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Marat Ibragimov

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EDUCATION

2023 *(exp)* MIT Sloan School of Management, Cambridge, MA, USA
Ph. D., Quantitative Marketing

2018 New Economic School, Moscow, Russia
M.A., Economics

2017 Moscow Institute of Physics and Technology, Moscow, Russia
M.S., Applied Physics and Mathematics

2015 Moscow Institute of Physics and Technology, Moscow, Russia
B.S., Applied Physics and Mathematics

RESEARCH INTERESTS

Substantive: Online retail, Targeted marketing, Consumer search, Product returns
Methodological: Machine learning, Econometrics, Mathematical modeling

WORKING PAPERS

"Customer Search and Product Returns" (2022) (with Siham El Kihal and John R. Hauser). *Job Market Paper*

"Leveraging the Power of Images in Predicting Product Return Rates" (2022) (with Daria Dzyabura, Siham El Kihal and John R. Hauser) Minor revision, *Marketing Science*

"Transferring Information Between Marketing Campaigns to Improve Targeting Policies" (2022) (with Artem Timoshenko, Duncan Simester, Jonathan Parker, and Antoinette Schoar)

WORK IN PROGRESS

"Guiding Customer Online Search by Optimizing Pre-search Filter Tools" (with John R. Hauser)

AWARDS, FELLOWSHIPS, AND GRANTS

ISMS Doctoral Consortium Fellow, 2022
MIT Sloan School of Management Fellowship, 2018-2023
The Petr Aven Scholarship, 2017-2018
The Leonard Blavatnik Scholarship, 2017-2018
The Boris Mints Scholarship, 2016-2017
New Economic School Fellowship, 2016-2018
Increased Federal Academic Scholarship, 2015
The Abramov-Frolov Scholarship, 2011-2014
Finalist in all-Russian subject Olympiad in Physics, 2011

ACADEMIC SERVICE

Ad-hoc reviewer: Management Science

TEACHING EXPERIENCE

2021-2023	MIT Sloan School of Management, Cambridge, MA, USA Teaching Assistant for John R Hauser, Listening to customer (MBA)
2021	MIT Sloan School of Management, Cambridge, MA, USA Teaching Assistant for John R Hauser, Seminar on Measurement Issues (PhD)
2018	New Economic School, Moscow, Russia Teaching Assistant for Stanislav Anatolyev, Econometrics III (Master of Arts in Economics)
2018	New Economic School, Moscow, Russia Teaching Assistant for Grigory Kosenok, Econometrics II (Master of Arts in Economics)
2018	New Economic School, Moscow, Russia Teaching Assistant for Michele Valsecchi, Econometrics I (Master of Arts in Economics)

INDUSTRY EXPERIENCE

2015 – 2016 Intern, Advisory Services – Performance Improvement, EY, Moscow, Russia

RELEVANT COURSEWORK

Computer Science	Machine Learning, Deep Learning, Inference and Information, Algorithms for Inference, Advanced Natural Language Processing
Economics	Graduate Microeconomics Sequence, Industrial Organization, Graduate Econometrics Sequence, Nonlinear Econometrics, Experimental Design and Causal Inference
Operations Research	Mathematical Programming, Optimization Methods, Theory of Operations Management

REFERENCES

John R. Hauser (co-chair)
Kirin Professor of Marketing
MIT Sloan School of Management
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Duncan Simester (co-chair)
NTU Professor of Marketing
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Daria Dzyabura
Professor of Marketing
New Economic School
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RESEARCH ABSTRACTS

"Customer Search and Product Returns" (2022) (with Siham El Kihal and John R. Hauser). Job Market Paper

Online retailers are challenged by frequent product returns with $428 Billion in merchandise returned to US retailers in 2020 (National Retail Foundation 2021). Typically, product returns are studied in a "purchase/post-purchase" framework. However, online retailers have access to the information which precedes the purchase decision -- consumer search. We demonstrate that pre-purchase information provides important insights about product returns. Using data from a large European apparel retailer, we (1) propose an empirical-theoretical framework that jointly models consumer search, purchase, and returns decisions (2) derive feasible methods to estimate parameters for our model, (3) provide theory and data indicating that using search filters, spending more time, and purchasing the last item searched are negatively associated with the probability of a return; (4) show how search data can improve the prediction of product returns, and (5) use the proposed framework to explore strategies for product return management which could help improve profits and consumer satisfaction.

"Leveraging the Power of Images in Predicting Product Return Rates" (2022) (with Daria Dzyabura, Siham El Kihal and John R. Hauser) Minor revision, Marketing Science

In online channels, products are returned at high rates. Shipping, processing, and refurbishing are so costly that a retailer's profit is extremely sensitive to return rates. In many product categories, such as the $500 billion fashion industry, experiments in real time are not feasible because the fashion season is over before sufficient return data are observed. We demonstrate that posted fashion-item images enhance return-rate selection of assortments. We develop three interconnected models: (1) a machine-learning model to predict return rates using images and other data available prelaunch. The model predicts well; robustness tests suggest it's hard to find a better-predicting model, (2) an optimal policy to maximize profit given the imperfect predictive model, and (3) an interpretable model based on automatically-extracted image-processing features. The interpretable model provides valuable insights with which to select and design fashion items for the website. Using data from a large European retailer (over 1.2 million transactions for nearly 10,000 fashion items), we demonstrate that machine-learning methods are practical, scale to large collections and repeated fashion seasons, and improve profit relative to models using non-image data. We illustrate visually how automatically-extracted features affect return rates. Finally, we illustrate how data available postlaunch help manage return rates.

"Transferring Information Between Marketing Campaigns to Improve Targeting Policies" (2022) (with Artem Timoshenko, Duncan Simester, Jonathan Parker, and Antoinette Schoar)

Targeting policies are typically trained using data from field experiments. For example, a luxury fashion retailer can decide which customers should receive a coupon for the Valentine's Day event using experimental data from a similar campaign implemented in the previous year. We demonstrate that firms can substantially improve targeting policies by augmenting the focal experiment with information from other marketing campaigns, even though the source campaigns may involve different marketing actions and different types of customers.