BANCA D'ITALIA
EUROSISTEMA

Mercati, infrastrutture, sistemi di pagamento

(Markets, Infrastructures, Payment Systems)

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March 2022

Number 20

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Approfondimenti
(Research Papers)

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The papers published in the 'Markets, Infrastructures, Payment Systems' series provide information and analysis on aspects regarding the institutional duties of the Bank of Italy in relation to the monitoring of financial markets and payment systems and the development and management of the corresponding infrastructures in order to foster a better understanding of these issues and stimulate discussion among institutions, economic actors and citizens.

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ISSN 2724-6418 (online)
ISSN 2724-640X (print)

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Via Nazionale, 91 - 00184 Rome - Italy
+39 06 47921

Designed and printing by the Printing and Publishing Division of the Bank of Italy

FLASH CRASHES ON SOVEREIGN BOND MARKETS – EU EVIDENCE

by Antoine Bouveret,* Martin Haferkorn,* Gaetano Marseglia** and Onofrio Panzarino**

Abstract

The development of electronic and automated trading in sovereign bond markets has been accompanied by a more frequent occurrence of flash crashes, i.e. episodes of sudden and abrupt price changes that are to a large extent reversed shortly afterwards. We focus our analysis on two flash events in the German and Italian bond markets and show how liquidity vanished ahead of the crashes, resulting in trades having a large price impact on prices. We document that, during the flash event of 29 May 2018, activity on Italian bonds futures and cash markets diverged: trading activity in futures surged, while it plummeted on the cash market. In addition, we show that the effects of flash events on the liquidity in the affected markets can last up to several weeks. Our findings call for increased monitoring of electronic trading markets, taking into account the pace of financial innovation, and for pursuing more integrated approaches in the presence of highly interlinked markets.

JEL Classification: G01, G10, G12, G18.

Keywords: Market liquidity, flash crash, sovereign bonds.

Sintesi

Lo sviluppo del trading elettronico e automatizzato nei mercati dei titoli sovrani si è accompagnato a una maggior frequenza di flash crashes, episodi in cui i prezzi dei titoli si muovono in maniera brusca e ampia, per poi riportarsi, poco dopo, su livelli prossimi a quelli precedenti. L'analisi si concentra su due eventi di questo tipo che si sono osservati sui mercati dei titoli di Stato tedeschi e italiani. Il lavoro mostra come la liquidità del mercato si sia drasticamente ridotta in occasione dei flash crashes, accrescendo l'impatto degli ordini sui prezzi negoziati. Il lavoro documenta una diversa reazione dei mercati cash e futures sui titoli di Stato italiani durante il flash crash del 29 maggio 2018: gli scambi si sono intensificati sul mercato derivato, mentre si sono ridotti sul mercato a pronti. Nel lavoro si mostra inoltre che gli effetti dei flash crashes sulle condizioni di liquidità dei mercati possono prolungarsi anche per diverse settimane. I risultati dell'analisi suggeriscono di rafforzare l'attività di monitoraggio sui mercati elettronici e la cooperazione tra le autorità di supervisione, tenendo conto del rapido progresso delle tecniche di negoziazione e dell'elevato grado di interconnessione tra i mercati.

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1. Introduction[1]

The occurrence of flash events has risen over the last decade, including several events that reached across asset classes. During flash events, asset prices suddenly experience outsized moves in one direction, followed quickly by a sharp reversal, usually in the absence of any significant macroeconomic news. Such events include the flash crash of May 6, 2010 in US equity markets (SEC-CFTC, 2010), the UK Sterling flash crash of October 7, 2016 (BIS, 2017, Noss *et al*., 2017) or the VIX tantrum of February 5, 2018 (Sushko and Turner, 2018).

While flash crashes in equity markets traditionally gain wide attention, flash events have also occurred in sovereign bond markets, which form the bedrock of the financial system. On March 13, 2014, a flash event occurred on Japanese government bond futures (Kurosaki *et al*., 2015). On October 15, 2014, the yield on the 10-year US Treasury bond fell by 37 basis points, then rebounded quickly and closed the day only 6 basis points below the previous closing level (JSR, 2015; Bouveret *et al*., 2015).

Sovereign bond markets form the backbone of the financial system. Sovereign bonds are used as benchmarks for the pricing of other fixed-income securities (such as corporate bonds)[2] and can also serve as high-quality liquid assets by banks to meet liquidity requirements. Sovereign bonds are also widely used for hedging, margining and collateral purposes. Finally, sovereign bonds are the primary sources of funding for most EU governments. A liquid and well-functioning sovereign bond market is therefore key to safeguard financial stability. Volatility in sovereign markets could spread quickly to related financial markets and create turmoil for market participants and sovereign issuers, as funding costs would rise to compensate for additional risk borne by investors.

So far, the impact of flash events has been limited, as the rapid change in prices quickly reversed without visible long-lasting consequences on liquidity or market participants.[3] From that perspective, flash events might not matter for financial stability, as they look like short-time technical anomalies, and might be the price to pay to be able to execute trades in milliseconds on otherwise orderly electronic markets. But flash events do raise questions about how developed markets react under stressed circumstances, especially if prolonged in time. Even though flash episodes are generally short-lived and followed by rapid price reversals, some longer-term impact could materialize and persist in financial asset prices. Market makers might reduce their participation, resulting in lower market liquidity, and investors might require an additional risk premium, particularly if the occurrence of flash events is believed as more likely than in the past. In addition, if flash events were to occur in a context of fragile market conditions, flash crashes could amplify the initial shock, and lead some investors to believe that the new low price reflects a fundamental shift in market sentiment, rather than a decline related to flash events (Himmelberg and Weldon, 2018). In such a context, flash crashes could have long-lasting consequences.

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[1] The views expressed are those of the authors and do not necessarily reflect the views of the European Securities and Markets Authority or the Bank of Italy. Any error or omissions are the responsibility of the authors. The authors would like to thank Lorenzo Braccini, Alain Chaboud, Kim Christensen, Giuseppe Grande, Cyrille Guillaumie, Claudio Impenna, Roberto Renò, Steffen Kern, Clara Vega, Christian Winkler, the ESMA Committee of Economic and Market Analysis and the ESMA Group of Economic Advisors for useful discussions and comments.

[2] For example, the performance of corporate bonds is often examined relative to that of sovereign securities issued in the same country, as the comparison allows to isolate yield changes due to variations in the credit risk of the private issuers.

[3] One exception is the episode of August 1, 2012 when Knight Capital, a leading market maker, lost $440 million in 45 minutes, leading to a 75% decline in its stock price and its sale to a competitor a few months later. The losses were caused by an algorithm used for testing which inadvertently went live, resulting in the trade of 397 million shares (Kapadia and Lin, 2019).

This article focuses on two sovereign bond market flash events in the German (May 7, 2015) and Italian sovereign bond markets (May 29, 2018). In both cases, sovereign bonds experienced one of their largest intraday changes in yields.

On May 7, 2015, volatility spiked in the German bund markets, as yields on long-term bonds surged by 20 basis points before coming back to their opening price of the day (BIS, 2016a). The rapid rise in yields occurred amid a severe deterioration of liquidity, as evidenced by the sharp decline in market depth on cash and futures markets. After the event, liquidity remained very low on long-term bonds in the next few months (Riordan and Schrimpf, 2015).

On May 29, 2018, the Italian sovereign bond market, one of the most liquid in the world, experienced an episode of extreme volatility, against the backdrop of political tensions. On that day, the yields on the 2-year bonds moved more than 180 bps within the day, while the 10-year yields increased by more than 40 basis points. Following the event, yields on Italian bonds partially reversed afterwards but remained high, amid low liquidity on both cash and futures markets.

This article provides an analysis of these two flash events. We document how liquidity evaporated during the flash events, using a range of high-frequency indicators related to trading and quoting activity. While most of our analysis focuses on the events of May 29, 2018 — and to a lesser extent of May 7, 2015 — we take this episode as an illustration of how risks related to market fragility can crystallise.

In this paper, we provide a series of findings. First, we detail the events of May 29, 2018: several flash crashes occurred on the Italian BTP futures while trading all but stopped on cash markets. Market liquidity provision significantly deteriorated on both markets, bid-ask spreads increased and market depth plummeted; however, trading volumes surged on futures, with small trade sizes, possibly reflecting heightened high-frequency trading activity. Second, we assess the impact of the flash event on liquidity in futures markets in the following days and find that liquidity remained low more than a week after the event. Third, we assess the impact of the event several weeks after and find a significant negative effect on market liquidity on the cash market, although declining over time.

Overall, we provide new evidence on the ongoing discussion about how changes in market structure might have made markets more exposed to flash-like events. The paper is organized as follows: Section 2 reviews recent developments in automated trading, their impact on liquidity and describes the structure of European sovereign bond markets; Section 3 takes a closer look at the two flash events in the BTP and Bund markets; Section 4 provides empirical results on the more prolonged implications for market liquidity after the materialization of flash crashes and Section 5 concludes.

2. Automated trading and structure of European sovereign bond markets

2.1 Automated trading in financial markets

Over the last two decades, electronic and automated trading has become widespread over a range of asset classes such as equities, futures, FX, and sovereign bonds.

Technological advances have enabled a greater use of rules-based automated trading – so called algorithmic trading (AT) – and promoted the diffusion of new trading strategies and market players, e.g. Principal Trading Firms (PTF).[4] These developments dramatically increased the operational flexibility given to market participants in the past years and gave rise to High-Frequency Trading[5] (HFT), which mostly relies on speed by minimizing the latency between orders submission and execution. Apart from execution, submitted orders also include modification or cancellation of previous orders sent to the platform, and affect both quoting and trading activity.

A full assessment of the positive and negative impacts of ATs and HFTs strategies on market quality is still under debate.[6] Available empirical evidence seems to support that in normal times AT and HFT strategies may provide benefits, as they offer efficiency gains to market participants by lowering transaction costs, improving market liquidity, and ultimately facilitating faster and more effective price discovery processes (Hendershott et al., 2011; Boehmer et al., 2012). However, automated trading has also given rise to concerns related to the illusion of liquidity and to the resilience of liquidity during stress periods (Bouveret *et al*., 2015; ECB, 2016, Kirilenko *et al*., 2017).[7]

During stressed market conditions, trading algorithms used by market participants may interact in intricate ways that may accentuate price dynamics, resulting in a sudden evaporation of liquidity and nearly instantaneous spill-over of stress and volatility to other markets. Analysing more than 100 flash crashes on equities, Belia *et al*. (2020) show that HFT market making strategies implemented by investment banks and by proprietary trading firms can amplify price movements. The high quote revision speed may adversely interact with investor risk aversion, as it increases execution risks given the major uncertainty regarding the price at which an order with unpredictable delay is sent to the platform and executed. The rapid decline in available liquidity might also be amplified by the liquidity illusion, as the level of market depth may fail to capture available market liquidity, as liquidity providers might duplicate orders across trading venues or cancel their limit orders before they can be matched by a market order.

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[4] Principal trading firms (PTFs) are smaller, non-bank firms that trade on electronic platforms using automated trading strategies (Bank of England, 2019). Typically, they trade on their own account and deploy proprietary trading strategies implemented at low latencies. PTFs are substantial short-term liquidity providers and relevant market participants in fast markets; they are active on a wide range of financial instruments, including shares, options, futures, bonds and ETFs. PTFs are privately held and generally face lighter regulation with respect to other financial entites (e.g., broker-dealers); limited financial information is usually available about many of them (Joint Staff Report, 2015). Those new market markers account for a large share of exchange trading activity (more than 50% for US Treasury cash and futures market; JSR, 2015).

[5] Automated trading (AT) is a technology in which order and trade decisions are made electronically and autonomously. High-frequency trading (HFT) is a subset of AT in which orders are submitted and trades executed at high speed, usually measured in microseconds, and a very tight intraday inventory position is maintained. HFT strategies seek to gain advantage from the ability to process information on market conditions quickly and react instantaneously. The strategies tend to result in a large number of small trades that are held for short periods and also tend to generate a high message traffic flow between the platform and high-frequency traders. To gain an edge in terms of computing speed, principal trading firms locate their servers physically close to an electronic platform’s matching engine (co-location services) and hence minimize latency.

[6] For example, in the FX market, Chaboud *et al.* (2014) find that algorithmic trading improves price efficiency, and Schlepper (2016) finds similar results for HFT activity on Bund futures (see ESMA (2016) for a review of the literature).

[7] Regarding liquidity illusion, as quotes are rapidly updated or cancelled, the liquidity displayed on the order book might overestimate the actual liquidity that can be tapped by market participants, as HFT can duplicate their quotes across venues and can cancel their offers before they are executed against. For European equities, ESMA (2016) reports that around 20% of HFT orders are duplicated and in around 25% of the trades, the trader cancels her duplicated quotes across venues, resulting in a large decline in offered quantities. For equities, such duplication of orders is related to the fragmentation of trading activity across venues.

Moreover, over the last decade, bank-based broker-dealers — the traditional market makers in sovereign markets — have significantly changed their liquidity provision by shifting from risk warehousing to risk distribution. Such changes reflect balance sheet optimization by banks, as risk warehousing is a balance sheet intensive activity. Under the risk-warehousing model, dealers would use their inventories to match their client orders, while under the risk-distribution model (or agency model), banks would act as brokers, by matching buyers and sellers without using their balance sheet. The shift to a risk-distribution approach is related to a combination of factors, including the changes in business models following the global financial crisis, technological advances, lower risk appetite and regulatory changes (Bouveret *et al*., 2015; BIS, 2014; 2016a-b). Post-crisis financial regulatory reforms addressed to the banking system are also questioned as relevant drivers in affecting dealers' capacity to provide market-making services.[8]

Market design also plays an important role in attracting HFTs strategies. Proximity services such as colocation, and other market features such as maker-taker fees or tick size can incentivize HFT firms to participate actively in some markets. HFT strategies can be more effectively deployed in markets based on a central limit order book (CLOB) system, where all market members can post limit and market orders. Such markets include venues where highly liquid instruments are negotiated, such as equities, exchange-traded derivatives – like futures – and sovereign debt in some countries. The BIS (2016) estimates that more than 50% of trading volume in benchmark US Treasury bonds (based on CLOB) can be associated with HFT strategies, while the European bond markets are believed to be less exposed to HFTs as the predominant quote-driven and request-for-quote protocols[9] are less attractive for HFTs compared with CLOB trading venues.

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[8] Assessing the impact of regulatory reforms on market liquidity is challenging, considering the multiple drivers at play. Some works examined the extent to which post-crisis reforms may have directly affected market-making capacity, but results are mutifaceted and still under debate. Some studies do not reveal particular deteriorations in the periods characterized by regulatory interventions, but even some improvements (Trebbi and Xiao, 2016, Adrian *et al*., 2015, Bessembinder *et al.*, 2016); in contrast, Dick-Nielsen and Rossi (2016) point that the reduction in the level of market-making inventories and the consequent higher transaction costs are undesirable effect of the new regulatory interventions.

[9] The Request-for-Quote protocol queries for executable prices quoted to multiple counterparties simultaneously.

2.2 The structure of European sovereign bond markets

The structure of the European sovereign bond market is different for each country, with different roles played by cash and future markets and different rules around primary dealers (AFME, 2020). For euro area countries with large sovereign bond markets such as France, Germany, Italy or Spain, market participants can trade sovereign bonds in the cash and futures markets.

For the cash market, sovereign bonds are traded on a number of trading venues and over-the counter. MTS market is the largest interdealer trading system for euro area government bonds (Pellizzon et al., 2014), where primary dealers and other large financial institutions can trade sovereign bonds. MTS is a wholesale, regulated, interdealer market, where Primary Dealers concentrate most of their trading activity. It is an electronic trading platform based on a quote-driven protocol, characterized by the presence of market-makers quoting on a continuous basis on both sides of the market.

On MTS Italy, orders and quotes on Italian government securities may be sent and modified at any time during the trading session, which takes place between 8:15 and 17:30.[10] Large orders are negotiated on the market with an average trade size (in nominal terms) of about €10 million; the minimum quoting and trading size is €2 million. Trades generally occur at the very first levels of the order book, as market participants seek to minimize transaction costs.[11] Typically, less than 2 minutes elapse from one trade to another, while quoting activity is significantly faster. Changes in the order book for the most liquid bonds occur at the millisecond level: on average, every 100 milliseconds a new quote (which is comparable to limit order on order-driven markets) is sent the platform and generally remains active for 2-5 seconds before being modified, cancelled or hit by an order. When market makers revise their quote proposals, they more often update the prices offered rather than the quantities.

Besides the cash market, investors can take positions on sovereign bonds by using derivatives and futures contracts in particular. Eurex, one of the largest derivatives exchanges in the EU, provides futures contracts on German, Spanish, French and Italian sovereign bonds at different maturities. Ejsing and Sihvonen (2009) show that volumes on Bund futures are close to 10 times larger than turnover on the underlying bund market, pointing to the role of futures markets for price discovery.[12] Similarly, trading volumes on BTP futures have also been increasing over time, with an average daily number of contracts of around 40,000 for 2Y futures and 120,000 for 10Y futures.

Eurex is an electronic order-driven platform based on a CLOB system, where participants provide liquidity by inserting limit orders and consuming liquidity by executing market orders. The regular trading session takes place between 8:00 and 19:00, with an opening auction at 8:00, and a closing auction at 19:00 (Eurex, 2019).

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[10] A Pre-Market phase takes place before (from 7:30) during which only market makers may operate and can post or revise their quotes; market makers may only view their own quotes and the automatic matching engine is not operational, i.e. no trades occur on the platform (see MTS (2019; 2020) for details).

[11] During the entire year 2018, around 90% (80%) of the BTP (BOT) trades occurred at the first price level, i.e. at the best prices; and the remaining trades were by large limited to the second level of the order book.

[12] According to the German Debt Management Office, in 2019 trading volumes on Bund futures were 8 times the volumes on the cash market, at €31 trillion and €4 trillion respectively (Deutsche Finanzagentur, 2019).

As with most electronic limit order book markets, HFT firms account for a large share of trading on futures. Hausch et al. (2017) report that HFT firms accounts for around 60% of the trades and 70% of the orders for Bund futures, yet around 40% of the volumes as HFT tend to execute smaller trades. Schlepper (2016) analyses HFT activity on the Bund Futures market and concludes that, during normal times, HFT activity improves the price discovery process. However, in times of high market stress HFTs behavior may exacerbate intraday price volatility and amplify the risk of market disruptions, as some HFTs reduce their provision of liquidity while other trade aggressively by consuming liquidity. Such negative externalities could spill over to the underlying cash markets, due to the arbitrage activities performed by market participants.

While market participants on cash and futures markets might differ, with higher HFT activity on futures, the two markets are highly interconnected through arbitrage mechanisms. Dealers and investors can hedge their positions on the cash market by using futures. Therefore, price dynamics between the two markets tend to evolve closely. As market liquidity improved, BTP futures contracts became increasingly supportive for market making activity, significantly strengthening interconnections between futures and cash markets (Bank of Italy, 2015). Nowadays, the two markets are strongly intertwined; their relationship appears as complex as fast and requires high-frequency data to be properly analysed along the dimension of price discovery, liquidity and volatility. Pellizzon et al. (2014) find that the futures market leads the cash market in terms of prices discovery; while the cash market leads the futures market in the liquidity discovery process. Both mechanisms are fast and normally occur in a matter of minutes, if not seconds. Nevertheless, at higher frequencies, a unidirectional propagation of volatility shocks from the futures to the cash market emerges (Panzarino *et al.*, 2016). This volatility transmission mechanism, which increases at higher frequencies, affects the liquidity conditions of the secondary (cash) market. Panzarino *et al.* (2016) show that when volatility shocks spillover from futures to the cash market, liquidity is reduced on MTS (Bank of Italy, 2015).

Against that background, some of the most liquid sovereign markets in the world have recently experienced short-term periods of extreme volatility, characteristic of ‘flash events’.

3. The events of May 29, 2018 in the Italian sovereign bond market

At the end of May 2018, the yields on Italian government securities recorded a marked rise across all maturities. The increase reflected a sharp rise in risk premia, stemming from uncertainty about economic policies and, especially, the stance of fiscal policy (Bank of Italy, 2018a).[13] In this context, the Italian Treasury held auctions on May 28 (CTZ and BTPi), 29 (BOT) and 30 (BTPs and CCTs). We analyse the flash event that occurred on May 29, by looking at a wide range of indicators across cash and futures markets, such as prices, volatility and other measures of market liquidity (e.g. bid-ask spread, market depth).

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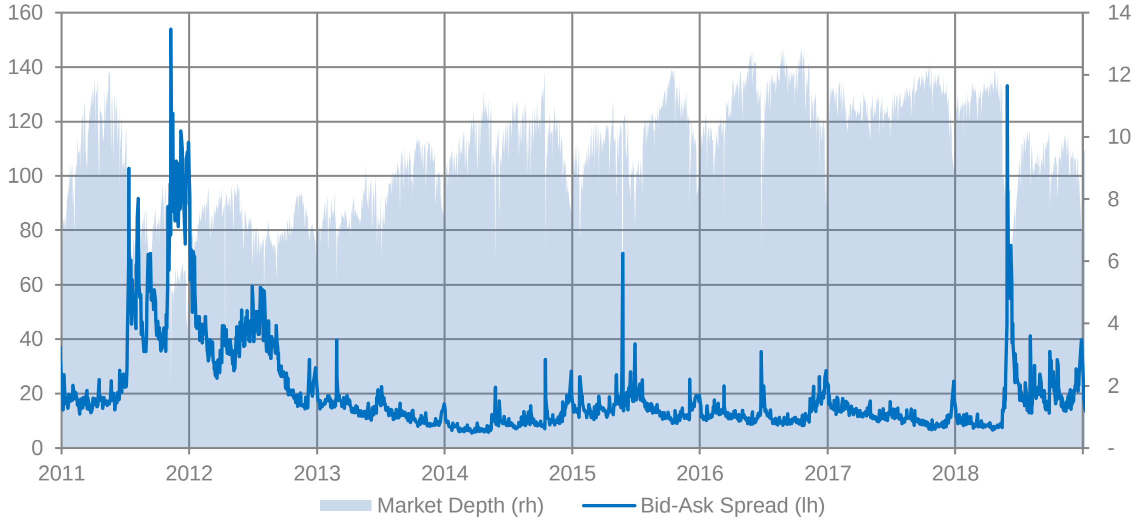
[13] On May 28, 2018, the President of the Italian Republic mandated Carlo Cottarelli to form a new government. Soon afterwards, two of the three political parties that had received the highest shares of votes in the March 2018 General Election announced that they would not support such government. This resulted in a steep increase in the risk of new and highly uncertain elections. On May 31, the deadlock was overcome and a new cabinet led by prime minister Giuseppe Conte was sworn in on June 1, 2018.

3.1 *The Italian sovereign bond market on May 29, 2018*

On May 29, 2018, yields on Italian 2Y sovereign bonds jumped more than 180 basis points from 0.77% to 2.61%, and 10Y yields increased by more than 40 basis points to 3.3%. The sharp intraday volatility was also visible in the futures market, with the price of the 10Y BTP futures witnessing an intraday variation of more than 7%. The intraday changes in the futures market were the highest on record, above levels reached during the European sovereign crisis.

Cera *et al.* (2018) and Bank of Italy (2018b) show that on that day, liquidity conditions deteriorated sharply on both the cash and futures markets. The bid-ask spread quoted on MTS was more than ten times larger than usual levels (Chart 1). Market depth was very thin and fell below €2 billion against an average of almost €11 billion since the beginning of the same year. As a consequence, it was largely not possible to execute large-size orders for the entire day (above €50 million). The deterioration in liquidity on MTS Cash was comparable in size, but more sudden and much more short-lived than that recorded during the 2011-12 sovereign debt crisis (Chart 1).

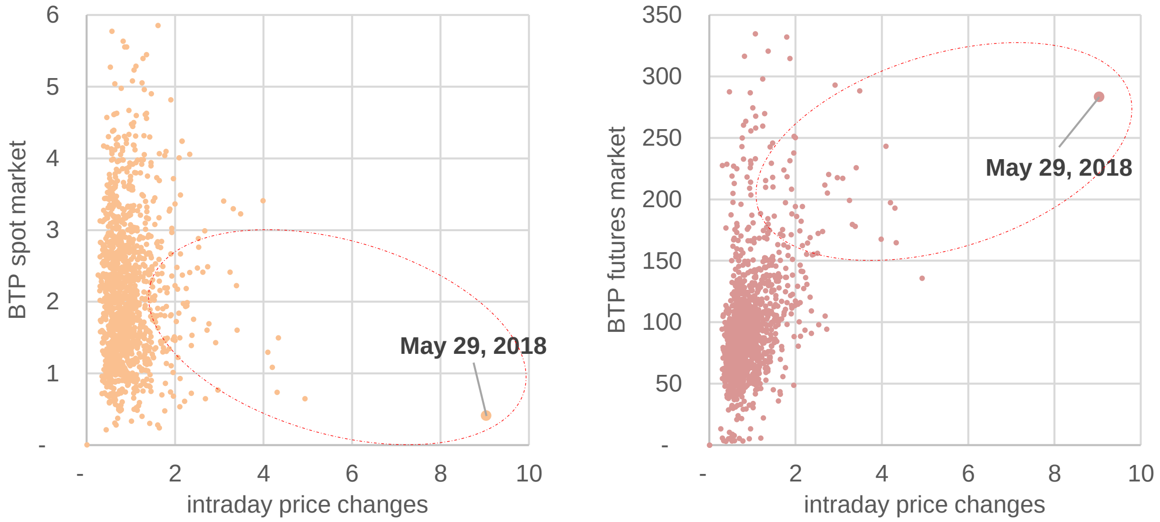
Chart 1: Bid-ask spread and market depth on MTS Cash.



Note: Daily averages of intraday data recorded at every 5-minute intervals for all bonds listed on the MTS order book. Averaged bid-ask spread expressed in price cents; market depth in billions of euro. Market depth is the average of offer-side and bid-side market depth at top 5 bid prices.
Source: Bank of Italy on MTS data.

The reaction across cash and futures markets differed significantly. The high intraday volatility on May 29 was associated with a very high turnover on the futures market and a remarkably low turnover on the underlying cash market (Chart 2). Traded volumes on MTS plummeted to around €2 billion (less than half than usual), while on the Eurex futures market the activity on both the short- and long-term contracts increased significantly. The two scatter plots in Chart 2 report the daily turnover observed on MTS Cash (left; y-axis) and Eurex (right; y-axis) market with respect to intraday price changes (max-min; x-axis) as recorded on the BTP long-futures contract the same day. On May 29, the intraday price change reached its maximum since the launch of the BTP futures market in 2009, with intraday moves greater than 9 hundred price ticks. At the same time, market activity on the Italian government bond markets bifurcated across the spot and the futures segment, in contrast with what happened for example in the 'flash rally' episode on the U.S. Treasury market (Bouveret *et al.*, 2015).

Chart 2: Scatter Plot: Market turnover and intraday price changes.



Note: Market turnover (y-axis) on the BTP spot (MTS Italy, billions of euro) and futures market (Eurex, thousands of contracts) and intraday price changes (max-min) on the BTP long-futures contract (x-axis, price units). Each dot corresponds to one trading day over the 2015-2019 sample period.

Moreover, as shown in Chart 2, such a 'bifurcation' observed in the trading activity across the two markets points to potential structural factors across markets. When intraday price changes are high (namely, in the tail of the distribution), trading activity on the futures market is more likely to surge; while trades on the cash market decrease. The bifurcation can be explained by different types of market participants. On MTS, only primary dealers trade BTP, and when uncertainty increases, dealers are likely to refrain from trading, resulting in a drop in trading activity. On Eurex, HFT firms account for a large share of trading, and usually HFT firms manage their inventory over very short time periods. When faced with volatility, HFT firms might step back, but firms with directional positions on futures, will need to reduce their positions, which will result in higher trading activity, as part of the 'hot potato' effect discussed in Kirilenko *et al.* (2017). Indeed, in several cases, flash events were associated with a surge in trading activity (Bouveret *et al.*, 2015).

3.2 *Intraday analysis: Price dynamics*

We use intraday data to analyse the price movements that took place on that day. For the cash market, we use second-by second intraday prices, quoted on MTS Cash from 9:00 to 17:00[14] for the two cheapest-to-deliver (CTD) bonds associated to the 2Y and 10Y BTP futures contracts.[15] Quote proposals — as sent by market makers to the trading venue — are employed to reconstruct the entire order book at the second precision.

For futures, we use data on 2Y and 10Y Italian futures traded on Eurex and provided by Morningstar. The dataset covers all the transactions, as well as the top 10 best bid and offers and is millisecond timestamped. Therefore, any update of the orderbook within the 10 best limits is reflected in our dataset.

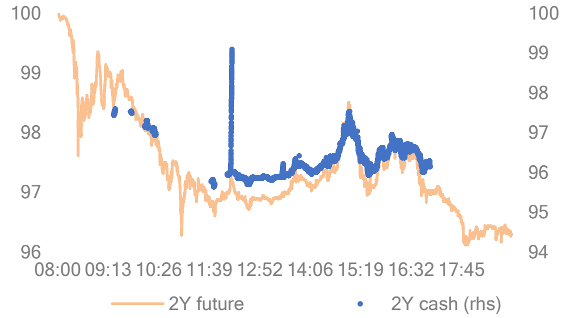


Chart 3: 2Y market

Note: Mid price on 2Y futures, second by second, rebased at 100=08:01 and mid price of 2Y CTD bond.
Sources: Morningstar, MTS, Bank of Italy, ESMA.

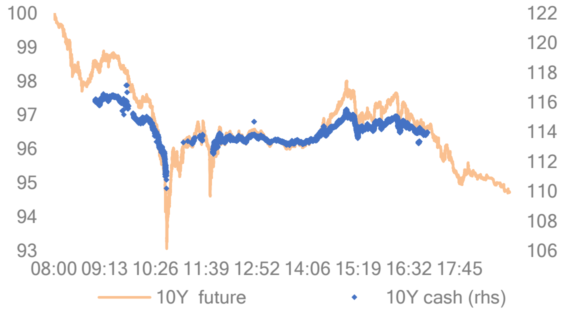


Chart 4: 10Y market

Note: Mid price on 10Y BTP futures, second by second, rebased at 100=08:01 and mid price on 10Y CTD bond.
Sources: Morningstar, MTS, Bank of Italy ESMA.

Charts 3 and 4 show the evolution of the mid-price of the 2Y and 10Y BTP futures as well as the related CTD bonds on May 29, 2018. While the price was highly volatile throughout the trading session, most of the turbulence took place during the morning trading session (08:00-12:00).

In the 2Y cash market, there was almost[16] no quotes between 08:00 and around 12:00, while in the future markets, quotes were continuously provided but there were at least two flash crashes: one around 08:23, when price dropped abruptly by 2% and another one around 11:00 (Chart 3), with the price decreasing by 1% in one minute.

In the 10Y cash market, quoting activity was also discontinued (yet to a lesser extent than on the 2Y) and erratic; around 10:40 the 10Y future contract experienced a flash crash, with the price dropping by 2.3% in one minute and market makers stopping to provide quotes on the cash market (Chart 4). A second flash crash occurred in the 10Y future contract around 11:45, with a price decline of 1.3% in one minute, and when trading resumed in the future market, market makers re-offered their quotes on the cash market.

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[14] As quoted prices may not result in actual transactions, we report data for the most liquid hours of the trading session. Activity is usually low just after market openings. Recalling that the MTS market opens at 8:15 (following a Preliminary market phase and a Pre-Market phase when no trades could take place; MTS, 2019;2020), trading activity typically start after 8:30. Although market makers may thus start to submit their quotes earlier in the morning and the order book begins to fill up, generally trades are quite scarce before 9:00, as quoted prices still incorporate wider bid-ask spread and market depth is still replenishing.

[15] In a physically-settled future contract, the seller of the future commits to delivering a bond to the buyer of the future at the expiry date. For futures on government bonds, a range of instruments can be delivered provided they meet the requirements, defined usually in terms of coupon or maturity. In that context, the cheapest-to-deliver bond is the cheapest government bond that fulfils all those criteria.

[16] On May 29, some prices were quoted just after 8:10, before they start diverging around 8:17 when the bid-ask spread became remarkably larger; no trades occurred and market makers interrupted their quoting activity until around 12:00.

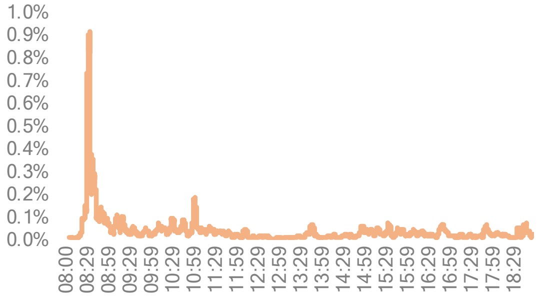
3.3 The morning session

Looking more closely at the morning session, on the 2Y future market, price dropped suddenly around 8:24, triggering a circuit breaker[17]. After a two-minute pause, trading resumed until 8:30, when a circuit breaker was triggered again. Following the second pause, trading resumed around 8:31 for a few seconds, before a circuit breaker was triggered for the third time. Then, around 8:33 trading resumed. Finally, around 11:00 another flash crash occurred with the price dropping suddenly followed by a rebound.

On the 10Y cash market, there were very few quotes before 8:35; afterwards the mid-price of the bond was stable until 09:15, when prices became very volatile. Around 10:40, as the price of the bond was dropping quickly, market makers stopped providing quotes until around 12:00.

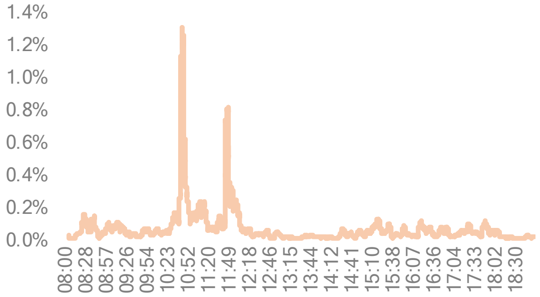
On the 10Y future market, prices started to drop around 10:40, as a flash crash occurred. Finally, the price of the 10Y contracts dropped again around 11:45, triggering a circuit breaker, and the price bounced back afterwards.

Chart 5: 2Y BTP futures



Note: 5 minute realized volatility on 2Y BTP futures.
Sources: Morningstar, ESMA.

Chart 6: 10Y BTP futures



Note: 5-minute realized volatility on 10Y BTP futures, second by second.
Sources: Morningstar, ESMA.

Charts 5 and 6 show the intraday realized volatility on futures contracts, using quoted price data at one-second intervals computed as the sum of squared returns over 5-minute intervals (see Andersen *et al.* (2003) for a discussion of measurement of intraday volatility).[18] One can clearly see that three episodes lead to a sudden sharp increase in volatility: the first episode in the 2Y contract around 08:30, the second on the 10Y contract at 10:40 and the third one at 11:45 on the 10Y contract.

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[17] Circuit breakers are mechanisms used by trading venues to monitor the market continuously and trigger a trading halt as soon as the price (or its variation) of an individual security or an index falls below or rises above a predetermined level (Guillaumie *et al*., 2020).

[18] Given our desire to examine intraday volatility patterns, we were required to estimate realized variances at relatively short time intervals, i.e. every 5 minutes, at the one-second sampling frequency. Unfortunately, as the sampling frequency increases, the realized variance measure suffers a well-known bias problem due to the presence of market microstructure noise in high-frequency data (see, e.g., Fang, 1996; Andreou and Ghysels, 2002; Hansen and Lunde, 2006; Liu *et al*., 2015). However, recent research shows that the optimal choice of sampling frequency hinges on the liquidity features of the asset and that more liquid stocks can be sampled at higher frequencies with no particular drawback. For example, Bandi and Russell (2008) show that optimal sampling intervals to compute realized variance are shorter than the intervals typically implemented and/or conjectured in the literature and resulted

In summary, while liquidity dried up in the cash market — with the trading activity becoming scarce and quotes diminishing until they fully disappeared — transactions were executed on futures, although amid limited market depth. BTP futures experienced sudden drops in at least four instances during the trading session: the first on the short-term contracts around 8:30 (with a series of trading halts); another one around 10:40 on long-term futures and slightly later on the short-term futures (around 11:00); a fourth one occurred around 11:45 on the long-term contract. Liquidity evaporated during market opening on the 2Y cash market, while the 10Y cash market was initially more resilient, despite episodes of highly volatile quotes.

Overall, price dynamics in the cash market erratically retraced futures trades, with long lasting episodes during which market makers stopped providing quotes.

3.4 *Identification of the flash events*

To assess more rigorously whether those episodes of volatility can be considered flash crashes, we follow Flora and Renò (2021) to identify flash events using the so-called 'V-shaped' statistic. The authors propose a method to identify flash events by allowing the drift of the asset price to explode at a faster rate than volatility. The intuition is that during flash events, the drift in asset price returns will increase (in absolute value) at a faster rate than the volatility of the asset price (computed over a slightly longer time horizon).

The authors start with the traditional semi-martingale model for asset prices, where the log-price of an asset X_t evolves according to a drift μ_t, a volatility component σ_t, and a jump component J_t :

$$dX_t = \mu_t dt + \sigma_t dW_t + dJ_t$$

with W_t a standard Brownian motion. The model is then broadened to allow for the drift and the volatility to explode:

$$dX_t = \mu_t dt + \sigma_t dW_t + dJ_t + \underbrace{\frac{c_{1,t}^-}{(\tau_v - t)^\alpha}\mathbb{1}_{\{t<\tau_v\}}dt + \frac{c_{1,t}^+}{(t-\tau_v)^\alpha}\mathbb{1}_{\{t>\tau_v\}}dt}_{\text{drift burst}} + \underbrace{\frac{c_{2,t}}{|\tau_v - t|^\beta}dW_t}_{\text{volatility burst}}$$

where $\tau_v \in \,]0,1[$ is the explosion point, $c_{1,t}^-$ and $c_{1,t}^+$ are the drift explosion coefficient before and after the explosion point, α is rate of explosion of the drift ($\alpha \in \,]0,1[$) and β is the rate of explosion for the volatility ($\beta \in [0,1/2[$). The authors show that a nonparametric test can be estimated based on the following V-statistic:

$$V_{\tau,n} = \sqrt{h_n} \cdot T_{\tau,n}^+ \cdot T_{\tau,n}^-$$

---

below the 5-minute interval for their sample of IBM quote data. In addition, we use quote data with calendar time sampling to compute realized variance that, as shown in Liu *et al.* (2015), generally leads to better realized measures for high frequencies (e.g. 1-second and 5-second), with respect to tick-time sampling.

where

$$T_{\tau,n}^{-} = \sqrt{\frac{h_n}{K_2^{-}}}\frac{\hat{\mu}_{\tau,n}^{-}}{\hat{\sigma}_{\tau,n}^{-}} \text{ and } T_{\tau,n}^{+} = \sqrt{\frac{h_n}{K_2^{+}}}\frac{\hat{\mu}_{\tau,n}^{+}}{\hat{\sigma}_{\tau,n}^{+}}$$

where the localized estimator of the drift (on the left side of the explosion point) is given by:

$$\hat{\mu}_{\tau,n}^{-} = \frac{1}{h_n}\sum_{i=1}^{N} K^{-}\left(\frac{t_{i-1}-\tau}{h_n}\right)(X_i - X_{i-1})$$

$$T_t^n = \sqrt{\frac{h_n}{K_2}}\frac{\hat{\mu}_t^n}{\sigma_t}$$

And the localized estimator of the volatility (on the left side of the explosion point) is given by:

$$\hat{\sigma}_{\tau,n}^{-} = \left(\frac{1}{h_n}\sum_{i=1}^{N} K^{-}\left(\frac{t_{i-1}-\tau}{h_n}\right)(X_i - X_{i-1})^2\right)^{\frac{1}{2}}$$

where h_n is a bandwidth parameter used to estimate log-returns and K_2 is a kernel function. This statistic compares the relative strength of drift and volatility around time t.

This statistic is an extension of the drift burst statistic of Christensen *et al.* (2020). Typically, during a flash event, the drift component of the return explodes at a faster rate than the volatility component. Therefore, high absolute values of the statistic indicate the presence of a sudden change in prices. However, the drift burst statistic is not always compatible with flash events, unlike the V-statistic, which allows to disentangle the case of a rapid change to a new price level ("gradual jump", in the terminology of Barndorff-Nielsen *et al*., 2008) with that of a 'V-shaped' price pattern. When (significantly) positive, the V-statistic captures trends, as the drift burst statistic; when (significantly) negative, it captures 'V-shapes' (for transient crashes) or 'Λ-shapes' (for transient surges).[19] We apply the V-statistic to BTP futures prices recorded on May 29, 2018 (Chart 7-8). We follow Flora and Renò (2021) and estimate the V-statistic across several testing times along the entire trading day (i.e. every 5 minutes), using 30-minutes intervals for computing the drift (i.e. the bandwidth), and 2-hours intervals for the volatility.[20]

Chart 7 shows that on 2Y futures the test statistic was strongly significant (when compared to its displayed confidence bands) early in the morning, around 8:24, when the first circuit breaker was triggered. In Chart 8, the V-statistic rather identifies the flash crash that occurred on the 10Y future around 10:40. Low values of the test statistic can also be observed around 11:00, on the 2Y future, and 40 minutes later on both contracts, when the circuit breaker was triggered on the 10Y contract. However, the V-statistic is not significant at the 1% level for those events. Using the same approach, we also identify two other flash events during the afternoon trading session, around 15:00 and 16:00 on both the 2Y and the 10Y future contracts; in both cases they were associated to transient surge in the trading prices (i.e. 'Λ-shape').

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[19] During a flash event, the V-statistic is negative because the drift changes sign and the statistic is the product of the drift burst statistic before and after the event.

[20] According to Flora and Renò (2021), the bandwidth should be proportional to the duration of the V-shape, that is the state of potential market inefficiency. Results are robust to the choice of different bandwidths (e.g., ranging from 15 minutes to 1 hour).

Chart 7: Flash crashes on short-term BTP future

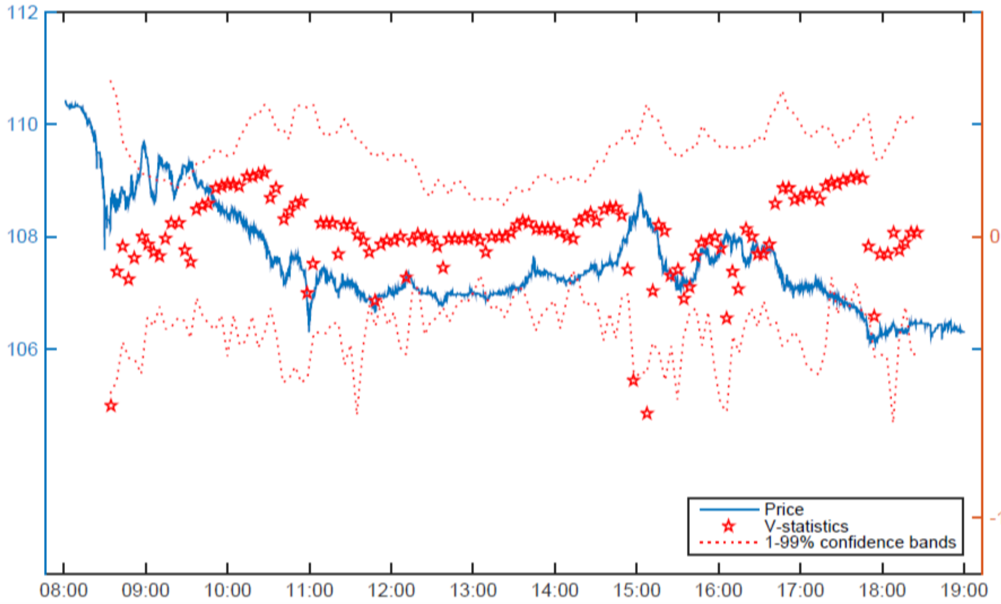
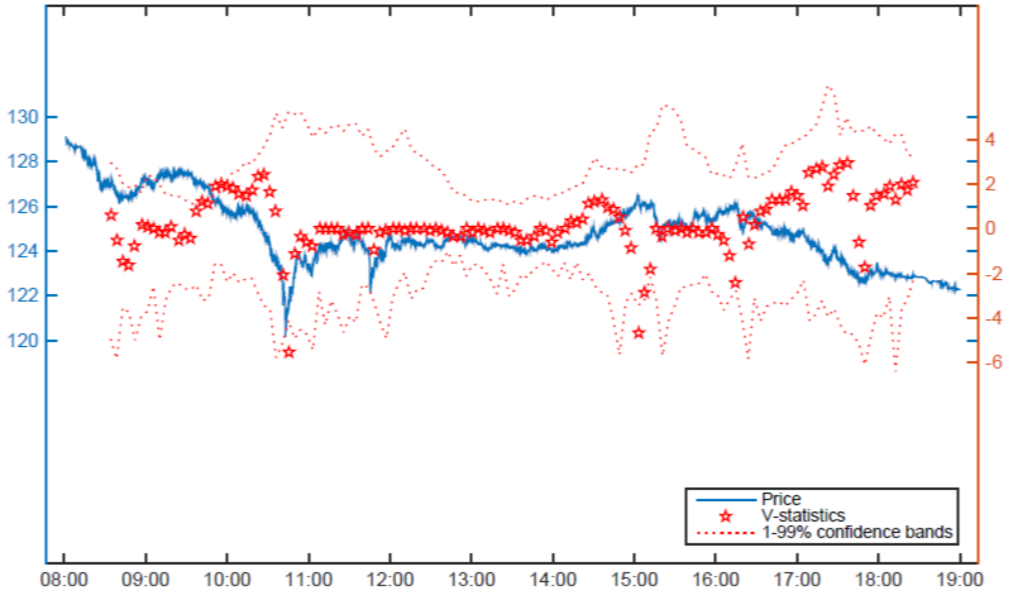


Chart 8: Flash crashes on long-term BTP future



Note: Blue lines are transaction prices for short-term (Chart 7) and long-term (Chart 8) future contracts on May 29, 2018, while red pentagrams are V-statistics computed following Flora and Renò (2021). Confidence bands for the individual tests are reported at 1% and 99% level, and computed using bootstrapping. Low values of the V-statistics (when compared to the displayed confidence bands) signal a strong 'V/Λ-shape'.

Overall, the analysis points to several flash events occurring at different times on May 29, 2018 in the futures market, and in some cases those flash events triggered circuit breakers. The same analysis was also conducted on the cash market, but the lack of quotes during most of the trading session forced us to focus only on some narrow intervals characterized by continuously quoting prices; in any case we obtained comparable results, as cash and futures prices are highly correlated.

3.5 *Intraday analysis: A closer look at market liquidity*

The magnitude of the price movements that took place on cash and futures markets on May 29, 2018 was exceptional. While large price variations can occur when fundamental news are released to the market, the fact that several flash crashes took place at different point in time indicates that other factors were at stake. In particular, flash crashes are associated with a sudden drop in liquidity, resulting in trades having a larger price impact than during normal times. We therefore look at market liquidity in the Italian sovereign bond market using a set of metrics such as quoted bid-ask spread, market depth and trade size.

On May 29, market depth on MTS order book for the two CTD bonds, measured by the average quantity offered at the bid and ask quotes, fell significantly compared to a week earlier: market depth was only 9% and 18% of levels as measured on May 22 (taken as an average trading day) on the 2Y and 10Y bonds respectively.

Chart 9: Short-term BTP futures, quoted prices and quantities on the CTD bond

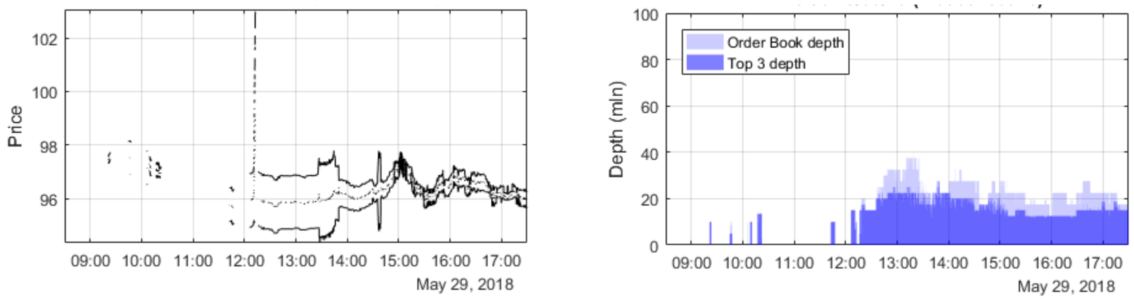
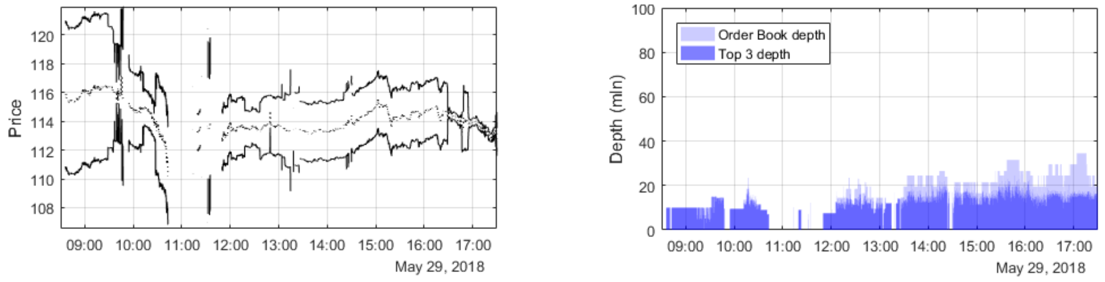


Chart 10: Long-term BTP futures, quoted prices and quantities on the CTD bond

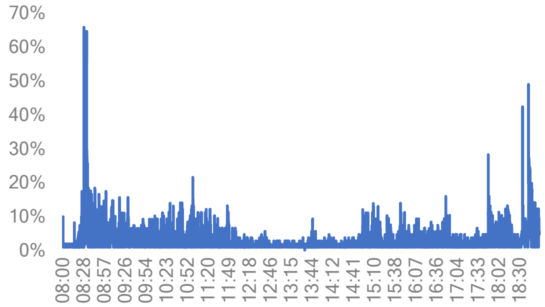


Note: Data for the CTD bond of the short-term (Chart 9) and long-term (Chart 10) BTP futures contracts. Quoted (ask, bid, mid) prices and quantities (all book, top 3 levels of the order-book) as detected on the MTS market, every second, from 8:30 to 17:30. Quoted quantities are the average between ask and bid quotes and are expressed in millions of euro.

In addition, during the stress event, quoting activity on the MTS market was repeatedly interrupted for several minutes for both CTD bonds (Charts 9 and 10). The lack of quotes was larger on the short-term CTD, where from market opening to around 12:00 barely no trading proposals were available in the MTS order book. Subsequently market depth recovered slightly but remained persistently below average though the rest of the trading day. Typically, roughly €150 million are present on both bid and ask side of the limit order book on the short-term CTD bond during the trading day (€80 million on the long-term CTD), while quoted quantities never exceeded €40 million on both CTDs on May 29.

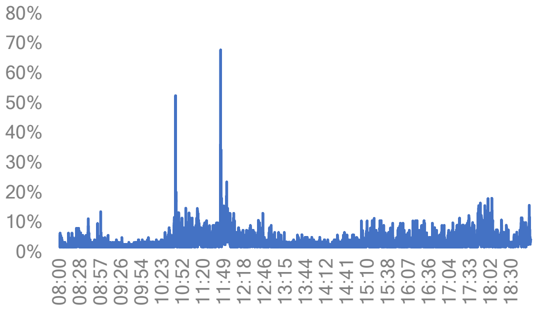
Similar patterns are observed on the long-term CTD bond: very low quantities were offered during the first hours of the day. At around 10:30, a remarkable drop in quoted price was observable in the long-term CTD bond, just before the interruption of the quoting activity. The sharp movement retraced dynamics observed on the futures contract where, conversely, the market activity was strongly increasing at the same time. Dealers stopped providing quotes until 12:00, when market weakly recovered together with the short-term contract. Using data on Italian retail market (MOT), Flora and Renò (2020) provide similar findings regarding the rapid deterioration of market liquidity. All indicators point to very low liquidity in the cash market, as market participants withdrew from making markets on MTS, resulting in very few trades.

Chart 11: Bid-ask spread on 2Y future



Note: Quoted bid-ask spread on 2Y BTP futures.
Sources: Morningstar, ESMA.

Chart 12: Bid-ask spread on 10Y future



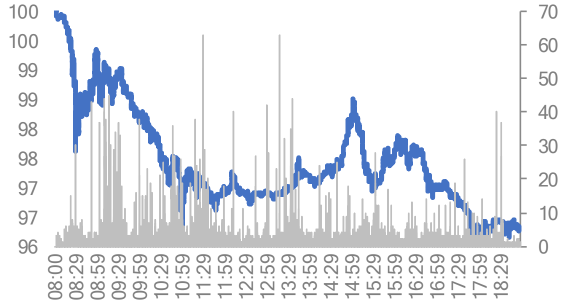
Note: Quoted bid-ask spread on 10Y BTP futures.
Sources: Morningstar, ESMA.

In contrast, trades and quotes occurred throughout the day on futures markets. However, a significative erosion of liquidity also materialized amid an abrupt increase in trading activity. Bid-ask spreads increased dramatically during the flash crashes as shown in Charts 11 and 12. Other indicators of market liquidity also plummeted during the trading day. Market depth, measured by the average number of contracts available at the top 10 limits to both buyers and sellers, fell for 2Y futures. On May 29, average market depth declined by 96% compared to a week earlier with 160 contracts offered against 3,400 contracts on May 22. Similarly, market depth dropped by 80% on 10Y futures, with average depth of less than 80 contracts against 310 contracts a week before. The very low levels of market depth from the beginning of the day bears similarity with the market conditions during the Sterling flash crash of October 2016 (BIS, 2017).

Those two events contrast other flash events on sovereign bonds or equities, where market depth was close to average before collapsing suddenly. In other words, flash events can be characterized by both average or low liquidity before the event. When flash events occur against the backdrop of significant news, could be more exposed to long-lasting effects, because the microstructure effects are comingled with more fundamental information. In those cases, flash events can amplify shifts in investor sentiment (Himmelberg and Weldon, 2018).

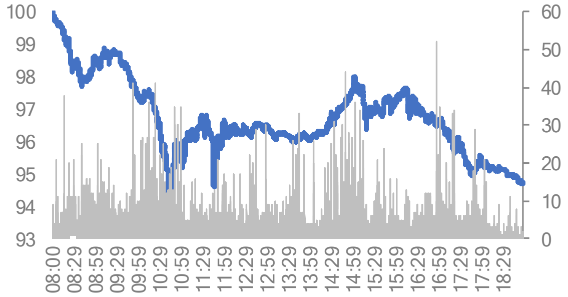
Despite low market depth, many transactions occurred throughout the day on both contracts, with an average of 33 trades per minute on the 2Y contract and 75 trades on the 10Y contract (Charts 13 and 14). Lower liquidity conditions, that also point to higher transaction costs, did not discourage the trading activity on the derivative contracts which, conversely, abruptly increased even during the most stressed periods.

Chart 13: Trading activity on 2Y future



Note: Mid price on 2Y futures, second by second, and number of trades.
Sources: Morningstar, ESMA.

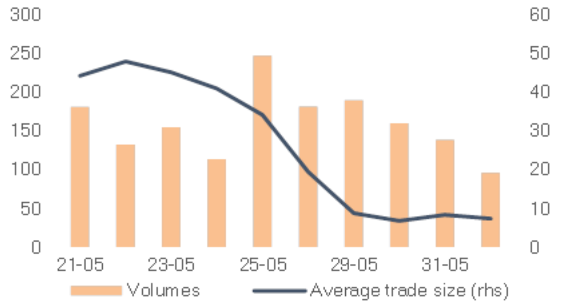
Chart 14: Trading activity on 10Y future



Note: Mid price on 10Y BTP futures and number of trades.
Sources: Morningstar, ESMA.

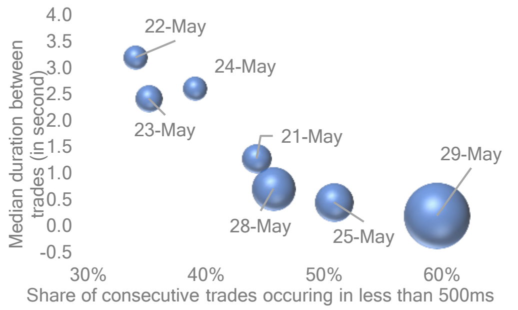
Compared to usual trading conditions (measured by the previous week), there were some significant shifts in trading patterns during and after the event. On 2Y futures, volumes traded on May 29 were close to the previous days, yet the average trade size fell to less than 10 contracts against 40 before the event (Chart 15). Similar patterns are also observed to a lesser extent on the 10Y contracts. In other words, on May 29 there were a lot of trades but for a smaller size, due to the lack of liquidity. Looking at the distribution of trades by size, on May 29, the share of 'small trades' (up to 5 contracts for each trade) jumped to 70% of all trades against less than 40% the few days before.

Chart 15: Trading activity on 2Y future, number of contracts and averaged trade size



Note: Number of contracts traded (in thousands) and average quantity per trade (rhs) on BTP 2Y futures (June contract).
Sources: Morningstar, ESMA.

Chart 16: HFT activity on 2Y future



Note: Share of trades and median duration between trades on 2Y futures. The size of the bubble is based on the number of trades
Sources: Morningstar, ESMA.

The decline in trade size can reflect two factors. First, the deterioration of market liquidity made it difficult (and very expensive) to execute large trades, therefore market participants had to split their trades into smaller slices. In addition, smaller trades can be seen as an indication of a more intense HFT activity, since HFT firms typically trade very frequently in small sizes.

To shed further light on HFT activity during the event, we estimate a proxy of HFT activity based on order book updates per second: a higher value indicates that firms are quickly able to update their orders, thereby reflecting higher HFT activity (see ESMA (2014) for an overview of identification strategies for HFT). We also use another proxy based on time elapsed between trades: we assume that consecutive trades executed over a short time frame (less than 500 milliseconds) are more likely to be related to HFT activity. Chart 16 shows that on May 29, the share of consecutive trades occurring rapidly was higher than the week before, with more than

60% of trades occurring within 500 milliseconds. Relatedly, the median duration between two trades was slightly less than 200 milliseconds, against more than two seconds on 22-24 May. The increase in consecutive trades can be a reflection of higher HFT activity as well as more frequent trades due to the high level of volatility which translates into more rapid updates of the order book.[21]

The comparison of market liquidity across cash and futures market yields a set of observations. First, liquidity measured by market depth evaporated quickly on both markets, while bid-ask spreads rose. Second, while trading activity plummeted on MTS, turnover was high on futures, with market participants executing a large amount of small trades over short timeframe, which are typically associated with HFT. The difference in behaviour during the flash events points to the different nature of market participants on MTS and Eurex, as well as different trading systems.

3.6 A comparison with the Bund flash crash of May 7, 2015

On May 7, 2015, the German sovereign bond market, one of the most liquid markets in the world, experienced high volatility, in the absence of any meaningful macroeconomic news (Charts 17 and 18). The 30-year yield surged by more than 30 bps from 1.10% to 1.40% in a few minutes (BIS, 2016a). Similar price action was seen in the future market.

We take a closer look at the long Bund future contract traded on Eurex. Around 11:08, the price of Bund futures across maturities started to dip, reaching a low around 11:16 before quickly rebounding. The flash crash can be seen in Charts 19 and 20, which shows that the flash crash was wider on the 30Y contract than on the 10Y contract, and that they both occurred at the same time. Similar as in the case of Italian futures, intraday volatility surged during the flash crash (Chart 20, blue line). Usually, intraday volatility is very limited on Bund futures, as indicated by the grey line showing the volatility the day prior to the flash crash. The average volatility on May 7 surged to 0.4%, around 15 times the average volatility of 30Y bund futures.

The occurrence of simultaneous flash events on both contracts is confirmed by the V-shape statistic, which is statistically significant around the event for both contracts (Charts 21 and 22).

Overall, the trading activity during the Bund futures flash crash is consistent with what was observed on the Italian futures market in May 2018: large drop in market depth and peak in volatility amid high turnover. These observations are also in line with the May 2010 flash crash on US equity markets and the October 2014 flash rally on the US Treasury market regarding price moves and volatility (SEC-CFTC, 2010; Kirilenko *et al*., 2014; Bouveret *et al*., 2015). However, there is an important difference between the Bund flash crash and the BTP flash event. In May 2018, the initial level of market depth at the beginning of the trading day was already very low. In contrast, for the Bund flash crash of May 2015 (and the US flash event on Treasuries), market depth was close to average levels at the beginning of the trading day and then suddenly dropped just before the flash event.

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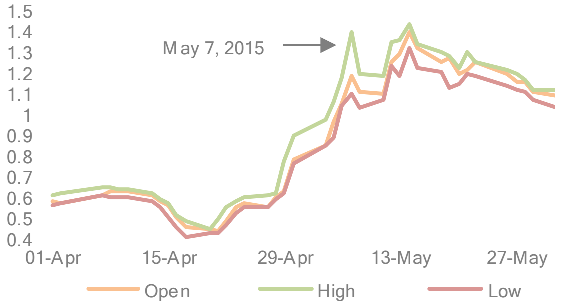
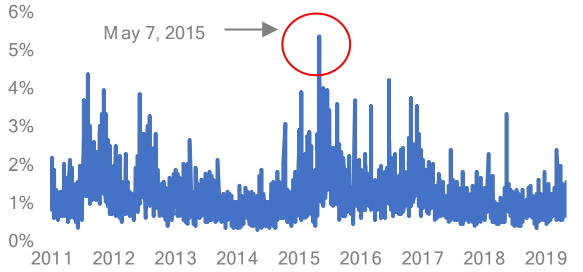
[21] Unfortunately, it is not possible to directly disentangle the increase due to HFT activity and the increase due to the increase in order book updates given that we lack instruments to separate the two. See Bouveret et al. (2015) for a method to estimate the share of reactive trades.

Chart 17: German sovereign yields around May 7



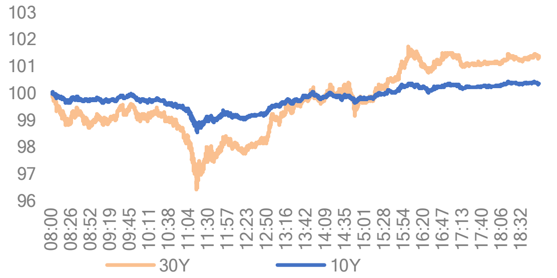
Note: Yields on 30Y German bonds, high, low and open, in %.
Sources: Thomson Reuters Eikon, ESMA.

Chart 18: Intraday price change on 30Y futures



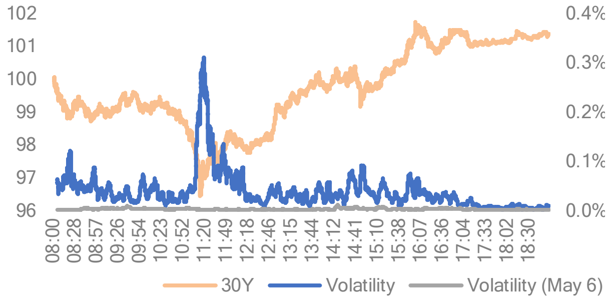
Note: Intraday price change (high-low) on German 30Y futures, in % of opening price.
Sources: Thoms Reuters Datastream, ESMA.

Chart 19: 30Y and 10Y Bund futures



Note: Mid price on 30Y and 10Y Bund futures, second by second, rebased a 100=08:01.
Sources: Morningstar, ESMA.

Chart 20: 30Y future price and volatility



Note: Mid price on 30Y Bund futures, and 5-minute realized volatility (rhs) second by second, rebased at 100=08:01.
Sources: Morningstar, ESMA.

Chart 21: 30Y Bund future

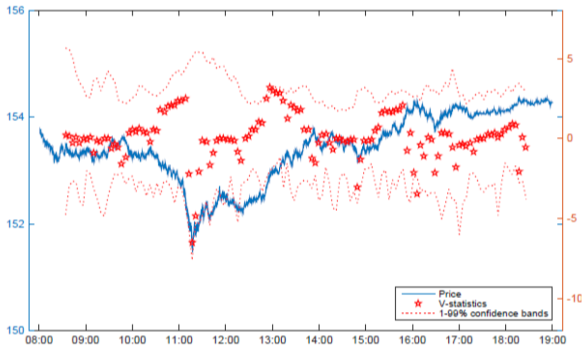
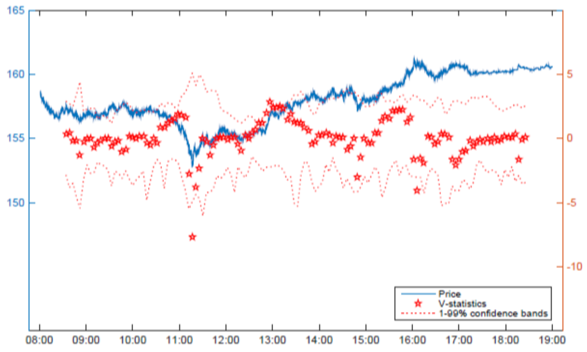


Chart 22: 10Y Bund future



Note: Blue lines are transaction prices for 30Y (Chart 21) and 10Y (Chart 22) Bund future contracts on May 7, 2015, while red pentagrams are V-statistics computed following Flora and Renò (2021). Confidence bands for the individual tests are reported at 1% and 99% level, and computed using bootstrapping. Low values of the V-statistics (when compared to the displayed confidence bands) signal a strong 'V/Λ-shape'.

4. Transient and lasting effects on market liquidity

Risks connected to the incidence of flash events are twofold. On the one hand, it is often believed that their occurrence is a signal for poor, ex-ante liquidity conditions. The occurrence of flash episodes seems to point to more fragile financial markets, which suffer liquidity ‘illusion’ phenomena when the available liquidity rapidly dries up when it is most needed. On the other hand, the occurrence of flash events could undermine investors’ confidence and discourage market participation. In addition, such events could lead to portfolio rebalancing, with a reduction in exposures to asset classes perceived as riskier than in the past.

Therefore, after materializing, a flash event could produce further pressure on the market and impact market liquidity, as market participants reduce their trading and quoting activity, which in turn lead to an increase in trading costs. Flash events could also result in increased funding costs for sovereign issuers, in the short run — if auctions took place on the day of the flash event — and also in the medium run if investors require higher yields to compensate for the risk of such events.[22] Even if flash events are short-lived phenomena, their negative implications for market quality could extend over time.

This section focuses on the more prolonged implications for market liquidity related to the materialization of flash events on the sovereign bond markets. In particular, we look at the following issues: (i) what is the short-term impact of flash events on liquidity? (ii) Do flash events have a lasting impact on market liquidity? (iii) How long does it take for market liquidity to come back to its pre-event level?

4.1 Short-term impacts of flash crashes in futures markets

The days following flash events tend to show a sharp deterioration in liquidity. For example, Bouveret *et al.* (2015) show that market depth remained very low on UST futures the week after the flash event of October 15, 2014.

We observe similar patterns for the two flash events related to Bunds (May 2015) and BTP futures (May 2018). For Italian futures, Charts 23 and 24 indicate that liquidity remained very low right after the event. For 2Y BTP futures, market depth was on average around €500,000 before May 29 (measured at 5 bps around mid-point). After the event, market depth fell by more than 95% to less than €10,000. Market depth on 10Y futures also remained very low after the event (Chart 24).[23]

The deterioration in liquidity and the increase in yields following a flash crash can also have a direct impact on the funding costs of sovereigns. Using a three-state Markow-switching model, Flora and Renò (2021) estimate that the increase in yields the day after the flash event cost the Italian Treasury between €250 and €650 million, as the Italian sovereign markets moved to a distressed state characterized by high volatility.

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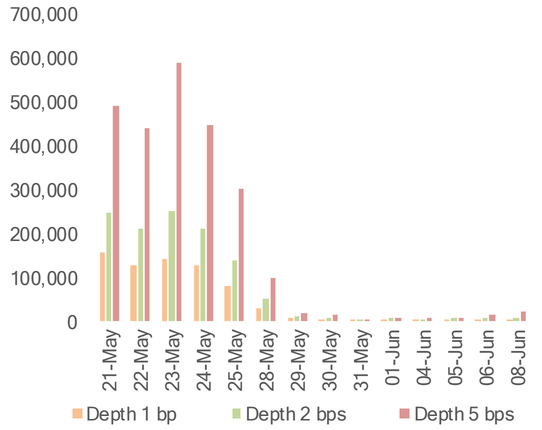
[22] Flora and Renò (2020) estimate that the May 29, 2018 flash crash had a cost of €450 million to the Italian Treasury.

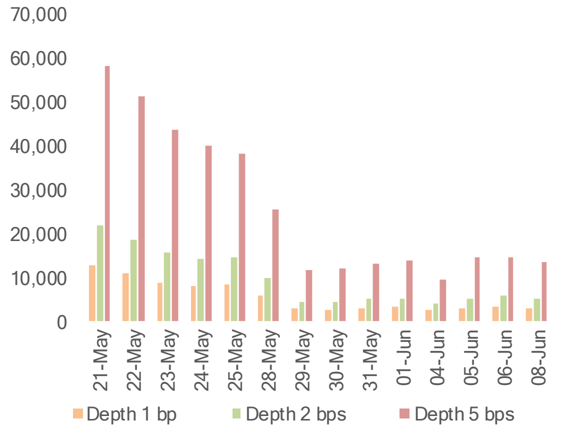
[23] This measure of market depth does not take into account the notional amount of the contract. For government bond futures traded on Eurex, the notional is €100,000.

Chart 23: Market depth on 2 Y BTP future



Note: Market depth on 2Y BTP futures, excluding spread, in euros.
Sources: Morningstar, ESMA.

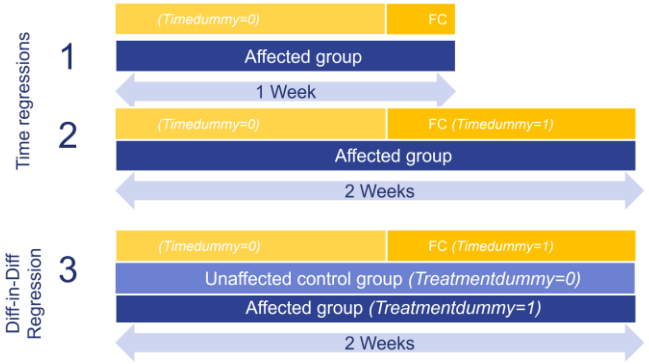
Chart 24: Market depth on 10Y BTP future



Note: Market depth on 10Y BTP futures, excluding spread, in euros.
Sources: Morningstar, ESMA.

To assess the potential impact of flash crashes on the liquidity of sovereign bond futures, we follow a multi-level approach. We use time series regressions to investigate the effects using several time periods. First, we run the regression only with data covering one week before as well as the day of the flash crash to document abnormal effects on the event day. Second, we extend the time range to two weeks to zoom into short-term shifts of liquidity. The time ranges and approaches are shown in Figure 1. As a robustness check, we use the difference-in-difference (DiD) approach to measure changes in liquidity compared to a control group, in line with related literature (Gomber *et al.*, 2016). The treatment group relates to the sovereign bond futures that experienced the flash event. For the analysis of the flash crash in the Italian market in May 2018, German sovereign futures constitute the control group, as German sovereign bonds were not directly impacted by events on the Italian futures market.[24]

Figure 1: Set up of the regressions


Time regressions
1
(Timedummy=0)
FC
Affected group
1 Week
2
(Timedummy=0)
FC (Timedummy=1)
Affected group
2 Weeks
Diff-in-Diff Regression
3
(Timedummy=0)
FC (Timedummy=1)
Unaffected control group (Treatmentdummy=0)
Affected group (Treatmentdummy=1)
2 Weeks

For the May 2015 (Bund) event, we are not able to run the robustness check via the DiD method due to a lack of valid (i.e. unaffected) control group. The reason behind this is that the German bunds are regarded very close to the risk-free rate for euro-denominated bonds. As a consequence, any movement in price or other indicator of German sovereign futures is propagated to other euro-denominated (sovereign) bonds. Hence, we are not able to run a robustness check on this event.

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[24] On that day, Bund futures saw limited intraday price moves (1.5% price range on that day) compared to Italian BTP (more than 8%).

We use data on sovereign bond futures traded on EUREX and retrieved from Morningstar. In using the same market for both events we ensure invariance of the market microstructure environment with respect to market makers and HFTs which are active on this platform and segment and trading schedule. Both sets of futures are denominated in the same currency (i.e. EUR) further putting them alike by being exposed to the same risk factors at currency level.

On the basis of this data set we estimate the following regression:

$$Y_{i,t} = \alpha_0 + \alpha_1 X_i + \alpha_2 T_t + \alpha_3 X_i T_t + \sum_{k=4}^{7} \alpha_k x_k + \alpha_{12} C_i + \varepsilon_{i,t}$$

where $Y_{i,t}$ is our liquidity measures (explained below), X_i is a dummy variable equals to one for Italian futures and zero for German futures, T_t is a dummy variable equal to one on the day of the flash crash and the following days and zero before, $X_i T_t$ is the interaction term, $\sum_{k=4}^{7} \alpha_k x_k$ are fixed effects for each instrument (two Italian sovereign futures contracts and two German sovereign futures). Finally, we include with $\alpha_{12} C_i$ several control variables, like the hour of the day and the minute, to reflect intraday liquidity patterns. We also run a similar regression leaving out the control group to capture the direct effect of the flash crash only considering the time dummy variable T_t that splits the dataset into a before and after period.

To investigate different aspects of the flash crash events we use three different samples. The first two samples only include instruments that are affected by the flash crash, essentially providing a before and after comparison. Consequently, the first sample only includes data from one week (i.e., five trading days) before the day of the flash crash. With this sample we aim at analysing how strong the adverse environment was at the event day where the flash crash occurred. The second sample extends the time window to make it symmetric, as it extended by one trading week (again five days) after the event to capture the medium-term effects of the crash. The third sample refers to our robustness check through the previously introduced DiD setup; as previously mentioned we only run the robustness check on the Italian event.

We use several liquidity measures that are estimated for each orderbook snapshot, amounting to about 40 million records per date and instrument. As the orderbook activity varies over the day, we obtain an unbalanced panel. Therefore, we reaggregate the data to one-minute intervals by calculating the mean of the liquidity measures. We also exclude implausible values (e.g. negative spreads) and outliers (thresholds as defined by median + 3 standard deviation). Once an implausible value is identified within one instrument, we eliminate the values for all other instruments within the same minute and day to keep the panel balanced before doing the actual liquidity analysis. To add further robustness to our analysis and to account potential concerns that outliers are linked to the flash crash (i.e. mainly occur during the event and potentially biasing our analysis) we additionally run the regressions including outliers. As expected the coefficients along with the number of observations change slightly, while the sign and significance stay at the same level.

As liquidity measures, we consider two order book indicators. The first one is the relative spread, which is widely used in the market microstructure literature to quantify implicit costs of trading. The relative spread is calculated as follows:

$$RelativeSpread = \frac{BestAsk - BestBid}{\frac{1}{2}(BestAsk + BestBid)}$$

One issue with relative spreads, is that it gives a measure of liquidity irrespective of the quantities offered at the best bid and ask. Therefore, we use a second measure based on market depth beyond the best price levels. We use the exchange liquidity measure (XLM) which measures the price impact of a buy and sell order with a predefined (euro) amount (Gomber *et al.*, 2013). It is calculated as follows:

$$XLM_B\,(V) = 10{,}000 * \frac{P_B(V) - MP}{MP}$$

$$XLM_S\,(V) = 10{,}000 * \frac{MP - P_S(V)}{MP}$$

$$XLM(V) = XLM_B(V) + XLM_S\,(V)$$

where MP is the midpoint and P_B and P_S are, respectively the prices of the buy and sell transactions based on the executed euro-amount (V). The advantage of this price impact measure is that it not only considers the top of the order book but it also quantifies the prices and quantities offered at other levels of the order book. These dimensions of the order book are important in markets where a high amount of HFTs are active, as HFTs typically quote relatively small volumes at the top of the book (Haferkorn and Zimmermann, 2014). In our regression we use different order sizes to measure different depths of the order book, i.e.,€5000 and €10000.[25] These amounts refer to the price in the order book and not to the notional of the future, hence they seem relatively small at first sight.

Table 1 shows the results of the estimation for the 2015 event, i.e., the flash crash event in the German sovereign futures. At first, we consider regressions (1)-(3) which show the effect on the event day compared against one week before. The effect of the flash crash on market liquidity is captured by the ‘Timedummy’ variable (equal to one the day of the flash crash). We observe only a marginal negative effect on the relative spread (1), i.e. trading became more expensive, but with a very low coefficient. Comparing this coefficient against the average relative spread in the period before, we see that the liquidity deteriorated by 1 percentage point. The picture becomes clearer once we start looking deeper into the order book with our price impact measures, i.e. ‘XLM 5K’ and ‘XLM 10K’, which quantify the costs of a roundtrip order sized €5000 and €10000 in basis points (bps), respectively. For these two measures we see a significant increase in trading costs (regression (2)/(3)). This is also confirmed by looking at both coefficients where we see a decrease of liquidity of 22.6% and 27.8% for the 'XLM 5K' and 'XML 10K' measures.

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[25] An order with the volume €5,000 would result in about 29 contracts (assuming a price of 174 per contract). As one German/Italian government contract at Eurex has a notional of €100,000 (Eurex, 2019), executing a one sided order of €5,000 would result in a notional amount of €2,900,000 (and this doubles to €5,800,000 for the €10,000 order).

In regressions (4)-(6) we extend the sample to one week after the flash crash. We observe a similar trend, i.e., a significant deterioration of liquidity across our liquidity 'XLM' measures while the effect on the relative spread is marginally negative. Regarding the strength of the effect, we see a slightly different picture compared to the day of the flash crash. Even though the liquidity is still significantly lower compared to before the event, in terms of spread (0.8%) and 'XML 5K' and 'XML 10K' (15.4%/21.8%), the relative changes indicate that conditions bettered compared to the flash crash day. Our findings indicate that both liquidity measures declined after the event. While the liquidity at the top of the order book (i.e. relative spread) is significantly lower, the bigger effect can be observed in the order book depth, more severely affected.

Next, we analyse the flash crash of May 2018 in the Italian sovereign futures traded on Eurex. The results are shown in Table 2. We first investigate the conditions at the event day itself when the crash occurred. Regressions 7 to 9 show that the relative spread is quite strongly affected (it doubled), and the costs of a roundtrip of an order of €5000 and €10000 became significantly more expensive on the flash crash day. In terms of magnitude, these costs increased by 136,3% for the '5K' order. For the '10K' order we were not able to calculate the roundtrip costs for every order calculation as there were not enough quantities offered at the top 10 limits which reduced our sample by 415 observations compared to the 'XML 5k' measure. For the cases where we were able to do the computation (3,849 observations), we observed a deterioration of 92,1%.

We then extend the sample with the same time period after the flash crash, to have a symmetric panel with five days before and after the flash crash (regressions 10-12). We witness a deterioration of the liquidity across our three liquidity measures, showing that the effect lasted beyond the actual event day and the negative effect on liquidity became slightly more severe in the days after the event than on the day of the event itself. On average, a roundtrip transaction with a size of €5000 (€10000) executed in the Italian futures became 4.4 bps (5.7 bps) more expensive. This result likely reflects the lower depth available in the order book in the days following the flash event (see Charts 23, 24 for reference). In addition, the depth available on the Bund futures market is far higher on average than that available on BTP futures contracts. As a result, when we use the same order size (€5000 and €10000) for both markets, this likely translates into higher (absolute) round trip costs.

In the final regression set (13-15), run for robustness reasons, we add the German sovereign futures to the data set as a control group to analyse whether we would see a decoupling of liquidity conditions between the treatment and control groups. In this difference-in-difference approach we need to focus on the interaction term ('Timedummy*Italian sovereign futures') which shows the effect of the flash crash. The results confirm our observations from the previous regressions (9)-(12). We see a significant deterioration of the relative spread as well as an increase in the cost of roundtrip orders compared to German sovereign futures.[26]

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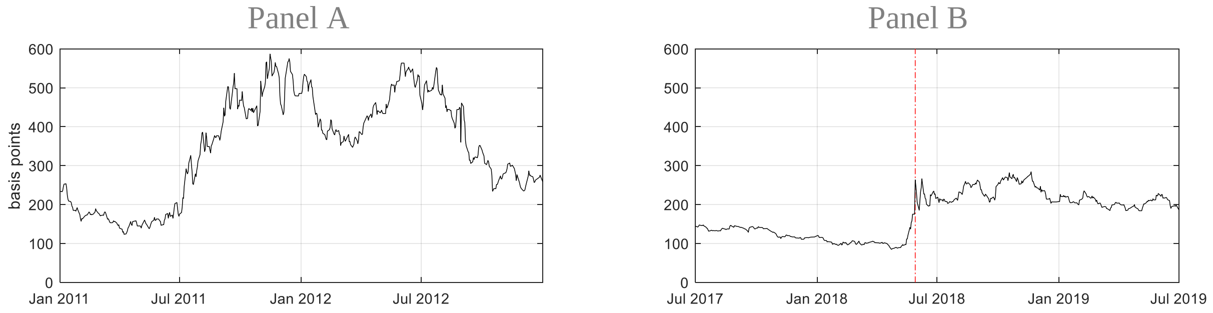
[26] To add further robustness to the results we run the same regressions using Italian sovereign futures with the September 2018 expiry date (not reported). While the results are comparable in terms of significance and effect direction the absolute effect size was much higher, mainly reflecting the usually low liquidity profile of these instruments in the very first days of June: futures contracts are typically rolled over with the approach of their

Compared to the results obtained for the 2015 Bund flash event, the value of the estimated coefficients is higher for the 2018 BTP event. The larger effect partially reflects the impact of political uncertainty on the price and liquidity of BTP futures compared to the 2015 episode, where there was no significant political event. As a result, the analysis is more complex in the Italian case, due to the lack of proper instruments to isolate the effect of one shock (political uncertainty) from the other (flash crashes), both occurring at the time. The analysis might thus comingle the two effects: the reaction of market participants to the significant political news (see footnote 13) as well as the occurrence of several flash crashes over the same period, which could be both associated with a reduction in market liquidity (JSR, 2015; Bouveret *et al*., 2015; Riordan and Schrimpf, 2015). This aspect (omitted variable bias) is addressed in the next section, where we provide a long-term analysis about the evolution of market liquidity conditions in the Italian sovereign bond market.

4.2 Lasting impacts and the relevance of the macroeconomic context: evidence from the Italian bond market

We now focus on longer time horizons, and take into account the macroeconomic context in which the flash event originated. When studying flash events, one aspect to consider is the nature of the information shock that – more or less unexpectedly – hits the market at the time. In contrast with other flash-like events, the information flow occurring on the Italian market on the eve and on the day of May 29, 2018, was remarkable. Growing uncertainty about the economic and fiscal policy stance in Italy had been accompanied by a sharp increase in the Italian credit default swap (CDS) spread (Chart 25, Panel B). In that period, the higher premium requested in CDS contracts also reflected an increased redenomination risk of the Italian debt in a new national currency (ISDA basis; Bank of Italy, 2018b). The increase was material and the CDS spread reached its five-years maximum at the end of May, when the relevant deterioration in market quality was experienced in the secondary market.

Chart 25: Italian sovereign credit default swaps (CDS)



Panel A

Panel B

Note: Daily CDS spreads on Italian sovereign credit default swaps (basis points). The time series is reported in two time periods: the 2011-12 sovereign debt crisis (on the left) and the 2-year window surrounding the flash event on May 29, 2018.

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expiration date and normally traders switch from the front month contract that is close to expiration (i.e. the June 2018 contract) to the next maturing contract (i.e. the September 2018 contract) in the days immediately preceding the expiration date (i.e. the 10th calendar day of the expiration month).

As noted in Section 3, the deterioration in liquidity conditions on the MTS market was comparable in size, and even more sharp, than that recorded during the 2011-12 sovereign debt crisis; the intraday price variation observed on the futures contracts on May 29, 2018, was the highest since the launch of the futures contracts. Despite this evidence the increase in the CDS spread was much larger in 2011 than in 2018 (Chart 25, Panel A), pointing to other factors at stake beside credit risk. Hence, although the information shock in May 2018 was material, the reaction of the market was very sharp, which arise questions with respect to the effective ability of the market to process new and material information. Well-functioning markets should be able to generate meaningful and consistent price signals also during periods of heightened financial stress or economic uncertainty (BIS, 2019).

We explore market liquidity dynamics and their drivers before, during, and after the flash event, through a set of different liquidity measures (see also Annex A for a descriptive analysis of different market liquidity metrics). We rely on previous works that examine the determinants of market liquidity in sovereign bond markets (Benos and Zikes, 2016; Pelizzon *et al.*, 2016) and conduct separate regressions for each liquidity metric, while controlling for the role of relevant market variables that might affect liquidity over time. The regressions are at a daily frequency, over the sample period from 250 days before, to 250 days after[27] May 29, 2018, and take the following form:

$$\Delta MktLiq_t = \alpha + \sum_{k=1}^{N} \theta_k \Delta MktLiq_{t-k} + \beta_1 Stress_t + \cdots$$

$$+\beta_2 \Delta MktVar_{t-1} + \beta_3 \Delta MktVar_{t-2} + \beta_4 Controls_t + \epsilon_t$$

where $MktLiq_t$ is one of the following liquidity metrics (expressed in log-levels): (i) the (quoted) bid-ask spread, computed in relative terms with respect to the mid-price and expressed in basis points; (ii) the market depth, defined as the quantities quoted by market makers and collected at different levels of the MTS order book (one, one-to-three, one-to-five level(s) of the book); (iii) the total market turnover, and (iv) the average trade size. $MktVar_{t-1}$ is a set of market variables, including the Italian sovereign CDS spread, the implied volatility of the S&P 500 (VIX) and a measure of intraday bond volatility, i.e. the realized volatility, based on high-frequency intraday returns; we also include variables related to the cost of unsecured and secured borrowing: the three-month Euribor-OIS spread and the spread between the general collateral (GC) repo rate and the ECB deposit facility rate. We also include a number of control variables $Controls_t$ for the dates of Eurosystem's asset purchase programmes (quantitative easing), the Italian Treasury's issuances on the primary market, the ECB monetary policy meetings and two indicator variables to identify market liquidity changes at month-ends and quarter-ends (namely, two variables that are equal to one on the last day of the period and zero otherwise), to be interpreted additively. Finally, we include a dummy variable ($Stress_t$), which takes the value of 1 on May 29 (and 0 otherwise), with the aim to capture other changes in market liquidity that are not explained by the factors included in our specification. To address potential endogeneity issues, all explanatory variables are lagged by one day. For all regressions, the number of lags is chosen using the Bayesian information criterion and *t*-statistics are calculated using the Newey-West (1987) estimator.

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[27] We also conduct the same estimations using different time windows (including 150, 200 and 300 days before and after the flash event) and we get comparable results.

The estimation results are reported in Table 3. All the liquidity metrics show a high degree of serial autocorrelation. The coefficients associated to variables that capture market conditions are generally significant, confirming that credit risk and market volatility are relevant drivers of market liquidity.

The macroeconomic environment played a key role in affecting market liquidity conditions during the materialization, and the aftermath, of the flash event. The contribution of each market variable may vary across different liquidity metrics, but the sign of the relationship is generally consistent and corroborates common evidence, with an increase in market volatility and/or credit risk being associated to lower liquidity conditions.

The credit risk premium on Italian government securities measured by CDS spreads is one of the most relevant drivers of market liquidity. A 10% increase in the CDS spread results in a 7% wider bid-ask spread (the following day); this result is quantitatively similar to estimates available in the literature (Pelizzon *et al.*, 2016). Market depth is mostly affected by volatility: when the VIX index increases by 10%, quantities quoted at the first and at the first three levels of the order book decrease respectively by 1.5% and 0.7% the following day. Such effect is consistent with risk-averse market makers which reduces their provision of liquidity when uncertainty rises (Grossman and Miller, 1988). Typically, the top levels of the order book are those that concentrate most of the liquidity available on the entire book. In addition, the majority of trades typically occurs only at the first level of the book, as market participants seek to minimize transaction costs. Only in very limited cases the most aggressive orders affect more than one price level in the order book, thus resulting in higher – albeit limited[28] – transaction costs.

In the case of a stress event, liquidity providers could pursue several trading strategies. In order to discourage trading flows that would otherwise lead them to acquire undesired, riskier, exposures market makers could temporarily apply larger premia to their quotes (resulting in wider bid-ask spreads) and revise, reduce, or even withdraw[29] quantities posted on the order book. Depending on their risk appetite, market makers could also revise their quoted prices with the aim to move quantities up or down the order book, and thus attracting more, or less, orders from other traders (just recalling that bonds are more often traded at the top levels of the order book). The most aggregated depth measures (for example considering the first five levels of the order book) could thus miss some information, as they might fail to capture strategies occurring among the very first levels of the book (in our results the aggregated depth measure from 1 to 5 levels turns to be the least reactive to macro variables).

When market depth is low, aggressive orders could more easily ‘walk through the order book’, thus resulting in higher transaction costs indeed. To minimize execution costs and mitigate the impact of their trades, market participants could choose to split their orders over time, thus reducing the trading size. Trading activity is expected to continuously adapt to changing market conditions indeed. Our results confirm this hypothesis and show that both credit risk and volatility affect trades' size and, to a lesser extent, market turnover.

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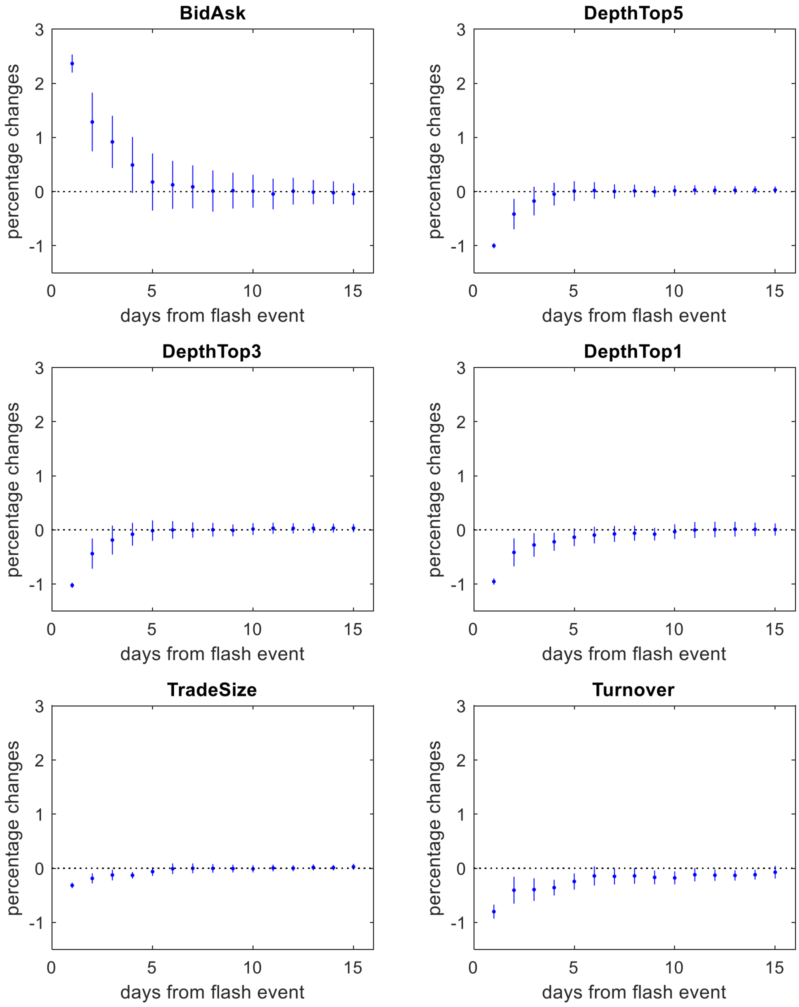
[28] In 2018, the price distance between the first two levels of the book was by large limited to 1-2 price cents for ten years securities.

[29] Before the flash event, market depth at the best price level for 10-year notes was on average around €20 million; the value dropped below €5 million at the end of May, close to the minimum allowed on the platform (€2 million). This indicates that during the stress episode many market makers opted to temporarily withdraw liquidity from the market.

Chart 26: Persistency of shocks to market liquidity metrics following the flash event



Note: These figures report market liquidity shocks that are not explained by factors included in our specification. For each liquidity measure, every figure reports size and (95%) significance intervals of the coefficients associated to the $Stress_t$ dummy. A set of separate regressions based on the previous specification is conducted, where $Stress_t$ identifies every window from one to 15 days after (and including) May 29.

In all regressions, the stress event dummy ($Stress_t$) remains statistically and economically significant, suggesting that the reduction in market liquidity is robust to variations in the macro variables. On May 29, 2018, all measures signalled a remarkable drop in market quality, even after controlling for all the factors included in our specification. Total market turnover shrank by an additional 0.8% on that day, and the trade size decreased by an additional 0.3%; all liquidity measures based on the MTS order book resulted significantly affected as well. Market variables included in our specification thus fail to capture the overall deterioration in market quality observed on May 29, thus signalling that market liquidity may overreact in time of high(er) stress. During flash events, price movements not related to economic fundamentals could further undermine market confidence and have an adverse impact on liquidity. These impacts could reinforce themselves, as market makers not only respond to information shocks but also react to others market participants' trading behaviours.

We further explore whether this unexplained component was also present in the days following the flash event. For each liquidity measure, we run a set of separate regressions based on our previous specification, but expanding the $Stress_t$ dummy in order to identify every window from 1 to 15 days after (and including) May 29. We collect in Chart 26 all the coefficients associated to the $Stress_t$ dummy (as well as their 95% significance interval). The results clearly show a transient dynamic: all coefficients progressively become economically and statistically less significant as the days get farther from the flash event. After 5-7 days, for most of the liquidity measures, the coefficients are not statistically different from zero, except for market turnover, which shows a slower decay. Following the flash event, economic uncertainty could discourage investors' demand over asset classes that are perceived as riskier than in the past; this could reduce trading activity on the market and result in more lasting impacts.

5. Conclusion

Flash events on sovereign bond markets can give rise to risks to market order and financial stability. During flash events very low liquidity leads to very high volatility, as trades have a very large price impact due to the limited willingness or ability of market makers to supply liquidity. Such events create risks for market participants due to the feedback loop between low liquidity and high volatility. Flash events can also raise costs for sovereign issuers, as investors might demand higher yields to compensate for the risk of flash events.

Based on two flash events that occurred on European sovereign bond markets, we show how liquidity can quickly evaporate on cash and futures markets. In addition, while trading activity came to a halt on cash markets, it continued on futures instruments, possibly due to higher HFT activity on CLOB markets.

We also look at market liquidity in the aftermath of flash events and show that liquidity remains depressed in the days and weeks following them. The deterioration in market quality remains significant even after controlling for relevant market factors affecting liquidity conditions, but it vanishes over two or three weeks. When measured by bid-ask spread or market depth, market liquidity is more likely to return faster to historical averages, while indicators based on trading activity (turnover and average trade size) point to more long-lasting effects of flash events.

The analysis calls for more work on interlinkages between cash and futures market, taking into account the different types of market participants as well as their trading behaviour in supporting market liquidity and price discovery mechanisms. Improving market monitoring is key. Market oversight needs to adapt to the pace of innovation in global electronic markets, and there is great merit in pursuing more integrated approaches in view of the significant contribution that some financial markets play on liquidity and price discovery mechanisms in other relevant, interlinked markets. Given the role of sovereign markets in the financial system, flash events in those markets can have detrimental effects beyond those observed in equity markets, calling for further reflections on ways to improve the resilience of sovereign markets.

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Table 1. Econometric results on Bund Futures in 2015 (German futures event). This table reports estimated coefficients from regressions of the Eurex market liquidity metrics. The regressions are at minute frequency and the sample period includes one week before and one after the event. First, we run the regression only with data covering one week before as well as the day of the flash crash to document abnormal effects on the event day (colulmns 1-3). Second, we extend the time range to two weeks to zoom into short-term shifts of liquidity (columns 4-6). The variable 'Timedummy' is zero before the event and one during and after the flash crash. The dependent variables are the relative spread and the exchange liquidity measure (XLM), which measures the price impact of a buy and sell order with a predefined (euro) amount. Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

	SPREAD (1)	XLM 5K (2)	XLM 10K (3)	SPREAD (4)	XLM 5K_ (5)	XLM 10K (6)
Timedummy	0.00000***	0.144***	0.198***	0.00000***	0.098***	0.155***
	(0.000)	(0.004)	(0.007)	(0.000)	(0.003)	(0.004)
Constant	0.0001***	0.680***	0.922***	0.0001***	0.749***	1.030***
	(0.00000)	(0.012)	(0.020)	(0.00000)	(0.012)	(0.016)
Instrument FE	Yes	Yes	Yes	Yes	Yes	Yes
Minute FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,539	7,449	7,338	12,555	12,381	12,126
Adjusted R^2	0.999	0.594	0.548	0.999	0.536	0.642

Table 2. Econometric results on Italian Futures in 2018 (Italian futures event). This table reports estimated coefficients from regressions of the Eurex market liquidity metrics. The regressions are at minute frequency and the sample period includes one week before and one after the event. First, we run the regression only with data covering one week before as well as the day of the flash crash to document abnormal effects on the event day (colulmns 7-9). Second, we extend the time range to two weeks to zoom into short-term shifts of liquidity (columns 10-12). Third, as a robustness check, we use the difference-in-difference (DiD) approach to measure changes in liquidity compared to a control group (German futures; columns 13-15). The variable 'Timedummy' is zero before the event and one during and after the flash crash. The variable Italian Futures is one for the affected group and zero for the control group. The dependent variables are the relative spread and the exchange liquidity measure (XLM), which measures the price impact of a buy and sell order with a predefined (euro) amount. * Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

	SPREAD	XLM 5K	XLM 10K	SPREAD	XLM 5K	XLM 10K	SPREAD	XLM 5K	XLM 10K
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Timedummy	0.0001***	3.510***	3.275***	0.0001***	4.385***	5.706***	0	0.085***	0.279***
	0	-0.092	-0.231	0	-0.046	-0.065	0	-0.017	-0.016
Timedummy*Italian sovereign Futures							0.0001***	4.275***	5.403***
							0	-0.031	-0.039
Constant	0.0001***	3.760***	5.862***	0.0001***	3.719***	5.740***	0.0001***	0.680***	1.035***
	0	-0.132	-0.16	0	-0.17	-0.198	0	-0.06	-0.062
Instrument FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,798	4,264	3,849	8,086	5,979	4,745	20,116	17,748	16,843
Adjusted R^2	0.533	0.619	0.743	0.422	0.635	0.682	0.686	0.808	0.84

Table 3. Market liquidity analysis on the MTS market. This table reports estimated coefficients from time series OLS regressions on different liquidity metrics: the quoted bid-ask spread, the quoted depth (at different levels of the order book), the market turnover and the average trade size. All dependent variables are expressed as percentage changes and the specification includes several lags, with the number of lags chosen using the Bayesian information criterion. The regressions are at daily frequency and the sample period extends from 250 days before, to 250 days after, May 29, 2018. 'Stress' is a dummy variable that takes the value 1 on May 29 and 0 otherwise; 'CDS' is a risk indicator measuring the daily changes in the Italian sovereign CDS premium; the 'VIX' index is included as a measure of global volatility; 'Euribor-OIS' is the difference between the three-month LIBOR and the three-month overnight indexed swap (OIS) rate; 'Reporate' is the one-day cost of secured lending. 'Issuances', 'ECB meetings' and 'QE' are indicator variables for the dates of treasury auctions, ECB monetary policy meetings and Bank of Italy purchases under the PSPP program, respectively. 'Month end' and 'Quarter end' are indicator variables for the last day of the month, quarter. All potentially endogenous explanatory variables are lagged by one day. The t statistics are calculated using the Newey-West (1987) estimator; *, ** and *** denotes significance at 10%, 5% and 1% respectively.

	Quoted Spread	**Depth (Top 5)**	**Depth (Top 3)**	**Depth (Top 1)**	**Trade Size**	**Turnover**
Stress	2.3641***	-1.0004***	-1.0229***	-0.9539***	-0.3160***	-0.8007***
Δ Liq $_{t-1}$	-0.5395***	-0.4388***	-0.4558***	-0.3459***	-0.7842***	-0.5010***
Δ Liq $_{t-2}$	-0.3346***	-0.2689***	-0.2606***	-0.2246***	-0.5400***	-0.3458***
Δ Liq $_{t-3}$	-0.1210***				-0.3896***	-0.2769***
Δ Liq $_{t-4}$					-0.1662***	
Δ CDS $_{t-1}$	0.7300**	-0.1016	-0.1936*	0.0173	-0.4547***	-0.3128
Δ CDS $_{t-2}$	0.5047	-0.0726	-0.0709	0.0193	-0.2551*	-0.1348
Δ VIX $_{t-1}$	0.0374	-0.0311	-0.0675*	-0.1536**	-0.1402***	0.2206
Δ VIX $_{t-2}$	-0.0603	0.0007	0.0136	0.1437**	-0.0139	-0.1659
Δ Intra Vol $_{t-1}$	0.0438	-0.0077	-0.0161	-0.0124	0.0031	-0.0377
Δ Intra Vol $_{t-2}$	0.0076	-0.0039	-0.0108	0.0038	-0.0062	-0.1211***
Δ Euribor-OIS $_{t-1}$	-0.3313	-0.0159	0.0001	0.1757	0.2479**	0.7004*
Δ Euribor-OIS $_{t-2}$	-0.1201	-0.1956**	-0.2146**	-0.2989**	0.2292	0.0502
Δ Reporate $_{t-1}$	0.0003	0.0001	0.0022	-0.0071**	-0.0013	-0.0048
Δ Reporate $_{t-2}$	0.0076***	-0.0009	0.0000	-0.0048**	-0.0002	-0.0077
Issuances	-0.0173	-0.0050	0.0011	-0.0035	-0.0223**	0.2278***
ECB meetings	0.3162***	-0.0875***	-0.0999***	-0.0599**	-0.0710**	0.0400
QE dates	-0.1419**	0.0617***	0.0620***	0.0688***	0.0658**	0.3117***
Month end	-0.0791*	0.0243	0.0311	0.0331	0.0034	0.0697
Quarter end	0.1490	-0.0460	-0.0631	-0.0624	-0.0869	-0.1621*
Durbin-Watson	1.98	1.8	1.88	2.01	2.06	2.03
Adj R^2	0.284	0.402	0.355	0.219	0.401	0.297
N	501	501	501	501	501	501

Annex A. A descriptive analysis of different market liquidity metrics on MTS in May 2018.

We employ a set of different liquidity metrics to investigate the evolution of market liquidity on MTS in the periods surrounding the flash event on the Italian sovereign bond market: the bid-ask spread, the market depth, the total turnover, and the average trade size.

Chart A shows the quoted bid-ask spread, computed in relative terms with respect to the mid-price and expressed in basis points. In the period surrounding the flash event, the bid-ask spread widened markedly. However, a gradual increase in the quoted spreads was already in place since May 15; that day, the press reported some leakages regarding a preliminary draft about the political agreement between the two political parties that were considering a government coalition. Some points covered in the document seemed to consider the potential, for Italy, to exit the European Union. After May 29, 2018, quoted spreads partially recovered until the end of the year, remaining around 35% wider if compared to the beginning of 2018; only during the 2019 quoted spreads returned to the ‘low’ levels observed before the event (around 5 basis points).

Chart B reports market depth. Quoted quantities are collected from the top five levels of the MTS order book, then summed and averaged through the trading day to obtain a daily series; both bid and ask quotes are considered. The measure is indicative of dealers’ willingness to accommodate trades coming from other competing dealers (i.e., low values point to worse liquidity conditions). On May 29, the average quoted quantities at the first five levels of the book reached the lowest level in the period under exam (below €20 million); as for the spread measure, quoted quantities gradually increased after the flash event but did not fully recover until the end of the year.

Finally, Chart C reports the daily turnover and the average trade size. These two measures could provide additional information about market liquidity dynamics. When no trades are executed on the market, the information content of the MTS order book may become less indicative of true market liquidity conditions; for example, quoted price may be less informative of the fundamental values of the traded securities if they fail to attract investors’ order flows.On May 29, quantities traded on the market were remarkably low if compared to the rest of the year. More notably, the overall path significantly differed from what observed for others liquidity measures: after the flash event, market turnover remained low and did not fully recover during the year, neither in the first months of 2019. Such a structural shift is also observable – albeit to a lesser extent – if we look at the series of the average trade size. Before the flash episode, the average size traded on a single bond on the market was about €12 million; after the event the same quantity has settled on slightly lower values, around €10 million.

In summary, all market quality measures significantly worsened around the flash event. The metrics based on the MTS order book (such as bid-ask spreads and market depth) progressively improved in the months after the flash event, and partially recovered until the end of the same year. In contrast, metrics based on trading activity (such as turnover and the average trade size) showed a slower recovery.

Quoted bid-ask spread

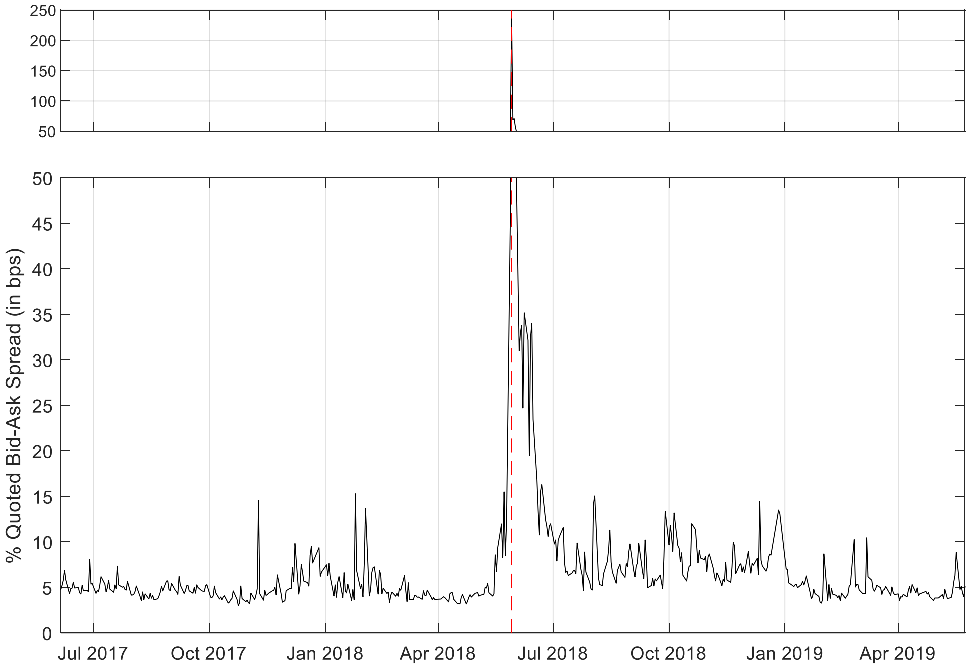

Chart A. Daily (half) bid-ask spread quoted on the MTS market every 5-minutes and then averaged along the trading day (from 10:00 to 17:00); it refers to the 10-year notes and is computed as the difference between the best ask and bid price and expressed as percentage of the mid-price (in basis points).

Quoted depth

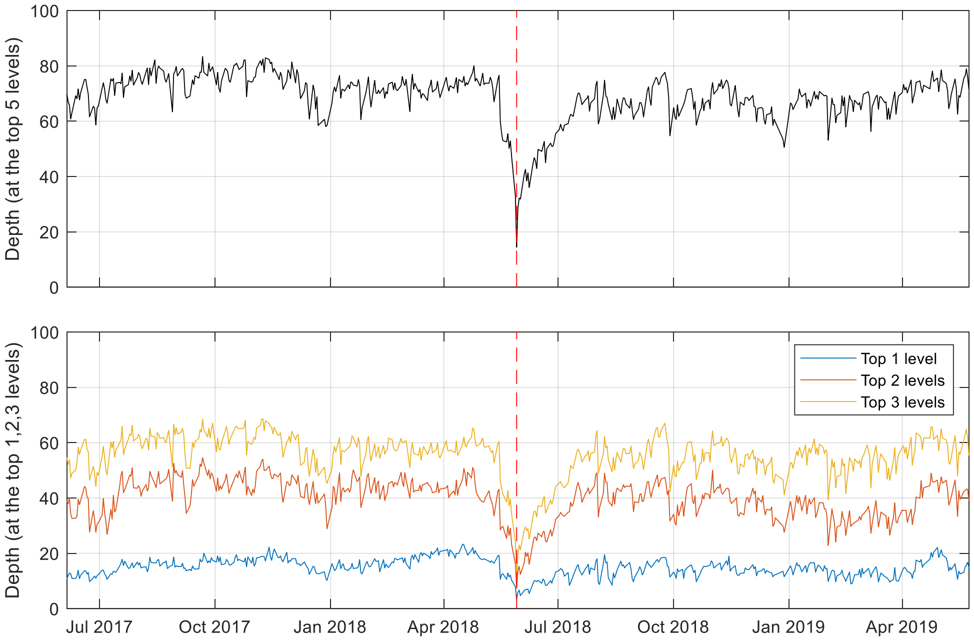

Chart B. Daily quantities quoted for the 10-year notes at the best one, two, three and five levels of the MTS order book. The statistics are computed from five-minute snapshots and then averaged along the trading day (from 10:00 to 17:00). Quoted quantities are the average between ask and bid quotes and are expressed in millions of euro.

Market Turnover and average trade size

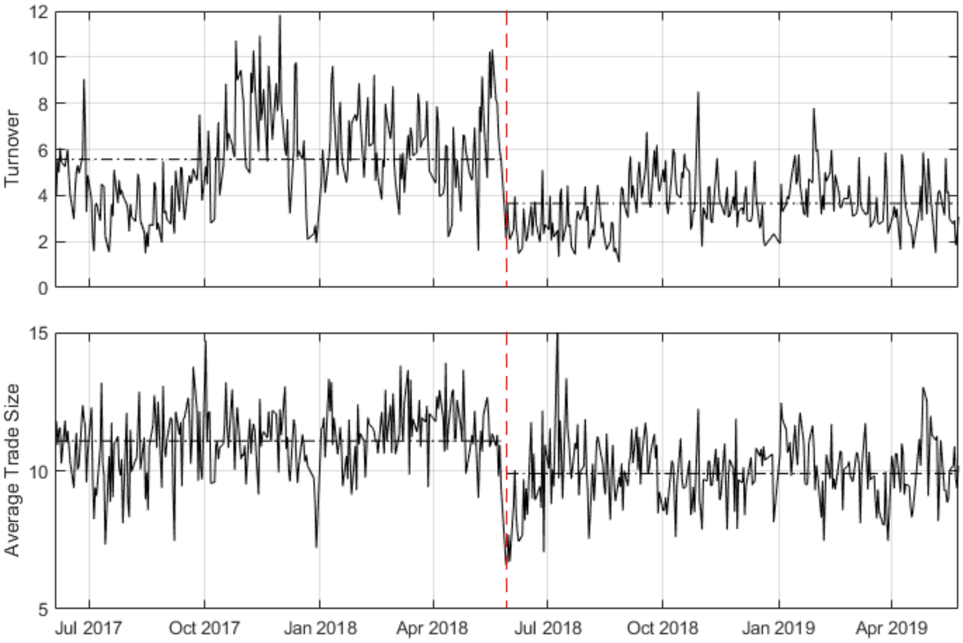

Chart C. Daily market turnover (in billions of euro) and averaged size traded (in millions of euro).

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