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Describing the dynamic nature of transactions costs during political event risk episodes[a]

Bluford Putnam | **Graham McDannel** | **Mohandas Ayikara** | **Lakshmi Sameera Peyyalamitta**

CME Group, Inc., Chicago, IL, USA

Correspondence
Bluford Putnam, CME Group, Inc., Chicago, IL, USA.
Email: Bluford.Putnam@cmegroup.com

Abstract

Transactions costs as measured by how wide the bid-ask spread expands to execute fully large trades is a dynamically evolving process, especially during political risk event episodes. Our research looks at four case studies of political event risk: The UK "Brexit" referendum of June 2016, the US elections of November 2016, the first round of the French Presidential election in April 2017, and the UK "snap" Parliamentary election in June 2017. Each of these political events represented cases where the date of the event was known while the pre-event expectations were dealing with highly polar possible outcomes. This created the possibility of pre-event bi-modal return expectation probability distributions, which would resolve into single-mode distributions as the outcome become known. We examine second-by-second order book data for the relevant futures products and describe how transactions costs dynamically evolved during the "outcome discovery" period and then the "post-outcome re-balancing" period.

KEYWORDS

bi-modal, event risk, futures, liquidity, options, transactions costs

1 | INTRODUCTION

Event risk comes with special risk management and trading challenges not faced during more typical periods where markets may be volatile, yet in a relatively consistent manner and responding to standard fundamental factors. Our research focuses specifically on event risk of the type where the date of the event is known, yet the outcome is both unknown and likely to display binary characteristics in its impact on market prices. Examples of such events include the UK "Brexit" referendum of June 2016, the US Presidential election of November 2016, the first round of the French Presidential election of April 2017, and the UK Parliamentary "snap" election in June 2017. The UK "Brexit" referendum was a clear binary choice—remain in the European Union (EU) or leave. The US and French Presidential elections, as well as the UK Parliamentary election, offered up nearly polar opposite candidates with very different visions for economic policies, creating the binary outcome risk of the type we are interested in examining.

There are very special challenges for risk managers when faced with political event risk of the type we are studying. Risk managers often build their models starting from traditional assumptions – normal distributions, linear behavior, robust liquidity, narrow bid–ask spreads, no price gaps, stable volatility regime, etc. While these assumptions might work acceptably well during relatively calm periods, when the risks do not require sophisticated management; the traditional assumptions about market dynamics and

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transactions costs can be deadly in an event risk episode. Namely, the potential for binary outcomes can generate pre-event return expectation distributions that are bimodal. Pre-event bimodal expected return distributions cannot be directly or easily derived from traditional market measures of volatility, such as historical standard deviation of returns or even implied volatility from options prices if the underlying option pricing model assumes normal or log-normal return distributions, no discreet price jumps (i.e., continuous prices), and a stable volatility regime (i.e., homoscedasticity), as is common with most basic options pricing models. That is, in event risk cases offering the potential for binary outcomes, the typical assumptions made in traditional trading, risk, and liquidity models do not apply. Indeed, pre-event return expectations may well incorporate nonstandard assumptions such as expectations of nonlinear behavior, non-normal expected return probability distributions, heteroscedasticity (i.e., volatility regime shift), and noncontinuous price behavior (i.e., price gaps or discrete jumps).

Our research motivation is to examine the liquidity and trading challenges when market participants face event risk around known dates with uncertain, yet potentially binary outcomes and where standard market behavior assumptions simply do not apply. Our research contribution is to explore metrics associated with liquidity risk and trading activity that go well beyond looking at trading volume and best bid–ask spread observations, looking deep into the order book to appreciate the evolving nature of transactions costs during a turbulent trading day. Studies, such as Irvine, Benton, and Kandel (2000) and Foucault, Kadan, and Kandel (2005), have examined the cost of a round trip trade using limit order book data. Our approach is to build on their work and try to show how the cost of trading, measured by how deep one goes into the order book (i.e., larger number of price ticks, as one moves deeper into the order book for futures markets), evolves in a dynamic manner during an event risk episode.

We utilize descriptive concepts such as the event "outcome discovery" period, during which market participants evaluate bits of information as they become available in real time to assess the outcome of the event. And then, we consider the "post-outcome rebalancing" period, during which the outcome is now known; however, considerable risk rebalancing and active trading is occurring.

We take specific futures contracts that were in the eye of the storm, so to speak, and describe how the nature of the order book evolved during the 24 hr[1] encompassing both the event "outcome discovery" period and the "post-outcome rebalancing" period. This takes us into the world of high-frequency, big data. Depending on the futures market, there can be over a billion message updates to the electronic order book in a turbulent 24-hr period. We reconstruct the order book to measure, second-by-second, how much transactions costs would need to be paid to execute fully an aggressing "buy" or "sell" trade of a given size. We can look for asymmetries in the order book as well as differences in how markets trade depending on whether one is in the "outcome discovery" period or the "post-event rebalancing" period.

In this study, we first provide a discussion of our research motivation along with a review of the literature that is especially relevant to event risk challenges we want to study. Next, we present our case study examples and offer an intuitive framework to appreciate the challenges posed when the pre-event expected return probability distribution is bimodal. We take as our research examples, the UK "Brexit" referendum of June 2016 focused on the British pound, the US Presidential election of November 2016 focused on the S&P500®, the first round of the French Presidential election of April 2017 highlighting the Euro, and the UK Parliamentary "Snap" election of June 2017 focused on the British pound.

Then, we turn to our empirical work providing practical, descriptive metrics relevant to how markets trade in the period just before and after the binary outcome becomes known. Whatever risk management trading strategy was developed, it means nothing if there is a lack of market liquidity when one needs it. Moreover, since event risk episodes are one-off and distinctly nonsuited for time series analysis, we have adopted a case study approach emphasizing descriptive analytics rather than a hypothesis testing approach.

In the concluding section, we discuss possible future research and explore risk management issues especially related to using options, when certain key underlying assumptions of typical options strategies are materially violated, specifically the assumption of no price jumps or continuous prices.

In anticipation of our closing summary, we have three intuitions related to event risk episodes worthy of consideration and more study:

- Event risk around known dates and likely binary outcomes may create pre-event bimodal expected return distributions that cannot be easily analyzed or directly detected with traditional standard deviation-based observations of historical prices or implied volatility derived from observed options prices.
- The likely existence of pre-event bimodal expected return distributions creates a material expected probability of a discreet price jump once the outcome becomes known.
- Short-dated options with a maturity immediately after the event date are an excellent tool for pre-event risk management. Futures markets offer attractive post-event

risk management and trading opportunities, since the pre-event bimodal expected return distribution immediately reverts to a single-mode expected return distribution once the outcome is known.

Our descriptive empirical work suggested two observations that may also be of interest for future research:

- Transactions costs during several of the event risk episodes we studied changed character as the event becomes known. During the "outcome discovery" period, trading volumes may be quite high even as large orders go deep into the order book. Trading volumes are likely to remain elevated during the event risk day after the outcome is known in the "post-outcome rebalancing" period; however, large orders may require less in transactions costs to be executed fully.
- Transactions costs during some of the event risk episodes we studied appeared to involve meaningful asymmetry in the order book between the buy-side and sell-side transaction costs distributions, which may evolve over the course of a turbulent trading day. Our intuitive (not empirical) interpretation is that the asymmetry is partly driven by the binary-type event risk we are studying. Once the outcome is known, there is typically a big winning side and a big losing side relative to the focus market. The losing side may involve a certain degree of "panic" activity, while the winning side can take their time in assessing the new information.

Not included in this study are other event risk episodes with known dates, such as central bank policy meetings or OPEC meetings, if the meetings are likely to involve key decisions—rates are changed or not, oil production is cut or not, etc—such that the expected outcomes are of a binary nature. There are other types of event risk, such as data releases which typically do not typically involve pre-event binary expectations, or there may occur genuine surprises where neither the date or the outcome or even the event is known in advance—such as a military action, a natural disaster. These types of event risk are not the focus of this study and are sufficiently different in character that our conclusions about "known date, binary outcome" events should not necessarily be extrapolated to them.

2 | REVIEW OF THE LITERATURE

The economic literature studying market liquidity and transaction costs is varied and deep. For our purposes, we note three distinct strands of research that bear on our study of event risk—(i) bid–ask spreads as a measure of transactions costs, (ii) the role of transactions costs in portfolio management, (iii) and the consequences of the shift to electronic trading platforms including availability of big data, the likelihood of time-varying liquidity conditions, and high-frequency trading as one source of liquidity for market participants.

The advent of floating exchange rates in the early 1970s was accompanied by intense interest in the interest rate parity arbitrage relationship among spot and forward exchange rates and the relevant short-term interest rates for each of the two currencies. Path-breaking research into transaction costs and liquidity in foreign exchange markets was conducted by Frenkel and Levich (1975, 1977) in two seminal papers. The first paper explored covered interest arbitrage and looked for the possibility of unexploited profits. Transaction costs and bid/ask spreads play a key role in whether there is the possibility of unexploited profits in foreign exchange spot and forward markets. The second paper looked closely at transactions costs during both tranquil and turbulent periods, a segmentation of market evolution that helped to motivate how we have characterized the different periods inside a turbulent trading day between "outcome discovery" and "post-outcome rebalancing" periods.

Following on the work of Frenkel and Levich, studies from Booth (1984), Clinton (1988), and Black (1991) continued the work of describing the interrelationships in foreign exchange markets between bid–ask spreads and transactions costs. Our study builds on these explorations into bid/ask spreads by going beyond daily data and being able to look past the best bid–ask prices and delve much deeper into the order book. The best bid–ask spreads define the lowest level of the order book; however, the notional value or number of contracts on offer may be quite small, such that large trades would not be able to be executed fully without further penetration of the order book involving wider bid–ask spreads. Nevertheless, the considerable research associated bid–ask spreads has provided motivation to reconstruct the whole order book, to look at its evolution over the course of a turbulent day and to describe transactions cost in terms of how deep an arbitrarily large trade would have had to go into the order book to be executed fully.

When studying the central limit order book, one looks at liquidity proxies. Studies, such as Irvine et al. (2000) and Foucault et al. (2005), among others, have examined the cost of a round trip trade using limit order book data. When traders look at the cost of trading, they are typically focused on the cost of the trade in terms of execution as well as the speed of execution, and how much the market may move during the time it takes to get the trade executed. Electronic trading, as discussed immediately below, has dramatically increased the speed with which one can get the trade executed, so long as one is willing to allow the trade (of a given size) to go deep into the order book.

Our data are based on futures market millisecond trade messaging aggregated into second-by-second time periods for trade execution. We do not attempt in this study simultaneously to measure how fast the price may be moving second by second. In this sense, we are still providing an incomplete picture; however, we want to build on the earlier cost of trading research and try to show how the cost of trading, measured by how deep one goes into the order book (i.e., larger number of price ticks widening the bid/ask spread), evolves in a dynamic manner during an event risk episode.

Another strand of the literature which motivated this research has its roots in the studies of Bertsimas and Lo (1998); Lo, Mamaysky, and Wang (2004); and Cao, Farnsworth, Liang, and Lo (2016). These studies take one into the realm of portfolio management and appreciating the role of transactions costs in the return-generation process. Moreover, these studies highlight the importance of the nature of assumptions one makes inside a portfolio regarding the role of transactions costs—from a simple approach assuming fixed transactions costs to the relevance of more sophisticated notions of how transactions costs may evolve. In our case, our motivation is to describe how transactions costs may evolve intraday during turbulent periods so as to better inform portfolio model builders as to which assumptions about transactions costs are more realistic and critical to the robustness of the risk management model.

The last strand of the research literature providing motivation for our study is focused on the electronification of trading, allowing for big data, time-varying liquidity, and high-frequency trading. For example, the work of Ian Domowitz (2002) focuses on liquidity and transaction costs in electronic markets, recognizing that how liquidity is provided and how it is priced evolves along with the technology of trading—namely the electronification of market activity over the last 20 years or so.

We note that our research in this project is exclusively related to exchange-traded futures using the electronic platform of CME Group, known as GLOBEX. GLOBEX came into existence back in the 1990s, first as an after-hours trading platform to supplement the human trading in the futures pits. By the early 2000s, GLOBEX had evolved into a 24-hr trading platform and electronic volume completely overshadowed human trading in the futures pits. By 2015, trading in most of the futures pits represented <2% of a day's volume, and CME Group moved to close most of its futures pit trading in favor of a one hundred percent electronic market place.

With the advent of mostly or fully electronic market places, the data sets available for liquidity and transaction costs analysis took a great leap forward. Electronification of markets led to new paths of research, including an examination of the time-varying properties of liquidity, as exemplified in the work of Goldreich, Hanke, and Nath (2005). A key contribution to the motivation of our research is the observation that not all data points are created equal, especially when the data points involve intraday patterns. Transactions costs and liquidity are going to be different for time zones, for products, around information flows, etc., and being able to study the time-varying properties of liquidity is critical. Other literature coming from the electronification of markets analyzed the impact on observed volatility, as in Orlowski (2015), which is a closely related topic to our study of liquidity during selected turbulent days.

Finally, we would like to highlight the high-frequency trading research by Menkveld (2013) and Brogaard, Hendershott, and Riordan (2014). Analyzing high-frequency data takes one into a new set of tools and challenges, and this literature is only beginning to scratch the surface of questions that can be asked and how insights can be formulated. The linkage from our examination of turbulent event risk days, and the role of high-frequency traders is key. Some high-frequency trading firms are essentially liquidity providers, leaving many passive orders, at different levels in the order book that are constantly updated and revised. Our research utilizes the concept of aggressing sellers and buyers (i.e., orders that when placed require immediate and full execution) as compared to passive orders, that may in part be provided by some high-frequency trading shops, which effectively make up the order book at any one point in time.

That is, the motivation for our research into intraday transaction costs embodies strands of literature focusing on best bid–ask spreads and then going deeper into the order book, the recognition of the critical role of transaction costs in the returns generated by portfolio management strategies, the observation that liquidity is time-varying, and the evolution to fully electronic markets populated with high-frequency traders. These key aspects of liquidity come together to build the foundation for this descriptive study of transaction costs during political event risk periods.

3 | PRE-EVENT BIMODAL EXPECTED RETURN DISTRIBUTIONS

We have several intuitive expectations about how binary event risk episodes might unfold, based primarily on the work of Putnam (2012) and Karagiannidis and Wilford (2015), both of which suggest the possibility of pre-event bimodal expected return distributions. Specifically, in the case of bimodal pre-event expected return probability distributions, we are especially interested (i) in the potential for price gaps or price discontinuities and (ii) the nature of the price discovery process as new information becomes available during the event "outcome discovery" period. Our perspective is that transactions costs are closely related to these characteristics of event risk episodes. To help frame the issues and before looking at the empirical data, we present a brief recap of the four events we examine in this study.

The **Brexit Referendum** of Sunday, June 23, 2016, provided a very nice case study to illustrate our intuition. Event risk episodes, such as the Brexit vote, are strikingly different from typical trading activity. Prior to the vote, one knew the date of the event but not the outcome, in terms of whether the UK would vote to "Leave" the European Union (EU) or to "Remain" inside the EU. One had to assess the probabilities of which way the binary election results would go. This created what is known in statistics as a bimodel distribution—that is, two rather distinct outcomes with little middle ground. So, before the event, market prices reflected the probability weighted average of either outcome "A" or outcome "B," that is, market prices were stuck in the middle ground. Once the result of the referendum became clear, market prices moved quickly to reflect the ultimate result.

This event risk process is not a surprise, as much as it might look like one. And, understanding the way the statistical probability distribution will shift in event risk—from bimodel before the event to a more normally distributed single mode after the event—should not be a surprise.

Delving deeper into the Brexit case study, as argued by Putnam (2016), we can hypothesize about the before and after probability distributions related to the Brexit referendum. Figure 1 shows the hypothetical "before" picture—prior to the Brexit vote; there were two possible outcomes, with the British pound centered around $1.50/GBP if the outcome was "Remain", and hypothetically centered around $1.32/GBP if the vote was to "Leave." As shown in Figure 2, when it became clear that the vote was to "Leave", the market recentered with a single-mode distribution with a much lower valuation for the British pound.

The actual second-by-second price movements on Friday, June 24, 2016, as the referendum results were digested by the market produced unusual turbulence. Figure 3 shows the prices for the nearby CME British pound futures contract as well as volumes, as the night and day unfolded. There is an extremely critical observation from the second-by-second unfolding of the price discovery process. Namely, there were several distinct price breaks, in this case downwards for the value of the British pound in terms of US dollars, as the referendum results were reported.

The price breaks occurred during what we have termed the "outcome discovery" period. These periods may last several hours or longer, especially in the case of political votes. Early referendum returns in the Brexit case came from two districts in England that highlighted the possibility that the pre-vote opinion polls might have been far off the mark. Later in the evening, the results filled-in across the UK and confirmed the earlier indications that a "Leave" outcome had occurred. As more and more market participants concluded that the vote had gone in the direction of leaving the EU, the British pound, as expected, came under intense selling pressure and experienced, for an overall decline by the close on 27 June of about 7%. The evolution of the British pound (USD per GBP) before and after the referendum is shown in Figure 4.

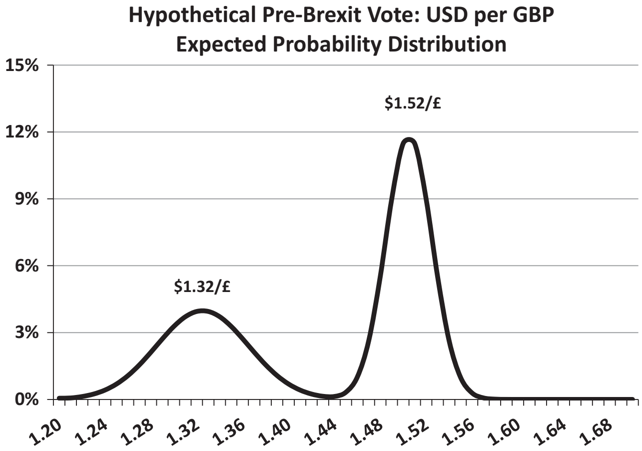

FIGURE 1 Pre-Brexit expected probability

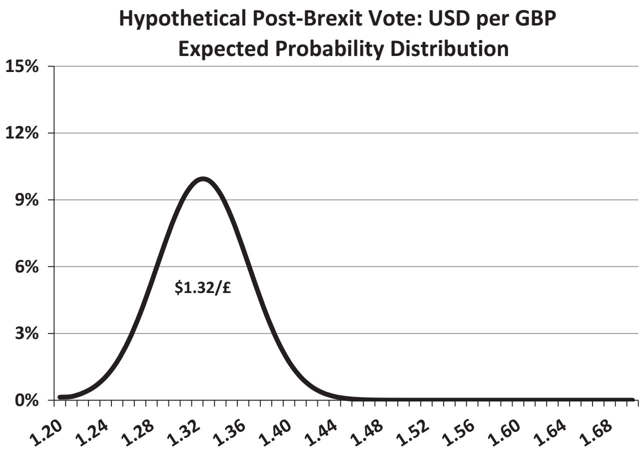

FIGURE 2 Post-Brexit expected probability

The **US Presidential election** of November 8, 2017, had some similar aspects. The two leading candidates from the major political parties were nearly polar opposites, particularly regarding some of the economic policies, such as infrastructure projects and big tax corporate cuts promised by the Republicans and higher taxes on the wealthier individuals promised by the Democrats. On election night, as the early returns were reported and a Republican victory seemed increasingly probable a second line of evaluation came into play. Not only would the Republican Party claim

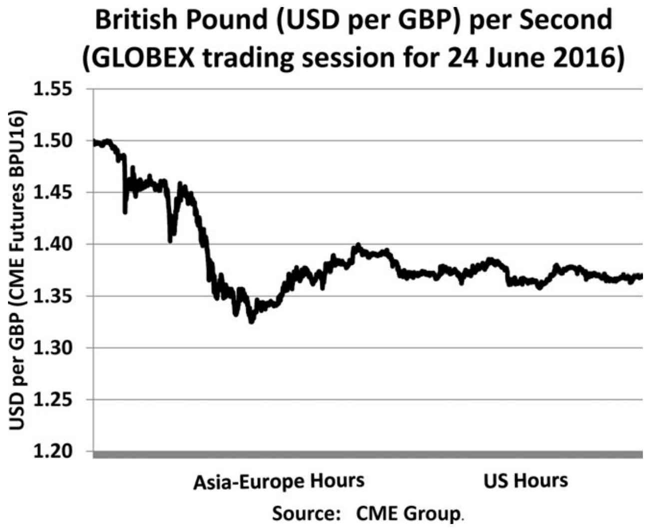

FIGURE 3 British pound on 24 June 2016

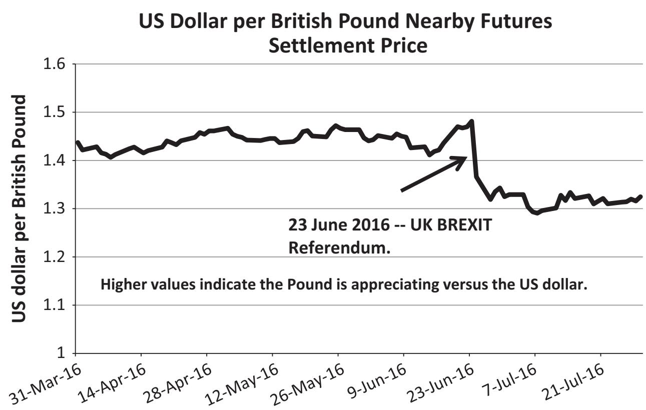

FIGURE 4 UK Brexit referendum

the Presidency; the Republicans would also control the US Senate, which was not necessarily expected, and the House of Representatives, which was expected. The overall outcome with a clean sweep of the Presidency and both Houses of Congress by the Republican Party led many market participants to conclude that the era of Washington gridlock would be over and that tax cut and infrastructure spending legislation might happen sooner and be more aggressive than might have occurred with a divided Congress. This insight drove a sharp turnaround in the S&P500® E-Mini futures contract overnight. As the extent of the Republican sweep became increasingly apparent, sentiment switched from negative to positive, and the S&P500® Index rose rapidly. The evolution of the CME E-Mini S&P futures price is shown in Figure 5 for the time before and after the US election.

Round one of the **French Presidential election** on April 23, 2017, also involved a polarizing binary choice between the National Front Party candidate, promising to

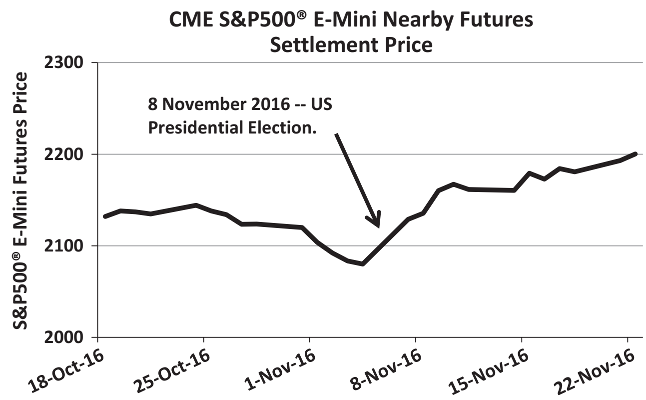

FIGURE 5 US elections

leave the Euro-zone and polling around 25%, versus several middle of the road candidates favoring continued participation in the European Union and polling from the mid-20% to the teens territory. As the evening unfolded and results became known, it was soon clear that the National Front did poorly relative to the pre-vote opinion polls, even though coming in second and earning a spot in the round two runoff Presidential election in early May. With Emmanuel Macron and his newly created party—La République en Marche (Republic on the Move, or REM)—winning the day and having a clear path to victory in the runoff, there was a "relief" rally in the Euro. The evolution of the Euro (USD per EUR) futures price is shown in Figure 6 for the time before and after the French election.

Our last case study involved the **UK Parliamentary election** on June 8, 2017, and the Voters of the UK provided another election surprise, by denying the Conservative Party an outright majority.

When UK Prime Minister Theresa May had called the "snap" election, the Conservative Party held a 20%-plus lead in the opinion polls. P.M. May expected to gain more seats in parliament and a bigger majority, while earning a

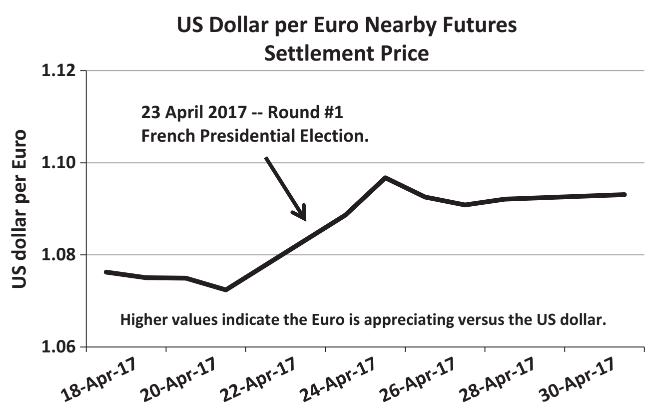

FIGURE 6 French elections

5-year term carrying her Government well past the two-year Brexit negotiations deadline. As the old English proverb goes: "there is many a slip twixt the cup and the lip". The Labour Party gained a net 32 seats, winning in districts formerly held by Conservatives, the Scottish National Party (SNP), and the UK Independence Party (UKIP), and ended up with 262 seats. The Conservatives lost 13 seats, leaving them with only 318 seats, just short of an outright majority, and needing to form a coalition with the Democratic Union Party (DUB) of Northern Ireland and their 10 seats to allow them to govern.

The UK campaign was highly interesting. The Conservatives emphasized "strong and stable" leadership in the person of Theresa May. The Labour Party campaigned on more money for health, for education, and for the police, all to be paid for by higher taxes on upper income Britons. In this sense, the "snap" election was not about Brexit. Indeed, the anti-EU party, UKIP, was wiped out, with Conservatives taking some of those seats and Labour taking some. That is, UKIP, having achieved a "Leave" outcome from the Brexit referendum back in June 2016, lost its *raison d'être*. The election was much more about the age gap —younger voters for Labour, older voters for the Conservatives, austerity versus more social programs, and, with the tragic terrorist violence in Manchester and London in May 2017, the election also turned on domestic security. So, while the election was not fought on Brexit, the outcome was expected to have a huge impact Brexit, and the type of exit that would be negotiated; hence, the British pound was in focus and lost value as the results become known.[2] The evolution of the British pound (USD per GBP) futures price is shown in Figure 7 for the time before and after the UK "snap" Parliamentary Election June 2017.

These four cases involved distinctly different choices, which we have characterized as leading to binary potential outcomes with very critical implications for certain financial markets. To different degrees, all four of these cases "surprised" market participants, in the sense that the pre-event expected probabilities were considerably off the mark, as the pre-vote opinion polls turned out to be extremely inaccurate.

What matters for analyzing this type of binary choice event risk, however, is not that the vote was considered a surprise. Pre-vote the probabilities favored one choice over the other, but the vote was considered likely to be close enough that market participants could not ignore the possibility of the lower probability outcome becoming the actual outcome. Even if the higher probability outcome had won the vote, markets would likely have been quite active, because of the need to "resolve" the pre-vote bimodal return expectations distribution into a single-mode distribution centered around the actual outcome. Thus, there was a very high likelihood of a discreet price gap occurring during the "outcome discovery" period, regardless of the outcome. Most market makers, providing liquidity, were aware of this, and it was to be expected that bid–ask spreads might widen as one moved deeper into the order book. Many option traders knew about the potential for price gapping, too, and some had adjusted their prices pre-vote.[3] Most option traders also knew that a price gap would mean that traditional delta hedging strategies conducted in the futures markets relative to the underlying index for the option would not necessarily work as planned. For these reasons, there was a strong presumption that liquidity costs might be very different between the "outcome discovery" period and the later "post-outcome rebalancing" period. And, by reconstructing the order book and simulating how deep trades go into the order book, we can provide a hypothetical transactions cost metric that allows us to empirically investigate how market trade during a stressful or turbulent event risk period.

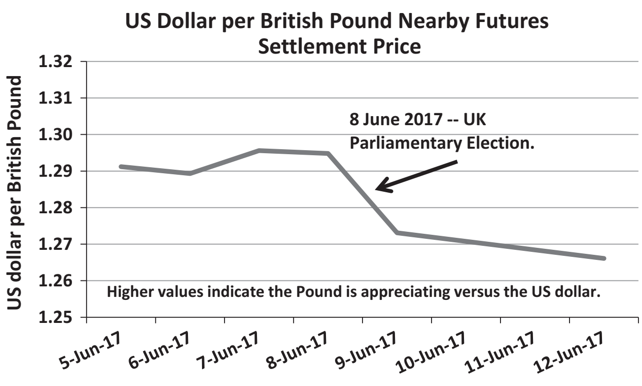

FIGURE 7 UK parliamentary elections

4 | DATA AND CONCEPTS USED IN THE STUDY

This is our initial study using order book data and cloud-based analytics based on products traded on exchanges operated by the CME Group.[4] The GLOBEX electronic trading platform receives a constant flow of "messages" which provide instructions for both passive or resting orders as well as aggressing orders to be executed in full immediately. Billions of messages are received every trading day. Resting orders are placed above or below the current market price, order are pulled, and orders are changed. It is an extremely dynamic process in this age of electronic futures trading.

Typically for descriptive purposes, the order book for CME products is divided into 10 levels, five above the current price and five below the current price. Each level of the order book represents a different number of "ticks" or price increments above or below the current price. A price tick is the size of incremental price movements allowed on a futures exchange. For example, if the tick size is 0.25, then price move from 100.25 to 100.50, and so on. Price tick sizes are different for each product on a futures exchange. This study uses the full set of data based on all messages related to trading orders, with individual orders and quotes at every price level for the given instrument.

A large buy order placed for immediate execution (an aggressing order in our terminology) would first hit the lowest level of the order book, but if it could not be fully executed at that level, it proceeds to the next level (greater number of ticks—higher cost of trading), and so on, until the order was fully executed or the large order had exhausted the order book and could not be fully executed.

Our approach was to aggregate messages by the millisecond and then further aggregate by the second. That is, every message that was received within the millisecond time frame was equal-weighted to create the resting or passive order book for that particular millisecond. The time sequence of the messages received during a given millisecond was not considered.

Lower orders of aggregation, by the minute or hour, are also possible; however, the granularity of the second-by-second approach seemed to yield the most robust description of how the order book was dynamically evolving.

As noted earlier, we focused only on a single product for each of the four election event risk episodes covered in this study. We chose to look at the specific product that had the most price action ahead of the event date that was clearly and directly related to the event in terms of how traders and market analysts were discussing the possible implication of the event, depending on which way the vote went. In some cases, this was an easy choice, such as the British pound for Brexit and the Euro for the French Presidential elections. Other cases, such as the US election was more arbitrary, given that several US equity indices, not just the S&P500® have actively traded futures markets, such as the Dow Jones Industrial Average and the NASDAQ 100. Also, the US Treasury note and bond futures products were extremely active as well during the US election. We chose to study the E-mini S&P500® nearby futures contract, as it was the contract most in the headlines and the spotlight. Future studies could choose to extend to more products. We should note, however, that organizing and processing such large data sets in a cloud environment for a research study of this nature is neither an easy nor inexpensive task. For a commercial enterprise, such as CME Group, the time and manpower assigned to such a study is constrained and focused on the most cost-effective approach that will answer questions which futures market participants desire to better understand regarding the dynamic nature of liquidity during event risk episodes. Over time, and as systems and tools are improved, we expect the costs of research to go down rather dramatically.

We chose to focus on the measure of liquidity related to a variable cost of trading as this was the metric that resonates most closely with market participants based on our experience. Even our definition of costs of trading, focusing on the tick size required to fully execute a given sized trade, is not complete. Traders pay fixed trading fees to the exchange which may vary by the volumes the market participant trades. Other measures of liquidity, such as volume of trades executed per second, answer questions related to activity levels but not costs, so we did not choose to use them in this study. Open interest was also a possible metric for looking at activity; however, it is not particularly useful to describe liquidity or costs of trading. Open interest effectively measures the outstanding number of contracts at any one time, usually the end of the day. Trading activity can destroy (or offset) open interest or create it. Many liquidity providers are extremely active traders, yet because of offsetting trades in a short time frame, these liquidity providers do not hold much open interest.

Our empirical research is largely descriptive. For our empirical observations into event risk, as previously noted, we chose to adopt the case study approach and examine four episodes: the Brexit referendum of June 2016, the US elections of November 2016, round one of the French Presidential election of April 2017, and the UK "Snap" Parliamentary election in June 2017. With Brexit, the market in the spotlight was the British pound. With the US elections, there were several markets in the spotlight, including the Mexican peso, US equities, and US Treasuries; however, we chose the headline S&P500® market to study. With the French elections, we took the Euro as our highlighted market, although French Government bonds were important as well. And for the UK parliamentary election, the British pound was the focus.

Our focus on transaction costs (in terms of price ticks) embodies the following concepts:

- For a given size order (i.e., 100 lots, 10 lots, 3 lots—100 lots is used in this study),
- Executed within a specified time frequency (i.e., second, minute, hour—seconds are used here),
- For a specified time of day (i.e., Asian daytime, European daytime, US daytime, customized time frame—we focus on the Asian & European trading hours, which captures our "outcome discovery" period, and compare that to the regular US trading hours, which captures our "post-outcome rebalancing" period), and
- For a given CME Group futures product (i.e., E-Mini S&P500®, British pound, and Euro are used in this study).

Our work depends on a set of definitions which we introduce to help frame the empirical work.

4.1 | Aggressing buyer

An "aggressing buyer" is one who places a buy order of any type that requires immediate execution and is converted by the electronic platform's trade matching engine into a market order. Given that that the participant is looking to purchase, the order is executed at the relevant ask price or prices available as the order pushing deeper into the book. An "aggressing buyer" is in contrast to a "passive buyer" who has placed an order for fill below the current market price and so the buy order is merely sitting or resting as a bid until triggered by an "aggressing seller".

4.2 | Aggressing seller

An "aggressing seller" is one who places a sell order of any type that requires immediate execution and is converted by the trade matching engine into a market order. Given that that the participant is looking to sell, the order is executed at the relevant bid price or prices available deeper in the order book. An "aggressing seller" is in contrast to a "passive seller" who has placed an order for fill above the current market price, and so the sell order is merely resting as an ask until triggered by an "aggressing buyer".

4.3 | Time aggregation of order book

Every buy or sell order is identified and applied to a reconstructed historical central limit order book. Leveraging the order book, we can derive market health statistics for each change in the order book, millisecond by millisecond. This derived data are equal-weighted to aggregate into a period, such as a second, as in this study. That is, the whole order book (10 levels) is reproduced in second-by-second fashion from the individual updated order book messages placed during that time frame. This is very big data. On a typical day in 2016 (not an event risk episode), for example, there were 2.3 billion messages updating the S&P E-Mini futures order book.

4.4 | Lot size

We are currently testing our methodology with a lot size ranging from 1 to 100 contracts. However, this is an arbitrary size and can be adjusted to represent more typical execution in a given product. For this study, we report only the results for a 100-lot trade, as we wanted to stress test the order book with a large size trade.

4.5 | Order execution simulation

We hit the reconstructed order book with a buy or sell order for the specified lot size for the time duration requested. We measure how many levels of the order book are required to fully execute the order and report the lot quantity-weighted average spread, in ticks, as required to execute the full order. Note that larger orders will typically be subdivided into several parts to be fully executed.

4.6 | ETH versus RTH

ETH refers to non-Chicago hours, effectively Asian and European trading hours, representing our "outcome discovery" period. RTH refers to regular trading hours in Chicago (formerly the "pit" hours) or effectively US trading hours for the "post-outcome rebalancing" period.

4.7 | Aggressing buyers versus sellers

Depending on any asymmetry in the order book, at any given time increment, it may be more favorable to execute a sell order rather than a buy order or vice versa.

4.8 | Big data and the cloud

The quantity of data related to every order placed is enormous. Nano-second-order data are moved to secure and scalable Amazon Cloud servers, where advanced open-source big data tools, such as "Apache Spark", a cluster computing framework, are applied to derive granular statistics in a scalable fashion. For reference, leveraging technology such as this, allows the calculation of these market health statistics on two billion records (the average number of order book records in the S&P E-mini futures complex for a given nonturbulent day in 2016) in a matter of minutes.

5 | DESCRIPTION OF EVOLUTION OF TRANSACTIONS COSTS DURING SELECTED EVENT RISK EPISODES

As discussed, for our four case studies, the event date was known and the outcome discovery period occurred in European or Asian time zone and not in regular US trading hours. Therefore, we look at transaction costs in two periods for each event. Period one is the "outcome discovery" period which for these case studies occurred during Asian and European trading hours. Then, we compare transactions costs to the "post-outcome re-balancing" period. That is, by the US morning the next day, markets were still experiencing elevated trading volumes, but the excitement (if you will) of the "outcome discovery" period had abated. Detailed results for each case are presented in Tables 4-7 below. First we highlight a few items of special interest from our descriptive empirical results.

5.1 | Skewness and kurtosis

For certain cases, we observe considerable skewness and kurtosis in the hypothetical cost to trade, as well as asymmetry between the "outcome discovery" and "post-outcome rebalancing" periods, and between the "winning" and "losing" sides of the trade, as shown in Table 1. That is, the distributions of transactions costs are decidedly not normal or log-normal distributions. And, the distributions can be very different between buy and sell orders and between the "outcome discovery" versus the "outcome discovery" period.

Historical exchange-traded futures and options market size can make a big difference. Three of our focus futures markets are for currencies, and one is the US S&P500® E-Mini equity index futures. The volume in the CME equity index futures markets on a typical day was well over 2 million contracts between January 2016 and June 2017 and was 7 million contracts on the day after the US Presidential election. By contrast, the volume in CME Euro futures and options on a typical day in the January 2016 through June 2017 period was about 250,000 contracts traded, with the day after round one of the French Presidential election seeing about 350,000 contracts change hands. The volume in the British pound futures and options on a typical day in the January 2016 through June 2017 period was about 130,000 contracts, while it soared to 550,000 contracts the day after Brexit and 400,000 the day after the UK Parliamentary election. See Table 2 for the comparative volume data.

That is, the CME equity index futures are a much larger market volume wise than currency futures, by an extremely wide margin, which probably goes a very long way toward explaining why there is considerably less skewness or kurtosis in the transactions costs in the US S&P500® E-Mini equity index futures compared to the currency market cases. By contrast, extreme skewness and kurtosis were observed on the "winning" (or sell the British pound) side of the Brexit case.

Transactions costs were expected to be higher during the "outcome discovery" period compared to the "post-outcome rebalancing" period. This was true for the US Presidential election, French Presidential election, and UK Parliamentary election, but not for the Brexit referendum. In the case of the Brexit referendum, transaction costs were elevated in both periods. The descriptive empirical cost to trade data is shown in Table 3.

TABLE 1 Skewness and kurtosis: "outcome discovery" versus "post-outcome rebalancing" periods

Event and side of trade	Outcome discovery		Post-outcome rebalancing	
	Skewness	Kurtosis	Skewness	Kurtosis
"Winning side of trade"				
Brexit: sell British pound	12.70	773.16	1.78	9.64
US election: buy S&P E-Mini	0.92	1.75	2.04	4.23
French election: buy euro	4.23	77.10	2.87	25.41
UK election: sell British pound	0.74	2.97	4.02	71.95
"Losing side of trade"				
Brexit: buy British pound	1.32	7.55	7.51	82.84
US election: sell S&P E-Mini	0.94	1.78	1.92	3.76
French election: sell euro	3.02	45.83	4.76	52.94
UK election: buy British pound	0.60	0.58	9.56	177.37

Source: CME Group, Economics, and Data Science.

5.2 | Ability to execute fully

For the S&P500® E-Mini futures, even on such a turbulent day, the order book was deep enough to fully execute a 100-lot aggressing buy or sell order. This was not true of the Euro and British Pound current futures market. During the Brexit event "outcome discovery" period, about 50% of the time a British pound 100-lot order could not be fully executed, with the longest consecutive

TABLE 2 Trading volume

Market and event	Contracts traded
CME equity index futures only	
Average daily volume (Jan/2016–June/2017)	2,300,296
US election day (11/9/16)	7,020,510
British pound futures and options	
Average daily volume (Jan/2016–June/2017)	131,478
Brexit (6/24/16)	546,677
UK parliamentary election (6/9/17)	410,664
Euro futures and options	
Average daily volume (Jan/2016–June/2017)	251,761
President election #1 (4/24/17)	353,008

Source: CME Group, Economics, and Data Science.

TABLE 3 Mean cost to trade for a 100-lot fully executed aggressing buy or sell trade

Event and period type	Buy (Ticks)	Sell (Ticks)	Buy minus sell tick difference	Outcome discovery versus post-outcome rebalancing percent difference: buy (%)	Outcome discovery versus post-outcome rebalancing percent difference: sell (%)
Brexit referendum (British pound)					
Outcome discovery	7.52	7.60	−0.07	−3.08	0.63
Post-outcome rebalancing	7.76	7.55	0.21		
US election (S&P500® E-Mini)					
Outcome discovery	2.21	2.21	0.00	67.26	66.32
Post-outcome rebalancing	1.13	1.14	−0.01		
French election (euro)					
Outcome discovery	2.81	2.76	0.06	20.42	19.22
Post-outcome rebalancing	2.29	2.27	0.02		
UK election (British pound)					
Outcome discovery	3.21	3.19	0.02	36.60	30.45
Post-outcome rebalancing	2.22	2.35	−0.13		

Source: Source: CME Group, Economics, and Data Science.

TABLE 4 Brexit

British pound (USD per GBP) CME futures contract maturing September 2016				
	CME globex trading day		24-Jun-2016	
	Regular US hours		Asian/European hours	
	Buy	Sell	Buy	Sell
Size of hypothetical trade				
In lots	100	100	100	100
When full execution can be accommodated by the order book				
Mean cost to trade in ticks	7.758	7.550	7.522	7.597
Median cost to trade	7.363	7.315	7.389	7.375
Standard deviation	3.107	1.650	2.090	2.177
Kurtosis	82.843	9.642	7.550	773.156
Skewness	7.510	1.783	1.325	12.705
When full execution was not possible				
Percent of time	12.43%	11.39%	51.02%	53.68%
Total number of seconds	3,579	3,280	27,550	28,987
Longest continuous period when full execution was not possible in seconds	118	532	271	399

Contract unit is GBP 62,500. Minimum price fluctuation (tick size) is 0.0001 USD per GBP increments ($6.25 USD). Source: CME Group, Economics, and Data Science.

period lasting 399 s for an aggressing sell order. During the French Presidential election event, there were only 77 s during the trading day when a Euro 100-lot order could not be fully executed, with the longest consecutive period lasting just 47 s. During the UK Parliamentary election event, there were only 23 s during the trading day when a British pound 100-lot order could not be fully executed, with the longest consecutive period lasting 22 s. Given the turbulence, these are very short periods for a large order not to be able to be fully executed, and they only occurred in the currency futures markets, not in the much larger equity index market. Moreover, most actual orders in all markets were of much smaller size. Even when a market participant wanted to buy (or sell) a very large quantity, they typically broke the trade into many smaller parts for execution. Tables 4–7, show the detailed descriptive empirical data for each of our four case studies.

TABLE 5 US elections

S&P500® E-Mini cme futures contract maturing December 2016				
	CME globex trading day		9-Nov-2016	
	Regular US hours		Asian/European hours	
	Buy	Sell	Buy	Sell
Size of hypothetical trade				
In lots	100	100	100	100
When full execution can be accommodated by the order book				
Mean cost to trade in ticks	1.127	1.137	2.209	2.207
Median cost to trade	1.000	1.001	2.113	2.103
Standard deviation	0.220	0.224	0.739	0.731
Kurtosis	4.228	3.760	1.750	1.779
Skewness	2.040	1.925	0.921	0.936
When full execution was not possible				
Percent of time	0.00%	0.00%	0.00%	0.00%
Total number of seconds	0	0	0	0
Longest continuous period when full execution was not possible in seconds	0	0	0	0

Contract unit is $50 × S&P 500 index. Minimum price fluctuation (tick size) is 0.25 index points = $12.50. Source: CME Group, Economics, and Data Science.

TABLE 6 French presidential election round #1

Euro (USD per EUR) CME futures contract maturing June 2017				
	CME globex trading day		23-Apr-2017	
	Regular US hours		Asian/European hours	
	Buy	Sell	Buy	Sell
Size of hypothetical trade				
In lots	100	100	100	100
When full execution can be accommodated by the order book				
Mean cost to trade in ticks	2.294	2.274	2.813	2.756
Median cost to trade	2.253	2.220	2.714	2.671
Standard deviation	0.410	0.428	0.649	0.661
Kurtosis	25.407	52.945	77.102	45.833
Skewness	2.872	4.765	4.230	3.023
When full execution was not possible				
Percent of Time	0.00%	0.01%	0.13%	0.14%
Total number of seconds	0	2	69	77
Longest continuous period when full execution was not possible in seconds	0	2	40	47

Contract unit is Euro 125,000. Minimum price fluctuation (tick size) is 0.00005 USD per EUR increments ($6.25 USD). Source: CME Group, Economics, and Data Science.

5.3 | Time-varying transactions costs

As measured by the number of ticks required to execute fully an arbitrarily sized 100-lot trade, transactions costs were time-varying during a turbulent day, such as the US Presidential election event (see Figure 8.) The degree to which transactions costs varied during the "outcome discovery" period appeared to depend on the magnitude of the expected economic impact from the election outcome; although generalizing from a sample size of four episodes is not wise. So, here we just present an illustrating chart of the second-by-second evolution of our

TABLE 7 UK "snap" parliamentary election

British pound (USD per GBP) CME futures contract maturing June 2017				
	CME globex trading day		9-Jun-2017	
	Regular US hours		Asian/European hours	
	Buy	Sell	Buy	Sell
Size of hypothetical trade				
In lots	100	100	100	100
When full execution can be accommodated by the order book				
Mean cost to trade in ticks	2.224	2.352	3.207	3.190
Median cost to trade	2.158	2.298	3.113	3.105
Standard deviation	0.634	0.392	0.655	0.658
Kurtosis	177.371	71.951	0.578	2.966
Skewness	9.563	4.018	0.603	0.741
When full execution was not possible				
Percent of time	0.86%	0.99%	0.04%	0.00%
Total number of seconds	248	286	23	1
Longest continuous period when full execution was not possible in seconds	147	129	22	1

Contract unit is GBP 62,500. Minimum price fluctuation (tick size) is 0.0001 USD per GBP increments ($6.25 USD). Source: CME Group, Economics, and Data Science.

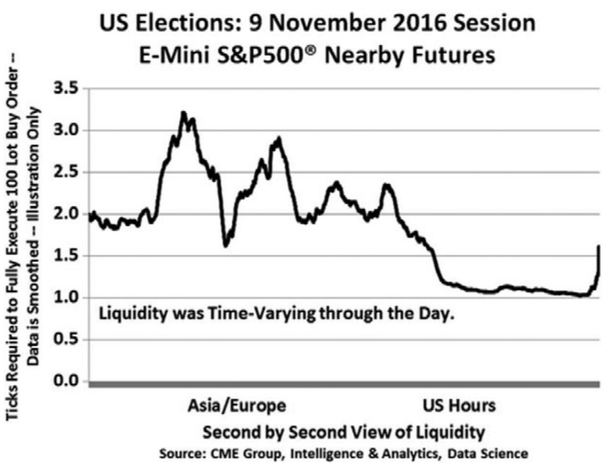

FIGURE 8 E-Mini and S&P futures transactions costs

liquidity metric during one specific, turbulent, event risk trading day.

6 | MANAGING EVENT RISK AND FUTURE RESEARCH

Typical descriptions of hedging activities are much too simplistic for event risk. In a classical hedging example, a farmer plants his crop in the spring, estimates the output for the fall, and hedges a portion of the expected output in the futures market. This is a directional hedge, as the farmer will produce a crop (long the commodity) and want to assure a portion of the expected profit (short the futures). The same type of risk management trades happens in the oil market, where a shale oil producer might see an attractive price, sells the futures along the maturity curve in relation to an anticipated output stream, and then simultaneously puts the rigs in place to extract the oil to deliver against the strip of futures hedges. These are directional hedges, and in most typical circumstances, they are extremely useful and effective for managing directional risks.

Event risk, though, is a more complicated scenario, when not only the direction is uncertain, but there is the likelihood of large price gaps, as suggested by a reasonable possibility of a pre-event bimodal expected return distribution resolving into a post-outcome single-mode distribution. Our view is that there is no one right way to manage political event risk, although one relatively straightforward approach would be to purchase a deep out of the money option, like an insurance policy with a very high deductible. Even with deep out of the money options, though, this approach can appear expensive, so more complex risk management approaches are sometimes worth a look, depending on the magnitude of the risks being taken.

Complex, multileg approaches are advocated by some risk management experts. An example is the "hedging the hedge" approach described by Dave Hightower of the Hightower Report. Hightower (2017) defines hedging the hedge as risk managers "... putting themselves in position to benefit from sudden violent moves in either direction." Whatever one decides to call it, these multileg event risk management approaches generally involve at least three (or more) components—selling a close to the money option to earn a premium, spending part of the premium on buying a deep out of the money option to provide insurance with a high deductible, and adding a small futures position to assist management of the directional component in the event risk. Moreover, these multileg event risk approaches are intended to be dynamic—meaning that as probabilities of outcomes change and prices move, one can decide to lift one or more of the legs, although generally keeping the deep out of the money insurance options. The complexity of these dynamic multileg risk management approaches is merely a reflection of the complexity of event risk.

What is important to remember is that traditional options hedging approaches, such as delta hedging, will fail badly in an event risk episode due to the likelihood of a material price jump, as well as the possibility of heightened transactions costs during the episode and a more permanent post-event shift in the volatility regime.

Turning to future research, the descriptive empirical work illustrated in this study suggests many testable questions. How does liquidity respond around data release times, such as US employment data? How does liquidity respond around scheduled central bank policy meetings? OPEC meetings? Etc. What is clear is that liquidity is not homogenous, not normally or log-normally distributed, and can evolve during the trading data in very different ways depending on the context and how information is released to the market and processed by market participants. When it comes to event risk, particularly, our research suggests that the working assumptions should never be normal distributions, linear processes, smoothly evolving patterns, and no discreet price gaps or pricing discontinuities.

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ENDNOTES

[1] Typically, for most CME Group operated exchanges during weekdays, GLOBEX runs for 23 hr a day, with a one-hour break between 16:00 hr and reopening at 17:00 hr Chicago time. That is, the "Monday" trading session begins at 1600 hr Chicago time on Sunday. For trading hours for specific products, please check the CME Group Web site: http://www.cmegroup.com/trading-hours.html.

[2] The British pound in the months after the Parliamentary election rebounded, as sentiment about the economy and the BREXIT negotiations shifted more positively.

[3] One might look at implied volatilities for options with an option pricing model such as Black-Scholes that assumes there are no price gaps and compare options expiring before and after the known date and then assume the differences may relate to event risk and not volatility shifts.

[4] All data used are commercially available, "depth of book" data, from the Market Data division of CME Group.

ORCID

Bluford Putnam http://orcid.org/0000-0002-0939-9797

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