# Predictive Tools for Merger Simulation

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**Abstract**

This paper develops new tools for predicting the price effects of horizontal mergers. Current merger simulation models typically rely on strong assumptions on firm behavior to map estimates of demand elasticity into predicted post-merger prices. We propose instead to operationalize the nonparametric identification intuition in Berry and Haile (2014) using state-of-the art Machine Learning tools to enhance merger simulation by selecting data-driven models that can offer improved predictive performance. This method is practical, and potentially useful to policymakers. Our approach may also suggest, as a by-product of the predictive model, new insights into firm behavior.

## Introduction

Antitrust agencies face the complex task of deciding whether to approve or challenge proposed mergers. These decisions shape the future of key industries, and can have an important impact on consumers. For example, in the US, the Federal Trade Commission and Department of Justice (DOJ) evaluate every year a multitude of mergers, challenging those that would reduce consumer welfare by increasing prices. Economists at antitrust agencies have thus to forecast whether a proposed merger would increase prices, and recommend that a merger be blocked or not.[1] [2]

A counterfactual prediction task - predicting post-merger prices - lies right at the core of a policy problem. As stated in the DOJ's Horizontal Merger Guidelines, "most merger analysis is necessarily predictive, requiring an assessment of what will likely happen if a merger proceeds as compared to what will likely happen if it does not." A well-developed toolkit of methods for merger simulation (henceforth, MS), rooted in economic theory, is used regularly by practitioners and academics. However, merger retrospectives indicate that current methods have a mixed record, and may yield predictions that depart significantly from realized post-merger prices (Weinberg, 2011; Weinberg and Hosken, 2013; Bjornerstedt and Verboven, 2016).

To investigate what can be improved, we start by taking a closer look at the MS procedure. A merger simulation, at a high level, consists of two steps: first we perform demand estimation, which yields a matrix of demand elasticities. In a second step, a model of firm behavior is used to estimate marginal costs and map elasticity estimates into predicted post-merger prices. A common finding in

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[1]In most investigations, merger simulations are part of a larger analysis conducted with a multiplicity of tools. "[Merger simulation] is rarely used as determinative evidence but [it] can provide good supporting evidence to a sound qualitative assessment of the merger." (Davis and Garces, 2010).

[2]This is an intentionally simplified description of merger policy, although it is useful to describe a large number of mergers where short-term price effects and market power are of first-order importance. Other long-term considerations, having to do with how current proposed mergers induce firms to accept and propose mergers in the future, may also be important (Nocke and Whinston, 2008; 2010).

merger retrospectives is that, whereas estimated demand elasticities are plausible, the supply side assumptions (typically, Bertrand-Nash Equilibrium of the static, market-level pricing game) are too strong and lead to unreliable predictions (Peters, 2006).[3]

Confronted with the shortcomings of current supply-side models, researchers have tried to better capture pre- and post-merger conduct, considering explicitly the dynamic nature of the incentives to collude (Igami and Sugaya, 2017). We propose a complementary approach: when the data are sufficiently rich, we can abandon restrictive models of supply-side behavior, and use data-driven algorithmic model selection procedures. In particular, we turn to Supervised Machine Learning (henceforth, ML) methods (for an overview, Hastie, Tibshirani and Friedman, 2009), a class of tools developed in statistics and computer science and optimized for prediction tasks. Supervised ML tools use the data to flexibly select a model that maximizes predictive performance, effectively exploiting the high dimensionality of the data while avoiding over fitting. The application of these methods in economics is in its early stages, but holds considerable promise especially where (counterfactual) prediction is at the center of an economic policy issue (Mullainathan and Spiess, 2017; Athey, 2017).

In practice, we start from the nonparametric identification intuition in Berry and Haile (2014), who show that - having identified the demand system and with an appropriate vector of instruments - one can identify an "inverse" supply-side equilibrium function under an index restriction on marginal costs. We argue that this restriction is plausible in an airline setting, and that the inverse supply function is all that's needed to perform counterfactual merger simulations. To operationalize this identification framework, we turn to supervised learning techniques, and especially to the "Deep IV" framework developed in Hartford et al. (2016), where deep neural network models are modified to account for endogeneity of regressors by including instruments.

As opposed to a purely predictive approach, which would simply extrapolate the post-merger prices out of the observed co-variation between airfares and market-level outcomes, we emphasize the importance of using at least some structure and economic theory to think about the problem. First, we account for the equilibrium nature of interactions among firms, and lean on our understanding of airline markets to construct instruments. Second, we estimate and use demand elasticities in our predictive exercise: these are not immediately available in the data, and require estimation of demand in a first step just like in the standard MS.

We apply our tools to predict (retrospectively) the effect of horizontal mergers in the airline industry. Besides being the object of landmark merger simulation studies which we'll use as benchmark, the airline industry displays two connected features that make it very well suited for our study. First, there's substantial variation, both cross-sectionally and in the time series, in market-level competitive conditions. This means that we get to observe across different markets many possible combinations of airlines competing with each other. Our data-intensive methods leverage this variation to extrapolate and predict the effects of a change in market structure. The second reason is the presence of several large mergers in this industry in the last decade, which we can use to retrospectively evaluate the performance of our tools.

On the one hand, our methods lean more on the data and less on assumptions on firm behavior. However, we also emphasize that the tools we use come with limitations. Although we can accommodate many hypotheses on static firm behavior, collusive behavior that generates complex intertemporal incentives is outside the scope of our framework. In particular, while we do incorporate more flexible assumptions on conduct in our model, we cannot predict an out-of-sample change in conduct, for instance due to the presence of coordinated effects (Miller and Weinberg, 2017).

[3] From the Abstract of Peters (2006): "I conclude that deviations from the assumed model of firm conduct play an important role in accounting for the differences between the predicted and observed price changes. This conclusion suggests that the predictive performance of merger simulation would benefit if more flexible models of firm conduct were incorporated into the methodology."

## Literature Review

Our work is related to well-established merger simulation techniques, based on the pioneering work of Farrell and Shapiro (1990), Werden and Froeb (1994) and Hausman, Leonard and Zona (1994). As in previous work, we rely on demand estimates from a discrete-choice model (Berry, Levinsohn and Pakes (1995); Nevo (2001)); we depart from previous models in using a flexible, nonparametric approach for the supply side as opposed to the more restrictive assumption of Bertrand-Nash competition - although several seminal papers test this assumption and examine sensible alternatives (Porter, 1983; Bresnahan, 1987; Nevo, 2001; Bjornerstedt and Verboven, 2016). The merger simulation toolkit has been discussed and implemented successfully in several applications (e.g. Nevo, 2000; Pinkse and Slade, 2004; Ivaldi and Verboven, 2005). Among the important lessons learned from this literature, we highlight the importance of tailoring the model to the specific nature of competition in the industry that's being examined, and being mindful of the impact of specific assumptions (Huang, Rojas and Bass, 2008).

A growing literature considers the retrospective analysis of mergers. Some of these studies (e.g. Borenstein, 1990; Hastings, 2004; Ashenfelter and Hosken, 2010) leverage rich pre- and post-merger data to assess the causal effect of mergers using differences-in-differences analysis or related techniques. Other studies (e.g. Peters, 2006; Weinberg, 2011; Weinberg and Hosken, 2013; Bjoernestedt and Verboven, 2016) perform a retrospective evaluation of merger simulation models by comparing their predictions with actual price changes post-merger. We also retrospectively analyze the measure of a standard merger simulation model in our work in order to compare its performance with our alternative data-driven merger simulation technique.

In this study, we build on previous work on the structural modeling of demand and supply in the airline industry. Important earlier studies (Berry, 1992; Ciliberto and Tamer, 2009; Ciliberto, Murry and Tamer, 2018) explicitly model market structure and route-level airline entry: we consider instead the structure of airline's network as exogenous, and focus on modeling demand and price changes in response to industry consolidation. We develop a model of demand for airline products as an input to both our standard merger simulation model, and our more flexible alternative; our demand model follows closely previous work by Berry, Carnall and Spiller (1996) and Berry and Jia (2010).

The main contribution of this paper is to propose a practical method to relax supply-side assumptions in order to increase the accuracy of prediction of post-merger prices. Previous studies have considered hypotheses on airline pricing behavior that depart from the standard static, complete information Bertrand-Nash behavior: Ciliberto and Williams (2014) investigate the hypotheses that multi-market conduct facilitates collusion among airlines, and Azar et al. (2018) and Kennedy et al. (2017) consider instead the possibility that horizontal ownership of airlines results in incentives to soften price competition. Although these are compelling hypotheses on airline behavior, we leave them out of our investigation to demonstrate how our methods work in a simple setup where we only focus on static, market-specific price incentives arising from the structure of demand and competition.

Our paper also builds importantly on the work of Berry and Haile (2014) on nonparametric identification in markets for differentiated products. Instead of using nonparametric IV techniques to implement our modeling and estimation of the supply side, we turn instead to the methods in Hartford et al. (2017), who explicitly combine IV estimation with neural network methods.

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