UNITED STATES DISTRICT COURT
SOUTHERN DISTRICT OF NEW YORK

THOMAS LAUMANN, FERNANDA GARBER, ROBERT SILVER, GARRETT TRAUB, DAVID DILLON and PETER HERMAN, representing themselves and all other similarly situated,

Plaintiffs

v.

NATIONAL HOCKEY LEAGUE, *et al.*

Defendants

CA No. 12-1817 (SAS)
ECF Case

FERNANDA GARBER, MARC LERNER, DEREK RASMUSSEN, ROBERT SILVER, GARRETT TRAUB, and PETER HERMAN, representing themselves and all other similarly situated,

Plaintiffs

v.

OFFICE OF THE COMMISSIONER OF BASEBALL, *et al.*

Defendants

CA No. 12-3704 (SAS)
ECF Case

[FILED UNDER SEAL]

DECLARATION OF DANIEL L. MCFADDEN

Emeritus Professor of Economics, University of California, Berkeley
Presidential Professor of Health Economics, University of Southern California

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I. Qualifications

1. My name is Daniel L. McFadden. I am the E. Morris Cox Professor Emeritus of Economics at the University of California, Berkeley and the Presidential Professor of Health Economics at the University of Southern California. I am also a principal at The Brattle Group. I received a Bachelor of Science degree in physics, with high distinction, in 1957 and a Ph.D. degree in behavioral science, with specialization in economics, in 1962. Both degrees are from the University of Minnesota.
2. I received the 2000 Nobel Memorial Prize in the Economic Sciences for developing methods and theory used in analyzing how consumers and households make choices from sets of discrete alternatives. My work is now a standard tool in analyzing consumer behavior in a wide variety of markets. It is used to determine how people choose one brand of product over others and how they decide to purchase one type of product over another. Discrete choice modeling is used to understand what product features consumers value and how they respond to price changes and to product information. My work is also commonly used in making public policy and regulatory decisions.
3. I received the 2000 Nemmers Prize in Economics, awarded by Northwestern University to recognize "work of lasting significance." In 1975, I received the John Bates Clark medal, awarded biennially to the economist under 40 judged to have made the greatest contribution to the profession. I also received the Frisch medal (1986), awarded biennially for the best empirical paper in *Econometrica*, the Outstanding Paper Award of the American Association of Agricultural Economics (1995), the Richard Stone Prize for the best paper in the *Journal of Applied Econometrics* (2002), and the Jean-Jacques Laffont Prize (2006) for lifetime achievement.
4. I have served as the E. Morris Cox Professor of Economics at the University of California, Berkeley, the Presidential Professor of Health Economics at the University of Southern

California, the James Killian Professor of Economics at the Massachusetts Institute of Technology, the Irving Fisher Research Professor at Yale University, and as a Fairchild Distinguished Scholar at the California Institute of Technology. I have been elected a Fellow of the American Academy of Arts and Sciences, of the National Academy of Science, and of the American Philosophical Society and have received an honorary LL.D. degree from the University of Chicago and honorary doctoral degrees from Huazhong University of Science and Technology, the University of London, the University of Montreal, the University of Buenos Aires, and North Carolina State University. I have served as President of the Econometric Society and as Chairman of the Berkeley Department of Economics. I served as President of the American Economics Association in 2005. I served as a technical advisor to the Antitrust Division of the U.S. Department of Justice on the analysis of anticompetitive impacts of several proposed mergers during 1995-1996.

5. My teaching areas include economic theory, econometrics, and statistics at the graduate level. I have published seven books and more than 100 professional papers.[1]

II. Assignment and Summary of Conclusions

6. I was asked by counsel for the Defendants in both of the above-captioned cases to examine the Declaration and Supplemental Declaration of Dr. Roger G. Noll.[2] I was asked, based on this review, to determine whether Dr. Noll uses a methodology consistent with standard practices in economics, whether the assumptions used in his model are consistent with the

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1 My curriculum vita is available at: https://www.dropbox.com/s/ay7ldbl1axz1bc4/McFadden%20CV.pdf.

2 Declaration of Roger G. Noll filed February 18, 2014 and Supplemental Declaration of Roger G. Noll filed September 19, 2014 (submitted in cases CA No. 12-3704 (SAS) and CA No. 12-1817 (SAS) in S.D.N.Y).

record in this case, and whether his conclusions are consistent with the results of his model. I was asked to focus particularly on the demand-side (*i.e.,* the consumer-side) of Dr. Noll's model.

7. Based on my review of Dr. Noll's declarations and his backup materials, I conclude that Dr. Noll employs methodologies that are not based on peer-reviewed, scientific standards and uses assumptions that are not supported by the facts of this case and the data available to him. I also find that, due to mathematical errors within his analysis, Dr. Noll's model and conclusions are unreliable and fail to meet accepted scientific standards. Specifically, Dr. Noll produces a model that:

   - Contrary to Dr. Noll's representation, does not follow the demand-side methodology presented in a paper by Drs. Gregory Crawford and Ali Yurukoglu or any other currently accepted methodology for estimating consumer demand.
   - In contrast to Dr. Noll's representations, does not produce impacts or damages that reflect viewership patterns.
   - Randomly ranks team prices in his but-for world based on an arbitrary computer input.
   - Is driven by overly simplistic marginal cost assumptions that have no economic or factual bases.
   - Does not account for the nature of sports viewing and the data available to him by double counting viewing time, resulting in mathematical errors in his utility maximization calculations.
   - Generates counter-intuitive results.

   For all these reasons, I find Dr. Noll's model to be methodologically unreliable in determining the damages caused by the leagues' use of home television territories (HTTs) and "blackouts" and cannot be used to demonstrate common impact among class members.

III. Demand Analysis in the Crawford and Yurukoglu Paper

8. In his original and supplemental declarations, Dr. Noll claims that his analysis is based upon a peer-reviewed article published in the *American Economic Review* in 2012 by Drs. Gregory

Crawford and Ali Yurukoglu (hereafter "C&Y").[3] In this paper, the authors consider the impact of moving from the current market structure in which television channels are sold as bundles to a counterfactual market structure in which consumers can select individual channels to purchase.

9. In the C&Y paper, the authors estimate the demand for each of 49 television channels. To do this, they use viewership data and records of cable television offerings, which include the pricing, market shares, and composition of channel bundles available to consumers. Importantly, the prices charged and bundles offered vary across designated market areas (DMAs) and across time.[4]

10. Of central importance, the variation in prices and offerings across the country and over time are what enable C&Y to estimate the sensitivity of consumers to prices, while being careful to avoid confounding price sensitivity with other effects.[5] Generally, to estimate price sensitivity using the data directly, a researcher would consider how the likelihood that a consumer purchases a product changes when the price of the product changes.

11. To measure a consumer's willingness-to-pay for a particular channel, C&Y combine sensitivity to price with the intensity of his or her preference for that channel. The intensity of preferences for an individual channel is estimated based on the amount of time a viewer spends watching the available channels as well as household demographics, such as race,

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3 Crawford, G. and Yurukoglu, A. (2012) "The Welfare Effects of Bundling in Multichannel Television Markets" *American Economic Review* Vol. 102(2): 643-685.

4 These data are supplemented with data from satellite television providers, whose offerings and prices do not vary across the country.

5 Because prices are correlated with unobserved characteristics of satellite and cable services (the C&Y paper mentions the quality of bundled internet service as an example), consumer sensitivity to prices are estimated using a method described in Berry, S., Levinsohn, J. and Pakes, A. (2005) "Automobile Prices in Equilibrium" *Econometrica* Vol. 63(4) 841-890.

income, education level, and whether there are children in the home. Additionally, C&Y estimate correlations between preferences for pairs of channels. Consider the relationship between CNN and MSNBC. Preferences for these channels may be positively correlated if consumers value news from a variety of sources or they may be negatively correlated if consumers have preferences for a specific source of news.[6]

IV. Dr. Noll's Model is Disconnected from the Market That he Studies

12. Dr. Noll considers demand for three league bundle products: (1) the National Hockey League's GameCenter LIVE™ internet streaming product, (2) Major League Baseball's MLB.TV internet streaming product, and (3) Major League Baseball's MLB EXTRA INNINGS℠ channel offered on DirecTV.[7] According to Dr. Noll, for each product, his model is built upon three pieces of information: viewership data, the market share for the existing league bundle, and the league's current profit margin. The model returns estimates of but-for world market shares and prices for the league bundle and team à la carte channels and an estimate of damages. Economic estimates that are reliable should be sensitive to changes in the viewing patterns of sports fans and insensitive to the model structure and estimation methods. This is not the case for Dr. Noll's model.

13. For each product, Dr. Noll's model is estimated using 62 equations. Of these, 60 equations are used to estimate parameters describing the distribution of viewers' tastes for each team. As I

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6 One of the contributions of the C&Y paper is that it reports estimates of the licensing fees that would be negotiated between content providers and distributors in the new market structure that would arise if channels were offered à la carte. I do not address those issues here, but understand that Dr. Ariel Pakes will contrast Dr. Noll's approach with the C&Y supply-side approach in a separate declaration.

7 For reference, see http://www.nhl.com/gcl/, http://mlb.mlb.com/mlb/subscriptions/index.jsp, and http://www.directv.com/sports/mlb.

will show, these parameters are essentially irrelevant to the price of the league bundle in the but-for world. Unlike C&Y, Dr. Noll's model does not use variation in prices or viewer characteristics to measure the sensitivity of consumer demand to price. Instead, the price of the league bundle is almost entirely determined by two equations involving the inverse of the profit margin and the market share of the league bundle. Neither the profit margin nor the market share of the league bundle are derived from the viewership data and instead are critical assumptions for which Dr. Noll provides no sound foundation.

14. To illustrate the disconnect between the market and Dr. Noll's model, I first test whether results from Dr. Noll's model are consistent with the range of hypothetical consumer preferences based upon extreme caricatures of sports fans. At these extremes, the model should produce no harm or damages, yet I find that the estimates of damages arising from Dr. Noll's model are nearly identical when using either data set based upon these caricatures or when using the actual data. This demonstrates that Dr. Noll's model for estimating damages is insensitive to viewer preferences for teams and fails to predict the market equilibria expected with these caricatures. Thus, Dr. Noll's model is implausibly insensitive to consumer preferences, which is a serious methodological flaw.

15. Furthermore, I demonstrate that any differences in prices of team telecasts found by Dr. Noll are driven entirely by an arbitrary computer input into a random number generator. Random number generators are commonly used in scientific computing, but under no circumstances should their use lead to random results. When this extraneous dependence is eliminated, Dr. Noll's model returns results where teams charge nearly identical prices despite having fan bases of different sizes and intensities.

16. Lastly, I consider the implications of Dr. Noll's arbitrary assumption regarding the relationship between the marginal costs of teams providing telecasts relative to the cost of providing the league bundle. Dr. Noll asserts that he has no data to justify this assumption and I show that his results are dependent upon his choice.

A. Dr. Noll's Results Are Not Driven by the Viewership Data

17. But-for world prices of team channels should be a function of fans' viewing preferences and of the availability of substitutes when HTTs are removed. If consumer preferences are sharply concentrated on favorite teams, then each team will have close to monopoly control over viewing by its out-of-market fans, whether through its own channel or through its claim on the distribution of profits from sales of the league bundle. Teams would have a disincentive to agree to league bundle pricing that undercuts their ability to price and sell their own channels. As a result, when there is a sharp concentration of viewing preferences, the but-for world market equilibrium will tend to be close to monopoly pricing for each team channel, with a league bundle price that is sufficiently high so that it does not undercut the pricing of each team's telecast, leading to a negligible league bundle share. Teams that have more avid fans dispersed outside their home markets should face less price sensitive demand and be able to charge higher prices for their products.

18. On the other hand, if consumers prefer to watch many teams without strong preferences for individual teams, consumers will be inclined to purchase the league bundle, rather than some portfolio of team channels. Here, individual teams will have a disincentive to offer and price team channels that are unprofitable on their own, which would undercut the profits distributed to them from the league bundle. In this extreme case of consumer preferences, individual teams would find it most profitable to forego offering their own channels and continue to receive distributions of profits from the league bundle.

19. In this section, I create hypothetical data sets to determine whether Dr. Noll's model accurately predicts these outcomes. First, consider a world where every fan is a generalist, watching the same amount of hockey or baseball as current viewers, but with equal preferences for all teams. To evaluate this world, I replace Dr. Noll's data set with one in which each viewer spends the same amount of time watching hockey as the corresponding viewer in the actual data, but this time is divided equally among all 30 teams. In this world, a

consumer would not view a single team's channel as a substitute for the league bundle, preferring instead the variety provided by the league bundle, which offers all 30 teams' telecasts. As described earlier, in this case, teams weighing the profit to be obtained from offering their own channel versus taking their share of profit from the league bundle would have a disincentive to offer a their own channels. Hence, there would be little competition driving the price of the league bundle lower and I would expect the but-for world predicted price and market share of the bundle to remain close to actual observed levels. Hence, in this extreme case of consumer preferences, there should be little to no damages, and certainly less than the amount Dr. Noll estimates using the actual viewership data.

20. In this "Fan of the Game" world, my implementation of Dr. Noll's model with the artificial data set generates a but-for world GameCenter LIVE price equal to $20.13 per month, as compared to an observed bundle price of $26.28. This result is nearly identical to the but-for world optimal bundle price of $20.08 that Dr. Noll estimates using the actual data. The market shares are also nearly identical and both are somewhat lower than the current market share of 1.63%. Dr. Noll's model finds damages where there should be little to none—a false positive.

21. At the other end of the spectrum, consider a world where there are only fans of a particular team, the San Jose Sharks. In this world, the average hockey fan watches the same amount of hockey as the average fan observed in the true viewership data, but that time is divided entirely among Sharks games. Here, a Sharks channel is a perfect substitute for the league bundle. Under Dr. Noll's conception of competition, the Sharks channel should price slightly below the league bundle (because Dr. Noll assumes that an individual team's channel has lower marginal costs than the league) and should be the only product with positive market share.

22. In this "Sharks Superfan" world, I find that the bundle price predicted by Dr. Noll's model is $20.03, nearly identical to that found using the actual viewership data. The market share for

the bundle is the same using these simulated data as using the actual data. The Sharks have more than twice the market share of the league bundle along with a lower price of $8.22. Under this pattern of viewership data, the league bundle maintains its market share and the Sharks cannibalize from the other teams' offerings. Given the lower price of the Sharks channel relative to the bundle, however, the league bundle should not have any share at all.

23. I perform the same analyses substituting "Fan of the Game" and "Superfan" datasets for the data from MLB.tv and DirecTV and find the same patterns of results. In particular, the share and price of the league bundle are insensitive to the underlying viewership data and, when the market is composed of "superfans," increased shares to these teams come at the expense of other teams, rather than the league.[8] Under either viewership pattern and for both MLB.tv and DirecTV, the difference in damages arising from the simulated data and the actual data is no more than 3.12%. Table 1 through Table 5 show the prices, damages, and market shares under the actual, "Fan of the Game," and "Superfan" data patterns for the NHL, MLB.tv, and DirecTV packages.

Table 1: Comparison of but-for world bundle prices under actual and alternative viewership data

Scenario	NHL	MLB.tv	DirecTV
Actual data	$20.08	$15.42	$25.25
Superfan viewership	20.03	15.39	24.99
Fan of the Game viewership	20.13	15.44	25.42

[8] When considering the "superfan" viewership pattern using MLB data, I evenly divide viewers into fans of the Athletics and the Mets. In the NHL, every team, including the Sharks, faces off against every other team in the league. This is not true in baseball; every American League team faces all the other teams in that league, but does not play every team in the National League and vice-versa. To ensure that all teams have some viewership, I include an equal number of fans of one American League team (the Athletics) and one National League team (the Mets) to ensure that all parameters in the model can be estimated. The logic remains the same as in the GameCenter LIVE case.

Table 2: Comparison of claimed damages under actual and alternative viewership data

Scenario	NHL	MLB.tv	DirecTV
Actual data	$1,526,409	$8,127,491	$15,590,857
Superfan viewership	1,538,718	8,180,153	16,076,902
Fan of the Game viewership	1,514,099	8,092,383	15,273,057

Table 3: Comparison of NHL GameCenter LIVE but-for world market shares under actual and alternative viewership data

Scenario	League	Sharks	Other teams
Actual data	1.54%	0.20%	4.69%
Superfan viewership	1.54%	3.52%	1.39%
Fan of the Game viewership	1.54%	0.19%	4.67%

Table 4: Comparison of MLB.tv but-for world market shares under actual and alternative viewership data

Scenario	League	Athletics	Mets	Other teams
Actual data	3.50%	0.22%	0.24%	7.15%
Superfan viewership	3.51%	3.12%	1.71%	2.81%
Fan of the Game viewership	3.51%	0.25%	0.25%	7.09%

Table 5: Comparison of DirecTV but-for world market shares under actual and alternative viewership data

Scenario	League	Athletics	Mets	Other teams
Actual data	2.49%	0.16%	0.21%	5.78%
Superfan viewership	2.50%	1.91%	1.53%	2.84%
Fan of the Game viewership	2.51%	0.19%	0.18%	5.76%

24. In sum, under Dr. Noll's model, the replacement data representing opposite ends of the viewership spectrum produce essentially the same predicted prices and market shares for the league bundles using Dr. Noll's model. The conclusion, then, is that Dr. Noll's model for

estimating damages is implausibly insensitive to viewership preferences for the teams. In fact, any viewership data can be used with Dr. Noll's model to generate the same damages estimates; the estimates vary by less than 4 percent even though the viewership preferences are changed from one extreme to another.

B. DR. NOLL DOES NOT ADDRESS THE POSSIBILITY OF SELECTION BIAS IN THE DATA

25. Dr. Noll's analysis implicitly assumes that all consumers have the same preferences for the teams as the small subset of consumers who purchased a league bundle. This assumption is contradicted by economic principles and the factual record in these cases. In particular, these subsets of purchasers have more intense interest in the sports overall than the typical hockey or baseball fan, thereby overestimating the value of a league bundle to a general fan.[9]

26. Additionally, the preferences of consumers who purchase a league bundle or team telecast in Dr. Noll's but-for world where HTT blackouts are removed are likely to differ from those who currently purchase the league bundle in the presence of HTTs. For example, a Boston resident with a passionate interest in the Bruins, but with no interest in the league bundle today, will be more interested in the league bundle in Dr. Noll's but-for world because the Bruins games will no longer be blacked out.

27. This lack of the representativeness of Dr. Noll's sample can cause sample selection bias. Dr. Noll fails to discuss the issue of sample selection bias or prove that his sample is representative for the target markets in both his current and but-for worlds.

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[9] Dr. Noll predicts that subscribers will more than triple in his but-for world and, for two-thirds of those subscribers, he has no viewership data whatsoever.

C. THE RANKING OF TEAM PRICES IS RANDOM

28. As I show in a previous section, the prices of the league bundles are insensitive to the underlying viewership data. Here, I show that the predicted team prices are themselves determined entirely at random. Specifically, I find that Dr. Noll's ordering of team prices is completely different if a single input buried deep in his computer code is altered. This should not happen in a scientifically-sound application of any model. This result is not based on changing Dr. Noll's approach or his generalized method of moments ("GMM") estimates—the only difference is the "seed" that begins the simulation used to determine the optimal prices.[10]

29. To illustrate this point, I performed Dr. Noll's experiment 500 times using a different seed each time. Table 6 and Table 7 show that every NHL and MLB team offered the most expensive plan and nearly all offered the least expensive plan over the course of these simulations. A team's typical (median) ranking is in the middle of the price distribution. When the result of a model is sensitive to an arbitrary computer input, the appropriate approach is to run the model several times, as I have done here, and report results based upon the average or median value from these simulations. In the case of Dr. Noll's model, the median price offered by each team is nearly identical, an implausible result.

30. This simulation illustrates that Dr. Noll's model is uninformative for ranking teams based upon the prices that they would set for their standalone channels. In providing a random price sensitivity for each consumer in his simulation, he introduces an arbitrary ordering to

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[10] Computers are entirely deterministic and unable to produce random numbers. Instead, they have a specific algorithm that is used to produce pseudo-random numbers. The value of a particular random number is a function of the previous value. A "seed" determines where this algorithm starts. It is arbitrary and there is no reason that any seed is preferable to another. Dr. Noll admits that this behavior would be troubling (Noll deposition at 297:10-298:7).

the teams in the but-for world. When the results are appropriately averaged across 500 simulations, each team is shown to have nearly identical median prices. This result is implausible, however, for teams with fan bases of varying sizes and intensities.

Table 6: Summary of prices and orderings from 500 simulations (NHL)

	Rank			Price	
Team	Min.	Max.	Med.	Med.	Noll
Anaheim	1	30	16	8.47	7.41
Boston	1	30	15	8.39	7.88
Buffalo	1	30	16	8.43	8.13
Calgary	1	30	17	8.36	7.82
Carolina	1	30	16	8.42	9.16
Chicago	1	30	15	8.40	8.39
Colorado	1	30	14	8.38	7.74
Columbus	1	30	16	8.46	8.14
Dallas	1	30	15	8.39	8.57
Detroit	1	30	16	8.44	8.17
Edmonton	1	30	16	8.46	9.11
Florida	1	30	15	8.43	7.72
Los Angeles	1	30	15	8.42	8.57
Minnesota	1	30	17	8.49	8.81
Montreal	1	30	14	8.37	8.63
Nashville	1	30	16	8.46	8.74
New Jersey	1	30	15	8.42	8.16
NY Islanders	1	30	16	8.44	9.47
NY Rangers	1	30	15	8.37	8.65
Ottawa	1	30	15	8.42	8.32
Philadelphia	1	30	15	8.39	8.48
Phoenix	1	30	16	8.44	7.32
Pittsburgh	1	30	16	8.43	9.01
San Jose	1	30	15.50	8.43	7.94
St. Louis	1	30	16	8.44	8.49
Tampa Bay	1	30	15	8.40	8.22
Toronto	1	30	16	8.43	7.61
Vancouver	1	30	15	8.39	8.64
Washington	1	30	17	8.48	8.62
Winnipeg	1	30	16	8.41	8.23

Table 7: Summary of prices and orderings from 500 simulations (MLB)

	MLB.tv					DirectTV				
	Rank			Price		Rank			Price	
Team	Min.	Max.	Med.	Med.	Noll	Min.	Max.	Med.	Med.	Noll
Anaheim	1	30	15	8.48	8.15	1	30	15	12.42	11.76
Arizona	1	30	17	8.54	8.59	1	30	17	12.49	13.01
Atlanta	1	30	16	8.52	8.39	1	30	17	12.56	12.29
Baltimore	1	30	16	8.51	8.53	1	30	17	12.52	12.83
Boston	2	30	15	8.51	8.88	1	30	15	12.41	13.26
Chicago	1	30	17	8.55	8.17	1	30	16	12.44	12.20
Chicago	1	30	15.50	8.49	7.79	1	30	15	12.40	11.85
Cincinnati	1	30	16	8.54	8.64	1	30	16	12.42	12.46
Cleveland	1	30	16	8.51	8.38	1	30	15	12.39	11.82
Colorado	1	30	16	8.51	8	1	30	15	12.42	11.87
Detroit	1	30	16	8.52	8.74	1	30	14	12.43	11.66
Florida	1	30	17	8.54	9.13	1	30	17	12.52	14
Houston	1	30	15	8.46	8.17	1	30	14	12.29	11.13
Kansas City	1	30	14	8.49	8.75	1	30	15	12.40	12.49
Los Angeles	1	30	15	8.50	8.41	1	30	15	12.46	12.15
Milwaukee	1	30	16	8.52	8.37	1	30	15	12.42	12.28
Minnesota	1	30	16	8.54	8.71	1	30	16	12.46	12.67
NY Mets	1	30	15	8.48	8.54	1	30	15	12.42	12.65
NY Yankees	1	30	16	8.50	8.57	2	30	15	12.42	12.40
Oakland	1	30	16	8.51	8.31	1	30	15.50	12.45	11.71
Philadelphia	1	30	15	8.50	8.76	1	30	18	12.58	13.35
Pittsburgh	1	30	14	8.46	8.76	1	30	15	12.40	12.28
San Diego	1	30	15	8.50	8.86	1	30	15	12.42	13.33
San Francisco	1	30	15	8.50	8.64	1	30	16	12.40	12.42
Seattle	1	30	15	8.50	8.43	1	30	16	12.52	14
St. Louis	1	30	15	8.50	8.34	1	30	15	12.44	11.89
Tampa Bay	1	30	16	8.51	8.46	1	30	16	12.45	11.57
Texas	1	30	15.50	8.49	8.20	1	30	15	12.43	12.06
Toronto	1	30	17	8.53	8.67	1	30	16	12.44	12.71
Washington	1	30	14	8.45	7.93	1	30	14	12.41	11.82

31. To further illustrate the implausibility of the results, I review the actual output of Dr. Noll's simulations. I understand that most NHL experts would expect the Rangers, Blackhawks, Penguins, Red Wings, Flyers, and Bruins would be among the NHL teams most capable of charging the highest prices for team-specific programming. Yet only one of these (the Penguins) is among the top five most expensive telecasts in Dr. Noll's results, which instead includes the Islanders, Hurricanes, Oilers, and Wild. Notably, these latter four teams also rank among the eight lowest but-for world market shares. These teams have small fan bases that, by random chance, have low sensitivities to price. Similarly, for MLB, the Yankees,

Cubs, and Braves are all outside Dr. Noll's top 10 most expensive team channels, yet I understand that most MLB experts would expect these teams to have strong followings willing to pay for team-specific telecasts. As I show above, these results, which are at odds with the real world, are merely an artifact of the sensitivity of Dr. Noll's approach to his chosen seed.

D. Dr. Noll's Model Depends on Overly Simplistic Marginal Cost Assumptions That Have No Economic or Factual Bases

32. In the previous section, I show that the ordering of team prices is random. In this section, I show that the level of team prices is not determined primarily by the viewing data, but rather by Dr. Noll's unfounded assumption that the marginal cost for a particular team channel is 1/30th of that for the league bundle.

33. Dr. Noll stated in his deposition that he has no cost data to measure the marginal costs of teams introducing their own channels.[11] Nowhere in either of his declarations does Dr. Noll justify or even address his 1/30th assumption for teams' marginal costs. He performs no analysis to show that the teams would have lower marginal costs than the league or even offer examples of any costs that would be lower for teams than the league.[12] Dr. Noll has no

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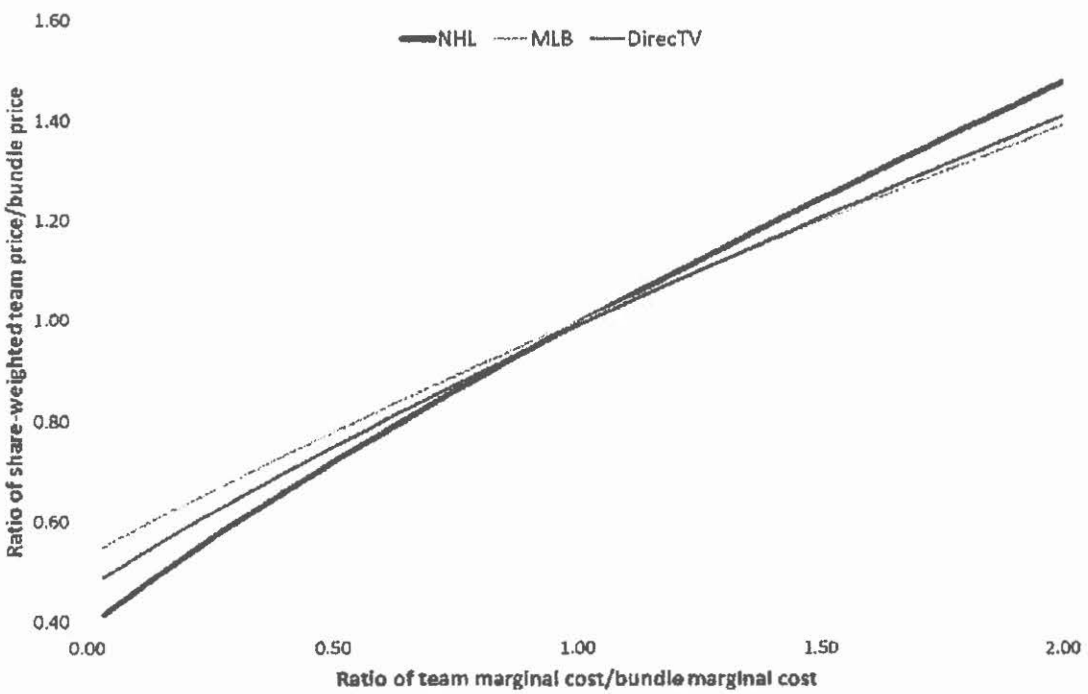
[11] Deposition of Roger Noll at 312:6-315:11.

[12] On the contrary, it is evident that the component of marginal cost associated with servicing a subscriber, including billing, providing content, determining digital rights, and collecting and processing payments, would be similar for the league bundle and an à la carte channel. Since these components of marginal cost are likely to be an important part of overall marginal cost, Dr. Noll's 1/30th assumption is implausibly low. A particular implication is that the sum of the marginal costs for a subscriber to a portfolio of all the individual team channels is likely to be substantially larger than the marginal cost of a subscriber to the league bundle. I understand that Dr. Janusz Ordover is discussing these issues in greater detail.

information that permits him to speak with any authority on the costs that a team would face in offering its own programming in the but-for world.

34. To test the sensitivity of Dr. Noll's model and results to his team marginal cost assumption, I use the parameters that he estimates using his GMM procedure, but I change the marginal costs of the teams used in the profit maximization step of his analysis. I maintain Dr. Noll's assumption that all teams have identical marginal costs and keep the league's marginal cost constant. I consider ratios of teams' marginal costs relative to the league's marginal cost that range from Dr. Noll's 1/30th assumption to a cost twice that of the league's marginal cost. The profit maximization calculation gives the price of the league bundle and the prices of each team's channel, from which I calculate an average team price that is weighted by the share of fans purchasing the channel.

Figure 1: The relationship between relative team marginal costs and relative team prices



Notes:
Share-weighted team price is the sum of the products of team shares and prices divided by the sum of team shares.
Source: Dr. Noll's Supplemental Report and The Brattle Group calculations.

35. Figure 1 shows the ratio of the share-weighted average team price to the bundle price across a range of teams' marginal costs relative to the league marginal costs, holding the league marginal cost fixed. As the teams' marginal costs increase relative to those of the league, the average price of the team products increases relative to that of the league bundle. This figure demonstrates that the relative price of team products is highly influenced by the assumed marginal costs of the teams rather than being derived from any measurement of demand. Given this sensitivity, a scientific approach requires careful measurement of team and league marginal costs because but-for world prices and damages are highly sensitive to these inputs. Dr. Noll's 1/30th marginal cost assumption is scientifically unacceptable.

V. Dr. Noll Does Not Follow the C&Y Approach in Estimating Demand

36. Dr. Noll does not follow the C&Y approach to estimate demand and it is misleading and inaccurate to claim to have done so. Furthermore, the method that Dr. Noll employs is not based on a current, sound economic methodology. In this section, I first contrast the general approach of Dr. Noll to that of C&Y. Then, I discuss how the nature of sports viewing as well as the specific data available necessitate altering the C&Y approach to account for "double counting."

A. Dr. Noll Cannot Rely on the C&Y Paper as Support for his Analysis

37. Dr. Noll's analysis seeks to estimate demand in a market where a consumer can choose from a league package, a single-team channel of the viewer's favorite team, or purchasing no programming at all. As an analogy to the C&Y framework, Dr. Noll considers the league bundle to be akin to a cable service and a single-team telecast to be akin to an individual channel.

38. First, unlike the C&Y approach, Dr. Noll does not consider variation in the price of each league bundle across consumers in the data. Prices do vary across consumers, with [redacted] of

GameCenter LIVE subscribers, [redacted] of MLB.TV subscribers, and [redacted] of DirecTV subscribers paying a price different from the one assigned by Dr. Noll.[13] He chooses to ignore this price variation, however, and instead assumes that all consumers pay the same price. Hence, he ignores the available price variation, yet nonetheless claims to measure consumer's sensitivity to prices.

39. Second, Dr. Noll ignores substantial geographic variation in game availability in each league bundle that leads fans to experience different effective prices per game. As an illustration, consider a fan of the Boston Bruins who lives in Manhattan. This fan cannot watch Bruins games against the Rangers, Islanders, or Devils on GameCenter LIVE because the HTTs of those three teams cover Manhattan and these games are therefore subject to blackouts on GameCenter LIVE. On the other hand, a Bruins fan living in San Francisco is within the HTT of a single team, the Sharks, and therefore can see more matches on GameCenter LIVE. As a result, the fan in San Francisco has more opportunities to watch his favorite team using GameCenter LIVE than does the fan in Manhattan, effectively providing more value for his money. Stated differently, the fan in Manhattan faces a higher effective price per game than the fan in San Francisco.

40. Furthermore, the Bruins fan in Manhattan also has the possibility of watching Bruins games on the local RSN when the team faces off against the Rangers, Islanders, or Devils. Hence, the value of the non-GameCenter LIVE opportunity is higher. Dr. Noll ignores how consumers' locations affect price variation.

41. Third, unlike C&Y, Dr. Noll does not permit consumer preferences to depend upon demographic factors, such as the location of the subscriber, which is available in his data. Nor does he consider correlation between consumers' preferences for teams, even though, as

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13 Noll Supplemental Declaration, Exhibits 1 and 2.

discussed further in the following section, consumer viewing times for teams are necessarily correlated because a game involves two teams. These correlation patterns influence how valuable a bundle of team channels is to a consumer relative to a standalone team channel.

42. These are three significant ways in which Dr. Noll's approach is substantively different from that used by C&Y in estimating the demand for broadcasts and there is no published academic paper that follows Dr. Noll's approach.[14]

B. Dr. Noll Inconsistently Counts Viewership

43. In the C&Y paper, "channels" have the meaning in common use in television broadcasting; *e.g.*, CNN, CBS, and ESPN are channels and subscriptions to packages of channels, such as "basic" or "premium sports," are offered by providers, such as cable companies and DirectTV. A feature of this definition is that channels are substitutes. There are no requirements that a consumer who spends an hour watching one channel, such as ESPN, also spends an hour watching a second channel, such as CNN. It is plausible in the C&Y paper to envision consumers as having preferences for individual channels.

44. In his application of the C&Y framework for his analysis, Dr. Noll uses the term "channel" to refer to a particular sports team, such as the Boston Bruins, and interprets time spent watching this team as time spent watching this channel. But league sporting events are matches between two teams, so an hour spent watching the Bruins play the Rangers is also an hour spent watching the Rangers play the Bruins. Dr. Noll handles this in his model by counting an hour spent watching a match between two teams twice, one hour for each team. But there is then a complementarity between times spent watching different teams; a viewer

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[14] Furthermore, I understand that Dr. Pakes discusses the gap between the C&Y approach and Dr. Noll's approach on the supply side of the market.

cannot watch one team without also watching its opponent. As described below, Dr. Noll is inconsistent in his handling of his double-counted watching times, leading to mathematical errors by failing to account for this complementarity in his model of consumer optimization. Double counting creates four major problems in Dr. Noll's analysis.

45. First, the time budget constraint is no longer defined consistently when the total time budget T and non-package viewing leisure time are counted in hours, while each hour of package viewing time is counted as two hours of viewing time, once for each team.[15]

46. Second, the first-order conditions that Dr. Noll uses to characterize utility maximization in this context are incorrect.[16] As a result of these mistakes in calculus, Dr. Noll mischaracterizes the utility maximization problem and the relationships that it implies between viewing times and tastes for teams. These errors contaminate Dr. Noll's GMM estimation of means and variances of the random taste parameters for each team.

47. Third, the model requires a constraint on the maximum amount of time that a viewer can watch any pair of teams face off against one another that accounts for both the actual schedules of the two teams and the blackouts experienced by that particular viewer as a result of HTTs. Dr. Noll does not account for these factors.

48. Fourth, in the profit maximization simulation, Dr. Noll fails to specify the utility function for the favorite team option consistently and instead single counts the hours viewed for the favorite team and does not consider hours viewing that team's opponents. These errors contaminate Dr. Noll's simulation of consumer values and demands under but-for world

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15 Additionally, the time budget should be based on the number of leisure hours available to the consumer, rather than, as Dr. Noll calculates, the maximum number of hours watched by any consumer.

16 The mathematical errors made by Dr. Noll are detailed in Appendix A.

conditions where both a team telecast and league bundle are available. This understates the value of a team channel to the viewer. As a result, his simulation of the choice between a team channel and the league bundle is biased.

VI. Dr. Noll's Model Produces Counterintuitive Results

49. Given all the methodological flaws in Dr. Noll's model (even considering only the demand side of his approach), it is not surprising that the model produces even more examples of results that do not comport with economic theory. Below I provide two additional examples.

A. Dr. Noll's Results Are Nearly the Same if Consumers Are Offered Their Least Favorite Team's Telecast Instead of Their Most Favorite

50. Dr. Noll's model offers the consumer a choice between the league bundle and a telecast of his favorite team or the option not to purchase any programming. Suppose instead that the consumer's only programming choices were the league bundle and a telecast of his *least* favorite team.[17] In this instance, the individual team telecasts should be nearly universally disfavored and therefore would not serve as a reasonable substitute for the league bundle for any fans. In the absence of true competition, the league bundle should maintain its current, observed price.

51. I used Dr. Noll's profit maximization model and his GMM estimates of the demand-side parameters to recalculate optimal prices for the league bundles and team telecasts. Table 8 shows the results of this analysis for the league bundle. Contrary to expectations based on economic principles, prices and market shares are nearly identical whether consumers are offered their favorite or least favorite team's telecast. Even more unbelievable, Table 9 shows

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[17] I identify a consumer's least favorite team in a manner analogous to Dr. Noll's selection of his favorite team.

that the share-weighted average price for the team telecasts are nearly the same when customers are offered their least favorite team's telecast as when they are offered their preferred team's telecast. In fact, there are nearly as many customers willing to purchase their least favorite team's telecast; the total market share of the teams is only slightly smaller for the least favorite team telecasts. Once again, Dr. Noll's model produces results that are implausible.

Table 8: League bundle prices and market shares when the bundle competes against either a favorite or least favorite team's telecast

	Favorite		Least favorite	
Bundle	Price	Share	Price	Share
NHL	$20.08	1.54%	$20.27	1.54%
MLB.tv	15.42	3.50%	15.46	3.51%
DirecTV	25.25	2.49%	25.87	2.48%

Table 9: Share-weighted average team telecast price and total team market shares when the bundle competes against either a favorite or least favorite team's telecast

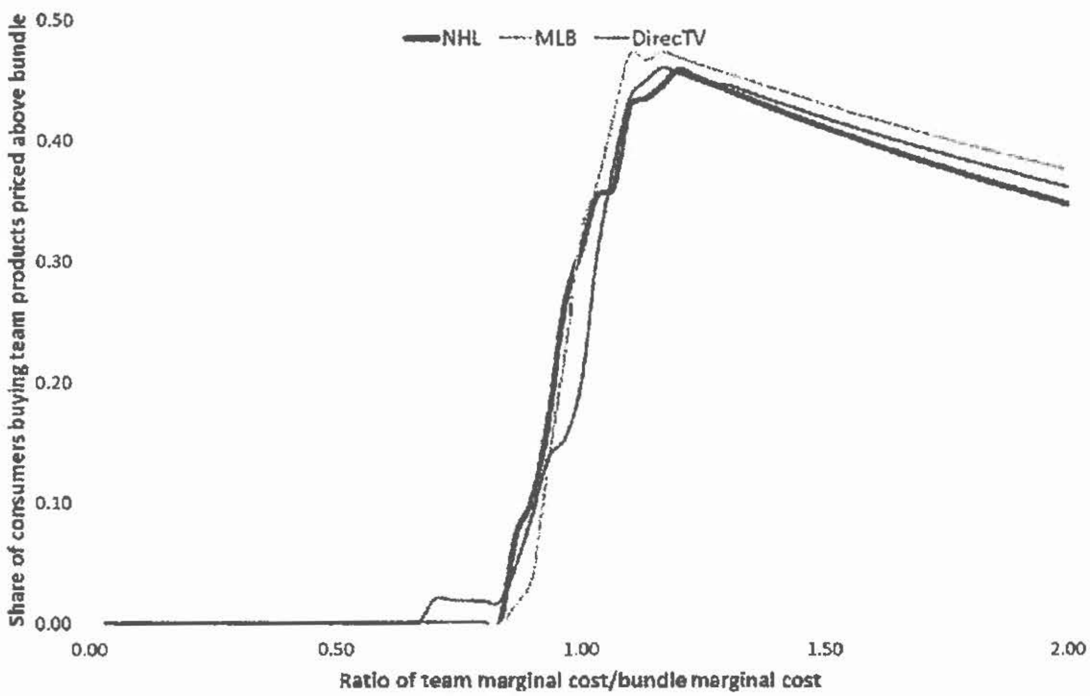
	Favorite		Least favorite	
Bundle	Price	Share	Price	Share
NHL	$8.34	4.89%	$8.29	4.78%
MLB.tv	8.48	7.60%	8.47	7.56%
DirecTV	12.36	6.15%	12.21	5.90%

B. Dr. Noll's Model Predicts That Some Fans Will Pay More for an Individual Team Telecast than for the League Bundle

52. As shown in Figure 1 and discussed previously, when the marginal cost of the team telecasts exceeds that of the league bundle, the average price of the team products exceeds that of the league bundle. This implies, however, that consumers are purchasing team products that are

more expensive than the league bundle. Figure 2 depicts the ratio of team to league marginal costs on the horizontal axis, as in Figure 1, and gives the proportion of purchasers of some programming who purchase a team telecast at a price higher than the price for the league bundle—that is, it gives the proportion of customers who pay too much. These customers pay too much because they elect to purchase a single team's telecast when they could pay less for the complete league bundle.

Figure 2: Proportion of purchasers choosing a team telecast priced above the league bundle



Notes:
Share-weighted team price is the sum of the products of team shares and prices divided by the sum of team shares.
Source: Dr. Noll's Supplemental Report and The Brattle Group calculations.

53. At low levels of team marginal costs, no individual team's product costs more than the league bundle. As marginal costs rise, some teams begin pricing above the price of the league bundle. When the marginal costs are the same for the teams and the leagues, over 20% of purchasers pay *more* than the cost of the league bundle for a team telecast. When each team's

marginal cost exceeds the league's marginal cost by 20%, then over 40% of purchasers pay more. This general relationship is true for all three league packages considered by Dr. Noll.

54. This result arises from the assumptions inherent in the particular logit formulation that Dr. Noll uses. He assumes that there are unobservable aspects of the league bundle that make it more or less appealing to some people than the channels offered by their own favorite teams. But every individual team channel is part of the league bundle. At the same price, every consumer ought to strictly prefer the bundle to the team channel. Dr. Noll's formulation of the consumer choice model does not recognize that each team channel is strictly a component of the league bundle, which therefore leads to this implausible result.[18]

55. Furthermore, there exists an extensive scientific literature demonstrating that the logit model in the basic form used by Dr. Noll does a poor job of predicting demand for products when products are very similar in their attributes or when one product dominates another.[19] Moreover, it is well known that using logit-based demand models may cause upward bias in estimates of the benefits that consumers derive from new products (like à la carte channels).[20]

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[18] It is possible that consumers like the online interface or mobile "app" for a team more than the league version. It is unlikely that these differences would be substantial enough for a fan to choose a single team channel over the complete league bundle, however. (There is no place for adding team channel-specific content, such as morning or drive-time shows, in Dr. Noll's but-for world that might justify choosing a higher-priced team-specific channel.)

[19] This is driven by the Independence of Irrelevant Alternatives (IIA) property; see, for example Train, K. (1986) Qualitative Choice Analysis: Theory, Econometrics and an Application to Automobile Demand MIT Press.

[20] See Petrin, A. (2002) "Quantifying the Benefits of New Products: The Case of the Minivan," *Journal of Political Economy* (Here, the author finds that "the microdata are important for demand and welfare measurement, primarily because they appear to free the model from a heavy dependence on the idiosyncratic logit error.") and Ackerberg, D. & Rysman, M. (2005) "Unobservable Product Differentiation in Discrete Choice Models: Estimating Price Elasticities and Welfare Effects," *RAND Journal of Economics.*

VII. Conclusions

56. Based on my review of both of Dr. Noll's declarations and his backup materials, I conclude that Dr. Noll has used methodologies and assumptions that fail to meet standards generally accepted in economics. As a result, Dr. Noll's approach is inadequate for estimating damages or for demonstrating common impact among class members.

Executed on November 12, 2014 at Berkeley, California

Daniel L McFadden

Appendix A. Mathematical Errors in Dr. Noll's Utility Maximization Formulation

This appendix summarizes the mathematical core of Professor Noll's model, and identifies where errors within his analysis occur. The notation mainly follows Professor Noll, but in some places defines additional variables and quantities to clarify his analysis.

Consider a sports league with J teams, labeled $j = 1,\ldots,J$. Consider consumers who are interested in watching games in this league, with viewing access through national and RSN programming and through subscription to league-supplied streaming services or cable channels, and additionally in the but-for world, through subscription to team-supplied streaming services. Define $t_{jk} \equiv t_{kj}$ to be the total time a consumer watches matches through a subscription service between teams j and k, both home and away for team j. These league-bundle match viewing times are the data used by Professor Noll. Define $t_{jj} = 0$. If matches between j and k are not available through the subscription service, say because the consumer is in the RSN of one of these teams, then $t_{jk} = 0$. There is an upper bound T_{jk} on the hours a consumer can watch matches between j and k, determined by the total number of games these teams play and the blackout rules for these games that apply to the particular consumer. Let $t_j = \sum_{k=1}^{J} t_{jk}$ denote the total time spent watching team j, T denote double the consumer's total budget of leisure time, and $t_0 = T - \sum_{j=1}^{J} t_j$ denote double the hours spent in "outside" leisure (including RSN viewing). Define

(1) $V_L = \max_{\{t_{jk}\}}\{\sum_{j=1}^{J} \gamma_j \log(1 + \sum_{k=1}^{J} t_{jk}) + \gamma_0 \log(1 + T - \sum_{j=1}^{J}\sum_{k=1}^{J} t_{jk})\}$,

(2) $V_0 = \gamma_0 \log(1 + T)$,

(3) $V_i = \max_{\{t_{ik}\}}\{\gamma_i \log(1 + \sum_{k=1}^{J} t_{ik}) + \sum_{k\neq i} \gamma_k \log(1 + t_{ik}) + \gamma_0 \log(1 + T - 2\sum_{k=1}^{J} t_{ik})\}$,

(4) $U_L = V_L - \alpha p_L + \varepsilon_L$

(5) $U_0 = V_0 + \varepsilon_0$

(6) $U_i = V_i - \alpha p_i + \varepsilon_i$

These formulas follow Professor Noll in double counting the times spent viewing matches, once for each team, and in defining T as the maximum observed double-counted hours spent viewing matches. Professor Noll does not account for upper bounds on viewing times T_{jk}. The subscript "L" corresponds to the league bundle, and the subscript "0" to the outside option, both assumed to be available choices for the consumer in the as-is world. The subscript "i" refers to a team channel for team i that Professor Noll assumes is added to the consumer's available choices in the but-for world. The price p_L of the league bundle can differ in the as-is and but-for worlds; let p_{Lai} and p_{Lbf} denote these respective prices. The price p_i of team channel i is defined only in the but-for world. The expressions U_L, U_0, and U_i are the consumer's final utilities of the league bundle, outside, and team channel alternatives. These expressions contain independent additive type 1 extreme value disturbances ε_L, ε_0, and ε_i. Professor Noll assumes that the parameters γ_j and α are heterogeneous among consumers, with independent log normal distributions. Professor Noll does not allow correlations among these random parameters.

Professor Noll's model implies that in the as-is world, the market share of the league bundle among consumers with given parameters γ_j and α is given by a logit model,

$$(7)\quad P_{L|\gamma\alpha,ai} = \frac{\exp(V_L - \alpha p_{Lai})}{\exp(V_0) + \exp(V_L - \alpha p_{Lai})},$$

and across all consumers is given by a mixed logit model that is the expectation of this logit model,

$$(8)\quad S_{Lai} = \mathbf{E}_{\{\gamma_j\},\alpha}\, P_{L|\gamma\alpha,ai}.$$

Professor Noll assumes that in the but-for world, a consumer is limited to choice between the league bundle, the outside option, and the team channel for one designated team i (determined by the largest γ_j in a simulation of the tastes of this consumer). The market shares of the league bundle and of designated team channels i among consumers with given parameters γ_j and α are then given by a multinomial logit model

$$(9)\qquad P_{L|\gamma\alpha,bf} = \frac{\exp(V_L - \alpha p_{Lbf})}{\exp(V_0) + \exp(V_L - \alpha p_{Lbf}) + \exp(V_i - \alpha p_i)},$$

$$(10)\qquad P_{i|\gamma\alpha,bf} = \frac{\exp(V_i - \alpha p_i)}{\exp(V_0) + \exp(V_L - \alpha p_{Lbf}) + \exp(V_i - \alpha p_i)},$$

and across all consumers are given by the expectations,

(11) $S_{Lbf} = \mathbf{E}_{\{\gamma_j\},\alpha} \sum_{i=1}^{J} \mathbf{1}(\text{i designated } |\{\gamma_j\}) P_{L|\gamma\alpha,bf}$

(12) $S_{ibf} = \mathbf{E}_{\{\gamma_j\},\alpha} \mathbf{1}(\text{i designated } |\{\gamma_j\}) P_{i|\gamma\alpha,bf}.$

The own price elasticity of $P_{i|\gamma\alpha,bf}$ is $-\alpha p_i(1 - P_{i|\gamma\alpha,bf})$, and the price elasticity of the market share (12) is a weighted average of these elasticities. Then, more popular teams with larger V_i will have lower price elasticities at common prices, and in but-for world equilibrium will find it profitable to charge higher prices for their team channels.

The major mathematical and logical errors made by Professor Noll within his analysis are the following:

1. The optimization problem in (1) is incorrectly characterized by Professor Noll as one in which consumers can freely choose levels of total time spent watching each team, rather than the one in which consumers choose levels of time watching matches between each pair of teams, subject to a maximum time imposed by the number of matches between each pair of teams and blackout rules that apply to these matches for the consumer in question. In a correct formulation of the optimization problem, total time spent watching each team is determined as a consequence of the optimized match watching times. Professor Noll's first-order-conditions for optimization fail to recognize these constraints, and hence mischaracterize the relationship between viewing times and taste parameters.

   Using the shorthand notation $t_j = \sum_{k=1}^{J} t_{jk}$ and $t_0 = T - \sum_{j=1}^{J} t_j$, the correct first-order conditions for the optimization (1) are

$$(13) \qquad \frac{\gamma_j}{1+t_j} + \frac{\gamma_k}{1+t_k} - \frac{2\gamma_0}{1+t_0} \begin{array}{ll} \leq 0 & \text{if } t_{jk} = 0 \\ = 0 & \text{if } 0 < t_{jk} < T_{jk} \\ \geq 0 & \text{if } t_{jk} = T_{jk} \end{array} \quad \text{for } 1 \leq j < k \leq J,$$

   where T_{jk} is the maximum number of hours that the consumer could possibly watch matches between teams j and k. There are J(J-1)/2 of these conditions, one for each of the viewing times t_{jk} for $1 \leq j < k \leq J$. Professor Noll instead solves the conditions

$$(14)\qquad \frac{\gamma_j}{1+t_j} - \frac{\gamma_0}{1+t_0} \begin{array}{ll} \leq 0 & \text{if } t_j = 0 \\ = 0 & \text{if } t_j > 0 \end{array}$$

for J values t_j for $1 \leq j \leq J$. The solution of (14) can give different values of t_i than those that result from solution of (13). For example, bounds $T_{1k} > 1$ and the parameter values $\gamma_1 = 3J$, $\gamma_2 = ... = \gamma_J = 2$, $\gamma_0 = 2(3+T-2J)$ in (13) have the solution $t_{1k} = 1$ for $k > 1$ and $t_{jk} = 0$ for $j,k > 1$, implying $t_1 = J - 1$ and $t_2 = ... = t_J = 1$. For these same parameter values, (14) has a solution with $t_1 > J - 1$ and $t_2, ..., t_J < 1$, which is logically impossible given the double counting of time spent watching matches. Because Professor Noll fails to obtain the correct optimal values for equation (1), his GMM estimation of the distributions of his random parameters that are based on the optimized values is statistically inconsistent. As a result, his further calibrations and simulations are also statistically inconsistent.

2. Professor Noll states incorrectly the utility function and optimization problem in (3), and consequently mischaracterizes the attractiveness of team channels relative to the league bundle. The correct first-order conditions for optimization of (3) are the J-1 conditions

$$(15)\qquad \frac{\gamma_i}{1+t_i} + \frac{\gamma_k}{1+t_k} - \frac{2\gamma_0}{1+t_0} \begin{array}{ll} \leq 0 & \text{if } t_{ik} = 0 \\ = 0 & \text{if } 0 < t_{ik} < T_{ik} \\ \geq 0 & \text{if } t_{ik} = T_{ik} \end{array} \qquad \text{for } k \neq i.$$

Professor Noll omits the contribution to utility in (3) from the viewing times of opponents of team i, and in optimization fails to take into account the upper bound T_{ik} on time that can be spent watching matches between i and k. Consequently he again solves the incorrect first-order conditions.

A plausible pattern of consumer tastes for viewing league sports is that there are substantial segments of the population that are primarily fans of specific teams with secondary interest in other teams, and a segment of the population that are "fans of the game" without strong team preferences. Within each of these segments, the random parameters $(\gamma_1,\ldots,\gamma_J)$ will have different means. For example, the fans of team j will have a high mean value of γ_j and low mean values for the remaining parameters. Then for consumers in the population that combines the segments that are fans of different teams, the parameters will tend to be negatively correlated, with a high value for one parameter associated with low values for the remaining parameters. On the other hand, "fans of the game" will have similar parameters for different teams, making them positively correlated. The choice behavior of these different segments in response to the availability of team channels will be substantially different, with fans of team j attracted to that team's channel, and "fans of the game" attracted to the league bundle. Professor Noll's model assumption that the random parameters are uncorrelated and log normally distributed cannot represent the plausible pattern of consumer tastes just described, and even the more general C&Y assumption of correlated log normally distributed taste parameters is not adequate to capture the patterns of tastes and demands in a segmented population; a mixture of multivariate log normal distributions with different means for each segment in the mixture would be required.