and a decrease in their volatility.

Finally, using the net short positions' reporting regime put in place during the market stress, a final regression assesses the effect of the bans on shorted shares. Shares that were shorted before the ban observed an even stronger increase in their illiquidity indicator and stronger decrease in their traded volumes compared to the other shares. However, they saw their volatility increase during the ban, signalling more uncertainty regarding their value.

As a robustness check, to gauge the possibility of a shift of short selling activity from banning jurisdictions to non-banning ones (i.e. a 'displacement' effect), a study of short-sellers activity patterns is presented, using publicly disclosed short position data reported to NCAs. Short sellers were classified according to their historical behaviour between the start of 2020 and the enactment of the bans, and the evolution of their positions during the period of the ban was analysed. Both the overall minor increase of NSPs in non-banning jurisdictions, and the absence of observable modification of active short sellers' behaviour before and after the ban, suggest that no visible displacement of short selling activity was observed during the bans.

This empirical analysis seeks to contribute to supervisory convergence in the context of the latest review of the EU short selling regulation[7], with the aim of taking stock of the experience gathered in 2020. It helps promote financial stability and understand the consequences of such policies, and improve their overall efficiency. The Final Report on the review of the short selling regulation[8] proposed targeted amendments to improve its operation, such as clarifying the procedures for the issuance of short and long-term bans, the prohibition of naked short selling and the calculation of net short positions and their publication.

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[7] See ESMA (2021), Consultation Paper - Review of certain aspects of the short selling regulation.
[8] See ESMA (2022), Final Report on the review of the Short Selling Regulation.

The remainder of this paper is organized as follows. Section 2 introduces the paper in the literature, and section 3 presents the data, the matching process, and the regression set-up. Section 4 presents the results, first in the overall set-up and then with specific analysis for the post-ban period, characteristics of the shares, sectoral effects, and for shorted shares. Finally, the analysis on displacement effect is presented in Appendix 2, while Appendix 1 contains additional tables and results.

2 Literature review

Most of the academic literature on short selling is framed with reference to Diamond and Verrecchia (1987), stating that, under efficient market conditions, short sellers are informed traders and constraining short sales reduces the informational efficiency of prices. Thus, constraining short sales is likely to have a negative impact on market quality. For instance, Saffi and Sigurdsson (2011) document that stocks with higher short selling constraints, measured by low stock lending supply and high borrowing fee, have lower price efficiency, and relaxing the short selling constraints does not lead to instability in the form of a higher probability of large negative stock returns. However, Hong and Stein (2003), modelling heterogenous market agents' behaviour, find that short bans aggravate price declines. This concern - i.e. that predatory short sellers can exacerbate downwards price movements – appears critical during stress conditions or for vulnerable companies: Brunnermeier and Oehmke (2014) find that predatory short selling can be responsible for a higher probability of default, especially for fragile financial stocks and during crisis periods, by contributing to a decline in stock prices.

These concerns led many regulators to prohibit or constrain short sales during the 2008 financial crisis and the Euro area debt crisis in 2012, providing natural experiment configuration assessing the impact of short selling activities in abnormal market conditions. However, this empirical literature assesses bans that affected financial stocks, introduced over financial stability concerns for the banking system, thus not entirely comparable to market-wide bans.[9] The most encompassing analysis, from Beber and Pagano (2013), covers the short selling bans imposed during the 2008 crisis in 30 countries and indicates that the bans were associated with a decrease in liquidity, with an increase in bid-ask spreads of 1.28 to 1.98 percentage points (compared to a sample average of 4%), and with a significant increase of the Amihud illiquidity indicator. In contrast, the introduction of disclosure requirements in some countries are associated with a significant improvement in market liquidity, i.e. associated with a reduction of 0.65 percentage points in the bid-ask spread. Similarly, Boehmer et al (2013), using intraday data on the 2008 short sale ban in the US, document a deterioration of liquidity

[9] Furthermore, one of the challenging aspects of assessing the impact of short selling bans from an empirical perspective is that the bans themselves (as well as the selection of banned stocks in most of the bans put in place before the 2020 European bans) may be endogenous, and thus the empirical identification of the effect of the intervention on market characteristics is challenging.

and market quality in response to the ban. Beber et al. (2018) also shows that short selling bans imposed both during the subprime crisis and the eurozone crisis had differentiated effects on non-financial corporations and financial institutions, whose banned shares experienced higher probability of default, greater volatility and price declines, particularly for banks.

Some NCAs carried out impact evaluations of the 2020 short selling bans. Consistent with prior empirical work in other crisis settings, Lopez and Pastor (2020) and Benhami et al. (2022) compare differences in national market quality between stocks subject to short selling restrictions and stocks not affected by the same restrictions. Comparing the French and Dutch equity markets, Benhami et al. (2022) observe that the ban is associated with a deterioration of the liquidity variables (+7 bps for the quoted spreads of banned shares), a decrease in volatility, with more pronounced effects on large caps, and no significant effect on returns. Comparing the Spanish and German equity markets, Lopez and Pastor (2020) identify similarly a negative impact of the ban on bid-ask spreads, but an increase in depth based on the Amihud illiquidity indicator.[10] Furthermore, the authors do not find evidence that the securities subject to the ban experienced a decrease in their trading volume or volatility, and no significant impact of the ban on prices, CDS spreads nor any specific impact on financial stocks was observed. Extending the analysis by looking at 14 selected EU countries and the UK[11] during the European bans, Siciliano and Ventoruzzo (2020) estimate a significant increase of bid-ask spreads of 14% for banned shares, and a decrease of the inverse of the Amihud illiquidity indicator by 0.1%, with more pronounced effects when separating between financial and non-financial stocks (the bid-ask spread of financial firms increased by 25.6% versus 14.4% for non-financial firms during the banned period).

Finally, making use of the publicly disclosed short selling positions from NCA websites in 2019 and 2020, Greppmair, Jank & Smajlbegovic (2020) study how short sellers evaluate the importance of fiscal space for individual companies. Their results indicate that short sellers adapted quickly, since short selling activity shifted upon the onset of the pandemic towards companies with low financial flexibility and in countries with limited fiscal space. Consistent with the notion that short sellers are informed investors, they entered their short positions prior to the enactment of the bans and many of these positions were closed before the end of the market crash. Indirectly, this confirms the findings of our descriptive analysis on the displacement effect, namely that no material change of NSPs took place from banning to non-banning jurisdictions during the ban period.[12] This strategy was profitable, as shorted firms with

[10] However, since this result is surprising and not in line with the rest of the empirical literature, the authors point out that further research on this issue is necessary, especially since Amihud levels for Spanish securities were higher than their German control group at the time of the ban, a difference that is attributed by the authors as country risk – with higher premia, such as those seen in Spain, resulting in shallower markets.

[11] The rationale behind the selection is not presented in the paper per se; however the 15 countries appear to be the biggest EU countries for share trading at the time (6 banning countries: Austria, Belgium, France, Greece, Italy, Spain; and Denmark, Finland, Germany, Ireland, Luxembourg, Netherlands, Portugal, Sweden, United Kingdom).

[12] See Appendix 2.

low liquidity buffers in low-rated countries experienced an abnormal return of -10% during the period of COVID-19 related market stress.

Furthermore, the European bans imposed from March to May 2020 are exceptional since they stated clearly that not only did the prohibition apply to shares, but it also prohibited any transaction which might constitute or increase a NSP on shares, involving any type of financial instruments including saving/preferred shares, depositary receipts, and derivatives.[13] Previous bans in 2008 and 2012 did not explicitly rule out the possibility of carrying out synthetic short strategies – for example through options. However, this substitute is costly and typically available only to sophisticated investors. This aspect is relevant since, analysing the US stocks during the 2008 financial crisis, Kolasinski et al. (2013) documents that the ban decreased market liquidity and increased the informativeness of short sales, and that both these changes were particularly strong for stocks with listed options. Similarly, Beber and Pagano (2013) observed more stringent effects of the bans on liquidity for small-cap stocks and for stocks that do not have listed options, suggesting that the availability of an option market allows investors to express short views on the banned stocks. However, since the 2020 European bans did not allow for the possibility to use the derivative markets, their effects on share liquidity should not be affected by the availability of listed derivatives. Thus, we test for this hypothesis by looking at the differentiated effect of short selling bans on shares with or without listed derivatives, and expect no difference between the two sub-samples.

Furthermore, an important feature of the SSR regime is the market-making exemption that implies that a number of market participants, mainly large banks, are still allowed to take short positions. Indeed, while bans may effectively curtail speculative short selling behaviours, the market making exemption means that the ban does not constitute a full constraint on short sales, an assumption on which the empirical literature analysing the short selling bans in 2008 is based.

3 Data and methodology

3.1 Dataset construction

The regressions are estimated on daily data, first for all EEA and UK shares[14], and then for selected samples of the dataset, to investigate whether the liquidity impacts vary with share

[13] Since the NSP is calculated as the sum of all short positions minus all long positions held by an investor in relation to restricted shares and related instruments, all relevant positions were prohibited; stemming from the purchases or sales of shares, options, swaps, futures, depositary receipts, index-related instruments, covered warrants, certificates and any other structured product whose effect is to create a NSP in a share subject to the ban.

[14] Since the data used in the analysis are encompassing the years 2019 and 2020, i.e. before the end of the Brexit transition period, and the amount of trading activities in the UK allows for increasing accuracy of the analysis during the matching process, the UK shares are included in the dataset as a control group.

characteristics. The following analysis focuses on the impact of the two months exchange-wide bans from 18 March to 18 May 2020, employing data from 13 January (2 months before the ban) to 31 July 2020 (2 months after the ban). The days of the short-term bans, on 13 and 17 March 2020, are excluded.[15]

The starting list of shares is created using the European Financial Instrument Reference Data System (FIRDS), from which the relevant instruments traded in Europe and UK are extracted for the full year 2019 and 2020 (common/ordinary shares, depositary receipts on equities, and preferred/preference shares based on the Classification of Financial Instruments), taking into account possible ISIN changes. Shares terminated before 2020, or for which the last received data is before 2020, as well as shares which have their principal trading venue located in a third country outside of the EEA are excluded.[16] For all these instruments, the relevant variables are extracted using ESMA Financial Instruments Transparency System (FITRS) and FIRDS databases, as well as market data. Table 7 in Appendix 1 provides descriptive information of the variables used and their definition.

Penny stocks, i.e. shares with an average price below EUR 1 in 4Q19 or in 1H20, are excluded from the sample, as well as new stocks without data in 2019. Furthermore, shares with daily returns equal to zero during more than 30% of our timeframe (signalling stale prices) are also excluded. Finally, to deal with possible data quality issues, we exclude shares with negative, missing or extreme average bid-ask spreads (higher than 10% during 2020), and the data is winsorized by eliminating the observations corresponding to the top and bottom 1% of bid-ask spreads. This process results in a removal of 4,935 stocks out of 8,290, corresponding to 60% of our starting sample and to 23% of its market capitalization. Each step of this cleaning process is described in Table 8 in Appendix 1. The final sample is composed of 3,355 stocks, 911 belonging to the treatment group (stocks from countries with short selling bans) and 2,444 to the control group. Table 9 in Appendix 1 provides descriptive information of the final sample by country.

3.2 Matching process

To increase the robustness of the analysis, sample matching is added as a pre-analysis step: the goal is to balance the treatment and the control groups (i.e. to achieve similar share characteristics in the two groups). Matching is a statistical technique used to construct a

[15] The one- or two-day bans imposed in March are too short-lived for a dedicated econometric analysis, and including those days in the data will impact the results.

[16] In the same manner, shares that are traded on a Regulated Market and that have a foreign issuer are excluded, in order to remove non-EEA depository receipts or shares that are from a foreign issuer and thus have very high market cap while not being really traded in the EEA.

comparison group in order to enable a comparison of outcomes among treatment and control groups while controlling for possible confounding factors (Gertler et al. (2011)).

Even though several matching techniques can be employed, we focused on two: Nearest Neighbour Matching (NNM) and Coarsened Exact Matching (CEM).[17] NMM selects the closest counterpart of each observation based on a weighted function of a defined set of covariates (i.e. a 'distance' measure), while CEM performs exact matching on a set of covariates, 'coarsening' the continuous ones into strata and discarding the strata that do not contain at least one treated and one control observation. In the final estimation, only the retained observations are used, but they are weighted by the size of the corresponding "stratum". Hence, this method allows for multiple control observations to be matched to a single treated observation, with weights correcting any potential imbalance of observations.

Both methods have been evaluated based on (i) the balance of results, measured by comparing share characteristics prior to and after the matching, (ii) the impact of each method on the sample size. In terms of balance, CEM is more powerful than the NMM method, but it is also more restrictive and has a higher chance of reducing the sample size.[18] Chart 4 in Appendix 1 shows the standardised mean differences between the treatment and control groups after carrying out both CEM and NNM matching in our sample. In this setting, CEM achieves a more balanced outcome, as shown by the fact that absolute standardised mean differences between treatment and control group for all matching variables are below the standard threshold value of 0.1. NNM method results in greater imbalance for specific information, despite performing well overall. This comes at the expense of a contained sample reduction: from a starting point of 911 treatment shares, CEM matches 858 (94%) while NNM matches all of them.

Based on these reasons, CEM has been chosen for the matching procedure, resulting in a final sample composed of 1,716 stocks, half belonging to the treatment group and half to the control group. Among a range of potential variables considered, the following set of information has been employed for the matching procedure[19]:

- average market capitalisation in 4Q19, in order to avoid any confounding impacts due to the pandemic and to the short selling bans;

[17] Propensity Score Matching (PSM) was assessed; however, since our setting did not satisfy the required assumptions, it was deemed not suitable for the analysis. The Synthetic Control Methods (SCM) approach was also considered but given our large sample of analysis it would have been impractical to construct a 'synthetic' control unit for each treatment share.
[18] Due to the coarsening of continuous variables, using CEM the observations for which a suitable match is not found will be dropped; on the other hand, the 'distance' approach is less powerful but also less restrictive in terms of observation filtering.
[19] The list is not exhaustive, and many potential alternatives could be considered. However, these choices are in line with related works in the literature and, in our opinion, guarantee a balanced outcome without losing a significant number of observations due to missing data.

- the share sectoral information, i.e. the classification of economic sectors from Refinitiv Eikon;
- liquidity status, using the liquidity assessment from ESMA transparency calculations, based on the free float, average daily number of transactions and average daily turnover at the share level for 2019 and 2020.[20]

Table 1
Description of the dataset after matching

Variable	No shares	p5	mean	wmean	median	p95	sd
Bid-ask spread	1,716	0.09	0.43	0.08	0.27	0.51	0.72
Amihud	1,715	0.00	0.63	0.02	0.02	0.13	10.07
Abnormal Return	1,712	-0.00137	0.00020	0.00028	-0.00001	0.00142	0.00280
Historical volatility	1,716	1.96	2.51	2.20	2.38	2.87	0.88
Intraday volatility	1,716	2.67	3.51	3.04	3.35	4.17	1.43
Market capitalisation.	1,716	74.68	2,299.08	18,972.28	330.57	1,728.07	6,193.17
Volumes	1,716	5.14	487.62	2,101.49	37.52	252.52	1,928.99
Fragmentation	1,714	1.02	1.74	2.80	1.49	2.32	0.78

Note: number of shares, mean, weighted mean (wmean) by market capitalisation, median, 5th and 95th percentile (p5, p95) and standard deviation (sd) for each dependent variable in the regressions. Bid-ask spreads in %, Amihud, historical volatility and intraday volatility multiplied by a 100, market capitalisation in EUR millions, volumes in thousands, fragmentation calculated as 1/Herfindahl-Hirschman Index (HHI).
Sources: Refinitiv, ESMA.

Table 10 in Appendix 1 shows the differences between the treatment and control groups, before and after the matching, and Table 11 presents the matched sample by country. Furthermore, to fulfil the parallel trends assumption needed for the difference-in-difference analysis, Charts 5 to 8 in Appendix 1 present the graphical evolution for both groups after the matching process and show that the distance between the treatment and control group remains constant over time prior to the ban enactment. Finally, Table 1 below presents a description of the main variables of the dataset, after the matching process.

3.3 Regression set-up

The difference-in-difference analysis of the impact of short selling bans on our set of dependent variables employs the following baseline regression model:

$$Y_{sct} = \alpha + \beta Treatment_s + \gamma Event_t + \delta Treatment_s * Event_t + \theta Controls_{sct} + FE + \epsilon_{sct}$$

where:

[20] According to MiFID II/MiFIR, a share is liquid if all of the following conditions are satisfied: (a) the free float of the share is not less than EUR 100 million for shares admitted to trading on a regulated market; (ii) the market capitalisation is not less than EUR 200 mn for shares that are only traded on MTFs; (b) the average daily number of transactions in the share is not less than EUR 250 mn; (c) the average daily turnover for the share is not less than EUR 1 million.

- Y_{sct} is one of the dependent variables for which the regression is estimated, i.e. bid-ask spreads, Amihud illiquidity indicator, abnormal return, intraday volatility or volumes traded. α is a constant, s represents the share, c the country and t the time index.
- $Treatment_s$ is a dummy variable equal to one over all trading days for shares in banned countries.
- $Event_t$ is a dummy variable equal to one for all shares during the validity of the short selling ban.
- $Treatment_s * Event_t$ is the interaction variable which isolates the effect of the treatment on the affected stocks. Its estimated coefficient is, hence, the most important coefficient of this regression.
- $Controls_{sct}$ is the set of control variables, either at stock level (market capitalisation, fragmentation indicator, volumes traded, intraday volatility) or at country level (stringency index). Additionally, VSTOXX is added as a proxy for the evolution of volatility on European markets.
- FE are the fixed effects included in the regressions. Stock fixed effects control for unobserved variables linked to each stock, and time fixed effects take into account the commonality in liquidity or returns. We present the regressions with both fixed effects combined (two-way fixed effects), keeping in mind the issues caused by multicollinearity.[21]

The difference-in-difference model estimates the impact of the bans on five main variables of interest: two variables to assess the liquidity of the equity market (bid-ask spreads and the Amihud illiquidity indicator), abnormal returns (to represent the evolution of prices), volumes traded, and a volatility measure. Standard errors are clustered at the stock level, following Beber and Pagano (2013).

Following Degryse et al. (2015) and ESMA (2017), we compute the bid-ask spreads using the closing ask and bid prices for each share (the difference between the highest price a buyer is willing to pay for a share and the lowest price a seller is willing to accept), and we normalise daily bid-ask spreads using the following formula to correct for nominal differences and make reliable comparisons across companies and countries:

$$Spread_{st} = \frac{(Ask\ Price_{st} - Bid\ Price_{st})}{Mid\ Price_{st}}$$

[21] When adding one or multiple fixed effects, share-invariant or time-invariant variables will be dropped from the regressions, as well as the variables ‘Event’ or ‘Treatment’ in the regression above.

The Amihud illiquidity indicator is the second measure of liquidity considered. It calculates the daily ratio of the absolute value of a stock return to its dollar volume, and thus serves as a rough measure of price impact:

$$Amihud_{st} = \frac{|Return_{st}|}{Volumes_{st} * Closing\ Price_{st}} * 10^6$$

Increasing values of Amihud indicate that the price return is less affected by trading volumes, and thus higher values indicate less-liquid stocks.

The volumes traded variable is based on the quantity of share traded daily, in order to observe the evolution of trading volumes, but separating this variable from price evolution. We normalise the bid-ask spreads, volumes and Amihud using a log transformation.

We calculate abnormal returns, which allow for an assessment of prices evolution and stock over/under-performing with respect to its reference market benchmark, by comparing for each share its daily returns with the returns of the benchmark national index multiplied by the share market beta[22], using:

$$Abnormal\ Return_{st} = Return_{st} - (Marketbeta_{sct} * Benchmark\ R_{ct})$$

Finally, in order to increase the robustness of the analysis, we use two different measures of volatility: first, we compute historical volatility as the standard deviation of a stock's log returns over two days. Second, we calculate the so-called high-low range volatility, or intraday volatility, based on daily high and low trading prices, using Parkinson’s (1980) approach:

$$Intraday\ Volatility_{st} = \sqrt{\frac{1}{4\,ln\,2}\left(\ln\,(\frac{High\ Price_{st}}{Low\ Price_{st}})^2\right)^2}$$

where $High\ Price_{st}$ is the stock *s* highest trading price on day *t*, and $Low\ Price_{st}$ is the stock *s* lowest trading price.

Furthermore, the following control variables were included:

- $Market\ capitalisation_{st}$, to control for firm size. As larger firms generally benefit from larger coverage by financial analysts, they tend to have larger trading volumes and possibly higher market liquidity.

[22] The market beta is the monthly historical beta calculated by Refinitiv Datastream for each share, and the variable employed as benchmark is the return of each national index of reference, using daily price from Refinitiv Datastream.

- $Market\ fragmentation_{st}$, calculated as the inverse of the Herfindahl-Hirschman Index, which is a widely used measure to determine the concentration of a market. Fragmentation can have a significant impact on market liquidity, since higher fragmentation can improve liquidity aggregated over all trading venues, but may lower liquidity in the reference market. The indicator is calculated daily at share level for on-exchange trading and is defined as:

  $Market\ fragmentation_{st} = \frac{1}{HHI_{st}}$, where for each st, $HHI_{st} = \sum_{j=1}^{M} \left(marketshare_{sj}\right)^2$, with M being the total number of venues that displayed trading in share s.

- $VSTOXX_t$, to control for daily volatility,

- $Stringency\ index_{ct}$, a daily measure of the strength of containment policies linked to the spread of the pandemic, which controls for the impact of the pandemic at the country level. This variable is measured as the daily average for each country of nine indicators pertaining to containment and lockdown policies (Oxford COVID-19 Government Response Tracker 2021).

- Following Beber and Pagano (2013), we also control for volatility among the explanatory variables, since it can affect market liquidity by changing the inventory risk of market makers.

- Other variables, such as turnover, Return on Equity, Return on Assets, Economic sentiment at the country level and country risk were tested but did not affect results or add value, and hence they are not presented.

The full dataset covers 1,716 European stocks between 13 January 2020 (i.e., two months before the ban) and 31 July 2020. Regarding the chosen timeframe, the same regressions were estimated using different timeframes (both shorter and longer timeframes were tested) with similar results, and these alternative estimations are not presented here. The paper presents the results of estimating the model for the proposed timeframe and, in addition, an alternative specification obtained by adding a dummy variable for the period after the ban, to assess whether the effects of the ban persisted after its termination (see subsections 4.2).

In line with previous empirical studies, the hypothesis tested in the analysis is that the imposition of a short selling ban, by preventing potentially informed investors to take new short selling positions, will slow down the price discovery process, and that such delayed resolution of uncertainty about fundamentals will decrease the liquidity of shares (measured here with bid-ask spreads and the Amihud illiquidity indicator). Since the usual rationale of regulators and policy makers to justify the introduction of short selling bans during periods of financial distress is the decrease of volatility, past bans were also usually share-specific, meaning targeting specific shares of sectors, but seldom market-wide. This is the first time 6 important European equity markets close all possibilities of short selling, including by explicitly prohibiting other type of short selling position through derivatives' use, for instance. Thus, the effects of those bans on volatility are different. In fact, bans targeting specific stocks and/or sectors can amplify concerns about specific shares, amplifying volatility, heightening uncertainty and increasing information asymmetry about the fundamentals (Liu (2015)). However, the hypothesis that we test here, since the European bans of 2020 are market-wide and concern all shares, is a decrease of short-term volatility, as well as trading volumes.

The expected effects on prices are more ambiguous: if the ability to short sell stocks increases the informational efficiency of market prices (see Saffi and Sigurdsson (2011)), a constraint on short selling, by slowing down price discovery, will be expected to sustain prices. However, short-sales constraints, by increasing the risk perceived by uninformed investors, can lead them to require higher expected returns (inducing lower prices), or lead to negative information not being incorporated into share prices under the ban, which would aggravate the price decline after the end of the ban (Hong and Stein (2003)).

4 Effects of the bans on market quality

4.1 Main results

The effects of the short selling ban on market liquidity for the concerned shares appear to be negative, as indicated by the sign and the statistical significance of the main variable of interest in the regression, the interaction between *Treatment* and *Event* (Table 2).

The short selling ban is correlated with a deterioration of the bid-ask spread of the concerned shares: the regression coefficient (0.077) is statistically significant and implies an average increase of 1.080 (=$e^{0.077}$), meaning bid-ask spreads increased by 8% for stocks in banned jurisdictions during the restriction, compared to the control group. Similarly, the coefficient for Amihud is significant and the ban is associated with an increase of 5.8% of the Amihud illiquidity indicator, confirming that the ban reduced liquidity of the concerned shares. The ban also had the effect of decreasing the volumes traded, with the significant coefficient showing an important decrease of -14.9% for shares traded under the ban.

Moreover, the impact on abnormal returns appears non-statistically significant and, furthermore, the adjusted R-squared for this dependent variable is small, showing that the percentage of the variance of abnormal returns explained by our model is minor. This suggests that the bans did not harm nor sustain market prices over the enactment period. In the literature, the effectiveness of short selling bans in supporting stock prices is ambiguous. Looking at excess returns during the 2008 financial crisis, Beber and Pagano (2013) show that the bans have not been associated with better stock price performance globally, with the US being the only exception. Similarly, Siciliano and Ventoruzzo (2020) estimates that shares' excess returns in the banned period in 2020 were, on average, 0.1% lower compared with firms in European countries that did not impose short selling bans.

Table 2
Main regression results

	Log bid-ask spread	Log Amihud	Abnormal returns	Intraday volatility	Log volumes
	(1)	(2)	(3)	(4)	(5)
Treatment*Event	0.077***	0.056***	-0.0003	-0.245***	-0.162***
	(0.013)	(0.022)	(0.0004)	(0.050)	(0.018)
Market capitalisation	-0.00001***	-0.0001***	0.00000***	-0.0001***	-0.00003***
	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00000)
Fragmentation	-0.012***	0.037***	0.0001	-0.028**	-0.074***
	(0.004)	(0.007)	(0.0001)	(0.012)	(0.006)
Stringency index	0.001***	-0.0002	0.00005***	0.004***	0.0004
	(0.0003)	(0.0005)	(0.00001)	(0.001)	(0.0004)
Volumes	-0.00001***	NA	0.00000	0.0002***	NA
	(0.00000)		(0.00000)	(0.00003)	
Intraday volatility	0.030***	0.007**	0.002***	NA	0.155***
	(0.002)	(0.003)	(0.0002)		(0.003)
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	217,945	204,088	221,133	223,583	219,291
Adjusted R^2	0.764	0.859	0.050	0.398	0.913

Note: Estimates of the regression, robust standard errors in parentheses. Standard errors are clustered at the stock level.
*** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
Sources: ESMA.

Finally, the volatility analysis highlights that shares in banned countries exhibited a lower degree of volatility during the ban period: the coefficients displayed in Table 2 imply a statistically significant reduction in volatility: compared to the sample average and the sample median in non-banning days (equal to 2.90 and 3.07, respectively), the coefficient implies a decrease of -8.4% (i.e., -0.245/2.9) and -80% (i.e., -0.245/3.07), respectively. Since the results for the historical volatility measure are similar, only the intraday volatility model is presented.

4.2 Post ban effect

Since market conditions did not normalise right after the lift of the ban, and to investigate any long-lasting effect of the ban, we propose an alternative specification of our baseline difference-in-differences analysis which considers separately the post-ban period, according to the following specification:

$$Y_{sct} = \alpha + \beta Treatment_s + \gamma Event_t + \delta Treatment_s * Event_t + \zeta PostBan_t +$$

$$\eta Treatment_s * PostBan_t + \theta Controls_{sct} + FE + \epsilon_{sct}$$

Where $PostBan$ is a dummy variable taking value 1 from 19 May to end of July (the post-ban period). Interacting this variable with the treatment allows to differentiate between the effects of the ban period itself and any prolonged effects afterwards (coefficient η) and are to be compared to the pre-ban period.

Table 3

Regression results, post-ban period variable

	Log bid-ask spread	Log Amihud	Abnormal returns	Intraday volatility	Log volumes
	(6)	*(7)*	*(8)*	*(9)*	*(10)*
Treatment*Event	0.094***	0.100***	-0.001**	-0.301***	-0.184***
	(0.016)	(0.028)	(0.001)	(0.062)	(0.024)
*Treatment*Post-ban*	0.037**	0.093***	-0.002***	-0.117**	-0.047*
	(0.015)	(0.031)	(0.0004)	(0.057)	(0.027)
Market capitalisation	-0.00001***	-0.00005***	0.00000***	-0.0001***	-0.00003***
	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00000)
Fragmentation	-0.012***	0.038***	0.0001	-0.028**	-0.074***
	(0.004)	(0.007)	(0.0001)	(0.012)	(0.006)
Stringency index	0.002***	0.0003	0.00004**	0.003***	0.0001
	(0.0003)	(0.0005)	(0.00001)	(0.001)	(0.0004)
Volumes	-0.00001***	NA	0.00000	0.0002***	NA
	(0.00000)		(0.00000)	(0.00003)	
Intraday volatility	0.030***	0.007**	0.002***	NA	0.155***
	(0.002)	(0.003)	(0.0002)		(0.003)
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	217,945	204,088	221,133	223,583	219,291
Adjusted R^2	0.764	0.859	0.050	0.398	0.913

Note: Estimates of the regression, robust standard errors in parentheses. Standard errors are clustered at the stock level.
*** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
The presence of stock and day fixed effects may result in dummy variables (here, VSTOXX) to be removed from the estimation due to multicollinearity.
Sources: ESMA.

The estimates in Table 3 show that even though the period of the ban itself had the stronger impact on liquidity variables, the period immediately afterwards is also associated with significantly higher bid-ask spreads (+3.8%) and illiquidity (+9.7% for the Amihud illiquidity indicator) in countries where a ban was implemented. Volatility and volumes continued to be lower for the shares constrained by the ban after it was lifted (respectively -3.9% and -4.6%).[23] The effect on abnormal return is significant, albeit small (-0.2%).[24]

4.3 Differentiated effects of the ban by share characteristics

The same type of analysis is then estimated taking into account different groups of stocks, in order to assess whether short selling bans had differentiated effects on the liquidity of stocks with specific characteristics (Table 4).

Firstly, we separate between the smallest (small-cap shares) and the largest (large-cap) market capitalisation of our sample[25], since liquidity is lower for small-cap stocks even in the absence of short selling constraints. Boehmer et al. (2013) argue that lower impacts of short selling restrictions on small-cap stocks should be expected, given that small stocks experience minor changes in the amount of shorting during the ban, and that the liquidity supply provided

[23] The impact on volatility is calculated here by comparing the regression coefficient with the sample median observed during the pre-ban period (-3.9%=-0.117/2.98).
[24] Similar results are observed in the same regression without controls and presented in Table 13 in Appendix 1.
[25] The regression is estimated separately for each quartile of the companies by capitalization, and the first (small-cap) and last (large-cap) quartiles of the dataset in terms of market capitalisation are presented in the table.

by market makers is less pervasive for small-cap stocks than for large-cap. While this explanation might not be entirely comparable to the European situation during the COVID-19-related market stress, it can be expected that in countries where large-cap stocks are overrepresented, the ban had stronger impact and was associated with larger increases in bid-ask spreads and in the Amihud illiquidity indicator, as well as stronger changes in volumes traded and volatility.

The results in Table 4 confirm that the bans greatly affected the liquidity of large-cap shares, with a strong increase of their bid-ask spreads (+15.9%), whereas they did not have significant impacts on small-cap shares. The Amihud illiquidity indicator corroborates that the adverse liquidity effect of bans was more pronounced for large-cap shares, with a statistically significant increase of the Amihud illiquidity indicator for large-cap of +32.7%, and for small-cap of –17.1%, i.e. an increase in liquidity for small-cap shares (Table 4). Volumes traded increased significantly for small-cap shares traded under the ban (+10.8%) but decreased markedly for large-cap (-31.3%). Volatility decreased significantly for small-cap (-7.9% compared to the small-cap median in non-banning days) and did not vary significantly for large-cap (Table 14 in Appendix 1).

Furthermore, to assess whether the bans affected shares differently depending on their fragmentation level, i.e. how their trading volumes are distributed across trading venues in Europe, we introduce a market fragmentation indicator calculated as the inverse of the Herfindahl-Hirschman Index for volumes traded by venue, and separate shares with and high and low market fragmentation.[26]

The impact of the bans on bid-ask spread does not appear statistically significant for shares with low trading fragmentation, meaning shares for which trading is heavily concentrated on one or few venues. However, bid-ask spreads widened significantly for shares with high trading fragmentation (+14.7%). The same discrepancy in liquidity deterioration is observed looking at the Amihud illiquidity indicator, with low fragmentation shares seeing an improvement of their liquidity (-9.6% of the illiquidity), while highly fragmented shares saw a major deterioration (+34.8%). Similarly, highly fragmented shares observed an important decrease of their traded volumes under the ban (-30.8%, Table 14 in Appendix 1), while the ban had no significant effect on volumes for low fragmented shares. Neither abnormal returns nor volatility were significantly affected by the ban regardless of the degree of fragmentation.

[26] Similarly, low (highly) fragmented stocks are defined as the first (last) quartiles in terms of market fragmentation of the dataset.

Table 4

Regression results, share characteristics, liquidity variables

	Log bid-ask spread					Log Amihud				
	Small-cap stocks	Large-cap stocks	Low-fragmented stocks	High-fragmented stocks	Impact of listed derivatives	Small-cap stocks	Large-cap stocks	Low-fragmented stocks	High-fragmented stocks	Impact of listed derivatives
	(11)	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*	*(18)*	*(19)*	*(20)*
Treatment*Event	0.007	0.140***	0.006	0.137***	0.173***	-0.183***	0.267***	-0.101*	0.299***	0.156***
	(0.024)	(0.023)	(0.025)	(0.022)	-0.024	(0.050)	(0.030)	(0.053)	(0.033)	-0.038
Market capitalisation	-0.004**	-0.00000	-0.0002	-0.00000	0	-0.019***	-0.00004***	-0.001	-0.00003***	-0.00004***
	(0.002)	(0.00000)	(0.0001)	(0.00000)	0	(0.005)	(0.00001)	(0.0004)	(0.00001)	-0.00001
Fragmentation	0.041**	-0.021***	NA	NA	-0.014***	-0.007	-0.001	NA	NA	0.046***
	(0.018)	(0.005)			-0.004	(0.051)	(0.008)			-0.007
Stringency index	0.002*	0.001	0.002***	0.001*	-0.0001	-0.0001	0.0002	-0.0001	0.0003	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	-0.0004	(0.001)	(0.001)	(0.001)	(0.001)	-0.001
Volumes	-0.0004***	-0.00001***	-0.0002*	-0.00001***	-0.00001***	NA	NA	NA	NA	NA
	(0.0001)	(0.00000)	(0.0001)	(0.00000)	0					
Intraday volatility	0.029***	0.026***	0.028***	0.019***	0.031***	-0.034***	0.125***	-0.041***	0.090***	0.094***
	(0.002)	(0.003)	(0.003)	(0.002)	-0.002	(0.004)	(0.005)	(0.004)	(0.006)	-0.004
Treatment*Event* Listed Derivatives	NA	NA	NA	NA	-0.04	NA	NA	NA	NA	0.168***
					-0.032					-0.049
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	50,049	57,274	53,042	56,548	112,033	43,303	57,160	46,081	55,792	110,006
Adjusted R^2	0.449	0.628	0.488	0.706	0.7	0.552	0.832	0.569	0.881	0.828

Note: Estimates of the regression, robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
The presence of stock and day fixed effects may result in dummy variables to be removed from the estimation due to multicollinearity.
Sources: ESMA.

Finally, since the 2020 short selling bans are the first bans that explicitly extended the ban not only to shares, but also their derivatives[27], we modify our baseline regression to assess the impact for shares that have derivatives. Without the extension of the ban to derivatives, the effects of short selling restrictions on bid-ask spreads should be stronger for stocks without derivatives, as Beber and Pagano (2013) concluded. Therefore, we anticipate no distinction between the two groups in the 2020 bans setup. In order to investigate whether the availability of derivatives plays a role in the liquidity effects of the bans, we create a dummy variable for shares for which there are listed derivatives (options, futures and warrants) in FIRDS. To investigate differentiated effects for subgroups of shares (i.e., shares with listed derivatives and, as described in the following sections, shares with net short positions prior to the ban and shares belonging to specific economic sectors), we perform the following triple difference regression:

$$Y_{sct} = \alpha + \beta Treatment_s + \gamma Event_t + \delta Treatment_s * Event_t + \zeta SG_s + \eta SG_s * Treatment_s$$

$$+\kappa SG_s * Event_t + \lambda SG_s * Treatment_s * Event_t + \theta Controls_{sct} + FE + \epsilon_{sct}$$

[27] During past short-selling bans, since the use of derivatives was not necessarily constrained, investors could still effectively take short positions by trading in the option markets. However, the 2020 bans are the first ones to explicitly ban the creation or increase of short net positions, that applies to shares but also to all related instruments included in the calculation of net short position, like saving/preferred shares, derivatives, depositary receipts, or funds whose return replicates the return or the reverse return of an index mainly composed by shares concerned by the bans.

Where variable $SG_s$is the dummy identifying whether a share s belongs to the subgroup of interest. In this setting, the coefficient of interest is λ, i.e., the one related to the triple difference (the interaction between treated group, treatment period and relevant subgroup). Moreover, since we observe that stocks with listed derivatives are usually large-cap, we estimate the regression only on the shares with the largest market capitalisation (i.e. the third and fourth quartiles of market capitalisation in the sample), allowing us to single out the effect of having listed derivatives from the market size effect.

Results show that the bans had a stronger impact on the liquidity of the stocks with listed derivatives, with an additional deterioration of the illiquidity indicator (+18.3%), an additional decrease of volumes traded (-14.4%) and increasing volatility (+23.2% compared to the median value in non-banning days), but no statistically significant effect on the bid-ask spreads.

4.4 Differentiated effects of the bans across sectors

To assess whether sectoral dynamics influenced the effects of the bans, we perform the same analysis focusing on sectors that were especially hit during the COVID-19 crisis. Most of the empirical literature on short selling bans analysed their effects during the past financial crisis, when bans were prompted by concerns about the stability of financial institutions, and in some countries targeted only financial institutions' shares. Thus, this literature focused on the differentiated effects of the bans on financial institutions, observing stronger negative impact on financials (Marsh and Payne (2012)).

However, the COVID-19 market stress was different, and so was the distribution of its adverse effects across firms and sectors of the economy. Thus, to test whether the sectoral effects were present during the COVID-19 related market stress, sectoral dummies were added to the baseline regression drawing on the triple difference setting introduced in the previous section. In particular, we look at the sectors that were mostly affected by the crisis, using the others as a benchmark. During the pandemic the stock market has priced in various dimensions of resilience, including each industry's immunity to social distancing requirements (Pagano et al. (2020)). To take this into account, the proposed benchmark group is constituted by the industrials, materials, consumer non-cyclical, energy and utilities sectors; while the sectors highlighted in the regression, and thus deemed as mostly affected by the market stress, are the financials, consumer cyclical, healthcare, real estate, technology and telecom sectors.[28] This latter group constitutes 38% of the shares in the matched dataset and 40% of its market capitalisation, assuring the representativeness of the results.

[28] The proposed list of groups is based on the observed returns for each sector in February and March 2020, as well as on the literature. However, the sectors deemed as "resilient" the COVID-19 related market stress can be subject to discussion and adjustments, and are constrained by the level of granularity accessible in the analysis.

Table 5
Regression results, sectoral effects

	Log bid-ask spread	Log Amihud	Abnormal returns	Intraday volatility	Log volumes
	(31)	*(32)*	*(33)*	*(34)*	*(35)*
Treatment*Event	0.084***	0.033	-0.0001	-0.230***	-0.151***
	(0.019)	(0.0)	(0.001)	(0.067)	(0.028)
Financials	0.073*	0.082	-0.001	-0.191	-0.087
	(0.041)	(0.066)	(0.001)	(0.160)	(0.056)
Consumer Cyclical	-0.003	0.113*	-0.001	-0.432***	-0.110**
	(0.033)	(0.060)	(0.001)	(0.145)	(0.054)
Healthcare	-0.087**	-0.170*	0.002	0.723***	0.146**
	(0.043)	(0.090)	(0.002)	(0.223)	(0.070)
Real Estate	0.041	0.025	-0.0004	-0.303*	-0.023
	(0.042)	(0.070)	(0.001)	(0.170)	(0.069)
Technology	-0.036	0.075	-0.001	0.107	0.027
	(0.038)	(0.058)	(0.001)	(0.153)	(0.053)
Telecom	-0.131	0.027	-0.003	0.520	0.002
	(0.095)	(0.111)	(0.002)	(0.358)	(0.099)
Market capitalisation	-0.00001***	-0.00005***	0.00000***	-0.0001***	-0.00002***
	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00000)
Fragmentation	-0.012***	0.038***	0.0001	-0.029**	-0.074***
	(0.004)	(0.007)	(0.0001)	(0.012)	(0.006)
Stringency index	0.001***	-0.0002	0.00005**	0.004***	0.0004
	(0.0003)	(0.0005)	(0.00001)	(0.001)	(0.0004)
Volumes	-0.00001***	NA	0.00000	0.0002***	NA
	(0.00000)		(0.00000)	(0.00003)	
Intraday volatility	0.030***	0.007**	0.002***	NA	0.155***
	(0.002)	(0.003)	(0.0002)		(0.003)
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	217,945	204,088	221,133	223,583	219,291
Adjusted R^2	0.764	0.859	0.050	0.399	0.913

Note: Estimates of the regression, robust standard errors in parentheses. Standard errors are clustered at the stock level.
*** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
The presence of stock and day fixed effects may result in dummy variables (here, VSTOXX) to be removed from the estimation due to multicollinearity.
Sources: ESMA.

The first finding is that, contrary to other analyses covering past crises of a financial nature (such as Beber et al. 2018), the financials subset did not seem to behave differently than other stocks during the COVID-19 market stress, with no significant effect for the shares under the ban except for an increase in bid-ask spreads (+7.5%). This might be explained by the fact that this crisis impacted both the financial sector and the real economy from the outset, which were also both supported by accommodative monetary policies and fiscal support at the European and national levels.

Furthermore, strong effects are observed for some of the sectors that were mostly hit by the pandemic-related market stress. The healthcare sector is the most impacted by the bans, with an improvement of liquidity (decrease in bid-ask spreads by -8.3% and in the illiquidity indicator by -15.6%), an increase in volatility (24.6%) and in volumes traded (+15.7%) for those shares during the ban period. On the contrary, shares under the bans from the consumer cyclical sector saw a deterioration of their liquidity (+12.0% of the Amihud indicator), a decrease in their volatility (-14.9%), but an increase in their traded volumes (+12.0%) during the period. Shares from the real estate sector saw a decrease in their volatility (-10.4%). The technology and telecom sectors were not significantly affected by the bans, suggesting that other characteristics have more importance in explaining the liquidity evolution of those shares under the ban. The impact on abnormal returns appears as non-statistically significant for all sectors.

These results confirm that, contrary to past crisis of a financial nature, where short selling bans affected in particular financial stocks, this crisis was of unprecedented nature, with many sectors affected by the market stress and by the bans. In this configuration the stocks that were at the heart of the crisis, namely from the healthcare sector, saw an important increase in their volatility, volumes as well as a surge in their liquidity, suggesting that information revelation was high for them.

4.5 Differentiated effects for shorted shares

Finally, to assess whether shorted shares were more heavily impacted by the bans, we identify those shares with short selling activity prior to the bans and modify our baseline regression according to the triple difference framework introduced in Section 4.3. Shares with short selling activity in this setting are defined as those for which a positive net short position has been notified in the days before the implementation of the coordinated European bans, that is for which at least one net short position holder reported a position equal to or higher than 0.1% of the issued share capital of the company. Information on shorted shares comes from regulatory data on aggregated net short position per issuer, notified to NCAs following the requirements introduced by the Short Selling Regulation. [29] The comparison between these two groups is feasible as it is based on pre-ban information, and aims at exploring whether the long term ban had any effects on those shares that were subject to short selling activity in the earlier phase of the COVID-19 market stress without considering how NSPs evolved in non-banning jurisdictions. Furthermore, considering the findings of the descriptive analysis on displacement effect (see Appendix 2), we believe the absence of a shift in short selling activity between banning and non-banning jurisdictions validates our approach.

The results show that shares that were shorted before the ban saw an important increase in the illiquidity indicator (+27.3%), confirming that the ban reduced their liquidity, but no significant effect on their bid-ask spreads. Contrary to other subgroups, shorted shares saw their volatility increase (+14.7% with respect to the sample median in non-banning days), while their volumes decreased even further compared to shares that were not shorted prior to the ban (-22.7%). This effect can be explained by the suppression of negative information in the

[29] Shorted shares are defined as those for which at least one positive net short position was notified between the 11 and 18 March 2020, no matter its value. According to Article 5(2) of SSR, any natural or legal person who has a net short position in relation to the issued share capital of a company shall notify the relevant competent authority, where its position reaches or falls below a relevant notification threshold. During the COVID-19 market stress, ESMA took the decision to lower the notification threshold from 0.2% to 0.1%, 2020, 0,2 % of the issued share capital of the company concerned and each 0,1 % above that. The European Commission adopted the decision to permanently lower the threshold from 0.2% to 0.1% in September 2021.

price discovery process, which may have created more uncertainty regarding their value in the absence of short selling possibilities.

Table 6
Regression results, shorted shares

	Log bid-ask spread	Log Amihud	Abnormal returns	Intraday volatility	Log volumes
	(36)	*(37)*	*(38)*	*(39)*	*(40)*
Treatment*Event	0.056***	-0.054*	-0.002*	-0.431***	-0.057**
	(0.015)	(0.029)	(0.001)	(0.068)	(0.025)
*Treatment*Event* Shorted shares*	0.007	0.242***	0.0003	0.427***	-0.258***
	(0.024)	(0.041)	(0.0001)	(0.099)	(0.034)
Market capitalisation	-0.00001***	-0.00005***	0.00000***	-0.0001***	-0.00003***
	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00000)
Fragmentation	-0.011***	0.038***	0.0001	-0.025**	-0.074***
	(0.004)	(0.007)	(0.0001)	(0.012)	(0.006)
Stringency index	0.001***	-0.0003	0.00005*	0.004***	0.0001
	(0.0003)	(0.0005)	(0.00001)	(0.001)	(0.0004)
Volumes	-0.00001***	NA	0.00000	0.0002***	NA
	(0.00000)		(0.00000)	(0.00003)	
Intraday volatility	0.030***	0.007**	0.002***	NA	0.156***
	(0.001)	(0.003)	(0.0002)		(0.003)
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	217,945	204,088	221,133	223,583	219,291
Adjusted R^2	0.765	0.859	0.050	0.398	0.913

Note: Estimates of the regression, robust standard errors in parentheses. Standard errors are clustered at the stock level.
*** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
The presence of stock and day fixed effects may result in dummy variables (here, VSTOXX) to be removed from the estimation due to multicollinearity.
Sources: ESMA.

5 Conclusion

The European long-term short selling bans of 2020 appear to have had mixed effects, since they entailed a deterioration of market liquidity but also diminished the volatility of the shares concerned. In line with the literature on the subject, constraining short sellers from opening short positions contributed to higher bid–ask spreads and higher Amihud illiquidity values. At the same time, considering the uncertainty linked to the COVID-19 market stress, curbing short selling activity with the purpose of avoiding disorderly downward price spirals appears to have contributed to a reduction in volatility for banned shares.

The econometric analysis undertaken did not identify statistically significant correlations with abnormal returns, suggesting that the policy did not harm nor sustain market prices over the enactment period. To further refine the impact assessment of short selling bans on liquidity, we take into account the fact that bid-ask spreads may be affected by stock-specific liquidity characteristics. The negative impact of the bans on liquidity is more pronounced for stocks with a large market capitalisation, highly fragmented shares, shorted shares, and for stocks with listed derivatives. The stocks that were at the heart of the crisis, namely from the healthcare sector, saw an important increase in their volatility, volumes as well as a surge in their liquidity, suggesting that information revelation was high for them during the ban period.

This empirical analysis contributed to supervisory convergence in the context of the latest review of the EU short selling regulation[30], with the aim of taking stock of the first coordinated market-wide short selling bans, and aiming at improving the overall efficiency of such policies.

References

Beber, A. and M. Pagano (2013), “Short selling bans around the world: evidence from the 2007-09 crisis”, Journal of Finance, Vol. 48, No. 1, pp.343-381.

Beber A., D. Fabbri, M. Pagano and S. Simonelli (2018), “Short selling bans and bank instability”, ESRB Working Paper series, n.64.

Benhami K., van Veldhuijzen L. and T. Schoolderman (2022), “Short selling ban impact – a comparison of the French and the Dutch markets”, Autorité des Marchés Financiers and Autoriteit Financiële Markten working paper, February.

Boehmer, E., C. M. Jones and X. Zhang (2013), “Shacking short sellers: the 2008 shorting ban”, The Review of Financial Studies Vol. 26, No. 6-2013, pp.1363-1400.

Brunnermeier, M. K. and M. Oehmke (2014), “Predatory Short Selling”, Review of Finance, No.18, pp.2153-2195.

Degryse H., F. de Jong and V. van Kervel (2015), The Impact of Dark Trading and Visible Fragmentation on Market Quality, Review of Finance, Volume 19, Issue 4, July 2015, pp.1587–1622.

Della Corte, P., Kosowski, R., and N. Rapanos (2020), “The Double-Edged Sword of the 2020 European Short Selling Bans”. Preliminary working paper.

Diamond, D., and R. Verrecchia (1987), “Constraints on short selling and asset price adjustment to private information”, Journal of Financial Economics, Volume 18, Issue 2.

ESMA (2017), “Technical advice to the European Commission on the evaluation of certain elements of the Short Selling Regulation”, pages 277-311.

Gertler, P., S. Martinez, P. Premand, L. Rawlings and C. Vermeersch (2011), Impact Evaluation in Practice, The World Bank Textbook.

Greppmair, S., S. Jank and E. Smajlbegovic (2020), “Betting on disaster: Short selling activity during the COVID-19 pandemic”, Working Paper.

Hale T., N. Angrist, R. Goldszmidt, B. Kira, A. Petherick, T. Phillips, S. Webster, E. Cameron-Blake, L. Hallas, S. Majumdar, and H. Tatlow (2021), “A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)”, Nature Human Behaviour.

Hong, H. and J. C. Stein (2003), “Differences of opinion, short-sales constraints, and market

[30] See ESMA (2021), Consultation Paper - Review of certain aspects of the short selling regulation.

crashes”, Review of Financial Studies 16, 487–525.

Jank, S., C. Roling and E. Smajlbegovic (2016), “Flying under the radar: the effects of short-sale disclosure rules on investor behaviour and stock prices”, Deutsche Bundesbank, Discussion Paper No. 25/2016.

Jones, C.M., A.V. Reed and W. Waller (2016), “Revealing shorts: an examination of large short position disclosures”, The Review of Financial Studies, Vol. 29, No. 12, pp.3278-3320.

Kolasinski, A. C., A. Reed and J. Thornock (2013), “Can Short Restrictions Actually Increase Informed Short Selling?”, Financial Management, Vol. 42, No. 1, 2013, pp.155–181.

Lopez, R.L and A. M. Pastor (2020), “Analysis of the effect of restrictions on net short positions on Spanish shares between March and May 2020”, Comision Nacional del Mercado de Valores.

Mazzacurati J. (2018), “The public disclosure of net short positions” in ESMA Report on Trends, Risks and Vulnerabilities 1-2018.

Pagano, M., C. Wagner and J. Zechner (2020), “Disaster Resilience and Asset Prices”, CEPR Discussion Paper 14773 and Covid Economics: Vetted and Real-Time Papers 21.

Parkinson, M. (1980), “The Extreme Value Method for Estimating the Variance of the Rate of Return”, The Journal of Business, No. 53, pp.61-65.

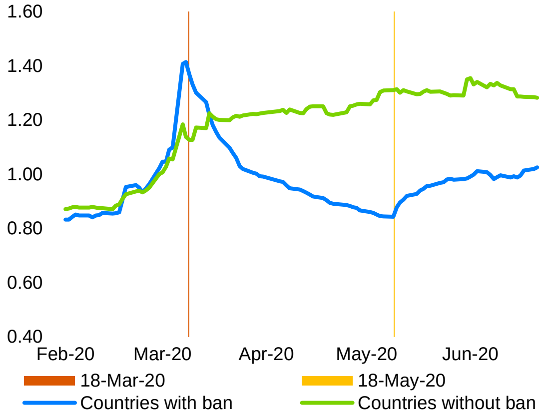
Reed, A. V. (2013), “Short Selling", Annual Review of Financial Economics, No. 5, pp.245-258.

Saffi, P. A. and K. Sigurdsson (2011), “Price Efficiency and Short Selling," Review of Financial Studies, No. 24, pp.821-852.

Siciliano, G. and M. Ventoruzzo (2020) “Banning Cassandra from the Market? An Empirical Analysis of Short selling Bans during the Covid 19 Crisis”, European Company and Financial Law Review, De Gruyter, Vol. 17(3-4), pp.386-418, June.

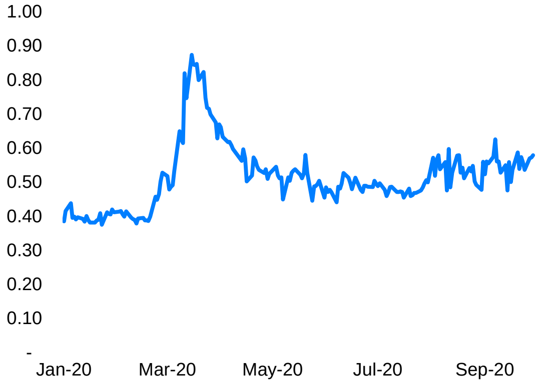
Appendix 1: Additional tables and graphs

Chart 1
Evolution of NSPs market value around the ban



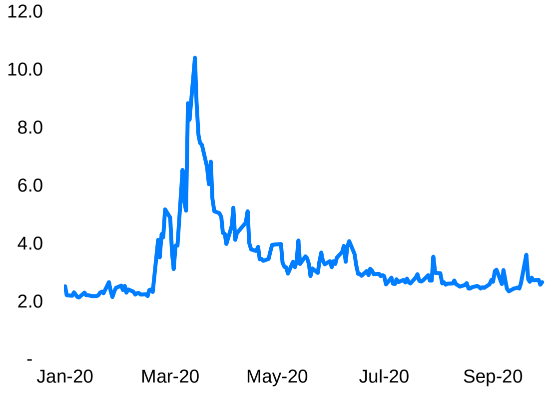
Note: Net short positions on the CEM matched sample, as a % of the total issued share capital, split by countries with ban and without ban. Applied issued share capital for reference of 10 February 2020.
Sources: NCAs, Refinitiv EIKON, ESMA.

Chart 2
Bid-ask spread around the ban



Note: bid-ask spread in % for the shares in the dataset, multiplied by a factor of 100.
Sources: Refinitiv, ESMA.

Chart 3
Intraday volatility around the ban



Note: Intraday volatility for the sahres in the dataset, calculated with the Parkinson formula, multiplied by a factor of 100.
Sources: Refinitv, ESMA.

Table 7

Description of variables used and definition

Variable	Notes	Frequency	Source	Time window
Market value	Market capitalization, in EUR millions	Daily	Refinitiv Datastream	2019, 2020
Prices: Open, Close, High & Low	In EUR	Daily	Refinitiv Datastream	2019, 2020
Ask, Bid prices	In EUR	Daily	Refinitiv Datastream	2019, 2020
Bid-Ask spread	In percent	Daily	Computed	2020
Trading volumes	In number of shares	Daily	ESMA FITRS	2019, 2020
Volumes	Number of shares traded, in thousands	Daily	Refinitiv Datastream	2019, 2020
Fragmentation	The inverse of the HHI index on the regulated markets at stock level	Daily	Computed using FITRS	2020
Liquidity flag	Liquidity assessment, ESMA transparency calculations	Flag	ESMA FITRS	2019, 2020
Sectoral information	Economic Sector of the company	Flag	Refinitiv Eikon	2020
Intraday price volatility	Using Parkinson formula	Daily	Computed	2020
Historical Volatility	Standard deviation of a stock's log returns over two days	Daily	Computed	2020
Amihud	Illiquidity indicator	Daily	Computed	2020
Abnormal returns	Comparing daily returns with the market beta and the share benchmark	Daily	Computed	2020
Derivatives listed	Options/Warrants/Futures listing of share	Flag	ESMA FIRDS	2020
National Index return	Value for each national index in EUR at country level	Daily	Computed using Refinitiv	2020
Market beta	Historical BETA by country	Monthly	Refinitiv Datastream	2020
Market Volatility	VSTOXX	Daily	Refinitiv Datastream	2020
Stringency	Log of Stringency index	Daily	OxCGRT	2020
Shorted shares	Net short positions above 0.1% of issued share	Daily	ESMA	2020

Table 8

Dataset cleaning process, impact on the number of shares and market capitalisation

	No shares	Market capitalisation
Full dataset	8,290	11,645,928
Penny stocks	2,988	241,014
New stocks	380	4,095
Invalid spreads	504	1,692,026
Winsorisation	142	12,710
Missing data	12	8,137
Stale prices	909	191,843
Final dataset	3,355	8,991,721
Change	*-60%*	*-23%*

Note: market capitalisation in EUR bn.
Sources: Refinitiv, ESMA.

Table 9

Descriptive statistics for the full dataset, by country

RCA	No obs	No shares	Volumes	Market cap	BA spread	Amihud	Historical. volatility	Intraday vol.
AT	5,215	35	924.2	84.0	0.105	0.005	2.222	3.456
BE	12,963	87	1,931.8	275.2	0.066	0.002	2.274	3.182
BG	2,682	18	8.7	1.3	1.106	0.491	1.651	1.732
CZ	1,490	10	101.9	18.5	0.099	0.006	1.517	1.902
DE	71,520	480	4,980.8	1,712.6	0.157	0.073	2.273	2.661
DK	16,688	112	3,293.1	392.8	0.037	0.001	1.696	2.583
EE	745	5	11.0	1.0	0.117	0.020	1.217	1.540
ES	13,559	91	30,775.8	522.6	0.027	0.001	2.205	3.123
FI	19,072	128	9,039.1	212.7	0.046	0.004	1.972	2.848
FR	61,984	416	28,844.9	2,091.6	0.053	0.003	2.177	2.996
GB	90,145	605	26,982.8	1,075.9	0.090	0.005	2.168	3.118
GR	7,450	50	3,029.6	28.8	0.165	0.027	2.614	3.368
HR	7,599	51	15.8	17.2	0.774	0.085	1.148	1.085
HU	2,980	20	427.2	19.0	0.075	0.021	2.247	2.812
IE	5,513	37	4,168.5	57.3	0.266	0.124	2.391	3.702
IS	149	1	113.2	3.2	0.256	0.006	1.590	1.590
IT	34,568	232	70,434.6	540.0	0.043	0.002	2.228	3.099
LT	149	1	5.6	0.0	0.270	0.119	2.524	3.441
LU	298	2	0.5	0.5	0.995	0.259	2.721	2.262
LV	298	2	1.0	0.1	0.154	0.129	1.221	1.454
NL	13,261	89	24,718.7	807.8	0.031	0.000	2.102	2.807
NO	9,685	65	1,181.4	31.6	0.264	0.099	2.664	3.838
PL	38,889	261	3,966.4	102.6	0.147	0.089	2.381	3.434
PT	2,533	17	3,495.4	54.1	0.072	0.012	1.776	2.641
RO	5,662	38	98.3	8.1	0.346	0.688	1.401	1.956
SE	73,755	495	31,559.4	686.2	0.051	0.006	2.299	2.941
SI	1,043	7	4.7	5.7	0.191	0.017	1.384	1.717

Note: bid-ask spreads, Amihud and volatility are weighted by market cap. Volumes in thousands, market capitalisation in EUR bn, bid-ask spread in %, and Amihud is multiplied by a factor of 100.
Sources: Refinitiv, ESMA.

Table 10

Differences in the main variables for the treatment and control groups, before and after the matching

	Before matching					After matching				
	Treated group		Control group		Difference	Treated group		Control group		Difference
	mean	sd	mean	sd		mean	sd	mean	sd	
Market capitalisation	4,450.5	14,541.3	2,241.7	8,583.9	2,209****	2,528.3	6,551.1	2,481.2	6,297.2	47.1
Sector: Financial (%)	0.19	-	0.10	-	0.09	0.10		0.10	-	0.0
Sector: Industrials (%)	0.19	-	0.19	-	0.0	0.20	-	0.20	-	0.0
Liquid Flag (%)	0.45	0.50	0.37	0.48	0.07**	0.42	0.49	0.42	0.49	-
Bid-ask spread	0.26	0.47	0.55	1.08	-0.29****	0.26	0.34	0.46	0.85	-0.21****
Intraday volatility	2.20	1.15	2.18	1.49	0.02	2.19	1.04	2.14	1.32	0.05
Volumes	677.10	4,087.44	222.15	934.09	454.95**	383.89	1,528.95	284.83	948.31	99.06

Note: Market capitalisation in EUR bn, sector and liquid flag in % of the dataset, bid-ask spread in %, intraday volatility multiplied by a 100, volumes in thousands. T test significance thresholds: **** p<0.0001, *** p<0.001, ** p<0.01, * p<0.05.
Sources: Refinitiv Datastream, FIRDS, FITRS, ESMA.

Table 11

Number of shares by country after the matching

Group	NCA	No shares	No shares	Group	NCA	No shares	No shares (%)
	FR	391	45.6%		SE	207	24.1%
	IT	212	24.7%		DE	195	22.7%
	ES	87	10.1%		GB	192	22.4%
Treatment	BE	86	10.0%		FI	65	7.6%
	GR	47	5.5%		DK	49	5.7%
	AT	35	4.1%		NL	42	4.9%
	Total	858	100.0%		NO	24	2.8%
					HR	19	2.2%
					PT	12	1.4%
				Control	RO	12	1.4%
					BG	9	1.0%
					HU	8	0.9%
					IE	8	0.9%
					CZ	6	0.7%
					SI	3	0.3%
					EE	2	0.2%
					LU	2	0.2%
					LV	2	0.2%
					IS	1	0.1%
					Total	1,232	100%

Sources: Refinitiv Datastream, FIRDS, FITRS, ESMA.

Table 12

Main regression results, without controls

	Log bid-ask spread	Log Amihud	Abnormal returns	Intraday volatility	Log volumes
	(1a)	*(2a)*	*(3a)*	*(4a)*	*(5a)*
Treatment*Event	0.089***	0.045***	0.0002	-0.164***	-0.199***
	(0.012)	(0.021)	(0.0004)	(0.052)	(0.021)
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	229,929	205,148	235,698	232,844	220,369
Adjusted R^2	0.773	0.859	0.027	0.393	0.893

Note: Estimates of the regression, robust standard errors in parentheses. Standard errors are clustered at the stock level. *** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
Sources: ESMA.

Table 13

Regression results, post-ban variable, without controls

	Log bid-ask spread	Log Amihud	Abnormal returns	Intraday volatility	Log volumes
	(6a)	*(7a)*	*(8a)*	*(9a)*	*(10a)*
Treatment*Event	0.100***	0.098***	-0.001**	-0.221***	-0.229***
	(0.016)	(0.028)	(0.0005)	(0.065)	(0.027)
Ban lift	0.021	0.099***	-0.002***	-0.105*	-0.057*
	(0.016)	(0.030)	(0.0004)	(0.055)	(0.030)
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	229,929	205,148	235,698	232,844	220,369
Adjusted R^2	0.773	0.859	0.027	0.393	0.893

Note: Estimates of the regression, robust standard errors in parentheses. Standard errors are clustered at the stock level.
*** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
Sources: ESMA.

Table 14

Regression results, share characteristics, volumes and volatility variables

	Intraday volatility					Log volumes				
	Small-cap stocks	Large cap stocks	Impact of listed derivatives	Low-fragmented stocks	High-fragmented stocks	Small-cap stocks	Large cap stocks	Impact of listed derivatives	Low-fragmented stocks	High-fragmented stocks
	(21)	*(22)*	*(23)*	*(24)*	*(25)*	*(26)*	*(27)*	*(28)*	*(29)*	*(30)*
Treatment*Event	-0.266**	-0.030	-0.638***	-0.143	0.108	0.103**	-0.376***	-0.244***	0.013	-0.368***
	(0.126)	(0.074)	(0.085)	(0.112)	(0.077)	(0.046)	(0.022)	(0.033)	(0.047)	(0.025)
Market capitalisation	0.007	-0.00004***	-0.00004***	0.001**	-0.00004***	0.010***	-0.00001***	-0.00002***	0.0001	-0.00002***
	(0.006)	(0.00001)	(0.00001)	(0.0002)	(0.00001)	(0.003)	(0.00001)	(0.00000)	(0.0001)	(0.00000)
Fragmentation	0.251**	0.008	-0.032***	NA	NA	0.120***	-0.032***	-0.075***	NA	NA
	(0.103)	(0.013)	(0.011)			(0.046)	(0.006)	(0.006)		
Stringency index	0.002	0.003**	0.003**	0.0002	0.005**	0.001	0.0003	0.001	0.001	0.00005
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.005)	(0.0005)	(0.001)	(0.001)
Volumes	0.0009***	0.0001***	0.0002***	0.003**	0.0001***	NA	NA	NA	NA	NA
	(0.001)	(0.00002)	(0.00003)	(0.001)	(0.00003)					
Intraday volatility	NA	NA	NA	NA	NA	0.156***	0.116***	0.125***	0.175***	0.131***
						(0.005)	(0.004)	(0.003)	(0.005)	(0.004)
Treatment*Event* Listed derivatives	NA	NA	0.624***	NA	NA	NA	NA	-0.156***	NA	NA
			(0.111)					(0.041)		
Fixed effects	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	51,640	58,625	116,869	54,737	57,512	49,720	58,161	114,903	52,513	56,978
Adjusted R^2	0.372	0.585	0.534	0.364	0.536	0.742	0.967	0.947	0.746	0.963

Note: Estimates of the regression, robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1. NA: Not Applicable – these variables were not included in the regression.
The presence of stock and day fixed effects may result in dummy variables to be removed from the estimation due to multicollinearity. Abnormal returns are never significant for each stock characteristic presented in the tables, and thus not shown in the table.
Sources: ESMA.

Chart 4
Standardized mean differences

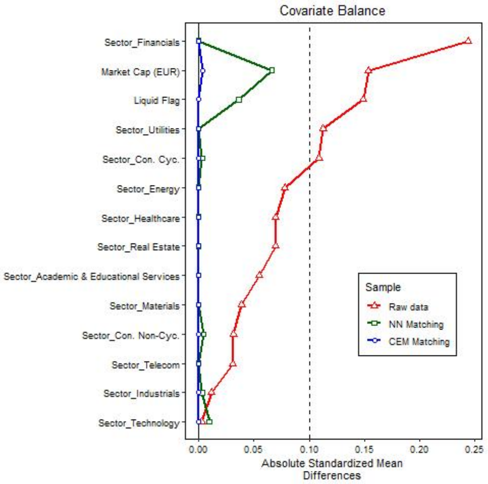
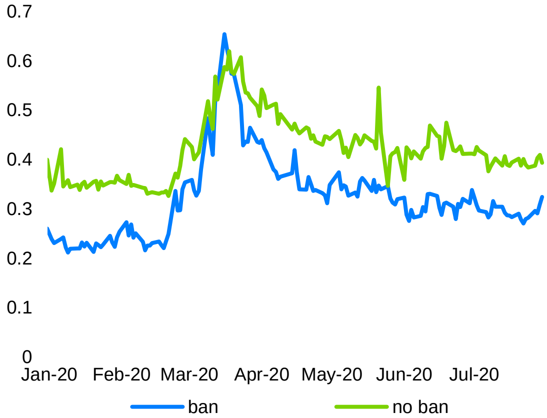
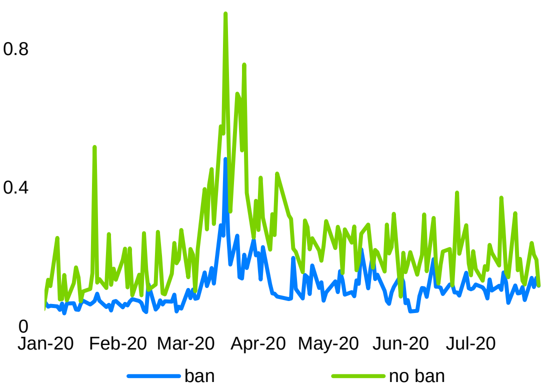


Chart 5
Bid-ask spreads parallel trends



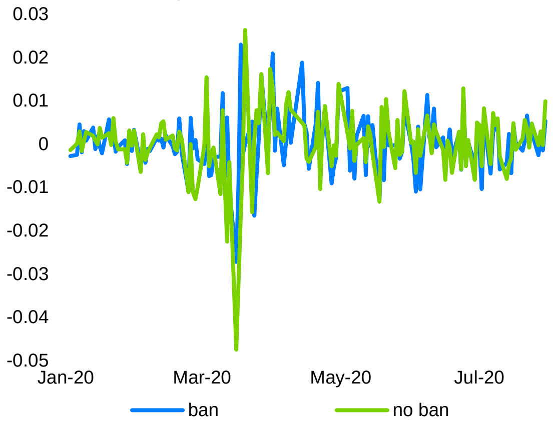
Note: bid-ask spreads in %, shares under the ban or not in the dataset.
Sources: Refinitiv, ESMA.

Chart 6
Amihud parallel trends



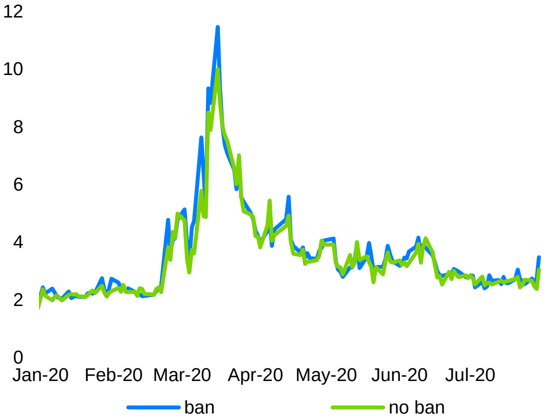
Note: Amihud illiquidity indicator for shares under the ban or not in the dataset, multiplied by a factor 100,
Sources: Refinitiv, ESMA.

Chart 7
Abnormal returns parallel trends



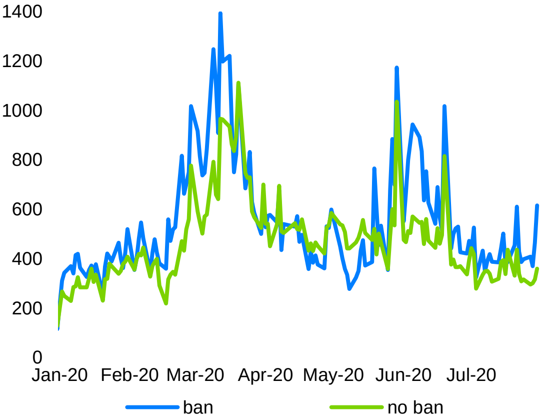
Note: Abnormal returns, for shares under the ban or not in the dataset.
Sources: Refinitiv, ESMA.

Chart 8
Volatility parallel trends



Note: Intraday volatility using Parkinson formula, for shares under the ban or not in the dataset, multiplied by a factor 100.
Sources: Refinitiv, ESMA.

Chart 9
Volumes parallel trends



Note: Number of share traded for shares under the ban or not in the dataset, in thousands.
Sources: Refinitiv, ESMA.

Appendix 2: Displacement effect analysis

We carry out an exploratory analysis to gauge the possibility of a shift in short selling activity from banning jurisdictions to non-banning ones (i.e. a 'displacement' effect) and the potential extent of such phenomenon.

However, given the fact that it is impossible to disentangle the effect of the ban from the effect of deteriorating economic conditions as a consequence of the COVID-19 pandemic, a causal impact of the short selling ban on displacement is not estimated. Nevertheless, descriptive information from various data sources provides useful indications as to whether such an effect actually materialised. The analysis relies on two different data sources:

i. aggregate short selling disclosures at share level for the matched sample employed in the market quality analysis[31];

ii. publicly disclosed short positions at position holder – share level (i.e. NSPs above the 0.5% of the issued share capital of the company disclosure threshold).[32]

First, the analysis focuses on the matched sample, for which we obtain the aggregate level of NSPs. Given the balanced nature of the matched sample of interest, constructed with the purpose of pairing similar stocks across banned and non-banned countries, the existence of a displacement effect would imply a drop in NSP levels for treatment shares, combined with a corresponding rise in NSP levels for control shares.

However, while short selling activity decreased for banned stocks in our sample - as expected, there is no clear reversal of NSPs towards non-banned shares (Chart 1 in Appendix 1). The evolution of short positions in our matched sample shows a large increase in short positions before the introduction of short selling restrictions across member states. By definition, in countries with short selling bans, NSPs started to decrease immediately after the introduction of the bans (a decline by 52 basis points between the enactment and the lifting of the ban). But the activity in non-banned jurisdictions also slows down significantly from mid-March onwards, i.e. after the introduction of short selling bans in other jurisdictions. The increase of NSPs from March to May 2020 is only 15 basis points, when the observed increase from

[31] SSR sets out a two-tier model for transparency of NSPs. At the lower threshold (0.2% of the issued share capital and each 0.1% above that), the notification of a position has to be made to the NCAs only. At the higher threshold (0.5% of the issued share capital and each 0.1% above that), positions have to be publicly disclosed for the information of other market participants.

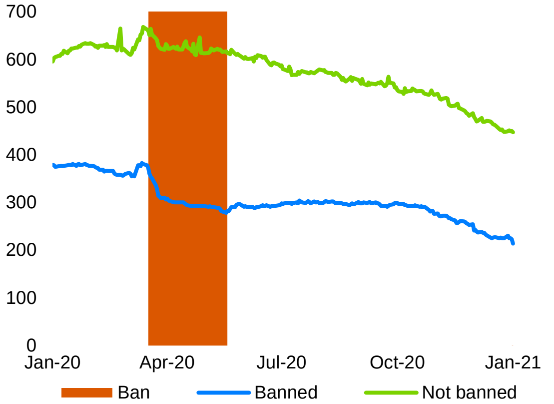
[32] The publication threshold is set out in Article 6 of SSR, which requires the public disclosure of net short positions that reach, exceed or fall below 0.5% of the issued share capital of the company. ESMA does not currently have access to notifications at position holder level, but at share level: for this reason, to analyse the behaviour of position holders, publicly disclosed data is used. This database provides meaningful information to both regulators for supervisory purposes, and to the market for transparency purposes. However, we also know that the public disclosure of NSPs influences the market outcome of short positions below and above the 0.5% disclosure threshold (ESMA 2017), and so different behaviour can be expected for position holders below the 0.5% public threshold.

February to March was 27 basis points, suggesting there is no clear displacement effect of short selling bans or reversal of NSPs towards non-banned shares.

As a second step, the activity of short sellers is examined through publicly disclosed NSP data, with the purpose of understanding whether the short selling ban impacted the behaviour of short sellers with high NSPs (i.e., short sellers reporting NSPs above the 0.5% threshold).

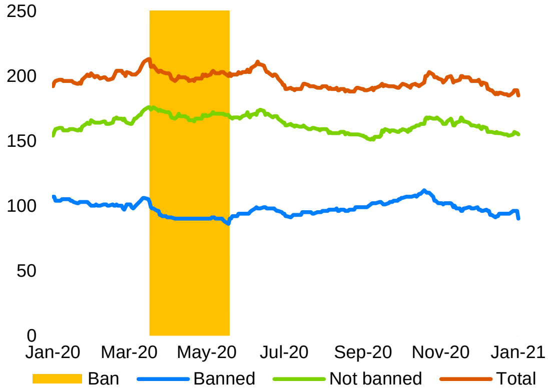
During the short selling ban, public NSPs decreased by 23% in banning countries and by 5% in non-banning countries (Chart 9). The number of overall active position holders declined moderately – from 207 to 200 (-3%) (Chart 10). In addition, the number of active position holders dropped from 99 (174) to 86 (170) in banning (non-banning) countries, a percentage decline of -13% (-2%). Overall, these numbers do not convey a displacement effect from banning countries to non-banning countries.

Chart 10
Number of publicly disclosed NSPs



Note: number of NSP in EEA countries, split by countries with and without short selling bans during the course of 2020. Data is relative to publicly disclosed NSP (those above 0.5% of the outstanding amount issued).
Sources: NCAs, ESMA.

Chart 11
Number of position holders with public NSPs



Note: number of active short sellers in EEA countries, split by countries with and without short selling bans during the course of 2020. Data is relative to publicly disclosed NSP (those above 0.5% of the outstanding amount issued).
Sources: NCAs, ESMA.

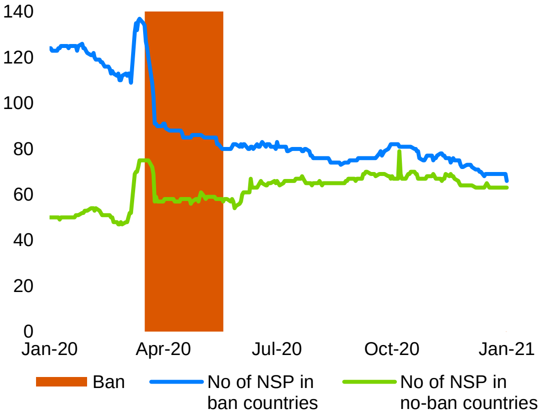
To check for further short selling pattern, position holders are grouped according to their historical behaviour between January 2020 and the enactment of the short selling ban, in order to obtain three classes:

1. 'Ban preference': holders that detain 50% (or more) of their positions in banned countries, on average.
2. 'No ban preference': holders that detain 50% (or more) of their positions in non-banned countries, on average.
3. 'No preference': holders that became active only after 18 March 2020 and, thus, cannot be classified in either of the two previous groups.

The number of investors classified in each of these three groups, and its evolution, is graphically described in Chart 11. Based on this classification, the evolution of NSPs and market exposure of these classes of position holders is analysed and is summarized in Chart 12 and 13 below.[33]

Chart 12

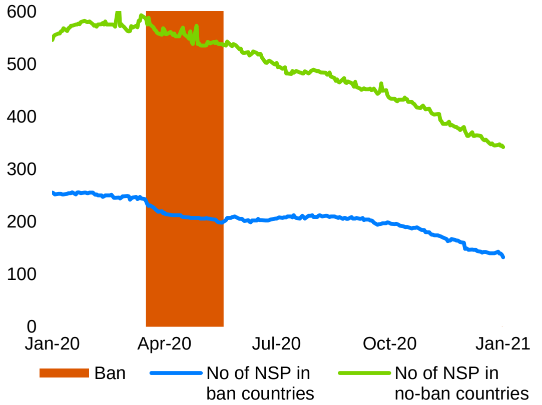
'Ban preference': number of publicly disclosed NSPs



Note: Number of NSP in EEA countries by position holders with 50 % or more of their positions between 1 January and 18 March 2020 in banned countries.
Sources: NCAs, ESMA.

Chart 13

'No ban preference': number of publicly disclosed NSPs



Note: Number of NSP in EEA countries by position holders with 50 % or more of their positions between 1 January and 18 March 2020 in non-banned countries.
Sources: NCAs, ESMA.

Despite the drop in outstanding NSPs in banning jurisdictions observed during the ban (Chart 11), investors with a preference for banning countries did not relevantly modify their shorting activity, and on 18 May 2020 still held 58% of their positions in banning jurisdictions, compared to 63% on the day of the ban enactment. Moreover, no significant impact is observed for the '*no ban preference*' group, which displays a slight decrease in NSPs for both banning and non-banning jurisdictions (Chart 12). Thus, these figures suggest that many investors who had already positioned themselves prior to the ban did not massively shift their NSPs from banning to non-banning jurisdictions as a consequence of the ban.

On the other hand, for the investors who were not active before the start of the short selling ban it is not possible to determine an ex-ante their propensity towards either banning or non-banning countries (hence the '*no preference*' group). During the bans, these short sellers had no choice but to take short positions in non-banning jurisdictions (Chart 14). Thus, for these investors the ban acted as a constraint on their short selling preferences: as soon as the ban ends, their exposure to banning jurisdictions starts to increase. Overall, the number of position holders belonging to the '*no preference*' group was lower than the other two groups during the

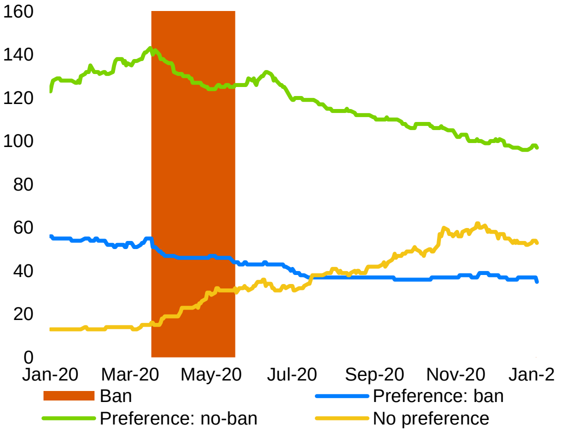
[33] The same classification exercise has been carried out by employing the market value of outstanding NSPs rather than the number of NSPs, leading to comparable results.

ban period (Chart 13), and the number and market exposure of their NSPs was also less important in size.

In conclusion, the analysis of publicly disclosed short selling data does not point towards a relevant impact of the short selling ban on position holders' preferences.

Chart 14

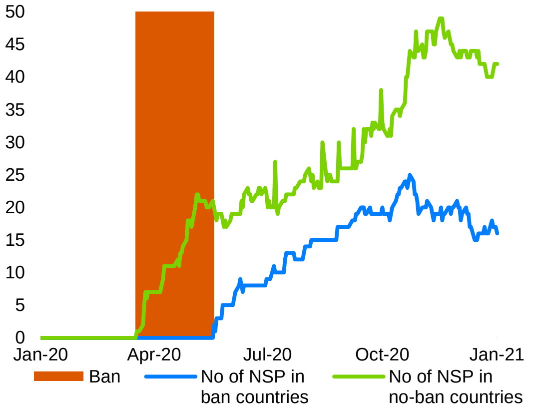
Number of position holders, by preference bucket



Note: number of active short sellers in EEA countries, split by preference in allocation of NSPs between 1 January and 18 March 2020.
Sources: NCAs, ESMA.

Chart 15

'No preference' group: number of public NSPs



Note: Number of NSP in EEA countries by position holders who did not have active positions in the period between 1 January and 18 March 2020.
Sources: NCAs, ESMA.