Shackled High Speed Traders?
Latency Reduction and Short Sale Bans

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Abstract

We explore the effects of two juxtaposed events – regulatory short sale bans and exchange efforts to facilitate high-frequency trading (HFT) – on multiple dimensions of market quality. Between 2011 and 2013, the Spanish Stock Exchange (SSE) launched a smart trading platform (SIBE-Smart) and introduced colocation facilities to attract HFT. During this time two short sale bans were imposed on the SSE. Comparing the time before and after these events, we find that the SSE's efforts did not attract increased HFT, either with the SIBE-Smart or with colocation. Liquidity and price efficiency declined. Colocation, implemented during the second ban, was accompanied by an across the board deterioration in market quality. Strikingly, SIBE-Smart, which was not introduced during but preceded a ban, also brought significant liquidity and price efficiency reduction. These results are in contrast to existing studies that show increased HFT resulting from technological inducements. We conclude that the beneficial effects of HFT on liquidity and price efficiency are negated in the presence of regulatory restrictions on trading.

JEL Classification: G14, L10

Keywords: High Frequency Trading; Short Sale Ban; Colocation; SIBE-Smart

1. Introduction

Technological innovations in the last decade have changed the trading landscape from one dominated by human intermediaries to a latency-reduction race amongst machines. This new trading paradigm, popularly known as high-frequency trading (HFT), has garnered immense interest from the media, in academia, and amongst regulators. The debate on whether HFT is a net benefit to investors continues, with evidence pointing to both positive as well as negative effects on market quality.[1]

This ambiguity about the impact of HFT in modern markets dominated by HFT is a special challenge to regulators and exchanges.[2] Regulators have to ensure that any proposed regulation curbs the undesirable effects of HFT without undoing the benefits. The dilemma is highlighted in this recent statement by Securities and Exchange Commission (SEC) Chair Mary Jo White: "The SEC should not roll back the technology clock or prohibit algorithmic trading, but we are assessing the extent to which specific elements of the computer-driven trading environment may be working against investors rather than for them."[3] At the same time, exchanges that adopt technologies to facilitate modern trading practices must keep in view that regulations may impact HFTs differently from other traders. Therefore any data-based evidence on

[1] Hendershott, Jones and Menkveld (2011) find that algorithmic trading (of which HFT is a subset) improves market quality by reducing spreads and adverse selection and improving the informativeness of quotes. Hasbrouck and Saar (2013) and Brogaard (2010) also document evidence of lower short-term volatility and better price discovery associated with HFT. Brogaard, Hagstromer, Norden, and Riordan (2015) find that although colocation provides informational advantages to HFT traders, overall market quality is improved after the introduction of colocation. However, more recent studies also document negative effects of HFT. Boehmer, Fong, and Wu (2012) find that algorithmic trading is detrimental to the market quality of small stocks. Baron, Brogaard, and Kirilenko (2012) show that HFT firms generally do not provide liquidity to markets, and in fact their most profitable trades are the ones that most aggressively take liquidity. Egginton, Van Ness, and Van Ness (2014) point to quote stuffing practices by HFTs. We discuss these and other related research in Section II.

[2] Although estimates of the total volume attributable to HFT are not easy to obtain, and depend on how exactly HFT is defined, as of 2009 HFT accounted for between 60-73% of all US equity trading, with that number falling to about 50% in 2012 and 2013. For a breakdown of HFT volume by year for US equities, see http://tabbforum.com/opinions/high-frequency-trading-an-important-conversation. For the Spanish market, citing BME as their source, Blas, González, and Villanueva (2011) estimate that HFT account for 25-30% of SSE total volume in 2010. A recent report by the European Securities and Market Authority (ESMA, 2014), estimates that HFT represent 32% of value traded, 29% of trades, and 46% of orders of the most frequently traded SSE-listed stocks.

[3] See full text of speech at http://www.sec.gov/News/Speech/Detail/Speech/1370542004312#.U86NC_ldWzd

the impact of regulation and technological improvements in modern markets should be of broad interest to regulators as well as to investors who are impacted by said rules.

In this study we aim to provide such evidence. Specifically, we examine whether HFTs respond to technological inducements in the presence of trading restrictions, and we study the net effect of the interplay of regulations and technological improvements on market quality. This is an important issue because studies that document the positive effects of HFT on market quality have generally examined markets without regulatory restrictions. We exploit a unique setting that spans the interspersing of two short sale bans with infrastructure upgrades and colocation to induce HFT on the Spanish Stock Exchange (SSE). We conduct multiple event studies with a view to understanding how various dimensions of market quality – liquidity, price efficiency, and market making costs/revenues – are impacted by the interaction of HFT with short sale restrictions.

Short sale bans are a common tool used by regulators around the world, mostly in times of precipitous price declines. Researchers generally agree that short sale bans have limited efficacy in stemming price falls and lead to worse market quality. However, to the best of our knowledge, whether the effects of short sale bans are alleviated or exacerbated by efforts to increase HFT has not been explicitly tested. Notably, two studies examine the effect of the 2008 short sale ban in the context of HFTs. Brogaard, Hendershott, and Riordan (2014) study HFT versus non-HFT short selling and use the 2008 ban as an instrument. They find that HFT short sales degrade market quality. Boehmer, Jones, and Zhang (2013) examine the effects of the U.S. short sale ban in 2008. They hypothesize that short sale bans should disproportionately damage liquidity in stocks where HFT firms are more active. However, in the absence of suitable data, they cannot verify this hypothesis. However, both these studies examine the U.S. market at a time when HFT was already a dominant player.

Our sample comes from the SSE at a time when it had little HFT activity, and we track market quality as the SSE adopts infrastructure upgrades to explicitly attract HFT.[4] We then examine how regulatory restrictions impede HFT activity, with related effects on market quality. Given the timeline of events in the SSE, we are able to examine whether markets are able to attract HFT with technological inducements in the presence of trading restrictions. Do the positive effects of HFT on market quality overcome the negative impact of short sale bans? Or do HFTs stay away from markets with regulatory restrictions, thereby exacerbating the negative effects of short sale bans? We address these and related questions by analyzing several pre- and post-event windows surrounding the introduction of the smart trading platform SIBE-Smart, colocation, and two short sale bans.

We document several findings. First, comparing the periods before and after all these events (SIBE-Smart, colocation, and the two bans), we find no overall increase in HFT activity. Meanwhile liquidity worsened: Dollar depth decreased, spreads increased, order book elasticity fell, and (Amihud) illiquidity increased. Price efficiency declined as return autocorrelations increased. The SIBE-Smart trading platform introduction, which did not directly coincide with a ban but followed the first ban and preceded the second ban, was actually accompanied by an across the board deterioration of all liquidity measures although it managed to attract a modest increase in HFT activity. In contrast, the colocation event, which was announced during the second short sale ban, was accompanied by a reduction in HFT activity and saw significant liquidity and price efficiency declines. This contrasts directly with the results presented in Brogaard,

[4] While direct estimates of HFT activity on the SSE are not available over our sample period, the Comision Nacional Del Mercado de Valores (CNMV) estimates that in 2011, the start of our sample period, the share of some prominent HFT facilitating platforms (e.g., Chi-X, Turquoise, and BATS) in the total trading volume of all Spanish listed stocks ranged from under 1% to 1.2%. See Table 17 of the CNMV Bulletin, Q2, 2014.

Hagstromer, Norden, and Riordan (2015), who find that colocation (without any regulatory restrictions) improves overall market depth and reduces spreads.

As expected, the short sale bans resulted in liquidity declines, with the second ban seeing a steeper reduction in liquidity than the first ban, perhaps because the second ban affected more stocks than the first. The sequence of events on the SSE also allows us to isolate the effects of colocation with and without the ban. We find that although HFT does not increase in either case, liquidity improves with colocation in the absence of a ban.

Taken together, our results indicate that the regulatory restrictions were serious impediments that the technological inducements could not overcome. HFT did not respond to the smart trading platform and colocation inducements, and the net result was a decline in liquidity and price efficiency. Overall the negative effects of short sale bans prevailed. These results, which are in contrast to the beneficial effects of HFT on liquidity and price efficiency documented by earlier studies, indicate that the positive effects of HFT on market quality are countervailed in the presence of regulatory restrictions on trading. Finally, our results also underscore the importance of non-U.S. market settings in arriving at conclusions about the effect of regulations and trading technology. There is an emerging body of literature that shows that many of the findings from U.S. markets do not generalize to other countries. We add to this international evidence on HFT, regulations, and market outcomes.[5]

The paper is organized as follows. In Section 2 we present a review of the literature. Section 3 describes the institutional details of the SSE and discusses the timeline of

[5] Brogaard, Hendershott, Hunt, and Ysusis (2014) find no effect of HFTs on institutional trading costs using a UK sample. Korajczyk and Murphy (2015) use a Canadian dataset and find HFTs are less active for large institutional trades. van Kervel and Menkveld (2015) find that HFTs initially provide liquidity but then trade with institutional trades, their evidence comes from Swedish data.

events spanned by our sample period. Section 4 discusses the sample selection and market quality metrics, and Section 5 presents our results. Section 6 presents robustness checks, and Section 7 concludes.

2. HFT and short sale ban

2.1. HFT and market quality

As technological advances replace old trading systems with newer and faster ones, regulators face challenges on how to adapt rulemaking to the new realities of modern markets. In the U.S., the SEC's effort to gauge the impact of HFT on market quality was accelerated by the Flash Crash of 2010, which many blamed on HFT (if not as a trigger, at least as a contributory factor). In March 2014, the SEC released a comprehensive review of the U.S. equity market structure, with half of the study devoted to reviewing the existing evidence on HFT. Around the same time (April 15, 2014), European regulators imposed some of the toughest regulations on high-frequency (HF) traders in the E.U. These new rules include limits to keep price increments for low priced securities from becoming too small, mandatory tests of trading algorithms, and a requirement on market makers to provide liquidity for a minimum number of hours each day.[6]

Both the U.S. and international evidence on the impact of HFT on market quality is mixed.[7] Malinova, Park, and Riordan (2014) use data from the Toronto Stock Exchange

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[6] For a complete list of all the rules, see the European Parliament News release at http://www.europarl.europa.eu/news/en/news-room/content/20140411IPR43438/html/MEPs-vote-laws-to-regulate-financial-markets-and-curb-high-frequency-trading.

[7] In this section, we provide a review of the international evidence on HFT, with a focus on European markets, given that our sample comes from the SSE. For a summary additional research on HFT that is not covered in footnote 1, see the review provided by the SEC at http://www.sec.gov/marketstructure/research/hft_lit_review_march_2014.pdf.

to examine how a tax on HF traders impacts market quality. They find that quoted and effective spreads increased and revenues to liquidity supply declined, indicating that a reduction in HFT activity harmed some dimensions of market quality. Jovanovic and Menkveld (2013) examine the entry of an HFT firm in the Dutch market and find a 15% decline in effective spreads and about 23% fall in adverse selection costs following the entry of this new HFT firm. Brogaard et al. (2013) do not find any evidence of increased institutional trading costs as a result of increased HFT activity facilitated by technology upgrades on the London Stock Exchange.

In contrast to these positive findings are other studies that document negative effects of HFT. Examining trades by HFT firms routed via a single broker in the London and Tokyo equity markets, Bershova and Rakhlin (2013) find mixed evidence: while spreads fall with higher HFT activity, short-term volatility increases. The Australian Industry Super Network, an umbrella organization representing savings and retirement funds, commissioned a study that concludes "HFT activities cost non-HFT market participants, including long term investors… up to $1.9 billion a year, with a best estimate of over $1.6 billion a year."[8] A study of foreign exchange markets conducted by the Bank of International Settlement finds that while HFTs can be beneficial to markets in normal times, they may be harmful to the functioning of markets in times of stress.[9] In sum, whether HFT provides net benefits is still open for debate, which makes it challenging to devise appropriate rules to regulate these low latency traders. Brogaard, Hagströmer, Nordén, and Riordan (2015) study a colocation upgrade at NASDAQ OMX Stockholm which improved connectivity of high-speed traders and find that liquidity increased for the overall market because high-frequency market makers used

[8] http://www.industrysuperaustralia.com/assets/Reports/Quantifying-HFT-costs-June-2013as-published.pdf.
[9] See full report at http://www.bis.org/publ/mktc05.pdf.

the enhanced speed to reduce their exposure to adverse selection and to better manage inventory.

2.2. Short sale bans and market quality

Researchers agree that short sellers perform a useful function by incorporating fundamental information into prices. Or, as Boehmer, Jones, and Zhang (2013) put it: “For the most part, financial economists consider short sellers to be the *good guys.*” Karpoff and Lou (2010) find that short sellers detect financial fraud in firms about 19 months before the misrepresentation is publicly revealed. In a similar vein, Desai, Krishnamurthy, and Venkataraman (2006) show that short sellers pay attention to firms’ accounting numbers and can anticipate earnings restatements several months in advance. Given the information-gathering role short sellers perform, it is no surprise that market quality declines when regulatory bans are imposed on short selling.

The 2008 recession and the following European debt crisis in 2010-2011 saw several countries around the world impose ad hoc short sale bans to try to stem price declines. In the U.S., the SEC issued an emergency order restricting naked short selling in July 2008, and followed that up with an outright short selling ban in September. Analyzing the effects of this ban, Boehmer, Jones, and Zhang (2013) find that market quality worsens because many algorithmic traders cannot act as informal market makers. With less competition, formal market makers can now charge greater rents for liquidity provision. Battalio, Mehran, and Schultz (2011) study a similar decline is U.S. stock markets following the S&P downgrade of the U.S. in 2011. They find that short sellers do not amplify stock price declines during times of market downturn.

The 2011 debt crisis saw the imposition of short sale bans in Greece, Turkey, Belgium, France, Italy, and Spain. Even in non-U.S. markets, the evidence points to dubious efficacy of short sale bans. Beber and Pagano (2013) study the effects of the 2008 stock price decline in 30 countries around the world. Comparing countries that did not impose a blanket ban on short-selling for all stocks to those that did, they conclude that the effect of such bans on stock prices is neutral at best. Bris, Goetzman, and Zhu (2006) analyze cross-sectional and time-series information from 46 countries and show that prices are more efficient in countries that allow and practice short sales.

3. Institutional details of the Spanish Stock Exchange and time line of events

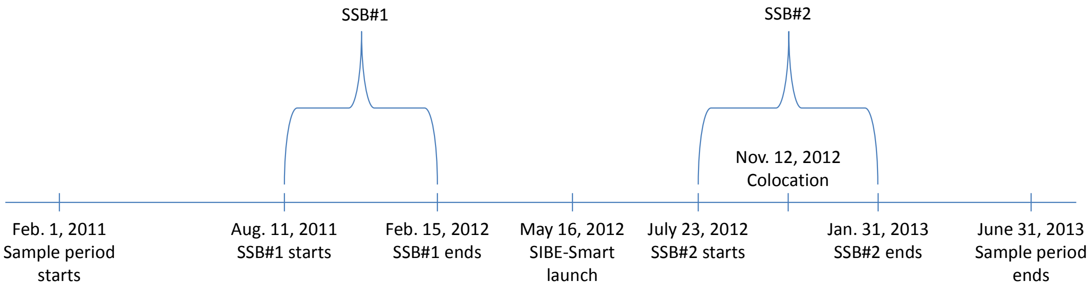
The SSE has four trading platforms: Madrid, Barcelona, Bilbao, and Valencia. Trading is linked through the electronic Spanish Stock Market Interconnection System (SIBE), which handles more than 90% of transactions. The benchmark index is the Ibex-35, a capitalization-weighted index comprising the 35 most liquid Spanish stocks traded in the continuous market. Trading on SIBE is conducted from 9 a.m. to 5:30 p.m., with an open outcry system from 10 a.m. to 11:30 a.m. After the steep declines in markets Europe-wide during 2008, to which Spain was no exception, the Ibex-35 recovered remarkably to become Europe's best performer in 2009. However, 2010 was a down year due to increased country risk and the weakness of the European financial sector. The index fell 17.43% after fluctuating in a very wide range of 35% between its peak and low. The drop in share prices, however, did not erode the levels of activity. Indeed, 2010 set a new record in SSE trading.

In response to the tailspin that the European markets witnessed in mid-2011, the European Securities and Markets Authority, a body that coordinates the European Union's market policies, issued a statement that all negative bets on stocks — in other words, short sales — would be curtailed in France, Belgium, Italy, and Spain effective

August 11. This ban lasted until February 15, 2012, when the Spanish securities regulator, the *Comisión Nacional del Mercado de Valores* (CNMV) announced that the prohibition on short sales of Spanish shares under the EU Short Selling Regulation (EU236/2012) was no longer in effect after February 15. However, as many market commentators had anticipated, once the ban was removed, prices declined precipitously, leading the CNMV to announce that "European shares have been hit with extreme volatility that might cause the disorderly functioning of financial markets." As a response, a second ban was introduced on July 23, 2012, which was subsequently lifted on January 31, 2013.

During this time the SSE also introduced major technology upgrades to integrate better with the bigger European exchanges and thereby attract HFT. Two major technology changes that facilitated faster trading were the upgrade of the SIBE-Smart platform and introduction of colocation. Recognizing that HFT in securities markets was an established fact and a natural progression in the wake of the widespread introduction of electronic markets and the increasing use of computerized trading systems, the SSE committed to developing their trading infrastructure and communications technology. As part of their effort, they rolled out the SIBE-Smart platform on April 16, 2012, to better adapt SSE's systems to new demands in terms of transaction speed and volume in the market. Continuing with this technological enhancement, the SSE began offering co-location capabilities at its Data Processing Center in Madrid on Nov. 12, 2012, enabling trading firms to install their own trading servers in close proximity to the exchange's trading engines and real-time price distribution systems. SSE officials stated that these efforts were expected to reduce latency and increase capacity for traders and directly facilitate HFT.[10]

Below, we present a schematic timeline showing the dates and events described above:



4. Sample selection and market quality measures

Our sample comprises the SSE-listed IBEX-35 constituents from January 2010 to December 2013. Due to index additions and deletions, our final sample includes 28 stocks that were index constituents throughout our sample period. We also separately examine the seven largest market capitalization (Blue Chip) stocks on the SSE, since previous studies document HF traders' preference for large and liquid stocks. For example, Hirschey (2011) finds that high frequency traders in his sample are more active in large than in small stocks (41% vs. 15%).

Our data come from the SSE's trade files which report all trades time-stamped up to the hundredth of a second before April 16, 2012 (SIBE-Smart) and milliseconds afterwards, and limit order book (LOB) files. For each trade, the record includes the price and size.

[10] See announcement at http://www.world-exchanges.org/news-views/bme-successfully-upgrades-spanish-stock-exchange%E2%80%99s-trading-platform

The order book files contain snapshots of the five best ask and bid quotes of the LOB taken each time the LOB changes as a result of trades, order submissions, cancelations, or modifications. For each LOB level we have the quote record, the number of orders at that quote, and the displayed depth.[11] Relatively large buy (sell) trades are allowed to walk up (down) the book. Thus, the trade price is actually the marginal price, that is, the price at which the last share of the trade was transferred. In the SSE, there are no round lot sizes. Thus, the minimum trade size is one share.

Both the trade and the LOB files contain a sequence code, allowing for a perfect match between trade and quotes. Since there are no price improvements (i.e., trades inside the spread) and every trade consumes liquidity either at the displayed ask or bid quote, it is straightforward to assign trade direction (i.e., buyer- or seller-initiated trades). A trade is classified as buyer-initiated (seller–initiated) if it consumes liquidity at the offer (demand) side of the LOB, which is commonly called the quote rule.

We filter out records from the opening, closing, and intraday short-lived call auctions in each file, so that only quotes and trades from the continuous session are left. We also filter out prearranged trades.

4.1. HFT activity measures

Hendershott, Jones, and Menkveld (2011) compute message traffic in share volume and in dollar value as proxies for algorithmic trading. We compute the following four daily proxies for high-frequency trading: message traffic per minute ($MTMIN_{id}$), message traffic per euro-volume ($MTV€_{id}$), message traffic per volume in shares (MTV_{id}), and the number of non-zero quote-midpoint changes ($CQMP_{id}$). We

[11] The SSE allows iceberg orders but the quote files do not provide information on hidden volume (see Pardo and Pascual, 2012, for details).

compute message traffic as the number of limit order book updates per day, which is equivalent to summing all order submissions, cancelations, and modifications.

4.2. Liquidity and market activity measures

Boehmer, Fong, and Wu (2013) find that algorithmic trading intensity impacts market liquidity. We follow the literature and compute several liquidity and market activity metrics. In the formulas below, $i \in \{1,\ldots,28\}$, $j \in \{1,\ldots,N_{id}\}$, and $t \in \{1,\ldots,T_{id}\}$ are the sub-index for stocks, LOB updates, and trades, respectively; N_{id} and T_{id} are the number of LOB updates and trades in day *d*, respectively; $m \in \{1,\ldots,M\}$ is the sub-index for regular 1-minute intervals within a SSE trading session. For a full-length ordinary session, *M* = 510.

The quote midpoint (q_{ij}) is the average between the best ask (a_{ij}^1) and bid (b_{ij}^1) quotes of the LOB. The relative bid-ask spread ($RSPR_{ij}$) is the bid-ask spread ($a_{ij}^1 - b_{ij}^1$), divided by q_{ij}. The relative spread for stock *i* and day *d* ($RSPR_{id}$) is obtained as the average of $RSPR_{ij}$ weighted by time

$$RSPR_{id} = \frac{\sum_{j=1}^{N_d} \tau_{ij} \times RSPR_{ij}}{\sum_{j=1}^{N_d} \tau_{ij}} \qquad [1]$$

where τ_{ij} is the duration (in milliseconds) of the *j*-th update of the LOB.

The accumulated displayed LOB euro-depth ($DEPTH€_{ij}$) is

$$DEPTH€_{ij} = \frac{1}{2}\left(\sum_{k=1}^{5} v_{ij}^{ak} a_{ij}^{k} + \sum_{k=1}^{5} v_{ij}^{bk} b_{ij}^{k}\right) \qquad [2]$$

where v_{ij}^{ak} (v_{ij}^{bk}) is the displayed depth (in shares) at the *k*-th ask (bid) level of the LOB for the *j*-th quote update. As in eq. [1], the average accumulated depth for stock *i* and day *d* ($DEPTH€_{id}$) is computed weighting $DEPTH€_{ij}$ by time.

Näes and Skjeltorp (2006) compute the elasticity of the ask side of the LOB at the *j*-th update ($LOBELAST_{ij}^{a}$) as

$$LOBELAST_{ij}^{a} = \frac{1}{5}\left[\frac{v_{ij}^{a1}}{v_{ij}^{a1}a_{ij}^{1}/q_{ij}-1}+\sum_{k=1}^{4}\frac{v_{ij}^{a(k+1)}/v_{ij}^{ak}-1}{a_{ij}^{k+1}/a_{ij}^{k}-1}\right]. \qquad [3]$$

The elasticity of the bid side of the LOB ($LOBELAST_{ij}^{a}$) is computed analogously. The LOB elasticity ($LOBELAST_{ij}$) is the average between $LOBELAST_{ij}^{a}$ and $LOBELAST_{ij}^{b}$. As before, we average $LOBELAST_{ij}$ by time in order to obtain the corresponding daily summary measure ($LOBELAST_{id}$).

We also compute the trade-weighted effective spread ($WESPR_{id}$), which is the effective spread ($ESPR_{it}$) weighted by trade size,

$$WESPR_{id} = \frac{\sum_{t=1}^{T} s_{it} ESPR_{it}}{\sum_{t=1}^{T} s_{it}} \qquad [4]$$

where s_{it} is the size (in shares) of the *t*-th trade, and $ESPR_{it}$ is two times the difference between the trade price (p_{it}) and q_{it}, the prevailing quote midpoint before trade *t*, multiplied by the trade direction (x_{it} = 1, buyer initiated; x_{it} = -1, seller-initiated).

$$ESPR_{it} = 2\left(p_{it} - q_{it}\right)x_{it}\,. \qquad [5]$$

Finally, Amihud's (2002) illiquidity daily measure ($AMIHUD_{id}$) is the absolute open-to-close return divided by the daily euro volume ($VOL€_{id}$)

$$AMIHUD_{id} = \frac{\left| p_{id}^{c} - p_{id}^{o} \right|}{VOL€_{id}} \times 10^{6} \qquad [6]$$

where p_{id}^{o} and p_{id}^{c} are the opening and closing prices of the day *d*.

RSPR, *ESPR*, *WESPR*, and *AMIHUD* are inverse measures of liquidity while *DEPH€* and *LOBELAST* are direct measures of liquidity. For market activity, we use the following three daily measures: *VOL* is the daily volume in shares; *TRDS* is the daily number of trades, and *VOL€* is the daily volume in euros, computed as

$$VOL€_{id} = \sum_{t=1}^{T} s_{it} p_{it} \qquad \mathbf{[7]}$$

4.3. Volatility and price efficiency measures

Our daily metric for stock price volatility is the realized volatility ($RVLT_{id}$), which is computed as the daily standard deviation of one-minute trade price returns,

$$RVLT_{id} = \sqrt{\frac{1}{M} \sum_{m=1}^{M} \left(r_{im} - \overline{r}_{id} \right)^{2}} \qquad [8]$$

where $r_{im} = \ln(p_{im}) - \ln(p_{im-1})$, and $\overline{r}_{id} = \sum_{m=1}^{M} r_{im}$.

We compute two daily proxies for price efficiency; the first-order autocorrelation of one-minute trade price returns ($AUTOC_{id}$), and the pricing error standard deviation ($PESTD_{id}$) estimated using Hasbrouck (1993). For each stock-day, we estimate a bi-variate VAR model for $\{r_t, x_t^s\}$, where r_t is the return of trade t and x_t^s is the signed trade size. We optimally choose the VAR lag using the Akaike Information Criterion (AIC), and the model is estimated by OLS. The $PESTD_{id}$ is obtained from the coefficients of the VMA representation of the VAR model and the variance-covariance matrix of the residuals.

4.4. Market making cost and profit measures

We estimate the revenue to liquidity providers using the realized spread ($RZDS_{id}$) and measure gross losses to liquidity demanders due to adverse selection using the price impact (PI_{id}) of a trade, as in Huang and Stoll (1996) and Hendershott, Jones, and Menkveld (2011). We estimate both measures for three alternative time horizons: one, 15 and 30 seconds after the trade.

The price impact of trade *t* (PI_{it}) is two times the difference between the midpoint prevailing Δ seconds after the focal trade (i.e., *t*+Δ) and the midpoint prevailing right before trade *t*, multiplied by the trade direction

$$PI_{it} = 2\left(q_{it+\Delta} - q_{it}\right)x_{it} \ . \qquad [9]$$

The daily average PI_{id} is computed weighting by trade size, as in eq. [4]. The realized spread for trade *t* is computed as

$$RZDS_{it} = ESPR_{it} - PI_{it} = 2\left(p_{it} - q_{it+\Delta}\right)x_{it} \, , \qquad [10]$$

and its daily average ($RZDS_{id}$) is computed weighting by trade size.

5. Results

In Section 5.1 we present the overall effects, from before the first change was introduced to after all of the changes are finished, to determine the net effect on market quality. In the subsequent subsections we present the effects of each individual change: SIBE-Smart in Section 5.2, the short sale bans in Section 5.3, and colocation in Section 5.4.

5.1. Overall effects: Comparison of the pre- and post-events periods

Table 1 presents the average descriptive statistics of our full sample as well as the Blue Chip stocks. Although the two samples have similar average stock prices, measures of HFT activity, liquidity, and volume are higher for the Blue Chip stocks than for the full sample.

[Table 1]

For example, while daily message traffic (which includes all updates to the limit order book) is about 46,397 for the full sample, it is more than twice that (100,037) for the Blue Chip stocks. The Blue Chips also have higher volume and depth, and lower bid ask spread, which is expected since they are the largest capitalization stocks in the SSE.

To evaluate the impact on market quality, in all the remaining results reported in this section, we estimate the event's impact on our variable(s) of interest by running a pooled regression. The general form of the regression is as follows:

$$Y_{id} = \alpha + \beta_E E_{id} + \beta_V VLT_{id-1} + \varepsilon_{id} \qquad [11]$$

where Y_{id} is each of the daily market quality metrics defined in Section 4 and E_{id} is a dummy for the event under consideration (SIBE-Smart introduction, Colocation, or short sale bans). The coefficient of interest is β_E, the coefficient of the dummy that represents the post-event period. It captures the difference in each dependent variable between the pre- and post-event period. We use one-period-lagged IBEX-35 volatility (computed as the daily high/low) as a control variable (VLT_{id-1}) because Cáceres, Moreno, and Rodriguez (2014) show that the short sale bans on the SSE affected volatility. We also report the estimated percentage change in each dependent variable, computed as $100\left[\beta_E \big/ \left(\alpha + \beta_V \overline{VLT}\right)\right]$. Standard errors are clustered by both stock and date using the procedure outlined in Thompson (2011). In each table, results for the full sample are presented in Panel A and results for the Blue Chip stocks are presented in Panel B.

We begin by examining changes in HFT activity in the SSE before and after the time window that includes the technology changes and short sale bans. The pre-events period is Feb 1, 2011 to Jun 31, 2011 and the post-events period is Feb 1, 2013 to Jun 31, 2013. We report four proxies for HFT. These are message traffic per minute (*MTMIN*), message traffic per euro volume (*MTV€*), message traffic per share volume (*MTV*), and the number of non-zero quote midpoint changes (*CQMP*). In Table 2, we present the changes in HFT activity measures in this period.

[Table 2]

For the full sample, there is a weak (significant at 10%) increase in message traffic per minute. None of the other proxies for HFT show any significant change between the pre- and post-periods. Even for the Blue Chip stocks, which are the most liquid and are expected to attract the most HFT attention (Hirschey, 2013), we find significant change in two of the four proxies –*MTMIN* and *MTV€* while the other two proxies – message traffic per share volume (*MTV*) and the number of non-zero quote midpoint changes (*CQMP*) show no change. Overall, there is weak, if any evidence that during our event window there was any significant boost to HFT activity on the SSE.

To examine changes in stock liquidity and market activity during this time, we examine liquidity and trading activity metrics that earlier research has linked to HFT. In Table 3 we report the estimated coefficients from the pooled regression model. The dependent variables are the relative bid-ask spread (*RSPR*), quoted depth (*DEPTH€*), order book elasticity (*LOBELAST*), trade weighted effective spread (*WESPR*), Amihud's (2002) illiquidity measure (*AMIHUD*), daily volume in shares *(VOL)* daily volume in euros (*VOL€*), and daily number of trades (*TRDS*). The first five measure liquidity and the last three capture market activity. Table 3 presents our results.

[Table 3]

By all measures, liquidity declines. For the full sample as well as the Blue Chip stocks, realized spread and trade-weighted effective spread increase while limit order book elasticity decreases. There is no offsetting increase in depth; in fact, depth shows no significant change in this period. For the full sample, the Amihud illiquidity measure shows a significant (at the 5% level) increase.

The three measures of market activity – share- and euro-volume and trade size – show similar changes. Most measures show a significant decline. Overall, the results are consistent with liquidity reduction in the SSE stocks during this period.

Since prior studies (e.g., Brogaard, Hendershott, and Riordan, 2014) show that HFT help incorporate information faster into prices and therefore make them more efficient, we next examine changes in price efficiency and volatility in our sample. Results are reported in Table 4.

[Table 4]

For the full sample, pricing error and volatility show little change; however, return autocorrelations increase significantly, indicating that prices became less efficient. For the Blue Chip stocks, there is weak evidence of a reduction in the standard deviation of pricing error (*PESTD*) calculated using the Hasbrouck (1993) method. There are no changes in other efficiency or volatility metrics. Overall, there is little evidence that the SSE stocks saw any appreciable increase in price efficiency during this period.

The SSE operates as a pure limit order book with no designated market makers or dealers. In order-driven markets Menkveld (2013) finds that some HFTs may take on a market-making role, while Kirilenko, Kyle, Samadi, and Tuzun (2014) find that during the U.S. Flash Crash in 2010, HFTs consumed liquidity through aggressive (liquidity demanding) orders and exacerbated the price declines. To examine the impact of the technological upgrades along with the short sale bans on market making profits and losses, we next estimate price impact and adverse selection (realized spread) measures computed one, 15, and 30seconds after each trade on the SSE. As before, we run a pooled regression equation to examine the changes in our variables of interest (*PI* and *RZDS*). Results are reported in Table 5.

[Table 5]

For the full sample, there is no change in realized spread, indicating that there is no significant change in the revenue earned by liquidity providers. Price impact increases at all horizons. Recalling the increase in autocorrelation of one-minute trade price returns (*AUTOC*) from Table 4, the increase in price impact reported here is consistent with order flow autocorrelation increasing during this period. The results for the Blue Chip stocks show similar increase in price impacts, but unlike the full sample, for these liquid stocks, the realized spreads fall significantly. So liquidity providers' revenues from making a market in these Blue Chip stocks fell in the post-events period. One explanation consistent with our results is that the changes may have attracted HFTs that follow arbitrage or speculative strategies (make directional bets) rather than the ones who adopt a market making role (Menkveld and Zoican, 2015).

5.2. Effects of the introduction of SIBE-Smart

SIBE-Smart was introduced on April 16, 2012 to seamlessly connect the SSE with the other exchanges in Europe and facilitate high-speed traders. To evaluate the impact of this technological upgrade and faster trading platform, we compute and test differences in the measures of various dimensions of market quality by comparing the pre-SIBE-Smart (March 1, 2012 – April 15, 2012) and post-SIBE-Smart (April 16, 2012 - May 31, 2012) period. In Table 6, we present the changes in HFT activity measures in this period.

[Table 6]

For the full sample (Panel A), all of the proxies of high speed trading except message traffic per volume show an increase post-SIBE-Smart introduction. Traffic per minute, volume (in euro) and number of quote mid-point changes all increase. For the Blue Chip stocks (Panel B), two of the four metrics (message traffic per minute and quote mid-point changes) show significant increases. Overall, the evidence suggests that the smart trading platform indeed succeeded in attracting the high speed traders.

We examine changes in stock liquidity and market activity following the SIBE smart introduction and report results in Table 7.

[Table 7]

By most measures, liquidity declines. For the full sample, relative spread and trade-weighted effective spread increase while limit order book depth and elasticity decrease. The Amihud illiquidity measure shows a significant (at the 1% level) increase. In terms of the measures of market activity, euro-volume and trade size show significant declines. Results for the Blue Chip stocks are similar. Overall, the results are consistent with liquidity reduction in the SSE stocks during this period in spite of the introduction of the smart platform which showed some ability to attract high speed traders.

SIBE-Smart may have facilitated high speed traders, but their activities do not seem to have improved liquidity in the SSE. So we next ask if there are any other benefits to this upgrade in terms of improvements in price efficiency and/or reduction in volatility. Results are reported in Table 8.

[Table 8]

For the full sample as well as the Blue Chip stocks there is significant increase in realized volatility, in return autocorrelation and in standard deviation of pricing errors. We do not find any evidence that the introduction of the SIBE-Smart platform helped improve the informativeness of prices by reducing pricing errors. Thus, our results are different from Riordan and Storkenmaier (2012), who analyze a technology upgrade on the Deutsche Boerse and find liquidity improvements due to reduction in adverse selection. They also find that prices become more efficient after the upgrade. In contrast, and similar to our findings, Menkveld and Zoican (2015) find that for a NASDAQ-OMX speed upgrade, spreads increase, possibly due to increased speculative trading by high frequency “bandits” who increase adverse selection costs. It appears that in our setting, the effect of regulatory uncertainties (the impending first short sale ban) countervail the positive effects of technology upgrades that accrue during normal times.

Finally we examine the effect of this technological upgrade on market making revenues and profits. As before, we report the regression coefficients with realized spreads and price impacts calculated at three time horizons – one, 15 and 30 seconds. Results are reported in Table 9.

[Table 9]

For the full sample as well as the Blue Chip stocks, there is no change in realized spread, indicating that there is no significant change in the revenue earned by liquidity providers. Price impact increases at all horizons.

5.3. Effects of the two short sale bans

The SSE banned short selling twice during our sample period. The first short sale ban began on August 11, 2011 and was lifted on February 15, 2012 and affected 16 stocks from the financial sector. There were no technological changes introduced during this ban. The second short sale ban began on July 23, 2012, and ended on January 31, 2013. However, while this second ban was in effect, the SSE introduced colocation on November 12, 2012. To control for this potentially relevant event, we limit the post-event period for the second short sale ban from July 23, 2012 to November 11, 2012. As in previous tests, we use a pooled regression model with the (*VLT(-1)*) control variable and a dummy for the second short sale ban, to indicate the "incremental" difference in any variable of interest during the second short sale ban, compared to the first short sale ban. This is captured by the SSB2 dummy in the reported results. We begin by examining the changes in HFT activity in the second ban, compared to the first ban. Results are presented in Table 10.

[Table 10]

For the full sample as well as the Blue Chip stocks, most metrics of HFT activity show a reduction, indicating that relative to the first ban, there is additional decline during the second ban. For example, compared to the first ban, the second ban saw an additional 75.89 fewer messages per minute, which is significant at the 1% level.

In Table 11 all liquidity measures show significant reductions during the second ban, relative to their first ban levels.

[Table 11], [Table 12]

This is true of the full sample as well as the Blue Chip stocks. Reflecting the findings in the previous sections, when examining the price efficiency and volatility impacts of the second ban, in Table 12 we find that while return autocorrelations increase, volatility shows no change.

[Table 13]

Market making costs in Table 13 also show the same patterns as before: increased realized spreads and price impacts at all three horizons during the second short sale ban, relative to the first ban.

5.4. Effects of the introduction of colocation

Colocation reduces latency of the high-speed traders, and research shows that this leads to improved market outcomes. Conrad, Wahal, and Xiang (2014) study a technological change on the Tokyo Stock Exchange that reduced latency and allowed for colocation. They find that after the upgrade price efficiency increased and trading cost declined.

To facilitate high-speed traders, the SSE introduced colocation services on November 12, 2012. The peculiar nature of this introduction of colocation was that it happened during a time when the Spanish stock market had a regulatory short sale ban ongoing. As mentioned before, the second short sale ban began on July 23, 2012 and ended on January 31, 2013. In this section, we test for differences in various metrics of market quality before and after colocation. First, we compare the "pre-colocation" period (July 23, 2013 – November 11, 2012), a time with banned short-selling and no colocation, with the "post-colocation" period (November 12, 2012 – January 31, 2013), a time with banned short-selling and colocation. This test isolates the effect of colocation during a short sale ban. Second, we compare the "pre-ban" period (April 16, 2012 – July 22, 2012), a time with no ban and no colocation, with the "post-ban" period (February 1, 2013 – June 31, 2013), a time with no ban but with colocation. This test isolates the effect of colocation without a short sale ban. These two tests together provide a total picture of how colocation affects the SSE stocks under a regime of short sale ban versus no short sale ban. Table 14 presents the results.

[Table 14]

The Post- vs. pre colocation dummy, which captures the effect of colocation in the presence of a short sale ban, shows declines in three of the four HFT proxies. This is expected, since regulatory impediments lead to a decline in HFT activity (Boehmer, Jones, and Zhang, 2013). Somewhat unexpectedly, we find similar reductions in HFT activity when comparing the effect of colocation without the ban (see the variable Post- vs. pre ban). The reductions are not significant in most of the Blue Chip stocks, but overall, our results robustly document that colocation did not produce any increase in HFT, with or without the short sale ban.

However, the liquidity and market activity impacts of colocation show some variation across the two event windows. In Table 15, we present the results of the effects of colocation, with and without ban, on liquidity and market activity.

[Table 15]

While we find an across-the-board decline in liquidity and market activity measures when comparing the period before and after colocation with the short sale ban (see variable Post- vs. pre colocation), we find that weighted and relative spreads decline, and depth and order book elasticity increase significantly when comparing the effects of colocation without the ban (see variable Post- vs. per ban). Overall, Amihud illiquidity significantly declines. This is consistent with the literature, which documents that increased HFT facilitated by colocation improves market liquidity characteristics. The richness of our unique setting allows us to show that such improvements do not accrue if there are regulatory restrictions to trading.

In Tables 15 and 16, we show that colocation is accompanied by volatility reduction but no significant change in realized spread, both with and without the ban.

[Table 15], [Table 16]

6. Robustness checks

In robustness checks we have tested the pre- versus post-ban time window for market quality effects of the first and the second short sale bans separately (instead of the incremental test of the second ban relative to the first, as presented in the main tables). Similar tests for liquidity and market activity metrics confirm the results presented: both bans show liquidity reduction but the second ban shows stronger declines. Price efficiency metrics and market making revenues estimated separately around each of the two bans show results consistent with those presented. All robustness check results are available from the authors.

7. Conclusions

Existing studies show that high-frequency traders, which largely dominate modern markets, improve liquidity and price efficiency but may also adversely select other investors and try to game other traders by creating congestion in the trading platforms. Our investigation of how HFT impacts markets reveals the key role of regulation in this equation: Whether HFTs have a positive or negative effect depends critically on the regulatory framework within which these fast traders operate. In this study we identify a unique timeline of events that allow us to shed light on how market quality if affected when regulatory restrictions are juxtaposed with technological inducements to facilitate HFT.

During 2011 and 2012, the SSE introduced two major technological changes to attract and facilitate HFT. On April 16, 2012 the SSE introduced the SIBE-Smart, a technologically upgraded trading platform, followed by colocation facilities on November 12, 2012. During this time, there were two short sale bans imposed by the SSE. The first ban ended just before the SIBE-Smart introduction and the second ban started before the colocation event and ended several months later. We use this juxtaposition of events and show how HFT activity, market liquidity, price efficiency, and market making costs/revenues are impacted.

We document several findings. First, overall there is no increase in HFT when comparing the periods before and after all these events. By most metrics, liquidity worsened and price efficiency fell. Although the SIBE-Smart introduction preceded the first ban and managed to attract a modest increase in HFT, it was accompanied by reductions in liquidity and price efficiency. In contrast, the colocation event was introduced during the second short sale ban and failed to boost HFT activity in any significant way, also leading to a worsening of market quality. Finally, our timeline also allows us to isolate the effects of colocation with and without a short-sale ban. In comparing the effects of colocation with and without a ban, we find that although HFT does not increase in either case, liquidity improves with colocation in the absence of a ban but declines rather steeply when the ban is in effect.

When regulatory restrictions are present, as in our setting, we fail to find the positive effects of HFT-friendly technological improvements that have been documented by previous studies. Our results indicate that the effects of regulatory restrictions create serious impediments that technological inducements may not be capable of overcoming.

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TABLE 1

Sample Statistics

We provide average daily statistics for the twenty-eight index constituents in our sample and seven blue chips of the SSE. Our sample period covers January 2010 to December 2013. We provide average statistics on market capitalization; transaction price; volume in shares and euros; number of trades; relative bid-ask spreads; displayed depth at the five best levels of the LOB, both in shares and euros; the absolute open-to-close returns; the ratio between the highest and the lowest trade price, and message traffic. We compute message traffic as the number of limit order book (LOB) updates per day, which is equivalent to summing all order submissions, cancelations, and modifications since. All orders in the SSE hit the LOB. We report standard deviations in parenthesis. We use the rank-sum statistic of Wilcoxon to tests for equality of medians.

	All stocks	Blue Chips	
	Mean	Mean	
Market Cap. (/10000)	1151334.09	3559233.79	***
	(1721046.88)	(2049702.52)	
Price	17.09	19.94	
	(16.82)	(24.55)	
Volume /10000)	551.43	1561.38	**
	(972.30)	(1507.33)	
Euro Volume (/10000)	4421.48	14026.56	***
	(7476.87)	(10346.16)	
Trades	2786.76	6650.74	***
	(2962.78)	(3950.21)	
Relative bid-ask spread	0.0016	0.0008	***
	(0.0006)	(0.0003)	
Depth	58181.41	74376.74	
	(91080.94)	(50423.75)	
Depth (€)	385433.38	792616.64	***
	(353945.77)	(507494.22)	
Abs. open-to-close returns	0.0142	0.0128	
	(0.0032)	(0.0023)	
Price high/low	0.0297	0.0268	
	(0.0061)	(0.0043)	
Message Traffic	46396.96	100037.46	***
	(43541.41)	(57042.96)	

***, **, * indicates statistically different at the 1%, 5% and 10% level, respectively

TABLE 2
Overall effect on HFT

We evaluate the impact of all the technological upgrades undertaken by the SSE from 2011 to 2012 in the search of lower latency on HFT activity. Our sample period covers from January 2011 to June 2013. In this analysis, we compare the "pre-events" (February 1st, 2011 – June 31st, 2011) and "post-events" periods (February 1st, 2013 - June 31st, 2013). This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. As dependent variable, we use the following daily proxies for high-frequency trading: message traffic per minute (MTMIN); message traffic per euro-volume (MTV€); message traffic per volume in shares (MTV), and the number of non-zero quote midpoint changes (CQMP). We compute message traffic as the number of limit order book (LOB) updates per day, which is equivalent to summing all order submissions, cancelations, and modifications. All orders in the SSE hit the LOB. Our explanatory variable is a dummy for the post-events period ("Post-Events"). We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks that were included in the SSE official index (the IBEX-35) uninterruptedly over the sample period. We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	MTMIN	MTV€	MTV	CQMP
Cons.	64.36 ***	0.2001 ***	0.0411 ***	4536.12 ***
Post-Events	19.16 *	0.0941	0.0070	-622.46
VLT(-1)	8.93 ***	0.0054	0.0002	864.05 ***
Obs.	5852	5852	5852	5852
Adj.-R2	0.0149	0.0144	0.0029	0.0144
F	138.41	68.43	23.09	95.15
% change †	*30%* *	*47%*	*17%*	*-14%*

Panel B: Blue Chips

Variable	MTMIN	MTV€	MTV	CQMP
Cons.	116.23 ***	0.0605 ***	0.0139 **	5818.00 ***
Post-Events	76.16 ***	0.0811 ***	0.0175	1135.07
VLT(-1)	21.48 ***	0.0018	-0.0004	1648.27 ***
Obs.	1463	1463	1463	1463
Adj.-R2	0.1046	0.3454	0.0562	0.0375
F	231.03	614.89	91.12	73.54
% change †	*65%* ***	*134%* ***	*126%*	*19%*

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 3
Overall effect on liquidity

We evaluate the liquidity effects of the technological upgrades undertaken by the SSE from 2011 to 2012 to reduce latency. Our sample period is January 2011 to June 2013. We compare the "pre-events" (February 1, 2011 – June 31, 2011) and "post-events" periods (February 1, 2013 - June 31, 2013). This table presents the estimated coefficients of a pooled regression with double-clustered standard errors, Thompson (2011). Dependent variables are the following liquidity and activity proxies: Relative spread (RSPR) is the quoted spread divided by the quote midpoint, weighted by time; Quoted depth (DEPTH€) is the average of the accumulated displayed euro depth at the five best ask and bid LOB quotes, weighted by time; LOB elasticity (LOBELAST) as in Näes and Skjeltorp (2006); effective spread (ESPR) is two times the difference between the trade price and the quote midpoint multiplied by trade direction (1 = buyer initiated; -1 = seller-initiated); effective spread is weighted by trade size (WESPR); Amihud's (2002) illiquidity measure (AMIHUD) is the absolute open-to-close return divided by the daily euro volume (x10^6). RSPR, WESPR, and AMIHUD are inverse measures while DEPH€ and LOBELAST are direct measures of liquidity. VOL is the daily volume in shares; VOL€ is the daily volume in euros, and TRDS is the daily number of trades. We use a dummy for the post-events period ("Post-Events") as an explanatory variable. We use the IBEX-35 volatility (computed as its daily high/low) lagged one period, as the control variable (VLT). Our sample consists of the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (28 stocks). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

TABLE 3 (Cont.)
Overall effect on liquidity

Panel A: All stocks

Variable	RSPR(x100)		DEPTH€		LOBELAST		WESPR(x100)		AMIHUD		VOL(/10^4)		VOL€(/10^6)		TRDS	
Cons.	0.0909	***	236000	***	26800	***	0.0870	***	0.0146	***	451.28	***	48.80	***	2555.38	***
Post-Events	0.0213	***	-4250		-3790	***	0.0234	***	0.0047	**	112.76		-21.23	**	-361.91	***
VLT(-1)	0.0083	***	-17900	***	-1340	***	0.0064	***	-0.0004		51.39	***	3.54	***	230.39	***
Obs.	5852		5852		5852		5852		5852		5852		5852		5852	
Adj.-R2	0.0606		0.002		0.0307		0.0443		0.0119		0.0033		0.0158		0.0044	
F	593.54		14.53		579.02		316.66		64.03		29.39		206.25		77.08	
% change †	*23%*	***	*-2%*		*-14%*	***	*27%*	***	*32%*	**	*25%*		*-43%*	**	*-14%*	***

Panel B: Blue Chips

Variable	RSPR(x100)		DEPTH€		LOBELAST		WESPR(x100)		AMIHUD		VOL(/10^4)		VOL€(/10^6)		TRDS	
Cons.	0.0516	***	476000	**	45900	***	0.0503	***	0.0025	**	1390.53	***	155.65	***	6144.32	***
Post-Events	0.0072	**	-63300		-6570	***	0.0099	***	0.0021		-300.76	***	-75.55	***	-1190.00	***
VLT(-1)	0.0041	***	-33500	**	-2360	***	0.0027	***	0.0001		152.46	***	11.95	***	652.77	***
Obs.	1463		1463		1463		1463		1463		1463		1463		1463	
Adj.-R2	0.0435		0.0157		0.0684		0.0708		0.0242		0.0114		0.0902		0.0223	
F	89.74		33.30		238.72		103.45		34.32		35.41		200.31		59.24	
% change †	*14%*	**	*-13%*		*-14%*	***	*20%*	***	*84%*		*-22%*	***	*-48%*	***	*-19%*	***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 4
Overall effect on realized volatility and price efficiency

We evaluate the impact of all the technological upgrades undertaken by the SSE from 2011 to 2012 in the search of lower latency on volatility and price efficiency. Our sample period covers from January 2011 to June 2013. In this analysis, we compare the "pre-events" (February 1st, 2011 – June 31st, 2011) and "post-events" periods (February 1st, 2013 - June 31st, 2013). This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use realized volatility and price efficiency proxies as dependent variables. Realized volatility (RVLT) is the daily standard deviation of 1-minute trade price returns. As efficiency proxies, we choose the autocorrelation of 1-minute trade price returns (AUTOC), and the pricing error standard deviation (PESTD) estimated using Hasbrouk (1993). We use a dummy for the post-events period ("Post-Events") as an explanatory variable. We use the IBEX-35 volatility (computed as its daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (28 stocks). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	RVLT(X100)	AUTOC	PESTD
Cons.	0.0756 ***	0.0619 ***	0.0214 ***
Post-Events	0.0045	0.0082 ***	0.0001
VLT(-1)	0.0097 ***	0.0020	0.0016 ***
Obs.	5852	5852	5852
Adj.-R^2	0.0521	0.0074	0.0051
F	291.93	22.60	34.06
% change †	*6%*	*13%*	*0%*

Panel B: Blue Chips

Variable	RVLT(X100)	AUTOC	PESTD
Cons.	0.0610 ***	0.0636 ***	0.0121 ***
Post-Events	0.0044	0.0055	-0.0012 **
VLT(-1)	0.0089 ***	-0.0004	0.0007 ***
Obs.	1463	1463	1463
Adj.-R2	0.1323	0.0031	0.0193
F	138.90	2.25	20.79
% change †	*7%*	*9%*	*-10%* **

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 5

Overall effect on market making costs and profits

We evaluate the impact of the technological upgrades undertaken by the SSE from 2011 to 2012 on market making implicit costs and profits. Our sample period covers from January 2011 to June 2013. In this analysis, we compare the "pre-events" (February 1st, 2011 – June 31st, 2011) and "post-events" periods (February 1st, 2013 - June 31st, 2013). This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use the price impact (PI) of trades and the realized spread (RZDS) (e.g., Huang and Stoll, 1996; Hendershott, Jones, and Menkveld, 2011) as the dependent variables. We consider three alternative horizons: 1, 15 and 30 seconds after the trade. The price impact is a measure of the informativeness of trades and, thus, adverse selection costs. The realized spread measures how much of the quoted bid-ask spread is earned by the liquidity provider. The realized spread is the effective spread minus the price impact. A dummy for the post-events period ("Post-Events") is our explanatory variable. We use the IBEX-35 volatility (computed as its daily high/low) lagged one period, as the control variable (VLT). Our sample consists of the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (28 stocks). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	RZDS-5"	RZDS-15"	RZDS-30"	PI-5"	PI-15"	PI-30"
Cons.	0.0350 ***	0.0300 ***	0.0264 ***	0.0398 ***	0.0449 ***	0.0485 ***
Post-Events	-0.0037	-0.0053	-0.0062	0.0178 ***	0.0194 ***	0.0203 ***
VLT(-1)	0.0003	-0.0007	-0.0014 *	0.0055 ***	0.0064 ***	0.0071 ***
Obs.	5852	5852	5852	5852	5852	5852
Adj.-R^2	0.004	0.0094	0.014	0.1342	0.1276	0.1189
F	25.1373	50.6662	67.1262	939.5477	859.6262	798.7403
% change †	*-11%*	*-18%*	*-24%*	*45%* ***	*43%* ***	*42%* ***

Panel B: Blue Chips

Variable	RZDS-5"	RZDS-15"	RZDS-30"	PI-5"	PI-15"	PI-30"
Cons.	0.0194 ***	0.0159 ***	0.0138 ***	0.0243 ***	0.0279 ***	0.0299 ***
Post-Events	-0.0078 ***	-0.0081 ***	-0.0077 ***	0.0123 ***	0.0126 ***	0.0122 ***
VLT(-1)	-0.0005	-0.0010 *	-0.0010 *	0.0035 ***	0.0040 ***	0.0040 ***
Obs.	1463	1463	1463	1463	1463	1463
Adj.-R2	0.1276	0.1394	0.1297	0.2688	0.2338	0.1928
F	170.67	166.49	134.46	466.40	388.54	323.45
% change †	*-40%* ***	*-51%* ***	*-56%* ***	*50%* ***	*45%* ***	*41%* ***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 6
SIBE-Smart effect on HFT

We evaluate the impact of the introduction of the SIBE Smart, the technologically updated and faster electronic trading platform of the SSE, on April 16th, 2012 on HFT activity. Our sample period covers from January 2011 to June 2013. In this particular analysis, we focus on the "pre-Smart" (March 1st, 2012 – April 15th, 2012) and "post-Smart" (April 16th, 2012 - May 31st, 2012) periods. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use the following daily proxies for HFT as explanatory variables: message traffic per minute (MTMIN); message traffic per euro-volume (MTV€); message traffic per volume in shares (MTV), and the number of non-zero quote midpoint changes (CQMP). We compute message traffic as the number of limit order book (LOB) updates per day, which is tantamount to summing all order submissions, cancelations, and modifications. All orders in the SSE hit the LOB. Our exogenous variable is a dummy for the post-Smart period ("Post-Smart"). We use the IBEX-35 volatility (computed as its daily high/low) lagged one period, as the control variable (VLT). Our sample consists of the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (28 stocks). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	MTMIN	MTV€	MTV	CQMP
Cons.	104.52 ***	0.3331 ***	0.0528 ***	5651.39 ***
Post-Smart	7.58 ***	0.098 *	0.0121	5478.93 ***
VLT(-1)	10.03 ***	0.0039 ***	-0.0011	1587.80 **
Obs.	1762	1762	1762	1762
Adj.-R^2	0.0073	0.0167	0.0041	0.0842
F	50.85	27.54	11.83	216.23
% change †	*7%* ***	*29%* *	*23%*	*96%* ***

Panel B: Blue Chips

Variable	MTMIN	MTV€	MTV	CQMP
Cons.	224.77 ***	0.1302 ***	0.0243 **	8358.08 ***
Post-Smart	26.81 ***	0.0101	-0.0023	8948.44 ***
VLT(-1)	20.21 ***	0.0005 ***	-0.0002	2802.86 **
Obs.	441	441	441	441
Adj.-R2	0.0207	0.0053	0.002	0.1051
F	27.06	2.56	3.41	86.05
% change †	*12%* ***	*8%*	*-9%*	*106%* ***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 7
SIBE-Smart effect on liquidity

We evaluate the impact of the introduction of the SIBE Smart, the technologically updated and faster electronic trading platform of the SSE, on April 16th, 2012 on liquidity. Our sample period covers from January 2011 to June 2013, but in this particular analysis we focus on the "pre-Smart" (March 1st, 2012 – April 15th, 2012) and "post-Smart" (April 16th, 2012 - May 31st, 2012) periods. This table provides the estimated coefficients of a pool regression model estimated with Thompson (2011) two-way clustered standard errors. We use liquidity and activity proxies as dependent variables. The relative bid-ask spread (RSPR) is the quoted bid-ask spread divided by the quote midpoint and weighted by time. Quoted depth (DEPTH€) is the average between the accumulated displayed euro depth at the five best ask and bid LOB quotes, also weighted by time. We compute the LOB elasticity (LOBELAST) as in Näes and Skjeltorp (2006). The effective spread (ESPR) is two times the difference between the trade price and the quote midpoint multiplied by the trade direction (1 = buyer initiated; -1 = seller-initiated). The effective spread is averaged weighting by trade size (WESPR). Amihud's (2002) illiquidity measure (AMIHUD) is the absolute open-to-close return divided by the daily euro volume (x106). RSPR, WESPR, and AMIHUD are inverse measures of liquidity while DEPH€ and LOBELAST are direct measures of liquidity. VOL is the daily volume in shares; VOL€ is the daily volume in euros, and TRDS is the daily number of trades. Our explanatory variable is a dummy for the post-Smart period ("Post-Smart"). We use the IBEX-35 volatility (computed as its daily high/low) lagged one period, as the control variable (VLT). Our sample consists of the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (28 stocks). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

TABLE 7 (Cont.)
SIBE-Smart impact on liquidity

Panel A: All stocks

Variable	RSPR(x100)		DEPTH€		LOBELAST		WESPR(x100)		AMIHUD		VOL(/10^4)		VOL€(/10^6)		TRDS	
Cons.	0.1032	***	212000	***	23400	***	0.0926	***	0.0233	***	496.06	***	48.21	***	2572.71	***
Post-Smart	0.0388	***	-47200	***	-4040	***	0.0422	***	0.0125	***	80.99	***	-16.69	***	303.46	***
VLT(-1)	0.0083	***	-8280	***	-1130	***	0.0051	***	-0.0038	**	45.50	***	3.90	***	219.66	***
Obs.	1762		1762		1762		1762		1762		1762		3892		3892	
Adj.-R^2	0.1297		0.0337		0.062		0.0752		0.0195		0.0031		0.0028		0.007	
F	733.72		176.73		513.48		200.61		30.83		21.18		34.84		85.67	
% change †	*38%*	***	*-22%*	***	*-17%*	***	*46%*	***	*54%*	***	*16%*	***	*-35%*	***	*12%*	***

Panel B: Blue Chips

Variable	RSPR(x100)		DEPTH€		LOBELAST		WESPR(x100)		AMIHUD		VOL(/10^4)		VOL€(/10^6)		TRDS	
Cons.	0.051	***	462000	***	43000	***	0.0489	***	0.0041	**	1446.34	***	123.15	***	6547.95	***
Post-Smart	0.0149	***	-103000	**	-6760	***	0.0153	***	0.0009	***	325.39	***	-0.52		792.66	***
VLT(-1)	0.0048	***	-27000	***	-2290	***	0.0034	***	-0.0003	*	151.18	***	6.28	***	552.06	**
Obs.	441		441		441		441		441		441		441		441	
Adj.-R2	0.1533		0.0963		0.1661		0.1827		0.0034		0.0168		0.0029		0.0201	
F	219.31		87.00		187.51		130.21		1.52		20.0113		2.3722		18.9818	
% change †	*29%*	***	*-22%*	**	*-16%*	***	*31%*	***	*22%*	***	*22%*	***	*-0.42%*		*12%*	***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.
† Control variable evaluated at the mean

TABLE 8
SIBE-Smart effect on realized volatility and price efficiency

We evaluate the impact of the introduction of the SIBE Smart, the technologically updated and faster electronic trading platform of the SSE, on April 16th, 2012 on volatility and price efficiency. Our sample period covers from January 2011 to June 2013, but in this particular analysis we focus on the "pre-Smart" (March 1st, 2012 – April 15th, 2012) and "post-Smart" (April 16th, 2012 - May 31st, 2012) periods. This table provides the estimated coefficients of a pool regression model estimated with Thompson (2011) two-way clustered standard errors. We use realized volatility and price efficiency proxies as dependent variables. Realized volatility (RVLT) is the daily standard deviation of 1-minute trade price returns. As efficiency proxies, we choose the autocorrelation of 1-minute trade price returns (AUTOC), and the pricing error standard deviation (PESTD) estimated using Hasbrouck (1993). Our explanatory variable is a dummy for the post-events period ("Post-Events"). We use the IBEX-35 volatility (computed as its daily high/low) lagged one period, as the control variable (VLT). Our sample consists of the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (28 stocks). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	RVLT(X100)	AUTOC	PESTD
Cons.	0.0769 ***	0.0640 ***	0.0212 ***
Post-Smart	0.0404 ***	0.0100 **	0.0100 ***
VLT(-1)	0.0089 ***	0.0000 ***	0.0010 **
Obs.	3892	1762	1762
Adj.-R^2	0.2877	0.0082	0.0725
F	1400.03	7.84	194.1182
% change †	*52%* ***	*16%* **	*47%* ***

Panel B: Blue Chips

Variable	RVLT(X100)	AUTOC	PESTD
Cons.	0.0613 ***	0.0549 ***	0.0104 ***
Post-Smart	0.0288 ***	0.0161 **	0.0025 ***
VLT(-1)	0.0090 ***	0.0012 ***	0.0007 ***
Obs.	441	441	441
Adj.-R2	0.4387	0.0284	0.1202
F	314.29	7.88	52.74
% change †	*47%* ***	*29%* **	*24%* ***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.
† Control variable evaluated at the mean

TABLE 9
SIBE-Smart effect on market making costs and profits

We evaluate the impact of the introduction of the SIBE Smart, the technologically updated and faster electronic trading platform of the SSE, on April 16th, 2012 on the market making implicit costs and profits. Our sample period covers from January 2011 to June 2013. In this particular analysis, we focus on the "pre-Smart" (March 1st, 2012 – April 15th, 2012) and "post-Smart" (April 16th, 2012 - May 31st, 2012) periods. We provide the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use the price impact (PI) of trades and the realized spread (RZDS) (e.g., Hendershott, Jones, and Menkveld, 2011) as dependent variables. We consider three alternative horizons: 1, 15 and 30 seconds after the trade. The price impact is a measure of the informativeness of trades and, this, adverse selection costs. The realized spread measures how much of the quoted bid-ask spread is earned by the liquidity provider. The realized spread is the effective spread minus the price impact. The explanatory variable is a dummy for the post-events period ("Post-Events"). We use the IBEX-35 volatility (computed as its daily high/low) lagged one period, as the control variable (VLT). Our sample consists of the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (28 stocks). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period. We refer to this later subsample as the "blue chips" of the SSE. We also report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	RZDS-5"	RZDS-15"	RZDS-30"	PI-5"	PI-15"	PI-30"
Cons.	0.0244 ***	0.0179 ***	0.0147 ***	0.0580 ***	0.0644 ***	0.0676 ***
Post-Smart	0.0081 *	0.0076	0.0069	0.0221 ***	0.0226 ***	0.0234 ***
VLT(-1)	-0.0023 ***	-0.0030 ***	-0.0034 ***	0.0060 ***	0.0067 ***	0.0071 ***
Obs.	1762	1762	1762	1762	1762	1762
Adj.-R^2	0.0076	0.007	0.0066	0.1505	0.1322	0.1227
F	15.1544	11.8253	10.2583	451.4918	409.8654	394.0068
% change †	*33%* *	*43%*	*47%*	*38%* ***	*35%* ***	*35%* ***

Panel B: Blue Chips

Variable	RZDS-5"	RZDS-15"	RZDS-30"	PI-5"	PI-15"	PI-30"
Cons.	0.0134 ***	0.0108 ***	0.0102 ***	0.0287 ***	0.0311 ***	0.0317 ***
Post-Smart	-0.0039	-0.0036	-0.0034	0.0151 ***	0.0149 ***	0.0146 ***
VLT(-1)	-0.0018 ***	-0.0021 ***	-0.002 ***	0.0046 ***	0.0049 ***	0.0049 ***
Obs.	441	441	441	441	441	441
Adj.-R2	0.0814	0.091	0.0913	0.2981	0.2768	0.2583
F	27.5979	27.9405	25.9747	210.8723	202.6588	202.4633
% change †	*-29%*	*-33%*	*-33%*	*52%* ***	*48%* ***	*46%* ***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.
† Control variable evaluated at the mean

TABLE 10
Short-selling bans: Comparative effect on HFT

The SSE banned short-selling two times within our sample period (January 2011 - June 2013). The first short-selling ban (SSB) run from August 11th, 2011 to February 15th, 2012 and affected only to 16 stocks from the financial sector (8 of them within our sample). The 2nd SSB started on July 23rd, 2012, and finished on January 31st, 2013. However, colocation was introduced within the second SSB, on November 12th, 2012. To control for this potentially relevant event, we limit the 2nd SSB period to July 23rd, 2012 to November 11th, 2012. We test for differences in the level of HFT within both SSB periods. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use the following daily proxies for HFT as dependent variables: message traffic per minute (MTMIN); message traffic per euro-volume (MTV€); message traffic per volume in shares (MTV), and number of non-zero quote midpoint changes (CQMP). We compute message traffic as the number of limit order book (LOB) updates per day, which equals to summing all order submissions, cancelations. All orders in the SSE hit the LOB. The coefficient of interest is "SSB2", a dummy for the 2nd SSB period ("SSB2"). We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	MTMIN	MTV€	MTV	CQMP
Cons.	97.97 ***	0.3426 ***	0.0552 ***	6027.38 ***
SSB2	-75.89 ***	-0.036	-0.0106 **	-2920.00 ***
VLT(-1)	14.04 ***	0.007	0	1262.23 ***
Obs.	5992	5992	5992	5992
Adj.-R^2	0.0891	0.0031	0.0047	0.05
F	903.74	12.62	31.49	414.51
% change †	*-77%* ***	*-11%*	*-19%* **	*-48%* ***

Panel B: Blue Chips

Variable	MTMIN	MTV€	MTV	CQMP
Cons.	228.93 ***	0.1442 ***	0.0274 **	11600.00 ***
SSB2	-185.13 ***	-0.0464 ***	-0.0057 ***	-5490.00 **
VLT(-1)	37.39 ***	0.0041 **	-0.0004	2834.54 ***
Obs.	1498	1498	1498	1498
Adj.-R2	0.2587	0.0783	0.0081	0.0919
F	529.69	100.99	29.24	170.53
% change †	*-81%* ***	*-32%* ***	*-21%* ***	*-47%* **

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 11

Short-selling bans: Comparative effect on liquidity

The SSE banned short-selling two times within our sample period (January 2011 - June 2013). The first short-selling ban (SSB) run from August 11th, 2011 to February 15th, 2012 and affected only to 16 stocks from the financial sector (8 of them within our sample). The 2nd SSB started on July 23rd, 2012, and finished on January 31st, 2013. However, colocation was introduced within the second SSB, on November 12th, 2012. To control for this potentially relevant event, we limit the 2nd SSB period to July 23rd, 2012 to November 11th, 2012. We test for differences in the level of liquidity within both SSB times. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use liquidity and activity proxies as dependent variables. The relative bid-ask spread (RSPR) is the quoted bid-ask spread divided by the quote midpoint and weighted by time. Quoted depth (DEPTH€) is the average between the accumulated displayed euro depth at the five best ask and bid LOB quotes, also weighted by time. We compute LOB elasticity (LOBELAST) as in Näes and Skjeltorp (2006). The effective spread (ESPR) is two times the difference between the trade price and the quote midpoint multiplied by the trade direction (1 = buyer initiated; -1 = seller-initiated). The effective spread is averaged weighting by trade size (WESPR). Amihud's (2002) illiquidity measure (AMIHUD) is the absolute open-to-close return divided by the daily euro volume (x106). RSPR, WESPR, and AMIHUD are inverse measures of liquidity while DEPH€ and LOBELAST are direct measures of liquidity. VOL is the daily volume in shares; VOL€ is the daily volume in euros, and TRDS is the daily number of trades. The coefficient of interest is "SSB2", a dummy for the 2nd SSB period ("SSB2"). We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks that included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

TABLE 11 (Cont.)
Short-selling bans: Comparative effect on liquidity

Panel A: All stocks

Variable	RSPR(x100)	DEPTH€	LOBELAST	WESPR(x100)	AMIHUD	VOL(/10^4)	VOL€(/10^6)	TRDS
Cons.	0.1132 ***	187000 ***	20000 ***	0.1109 ***	0.0196 ***	348.28 ***	33.87 ***	2149.84 ***
SSB2	0.0470 ***	-40100 **	-3800 ***	0.0571 ***	0.0179 ***	-58.07	-14.97 ***	-726.31 ***
VLT(-1)	0.0172 ***	-4460	-1020 ***	0.0117 ***	0.0008	52.06 ***	2.99 ***	200.83 ***
Obs.	5992	5992	5992	5992	5992	5992	5992	5992
Adj.-R2	0.1316	0.0162	0.0538	0.0969	0.0251	0.0063	0.0158	0.0213
F	1107.45	123.49	848.03	676.91	120.44	93.26	208.82	299.21
% change †	*41%* ***	*-21%* **	*-19%* ***	*51%* ***	*91%* ***	*-17%*	*-44%* ***	*-0.34* ***

Panel B: Blue Chips

Variable	RSPR(x100)	DEPTH€	LOBELAST	WESPR(x100)	AMIHUD	VOL(/10^4)	VOL€(/10^6)	TRDS
Cons.	0.0549 ***	383000 ***	36000 ***	0.0570 ***	0.0031 **	1128.20 ***	108.86 ***	5317.02 ***
SSB2	0.0307 ***	-101000 *	-7910 ***	0.0252 ***	0.0040 *	-279.58 ***	-47.79 ***	-1790.00 ***
VLT(-1)	0.0087 ***	-13700	-1760 ***	0.0057 ***	0.0001	175.18 ***	10.41 ***	631.30 ***
Obs.	1498	1498	1498	1498	1498	1498	1498	1498
Adj.-R2	0.1477	0.048	0.1653	0.1864	0.043	0.0331	0.0839	0.0892
F	194.76	61.70	398.39	278.82	55.39	86.63	161.42	176.03
% change †	*56%* ***	*-26%* *	*-22%* ***	*44%* ***	*129%* ***	*-25%* ***	*-44%* ***	*-34%* ***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.
† Control variable evaluated at the mean

TABLE 12

Short-selling bans: Comparative effect on realized volatility and price efficiency

The SSE banned short-selling two times within our sample period (January 2011 - June 2013). The first short-selling ban (SSB) run from August 11th, 2011 to February 15th, 2012 and affected only to 16 stocks from the financial sector (8 of them within our sample). The 2nd SSB started on July 23rd, 2012, and finished on January 31st, 2013. Colocation began within the second SSB, on November 12th, 2012. To control for this potentially relevant event, we limit the 2nd SSB period to July 23rd, 2012 to November 11th, 2012. We test for differences in the level of volatility and price efficiency within both SSB periods. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. Realized volatility (RVLT) is the daily standard deviation of 1-minute trade price returns. As efficiency proxies, we choose the autocorrelation of 1-minute trade price returns (AUTOC), and the pricing error standard deviation (PESTD) estimated using Hasbrouk (1993). The coefficient of interest is "SSB2", a dummy for the 2nd SSB period ("SSB2"). We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	RVLT(X100)		AUTOC		PESTD	
Cons.	0.0815	***	0.0638	***	0.0254	***
SSB2	0.0058		0.0085	***	0.0111	***
VLT(-1)	0.0171	***	0.0010		0.0036	***
Obs.	5992		5992		5988	
Adj.-R2	0.2129		0.0059		0.0671	
F	1240.85		18.00		420.58	
% change †	*7%*		*13%*	***	*44%*	***

Panel B: Blue Chips

Variable	RVLT(X100)		AUTOC		PESTD	
Cons.	0.0647	***	0.0562	***	0.0116	***
SSB2	0.0081		0.0039		0.0060	***
VLT(-1)	0.0153	***	0.0035	**	0.0018	***
Obs.	1498		1498		1498	
Adj.-R2	0.3596		0.0101		0.212	
F	467.82		7.73		268.51	
% change †	*12%*		*7%*		*52%*	***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 13

Short-selling bans: Comparative effect on market making costs and profits

The SSE banned short-selling two times within our sample period (January 2011 - June 2013). The first short-selling ban (SSB) run from August 11th, 2011 to February 15th, 2012 and affected only to 16 stocks from the financial sector (8 of them within our sample). The 2nd SSB started on July 23rd, 2012, and finished on January 31st, 2013. Colocation began within the second SSB, on November 12th, 2012. To control for this potentially relevant event, we limit the 2nd SSB period to July 23rd, 2012 to November 11th, 2012. We test for differences in market making costs and profits within both SSB times. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use the price impact (PI) of trades and the realized spread (RZDS) (e.g., Hendershott, Jones, and Menkveld, 2011) as dependent variables. We consider three alternative horizons: 1, 15 and 30 seconds after the trade. The price impact is a measure of the informativeness of trades and, thus, adverse selection costs. The realized spread measures how much of the quoted bid-ask spread is earned by the liquidity provider. The realized spread is the effective spread minus the price impact. The coefficient of interest is "SSB2", a dummy for the 2nd SSB period ("SSB2"). We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks that included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, computed as [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All IBEX Stocks

Variable	RZDS-5"		RZDS-15"		RZDS-30"		PI-5"		PI-15"		PI-30"	
Cons.	0.0425	***	0.0365	***	0.0331	***	0.0549	***	0.0608	***	0.0641	***
SSB2	0.0205	***	0.0201	***	0.0188	***	0.0140	***	0.0143	***	0.0156	***
VLT(-1)	0.0015		0.0005		-0.0003		0.0089	***	0.0098	***	0.0107	***
Obs.	5992		5992		5992		5992		5992		5992	
Adj.-R2	0.0383		0.0354		0.0308		0.1098		0.107		0.1077	
F	256.45		216.57		173.38		751.85		724.47		724.63	
% change †	*48%*	***	*55%*	***	*57%*	***	*26%*	***	*24%*	***	*24%*	***

Panel B: Blue Chips

Variable	RZDS-5"		RZDS-15"		RZDS-30"		PI-5"		PI-15"		PI-30"	
Cons.	0.0173	***	0.0137	***	0.0124	***	0.0325	***	0.0361	***	0.0374	***
SSB2	0.0086	**	0.0065	**	0.0043		0.0108	***	0.0129	***	0.0150	***
VLT(-1)	-0.0005		-0.0008		-0.0010		0.0053	***	0.0056	***	0.0058	***
Obs.	1498		1498		1498		1498		1498		1498	
Adj.-R2	0.0769		0.0473		0.0266		0.1835		0.1876		0.1937	
F	79.55		45.41		23.65		286.03		290.11		299.62	
% change †	*50%*	**	*47%*	**	*35%*		*33%*	***	*36%*	***	*40%*	***

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 14
Colocation: effect on HFT

In the SSE, colocation services were introduced on November 12th, 2012, within a short-selling ban period that started on July 23rd, 2012 and finished on January 31st, 2013. We test for differences in the level of HFT before and after colocation. Firstly, we compare the "pre-colocation" period (July 23rd, 2013 – November 11th, 2012), a time with banned short-selling and no colocation, with the "post-colocation" period (November 12th, 2012 – January 31st, 2013), a time with banned short-selling and colocation. Secondly, we compare the "pre-ban" period (April 16th, 2012 – July 22nd, 2012), a time with no ban and no colocation, with the "post-ban" period (February 1st, 2013 – June 31st, 2013), a time with no ban but with colocation. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. Our dependent variables are daily proxies for high-frequency trading: message traffic per minute (MTMIN); message traffic per euro-volume (MTV€); message traffic per volume in shares (MTV), and the number of non-zero quote midpoint changes (CQMP). We compute message traffic as the number of limit order book (LOB) updates per day. We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks that included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, given by [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	MTMIN		MTV€		MTV		CQMP		Obs.
Cons.	39.17	***	0.2971	***	0.0445	***	3322.88	***	3808
Post- vs. pre-colocation	-3.00		-0.1245	***	-0.0158	***	-2200.00	***	
VLT(-1)	7.03	***	0.0109		0.0000		1173.18	***	
Adj.-R2	0.0206		0.0312		0.0159		0.1055		
% change †	*-8%*		*-42%*	***	*-36%*	***	*-66%*	***	
Cons.	106.73	***	0.429	***	0.06	***	12300.00	***	4816
Post- vs. pre-ban	-22.34	**	-0.148	**	-0.0155		-8920.00	***	
VLT(-1)	8.46	***	0.0125	**	0.0021	***	1129.20	***	
Adj.-R2	0.0168		0.0225		0.0088		0.1953		
% change †	*-21%*	**	*-34%*	**	*-26%*		*-72%*	***	

Panel B: Blue Chips

Variable	MTMIN		MTV€		MTV		CQMP		Obs.
Cons.	94.16	***	0.099	***	0.0206	*	7366.46	**	952
Post- vs. pre-colocation	-5.01		-0.0106		-0.0031		-4630.00	***	
VLT(-1)	16.75	***	0.0036		0.0000	***	2334.67	***	
Adj.-R2	0.0511		0.0141		0.0030		0.1794		
% change †	*-5%*		*-11%*		*-15%*		*-62%*	***	
Cons.	222.88	***	0.1359	***	0.0235	*	18000	***	1204
Post- vs. pre-ban	-26.27		0.007		0.0084	*	-11600	***	
VLT(-1)	19.22	***	0.0011		-0.0007	***	1966.87	**	
Adj.-R2	0.0262		0.0016		0.0119		0.1990		
% change †	*-12%*		*5%*		*36%*	*	*-64%*	***	

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 15
Colocation: effect on liquidity

In the SSE, colocation services were introduced on November 12th, 2012, within a short-selling ban period that started on July 23rd, 2012 and finished on January 31st, 2013. We test for differences in liquidity before and after colocation. Firstly, we compare the "pre-colocation" period (July 23rd, 2013 – November 11th, 2012), a time with banned short-selling but no colocation, with the "post-colocation" period (November 12th, 2012 – January 31st, 2013), a time with banned short-selling and with colocation. Secondly, we compare the "pre-ban" period (April 16th, 2012 – July 22nd, 2012), a time with no and no colocation, with the "post-ban" period (February 1st, 2013 – June 31st, 2013), a time with no ban but with colocation. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. Our dependent variables are liquidity and activity proxies. The relative bid-ask spread (RSPR) is the quoted bid-ask spread divided by the quote midpoint and weighted by time. Quoted depth (DEPTH€) is the average between the accumulated displayed euro depth at the five best ask and bid LOB quotes, also weighted by time. We compute LOB elasticity (LOBELAST) as in Näes and Skjeltorp (2006). The effective spread (ESPR) is two times the difference between the trade price and the quote midpoint multiplied by the trade direction (1 = buyer initiated; -1 = seller initiated). The effective spread is averaged weighting by trade size (WESPR). Amihud's (2002) illiquidity measure (AMIHUD) is the absolute open-to-close return divided by the daily euro volume (x106). RSPR, WESPR, and AMIHUD are inverse measures of liquidity while DEPH€ and LOBELAST are direct measures of liquidity. VOL is the daily volume in shares; VOL€ is the daily volume in euros, and TRDS is the daily number of trades. We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks that included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, given by [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

TABLE 15 (Cont.)
Colocation: effect on liquidity

Panel A: All IBEX Stocks

Variable	RSPR(x100)	DEPTH€	LOBELAST	WESPR(x100)	AMIHUD	VOL(/10^4)	VOL€(/10^6)	TRDS	Obs.
Cons.	0.1009 ***	252000 ***	23000 ***	0.1056 ***	0.0149 ***	295.68 ***	20.92 ***	1397.90 ***	4452
Post- vs. pre-colocation	0.0372 **	7189 **	-2820 ***	0.0424 ***	0.0118 ***	200.08	1.03	76.79	
VLT(-1)	0.0143 ***	-28700	-1350 ***	0.0090 ***	0.0020	49.82 ***	2.16 ***	211.34 ***	
Adj.-R2	0.0516	0.0031	0.012	0.0437	0.0136	0.0056	0.0031	0.0118	
% change †	*37%* **	*3%* **	*-12%* ***	*40%* ***	*79%* ***	*67%*	*5%*	*5%*	
Cons.	0.1511 ***	150000 ***	17600 ***	0.1345 ***	0.0269 ***	591.36 ***	35.96 ***	2870.87 ***	4816
Post- vs. pre-ban	-0.0350 ***	64800 **	4117 ***	-0.0224 ***	-0.0058 **	16.55	-4.40 ***	-538.59 ***	
VLT(-1)	0.0062 ***	-9010 ***	-635 ***	0.0054 ***	-0.0013 **	27.88 ***	1.40 ***	156.01 ***	
Adj.-R2	0.0891	0.0358	0.0465	0.0272	0.0047	0.0044	0.0030	0.0067	
% change †	*-23%* ***	*43%* **	*23%* ***	*-17%* ***	*-22%* **	*3%*	*-12%* ***	*-19%* ***	

Panel B: Blue Chips

Variable	RSPR(x100)	DEPTH€	LOBELAST	WESPR(x100)	AMIHUD	VOL(/10^4)	VOL€(/10^6)	TRDS	Obs.
Cons.	0.0513 ***	452000 ***	39700 ***	0.0590 ***	0.0039 **	832.26 **	67.23 ***	3529.15 ***	1113
Post- vs. pre-colocation	0.0200 *	85400 *	-3660 ***	0.0148 **	0.0016	-122.19 **	-4.92	-284.55	
VLT(-1)	0.0081 **	-54700	-2540 **	0.0034 ***	0.0005	181.89 ***	7.88 ***	630.90 ***	
Adj.-R2	0.0643	0.0099	0.0175	0.0399	0.0051	0.0430	0.0277	0.0701	
% change †	*39%* *	*19%* *	*-9%* ***	*25%* **	*41%*	*-15%* **	*-7%*	*-8%*	
Cons.	0.0745 ***	276000 ***	32000 ***	0.0704 ***	0.0043 **	1862.84 ***	116.50 ***	7276.41 ***	1204
Post- vs. pre-ban	-0.0122 ***	99900 **	4822 ***	-0.0073 *	0.0007	-635.33 **	-22.79 ***	-1870.00 ***	
VLT(-1)	0.0023 ***	-14100 **	-1000 ***	0.0012	-0.0001 ***	78.66 ***	4.66 ***	411.29 ***	
Adj.-R2	0.0749	0.0865	0.0551	0.0308	0.0035	0.0388	0.0246	0.0565	
% change †	*-16%* ***	*36%* **	*15%* ***	*-10%* *	*16%*	*-34%* **	*-20%* ***	*-26%* ***	

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 16
Colocation: effect on realized volatility and efficiency

In the SSE, colocation services were introduced on November 12th, 2012, within a short-selling ban period that started on July 23rd, 2012 and finished on January 31st, 2013. We test for differences in volatility and price efficiency before and after colocation. Firstly, we compare the "pre-colocation" period (July 23rd, 2013 – November 11th, 2012), a time with banned short-selling but no colocation, with the "post-colocation" period (November 12th, 2012 – January 31st, 2013), a time with banned short-selling and with colocation. Secondly, we compare the "pre-ban" period (April 16th, 2012 – July 22nd, 2012), a time with no ban and no colocation, with the "post-ban" period (February 1st, 2013 – June 31st, 2013), a time with no ban but with colocation. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. Realized volatility (RVLT) is the daily standard deviation of 1-minute trade price returns. As efficiency proxies, we choose the autocorrelation of 1-minute trade price returns (AUTOC), and the pricing error standard deviation (PESTD) estimated using Hasbrouck (1993). We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks that included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, given by [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	RVLT(X100)		AUTOC		PESTD		Obs.
Cons.	0.0890	***	0.0700	***	0.0362	***	3808
Post- vs. pre-colocation	-0.0133	***	0.0131	***	-0.0053	***	
VLT(-1)	0.0164	***	0.0020		0.0038	***	
Adj.-R2	0.2179		0.0084		0.0533		
% change †	*-15%*	***	*19%*	***	*-15%*	***	
Cons.	0.1182	***	0.0680	***	0.0328	***	4870
Post- vs. pre-ban	-0.0338	***	0.0021		-0.0100	***	
VLT(-1)	0.0073	***	0.0020	*	0.0009	***	
Adj.-R2	0.2467		0.0009		0.0659		
% change †	*-29%*	***	*3%*		*-30%*	***	

Panel B: Blue Chips

Variable	RVLT(X100)		AUTOC		PESTD		Obs.
Cons.	0.0757	***	0.0555	***	0.0173	***	952
Post- vs. pre-colocation	-0.0228	***	0.0096	**	-0.0021		
VLT(-1)	0.0141	***	0.0053	***	0.0020	***	
Adj.-R2	0.5306		0.0151		0.1025		
% change †	*-30%*	***	*17%*	**	*-12%*		
Cons.	0.0968	***	0.0659	***	0.0164	***	1204
Post- vs. pre-ban	-0.026	***	-0.0016		-0.0039	***	
VLT(-1)	0.006	***	0.0022		-0.0001		
Adj.-R2	0.4112		0.0026		0.0921		
% change †	*-27%*	***	*-2%*		*-24%*	***	

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean

TABLE 17
Colocation: effect on market making costs and profits

In the SSE, colocation services were introduced on November 12th, 2012, within a short-selling ban period that started on July 23rd, 2012 and finished on January 31st, 2013. We test for differences in market making profits and costs before and after colocation. Firstly, we compare the "pre-colocation" period (July 23rd, 2013 – November 11th, 2012), a time with banned short-selling but no colocation, with the "post-colocation" period (November 12th, 2012 – January 31st, 2013), a time with banned short-selling and with colocation. Secondly, we compare the "pre-ban" period (April 16th, 2012 – July 22nd, 2012), a time with no ban and no colocation, with the "post-ban" period (February 1st, 2013 – June 31st, 2013), a time with no ban but with colocation. This table provides the estimated coefficients of a pool regression model with Thompson (2011) two-way clustered standard errors. We use the price impact (PI) of trades and the realized spread (RZDS) (e.g., Huang and Stoll 1996) as the dependent variable. We consider three alternative horizons: 1, 15 and 30 seconds after the trade. The price impact is a measure of the informativeness of trades and, thus, adverse selection costs. The realized spread measures how much of the quoted bid-ask spread is earned by the liquidity provider. We use the IBEX-35 volatility (computed as the daily high/low) lagged one period, as the control variable (VLT). Our sample consists of all the SSE stocks that included in the SSE official index (the IBEX-35) uninterruptedly over the sample period (Panel A). We report separated results for seven index constituents that were always at the top ten by market capitalization over the sample period ("blue chips," Panel B). We report the implicit estimated percentage change in each proxy, given by [Post-Events/(Cons+VLT(-1)*mean(VLT))]x100.

Panel A: All stocks

Variable	RZDS-5"	RZDS-15"	RZDS-30"	PI-5"	PI-15"	PI-30"	Obs.
Cons.	0.0617 ***	0.0555 ***	0.0512 ***	0.0723 ***	0.0784 ***	0.0827 ***	3808
Post- vs. pre-colocation	-0.0018	-0.0014	-0.0016	-0.0191 ***	-0.0195 ***	-0.0193 ***	
VLT(-1)	0.002	0.0009	0.0000	0.0075 ***	0.0085 ***	0.0095 ***	
Adj.-R2	0.0042	0.0012	0.0003	0.1285	0.125	0.1207	
% change †	*-3%*	*-3%*	*-3%*	*-26%* ***	*-25%* ***	*-23%* ***	
Cons.	0.0308 ***	0.0243 ***	0.0208 ***	0.0796 ***	0.0860 ***	0.0895 ***	4816
Post- vs. pre-ban	0.0019	0.0013	0.0001	-0.0212 ***	-0.0206 ***	-0.0194 ***	
VLT(-1)	-0.0005	-0.0012 *	-0.0017 **	0.0051 ***	0.0058 ***	0.0063 ***	
Adj.-R2	0.0011	0.0019	0.0023	0.1355	0.1133	0.0951	
% change †	*6%*	*5%*	*0%*	*-27%* ***	*-24%* ***	*-22%* ***	

Panel B: Blue Chips

Variable	RZDS-5"	RZDS-15"	RZDS-30"	PI-5"	PI-15"	PI-30"	Obs.
Cons.	0.0271 ***	0.0220 ***	0.0191 ***	0.0450 ***	0.0500 ***	0.0528 ***	952
Post- vs. pre-colocation	0.0047	0.0062 *	0.0062 **	-0.0160 ***	-0.0175 ***	-0.0174 ***	
VLT(-1)	-0.0009	-0.0015	-0.002 **	0.0046 ***	0.0052 ***	0.0056 ***	
Adj.-R2	0.0274	0.0515	0.0622	0.2841	0.2827	0.2636	
% change †	*17%*	*28%* *	*33%* **	*-35%* ***	*-35%* ***	*-33%* ***	
Cons.	0.0097 ***	0.0071 ***	0.0059 ***	0.0467 ***	0.0493 ***	0.0504 ***	1204
Post- vs. pre-ban	0.0034 **	0.0018	0.0009	-0.0093 ***	-0.0076 ***	-0.0068 ***	
VLT(-1)	-0.0014 ***	-0.0016 ***	-0.0014 ***	0.0031 ***	0.0034 ***	0.0032 ***	
Adj.-R2	0.0602	0.0421	0.0249	0.1594	0.1179	0.088	
% change †	*35%* **	*25%*	*15%*	*-20%* ***	*-15%* ***	*-13%* ***	

***, **, * indicates statistically significant at the 1%, 5% and 10% level, respectively.

† Control variable evaluated at the mean