Predicting the Price Effects of Airline Merger

by

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Abstract

This paper uses a neural network to predict the post-merger price effects of a merger between United Airline and Frontier Airlines from 2009 to 2010, and compares these predictions with observed prices. Using data taken from the Airline Origin and Destination Survey of the Bureau of Transportation Statistics, we chose to focus on the the two mergers that took place between 2009 and 2010, in which United Airline and Republic Airways becomes the resulting entity after the acquisitions. We construct an entity flag variable to indicate which airline become the resulting entity and separately discussed on their predicted price effect. Using neural network we construct, we are able to find the hyper-parameter that give us the best performance mode with the desirable prediction error.

1 Introduction

In 1978, President Jimmy Carter signed the Airline Deregulation Act, shifting American air transport from being regulated as a utility to operating as a conventional business in response to the bureaucratic rigidity and inefficiencies of the Civil Aeronautics Board, the federal regulatory body which had previously controlled interstate air transport. This act made it far easier for new airlines to enter the market, drastically increasing the degree of competition in the field. The airlines that had previously been governed by the CAB became known as "legacy airlines", and tended to have greater amenities and a greater focus on long-haul flights than the newer airlines that cropped up.

By and large, the Airline Deregulation Act can be said to have succeeded, in that prices fell due to the increased competition, although this same competition, combined with other factors such as labor disputes, saw some legacy airlines fall into bankruptcy.

However, one airline's loss can be another's gain, as several of these airlines, both legacy and non-legacy, demonstrated, when they acquired their ailing former competitors in order to strengthen their own presence in the market. In the years and decades following deregulation, many of these carriers folded into one another in a series of mergers and acquisitions until by 1991, only seven transcontinental legacy airlines remained. At time of writing, that number is down to three: Continental Airlines, American Airlines, and United. Naturally, this level of concentration of market share led some to worry among economists and consumers alike that control of the American long-distance air travel market was being consolidated to the point of oligopoly, and questioning whether or not these mergers were actually good for consumers, or whether they might be reversing the effects of the competition that drove down air fare prices to begin with.

2 Data

The data used in this paper is gathered by the Airline Origin and Destination Survey (DB1B), delivered by the Bureau of Transportation Statistics [BTS,]. The Bureau of Transportation Statistics collects a 10% sample of airline tickets by reporting airline information, and thus comes the DB1B survey. The origin, destination, and other travel information for passengers are included in the data. This information is used to calculate passenger flows, market shares for air carriers, and air traffic trends. Besides the original airline line data, we also include information on origin and destination cities to estimate the market circumstance.

Table 1 shows all the variables used as predictors in this paper.

Variable Name	**Description**
Numbers of Carriers	How many carriers exist for one route, reflecting the competitors of each route. This is a continuous variable.
Average Distance	Weighted mean of travelling distance on the number of passengers.
Origin	The origin city of one route recorded as a nominal variable
Destination	The origin city of one route are recorded as a nominal variable.
Population Origin	The population of the origin city, which may affect the market size. This is a continuous variable.
Population Destinations	The population of the destination city, which may affect the market size. This is a continuous variable.
Herfindahl-Hirschman Index (HHI)	This is a measure to calculate by squaring the market share of an entity and then sum up all of them in a market. This is a continuous variable.
Total Passenger	The number passenger in this route.
Hub Route	Whether this route is a hub route. This is a binary outcome coded as 0 and 1.
Vacation Route	Whether this route is a vacation route. This is a binary outcome coded 0 and 1.
Slot Controlled	Whether this route is slot controlled. This is a binary outcome coded as 0 and 1.
Market Income	The median of the income of city.
Average Price	Weighted mean of ticket fare on the number of passengers.

Table 1: Variables

3 Merger Retrospective

3.1 Description of the Merger

This report mainly focused on two airlines, United Airlines and Frontier Airlines [ma,]. We only focused on the mergers between 2006 and 2018. Thus, the Mergers we focus on are listed in Table 2. The first merger case is that of Republic Airways' acquisition of Denver-based Frontier Airlines Holdings. This merger was announced on August 14, 2009 and completed on October 1, 2009. The second merger case we examined was that of United Airlines and Continental Airlines' 8.5 billion dollar 2010 merger. United Continental Holdings, Inc. is name of the holding company for this new business, while United Airlines remained the name of the airline. In the first case, Frontier Airlines is not the resulting entity, but in the second case the united airline is the resulting one. Exploring the differences on the resulting entity's impact to the price could also be of interest, and thus we create a new variable, entity flag, to indicate whether a company's market share in any particular market was absorbed by the resulting entity, or if it withdrew from that market following the merger. As for the time period, we decided to choose 2009's second quarter and 2010's first quarter as the time period before the merger, and fourth quarter 2009 and fourth quarter 2010 as the time period after the merger.

Merger	**Announced**	**Closed**	**Resulting Entity**
Republic Airline/ Frontier Airline	8/14/2009	10/1/2009	Frontier Airlines
United Airline/ Continental Airline	5/3/2010	10/1/2010	United Airlines

Table 2: Merger cases used in this report

3.2 Data Analysis Method

Nonlinear supervised learning algorithms were applied in the analysis, and we decided to choose neural network [neu,] as the method to predict. Neural networks are a set of algorithms built on ideas taken from the field of neuroscience, analogous to the method that a living brain's neurons transfer and process information. In this algorithm, we build a multi-layer network of nodes, pass the information from the input layers to multiple hidden layers, and then pass it to the output layers. At each stage, a series of initially random transformations are applied to the inputs, with each iteration being compared to the ones before. This comparison is then used to determine the next set of functions to be applied to each neuron's inputs to determine it's output, leading to a gradual improvement over many generations, mimicking the processes of natural selection to find the algorithm that most closely fits the data on which we train the model.

There are many benefits to our use of neural networks. First off, neural networks require less formal statistic assumption than many other models, and thus less limitation for given data. For some models, like simple linear regression, if the data is not normal or in categories, the assumption check will fail. However, neural networks are resilient to this issue. Second, neural nets are very good at estimating complex non-linear relationships. From the previous exploration in class, we already know the relationships between given predictors and outcome might not be linear, thus forming the possibility of multinomial model. Using neural networks, we can easily fix this situation. Third, neural networks can detect the interactions between all predictors. In this report, we apply many predictors which theory tells us might interact with each other in any number of complex ways, and we do not want to lose the effects of these interactions. For these reasons, we arrived at the conclusion that a neural network is the most appropriate model to use.

The tuning parameters, a.k.a. hyperparameters, in neural networks are mostly about the number of layers and number of nodes. We will specify a hyperparameter metric and find the one works best for the prediction error, as our purpose in the report is to predict the behavior of the market under a hypothetical merger, rather than provide a general explanation for price behavior or another variable.

3.3 Results and Discussion

3.3.1 Descriptive Analysis

Before conducting model training, we need to first do some descriptive analysis, to show the general characteristics of data and some tendency about how the price change. Table 3 describe the proportions of discrete variable and the means of continuous variables, both on the timepoint of 2009 second season.

United Airline (code UA)		
Continuous variable: Mean		
	Before Merger	After Merger
Price	189.08	210.68
Passenger	488.27	442.95
Distance	1310.57	1277.27
Number of firms	1418.19	1667.40
HHI	5023.87	5057.97
Population mean	37571.67	37576.61
Discrete variable: Ratio		
Hub	98.52%	98.37%
Vacation	34.41%	33.85%
Slot	13.28%	12.89%

Frontier Airline (code F9)		
Continuous variable: Mean		
	Before Merger	After Merger
Price	151.15	169.71
Passenger	387.47	336.26
Distance	1578.47	1566.20
Number of firms	1442.20	1793.88
HHI	4444.93	4535.39
Population mean	37475.24	37703.86
Discrete variable: Ratio		
Hub	99.33%	99.56%
Vacation	25.33%	27.53%
Slot	6.67%	11.67%

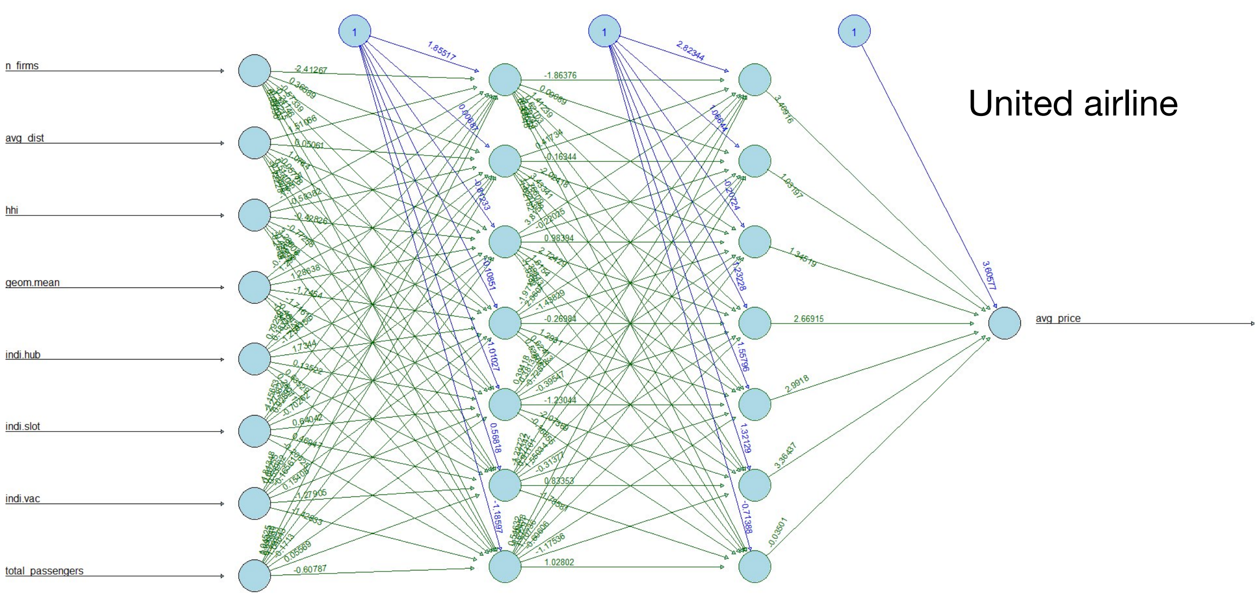
Table 3: Descriptive Analysis

We can observe that both companies having a price increase, but a decrease on number of passengers. The distance has a slightly decrease. However, the number of firms and HHI increased a lot. For United Airlines, the indicators of hub routes, vacation and slot routes decrease, but for Frontier Airlines, we observe an increase in these indicators.

3.3.2 Model training: Before merger

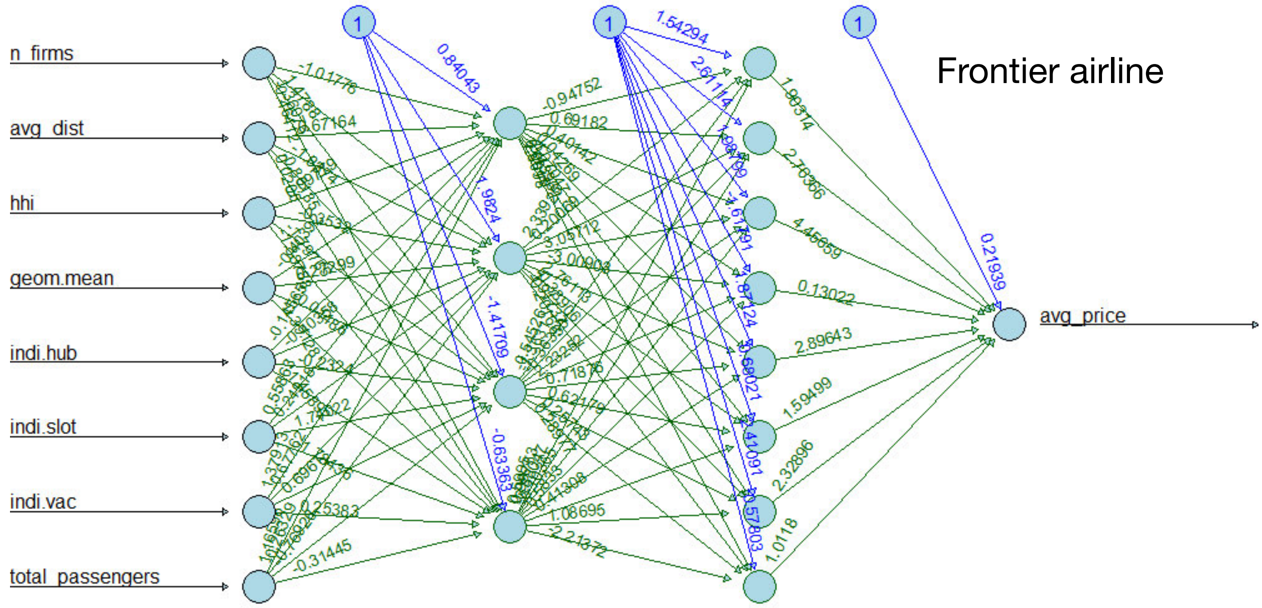
We first constructed a three-layer neural network model for United Airlines average price before the merger, and tuning the parameters. Comparing the various iterations of this model based on the RSS they yield on the test set, we finally find that, in Figure 1, by using the hyperparameter (4, 5, 2) we can get the best predictive performance out of our model, with the neural network below:

Figure 1: Neural network for predicting the price of United Airline



Similarly, in Figure 2, we built neural network for predicting the price of Frontier Airline.

Figure 2: Neural network for predicting the price of Frontier Airline



Using these two models, we added one further parameter: the merger parameter. We coded this value to be set to 1 as for the resulting entity, 0 as not. With this coefficients of neural network output, we can then calculate whether they are influenced by the merger.

3.3.3 Model Performance: After the Merger

With the model before the merger, we can now predict how merger will influence the price. We add the previous price into the predictors, and then train a model after the merger, adding a hidden layer of previous prices. With this prior, in Figure 3 and Figure 4, we generate two additional neural networks:

Figure 3: Neural network for predicting the price of Frontier Airline

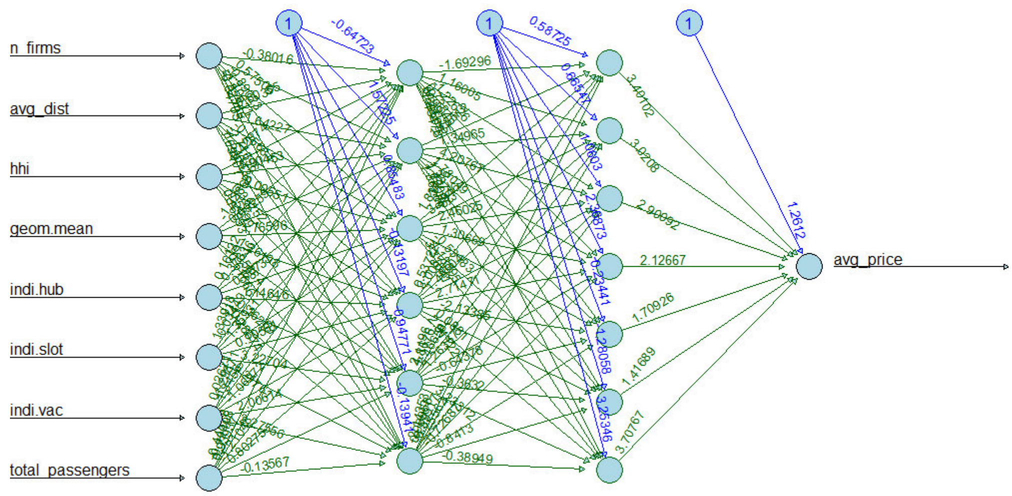
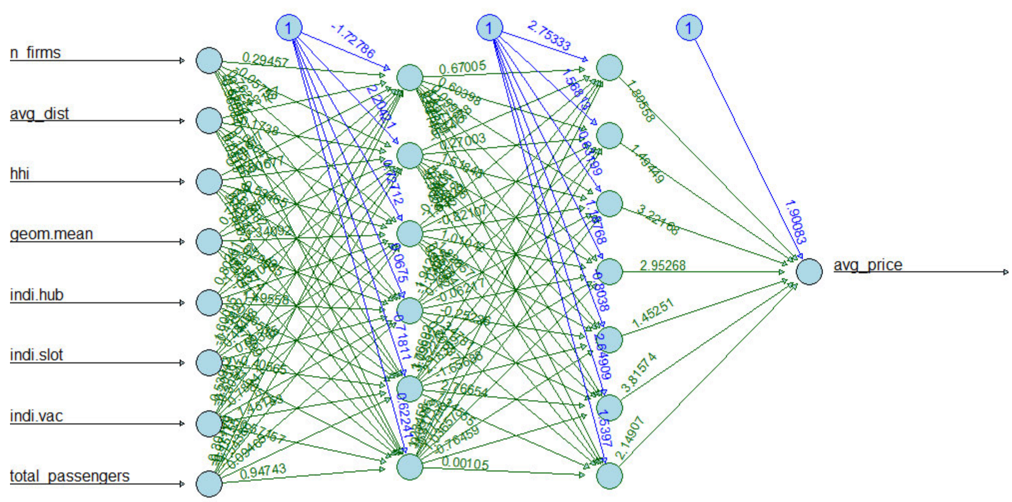


Figure 4: Neural network for predicting the price of Frontier Airline



4 Comparison to Industrial Organization Merger Simulation Framework

While we utilized a data-driven approach to determine the impact of a merger on consumer prices, an alternative way are merger simulations using structural models.

In his paper "Evaluating the Performance of Merger Simulation: Evidence from the U.S. Airline Industry", [Peters, 2006] analyzes the the efficiency of a simulation based approach to predict post-merger consumer prices. He does so, by combining an estimated structural model of consumer demand with an assumed model of pricing behavior by the airline firms to predict post-merger prices.

[Peters, 2006] approach consists of three steps. The first step calculates a function of consumer demand using pre-merger data. To do this, [Peters, 2006] uses a discreet choice model with random utility. Consumers utility herein is determined as a function of prices, flight frequency, airport presence, travel distance, whether or not the flight is non-stop and an unobserved variable for product quality. The next step is then to retrieve pre-merger marginal costs, which is achieved by determining the difference between the observed prices and the estimated markups [Peters, 2006, p.16]. However, a critical assumption that has to be made at this point is how markups change from pre- to post-merger. As [Peters, 2006] notes, due to the very nature of large scale mergers there may be a risk of changes in the price setting behavior from a competitive one towards an oligopolistic one, therefore potentially increasing markups and prices. The last step in the simulation process is then to predict post-merger prices, using the parameters for demand, the unobserved product quality and the marginal costs.

Both methodologies, the data-driven neural network and the theoretical model of demand and supply, offer their advantages and disadvantages. While it may certainly be difficult to make appropriate assumptions about the underlying model parameters, as a result of which outcomes may vary greatly, the simulation approach is generally more suitable to ascertain how certain changes in the market structure or consumer demand affect post-merger prices. Contrary to the simulation approach, neural networks are highly flexible and are not specifically dependent on any underlying assumptions and are therefore expected to offer better predictive results than a simulation based approach. The improved accuracy of neural networks however, comes at the cost of interpretability, whereby it is not possible to infer what underlying mechanisms determine potential changes in consumer prices. Furthermore, like most machine learning algorithms, neural networks suffer from potential overfitting and may perform poorly if the mergers used to train the model do not share the same characteristics as the predicted model.

5 Conclusion

In our paper we predicted the fictional merger of Republic Airline and Frontier Airline with Frontier Airline as the resulting entity and United Airline and Continental Airline with the resulting airline being United Airlines. Our initial analysis shows us that both the companies saw price increase. We then built a three-layer neural network model for both United and Frontier airlines average price before the merger. We achieved the best predictive performance of our model using hyperparameter (4,5,2). Further we added a merger parameter to confirm the influence of the mergers.

References

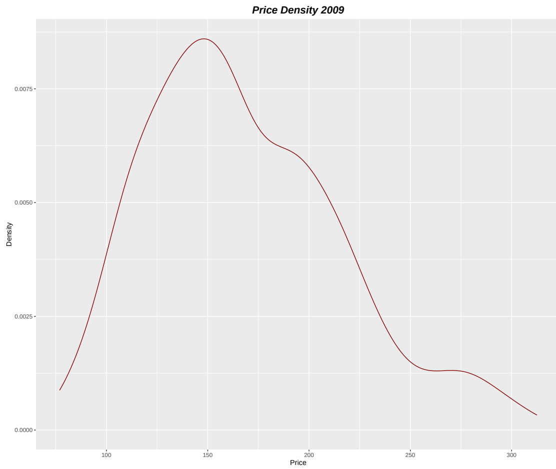
[ma,] Airlines for america. https://www.airlines.org/dataset/u-s-airline-mergers-and-acquisitions/. Accessed: 2022-12-16.

[BTS,] Bureau of transportation statistics. https://www.transtats.bts.gov/DatabaseInfo.asp?QO_VQ=EFI&DB_URL=. Accessed: 2022-12-16.

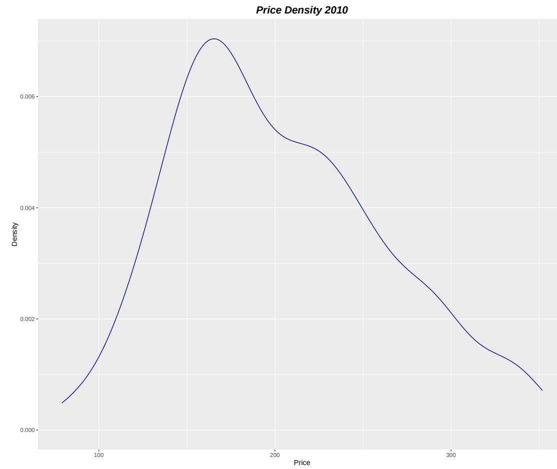
[neu,] R package: Neural net. https://cran.r-project.org/web/packages/neuralnet/neuralnet.pdf. Accessed: 2022-12-16.

[Peters, 2006] Peters, C. (2006). Evaluating the performance of merger simulation: Evidence from the us airline industry. *The Journal of law and economics*, 49(2):627–649.

6 Appendix

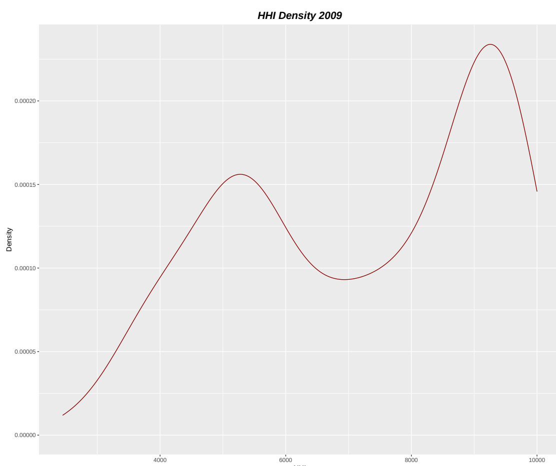


(a) Price Density - 2009

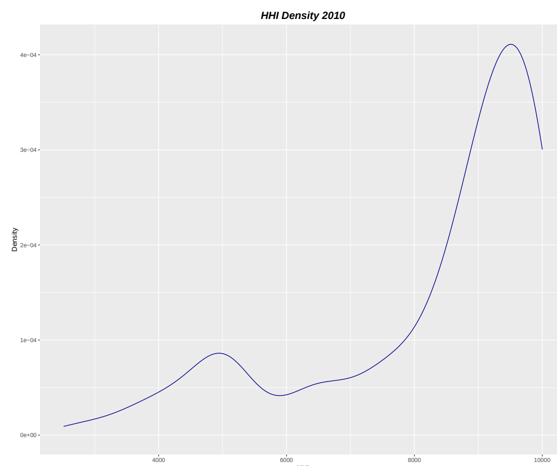


(b) Price Density - 2010

Figure 5: Price Density in 2009 and 2010



(a) HHI Density - 2009



(b) HHI Density - 2010

Figure 6: HHI Density in 2009 and 2010

Figure 7: HHI versus average prices at the market level for the second quarter of 2009

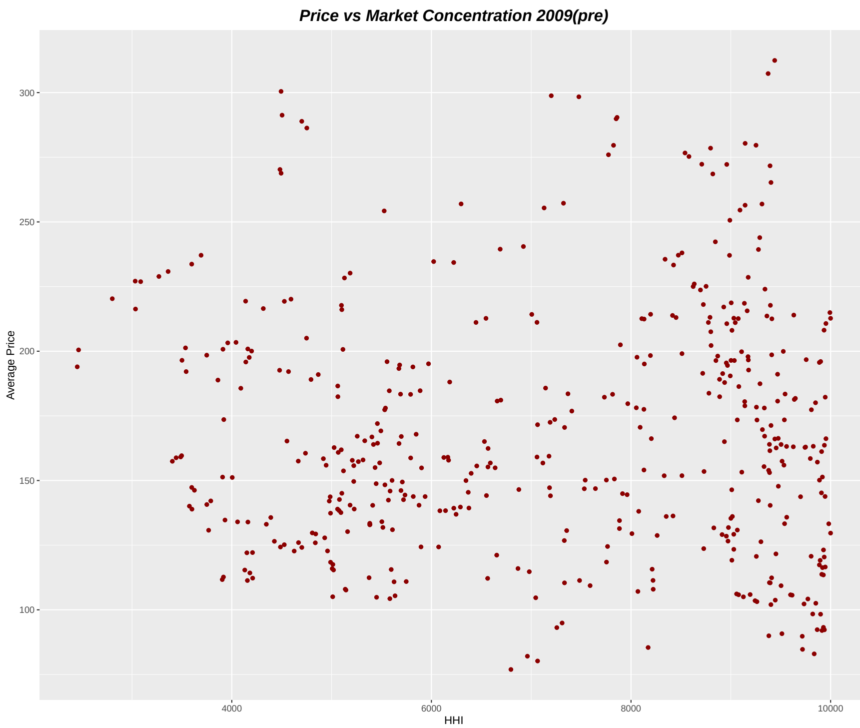


Figure 8: HHI versus average prices at the market level for the second quarter of 2010