Computational Economics: Problem Set 1

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A brief summary of interests in economics

- In-text citations of relevant books/articles on the topic of interest.
- A list of references.
- At least one equation.
- At least a figure.

I am not primarily from economics doctoral program (currently in the marketing program), so I am taking this course to acquire relevant computational techniques and a precise understanding of how widely used algorithmic processes function of borrowing some economic techniques mainly for computational techniques of optimization and simulations. I remain interested in applying economic theory, particularly in extending my research on basic microeconomic foundations, since quantitative marketing originates in demand theory and structural models of price and quantity (however, these days the model specification and identification methods are evolving and being distinguishable from traditional economics model but deeply rooted in economics). Currently, I am investigating how policy shocks (regulations or ban, or introducting tax benefits or incentives) affect market outcomes (e.g., price, sales, profits, markups, product choice, product characteristics, dynamic consequences, consumer surplus, and welfare) using a reduced-form approach. If possible, and if time allows before completing my job market paper, I also intend to incorporate a small structural model or counterfactual policy simulation to capture broader effects beyond a specific policy shock.

At present, my primary focus is an automobile dataset, examining how various policy shocks or regulatory effects influence automobile demand and sales, and the subsequent consequences for consumer welfare and surplus. The example of similar research in marketing can be found in He et al., (2023) [7], which is seeking the tax creidt incentive on electronic vehicle sales. Do such policies truly generate the market outcomes policymakers intended at the design stage? Since industrial organization (IO) emphasizes analyzing market outcomes and equilibria through structural models, structural modeling knowledge is essential—even when working with policy shocks. My goal is to highlight more robust economics-based insights by combining simulations and computational analysis, extending immediate reduced-form outcomes into dynamic predictions grounded in economic theory. Berry, Levinsohn, and Pakes (1995) [4] remains a canonical reference here. Although my current work is centered on automobiles, I am also interested in extending to other durable goods. Of course, demand and sales are shaped not only by

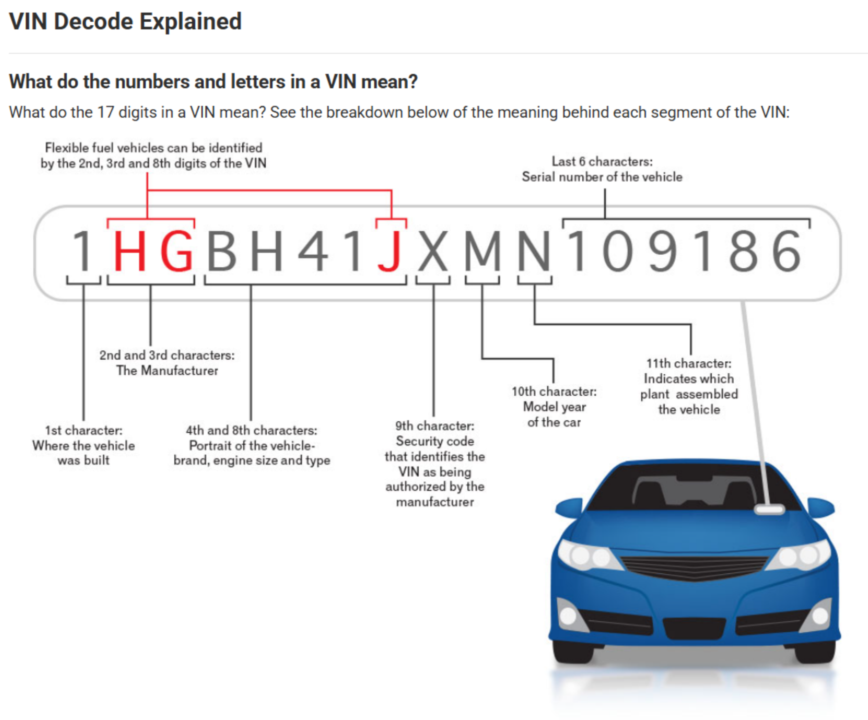

Figure 1: Automobile VIN code interpretation

price but also by market structure (e.g., monopoly, oligopoly), which must be carefully accounted for in analysis. Moreover, I aim to incorporate the dynamics of aftermarkets (Akerlof, 1970) [1], including both used and new vehicles, and the intertemporal decision-making of consumers.

In today's economy, digital markets are increasingly central. The rise of platforms, online auctions, and new buyer–seller interactions highlights the importance of platform-specific constraints and features, which I also hope to integrate into my research.

As a marketing student, I am also strongly drawn to behavioral economics, particularly framing effects. For example, Park et al. (2022) [8] examines how framing alters consumer perception using Amazon pricing data. This resonates with Kahneman and Tversky's work on reference dependence and loss aversion [9], but in a natural marketplace setting. Such studies illustrate the divergence between normative and descriptive decision-making: consumers "should" evaluate absolute prices but are in fact swayed by presentation. This normative–descriptive gap motivates much of my research. Moreover, it raises important policy questions, since firms can exploit behavioral biases in ways that existing regulations overlook. This directly connects to my broader interest in behavioral economics, public policy, and consumer protection. The paper's combination of marketplace data (IO/marketing perspective) with behavioral mechanisms (framing and reference dependence) exemplifies the type of cross-disciplinary work I find most exciting.

On the methodological side, I am especially interested in causal inference. Since marketing research often focuses on causal effects—with predictions tied to longer-term impacts—robust causal estimation is critical. Many state-of-the-art approaches are computationally intensive. For instance, the synthetic difference-in-differences method (Arkhangelsky et al., 2021) requires extensive bootstrapping for standard error estimation, often involving hundreds or thousands of iterations that can take days to compute [2]. I therefore seek deeper expertise in computationally efficient techniques. Another challenge lies in the fundamental counterfactual problem: observational data only reveal one potential outcome, forcing us to estimate what would have occurred absent treatment [3]. Much research is devoted to improving the accuracy of such counterfactual estimation, and machine learning methods are increasingly used not only for predictive accuracy but also to enhance causal inference.

After estimating average causal effects, marketing research often proceeds to subgroup analysis, exploring heterogeneous treatment effects via methods such as causal forests or panel-adapted double machine learning (DML). Causal forests use nonparametric tree-based algorithms to estimate conditional average treatment effects (CATE), identifying nonlinear relationships between treatment heterogeneity and covariates without predefining functional forms. However, with clustered or panel data, the i.i.d. assumption underlying standard causal forests is violated, requiring adjustments to avoid bias. For high-dimensional covariates—such as text, images, or multimodal embeddings, which are increasingly common in marketing—panel-adapted DML can estimate average treatment effects (ATE) and structured heterogeneity across brands, products, or time. Building on Chernozhukov et al. (2018), DML orthogonalizes treatment effect estimation against high-dimensional controls via machine learning [5], while incorporating unit and time fixed effects for repeated observations. Predefined heterogeneous groups (e.g., green vs. non-green vehicles) can still be incorporated, allowing interpretable subgroup analysis while maintaining panel structure.

Finally, demand estimation—central to marketing and rooted in economic theory—is undergoing transformation with the rise of digital platforms and unstructured big data. Recent work, such as Compiani et al. (2025) [6], demonstrates how these new methods extend demand estimation into novel data environments. I aim to use such state-of-the-art causal and demand estimation techniques to deepen my research agenda, building on the computational and econometric foundation provided by this course.

References

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