Testimony before the

U.S. HOUSE OF REPRESENTATIVES
COMMITTEE ON FINANCIAL SERVICES

TASK FORCE ON ARTIFICIAL INTELLIGENCE

regarding

“Robots on Wall Street: The Impact of AI on Capital Markets and Jobs in the Financial Services Industry”

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Thank you, Chairman Foster, Ranking Member Loudermilk, and distinguished members of the Task Force. It is an honor to be asked to testify today before your Committee. The following remarks constitute my personal opinion, and do not necessarily represent the views of the organizations listed in my affiliation.

I am a professor of practice at Cornell University, where I teach machine learning courses at the School of Engineering. Between the years 2011 and 2018, I was a research fellow at Lawrence Berkeley National Laboratory (U.S. Department of Energy), where I conducted research on the use of supercomputers for the analysis of financial Big data. Concurrently with my academic research, over the past 20 years I have held senior executive positions at some of the largest asset managers in the world. I therefore offer my testimony as an academic with a deep practical understanding of the state of the art in the financial industry.[1]

I have divided this testimony into four sections, which discuss: (1) several types of automation currently being deployed in capital markets and the financial sector, and how they

[1] For further information, please visit www.QuantResearch.org

affect decision-making; (2) how machine learning[2] (ML) and automation can help and hurt workers by disruption of the current and future financial services workforce; (3) what "RegTech" is and how ML can be deployed to help regulators better supervise financial institutions; and (4) algorithmic bias.

1. The rise of algorithmic finance

As a consequence of recent advances in pattern recognition, big data and supercomputing, ML can today accomplish tasks that until recently only expert humans could perform. An area of particular interest is the management of investments, for several reasons. First, some of the most successful investment funds in history happen to be algorithmic. A key advantage of algorithmic funds is that their decisions are objective, reproducible, and can be improved over time. A second advantage is that algorithms can be automated, leading to substantial economies of scale and cost reductions. A third advantage is that algorithmic investments address the all-important concern of conflicts of interest, which are so pervasive among financial institutions.

For the above reasons, today the great majority of financial firms increasingly offer some form of algorithmic products. According to studies, more that 34% of the total hedge fund assets under management are currently invested using algorithmic strategies, for over $1 trillion dollars (Preqin [2018]).[3] This figure does not include factor-based mutual funds and exchange traded funds offered to retail investors, so the total assets of algorithmic-managed investments could be close to $2 trillion.

[2] Throughout this testimony I focus on the subset of AI that deals with modelling data, known as machine learning.
[3] https://www.ft.com/content/ff7528bc-ec16-11e7-8713-513b1d7ca85a

While there has been substantial hype around the application of ML to financial problems, there have also been remarkable successes on a wide range of use cases (López de Prado [2018, 2019a]).[4] Examples of ML automation that have replaced humans, or have the potential to replace humans in the short terms, include the following:

- **Order execution**: algorithms are responsible for the lion share of transactions in electronic markets. Since the enactment of Reg NMS in 2005, these algorithms have fully automated the jobs of tens of thousands of execution traders worldwide. Market makers and position takers have adopted this technology, not only because of its speed and scalability, but also because of its ability to process in real time large amounts of microstructural information, leading to better outcomes (Easley et al. [2013]).
- **Pricing, risk management, pattern recognition**: ML algorithms are particularly powerful at modeling complex non-linear interactions between variables. Knowledge graphs uncover hidden connections between securities that are not obvious to human experts. Regime switch algorithms detect changes in patterns, which require the recalibration of models. Banks are using ML algorithms to price their structured products, and manage their risks, with material improvement over traditional valuation methods (Buehler et al. [2019]).
- **Portfolio construction, bet sizing, asset allocation**: ML algorithms have also proven their ability to build better investment portfolios compared to classical quantitative methods (López de Prado [2019b]), and avoid behavioral biases in bet sizing (López de Prado [2018]). Eventually, we can expect that ML algorithms will be involved in the

[4] https://ssrn.com/abstract=3365271

allocation of tens of trillions of dollars, replacing human discretion and the more traditional econometric methods (López de Prado [2019c]).

In other areas, ML is presently best used to enhance and support the role of human experts:

- **Credit ratings, scoring, fraud detection**: ratings agencies routinely use ML algorithms to monitor the credit worthiness of debt issuers, and recommend revisions when they detect material changes in companies' ability to meet their obligations.[5] Credit card companies, insurance companies and banks use ML algorithms to flag transactions that are potentially fraudulent.[6]
- **Sentiment extraction, recommender systems**: algorithms classify tens of thousands of news articles a day, and help determine whether particular stocks are the subject of positive or negative narratives. Recommender systems suggest stocks that could benefit from specific narratives spreading through the media (Sohangir et al. [2018]).

2. Algorithms and jobs: challenges and opportunities

Financial firms employ tens of thousands of analysts to model financial datasets. This silo approach made sense in the past, because financial data was largely proprietary and datasets were small. Today, data vendors offer a wide range of datasets that were not available a couple of years ago. As a result, some technology firms have begun to distribute this data and crowdsource the jobs of data analysts through tournaments.

In a tournament, an organizer proposes an investment challenge (e.g., the forecasting of stock prices) and distributes the data needed to solve this challenge to a crowd of data scientists.

[5] https://bit.ly/33yWPnC
[6] https://www.fico.com/blogs/5-keys-using-ai-and-machine-learning-fraud-detection

Because tournament organizers use their knowledge of financial markets to narrowly define the investment problem, tournament participants can work on this problem, even if they lack financial knowledge and they are not employees of financial companies (López de Prado and Fabozzi [2019]).

The tournament approach has the potential to disrupt some of the highest paying jobs in finance. For example, asset managers could crowdsource their entire research function, by organizing tournaments where millions of data scientists from outside the financial sector participate. Insurance companies could crowdsource their actuarial models.

Financial ML creates a number of challenges for the 6.14 million people employed in the finance and insurance industry, many of whom will lose their jobs, not necessarily because they are replaced by machines, but because they are not trained to work alongside algorithms.[7] The retraining of these workers is an urgent and difficult task. But not everything is bad news. Minorities are currently underrepresented in finance.[8] As technical skills become more important than personal connections or privileged upbringing, the wage gap between genders, ethnicities and other classifications should narrow. The key is to ensure equal access to technical education. In finance, too, math could be "the great equalizer."

Retraining our existing workforce is of paramount importance, however it is not enough. We must make sure that America retains the talent it develops. The founders of the next Google, Amazon or Apple are this very morning attending an engineering or math course at one of our Universities. Unlike in the past, odds are that these future entrepreneurs are in our country on a student visa, and that they will have a very hard time remaining in the United States after their

[7] https://datausa.io/profile/naics/finance-insurance
[8] According to the Board Center for Financial Planning, less than 3.5% of all the 80,000 Certified Financial Planners (CFPs) in the United States are black or latino. The situation is likely worse in asset management firms. https://prn.to/2PcBaNc

graduation. Unless we help them stay, they will return to their countries of origin with their fellow students, to compete against us in the near future, hindering our competitive advantage.[9]

3. RegTech

The term RegTech refers to the collection of technologies in general, and ML technologies in particular, that assist and support the functions specifically assigned to regulatory agencies, such as financial oversight, preservation of market integrity and prosecution of market manipulators. The applications of ML in this space are very diverse. In this testimony I will focus on two examples that I believe are implementable in the short term.

3.1. Crowdsourcing the detection of market manipulators

One of the most challenging tasks faced by regulators is to spot the actions of market manipulators among oceans of data. This is, quite literally, like searching for a needle in a haystack. A practical approach is for regulators to enroll the help of the data science community, following the example of Kaggle competitions, or the Netflix prize.

Between 2006 and 2009, Netflix held a tournament to improve their movie recommender algorithms. Data scientists received a training set containing information regarding over 100 million ratings contributed by almost half a million users. The data was anonymized, to protect the privacy of Netflix customers. The winning team improved Netflix's forecasting power by about 10%, and received a prize of $1 million.[10]

Following this example, regulators could anonymize transaction data, and offer it to the worldwide community of data scientists, who would be rewarded with a portion of the fines

[9] https://www.svcip.com/
[10] https://www.netflixprize.com/assets/rules.pdf

levied by regulators against wrongdoers. The next time that financial markets experience a "flash crash," the tournament approach could lead to a faster identification of potential market manipulators.[11]

3.2. Detection of false investment products

A pervasive mistake in financial research is to take some data, and simulate the historical performance of alternative variations of an investment algorithm, until a false positive result comes out. This methodological error is known as "backtest overfitting," and it is so notorious among statisticians that we consider it scientific fraud (Bailey et al. [2014]). Academic financial journals are filled with such pseudo-discoveries. Financial firms offer online tools to overfit backtests, and even large hedge funds constantly fall into this trap, leading to investor losses.[12]

Years ago, financial firms realized that peer-reviewed journal articles were an extremely effective marketing tool, and a way to circumvent SEC rules against false advertising (Fabozzi and López de Prado [2018]). This has led financial firms to launch investment products based on overfit backtests, with great commercial success followed by disappointing performance.

Although there are no laws specifically prohibiting funds based on overfit backtests (yet), investors may have a legal case against this widespread investment malpractice that professional associations of mathematicians have deemed unethical. Such offenders are abusing the public trust earned by *bona fide* scientists. As legal analysts and regulators learn more about these unethical or negligent practices, laws and regulations should be passed to finally curtail some of these abuses.

[11] https://www.bloomberg.com/news/articles/2015-04-22/mystery-trader-armed-with-algorithms-rewrites-flash-crash-story

[12] An intuitive explanation of backtest overfitting can be found in this video: https://youtu.be/4oBMvlQ_sxs

One solution is to require financial firms to record all backtests carried out in the development of a product. With this information, auditors and regulators can apply ML techniques to compute the probability that the strategy is overfit, and this probability could be reported in the funds' promotional material (Fabozzi and López de Prado [2018], López de Prado [2019d]). In other experimental fields, like in medical research, logging all trials is standard operating practice.

A second solution is to require that financial firms disclose in their promotional materials whether their product is based on flawed academic publications, that is, peer-reviewed papers where the authors failed to disclose the full extent of the experiments conducted. This makes sense, because backtest overfitting constitutes scientific malpractice, and funds should be held responsible when this malpractice costs investors their savings.

A third solution is to require financial firms to conduct their research following the protocol of ML tournaments. In ML tournaments, researchers only have access to a portion of the data. Because part of the data is remains hidden, researchers cannot overfit their backtests. Tournaments offer a viable alternative to the traditional backtesting paradigm (López de Prado and Fabozzi [2019]).

4. Algorithms and bias

Financial professionals are confronted with conflicts of interest every day: in granting a loan, classifying a company, recruiting talent, predicting earnings, forecasting inflation, etc. When these individuals are asked to make judgment calls, there is a risk that they fail to comply with their fiduciary duties, or that they impose their biases on others.

In some situations, investors may be better served when a machine makes the calls, based on facts learned from hard data. Furthermore, machines will comply with the law, always, when programmed to do so.

This does not mean that algorithms will make flawless decisions. When trained incorrectly, ML algorithms can incorporate human biases. The good news is, we have a better chance at detecting the presence of biases in algorithms, and measure that bias with greater accuracy than on humans, because we can subject algorithms to a batch of blind randomized controlled experiments. It is easier to monitor and improve an algorithmic decision process than one relying entirely on humans. Algorithms can assist human decision-makers by providing a baseline recommendation that humans can override, thus exposing potential biases in humans.

As algorithmic investing becomes more prevalent, Congress and regulators can play a fundamental role in helping reap the benefits of financial AI, while mitigating its risks.

Thank you for the opportunity to contribute to this hearing. I look forward to answering your questions.

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Biography

Dr. Marcos López de Prado is the CIO of True Positive Technologies (TPT), and Professor of Practice at Cornell University's School of Engineering. He has over 20 years of experience developing investment strategies with the help of machine learning algorithms and supercomputers. Dr. López de Prado launched TPT after he sold some of his patents to AQR Capital Management, where he was a principal and AQR's first head of machine learning. He also founded and led Guggenheim Partners' Quantitative Investment Strategies business, where he managed up to $13 billion in assets, and delivered an audited risk-adjusted return (information ratio) of 2.3.

Concurrently with the management of investments, between 2011 and 2018 Dr. López de Prado was a research fellow at Lawrence Berkeley National Laboratory (U.S. Department of Energy, Office of Science). He has published dozens of scientific articles on machine learning and supercomputing in the leading academic journals, is a founding co-editor of *The Journal of Financial Data Science*, and SSRN ranks him as the most-read author in economics. Among several monographs, Dr. López de Prado is the author of the graduate textbooks *Advances in Financial Machine Learning* (Wiley, 2018), and *Machine Learning for Asset Managers* (Cambridge University Press, forthcoming).

Dr. López de Prado earned a PhD in financial economics (2003), a second PhD in mathematical finance (2011) from Universidad Complutense de Madrid, and is a recipient of Spain's National Award for Academic Excellence (1999). He completed his post-doctoral research at Harvard University and Cornell University, where he is a faculty member. In 2019, Dr. López de Prado received the 'Quant of the Year Award' from *The Journal of Portfolio Management*. For more information, visit www.QuantResearch.org