NBER Digital Economics and AI Tutorial 2026 Application

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Background

I am a third-year PhD student (enrolled in Fall 2023) and have completed all required coursework and the comprehensive exam. My graduate training includes graduate-level courses offered by Anderson, the Economics department, the Statistics Department, and the Electrical and Computer Engineering Department, covering topics in Microeconomics, Econometrics, Industrial Organization, Marketing, and Machine Learning. This coursework has equipped me with tools in structural industrial organization and causal inference, and I have a growing interest in incorporating machine learning techniques when they can enhance my research work.

Research Projects

The rapid growth and dominance of digital platforms, and the increasing development and integration of AI tools have created many new and important research opportunities. I am particularly interested in how firms compete in such an environment and how platforms, sellers, intermediaries, and consumers interact with one another. I am currently working on two research projects with Professor Brett Hollenbeck (my committee chair; additional committee members to be determined).

Online marketplaces have received growing attention, with empirical work largely focusing on the demand side, and typically assuming that sellers setting prices follow Nash Bertrand competition. In our first project, leveraging a commission reduction policy[1] in Amazon's Clothing & Accessories category, we examine whether this standard assumption holds and, if not, identify which alternative pricing strategies better describe seller behavior. In one direction, there is a growing literature arguing that algorithmic pricing may lead to implicitly coordinated outcomes (Calvano et al. (2020), Miklós-Thal and Tucker (2019), Brown and MacKay (2023), Asker et al. (2022)). In the other direction, sellers may rely on simple heuristics far away from the profit-maximization benchmark. We use a falsification framework based on the RV test (Rivers and Vuong (2002)), following Duarte et al. (2024). The idea is that instruments shift markups but not unobserved marginal cost, allowing the RV model-selection procedure to choose the conduct model whose predicted markups best align

[1] Source: https://sellingpartners.aboutamazon.com/Update%20to%20US%20referral%20and%20Fulfillment%20by%20Amazon%20fees

with the instrument-induced variation. Applied to our pilot study of the women's athletic socks market, we consider three pricing models, Nash Bertrand, collusion, and rule-of-thumb pricing, and find stronger support for Nash Bertrand pricing. We are now scaling up on the demand estimation and conducting tests for all apparel markets, with the goal of linking the strength of support for Nash–Bertrand competition to the degree of (likely) algorithm adoption, proxied by price-change intensity. We believe that our project will provide evidence on how firms actually compete in digital marketplaces and clarifies when standard supply-side assumptions remain valid in likely-algorithm-mediated environments. These results will inform empirical researchers studying online markets and have implications for the pass-through of platform commission fees and for policy discussions about competition in online commerce.

An additional contribution of this project is that we have developed a flexible algorithm to reverse-engineer truncated sales statistics commonly reported on digital marketplaces, such as Amazon's "300+ bought in past month" figures. We design an optimization-based smoothing algorithm that reconstructs daily sales from rolling 30-day truncation windows, incorporates special-event shocks (e.g., Prime Day), and accommodates various regularization schemes (absolute, relative, adaptive). Our simulations across a range of data-generating processes show that the algorithm-implied sales consistently outperform estimates based on applying the truncation rule directly. We believe that this flexible tool will support more precise empirical analysis, especially given that sales, arguably the most important outcome variable besides price in most studies of digital marketplaces, are rarely observed in raw form.

For the second project, we focus on affiliate marketing, an important and rapidly growing setting in the digital economy where influencers, blogs, and legacy publications embed product links in their content and earn commissions when consumers purchase through those links. The growing use of large language models for product discovery and recommendation further heightens the importance of understanding this industry, as AI driven recommendation tools may rely on, reinforce, or compete with affiliate linked content at scale. Yet despite the prominence of these practices, little academic research rigorously documents the structure of this industry.[2] This project seeks to bring new data to this setting and answer several central questions: how often affiliate payments are disclosed and whether there is evidence of non-disclosed biased recommendations; how affiliates and influencers compete for consumer traffic and commissions; and does the use of affiliate payments serve anti-competitive purposes for large online retailers like Amazon.com compared to smaller rivals. To answer these questions, we are constructing a novel panel dataset that traces the main affiliate traffic sources, beginning with top Google search queries related to affiliate marketing and building historical coverage using the Wayback Machine. We believe that this project will provide the first systematic evidence on how affiliate marketing operates, and will improve our understanding of how brands, affiliates, influencers, platforms, and consumers interact in shaping the online demand.

[2]There is a related literature on influencers and sponsored social media posts. This literature primarily studies posts made for upfront payments and has focused on detecting undisclosed sponsored content (Ershov et al. (2025), Ershov and Mitchell (2025), Bairathi and Lambrecht (2023)) and the choice by influencers of whether to make sponsored posts (Nistor et al. (2024)).

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