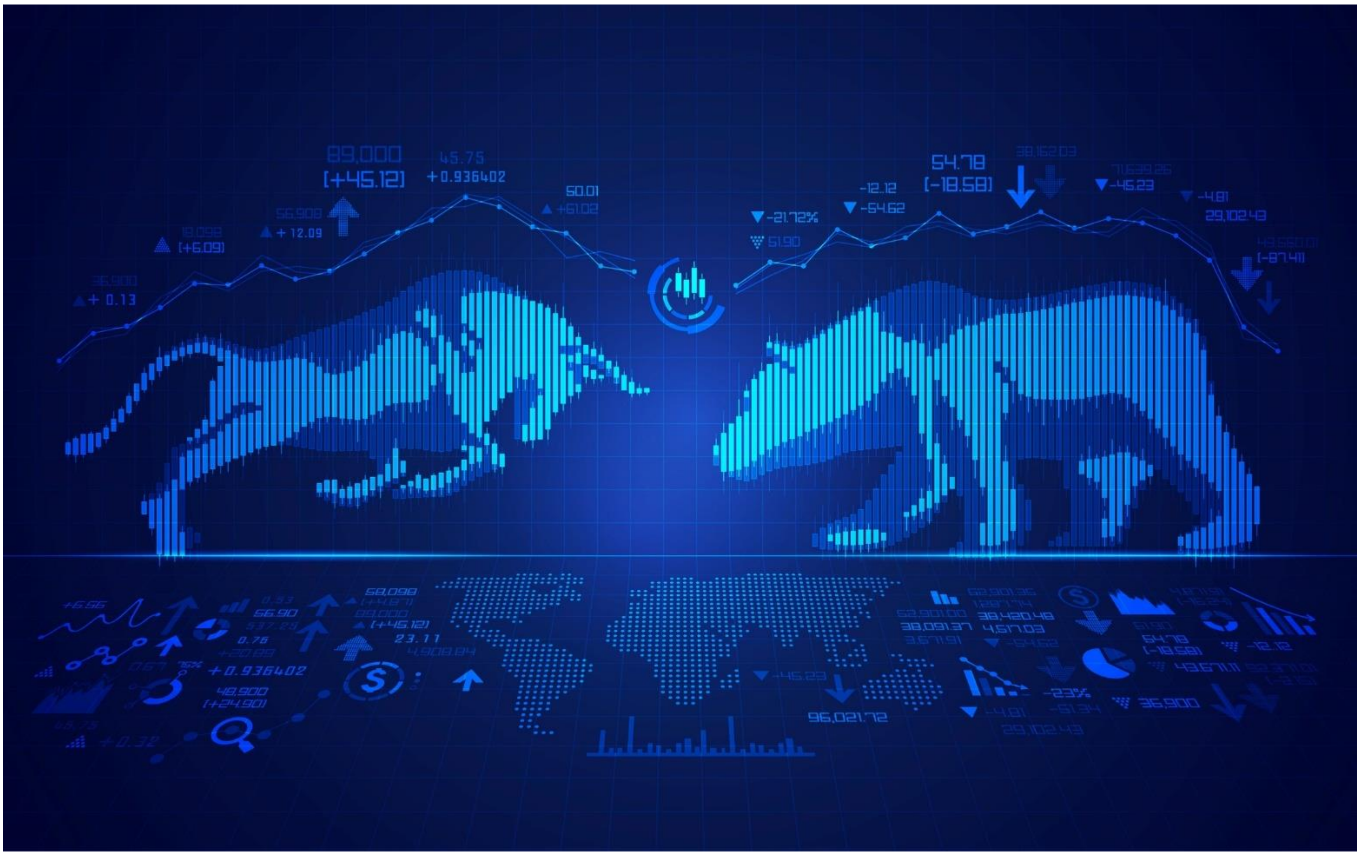
Market microstructure

Electronic markets under the microscope




Sandrine Ungari
+44 20 7762 5214
sandrine.ungari@sgcib.com


Gilles Drigout
+33 1 42 13 74 50
gilles.drigout@sgcib.com

Content

Electronic markets under the microscope

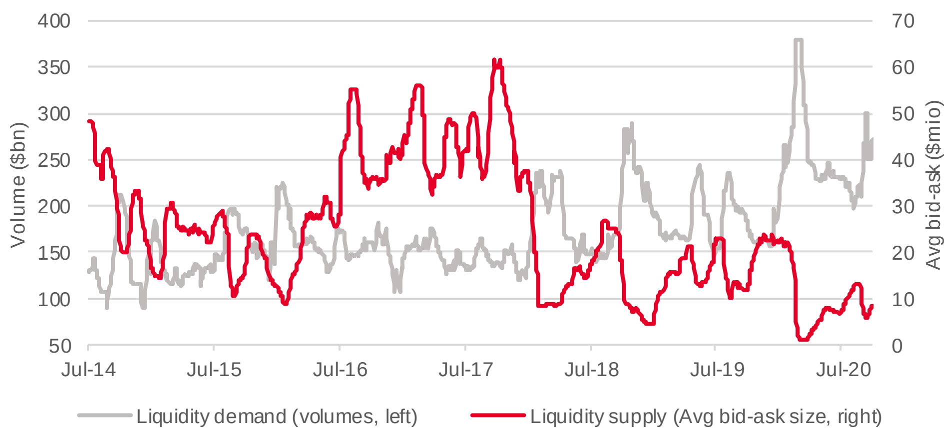
Markets have been proven resilient in the context of a global pandemic that has forced central bankers to resort to unprecedented levels of quantitative easing, year-to-date.

But the new COVID-19 economy has yet to be understood and has already revealed structural changes in the dynamics of risky assets. Global markets have experienced a sharp bear market in March and April of this year, followed by a spectacular recovery. As Gavyn Davies writes in the *Financial Times*: "Any investor who succeeded in navigating both legs of this reversal was either very skilled, or very lucky"[1]. More than ever, understanding the price formation process is key in modern quantitative finance.

Prices moves are the result of a fight between two opposing forces throughout the trading session: the selling flows from the bears fighting the buying flows from the bulls. Trade after trade, prices move in the direction of the stronger camp. In that fight, market makers play the central role of liquidity providers. And their behaviour matters greatly.

March 2020, for example, was characterised by very thin liquidity in very high volumes[2]. Demand from liquidity takers was strong, with high volumes being exchanged every day. But supply by liquidity providers collapsed: the median size available to trade at the prevailing price reached record low levels.

Liquidity supply at a record low in March 2020



Source: SG Cross Asset Research/Cross Asset Quant

The first lockdown measures ignited this now quite common feedback loop: as the demand to trade increases substantially, investors are much keener to execute trades and are far less price sensitive than they usually are. Prices fall and rise in a greater range.

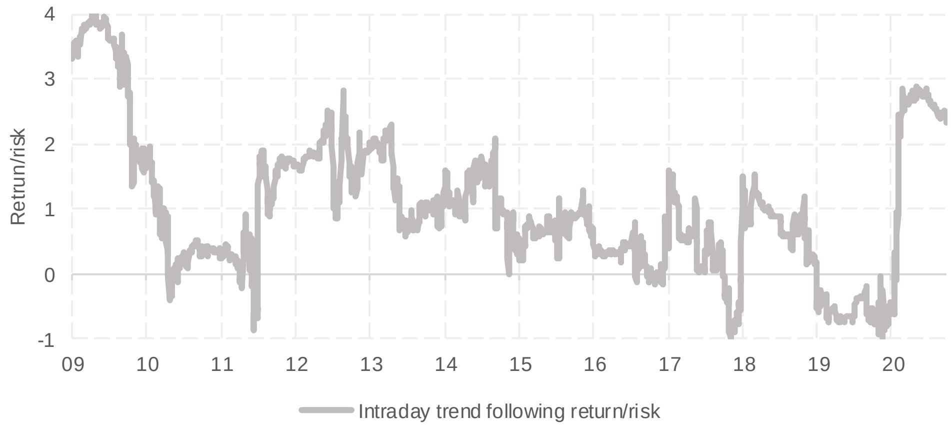
An increase in price volatility generally pushes market makers to reduce the size on offer at or near the fair price as liquidity dries up. And consequently, realised volatility increases even more. In March 2020, realised volatility reached historical levels that had not been seen since September 2008.

[1] https://www.ft.com/content/cd8e2299-161b-4f17-adad-ac6d8a730049

[2] Risk Premia Outlook - The bear necessities, March 2020.

How can investors position for such events? This is a question we addressed last year[3], when we discussed a strategy that tracks intraday trends in liquid future markets. This strategy, the intraday trend following strategy, proved to be very resilient during the March sell-off. It has acted as an effective liquidity crisis hedge.

How to benefit from intraday trends

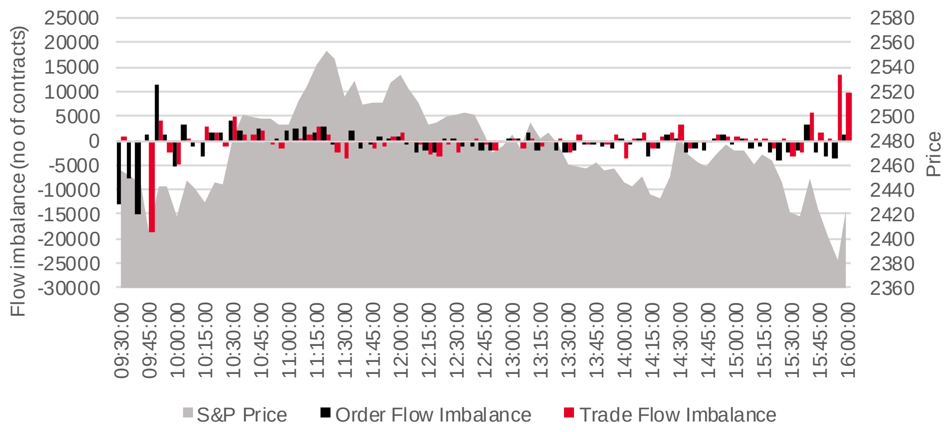


Source: SG Cross Asset Research/Cross Asset Quant

As it turns out, when liquidity is scarce and liquidity takers dominate the trading session, intraday trends are strong. This strategy, which follows the herd of traders, performs handsomely. When liquidity providers dominate, prices trend less during the day. The returns of such a strategy are less appealing. Can investors detect one of those two market regimes?

Trades are only the tip of the iceberg and an important quantity of valuable information lies beneath the surface, at the order book level. Order book information is a highly complex and big data set, which investors can access though data providers or exchanges. We introduce two indicators, the Order Flow Imbalance (OFI) and the Trade Flow Imbalance (TFI), which are calculated throughout the trading day.

Order Flow Imbalances and Trade Flow Imbalances on 23 March 2020



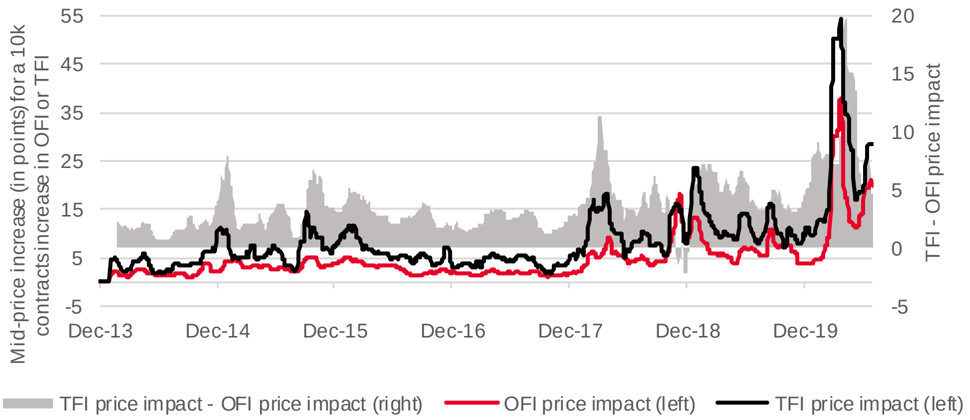
Source: SG Cross Asset Research/Cross Asset Quant

[3] Short-term trend following - How to monetise intraday trading patterns, April 2019

The Order Flow Imbalance measures the imbalances in the order book between supply and demand at the best bid and ask prices. The Trade Flow Imbalance measures the asymmetry between buying flows and selling flows during the trading day. Both indicators are derived using terra-bytes worth of tick data and measure precisely how and why prices are going up or down.

Unsurprisingly, there is a strong relationship between the variation of prices during the day and those two indicators: when the flow imbalances are in favour of buyers, prices are going up and vice-versa. The statistical and linear relationship between the variation of prices and the variations in flow imbalances is called the price impact. The price impact is defined as the coefficient of the regression, where price variation is the dependent variable and the OFI or the TFI are the independent variables.

Historical values of OFI and TFI price impact coefficients



Source: SG Cross Asset Research/Cross Asset Quant

The OFI price impact and the TFI price impact are not constant over time and have become much stronger and much more volatile over the recent past. In addition, trades tend to have a stronger impact on prices, but not always. For example, in December 2018, quotes have had a much bigger impact on prices then trades.

Arguably, in a market dominated by liquidity takers, like in March 2020, trades have a much bigger impact on prices than usual. In a market dominated by liquidity providers, quotes have a bigger impact on prices than usual. If this assumption is correct, the price impacts could be used to decide whether or not to follow trends during the day.

We use these two indicators to forecast the expected return of the intraday-trend strategy. The decision to follow trends intra-day is triggered if the forecasted expected return is positive. Abiding to such a rule does not change the performance statistics of the strategy. Most importantly, it reduces the amount of trades and the associated risks of underperformance.

Statistics (2014-2020)

	Return	Risk	Return/risk	Max Drawdown	Average leverage	Percentage time invested
Unfiltered strategy	3.5%	5.3%	0.67	-5.9%	100%	100%
Filtered strategy	3.4%	5.3%	0.65	-5.5%	42%	80%

Source: SG Cross Asset Research/Cross Asset Quant

The rest of the paper is organised as follows. In a first part, we take a dive deep into the market microstructure and look at how the structure of the order book influences the price formation process. In a second part, we introduce our two indicators, the Order Flow Imbalance (OFI) and the Trade Flow Imbalance (TFI) and we show how that information can be used to better follow the crowd during the trading day.

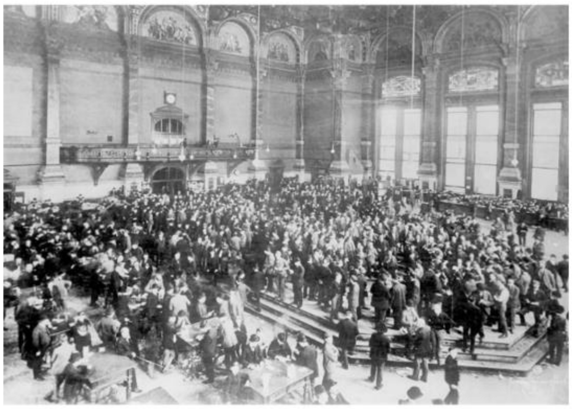
A deep dive into the market microstructure

From open outcry to modern low latency trading

Established in 1848, the Chicago Board of Trade (CBOT) is one of the oldest derivatives exchanges in the world. It began as a non-profit association of US commodities merchants. For the first decade, the CBT served as a meeting place for merchants to discuss commercial agreements and resolve contract disputes. With the exchange of the first forward contracts, participants ensured future delivery of a commodity at a specified price. The emergence of secondary markets for forward contracts soon followed. This was an early form of what became modern futures exchanges.

Traders gathered in a "pit" exchanging contracts in open outcry. Until the late 1880s, exchanges still lacked proper clearinghouses although rudimentary parts of it were already in place. Direct settlements were uncommon. Offsetting purchases and sales between participants were rarely balanced. Brokers gathered in ring settlements to find other brokers who wished to settle open counter-positions and often used runners to search offices and corridors for the counterparties.

Chicago Board of Trade, early 20th century



Source: Encyclopaedia of Chicago

Modern futures markets hardly resemble the late 19th century exchanges. Although open outcry still exists, most of the market activity now takes place on electronic platforms. Market events are timestamped at the microsecond level and fibre-optic cables link high frequency trading (HFT) computers in New York to Chicago's exchanges.

Futures trading is no longer limited to commodities. Trading volumes on financial futures dwarf those of commodities futures. Futures contracts are traded on a wide range of assets from equity indices and Treasury bonds to FX and even cryptocurrencies. And derivatives markets now have a centralised regulator – the Commodity Futures Trading Commission (CFTC). Created in 1974, it oversees all futures contracts traded on US exchanges.

The improvement of trading technology has led to the emergence of High Frequency Trading (HFT) that looks to exploiting arbitrage opportunities at the microsecond level. Whether or not this kind of trading leads to better price efficiency is still a subject of debate but studies have shown that a large proportion of trades occur on behalf of either quantitative funds or HFT participants[4].

What is microstructure exactly and why should we care?

As the etymology of the word suggests, microstructure is linked to the microeconomics of financial markets. But microstructure theory does not limit itself to the most granular interactions. Microstructure theory also provides arguments to explain macroscopic financial events, like the flash crash in May 2010 on the US market[5] and other subsequent crashes in Treasuries futures, in currencies, or other equity markets[6].

Studying market microstructure shows an alternative way to deal with prices and their formation process. Most practitioners in finance adopt a top-down approach to prices, by considering them as inputs. In contrast, microstructure takes a bottom-up view by considering prices as the result of a complex process and by focusing on their underlying mechanics[7].

Researchers in market microstructure usually spend a lot of time on the role that exchanges, and market organisations play in the formation of prices and in the appearance of liquidity and of volatility[8]. They focus mainly – but not only – on key concepts such as the size of a tick, market fragmentation, or the nature of participants.

Market prices for listed assets are not continuous, and the size of a tick is the minimal increment in price for a traded asset. Tick size is a key parameter for modelling the behaviour of intra-day volatility[9]. In practice, the bid/ask spread is proportional to the tick size. The smaller the tick, the higher the incentive for market makers to trade higher volumes. On the other hand, the larger the tick, the more important is the price variation at each trade.

Market fragmentation refers to an asset being traded over competing exchanges and venues. The more venues, the more fragmented the market becomes. A high level of fragmentation is common in the trading of US and European equity single stocks, cash bonds, currencies, as well as cryptocurrencies. The level of fragmentation is of key importance to understand where the liquidity is located and how it changes across time. Listed derivatives markets such as futures and options are not fragmented.

Lastly, the nature of market participants matters. If liquidity providers are in greater numbers than liquidity takers, markets are more liquid. If there is a high level of intermediation, participants trade mainly through brokers, leading potentially to netting at the broker level and less visible liquidity at the exchange level.

For longer term investors, having a better understanding of the market microstructure is well worth the effort: liquidity and volatility transmission mechanisms become clearer as we study their bottom-up formation process. Execution and transaction cost management is now a key component of the success of a systematic investor. Finally, as we will show in the last section

[4] Quants and HFT account for over half of all US equity markets according to Tabb Group and as reported by the FT.

[5] https://en.wikipedia.org/wiki/2010_flash_crash

[6] https://en.wikipedia.org/wiki/Flash_crash

[7] Jean-Philippe Bouchaud, Julius Bonart, Jonathan Donier, Martin Gould - Trades, Quotes and Prices: Financial Markets Under the Microscope

[8] Maureen O'Hara – Market Microstructure Theory'

[9] Sophie Laruelle, Charles-Albert Lehalle - Market Microstructure in Practice

of this document, information obtained during the trading day has a spill-over effect on the following few days.

A keystone of modern markets: the order book

Markets allow two categories of participants with contrary objectives to interact: buyers and sellers. At first, the problem seems unsolvable as buyers want to buy at cheap prices and sellers want to sell at high prices.

Without a third-party arbitrator, it seems doubtful that an optimal trading decentralised process can emerge. The greed of both sides could result in little or even no transaction occurring at all. Even in the early days of open outcry markets certain participants, known as market makers, were responsible of posting buy and sell offers to ensure the prevalence of a two-way markets. But the profitability of such an activity was and still is not guaranteed. To make up for the pitfalls and attract participants, privileges have been granted by exchanges to market makers such as the capacity to execute large orders away from the market or the right to trade in a dual capacity.

In today's markets, the most common organisation is a centralised digital exchange where participants post their trade requests through orders. An order is a commitment to buy or sell a given asset at a given price – or better than the given price – and a specific quantity. Some orders might also include a time horizon for which the order is valid.

Upon its arrival on the exchange, an order is timestamped and processed through a matching algorithm. If the algorithm finds order in the opposite direction that matches the prices and quantity, then the order is executed, and a transaction takes places. If the order cannot be matched instantly it then goes into a public inventory of all unsatisfied orders grouped by direction and price.

That public inventory is called the **limit order book**. It therefore represents, at a given time, the set of unmatched desires to trade, or put differently, the set of all **visible** trading opportunities.

Orders that are matched and executed as they arrive on the exchange are called the **market orders** or **trades**. The remaining ones are called the **limit orders** or simply **quotes**. Besides terminology, these two types of orders reveal a fundamental difference: limit orders add new opportunities to trade in the order book. Market orders do not.

This difference is fundamental and highlights the interplay between liquidity takers and liquidity providers, which we will discuss in greater detail in the following sections.

The case of S&P ES-Mini futures

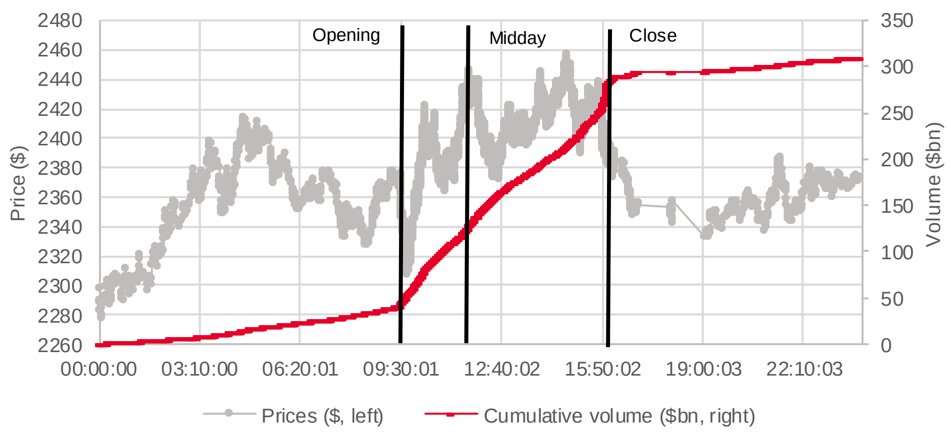
One of the most traded futures in the world is the S&P ES-Mini future. This contract was introduced in 1997 by the CME, when the value of the standard contract on the S&P became too large for small traders. In 2020, the average daily volume traded on this future has been in excess of $200bn in 2020[10].

A day in the life of a trader on the S&P ES-Mini future

The order book contains a wealth of information that can be very useful in understanding liquidity as well as price formation. As an example, below we focus on a trading session and a contract with a particularly high trading volume: the ES-Mini June 2020 futures contract on 19 March 2020.

The following graph shows the price and cumulative volume during that day. We use a sampling method called dollar bars, which consists of snapshotting the prices every time a pre-defined clip of notional is traded. We are using a $50mio notional value and we reduce the dataset from 1 million data points to approximately 6000 data points. This sampling method highlights visually how heterogenous the trading session can be in terms of trading activity.

An heterogenous trading day – the case of 19 March 2020



Source: SG Cross Asset Research/Cross Asset Quant

Trading is generally continuous over a 24-hour periods. On 19 March 2020, $50bn had already changed hands between midnight and 9am. During that particular night, prices moved within a 100 points range from $2300 to $2400. Right after the cash opening auction at 9.30am, futures prices went into a steep rally until midday. An additional $100bn was traded.

After a fast pull-back correction, bulls kept on winning the price battle after a $50bn fight. In the last half hour before the cash closing auction, the market was very tense, and prices were volatile. More than $100bn worth of S&P contracts were being exchanged, leaving the futures price in positive territory for the day by 4:05pm. Then volumes evaporated and prices suddenly dropped to early morning levels. Nevertheless, contracts worth $30bn were still traded between 5pm and midnight.

[10] At the time of writing, the number of contracts traded every day is on average $1.8mio. The contract face value is $3263 and the value of one point is $50. The daily volume in dollar terms is simply the product of those three numbers.

A look at latency

Latency is defined here as the time difference between two consecutive quotes or between two consecutive trades. A small latency between trades tends to happen in markets where the bid meets the ask very fast. A small latency between quotes means that market makers are very active in working on positioning themselves on the order book.

We first investigate the latency of trades over a 24-hour period. Our dataset comprises of quotes and trades on the first limit[11] on the order book. They are timestamped at the millisecond resolution: if successive trades or quotes occur under a millisecond, they will have the same timestamp. As an example, the table below shows a few trades and quotes that happened at 11am on 19 March 2020 for the S&P futures expiring in June (ESM0). At that time within one minute on that particular day, 239 book events happened in the order book.

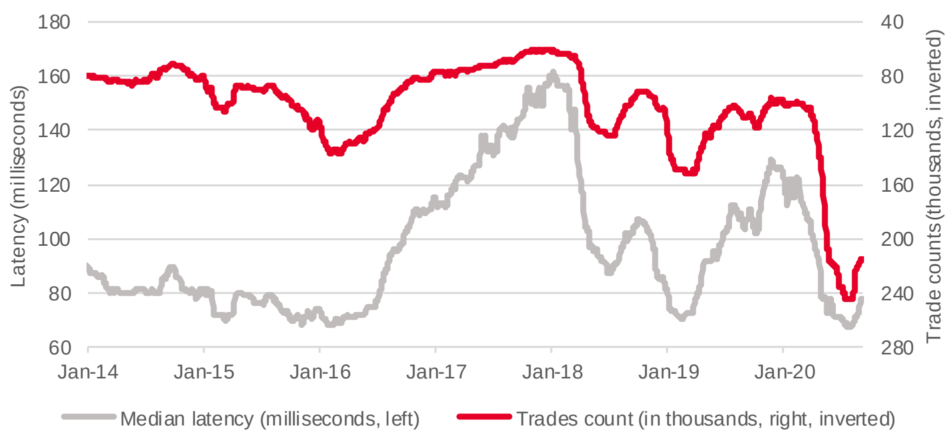
A few trades and quotes at 11am on 19 March 2020

	Best ask size (#contracts)	Best bid size (#contracts)	Deal size (#contracts)	Best bid price ($)	Deal price ($)	Best ask price ($)	Event type
2020-03-19 11:00:00.042000	10	3	3	2411	2411	2411.25	Trade order
2020-03-19 11:00:00.042000	10	8	0	2410.75	2411	2411.25	Limit order
2020-03-19 11:00:00.042000	10	7	0	2410.75	2411	2411.25	Limit order
2020-03-19 11:00:00.042000	10	6	0	2410.75	2411	2411.25	Limit order
2020-03-19 11:00:00.042000	10	5	0	2410.75	2411	2411.25	Limit order
2020-03-19 11:00:00.042000	2	5	0	2410.75	2411	2411	Limit order
2020-03-19 11:00:00.042000	2	4	0	2410.75	2411	2411	Limit order
2020-03-19 11:00:00.042000	2	4	2	2410.75	2411	2411	Trade order
2020-03-19 11:00:00.042000	11	3	0	2410.75	2411	2411.25	Limit order
2020-03-19 11:00:00.047000	11	3	1	2410.75	2411.25	2411.25	Trade order
2020-03-19 11:00:00.047000	10	3	0	2410.75	2411.25	2411.25	Limit order
2020-03-19 11:00:00.047000	10	4	0	2410.75	2411.25	2411.25	Limit order
2020-03-19 11:00:00.047000	10	5	0	2410.75	2411.25	2411.25	Limit order

Source: SG Cross Asset Research/Cross Asset Quant

The following graph shows the median latency as well as the daily count of trades for the most liquid ES-Mini contract. Half of the trades generally occur below 200ms. That is twice as fast as it takes for the average human to blink an eye.

Median trade latency (in milliseconds) and daily trade count for ES-Mini



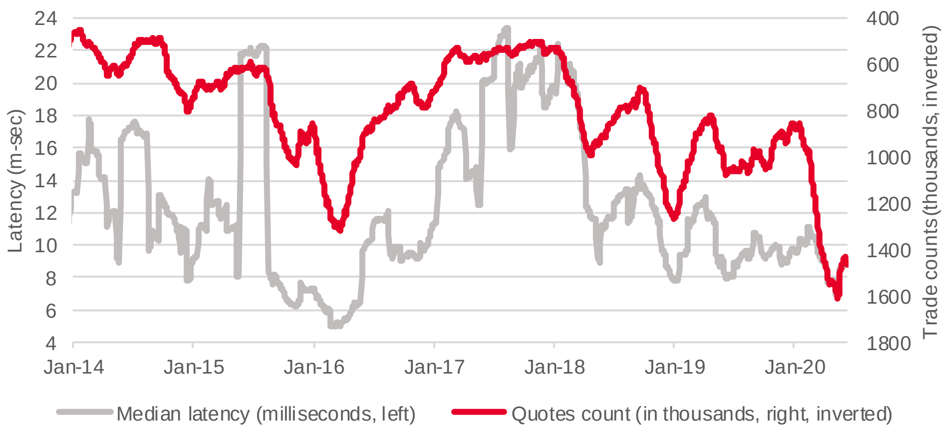
Source: SG Cross Asset Research/Cross Asset Quant

[11] The first limit, or Level 1 trades and quotes, is an order to buy or sell at the best available prices. The higher ranked limits are orders to buy at a higher price or sell at a lower price.

Obviously, the trade latency is related to the number of trades that happen on the market. There has been a sharp decline in the median trade latency (below 120ms) since the VIX crash of 2018 with an associated pickup in the number of daily trades. Over the period, the traded volumes have also had ebbs and flows, but everything else being equal, latency has become smaller and trades more frequent.

Looking at quotes' latency brings an alternative view to the shift in the microstructure. While trades depend on the willingness to exchange assets, quotes depend on the willingness to contribute to the price formation process. Since 2018, half of Level 1 quotes have had a latency of under 10ms and over a million quotes a day has become the norm. This reveals a structural change in how liquidity providers show liquidity: smaller quotes posted more frequently.

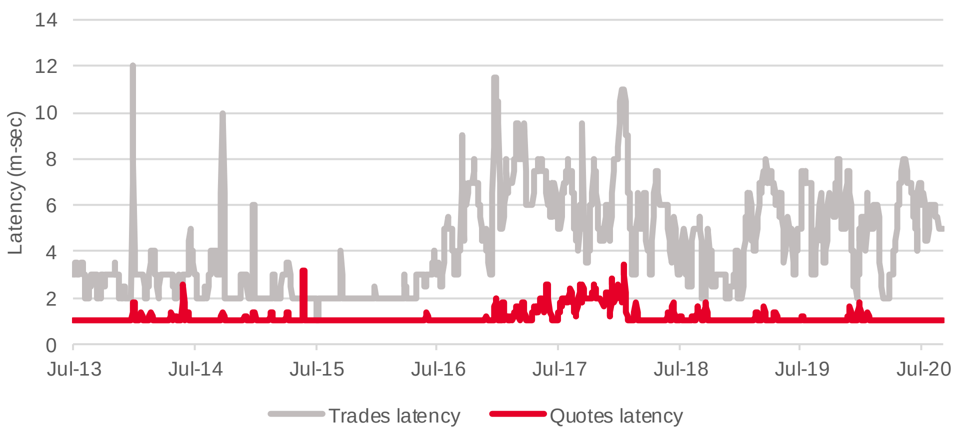
Median quotes latency (in milliseconds) and daily quotes count for ES-Mini



Source: SG Cross Asset Research/Cross Asset Quant

The ultra-low latency orderbook events is defined as the average latency of the lowest quartile of trades and quotes latencies. Ultra-low latency trades occur below 10ms apart and ultra-low latency quotes below 2ms apart. Although beyond the scope of this article, studying below 1ms order book dynamics is an active research field among academics and practitioners.

Ultra-low latencies trades and quotes across time (in milliseconds)



Source: SG Cross Asset Research/Cross Asset Quant

What is liquidity really? How to measure it?

Market orders, a.k.a. trades, and limit orders, a.k.a. quotes, differ mostly in that the former withdraw trading opportunities while the latter increases the set of trading opportunities.

Market order issuers are said to be **liquidity takers**. Limit orders issuers are said to be **liquidity providers**. Market participants who engage into buying or selling a security are generally the liquidity takers. Market makers are generally the liquidity providers. Liquidity could be loosely defined as the set of **current available trading opportunities**.

The complexity of the organisation of the market has blurred the definition and the perception of liquidity. We distinguish two type of liquidity:

There is the **visible liquidity** that can be measured and observed by anyone monitoring the Level 1 trades and quotes. In other words, visible liquidity is the ability to trade a large size close to a perceived fair price of the instrument being traded.

And there is the **hidden or latent liquidity** that will not be visible to most market participants, such as the quotes that exist beyond the first level in the order book, or such as the trades that are netted by market makers without going through the exchange.

Back in the early days of trading floors, market specialists or market makers were privileged participants that had the sole mandate to provide liquidity. Today, limit order books are open to everyone willing to offer or take liquidity by issuing market and limit orders.

This change of organisation is important as it highlights that participants might choose to provide or to take liquidity based on the prevailing market conditions. A market making algorithm can, for instance, temporarily become a liquidity taker if it spots another liquidity provider that shows quotes at attractive levels. When market conditions become very hostile to market making activity, the participants can simply decide to stop their activity and to leave the market with a very thin level of liquidity.

To better understand this, let us investigate the risk profile of a liquidity provider. When liquidity takers favour selling all at the same time, liquidity providers must buy large quantities, which they can off-load only at a later stage. Market making can be relatively costly during a bear run.

For example, in the case of a panic sell-off like in March 2020, sellers are dominating the market. Liquidity providers have a high probability of getting caught in a long position and suffer significant losses. On the contrary, when liquidity takers are split between buyers and sellers, prices tend to revert quickly. Liquidity providers benefit from buying low and selling high.

In order to reduce its risk, the liquidity provider might reduce the number of visible quotes but might still provide large hidden liquidity. This was precisely what occurred during the COVID-19 linked sell-off in March 2020, a topic we will discuss in greater detail in the following section.

The above discussion shows how complex the notion of liquidity is.

First, liquidity is not constant. Modern market organisation tends to exacerbate liquidity crunches. Second, available liquidity can diminish under the effect of liquidity fragmentation, when quotes are more frequent and smaller. Last, the mere definition of liquidity is multifaceted: only the liquidity present on the first level of the order book is observable by most market participants.

We define three indicators to assess the evolution of liquidity and the relative strength of liquidity takers and liquidity providers:

- Liquidity demand: it reflects the liquidity takers activity and it is measured as the total traded volume expressed in dollar terms.
- Liquidity supply: it reflects the liquidity providers activity and it is measured as the average bid and ask sizes from Level 1 quotes expressed in notional terms. It is a proxy for the average instantaneous liquidity, or the average liquidity available on the top of the order book.
- Quote-to-trade ratio: it measures the occurrences of quotes versus trades.

Quant box: Liquidity indicators definition

Liquidity demand:

Let (p_t, s_t) denote the set of deal prices and sizes over some time period (daily in our case) and P the point value of the contract in USD. Then the demand liquidity indicator (in notional terms) is calculated as:

$$Demand = P \times \sum_t p_t \times s_t.$$

Liquidity supply:

Let (a_t, s_t^a) and (b_t, s_t^b) denote respectively the best ask and bid prices and sizes quotes and Q the number of quotes over some time period. Here we use only Level 1 quotes. Then the liquidity supply indicator is expressed as:

$$Supply = \frac{P}{2Q} \times \sum_t (a_t \times s_t^a + b_t \times s_t^b).$$

Quote-to-trade ratio:

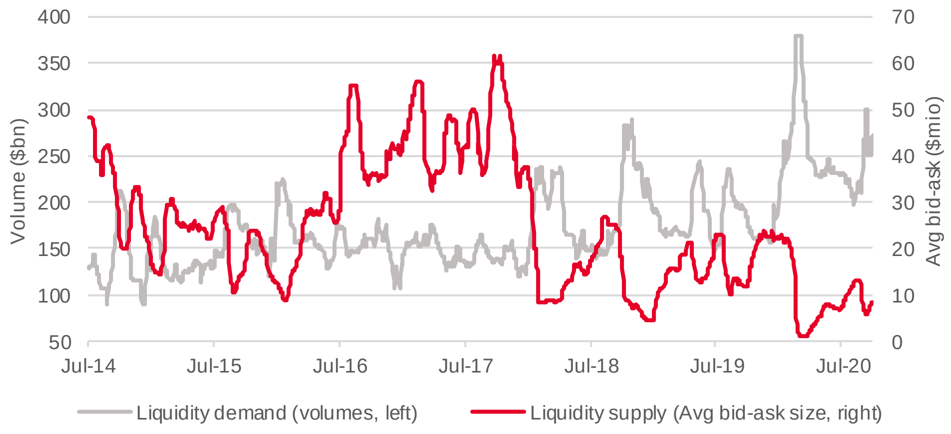
Over a given time period, let Q denote the number of quotes and $\mathcal{T}$ the number of trades. The relative activity indicator is the ratio of the number of quotes to the number of trades:

$$Relative\ Activity = {}^{Q}/_{\mathcal{T}}$$

The COVID-19 liquidity crunch

Liquidity supply and demand come and go as a function of the market environment. A shift towards lower visible liquidity started in February 2018, with the VIX ETNs crash. Several hypotheses could explain it.

S&P liquidity demand and supply



Source: SG Cross Asset Research/Cross Asset Quant

First, regulations post GFC have forced banks to gradually reduce their activities constrained by capital, such as market making. Proprietary trading firms with lower capital provisions partly took over. A combination of consolidation among those firms[12], and potential misfortunes during February 2018 has reduced the number of liquidity providers and increased the market share of those remaining in business. In 2020, it is estimated that the number of market makers shrunk by as much as ten times the number of market makers a decade ago[13].

Second, the dynamics of liquidity has evolved over the past years. Visible liquidity has declined, and arguably has been transferred to the higher levels of the order book. Moreover, the decline of average sizes best offered might also be the result of a more fragmented and lower latency liquidity.

Lower visible liquidity arguably creates a feedback loop on the potential realised volatility, like what investors observed in March 2020:

At the onset of the COVID-19 crisis, the demand to trade increased substantially. Volumes increased up to $380bn per day. Investors were much keener to execute trades and were far less price sensitive than they usually are. Prices started to fall and rise in a greater range.

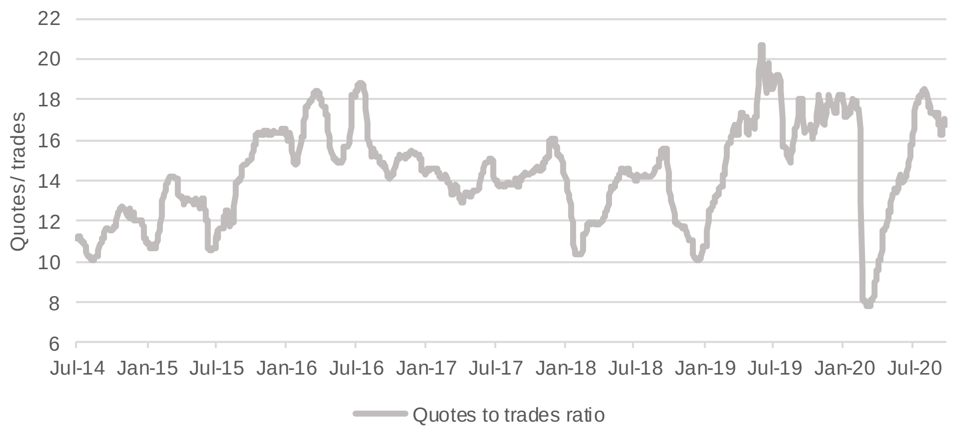
An increase in volatility generally pushes market makers to reduce the size on offer at or near the fair price. In March, the average size on offer collapsed to just $2mio. Liquidity dried up and consequently, realised volatility reached historical levels that had never been seen since September 2008.

[12] https://www.euromoney.com/article/b12xygh1tx5zpw/equity-markets-high-speed-traders-consolidate

[13] https://www.wsj.com/articles/thin-liquidity-in-stock-futures-raises-risk-of-more-wild-market-moves-11583365788?mod=mhp

Conversely, the number of quotes collapsed with respect to the number of trades, as market makers were more busy trading than quoting. Limit orders were updated as frequently as every 7 milliseconds, twice as less as the usual frequency. In times of stress when liquidity takers are under pressure, liquidity fragmentation tends to increase.

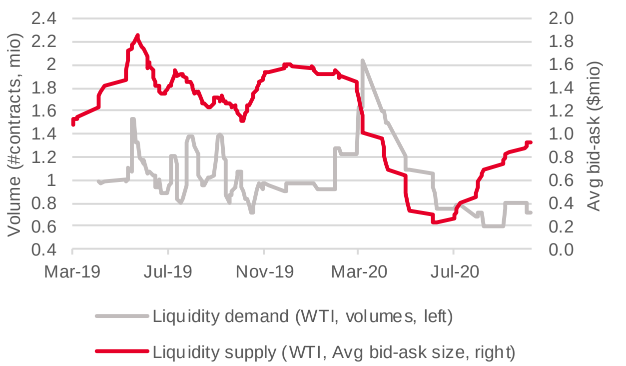
Quotes to Trades ratio versus Quotes Duration, S&P E-Mini futures



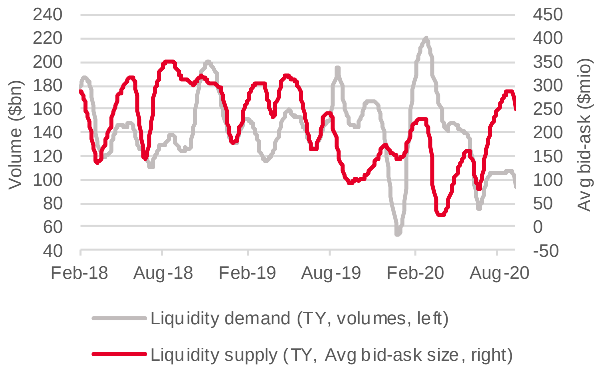
Source: SG Cross Asset Research/Cross Asset Quant

The change of liquidity regime and the amplification of price moves in March 2020 was uniform across assets: in all three major asset classes, equities, rates and commodities, the sell-off was characterised by record high volumes and paper-thin liquidity.

WTI futures supply and demand



US Treasury 10Y futures supply and demand



Source: SG Cross Asset Research/Cross Asset Quant

As we will see in the following section, when liquidity demand is strong versus liquidity supply, intraday prices tend to follow a repeatable trending pattern. Strategies actively following those trends can help investors monetising the pattern and act as an efficient hedge against a liquidity crunch.

Order book information and trading algorithms

Investors can gain access to the order book information though data providers or exchanges themselves. This is a highly complex and big data set. Is there valuable information hidden in this data set?

The following discussion addresses this question in the context of one specific strategy: the intraday trend following strategy[14]. This simple trading rule consists in following trends in prices during the trading day. There is a strong relationship between intra-day trends and price action. And here is why.

Price moves are the result of a fight between two opposed forces throughout the trading session: the selling flows from the bears fighting the buying flows from the bulls. Trade after trade, prices move in the direction of the stronger camp. But trades are only the tip of the iceberg and an important quantity of information lies beneath the surface, at the order book level.

In the following, we analyse the order book events and quantify the imbalance between buyers and sellers. We claim that using order book events data rather than trade-based data has superior explanatory power on contemporaneous short-term price changes and can in turn be used as a trading signal.

Order flow imbalances

High frequency traders are obsessed with measuring the price impact of order book events for a reason as order flows drive the dynamic of price movements.

We now introduce an indicator first described by Rama Cont et al.[15], the order flow imbalance (OFI). This indicator measures the imbalances in the order book between supply and demand at the best bid and ask prices.

Our dataset consists of historical best bid and ask prices as well as the corresponding offered quantities. A change in one of these four inputs results in what is called an order book event. We assume that order book events fall in either one of these three groups:

- **Limit orders addition:** arrival of new limit orders in either side of the book that increases the available liquidity. The arrival of new bid orders is interpreted as an increase in demand, while that of new ask orders as an increase in supply.
- **Limit orders cancellation:** cancellation of limit orders in either side of the book. Cancellation of bid orders is interpreted as a decrease in demand. Cancellation of ask orders is interpreted as a decrease in supply.
- **Market orders:** an effective buy or sell order. These orders take liquidity from the market. A buy order will be executed – at least partially – at the best ask price and a sell order will trade at the best bid price.

[14] Please see the note Short-term trend following – How to monetise intraday trading patterns, April 2019, SG Cross Asset Quant Research

[15] See The price impact of order book events, March 2011, Rama Cont, Arseniy Kukanov, and Sasha Stoikov

Trade data is only a subset of those order book events. In the case of liquid futures markets, quote-based events outnumber trade-based events. This is typical of mature markets with ample liquidity and various market marking participants maintaining large pools of bid / ask quotes.

Following Rama Cont et al., we define the order flow imbalance as an aggregated indicator of supply and demand over a given period. The greater the buying pressure, the more positive this indicator should be and conversely. Here is how it relates to order book events:

1/ The buying pressure increases if demand increases or if supply decreases.

Demand increases either if bid prices increase or bid quantities increase. Buyers are willing to buy at higher prices or want to lift larger amounts.

Supply decreases if ask prices increase or ask quantities decrease. In this case, buyers are lifting the offer, thus taking quantities off the ask side and increasing the seller's prices.

2/ The selling pressure increases if supply increases or demand decreases.

Supply increases either if ask prices decrease or ask quantities increase. Sellers rush in with selling orders at ever lower prices and bigger sizes.

Demand decreases when bid prices head lower or bid quantities decrease. Buyers are retreating with smaller buying orders at lower prices.

The table below summarises these contingent effects.

Anatomy of demand and supply dynamics

	Bid price and/or bid quantity…	Ask price and/or ask quantity…
…increase	Demand increase, buying pressure, OFI up	Supply increase, selling pressure, OFI down
…decrease	Demand decrease, selling pressure, OFI down	Supply decrease, buying pressure, OFI up

Source: SG Cross Asset Research/Cross Asset Quant

Calculating the OFI requires looking at tick data and at the variations of ask and bid prices between two ticks. The OFI indicator is the sum of fours quantities, calculated over a pre-defined time window:

- The quantity offered at the current tick, if the price at the bid increases between two ticks or remains constant,

- Minus the quantity offered at the previous tick, if the price at the bid decreases between two ticks or remains constant,

- The quantity asked at the current tick, if the price at the ask increases between two ticks or remains constant,

- Minus the quantity asked at the previous tick, if the price at the ask decreases between two tick or remains constant.

For those more comfortable with equations, the formula used to calculate the indicator is detailed in the box on the next page.

Quant box: order flow imbalance indicator (OFI)

Given a period of observation $[t, t + \Delta t]$ (usually Δt ranges from a few seconds to a few minutes), we denote by $N(t + \Delta t)$ the number of order book events that occurred in the period.

For each of those events we will denote by P_n^B and P_n^A the best bid and best ask prices and by q_n^B and q_n^A the respective quantities. The order flow imbalance contribution for the nth order event is defined as:

$$e_n = q_n^B \boldsymbol{I}(P_n^B \geq P_{n-1}^B) - q_{n-1}^B \boldsymbol{I}(P_n^B \leq P_{n-1}^B) - q_n^A \boldsymbol{I}(P_n^A \leq P_{n-1}^A) + q_{n-1}^A \boldsymbol{I}(P_n^A \geq P_{n-1}^A).$$

Where $I(E)$ is the identity function of the event E: it is equal to one if the event occurred and it is equal to zero if it did not occur.

All individual contribution are aggregated over the period into the OFI indicator:

$$OFI(t + \Delta t) = \sum_{n=N(t)+1}^{N(t+\Delta t)} e_n.$$

The formula above deserves further explanations. First the indicator is homogenous to a quantity of futures contracts: a positive value of +10 is interpreted as an instantaneous supply impact of ten contracts. Conversely, a value of -10 is interpreted as an instantaneous demand impact of ten contracts.

Second, all these quantities relate to contracts being added / removed from the market. In the case of increasing bid prices, the additive contribution ($+q_n^B$) represents contracts that were added to the market by a buy limit order or by a cancellation of a sell order. Conversely, in the case of decreasing bid prices, the negative contribution ($-q_{n-1}^B$) represents contracts that were taken off the market because of a sell market order or a buy order cancellation.

Last, when prices remain the same, the contribution is equal to the difference in quantities between two consecutive order events. In the case of constant bid prices for instance, the contribution represents what was added by buyers or what was removed due to either a market sell order or a buying order cancellation. The same reasoning applies to ask prices, but with the opposite sign.

Hit the bid, lift the ask

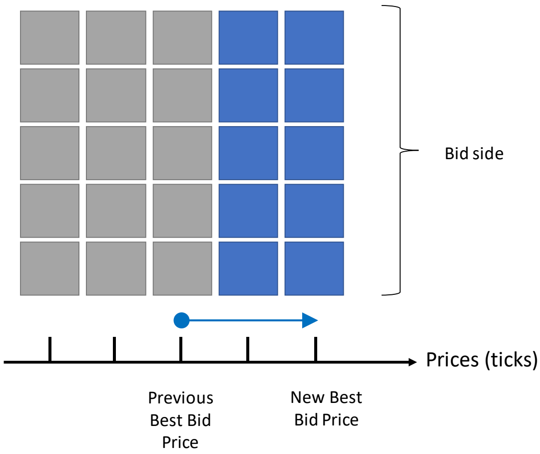
In the present section we follow the approach described by Rama Cont et al[16]. They use a simple deterministic model of the order book to relate OFI levels to price changes.

In their work, the authors assume that all limit levels in the order book have an equal size, or market depth, denoted by D. They also assume limit orders and cancellations to happen only at the best bid price for buy orders and at the best ask price for sell orders. Although simplistic, this model allows to derive deterministic relations between order arrival and best bid / ask prices.

As in the previous section we will discuss in turn the price impact of each order event. For the sake of clarity, we assume in the following the market depth to be $D = 5$ contracts.

- **Limit buy order**: these orders increase liquidity in the order book by adding contracts to the bid side. For instance, if a limit buy order of ten contracts arrives in the order book, the order will move the bid price up $10/D = 2$ ticks. We denote by L^b the aggregate size of limit bid orders over a given period.

Impact of a ten contracts limit buy order: moves the best bid price up 2 ticks

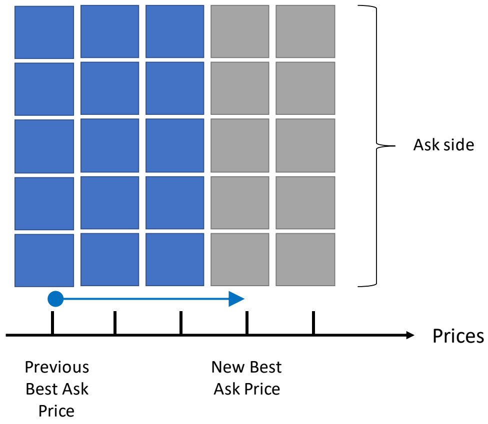


Source: SG Cross Asset Research/Cross Asset Quant

- **Market buy orders:** these orders will lift the ask and be executed at the best ask price, hence removing contracts on the ask side. A market buy order of 15 contracts, for instance, will move the ask price up $\frac{15}{D} = 3$ ticks. We denote by M^b the aggregate size of market buy orders.

[16] See The price impact of order book events, March 2011, Rama Cont, Arseniy Kukanov, and Sasha Stoikov

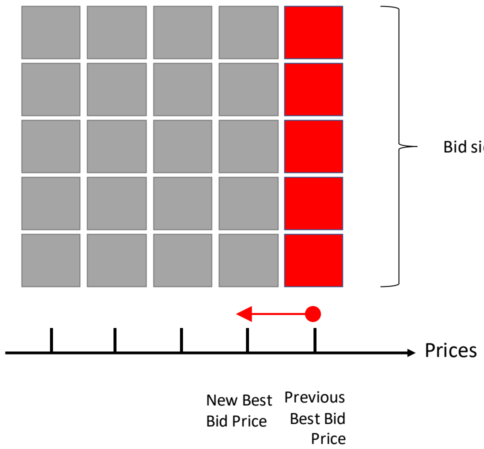
Impact of a 15 contracts market buy order: moves the best ask price up 3 ticks



Source: SG Cross Asset Research/Cross Asset Quant

- **Cancel buy order**: cancellation decrease liquidity by removing contracts from the bid size. For instance, if buy orders for five contracts are cancelled, the cancellation will move the bid price down $-5/D = -1$ ticks. We denote by C^b the aggregate size of cancelled buy orders.

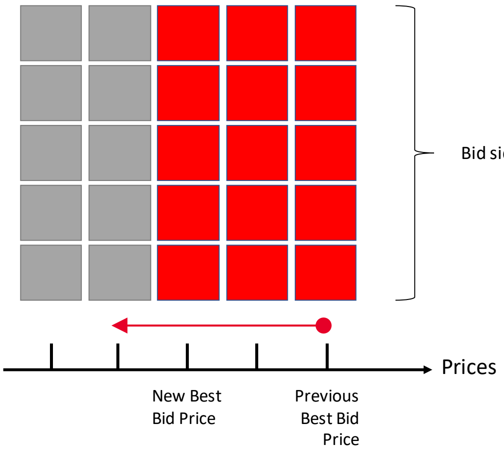
Impact of a five contracts cancel buy order: moves the best bid price down 1 tick



Source: SG Cross Asset Research/Cross Asset Quant

- **Market sell orders:** these orders will hit the bid and be executed at the best bid price, hence removing contracts on the bid side. A market sell order of 15 contracts, for instance, will move the bid price down $-\frac{15}{D} = -3$ ticks. We denote by M^a the aggregate size of market sell orders.

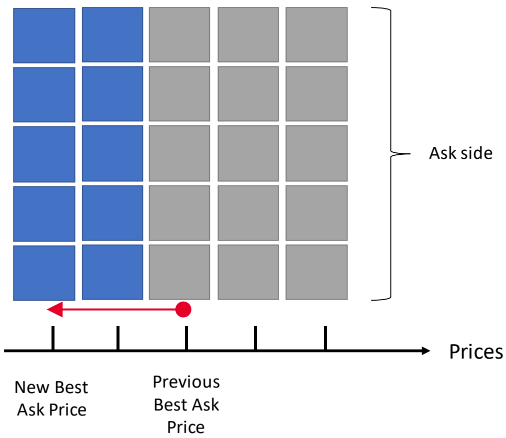
Impact of a 15 contracts market sell order: moves best bid price down 3 ticks



Source: SG Cross Asset Research/Cross Asset Quant

- **Limit sell order**: these orders increase liquidity in the order book by adding contracts to the ask side. For instance, if a limit sell order of ten contracts arrives in the order book. The order will move the ask price down $-\frac{10}{D} = -2$ ticks. We denote by L^a the aggregate size of limit sell orders over a given period.

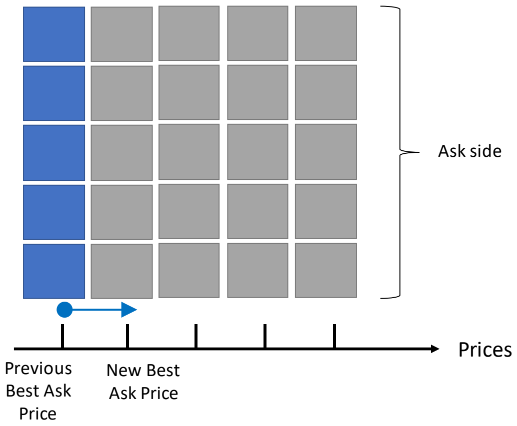
Impact of a ten contracts limit sell order: moves the best ask price down 2 ticks



Source: SG Cross Asset Research/Cross Asset Quant

- **Cancel sell order**: cancellation decreases liquidity by removing contracts from the ask size. For instance, if sell orders for five contracts are cancelled, the cancellation will move the ask price up $5/D = 1$ ticks. We denote by C^a the aggregate size of cancelled sell orders.

Impact of a five contracts cancel sell order: moves best ask price up 1 tick



Source: SG Cross Asset Research/Cross Asset Quant

By aggregating all these contributions, we come up with three equations[17] : one for the change in bid prices:

$$\Delta P^{bid} = \frac{L^b - C^b - M^a}{D}$$

One for the change in ask price:

$$\Delta P^{ask} = \frac{-L^a + C^a + M^b}{D}$$

And one for the mid-price change, defined as the average between the bid price change and the ask price change:

$$\Delta P^{mid} = \frac{L^b - C^b - M^a - L^a + C^a + M^b}{2D}$$

From the discussion in the previous section, by aggregating each event contribution one can show that:

$$OFI = L^b - C^b - M^a - L^a + C^a + M^b$$

Finally, the expression below shows the linear relation between the mid prices change to the contemporaneous OFI:

$$\Delta P^{mid} = \frac{OFI}{2D}$$

In this model, the variations in prices are entirely determined by the order flow imbalances.

[17] In the following three equations, rounding errors may have occurred and are being ignored.

In practice, the assumptions made above on the order book dynamic are not verified. Limit orders and order book depth are of varying sizes. But over short periods of times we might expect these assumptions to hold *on average*. The variation in prices are linearly related to the order flow imbalance:

$$\Delta P^{mid} = \beta^{quotes} \times OFI + \varepsilon$$

The slope coefficient β^{quotes} defines the **OFI price impact**, that is the magnitude of the order book imbalance impact versus short-term price changes. In a later section we will investigate the empirical evidence of this relation using standard linear regression techniques.

A trade-based indicator: the trade flow imbalance

In order to assess the impact of trades and compare it to the impact of quotes on prices we derive an indicator, the trade flow imbalance (TFI), that is solely based on market orders. The TFI is simply defined as the total size of buy orders, minus the total size of sell orders, over a given period.

The events used to calculate the trade flow imbalance are a subset of those used to calculate the OFI. In other words, the OFI includes market orders and quotes events whereas the TFI only includes market order events.

Quant box: trade flow imbalance indicator (TFI)

Given a period of observation $[t, t+\Delta t]$ let $N^{Trade}(t+\Delta t)$ denote the number of market orders (buy or sell) that were issued between t and $t+\Delta t$. The trade imbalance indicator is defined as the difference between the cumulative size of market buy orders and the cumulative size of market sell orders:

$$TI(t+\Delta t) = \sum_{n=N(t)+1}^{N(t+\Delta t)} b_n - \sum_{n=N(t)+1}^{N(t+\Delta t)} s_n,$$

where b_n is the size of the nth buy market order and s_n is the size of the nth sell market order.

Like in the case of quotes price impact, we assess statistically the **TFI price impact**:

$$\Delta P^{mid} = \beta^{trades} \times TFI + \varepsilon.$$

It can be interpreted as the magnitude of the trade imbalance impact versus short-term price changes.

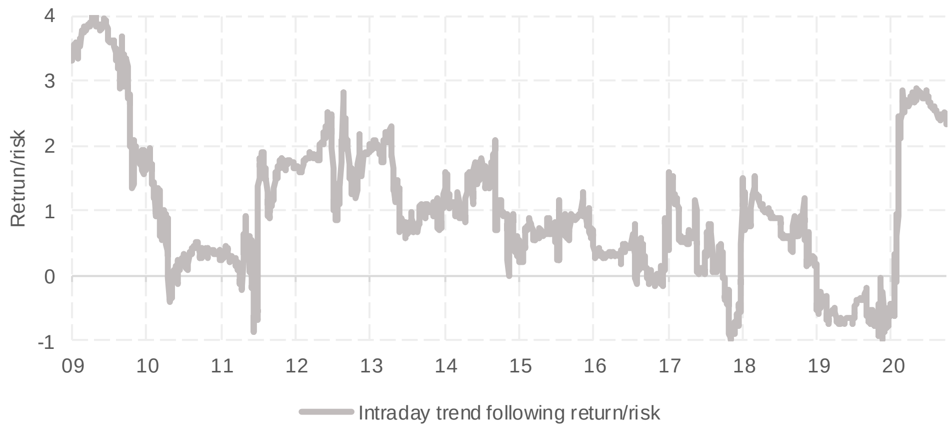
A journey in day trading

Back in April 2019[18], we detailed a simple, yet very useful strategy for day traders, the intraday trend following strategy.

It follows a simple trading rule. A trader starts the day with no position at all and then gradually builds up a position that is proportional to the intraday trend during the trading day. If at any given time in the trading day the current price is high relative to the previous day's close, then a long position is built. Conversely, if the current price is low, then the rule builds a short position. If the market shows no clear signs of a trend then no position is taken. All remaining positions are unwound at the end of the day.

This strategy has performed handsomely recently, but the P&L profile seems to indicate that there are times when this strategy performs, and at other times, when the performance stalls.

How to monetise intraday trends



Source: SG Cross Asset Research/Cross Asset Quant

As detailed previously, the expected return of such a strategy on the S&P is proportional to the level of realised volatility: it tends to perform well in a high volatility regime. In addition, this strategy also acts as a liquidity provider when it unwinds positions at the close just when market participants constrained to trade are taking the opposite position.

[18] See Short-term trend following – How to monetise intraday trading patterns, April 2019

Surfing the liquidity wave

The price discovery process during a trading day is driven by the balance between liquidity providers and liquidity takers. Put in a simplistic manner, liquidity providers are those who issue limit orders and liquidity takers are those who issue market orders. Of course, this is not entirely true as some aggressive limit orders can be treated as market orders.

Market regimes in which liquidity providers dominate are often synonymous with short-term price fluctuations and lower daily volatility. In such environments, no clear price direction emerges and following intra-trends might be costly.

Market regimes in which liquidity takers dominate are often those periods where panic or folly seizes market participants. This is when trends form during the day.

Day traders might want to minimise the cost of trading this strategy in quiet periods and ride the liquidity wave in a turmoil. The rest of this report thus presents a methodology in which to do so.

The indicators

We calculate indicators based on the order book information, which potentially relates to the intraday trend following strategy and could forecast the return of such a strategy.

We test these indicators without prior assumption. We select the ones that explain in-sample a substantial proportion of the daily variation of the strategy performance and exhibit good out-of-sample forecasting properties.

The list of indicators contains more than 250 variations but can be summarised into the following categories:

- Daily observations of OFI price impact and TFI price impact[19] at various snapshot times throughout the day and measured over various time windows. For example, we calculate the mid-price variations between 3.50pm and 3.55pm, as well as the OFI and TFI during the same period. We regress the mid-price variations on the OFI and/or the TFI, using a rolling time window, ranging from five days to 20 days,

- Daily realised volatility of SPX futures at various snapshot timestamps prior to the close and over various rolling windows,

- Daily returns of SPX futures at various snapshot times prior to the close,

- Daily observations of VIX futures prices at the close.

[19] As detailed in the previous section, the price impact is defined as the coefficient of the regression, where prices variation is the dependent variable and the OFI is the independent variable. The trade-based price impact is defined as the coefficient of the regression, where prices variation is the dependent variable and the TFI is the independent variable.

The methodology

We use a simple, yet efficient, two-step methodology to reduce the number of possible indicators.

The first step selects the set of efficient variables using an in-sample performance statistic as outlined below.

We regress the returns of the intraday trend following strategy with the indicators listed above on a rolling window of 20 days. We use 250 univariate models, but also bivariate models with all possible pairs of indicators.

We obtain one regression model per indicator or pair of indicators and for every day of our data sample. We measure the in-sample residual sum of square error (RSS). We select the ten indicators with the lowest average RSS and lowest standard deviation of rolling RSS. The Quant box below details this process.

Quant box: the methodology with equations

Let $\pi(t)$ denote the expected profit and loss of the strategy on a given date t and $X(t)$ the value of one of the indicators. For the sake of simplicity and to avoid overfitting issues, we assume that the daily performance of the strategy and the exogenous indicator relate one to another in a linear fashion:

$$\pi(t) = \gamma X(t).$$

Of course, this relation might always not hold, and the estimation must be done dynamically. Using rolling linear regressions on 20 days windows, we fit the linear model:

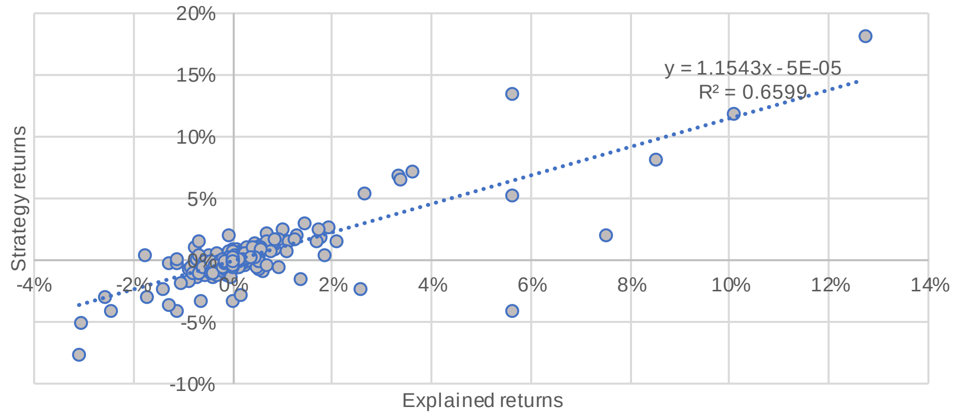
$$\pi(t) = \gamma_t X(t) + \epsilon_t$$

for various indicators and compare their in-sample residual sum of squares (RSS) or rolling windows of $T = 20$ days:

$$RSS(X, t, T) = \sum_{t=0}^{T} (\pi(t-u) - \hat{\gamma}_{t-u} X(t-u))^2$$

This first step selects exclusively bivariate predictors with the OFI price impact and the TFI price impact as top predictors. The graph on the next page shows the average explained cumulative performance for the top ten selected predictors as well as the cumulative returns of the intraday strategy. As it turns out, the top ten indicators explain as much as 65% of the returns of the intraday trend strategy.

Top ten indicators explain 65% of the intra-day trend performance



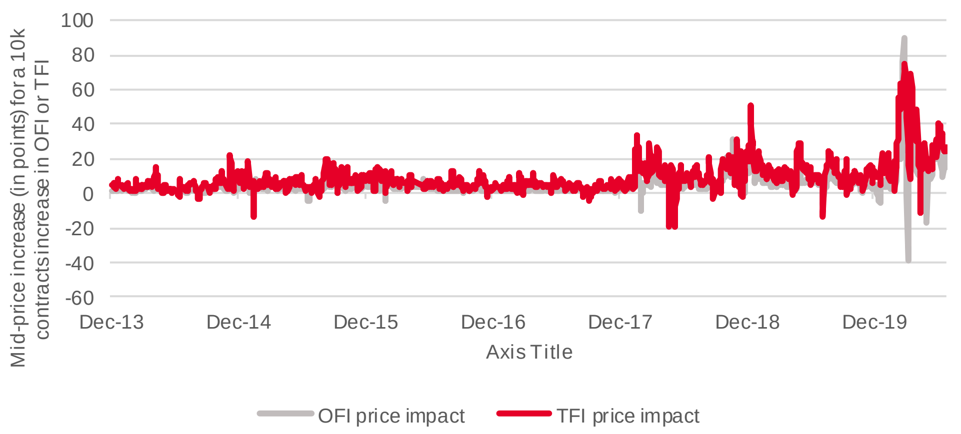
Source: SG Cross Asset Research/Cross Asset Quant

The second step consists in forecasting the expected performance of the intraday trend strategy at the start of the trading day for the next trading session.

From the calculations detailed above, we already know how the P&L of the strategy relates to the OFI and TFI indicators. We now need to forecast those indicators at the start of the trading day, which will then give us an estimate of the expected P&L of the strategy for the next trading session.

Forecasting the TFI and the OFI value accurately is a difficult task as no single time series model is going to exactly capture the dynamics of those indicators. But the historical behaviour of the OFI and TFI hints at a dynamic similar to that of volatility in financial markets. They seem to have fat tails, a positive skew and tend to cluster in a high-level and a low-level regime.

Historical values of OFI and TFI price impact



Source: SG Cross Asset Research/Cross Asset Quant

Classical statistical Dickey-Fuller tests do not reject stationarity at the 5% level for both OFI and TFI historical price impacts. ARMA[20] models are therefore well suited to model the OFI and TFI indicators.

An ARMA model is a time series model that combines both an auto regressive (AR) model and a moving average (MA) model. The AR part accounts for the linear dependence of the variable X_t to its past values $X_{t-1}, X_{t-2}, ..$ The MA part accounts for long-term memory of past unpredictable shocks. The ARMA fitting procedure is as follows: we select a set of rolling time windows from five days to 20 days. For each of the time window we calibrate an ARMA model[21]. We then average the forecasts across the various time windows.

At the end of this calculation, we obtain ten forecasts, one for each indicator that has been selected in the first step described earlier. Those are the indicators that best explain the daily variation on the intraday trend strategy. In turn, these ten forecasts are used to calculate the expected value of the intra-day trend strategy for the next day. These ten expected values are averaged to avoid overfitting coming from a selection bias. That average is our final forecasted return for the intraday trend strategy on the next trading day.

With this expected forecasted return, we filter the strategy by allocating capital to the intraday trend signal the following day when a positive return is forecasted by our model. The graph below shows cumulative risk-adjusted performance for both unfiltered and filtered intraday strategies. Interestingly, the filtered version of the strategy can deliver comparable risk adjusted returns by only trading 80% of the time and at 40% leverage. This significantly reduces costs and operational risks.

Cumulative risk-adjusted performance for filtered and unfiltered intraday trend strategy

Source: SG Cross Asset Research/Cross Asset Quant

Statistics (2014-2020)

	Return	Risk	Return/risk	Max Drawdown	Average leverage	Percentage time invested
Unfiltered strategy	3.5%	5.3%	0.67	-5.9%	100%	100%
Filtered strategy	3.4%	5.3%	0.65	-5.5%	42%	80%

Source: SG Cross Asset Research/Cross Asset Quant

[20] For more, please refer to Ruey S. Tsay - Analysis of Financial Time Series

[21] The ARMA order parameters are set by looking at the historical autocorrelation and partial autocorrelation functions on the whole dataset. We chose a lag of 5 for the AR part and a lag equal to the size of the rolling window for the MA part. Appendix 1 details how order parameters are chosen.

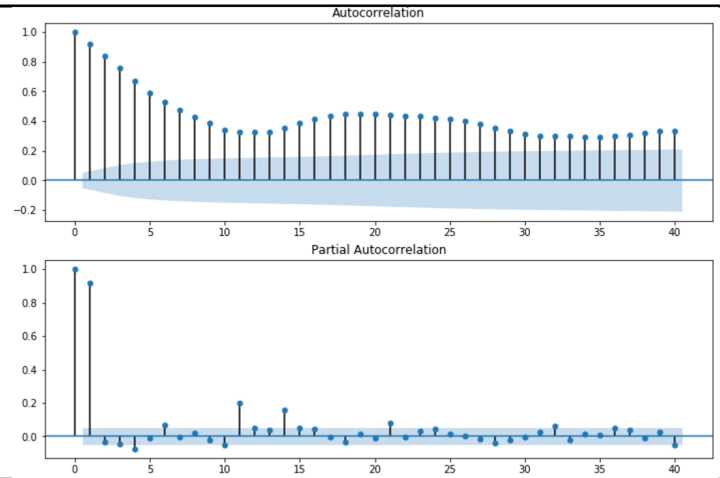
Appendix 1: How to set the order parameter of an ARMA process

Partial autocorrelation helps in setting the auto regressive (AR) order parameter and the autocorrelation function helps set the moving average (MA) order parameter.

The partial auto-correlation function shows the correlation between a series with the residuals of its value linearly explained by its lags. A partial auto-correlation above the confidence-level interval for a given lag denotes an auto-regressive property at that lag. On the following charts, we can see that the lags up to the fifth lag are above the confidence-level interval. We chose an order parameter of 5 for the AR part of the model.

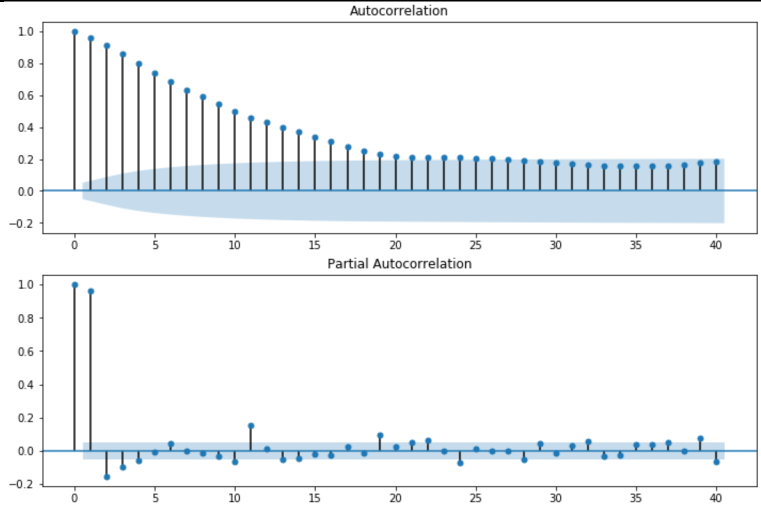
The autocorrelation function looks at the correlation of a series with all its lags (one day, two days etc). When the autocorrelations of a low order are high, this means the values of this series are persistent. For OFI and TFI, the autocorrelation remains significantly positive for higher order lags. These indicators retain a long-term memory of past shocks. We chose an order parameter for the MA part of the model equal to the window on which the model is calibrated.

OFI price impact autocorrelation and partial autocorrelation



Source: SG Cross Asset Research/Cross Asset Quant

TFI price impact autocorrelation and partial autocorrelation



Source: SG Cross Asset Research/Cross Asset Quant

References

Cross-asset quant – research papers

[XQ7] "Remember the last time rates were high? Winter trends 2017", February 2017

[XQ9] "Short-term trend following – How to monetise intraday trading patterns", April 2019

Risk premia

[RP1] 'Risk premia outlook - From too slow to too fast? Factoring in a higher rate world', December 2016

Web resources

[JS20] 'Joseph Santos, South Dakota State University- A History of Futures Trading in the United States',

Books

[JB18] 'Jean-Philippe Bouchaud, Julius Bonart, Jonathan Donier, Martin Gould - Trades, Quotes and Prices: Financial Markets Under the Microscope', 2018

[CL18] 'Sophie Laruelle, Charles-Albert Lehalle - Market Microstructure in Practice', 2018

[AC15] 'Álvaro Cartea, Sebastian Jaimungal, José Penalva - Algorithmic and High-Frequency Trading', 2015

[BJ10] 'Barry Johnson - Algorithmic Trading and DMA: An introduction to direct access trading strategies', 2010

[RT10] 'Ruey S. Tsay - Analysis of Financial Time Series', 2010

[LH02] 'Larry Harris - Trading and Exchanges: Market Microstructure for Practitioners', 2002

[MO95] 'Maureen O'Hara – Market Microstructure Theory', 1995

Academic papers

[ES19] 'Eduard Silantyev – Order flow analysis of cryptocurrency markets', 2019

[RC19] 'Rama Cont, Francesco Capponi - Trade Duration, Volatility and Market Impact', 2019

[JB17] 'Bence Toth, Zoltan Eisler, Jean-Philippe Bouchaud - The short-term price impact of trades is universal', 2017

[RC15] 'Rama Cont, Arseniy Kukanov - Optimal order placement in limit order markets', 2015

[RC14] 'Rama Cont, Arseniy Kukanov, Sasha Stoikov - The Price Impact of Order Book Events', 2014

[RC12] 'Rama Cont, Adrien de Larrard - Order Book Dynamics in Liquid Markets: Limit Theorems and Diffusion Approximations', 2012

[RC11] 'Rama Cont - Statistical Modeling of High Frequency Financial Data: Facts, Models and Challenges', 2011

[JB09] 'Zoltan Eisler, Jean-Philippe Bouchaud, Julien Kockelkoren - The price impact of order book events: market orders, limit orders and cancellations', 2009

[JB09b] 'Jean-Philippe Bouchaud - Price Impact', 2009

[RC08] 'Rama Cont, Sasha Stoikov, Rishi Talreja - A Stochastic Model for Order Book Dynamics', 2008


Global Head of Economics,
Cross-Asset & Quant Research
Kokou Agbo Bloua
+44 20 7762 5433
kokou.agbo-bloua@sgcib.com


Head
Andrew Lapthorne

SOCIETE GENERALE GLOBAL QUANTITATIVE, INDEX AND ETF RESEARCH


Deputy Head
Sandrine Ungari

X ASSET QUANT


London
Head of Cross Asset Quant
Sandrine Ungari
+44 20 7762 5214
sandrine.ungari@sgcib.com


Paris
Olivier Daviaud
+33 142137283
olivier.daviaud@sgcib.com


Paris
Gilles Drigout
+33 1 42 13 74 50
gilles.drigout@sgcib.com


Paris
Abhishek Mukhopadhyay
+33 1 42 13 97 16
Abhishek.mukhopadhyay@ sgcib.com


London
Kunal Thakkar
+44 20 7550 2158
kunal.thakkar@sgcib.com

EQUITY QUANT


London
Head of Equity Quant
Andrew Lapthorne
+44 20 7762 5762
andrew.lapthorne@sgcib.com


London
Georgios Oikonomou
+44 20 7762 5261
georgios.oikonomou@sgcib.com


London
Rui Antunes
+44 20 7762 5875
rui.antunes@sgcib.com


New York
Solomon Tadesse, PhD
+1 2122786484
solomon.tadesse@sgcib.com


Hong Kong
Puneet Singh
+852 21664141
puneet.singh@sgcib.com

INDEX RESEARCH


London
Head of Index Research
John Carson
+44 20 7762 4979
john.carson@sgcib.com


Paris
Yohan Le Jallé
+33 1 42 13 71 61
yohan.le-jalle@sgcib.com


Hong Kong
Pranav Grover
+852 2166 5934
pranav.grover@sgcib.com

ETF RESEARCH


Paris
Head of ETF Research
Sébastien Lemaire
+33 1 42 13 43 46
sebastien.lemaire@sgcib.com


Paris
Laure Genet
+33 1 58 98 44 09
laure.genet@sgcib.com


Bangalore
Lalatendu Khandagiri
+91 80 6731 9333
lalatendu.khandagiri@sgcib.com


Bangalore
Sunil Vaderahalli Dayananda
+91 80 6731 6861
sunil.vaderahalli-dayananda@sgcib.com

Macro & Strategy

Institutional Investor 2020

#3 Multi Asset Research
(#1 Alain Bokobza)

#3 Quantitative/Database Analysis
(#3 Andrew Lapthorne)

#1 Index Analysis
(#3 Yohan Le Jalle; #5 Georgios Oikonomou; #8 Sebastien Lemaire)

ANALYST CERTIFICATION

Each author of this research report listed on the cover hereby certifies that the views expressed in the research report accurately reflect his or her personal views, including views about subject securities or issuers mentioned in the report, if any. No part of his or her compensation was, is or will be related, directly or indirectly to the specific recommendations or views expressed in this report.

The analyst(s) who author research are employed by SG and its affiliates in locations, including but not limited to, Paris, London, New York, Hong Kong, Tokyo, Bangalore, Frankfurt, Madrid, Milan, Geneva, Seoul, Warsaw and Moscow

CONFLICTS OF INTEREST

This research contains the views, opinions and recommendations of Societe Generale (SG) credit research analysts and/or strategists. To the extent that this research contains trade ideas based on macro views of economic market conditions or relative value, it may differ from the fundamental credit opinions and recommendations contained in credit sector or company research reports and from the views and opinions of other departments of SG and its affiliates. Credit research analysts and/or strategists routinely consult with SG sales and trading desk personnel regarding market information including, but not limited to, pricing, spread levels and trading activity of a specific fixed income security or financial instrument, sector or other asset class. Trading desks may trade, or have traded, as principal on the basis of the research analyst(s) views and reports.

As a general matter, SG and/or its affiliates normally make a market and trade as principal in fixed income securities discussed in research reports. SG has mandatory research policies and procedures that are reasonably designed to (i) ensure that purported facts in research reports are based on reliable information and (ii) to prevent improper selective or tiered dissemination of research reports. In addition, research analysts receive compensation based, in part, on the quality and accuracy of their analysis, client feedback, competitive factors and SG's total revenues including revenues from sales and trading and investment banking.

IMPORTANT NOTICE: Sections of this publication that are contributed by non-independent analysts should not be construed as investment research as such have not been prepared in accordance with legal requirements designed to promote the independence of investment research. Therefore, even if such sections contain a research recommendation, such sections should be treated as a marketing communication and not as investment research. SG is required to have policies in place to manage the conflicts which may arise in the production of its research, including preventing dealing ahead of investment research.

IMPORTANT DISCLAIMER: The information herein is not intended to be an offer to buy or sell, or a solicitation of an offer to buy or sell, any securities or security-based swaps and has been obtained from, or is based upon, sources believed to be reliable but is not guaranteed as to accuracy or completeness. Material contained in this report satisfies the regulatory provisions concerning independent investment research as defined in MiFID. Information concerning conflicts of interest and SG's management of such conflicts is contained in the SG's Policies for Managing Conflicts of Interests in Connection with Investment Research which is available at https://www.sgmarkets.com/#/compliance/equity or https://www.sgmarkets.com/#credit/compliance SG does, from time to time, deal, trade in, profit from, hold, act as market-makers or advisers, brokers or bankers in relation to the securities, or derivatives thereof, of persons, firms or entities mentioned in this document and may be represented on the board of such persons, firms or entities. SG does, from time to time, act as a principal trader in equities or debt securities that may be referred to in this report and may hold equity or debt securities positions or related derivatives. Employees of SG, or individuals connected to them, may from time to time have a position in or hold any of the investments or related investments mentioned in this document. SG is under no obligation to disclose or take account of this document when advising or dealing with or on behalf of customers. The views of SG reflected in this document may change without notice. In addition, SG may issue other reports that are inconsistent with, and reach different conclusions from, the information presented in this report and is under no obligation to ensure that such other reports are brought to the attention of any recipient of this report. To the maximum extent possible at law, SG does not accept any liability whatsoever arising from the use of the material or information contained herein. This research document is not intended for use by or targeted to retail customers. Should a retail customer obtain a copy of this report he/she should not base his/her investment decisions solely on the basis of this document and must seek independent financial advice.

The financial instruments discussed in this report may not be suitable for all investors and investors must make their own informed decisions and seek their own advice regarding the appropriateness of investing in financial instruments or implementing strategies discussed herein. The value of securities and financial instruments is subject to currency exchange rate fluctuation that may have a positive or negative effect on the price of such securities or financial instruments, and investors in securities such as ADRs effectively assume this risk. SG does not provide any tax advice. Past performance is not necessarily a guide to future performance. Estimates of future performance are based on assumptions that may not be realized. Investments in general, and derivatives in particular, involve numerous risks, including, among others, market, counterparty default and liquidity risk. Trading in options involves additional risks and is not suitable for all investors. An option may become worthless by its expiration date, as it is a depreciating asset. Option ownership could result in significant loss or gain, especially for options of unhedged positions. Prior to buying or selling an option, investors must review the "Characteristics and Risks of Standardized Options" at http://www.optionsclearing.com/about/publications/character-risks.jsp. or from your SG representative. Analysis of option trading strategies does not consider the cost of commissions. Supporting documentation for options trading strategies is available upon request.

Notice to French Investors: This publication is issued in France by or through Societe Generale ("SG") which is authorised and supervised by the Autorité de Contrôle Prudentiel et de Résolution (ACPR) and regulated by the Autorité des Marchés Financiers (AMF).

Notice to U.K. Investors: Societe Generale is a French credit institution (bank) authorised by the Autorité de Contrôle Prudentiel (the French Prudential Control Authority) and the Prudential Regulation Authority and subject to limited regulation by the Financial Conduct Authority and Prudential Regulation Authority. Details about the extent of our authorisation and regulation by the Prudential Regulation Authority, and regulation by the Financial Conduct Authority are available from us on request.

Notice to Swiss Investors: This document is provided in Switzerland by or through Societe Generale Paris, Zürich Branch, and is provided only to qualified investors as defined in article 10 of the Swiss Collective Investment Scheme Act ("CISA") and related provisions of the Collective Investment Scheme Ordinance and in strict compliance with applicable Swiss law and regulations. The products mentioned in this document may not be suitable for all types of investors. This document is based on the Directives on the Independence of Financial Research issued by the Swiss Bankers Association (SBA) in January 2008.

Notice to Polish Investors: this document has been issued in Poland by Societe Generale S.A. Oddzial w Polsce ("the Branch") with its registered office in Warsaw (Poland) at 111 Marszałkowska St. The Branch is supervised by the Polish Financial Supervision Authority and the French "Autorité de Contrôle Prudentiel". This report is addressed to financial institutions only, as defined in the Act on trading in financial instruments. The Branch certifies that this document has been elaborated with due diligence and care.

Notice to U.S. Investors: For purposes of SEC Rule 15a-6, SG Americas Securities LLC ("SGAS") takes responsibility for this research report. This report is intended for institutional investors only. Any U.S. person wishing to discuss this report or effect transactions in any security discussed herein should do so with or through SGAS, a U.S. registered broker-dealer and futures commission merchant (FCM). SGAS is a member of FINRA, NYSE and NFA. Its registered address at 245 Park Avenue, New York, NY, 10167. (212)-278-6000.

Notice to Canadian Investors: This document is for information purposes only and is intended for use by Permitted Clients, as defined under National Instrument 31-103, Accredited Investors, as defined under National Instrument 45-106, Accredited Counterparties as defined under the Derivatives Act (Québec) and "Qualified Parties" as defined under the ASC, BCSC, SFSC and NBSC Orders

Notice to Singapore Investors: This document is provided in Singapore by or through Societe Generale ("SG"), Singapore Branch and is provided only to accredited investors, expert investors and institutional investors, as defined in Section 4A of the Securities and Futures Act, Cap. 289. Recipients of this document are to contact Societe Generale, Singapore Branch in respect of any matters arising from, or in connection with, the document. If you are an accredited investor or expert investor, please be informed that in SG's dealings with you, SG is relying on the following exemptions to the Financial Advisers Act, Cap. 110 ("FAA"): (1) the exemption in Regulation 33 of the Financial Advisers Regulations ("FAR"), which exempts SG from complying with Section 25 of the FAA on disclosure of product information to clients; (2) the exemption set out in Regulation 34 of the FAR, which exempts SG from complying with Section 27 of the FAA on recommendations; and (3) the exemption set out in Regulation 35 of the FAR, which exempts SG from complying with Section 36 of the FAA on disclosure of certain interests in securities.

Notice to Hong Kong Investors: This report is distributed or circulated in Hong Kong only to "professional investors" as defined in the Securities and Futures Ordinance (Chapter 571 of the Laws of Hong Kong) ("SFO"). Any such professional investor wishing to discuss this report or take any action in connection with it should contact SG Securities (HK) Limited. This report does not constitute a solicitation or an offer of securities or an invitation to the public within the meaning of the SFO.

Notice to Japanese Investors: This publication is distributed in Japan by Societe Generale Securities Japan Limited, which is regulated by the Financial Services Agency of Japan. This document is intended only for the Specified Investors, as defined by the Financial Instruments and Exchange Law in Japan and only for those people to whom it is sent directly by Societe Generale Securities Japan Limited, and under no circumstances should it be forwarded to any third party. The products mentioned in this report may not be eligible for sale in Japan and they may not be suitable for all types of investors.

Notice to Korean Investors: This report is distributed in Korea by SG Securities Korea Co., Ltd which is regulated by the Financial Supervisory Service and the Financial Services Commission.

Notice to Australian Investors: For Documents Distributed in Australia by SG Securities (HK) Limited: This document is distributed by SG Securities (HK) Limited, a Registered Foreign Company and Foreign Financial Services Provider in Australia (ARBN 126058688) that is exempt from the requirement to hold an Australian financial services licence under the Corporations Act 2001 ("Act"). SG Securities (HK) Limited is regulated by the Securities and Futures Commission under Hong Kong laws, which differ from Australian laws. The information contained in this document is only directed to recipients who are wholesale clients as defined under the Act.

Notice to Indian Investors: Societe Generale Global Solution Center Pvt. Ltd (SG GSC) is a 100% owned subsidiary of Societe Generale, SA, Paris. Societe Generale SA is authorised and supervised by the Autorité de Contrôle Prudentiel et de Résolution (ACPR) and regulated by the Autorité des Marchés Financiers (AMF). Analysts employed by SG GSC do not produce research covering securities listed on any stock exchange recognised by the Securities and Exchange Board of India (SEBI) and is not licensed by either SEBI or the Reserve Bank of India.