SIAM ACTIVITY GROUP
Financial Mathematics and Engineering

NEWSLETTER | Autumn 2019

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CHAIR'S WELCOME

Dear Colleagues and Friends,

It has been a great pleasure serving on the SIAG/FME executive over the last several years. Since I first began tenure on the executive seven years ago, we have seen the community grow in size, diversity, and research directions. The talent that we have, and that we see coming into our community, is outstanding in its in ability to look at old problems in new ways, tackle new problems with the wide array of tools and techniques that we have at our disposal, and develop new methodology for how to approach mathematical problems that are rooted in application.

Currently, at the heart of much innovation is how we are incorporating data into our modeling and analysis. However, it is not just data-driven analysis that is seeing much attention and energy, areas such as risk measures, volatility modeling, systemic risk, stochastic control, mean-field games, principal-agent problems, and their applications is full of interesting new problems and activity. This diversity of the ecosystem within our community is what makes it so vibrant and interesting.

I would like to highlight the exciting announcement from the SIAM Journal on Financial Mathematics editor in chief that the journal will now be accepting SIFIN Short Communications (of 10 pages or less). As well, we have two new op-ed pieces, one by Álvaro Cartea and Charles-Albert Lehalle on "Optimizing Flows of Financial Institutions" and the other by Martin Larsson on "Stochastic Convolutions in Finance: Rough Volatility, Momentum, and Energy". Please, continue to send us your wide-appeal op-ed pieces for consideration.

Have a wonderful remainder of the academic year and thank you all for the continual support of the SIAG/FME community... it has been a pleasure to serve!!!

Kind regards,

Sebastian Jaimungal,
Chair SIAG FME

Francesca Biagini, University of Munich, Germany
Secretary

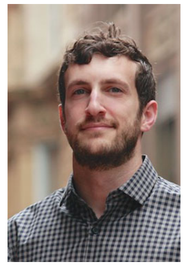
Agostino Capponi, Columbia University, USA
Program Director

Sebastian Jaimungal University of Toronto, Canada
Chair

Tim Leung, University of Washington, USA
Vice Chair

SIAM FME 19 CONFERENCE REPORT

In June, we had our biennial meeting held at the University of Toronto. Registered attendance was 375 — the largest solo SIAM FM meeting by far! The themes in the conference reflected the rapid evolution that the field is experiencing, and the diversity of research interests within our growing community. The conference program this year featured two tutorials, one focused on topics of machine learning in finance, and the other centered around simulation methods in Finance; two industrial mini-symposia; two panel discussions (one on systemic risk and the other on Fin Tech and AI); and a number of sessions covering both emerging topics, such as machine learning and financial technology, as well as core topics including systemic risk, mean-field games, and stochastic control.



Daniel Lacker

Mykhaylo Shkolnikov

Philippe Casgrain

Three SIAG prizes were awarded during the conference. The **SIAM Early Career Prize** was awarded jointly to Daniel Lacker and Mykhaylo Shkolnikov, while Philippe Casgrain received the **Conference Paper Prize**. A third prize was introduced this year to recognize the best student poster. The co-winners of the poster competition were Chiheb Ben Hammouda and Raul Guarini.

The Conference also featured the SIAG Business Meeting. The discussions primarily focused around the location for the next meeting, as well as the time schedule of events during the conference. As the SIAM-FME community grows, it becomes important to find efficient ways to run the conference: lighter days but longer lasting conference or full but less days. The Activity group also discussed ideas and approaches to attract sponsorship from the private sector to support the organization of future conferences.

The Activity group also discussed its new developed initiatives, including the intention of organizing a Gene Golub summer school in Financial Mathematics to attract young talent to the field and raise awareness. In addition, the Activity Group highlighted the intention of broadening the visibility of the SIAM-FME group through the organization of clusters and tracks at major conferences, building on the success of the 2018 SIAM Annual Meetings and of the 2019 ICIAM.

NEW SIAM FELLOW

Michael B. Giles, University of Oxford, is being recognized for contributions to numerical analysis and scientific computing, particularly concerning adjoint methods, stochastic simulation, and multilevel Monte Carlo.

Society for Industrial and Applied Mathematics recognizes distinguished work through Fellows Program. These distinguished members were nominated for their exemplary research as well as outstanding service to the community. Through their contributions, SIAM Fellows help advance the fields of applied mathematics and computational science. These individuals will be recognized for their achievements during the SIAM Annual Meeting, happening July 9-13 in Portland, OR.

SIFIN SHORT COMMUNICATIONS

On June 4, 2019 in Toronto, during the meeting of the editorial board of the SIAM Journal on Financial Mathematics (SIFIN), it was decided to create a “Short Communications” section of the journal. Submissions to this section should not be longer than 10 pages. They will be reviewed under the same standards of quality than for regular articles, but the review time will be kept under one month with the only possible outcomes “accept”, “minor revision”, or “reject”, but no “major revision”.

Of course, any area of financial mathematics is welcome in this new section, but one of the intents was to provide a venue for the growing number of submissions dealing with machine learning based algorithms applied to financial problems (the title does not need to start with “Deep. . . ” but it is a trend I am seeing!)

I am looking forward to receiving your short communications.

To submit, select “Short communications” as the manuscript type on the online submission form. For more information, please visit the SIFIN Instructions for Authors page.

Jean-Pierre Fouque,
SIFIN Editor-in-Chief

ICIAM 2019 CONFERENCE REPORT

Financial Math is well represented at the 9th International Congress on Industrial and Applied Mathematics (ICIAM), which took place in Valencia, Spain, this summer. SIAG-FME organized a dozen minisymposia with modern topics including, machine learning in finance, mean field games, calibration & inverse problems, invest rate models, as well as insurance and power markets. These thematic minisymposia, along with a number of contributed sessions, spanned over five days with hundreds of participants during the conference.

OPTIMIZING FLOWS OF FINANCIAL INSTITUTIONS

Álvaro Cartea[1] and Charles-Albert Lehalle[2]

[1] *University of Oxford*
[2] *Capital Fund Management*

The last twenty years have seen a surge in the academic literature that studies financial flows and the trading activity of stakeholders in financial markets, e.g., asset managers, banks, proprietary firms. The literature on optimal trading employs techniques that are at the interphase of empirical modeling, stochastic control, data science, and stochastic games, and develops tools to cope with the ever-changing financial landscape and regulatory requirements. These tools provide stakeholders a number of ways to deal with risks associated to their business and to deal with liquidity constraints that affect their trading strategies.

Stakeholders bear the costs of trading in and out of positions to keep their risk profile and exposure within a target. This target could be self-imposed or could be enforced by financial authorities. Ideally, stakeholders have access to optimal strategies that minimize the impact that trading costs and other frictions have on their profits. Without clearly designed tools to optimize flows and trading activity, it would be difficult for market participants to meet regulatory requirements, and financial authorities would feel less confident in enforcing strict risk controls if the market lacks mechanisms to unwind risk in an timely and cost-effective manner.

Financial institutions sell and buy products that are exposed to fluctuations in the prices of other instruments and securities, e.g., equity, bonds, commodities, and are also exposed to variations in macroeconomic variables and indicators such as GDP growth, unemployment, and inflation. A recurrent question is how to hedge or mitigate the exposure to these risks. The early work of Louis Bachelier Bachelier (1900), followed almost one century later by that of Black and Scholes (1973) and Merton et al. (1973), shows how to hedge risks with a *replication* strategy.

Although this procedure, known as *risk replication*, has well-known limitations, it was instrumental in the development of financial markets in the 80s and 90s. Key to replicating risk exposures is the availability and liquidity of standardized products – liquidity refers to the ability of trading large quantities of the asset over short periods of time with minimum price impact. Liquidity may be considered the "fuel" of financial markets and it is at the centre of the discussions and policies of regulators and an important field of study for academics, including Nobel prize recipients (see for instance Engle et al. (2012)).

Financial flows to trade large orders are typically controlled by a *trading speed*: trading slow minimizes trading costs (e.g., those that stem from the liquidity available at the best prices in the market), but is exposed to adverse price changes over the trading window, while trading fast reduces the exposure to price changes, but increases trading costs. A classical approach to determine the optimal trading speed when executing large trading flows is to formulate the problem as a stochastic control problem, where the state variables are (i) the remaining quantity of the asset or contract to buy or sell, and (ii) the cash account of the investor, whose value is highly sensitive to price pressures implied by the trading speed; and (iii) the price of the traded asset, which is impacted by the buying and selling pressure of the investor.

In financial markets, the price of a traded instrument is obtained using a double auction process, where the buy and sell pressure of market participants plays a key role in how clearing prices are determined. Specifically, throughout this process, stakeholders constantly digest information and update their beliefs to make decisions (i.e., adjust their trading speed) that affect the supply and demand of the instrument, which determine at each point in time, its equilibrium price. This price formation process can be modelled as a *liquidity game*, where market participants provide and consume liquidity in a *mean field-like pool of liquidity*. The emptiness or fullness of the liquidity pool determines the instantaneous cost of buying and selling financial products. While the first mathematical frameworks for optimal trading focused on one trader and considered the aggregation of all other participants as a "stationary mean-field", most often modelled as a martingale process, recent work has shown how to take into account the simultaneous and anticipative decisions of all traders using Mean Field Games. The first article in this direction, Lachapelle et al. (2016), is co-authored by a 1994 Fields medalist. It is rare that an academic domain attracts the attention of both Nobel and Fields recipients! Beyond this anecdote, the combination of financial uncertainty and backward optimization in a game driven framework is an interesting challenge. For example, one of the theories put forward to explain the *flash crash* in May 6 2010 postulates that initial price declines triggered by the actions of one large investor were exacerbated by high-frequency traders. These traders used sophisticated algorithms and technology to quickly make trading decisions based on the state of the limit order book, and could be seen as interacting with the mean-field represented by the universe of small end investors.

In practice, to compute an optimal trading speed, insurance companies and asset managers (which are allocating pooled capital on equity shares, corporate and government bonds, currencies, etc.) implement solvers of optimization problems, which draw knowledge from the large body of academic literature in finance. Also, investment banks and market makers implement similar solvers to control the speed at which they take positions in the market to offsets their risks. While these risk replication strategies contribute to the provision of liquidity in financial markets and to an efficient allocation of risks, their development and execution require effort and resources. For example, one key ingredient, which is no small task, is to estimate transaction costs and other frictions in the market. This requires companies to record, store, and process unprecedented large amounts of data (they are around 50,000 trades per day for a liquid stock in exchanges where information is updated at a micro-second frequency). It also requires computer power to run and implement optimization solvers in real-time and at different time scales – most of the time a risk-control driven layer of optimization updates its decisions for horizons of few hours, while interactions with the double-auction games take place at horizons of few seconds.

Moreover, a choice has to be made between: an isolated optimization process for each traded instrument or a global optimization process that involves all available instruments; the former is faster and the latter is the optimal (first best), but much more difficult to design and carry out. The industry largely relies on academic results to develop models and frameworks and to implement solutions. Beyond the hundreds of thousands of results appearing on Google Scholar under the "*optimal trading*" label, books such as those by Cartea et al. (2015), Guéant (2016) and Lehalle et al. (tion), summarize the state of the art, so that the industry can incorporate cutting-edge knowledge in their day-to-day trading decisions.

Last but not least, optimal trading does not escape from the recent rise of Machine Learning (ML). A recurrent topic one has to address is how to build short-term predictors of: price innovations, provision and demand of liquidity, see Cartea et al. (2018). These predictors employ information from many sources, including the current and recent auctions, and the predictors are designed so that they can be implemented within an optimal trading process. Notice that it is not obvious how to account for the uncertainty attached to ML generated models in more classical dynamic optimizations. And it seems that ML-inspired approaches, like Reinforcement Learning, open the door to obtaining numerically tractable solutions of high-dimensional stochastic control problems.

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STOCHASTIC CONVOLUTIONS IN FINANCE: ROUGH VOLATILITY, MOMENTUM, AND ENERGY

Martin Larsson

Carnegie Mellon University

Abstract

Stochastic differential equations are the bread and butter of financial mathematics. But they are not always the most appropriate tool. In these brief musings I train the spotlight on one of their lesser known cousins: stochastic convolution equations. How and why can stochastic convolutions add value in financial modeling? Read on and find out.

Stochastic differential equations (SDEs) are the bread and butter of financial mathematics. Just think of the Black–Scholes–Merton model, where the price of a stock or an index is modeled by geometric Brownian motion, $dS_t/S_t = \mu dt + \sigma dW_t$. Or, think of the spot variance in the Heston model, $dv_t = \lambda(\theta - v_t)dt + \eta\sqrt{v_t}dB_t$. In fact, the majority of all continuous-time stochastic models used in financial mathematics—many of them highly complex—are specified in terms SDEs.

This is not always a natural choice. Models based on SDEs share properties that are sometimes at odds with the reality they are meant to describe.

A prime example is the characteristically squiggly appearance of the sample paths of Brownian motion. These sample paths are "rough"; for instance, they are nowhere differentiable. This is good news for someone looking to model the erratic swings of stock prices. But someone interested in the erratic swings of stock price *volatilities* might be less impressed. To them, Brownian motion might look *too smooth*! In fact, mounting empirical evidence suggests that equity volatilities are far more oscillatory than Brownian motion; see Gatheral et al. (2018), Bennedsen et al. (2016), and Fukasawa et al. (2019). SDEs, like the Heston spot variance, will fail to capture this striking level of roughness. Other models are needed.

Here is one possibility: model the spot variance v_t by

$$v_t = \exp\left(\int_0^t \frac{1}{(t-s)^\gamma} dB_s\right), \tag{1}$$

where γ is a positive parameter and, of course, B is standard Brownian motion. This particular model is a bit too simplistic to be useful in practice. Still, it captures the essence of the *rough fractional stochastic volatility* (RFSV) model of Gatheral et al. (2018), and the *rough Bergomi* model of Bayer et al. (2016).

To understand why, look again at (1). One could be forgiven for thinking that this looks rather similar to geometric Brownian motion. In reality, the two are very different: unlike geometric Brownian motion, (1) involves a *stochastic convolution* of the Brownian motion. This is an expression of the form

$$\int_0^t K(t-s)dB_s \tag{2}$$

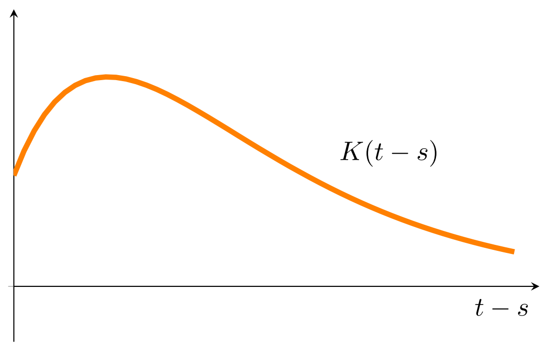
for some deterministic function K (a.k.a. "kernel"). What's more, the kernel $K(t-s) = (t-s)^{-\gamma}$ in (1) has a singularity at $t-s=0$. This makes the convolution (and hence v_t) extremely sensitive to increments dB_s in the recent past. As a result, the sample paths are exceedingly rough.

Mathematically speaking, while not entirely trivial, the model (1) can be analyzed with only moderate effort. A big reason is that there is an explicit formula for v_t. But there are natural situations where no such formula exists. The *rough Heston model* of El Euch et al. (2018) and El Euch and Rosenbaum (2019) models the spot variance as the solution of a *stochastic convolution equation*, namely

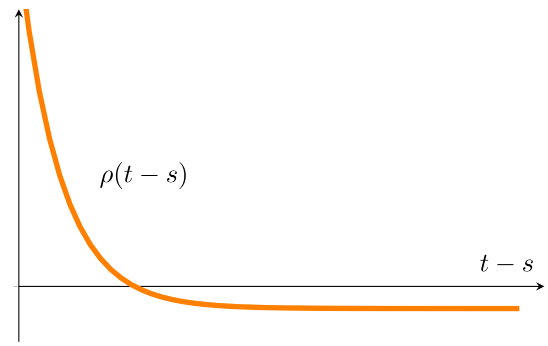
$$v_t = v_0 + \int_0^t K(t-s)\Big(\lambda(\theta - v_s)ds + \eta\sqrt{v_s}dB_s\Big). \tag{3}$$

If it were not for the kernel K, this would have looked like the usual Heston model written in integral form. But the kernel is there, and with it, a t inside the integrand in addition to the t in the upper integration limit. This drastically alters the mathematical structure of the equation. Moreover, in contrast to (1), the process v_t also appears on the right-hand side. We therefore have a *bona fide* equation for v_t, and must first ask whether a solution even exists and is unique, let alone what its properties are.

Much of this has been done, and lots is known about (3). We know that a solution exists, is unique in distribution, remains nonnegative, has a characteristic function that we can compute, and so on. Still, even for this basic specification, it is *not* known (to the best of my knowledge) whether pathwise uniqueness holds, or whether the solution remains strictly positive. For SDEs, the answers to these questions have been known for half a century thanks to the work of Feller, Yamada, Watanabe, etc.



(a) Hump-shaped kernel K



(b) Resolvent kernel ρ of K'

Now back to modeling. We have seen that stochastic convolutions can be effective in creating models with very rough sample paths, which is important in some applications. However, the kernel K in (2) leads to another phenomenon as well: *history dependence*. In financial language, Brownian increments dB_s represent "shocks", and the integral in (2) aggregates these shocks. Because of the kernel, the impact at time t of a past shock dB_s with $s < t$ is weighted by a number $K(t-s)$ which depends on *how long ago* the shock occurred. If K is decreasing, the lasting impact of a particular shock dB_s decays as it recedes farther into the past.

It should come as no surprise that this dynamic is present in various situations of interest in finance. An example is *time series momentum*, which has been thoroughly documented in the empirical finance literature starting with Moskowitz et al. (2012). The central finding is that positive returns tend to be followed by further positive returns, and correspondingly for negative returns—at least over the short and medium term. Over the long term, there is evidence of reversal.

With the right choice of kernel, (2) becomes a natural toy model for log-returns with time series momentum. To see this, write X_t for the convolution in (2), and suppose the kernel K is continuously differentiable. In this case, the log-return dynamics takes the form

$$dX_t = \left(\int_0^t \rho(t-s) dX_s \right) dt + dB_t, \tag{4}$$

where ρ is a new kernel related to K, the so-called *resolvent* of the derivative K'.[a] With a hump-shaped kernel K as in Figure 4a, the resolvent kernel ρ is initially positive and then negative as in Figure 4b. Now look back at the form (4) of the asset returns. The given shape of $\rho(t-s)$ implies that recent positive log-returns dX_s contribute positively to the drift, while recent negative log-returns contribute negatively. This is momentum. Over the long term however, positive returns contribute negatively to the drift, meaning reversal over longer time horizons.

Stochastic convolutions make an appearance in other application areas as well, for example models for energy finance, see Barndorff-Nielsen et al. (2013) and Bennedsen (2017), and models for irreversible investment along the lines of Cantor and Lippman (1995) and Sonin (1995). Barndorff-Nielsen and Schmiegel (2008) apply them to problems in turbulence. They are also a great tool for specifying jump models. For example, the intensity of a self-exciting jump process such as a Hawkes process can be viewed as the solution of a stochastic convolution equation with jumps. These equations look similar to (3), but with a jump process (actually, the Hawkes process itself) replacing the Brownian motion. Hawkes processes and their relatives have extremely broad applicability, from arrivals of limit orders to earthquake modeling and neurons firing, to mention but a few.

[a] All this requires some computations. It is not supposed to be obvious.

PAST EVENTS

4TH EASTERN CONFERENCE ON MATHEMATICAL FINANCE (ECMF)

October 25-27, 2019

Boston University, Boston, MA, USA

MAFIA - MATHEMATICAL FINANCE AND ANALYSIS SYMPOSIUM IN HONOR OF PHILIP E. PROTTER

September 20-21, 2019

Columbia University, New York, NY, USA

INTERNATIONAL CONGRESS ON INDUSTRIAL AND APPLIED MATHEMATICS (ICIAM 2019)

July 15-19, 2019

Universitat de València, Valencia, Spain

6TH WORLD CONGRESS ON GLOBAL OPTIMIZATION (WCGO 2019)

July 8-10, 2019

Metz, France

PAST EVENTS

COMMODITY AND ENERGY MARKETS ASSOCIATION (CEMA) ANNUAL MEETING 2019

June 21-22, 2019

Carnegie Mellon University, Pittsburgh, PA, USA

WORKSHOP ON DATA SCIENCE AND OPTIMIZATION

June 17-18, 2019

University of Washington, Seattle, WA, USA

9TH GENERAL AMAMEF CONFERENCE

June 11-14, 2019

Paris, France

RUTGERS EQUILIBRIUM THEORY SUMMER SCHOOL & WORKSHOP

June 10-13, 2019

Rutgers University, New Brunswick, NJ, USA

SOUTHERN CALIFORNIA APPLIED MATHEMATICS SYMPOSIUM

April 27, 2019

California Institute of Technology, Pasadena, CA, USA

All this may sound good on paper, but are models involving stochastic convolutions amenable to analysis? Put bluntly, can we compute stuff with them? Answer: yes and no. There have been substantial advances with regards to numerical simulation techniques such as the Hybrid scheme of Bennedsen et al. (2017). We do have basic results on existence and uniqueness going back to Protter (1985) and more recently Abi Jaber et al. (2019), among many others. Specifications analogous to affine diffusions have been studied by Abi Jaber et al. (2017). Progress toward Feynman–Kac type representations involving path-dependent partial differential equations have been made by Viens and Zhang (2017), to mention but a few contributions.

Still, we do not yet have the same range of tools that exist for SDEs, where the Markov structure and availability of Itô calculus are of tremendous help. Lots of work remains in order to develop a comparably diverse, complete, and convenient set of mathematical tools that can be brought to bear on problems in finance and other areas.

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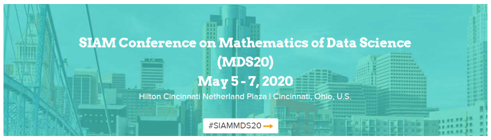
UPCOMING EVENTS

AMS SHORT COURSE ON MEAN FIELD GAMES

January 13-14, 2020

Hyatt Regency at the Colorado Convention Center, Denver, CO, USA



SIAM CONFERENCE ON MATHEMATICS OF DATA SCIENCE

May 5-7, 2020

Hilton Cincinnati Netherland Plaza, Cincinnati, OH, USA

11TH WORLD CONGRESS OF THE BACHELIER FINANCE SOCIETY

June 1-5, 2020

Hong Kong, China

2ND JOINT SIAM/CAIMS ANNUAL MEETING (AN20)

July 6-10, 2020

Sheraton Centre Toronto Hotel, Toronto, Ontario, Canada

We are proud to announce the newly elected SIAG/FME officers:

Chair: Agostino Capponi
Vice Chair: Birgit Rudloff
Program Director: Igor Cialenco
Secretary: Stephane Sturm

The retiring officers wish to thank the SIAG/FME community for the trust and support demonstrated over the last three years. It has been a privilege to serve the community!

Ad Majora,

Francesca, Tim and Sebastian