Digital Economics and AI Tutorial — Application

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A short description of the course of graduate study pursued and the years of enrollment in the PhD program:

PhD program in Accounting, 5th year student. Advisor: Professor P. Wysocki.
MA in Economic Policy in Global Markets - Central European University, 2016.
MA in Economics, Department of World Economy and International Affairs - Higher School of Economics, 2014.
BS in Economics - Lomonosov Moscow State University, 2012.

A short description of research interests, any research projects that are in process:

Research interests: disclosure, disclosure properties, capital markets, Generative AI and its applications.
Methods: causal inference, machine learning, Natural Language Processing, Large Language Models.

My research investigates how data transforms market competition and how Large Language Models (LLMs) can be used to analyze financial information, focusing on both their applications and limitations. Specifically, I study how digital platforms, e.g., Amazon, use internal data from third-party sellers to develop competing products and evaluate data regulation approaches through empirical analysis. In my work on financial communication, I use earnings calls as a setting and develop a novel measure of executives' clarity using LLMs, demonstrating its relationship with traditional linguistic metrics and information asymmetry in the market. In a co-authored paper, we systematically evaluate the reliability of LLMs in financial analysis, documenting that while these models show high response rates for basic financial queries, they demonstrate significant accuracy concerns. This work advances our understanding of how data and artificial intelligence affect market competition and information quality, with direct implications for regulatory policy and corporate practice.

The following are abstracts from some of my work.
Regulating Data Usage on Dual Platforms (with ***Malika Korganbekova***). We examine the necessity and the design of data usage regulation in B2B markets, particularly focusing on concerns regarding platforms like Amazon that function as both marketplaces and sellers. The key issue is the alleged use of internal Amazon data to replicate top-performing products from third-party sellers. Using Deep Learning tools, we analyze visual and textual similarity measures between 624 Amazon Basics and 2 million third-party seller products. The findings reveal significant and consistent similarities between private label and third-party products across multiple product categories. Additionally, our research questions the effectiveness of duration-based regulation proposed by the European Union. It shows that Amazon takes an average of 2.5-3 years to imitate a product, while smaller sellers' products require approximately 5 years. This indicates that duration-based data regulation provides Amazon with ample time to collect data, suggesting the need for a different seller-targeted data regulation approach.
Executive Clarity in Earnings Conference Calls (***solo-authored, 3rd year Summer paper***). This paper examines the clarity of executives' answers in earnings conference calls. I posit that clearer answers

reduce the information processing costs for investors and decrease the likelihood of diverse interpretation. Using Large Language Models (LLMs), I measure the clarity of answers and find that it is negatively associated with the number of uncertain words, markers of non-answers, readability and positively associated with the use of numbers. I further show that my measure is negatively associated with information asymmetry and show that it is robust to adding commonly used linguistic metrics that may proxy for clarity. The results suggest that LLMs can be employed for financial text classification, even in complex and dynamic settings such as human communication.

Large Language Models and Financial Analysis: Early Evidence (with ***Jesse Chan, Aliya Korganbekova, and Eddie Riedl***). Motivated by the rapid evolution of large language model (LLM) applications—as well as survey evidence indicating interest in applying LLMs to financial and investment queries, and expectations for high levels of accuracy—we explore LLM reliability for financial analysis. We assess three common LLMs—ChatGPT-3.5, ChatGPT-4.0 and Bard—for their responsiveness and accuracy to queries for basic quantitative and qualitative financialfinancial data (total assets,ornet income, CEO name, or largest asset category) for a random sample of 500 US firms from 2016–2020. We document high response rates, with the LLMs providing usable numerical answers for 80-100% of queries. However, we find low response accuracy: less than 1% of total asset (4% of net income)responses match Compustat benchmarks, with mean errors for total asset (net income) exceeding 35% (230%). While GPT-4.0 is the most accurate, it also is the least responsive—suggesting potential trade-offs in LLM performance. We also document lower LLM responsiveness and accuracy for firms that are smaller, loss-making, and not engaging in material acquisitions. Finally, we document that LLM responses exhibit significant correlations with reported amounts for both peer firms and adjacent fiscal years for the same firm, suggesting within-firm confusion across fiscal years as likely sources of errors. We conclude that current LLM application to financial analysis use cases warrant validation of financial inputs.