Corporate Investigations 2020
A practical cross-border insight into corporate investigations
Fourth Edition

Featuring contributions from:

Allen & Overy
Allen & Gledhill
Bär & Karrer Ltd
Beccar Varela
Blake, Cassels & Graydon LLP
Bloomfield Law Practice
Borenius Attorneys Ltd
Byrne and Partners LLP
De Roos & Pen
Debevoise & Plimpton LLP
Dechert LLP
ESENYEL & PARTNERS Lawyers and Consultants
Gilbert + Tobin
Guidehouse
Hammarskiöld & Co
Iwata Godo
Kammeradvokaten/Poul Schmith
LC Lawyers LLP
Lydian
Morais Leitão, Galvão Teles, Soares da Silva & Associados
Morgan, Lewis & Bockius LLP
MZM Legal
Norton Rose Fulbright LLP
Norton Rose Fulbright South Africa Inc
Nyman Gibson Miralis
Pinheiro Neto Advogados
Rahman Ravelli
Solszynski Kawecki & Sziłczak
ŠunjkaLaw
Wikborg Rein
Wolf Theiss
# Expert Chapters

1. France’s CJIP Guidelines Leave Little Doubt That France Will be an Active Player in Global Anti-Corruption Enforcement  
   Roger A. Burlingame, Laurent Martinet, Jacques Sivignon & Karen Coppens, Dechert LLP

   Aziz Rahman, Rahman Ravelli

15. How Can Artificial Intelligence Augment the Investigative Process?  
   Tim Mueller & James Siswick, Guidehouse

21. Asia Pacific Overview  
   Phillip Gibson, Dennis Miralis & Rachel Le Bransky, Nyman Gibson Miralis

---

# Q&A Chapters

28. Argentina  
   Beccar Varela: Maximiliano D’Auro & Rodrigo Allende

35. Australia  
   Gilbert + Tobin: Elizabeth Avery & Richard Harris

44. Belgium  
   Lydian: Jan Hofkens & Yves Lenders

51. Brazil  
   Pinheiro Neto Advogados: José Alexandre Buaiz Neto & Ana Victória Linhares Rezende

58. Canada  
   Blake, Cassels & Graydon LLP: Iris Fischer & Liam Kelley

65. China  
   LC Lawyers LLP: Kareena Teh, Philip Kwok & Catherine Wong

71. Czech Republic  
   Wolf Theiss: Jitka Logesová & Jaromír Pumr

77. Denmark  
   Kammeradvokaten/Poul Schmith: Tormod Tingstad & Martin Sønnersgaard

84. England & Wales  
   Byrne and Partners LLP: Emma Brooks

91. Finland  
   Borenius Attorneys Ltd: Markus Kokko & Vilma Haavisto

97. France  
   Norton Rose Fulbright LLP: Christian Dargham & Caroline Saint Olive

103. Germany  
   Debevoise & Plimpton LLP: Dr. Thomas Schürre & Dr. Friedrich Popp

108. Hong Kong  
   LC Lawyers LLP: Kareena Teh, Alex Mok & Catherine Wong

114. India  
   MZM Legal: Zulfiquar Memon, Parvez Memon & Chirag Naik

121. Japan  
   Iwata Godo: Akira Matsuda & Minako Ikeda

128. Netherlands  
   De Roos & Pen: Niels van der Laan & Jantien Dekkers

134. Nigeria  
   Bloomfield Law Practice: Adekunle Obebe & Solomon Oshinubi

139. Norway  
   Wikborg Rein: Elisabeth Roscher & Geir Sviggum

146. Poland  
   Sołtysiński Kawecki & Szlęzak: Tomasz Konopka

152. Portugal  

158. Serbia  
   ŠunjkaLaw: Tomislav Šunjka

165. Singapore  
   Allen & Gledhill: Jason Chan & Lee Bik Wei

170. South Africa  
   Norton Rose Fullbright South Africa Inc: Andrew Keightley-Smith & Sabeeha Kathrada-Khan

178. Sweden  
   Hammarskiöld & Co: Sandra Kazanova & Nina Sna Karaman

184. Switzerland  
   Bär & Karrer Ltd.: Andreas D. Länzlinger & Sarah Mahmud

192. Turkey  
   ESENYEL & PARTNERS Lawyers and Consultants: Selcuk Esenyel

197. United Arab Emirates  
   Morgan, Lewis & Bockius LLP: Rebecca Kelly & Chris Warren-Smith

204. USA  
   Dechert LLP: Jeffrey A. Brown & Roger A. Burlingame
How Can Artificial Intelligence Augment the Investigative Process?

Guidehouse

Abstract

This article considers possible avenues where the use of artificial intelligence (AI) could improve the effectiveness and efficiency of the investigative process. In addition, we consider some specific applications and regulatory and/or policy encouragement for the use of AI technology in investigations and regulation to determine what role, if any, we should assign to this emerging and maturing technology.

I. Introduction

As Kai-Fu Lee explains in his recent book, AI Superpowers: China, Silicon Valley, and the New World Order, AI and machine learning have moved from the age of discovery to the application and implementation stage. Data scientists have made major leaps in the past decade to get us here. The complex algorithms have been written, the keys to manipulating massive datasets are known, and the technology is universal enough to be applied to a wide array of business problems.

The application of AI is certainly happening all around us. Doctors are using it to more accurately diagnose cancer, Automated Teller Machines (ATMs) use it to determine the hand-written numbers on deposited checks, it is even being used to identify lead pipes in the U.S. state of Michigan, and with increased proficiency, financial institutions are using it to more effectively and efficiently detect financial crime. The potential for application of AI is seemingly limited only by our imagination. Applying AI to everyday business tasks, however, is not without challenges.

As Sebastian Thrun, a founder of Google X and Google’s self-driving car team, said, “Nobody phrases it this way, but I think that artificial intelligence is almost a humanities discipline. It’s really an attempt to understand human intelligence and human cognition.” With this view in mind, this article will explore the possible applications of AI in the context of corporate investigations.

II. Artificial Intelligence — the Basics

Paul Daugherty and H. James Wilson, in their book, Human + Machine, Reimagining Work in the Age of AI, define AI as “systems that extend human capability by sensing, comprehending, acting, and learning.” Technology and advancements in AI continue to improve at an unprecedented rate and scale. In 2018, the AI industry’s total revenue was USD $9.5 billion. By 2025, annual global AI revenue is expected to grow to $118.6 billion. As recently as October, a new leap was made in computer technology when Google built a computer of “quantum supremacy”, which can perform a computation in 200 seconds that would take the fastest supercomputers about 10,000 years to calculate. These advancements have also extended into the specific area of AI known as machine learning (ML), which is by far the most widely used AI in compliance and investigative applications. Traditionally, machine learning is divided into two tasks: unsupervised; and supervised learning.

A. Supervised Learning

Supervised learning is the process by which categorised training data is used to teach a model to make predictions about future data. Supervised learning is widely used across a variety of industries. The ATM example referenced above is an application of ML where the system was trained to use handwritten checks “categorised” by humans with the digital equivalent of the handwritten numbers. Once the model is shown enough handwritten variations of each number and associates it with a digital equivalent, it learns to recognise the “features” that make a hand-written seven a “7” and a handwritten three a “3”. In another example, a photo-forensics expert used millions of indecipherable, pixelated pictures of licence plates to train a model to recognise the digital equivalents. Detectives working on a crime that was unsolved for years suddenly had a new lead – the licence plate number of the car the suspect was driving.

B. Unsupervised Learning

Unsupervised learning is the process where inferences are drawn from uncategorised data to analyse and identify patterns and underlying structures. In other words, an algorithm is trained using information that is neither classified nor labelled, which allows the algorithm to act on that information without guidance or bias. Unsupervised learning algorithms can perform more complex processing tasks than supervised learning systems. One common use of unsupervised learning is to segment or “cluster” a large dataset – for example, a financial institution’s list of customers. The model is also provided input about each customer, such as occupation, address, age, and their transaction activity history. Without the interference of human bias, the model “clusters” the customers based on their behaviour.

III. Investigations — the Challenges

With the understanding of the basic capabilities of AI and ML, we can now look at some of the challenges faced during a corporate investigation to determine whether there could be some application of AI and ML in this space.
Investigations vary in type and complexity. Financial investigations pursue the identification of embezzlement, money laundering, fraud, tax evasion, and other white-collar crimes. With internal cases, the investigator may need to look into employee misconduct like theft, harassment, or substance abuse. An investigator looking for corruption might uncover bribery, illegal foreign exchange, corporate fraud, and industrial espionage.

At the core of an investigation, the investigator typically must demonstrate that: 1) the methodology used to conduct the investigation was sound; 2) that based on the information available, sufficient steps were taken to rule out uncertainty; 3) that all material facts were established, evaluated, and discerned from opinion; and 4) the report or findings of the investigation can be relied on. The success of an investigation almost always hinges on the ability to collect, process, and analyse data.

### A. Collecting ALL the Relevant Data

The collection phase might involve interviews and location inspections, but inevitably also requires searching through a variety of data sources to gather potentially relevant information relating to the focal subject and related parties to the investigation.

Companies collect, process, and store more information than ever before and whilst the growth in data volume is impressive, even more so is the expanding variety of data sources generating that volume. It is not just the sheer volume of data that investigators must contend with, but also the different types and sources of data that exists. The likelihood that important correlations and patterns may exist in the multitude of data sources contributes to the challenge referred to above of demonstrating that all material facts have been considered.

Data sources are likely to include structured and unstructured data. Information contained on personal and business mobile devices, internet of things devices, and social media platforms, as well as other information like bank account records, transaction data, and computer files, can all form part of the corpus of information the investigator has to evaluate.

The proliferation of data is essentially causing a blurring of the lines between private company communication and public communication streams outside of company networks. It has been reported that 67% of people in the UK and 70% of people in the U.S. regularly use social media, and that internet penetration in North America and Europe exceeds 90%. 7 Any piece of this unknown content could be useful to an investigation. We just do not know what we do not know, and this cycle of ever-increasing data creation magnifies the risks we face as organisations and investigation professionals.

As such, something that can ingest vast amounts of data, quickly spot anomalies and patterns, and provide a plain language explanation of connections, would almost certainly alleviate the challenges associated with the preliminary collection and analysis of information, and at least begin to pierce the veil of the unknown.

### B. Data Overload — How to Effectively and Efficiently Analyse Data

Once data is collected, investigators will then analyse what they have found, looking for the smoking gun, so to speak. Standing at the beginning of an investigation, it is difficult not to wonder how we might wrap our evaluation capability around this widening river of data to whittle it down to relevance and, assuming we are in fact able to create a manageable data pool, how we would draw insights from it in the most effective and efficient way. This is the second challenge investigators face in the investigative process.

When data volumes are small, basic analytical skills and spreadsheets might be adequate to handle rudimentary analysis of structured data obtained from enterprise systems and other software applications. This process, however, is time-consuming and often necessitates review on a sample basis for large datasets, given these constraints.

This, in turn, hampers the effectiveness of the investigative process because larger patterns of activity across a complete dataset might not be detected if the anomalous data transactions lie outside a sample set.

To further complicate the challenges faced, the in-depth analysis, across a vast amount of data types and sources, needs to be done in a cost-effective manner. This pressure on cost and the required speed of the investigative process – without compromising quality – places investigation teams at a constant disadvantage and often results in analyst fatigue.

### IV. Can AI Help?

AI is typically far more effective than human investigators at the following tasks: 1) mining structured and unstructured data to determine themes and patterns; 2) connecting nonobvious dots related to regularity, timing, and behaviour to report on where, and to what extent, they appear in each information artifact; 3) effectively sorting text and email messages, audio files, call recordings, and other unstructured data into practicable collections for human evaluation; and 4) identifying potential relationships between parties involved in misconduct, fraud, or corruption through internal and external connections.

Both supervised and unsupervised techniques hold promise for extraction of more relevant information from the vast range of data sources to then be processed by the investigations team.

#### A. Text Mining

Text mining, in the broad sense, is the process of converting text into data to effectively and efficiently retrieve needed information or generate knowledge about the text.

It is believed that the amount of unstructured data grows at a rate of 20%–30% per year and, by the year 2025, about 80% of the data in the data universe will be in the form of unstructured data.8 The masses of data need to be “harvested” to generate insight (i.e., inference) and foresight (i.e., prediction). The central task of unstructured data analytics is to understand the text; this understanding mimics human intelligence by inferring from the text its themes, concepts, and ideas.

Topic modelling and document clustering are some of the techniques that are based on text mining.

1. **Topic Modelling**

   Topic modelling is a technique used in the field of text mining to automatically derive a topic from unstructured text. It is an unsupervised approach that uses the notion that documents are made up of topics and that some words are related to each other based on a topic. The methods used for topic modelling range from probabilistic-based methods that assign each word a probability of being associated with a topic, to methods that use groups of words and word frequency to assign a topic. This method might be used to determine that a group of words found in a document like “lawyer”, “judge”, and “courtroom” would be assigned to a topic like Law, whereas words like “desk”, “pens”, and “paper” could all be assigned to a topic like Office Supplies.
This technique could be helpful in the investigative process where the structure of the investigation actions is being determined. For example, instead of one investigator reviewing all the social media posts and another investigator all the financial transactions, this can help to group the emails and transactions related to a topic so that the investigation team focuses on themes rather than data-type workstreams.

2. Document Clustering

The topics derived from text can then be used to optimise the investigation process and document clustering. Each document could have several different topics, the topics could be present in multiple sections of the document, thus occurring more often. By identifying topics and then using measures such as the probability of the topic in the text or the frequency of terms related to a topic in the text, clustering techniques can be used to group together documents that have similar topics. This can drastically speed up the investigation process.

Topic modelling and document clustering can be used in the analysis phase of the investigative process, where there may be a hundred documents clustered together because the most frequent theme in each is a trade with country ABC. Each document thus shares this theme. Then, some of the less frequently mentioned themes in each document are used to find additional connections to the trade-with-country-ABC theme, like mention of the element uranium or a specific vendor name. It is now possible to have a new theme of trades with country ABC involving uranium and the specific vendor.

B. Behavioural Analytics

Behavioural analytics identifies persistence in behaviour and/or significant changes in behaviour traditionally over a period of time. The customers’ behaviour is characterised based on many features that capture more than the nominal characteristics (e.g., customer type) of the customers. A feature could be the number of trades during a time period or number of trades within a high-risk jurisdiction over a time period. Using these features, topological data analysis (TDA) can be applied to create networks of entities and be used for anomaly detection. TDA uses unsupervised and semi-supervised machine learning to create families or groups that are built based on similar typology. Through geometrical analysis, TDA exposes the true structure of the data to identify trends and relationships that standard approaches often fail to recognise.

1. The Network

TDA builds a complete network of all entities based on the features provided. It takes features and projects them into a lower dimensional space, which provides a clearer representation of the shape of the population. The population is represented by nodes and links between each node. Nodes are entities that share similar attributes based on the features provided. Nodes are connected to other nodes based on node similarity. The linkage of nodes provides a complete network of the underlying population.

This network can be used to find links between entities that may not have been as apparent through standard approaches. It can also be used for segmentation and anomaly detection.

Say, for example, person X is a director of company ABC and made payments to person Y from the company account. X has two features, the company he or she is a director of and the payments made to Y. The nodes in the network would be made of other directors who make similar payments and could be connected to other nodes that are somewhat similar but not enough to be in the same node.

2. Segmentation

Segmenting entities based on limited features does not provide the information that can lead to hidden patterns and suspicious activity.

Since the networks that TDA generates use the geometric and topological structure of the data, the shapes produced can also be used for segmentation purposes. Unlike standard approaches, these segments are created based on features that better represent entities’ behaviour, which results in a more homogeneous segment grouping than traditional segmentation characteristics. These groups are now made up of entities that on the surface may not have been considered similar before, but now, with the advanced approach, new patterns of suspicious activity can be identified. Traditional segments are often based on external factors such as industry, account type, risk rating, or person vs. corporations. These factors have no definitive relationship to expected behaviour.

Wrongdoers will most often attempt to hide their tracks or information that links them, in an obvious way, to suspicious activity. As such, segmentation could be a useful method of connecting less obvious patterns of activity – like grouping payments not by time stamp or date but rather by similar consecutive payment sequences.

3. Anomaly Detection

In addition to segmentation, these networks can be used for effective anomaly detection. The network of nodes is connected based on similarity, some nodes sharing a stronger connection than others. The TDA model may also produce a node or group of nodes that is completely disjointed from the rest of the population. What this represents is a group of entities that is vastly different from the rest of the population, so much that not even a weak link can be made to most of the population, based on their behaviour. The group can be labelled as anomalies and should be investigated accordingly.

A potential scenario where this would be useful from an investigation’s perspective is identifying when a traders’ normal pattern of activity changed drastically in frequency, amounts, and time between trades, etc.

4. Change in Behaviour

An additional benefit of segments defined by behavioural features is that entities can be monitored for how they move or drift from segment to segment. Certain changes from one behavioural segment to another may represent potentially suspicious activity and require additional scrutiny. For example, a periodic customer review based on a change in behaviour is a valuable, data-driven metric, rather than just triggering investigations based on the passage of time.

V. The Regulators are Using AI

Financial technology has grown within the private sector. Regulatory technology is following suit, using digital tools to make regulatory compliance easier – so much so that enforcement agencies are starting to use it themselves. AI has proven useful specifically within financial regulatory spaces.

For example, the Financial Conduct Authority (FCA) in the UK is using data science and analytics to deepen its oversight work. Just last month, the FCA announced that it is working on a new data analytics program and turning to a new cloud system to better employ advanced analytics to reduce the cost...
of regulatory reporting. The UK Serious Fraud Office also employs AI in financial crime and corruption investigations.

The U.S. Securities and Exchange Commission (SEC) uses AI and behavioural analytics. Topic modelling and other clustering techniques analyse and produce groups of “like” documents within SEC filings that identify both common and outlier behaviour. Additionally, the SEC works to apply algorithms developed from unsupervised machine learning to new data from filings.

At this point, the use of AI in internal corporate investigations is anticipated and often expected by regulatory bodies. Enforcement agencies anticipate companies are doing their own internal monitoring, and AI is often the best way to do so. In April 2019, the U.S. Department of Justice (DOJ) released updated guidance to prosecutors working on compliance enforcement. The DOJ identified one hallmark of an effective compliance program as “its capacity to improve and evolve” and specifically pointed to improvements that ensure programs are “not stale.”

Another such hallmark the DOJ identified is “the existence of a well-functioning and appropriately funded mechanism for the timely and thorough investigations of any allegations or suspicions of misconduct.” Capacity to improve? Not stale? Timely and thorough? Those all sound like adjectives that describe work well-placed in the AI fold. As agencies themselves employ similar technology to make compliance and regulatory-related activities faster and easier, they are coming to expect the same from the organisations they are overseeing.

AI is an effective tool to supplement ongoing efforts to identify inappropriate activity.

VI. Limitations of AI

AI will continue to develop in ways we can hardly imagine. However, machines are not the only solution. AI cannot (at least not yet) take the place of human intuition – no matter how advanced the technology becomes. It is intuition that allows a skilled investigator to take a cue from deception indicators on where to steer the line of questioning and to show empathy when building rapport with a suspect.

In our opinion, machines are far from conducting investigations, compliance checks, or auditing on their own. For the time being, responsible innovation requires human intervention in the examination and analysis of the results from machine models. It does, however, allow us to spend time and effort where it is likely to yield the best results. Humans doing repetitive tasks and canvassing huge amounts of data in the hope that one might find the needle is hardly a good use of corporate budgets, especially in the face of a suitable, often more cost-effective alternative.

Additionally, limitations arise when there are many investigations at play. Multiple internal investigations can usually be streamlined within an organisation, but cross-company investigations make matters difficult because legal challenges may arise. For example, in the international space, different countries’ local data privacy laws may prevent data transfers across borders. In this case, human investigators are not subject to the same transfer restrictions. So, the technical data team must intimately understand the data being incorporated into the algorithms.

AI can move quickly and with a great deal of autonomy in, for example, the online retail space where there is access to full transaction histories – that is, complete outcomes for each action. For instance, you viewed product A and product B and bought product C. In investigations, however, when trying to uncover a modus operandi for a fraudulent scheme, for example, the actions and outcomes could be different for each scheme, which makes it much harder to train a model to detect potentially fraudulent actions.

Beyond this, in terms of interpreting AI there are several variables that need to be accounted for regarding decision-making. The use of AI needs to be explainable, but it is up for debate as to what level of detail that explanation needs to have. An expert, a chief executive, and a consumer all require different levels of explanation and all must be accounted for.

Companies require horizontal alignment when using AI in corporate investigations, as consensus among technical, legal, and compliance teams is essential. There is no “one size fits all” approach to AI technology, since each company has unique challenges and opportunities.

VII. The Future of AI – Is There a Call to Action?

The benefits of using artificial intelligence algorithms to reduce the noise in an investigative process where there is a plethora of structured and unstructured data to whittle through is obvious. If performed alongside a skilled investigator, this is an effectiveness and efficiency catalyst. The use of AI in investigations, for the time being, is about augmentation, rather than automation.

Augmented intelligence explores the use of AI and ML techniques to augment and support human activity. Augmented analytics use automated ML to transform how analytics content is developed, consumed, and shared, and includes automated data preparation, automated model and insight generation, and automated visualisation generation and natural language-narrated insights.

Gartner predicts that by 2022, 30% of organisations will use explainable AI models to build trust with business stakeholders, up from almost no usage today. The future of AI is unpredictable. Ten years ago, some realities of today were reserved for science-fiction writers.

To round off the Sebastian Thrun quote that artificial intelligence is perhaps an attempt to better understand human behaviour, it seems that Google co-founder Larry Page articulated the current benefit of AI well when he said: “Artificial intelligence would be the ultimate version of Google. The ultimate search engine that would understand everything on the web. It would understand exactly what you wanted, and it would give you the right thing. We’re nowhere near doing that now. However, we can get incrementally closer to that, and that is basically what we work on.”

Acknowledgments

The authors would like to acknowledge the substantial assistance of their colleagues, Leo van der Westhuizen, Rachel Sazanovicz and Mikayla Harris in the preparation of this chapter.

Endnotes

2. Sebastian Thrun is an entrepreneur, educator, and computer scientist from Germany. At Google, he founded Google X and Google’s self-driving car team. He is also an Adjunct Professor at Stanford University and at Georgia Tech.


How Can Artificial Intelligence Augment the Investigative Process?

Tim Mueller is a member of Guidehouse’s Global Investigations and Compliance (GIC) practice. He leads the technology and data analytics team within GIC which focuses on assisting clients with selection, implementation and review of anti-money laundering (AML) and sanctions screening technology platforms. His team works with clients to: incorporate machine learning and artificial intelligence into current AML platforms; evaluate systems governance; review risk coverage for transaction monitoring detection scenarios and sanctions name matching algorithms; perform system tuning to maximise effectiveness while minimising false positives; perform model validation projects for AML and sanctions systems; and, support data handling and analytics for large-scale file and transaction reviews. Recent projects have involved assisting both regulators and financial institutions with providing the information technology functionality necessary to comply with BSA/AML requirements, including the recent New York State Department of Financial Services Regulation Part 504.

Prior to joining Guidehouse, Tim was a Managing Director/Partner at KPMG Consulting. In addition to his career in consulting, Tim led a real estate investment and property management company, commercial mortgage origination software groups, and a start-up technology company.

Guidehouse
685 Third Avenue
New York
NY 10017
USA
Tel: +1 646 227 4402
Email: tmueller@guidehouse.com
URL: www.guidehouse.com

James Siswick is a Managing Director based in London and leads the European Global Investigations & Compliance practice. He has over 20 years of consulting experience, specialising in financial crime since 2007. James’s background is in technology risk and data analytics. He has led some of Europe’s largest data-driven financial crime investigations and has significant experience of advising clients on technology related matters. He has experience advising many of Europe’s leading banks and working in the insurance and investment management sectors as well as other industries outside of Financial Services.

Guidehouse
Woolgate Exchange
25 Basinghall St.
London EC2V 5HA
United Kingdom
Tel: +44 2076 610570
Email: james.siswick@guidehouse.com
URL: www.guidehouse.com

Guidehouse is a leading global provider of consulting services to the public and commercial markets with broad capabilities in management, technology, and risk consulting. We help clients address their toughest challenges with a focus on markets and clients facing transformational change, technology-driven innovation, and significant regulatory pressure. Across a range of advisory, consulting, outsourcing, and technology/analytics services, we help clients create scalable, innovative solutions that prepare them for future growth and success. Headquartered in Washington DC, the company has more than 7,000 professionals in more than 50 locations. Guidehouse is a Veritas Capital portfolio company, led by seasoned professionals with proven and diverse expertise in traditional and emerging technologies, markets, and agenda-setting issues driving national and global economies. For more information, please visit: www.guidehouse.com.

www.guidehouse.com
ICLG.com

Current titles in the ICLG series

Alternative Investment Funds  Enforcement of Foreign Judgments  Outsourcing
Anti-Money Laundering  Environment & Climate Change Law  Patents
Aviation Law  Family Law  Pharmaceutical Advertising
Business Crime  Financial Services Disputes  Private Client
Cartels & Leniency  Fintech  Private Equity
Class and Group Actions  Foreign Direct Investments  Product Liability
Competition Litigation  Franchiae  Project Finance
Construction & Engineering Law  Gambling  Public Investment Funds
Copyright  Insurance & Reinsurance  Public Procurement
Corporate Governance  International Arbitration  Real Estate
Corporate Immigration  Investor-State Arbitration  Sanctions
Corporate Investigations  Lending & Secured Finance  Securitisation
Corporate Recovery & Insolvency  Litigation & Dispute Resolution  Shipping Law
Corporate Tax  Merger Control  Telecoms, Media and Internet Laws
Cybersecurity  Mergers & Acquisitions  Trade Marks
Data Protection  Mining Law  Vertical Agreements and Dominant Firms
Employment & Labour Law  Oil & Gas Regulation

The International Comparative Legal Guides are published by global legal group