

ECONOMICS COMMITTEE NEWSLETTER

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Welcome

It is my pleasure to welcome you to the Spring 2015 volume of our newsletter. The newsletter aims to provide a forum where Antitrust Section and Economics Committee members can share their views on topics related to the relationship of antitrust law and economics.

In this edition of the newsletter, we have three articles by economists and practitioners in the field. Sean Durkin explores potential consumer benefits of deceptive marketing. Dov Rothman and Aaron Yeater show that countercyclical price movements do not support an inference of collusion. And Ai Deng illustrates potential pitfalls in time series regression analysis. Whatever your background, these articles will provide valuable insights and perspectives.

This newsletter is intended to provoke discussion. As a result, the opinions expressed in this newsletter are only those of the authors. In addition, the opinions found herein do not reflect those of the editors, members of the Economics Committee, their employers, or the Antitrust Section of the ABA.

Please enjoy!

Sincerely,

Mark W. Nelson, Editor

Call for Articles

We are always looking for articles for future issues of the newsletter. If you have an article or an idea for an article of about 1500 words in length regarding the current or improved use of economics in analyzing issues of antitrust law, by all means, please share it with us.

Contact Mark W. Nelson at mnelson@cgsh.com for more information.

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Deceptive Marketing Practices: How Some Consumers Benefit When Others are Deceived

Sean Durkin¹

Many recent cases include allegations that false advertising, disparagement, or other deceptive practices constitute anticompetitive conduct. These allegations are often part of claims that a defendant has engaged in a broader set of anticompetitive conduct. For example, the DOJ's complaint against Intel alleged that Intel manipulated CPU performance benchmarks and deceived customers as one of several forms of conduct that allegedly strengthened and maintained its monopoly.² Recently, however, a Texas jury found Becton-Dickinson guilty of attempted monopolization based solely on its allegedly false advertising, even though the plaintiff also alleged that Becton-Dickinson engaged in anticompetitive contracting practices.³

Courts have generally adopted the consensus view of legal scholars that the presumption should be that false advertising and other deceptive promotional practices have a *de minimis* effect on competition. According to this consensus view, deception is unlikely to have a large effect on relative demand for rivals' products, in part at least, because few consumers are likely to be deceived. Consumers have many sources of information other than a company's claims about its own or its rivals' products, and rivals can counter the effects of deception by engaging in their own promotional activities. Thus, even if deception harms competitors, that harm will, except in rare cases, be insufficient to harm competition, so allegations of deceptive practices should be restricted to tort claims.

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² See, <http://www.ftc.gov/sites/default/files/documents/cases/091216intelcmpt.pdf>.

³ See, *Retractable Technologies, Inc. and Thomas J. Shaw v. Becton Dickinson & Company*, No. 2:08-cv-16 (M.D., Sept. 19, 2013).

In many of the recent cases, however, plaintiffs and their experts have argued that deceptive practices have contributed to monopoly acquisition or maintenance without any allegation that a large share of buyers were deceived. For example, as part of their antitrust claims against Keurig Green Mountain, plaintiffs claimed that Keurig made false and disparaging statements about its competitors' portion packs.⁴ Similarly, as part of their claims against News America Marketing, plaintiffs claimed that News America deceived their customers by disparaging their rivals' compliance rates.⁵ Microsoft is still being sued for creating fear, uncertainty, and doubt about its rivals products during the 1990s.⁶ The implicit, and sometimes explicit, claim by plaintiffs in these cases is that deception should be considered anticompetitive conduct, even if few buyers are actually deceived, because deception raises rivals' costs and has no procompetitive justification.

This article discusses why deceptive promotional practices may not harm competition even if it cannot be countered by rivals and a large share of buyers is deceived. By deceptive promotional practices, I mean practices that impact the willingness to pay for a company's product relative to its rivals' products. Thus, deceptive promotional practices could be a company making false statements about the quality of its own products and/or the quality of its rivals' products. For example, the FTC alleged that Intel manipulated the performance benchmarks which deceived consumers and gave an incorrect impression of the performance of Intel processors relative to AMD processors.

This article shows that promotion of a seller's product, whether deceptive or truthful, can increase competition between sellers by inducing them to more aggressively compete for buyers who would otherwise view the

⁴ See e.g., *In Re: Keurig Green Mountain Single Serve Coffee Antitrust Litigation*, JBR, Inc. v. Keurig Green Mountain, Inc., No. 1:15-cv-04242-VSB-HBP (First Amended and Supplemental Complaint, November 25, 2014).

⁵ See, *The Dial Corporation, et. al. v. News America Marketing, LLC*, No. 2:12-cv-15613-AJT-MKM (Second Amended Complaint, March 26, 2013).

⁶ See, *Go Computer, Inc., v. Microsoft Corporation*, No. CGC-05-442684 (Fifth Amended Complaint, June 29, 2005.)

two products as close substitutes. While deception reduces the sales of the deceiving firm's rivals and harms buyers who are deceived, buyers who are not deceived can be better off because deception leads to lower prices for them.

The basic intuition is that, when sellers cannot price discriminate, they may not compete aggressively for buyers who view their products as close substitutes for their rivals' product because it would require them to lower prices to loyal buyers with more inelastic demand. Advertising and promotion is often targeted at buyers who view rivals' products as close substitutes. When promotion raises the willingness-to-pay for a seller's products, it can induce sellers to compete more aggressively for those buyers.

This implies that the assertion that deceptive practices have no procompetitive justification is incorrect. Buyers that are not affected by the promotion benefit because it increases competition for those affected by the promotion. When the promotion is deceptive, deceived buyers are harmed because they are deceived and not due to any harm to competition caused by the deception.

In addition, this article sheds light on claims often made by classes of plaintiffs under state consumer protection statutes that deceptive practices lead to higher prices for all consumers. The economic logic behind these claims is that deception, even of a limited number of consumers, artificially raises the demand for the defendant's product, causing all consumers to pay higher prices. The analysis in this paper shows that artificially raising the demand for some buyers need not lead to higher prices for all consumers. In fact, deceiving some customers can cause prices to be lower for consumers who were not deceived. This has implications for both class certification and damages issues in these cases.

A. Background

For some time, legal scholars have debated whether deceptive promotional practices should be considered antitrust violations. There is a general consensus that while the deceptive promotional activity harms competitors it is unlikely, except in rare circumstances, to harm competition.

Deception is unlikely to harm competition because a large share of consumers is unlikely to be deceived, in part at least, because rivals can counter with their own promotion.⁷

Areeda and Hovenkamp argue that there should be a presumption that deception has a *de minimis* effect on competition unless the plaintiff can show that the promotional activities were: (1) clearly false, (2) clearly material, (3) clearly likely to induce reasonable reliance, (4) made to buyers without knowledge of the subject matter, (5) continued for prolonged periods, and (6) not readily susceptible to neutralization, or other offset, by rivals.⁸ If plaintiffs are unable to meet this burden, they argue that deceptive promotional practices should be limited to tort statutes such as the Lanham Act. Courts have generally adopted this consensus view in cases alleging anticompetitive deceptive promotion.⁹

The alternative view often expressed by plaintiffs and their experts is that, because it has no procompetitive justification, deception should be considered an antitrust violation because it makes it harder for rivals to compete and raises their costs. This is consistent with the view, expressed by some, that there is little harm from treating tortious conduct as an antitrust violation because one need not be concerned about false positives if the conduct has no procompetitive justification.¹⁰

From a practical standpoint, there are at least two reasons why plaintiffs would prefer to have their claims evaluated under the Sherman Act

⁷ See Patricia Schultheiss and William E. Cohen, *Cheap Exclusion: Role and Limits*, at 4-5. http://www.ftc.gov/system/files/documents/public_events/section-2-sherman-act-hearings-single-firm-conduct-related-competition/section2cheapexclusion.pdf

⁸ 3B PHILLIP E. AREEDA & HERBERT HOVENKAMP, *ANTITRUST LAW* ¶¶ 782a-b, at 321 (3d ed. 2008).

⁹ See Patricia Schultheiss and William E. Cohen, *Cheap Exclusion: Role and Limits*, at 4-5. http://www.ftc.gov/system/files/documents/public_events/section-2-sherman-act-hearings-single-firm-conduct-related-competition/section2cheapexclusion.pdf.

¹⁰ Susan A. Creighton, D. Bruce Hoffman, Thomas G. Krattenmaker & Ernest A. Nagata, *Cheap Exclusion*, 72 *ANTITRUST L.J.* 975, 989 (2005).

rather than tort statutes. First, plaintiffs would be entitled to treble damages for violations of the Sherman Act. Second, a plaintiff with, for example, a weak case that a defendant's contracting practices are exclusionary may want to include a false advertising claim in the hope that a jury will believe that the deception is sufficiently objectionable that it finds the defendant in violation of the Sherman Act even if the contracting practices were not exclusionary.

Economics does not generate any unambiguous predictions about the effect of deceptive advertising on competition and consumers. There has been some economic analysis of the effectiveness of truthful advertising and promotion on competition.¹¹ Informative advertising has been shown to be able to increase competition and lead to lower prices because buyers that are better informed about prices or product characteristics have more elastic demand. Persuasive advertising, on the other hand, has been shown to potentially reduce competition and lead to higher prices because it allows sellers to better differentiate their products, making demand more inelastic. However, some have noted that when sellers cannot price discriminate, the ability of a seller to differentiate its products through persuasive advertising can increase competition by increasing the willingness-to-pay for marginal customers.¹²

There is, however, little to no economic analysis that examines the effect of deceptive promotion on competition. Below, I present a framework for assessing whether the type of deceptive promotion at issue in recent cases can harm competition and consumers by reducing competition.

B. Example

Suppose there are two sellers that sell one product and that both have a constant marginal cost of 5. Assume also that there are three types of buyers that purchase one unit of the product. Loyal buyers will only buy from

¹¹ Anthony J. Dukes, *Advertising and Competition*, *Advertising and Competition*, in ISSUES IN COMPETITION LAW AND POLICY 515 (ABA Section of Antitrust Law 2008).

¹² See, Gary S. Becker and Kevin M. Murphy, *A Simple Theory of Advertising as a Good or Bad*, 108 Q. J OF ECON., (4), 955-56 (1993).

Seller 1 and are willing to pay 20 for Seller 1's product. Sophisticated buyers view the products from Seller 1 and 2 as substitutes and buy the cheapest product. In the absence of any promotion, naïve buyers are identical to sophisticated buyers, but promotion by Seller 1 can increase the naïve buyers' willingness-to-pay for its product. Assume naïve and sophisticated buyers are willing to pay 12 for either seller's products without any promotion. Assume also that each seller knows there are 40 loyal, 40 naïve, and 20 sophisticated buyers but that neither seller knows which customers are loyal, naïve, and sophisticated.

One can think about Sellers 1 and 2 hypothetically as Intel and AMD. There may be some loyal buyers that will only buy PCs with Intel processors. Sophisticated buyers may not care whether their PC has an AMD or Intel processor and will buy whichever PC is cheaper and cannot be influenced by Intel's promotional efforts. This may be because they rely on other sources of information rather than Intel's promotional activities. Intel's promotional efforts may, however, increase naïve buyers' willingness-to-pay for its product relative to the AMD product.

In this hypothetical example, the assumption that only Intel can promote its products means the promotional activities under consideration are those that cannot be countered by AMD. The assumption that sellers cannot distinguish between the different types of customers means they cannot price discriminate.

1. Outcomes with no promotion

Consider first what happens when Seller 1 does not promote its products. Seller 1 has loyal buyers over which it effectively has monopoly power, and it can charge them their willingness-to-pay. If it only sells to loyal buyers, Seller 1 charges a price of 20. With a marginal cost of 5, it earns a profit of 15 per unit for 40 units for a total profit of 600.

For Seller 1 to be willing to lower its price to compete for naïve and sophisticated customers, it would have to earn a profit of at least 600. Thus, Seller 1's minimum price is 11. At that price, it earns a profit of 6 per unit and sells a total of 100 units. Since Seller 2 has no loyal customers, its minimum

price equals its marginal cost of 5. If Seller 1 charges its minimum price Seller 2 can charge a price just below 11 and capture all the sales to naïve and sophisticated customers.

Therefore, without any promotion, Seller 1 charges a price of 20 and sells only to loyal customers, while Seller 2 charges a price just below 11 and sells to the naïve and sophisticated customers. Since the price paid by loyal customers equals their willingness-to-pay, their surplus equals zero. The surplus for the 60 naïve and sophisticated customers equals 1 per customer because they pay 11 and have a willingness-to-pay of 12. The average price for all customers without promotion is 14.6. (See Table 1 for all the relevant values.)

TABLE 1

	Seller 1	Seller 2
Marginal cost	5	5
Loyal buyers	40	0
Non-contested price	10	10
Willingness-to-pay of loyal buyers	20	
Willingness-to-pay of sophisticated buyers	12	12
Willingness-to-pay of naïve buyers without promotion	12	12
Minimum price without promotion	11	5
Price without promotion	20	11
Sales without promotion	40	60
Profits without promotion	600	360
Customer surplus without promotion	0	60
Profits with loyalty discounts	200	100
Minimum price with promotion	11	5
Willingness-to-pay of naïve buyers without promotion	18	12

	Seller 1	Seller 2
Price with promotion	13.5	11
Sales with promotion	80	20
Gross profits with promotion	680	120
Customer surplus with promotion	440	20
Customer surplus with promotion	200	20

2. Outcomes with promotion

By promoting its products, Seller 1 can raise naïve customers' valuation of its product relative to their valuation of Seller 2's product. If the increase in the willingness-to-pay for Seller 1's product is sufficiently large, then Seller 1 may be able to profitably compete for naïve customers.

To determine whether Seller 1 can profitably compete for naïve customers, we need to know Seller 1's minimum price to compete for naïve customers. Recall that it earns a profit of 600 if it only competes for loyal customers, so its minimum price gives it a profit of 600 if it sells to the 40 loyal customers and 40 naïve customers. Seller 1's minimum price is now 12.5 because if it charges 12.5 it earns a per unit profit of 7.5 per unit, so its total profit on 80 units is 600.

Seller 2's minimum price also changes when promotion is possible. Since Seller 1 would never price below 11, Seller 2 can price just below 11 and sell to sophisticated customers no matter how much Seller 1 promotes its products. If so, it earns a profit of 6 per unit on the 20 sophisticated customers for a total profit of 120. If Seller 1 promotes its products, then Seller 2 will lower its price below 11 to compete for naïve customers as long as the profits it earns from doing so are not less than 120. Seller 2's minimum price is 7.5 because it would earn 2.5 per unit on sales to 60 customers for a total profit of 120.

Given these minimum prices, the next question is whether Seller 1 can sufficiently raise the willingness-to-pay of naïve buyers so that they would prefer buying from Seller 1 if both sellers charge their minimum prices. Since

the difference between Seller 1's minimum price and Seller 2's minimum price is 5, Seller 1's promotion has to raise naïve buyers' willingness-to-pay by 5, from 12 to 17.

For example, suppose that Seller 1's promotion raises naïve buyers' valuation to 18. If so, Seller 2 would need to price below its minimum price to sell to naïve customers, so it will not find it profitable to compete for those customers. If naïve buyers have a willingness-to-pay of 18, Seller 1 can charge above its minimum price and sell to naïve buyers. If it charges just below 13.5, naïve buyers will prefer to buy from Seller 1. At a price of 13.5, Seller 1 will earn a profit of 8.5 per unit on sales to 80 customers for a total of 680 which exceeds the profits it earned without promotion. Thus, Seller 1 will find it profitable to promote its products if the promotional costs of increasing naïve buyers' willingness-to-pay by at least 6 are less than 80. If so, then Seller 1 will promote its products and compete for sales to naïve buyers.

3. Comparing outcomes with and without promotion

Suppose that the profit maximizing level of promotion for Seller 1 leads to an increase in naïve buyers' valuation of Seller 1's product to 18. How does that promotion affect buyers and sellers?

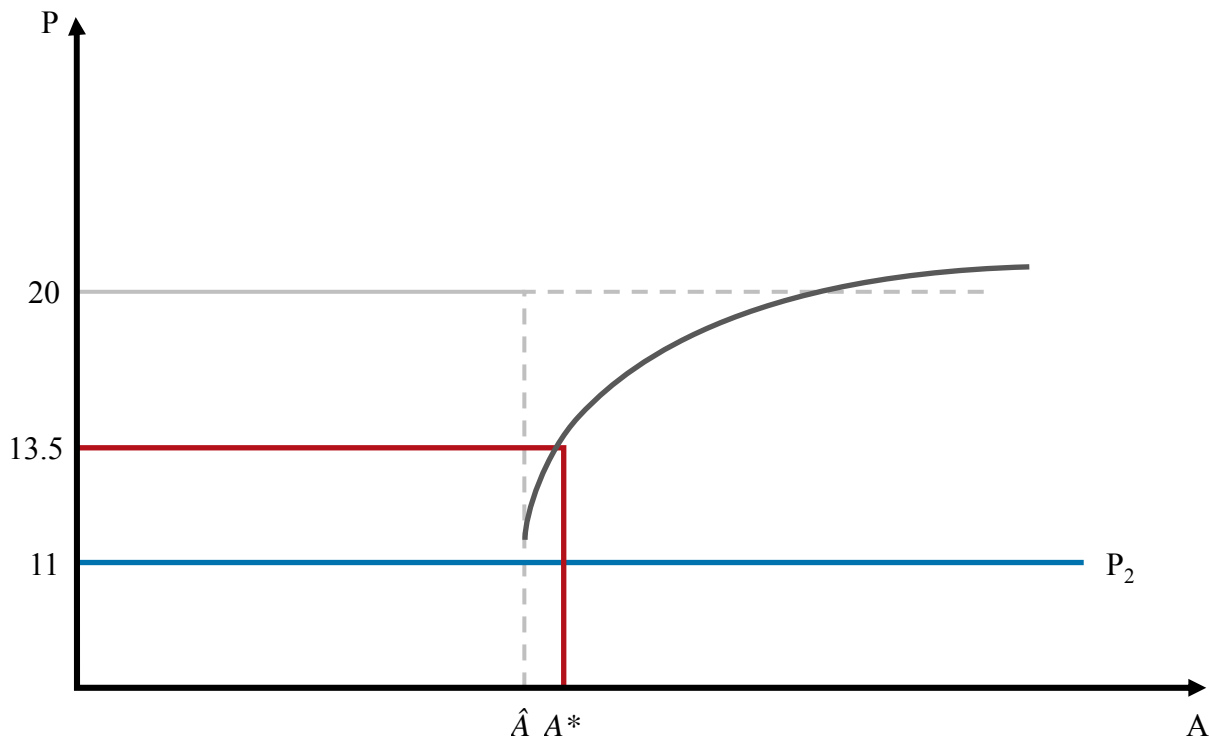
The increase in competition, due to the promotion, benefits both loyal and naïve buyers. Loyal buyers pay 13.5 rather than 20, so their surplus rises to 6.5 per customer. Naïve buyers also pay 13.5 which is higher than the 11 they pay without promotion, but their surplus rises to 4.5 per customer because their willingness-to-pay has risen to 18. Sophisticated buyers' surplus is unchanged because they still pay 11 and there is no change in their valuation of Seller 2's product. Total buyer surplus rises to 460 from 60 without promotion. Average prices fall from 14.6 without promotion to 13 with promotion.

The increase in competition harms Seller 2. Its profits are 350 without promotion and 120 with promotion. Because of the inability to price discriminate, Seller 2 had an advantage competing for naïve customers without promotion because it does not have any loyal customers. As a result,

it does not lose profits by reducing its price. By promoting its product, Seller 1 can offset Seller 2's advantage, so Seller 2 loses sales to naïve customers.

Figure 1 illustrates the effect of promotion on prices graphically by showing how the profit maximizing prices of the two sellers changes as the level of promotion by Seller 1 increases. The black line represents seller 1's price. For low levels of promotion below \hat{A} , Seller 2 can profitably price low enough to induce naïve buyers to buy its products even though they have a higher valuation of Seller 1's product. As a result, Seller 1 prices at 20, and Seller 2 prices at Seller 1's profit neutral price of 11. Seller 1 would never choose levels of promotion below \hat{A} because it would be devoting resources to promotion even though it would not make sales to naïve buyers. Once the level of promotion reaches \hat{A} , then the difference in naïve buyers' valuation of Seller 1's product relative to Seller 2's product is sufficiently large that Seller 1 would reduce its price to 12.5 and compete for naïve buyers. It may be profit maximizing for Seller 1 to choose a level of promotion above \hat{A} , because the difference in naïve buyers' valuation rises as the level of promotion rises.

Figure 1



If A^* represents the profit maximizing level promotion and naïve buyers' valuation of Seller 1's product is 18 at A^* , then Seller 1 charges a price of 13.5.

4. Outcomes with deceptive promotion

Suppose now that Seller 1's promotion is deceptive in that it artificially raises naïve customers' willingness-to-pay. The fact that the promotion is deceptive has no effect on competition. Deception causes Seller 1 to reduce prices and compete for naïve customers in the same way that truthful advertising does, and loyal customers benefit. Prices are the same with truthful and deceptive promotion, so deceptive promotion causes average prices to fall relative to no promotion.

The only difference between deceptive and truthful advertising is its effect on the surplus of the naïve customers. Their surplus is negative 1.5 because they pay 13.5 but their true valuation is only 12. Total surplus across all buyers is 220 which is less than with truthful promotion, but still more than with no promotion. Thus, the negative effect of deception on the deceived buyers is less than the positive effect on buyers that are not deceived. Since deception has no effect on sophisticated customers, any harm is limited to the naïve customers. Moreover, that harm does not come about because of a reduction in competition because the deception has actually increased competition.

C. Implications

1. Implications for antitrust cases

The argument that there should be a presumption that deceptive promotion does not harm competition is based on the belief that deceptive practices are not likely to deceive a large share of buyers and, therefore, are unlikely to affect competitors sufficiently to harm competition, except in rare cases. The analysis above provides another reason why deception is unlikely to harm competition. Deception can increase competition even if a large share of buyers is deceived.

Proponents of treating deceptive promotion and other torts as antitrust violations have often claimed that the conduct has no procompetitive justification. As a result, allowing deception claims to be part of antitrust cases will not discourage any procompetitive conduct. This analysis shows that this argument is incorrect. First, deceptive promotion can increase competition and benefit buyers, so it does have procompetitive effects. Second, truthful promotion has an even greater beneficial effect on buyers, but companies may be cautious about engaging in truthful promotion if they run the risk that they will be subject to antitrust scrutiny over their advertising if there is any dispute about its accuracy. This is particularly important because, as discussed above, juries may be more willing to find a defendant guilty of anticompetitive conduct because they find deception objectionable.

This does not rule out the possibility that deception can harm competition. Deception reduces sales of the sellers that cannot counter their rivals' deceptive promotion. If a company cannot cover its fixed costs as a result of the reduction in sales, then the deception can harm competition. The same could be true if the reduction in sales raised a company's marginal costs. Even if this happens, however, these potentially adverse effects would have to be weighed against the fact that the deception has increased competition.

2. Implications for class action cases brought under consumer protection statutes

The above analysis also has implications for assessing consumer class action claims that they paid higher prices because of deceptive practices. For example, in addition to the FTC's allegations that Intel's alleged manipulation of CPU performance benchmarks harmed competition, Intel has been sued by classes of consumers under different state consumer protection statutes claiming that they paid higher prices because of the alleged deception.¹³

¹³ Janet Skold and David Dossantos v. Intel Corporation, Hewlett Packard Company, Superior Court of the State of California for the County of Santa Clara, Case No. 1-05-CV-039231.

Plaintiffs in class action cases involving deceptive promotion argue that it has a common impact on all buyers of a defendant's product because it artificially raises demand, leading to higher prices for all buyers. In other words, the common harm suffered by class members is because the deception of some buyers led to higher prices for all buyers.

The analysis above shows that the economic logic behind these claims is incorrect. First, even if deception artificially increases demand for a seller's product, it need not lead to higher average prices. Second, if deception leads to higher average prices, some buyers can pay lower prices because deception can increase competition. Thus, there is not necessarily a class wide common impact because buyers that are not deceived benefit from the deception. Thus, plaintiff classes cannot satisfy Rule 23 or equivalent state statutes simply by claiming that deception led to higher demand for some class members.

D. Conclusion

Evaluating the competitive effects of deceptive promotion through the economic framework described in this article has several important implications. First, when sellers' promotional efforts raise the willingness-to-pay of marginal buyers, it can increase competition and lead to lower prices on average. Second, the effect of promotion on competition is independent of whether the promotion is deceptive or truthful. Third, while buyers can be harmed by deceptive promotion, any harm that occurs is not necessarily because of a reduction in competition. Fourth, deceptive promotion can lead to higher prices for deceived buyers and lower prices for all other buyers, so there is not necessarily a common price impact of deceptive promotion on all buyers of a seller's product.

The Fallacy of Inferring Collusion from Countercyclical Prices

Dov Rothman¹

Aaron Yeater²

1. Introduction

In a number of current antitrust lawsuits alleging cartel conduct, plaintiffs claim that defendants increased prices during periods of weak demand (e.g., during an industry downturn), and they assert that such price increases are evidence of collusion.

For example, in *Florida Cement and Concrete Antitrust Litigation*, plaintiffs cite as evidence of collusion that “notwithstanding the substantial reduction in demand, certain Defendants announced a nearly identical 30% increase in ready-mix concrete prices. . . .”³ And in a similar case involving manufacturers of gypsum board, plaintiffs assert as evidence of collusion that “[a]bsent collusion, if input costs remain stable or fall, and demand is flat, prices would be expected to remain flat or fall as well. That all Defendants’ prices rose substantially in 2012, despite competitive conditions dictating stable or falling prices, is indicative of collusion.”⁴

Plaintiffs’ argument in these matters is straightforward: absent collusion, weak demand should lead firms to lower prices; thus, higher prices during periods of weak demand are evidence of collusion.

In this article, we explain that the plaintiffs’ logic is based on an oversimplified economic framework. In actual markets, prices may go up or down when demand changes. Absent collusion, prices may be lower during

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² Vice President, Analysis Group.

³ *In Re: Florida Cement and Concrete Antitrust Litigation*, Fourth Consolidated Amended Complaint, January 4, 2011, p. 13.

⁴ *In Re: Domestic Drywall Antitrust Litigation*, Direct Purchasers’ Consolidated Amended Class Action Complaint and Demand for Jury Trial, June 24, 2013, p. 29.

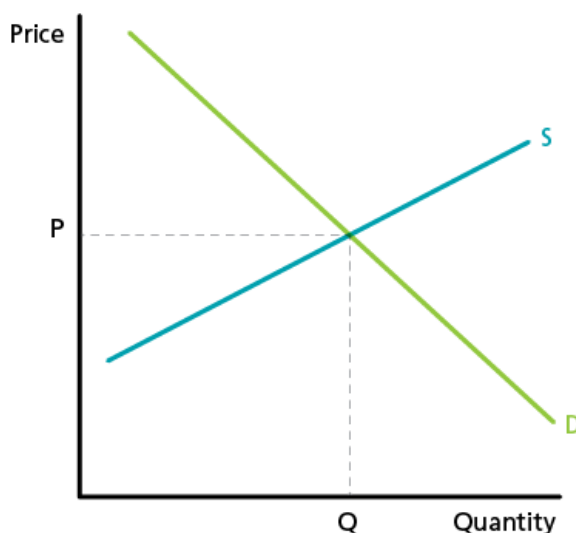
periods of strong demand and prices may be higher during periods of weak demand. In other words, one cannot infer collusion from the mere observation of higher prices during periods of weak demand.

2. The Relationship between Price, Demand, and Collusion

Plaintiffs improperly rely on a simple microeconomics textbook model to assert that any observation of increased prices during periods of weak demand necessarily implies collusion. In so doing, plaintiffs implicitly assume a world of perfect competition. In such a world, the equilibrium price is determined by the intersection of the market supply and market demand curves, and each seller is able to sell as much as it wants at the market price (see Figure 1).

Figure 1 shows that the intersection of these curves – where supply meets demand – determines the equilibrium price and quantity.

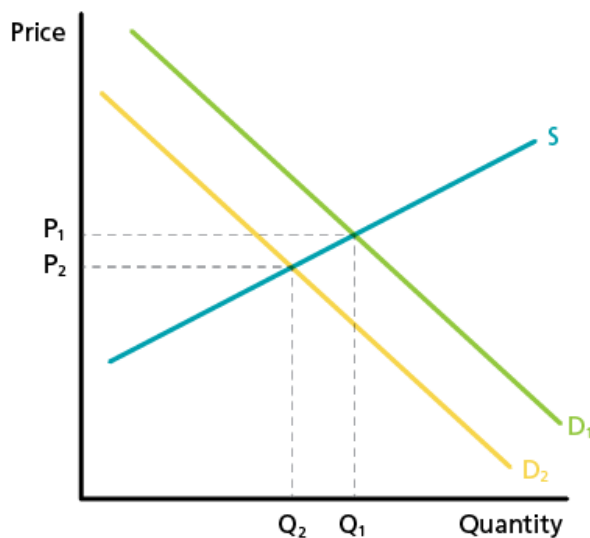
Figure 1: Simple model of supply and demand



In a world characterized by perfect competition, any weakening of demand is equivalent to a shift in the market demand curve. Any reduction in supply – say due to an increase in the cost of an input – is equivalent to a shift in of the market supply curve.

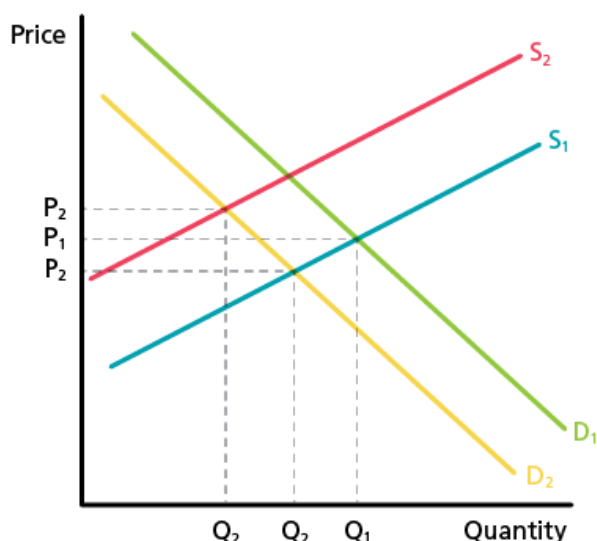
Figure 2 shows what happens when demand shifts inward from D_1 to D_2 and the supply curve remains unchanged (i.e., does not shift): price falls from P_1 to P_2 , and the quantity transacted also falls.

Figure 2: Simple Model of Supply and Demand



In this simple world of perfect competition, absent collusion, and assuming all else is equal, a weakening or shifting in of the demand curve necessarily implies a decline in price. Prices can only increase if there is also a shifting in of the supply curve, as shown in **Figure 3**. Plaintiffs argue that absent an increase in input prices, this must imply collusion.

Figure 3: Simple Model of Supply and Demand



In a world characterized by perfect competition, plaintiffs' very simple view of the world is correct. However, in any other world – in particular in a world in which sellers do not sell identical products and thus have at least some control of the price that they charge – plaintiffs' reliance on the conclusions based on a model of perfect competition are both misguided and likely incorrect.

3. Economic Analysis

3.1. Elasticity of Demand

Although many if not most goods are sold in markets in which competition is prevalent, in the real world perfect competition rarely exists. Rather, in most markets, sellers have some ability to choose their prices (in large part because they sell differentiated products). And when sellers have some ability to choose their prices, the relationship between demand and price is not as straightforward as plaintiffs would have the courts believe. Where sellers are not pure price takers, *a priori*, it is not possible to infer collusion simply from the mere observation of increased prices during periods of weak demand.

To appreciate why one cannot make such an inference, it is helpful to think about how firms set prices in a world in which sellers compete by

selling differentiated products. From an economist's perspective, sellers set prices based in part on the elasticity of the demand the seller faces. Formally, the elasticity of demand is the percent change in quantity sold for a given percent change in price. All else equal, when the seller faces more elastic demand, the seller will set a lower price. Intuitively, when demand is relatively elastic—e.g., consumers can readily substitute other products for the seller's product—a price increase will result in a relatively large drop in the quantity of products that are sold – and vice versa. Thus, when demand is relatively elastic, although a higher price results in a higher per-unit profit margin on the sales that remain, the relatively large decrease in quantity sold dominates and constrains the seller from increasing price.

The logic is identical when demand is relatively inelastic: a reduction in price results in a relatively small increase in quantity sold and an increase in price results in a relatively small decrease in quantity sold. Thus, when demand is relatively inelastic, a lower price results in a lower per-unit profit margin and the increase in quantity sold is not enough to compensate the seller. Consequently, it makes sense for the seller to set a relatively high price.

This economic reasoning has important implications regarding the question of whether or not it is appropriate to infer collusion based solely on the observation of higher prices during periods of weak demand.

During an industry downturn or recession, the demand that sellers face may change in two interrelated ways. First, the overall level of market demand may fall as customers exit the market. However, as such exit occurs, it is also the case that the elasticity of demand sellers face may *also* change. For example, if the customers who are relatively price sensitive drop out of the market during an industry downturn, the remaining demand that sellers face will likely become less elastic. In response, acting unilaterally, sellers may be less inclined to reduce prices and may even raise prices.⁵ In other words, contrary to plaintiffs' allegations, it is not possible to infer collusion

⁵ Intuitively, if the price-sensitive customers drop out of the market, price reductions may not generate sufficiently large increases in quantity sold, and so the primary effect of reducing price is a lower margin.

simply from an observation that sellers raise their prices during periods of weak demand.

Recent research explains the superficial logic of inferring collusion from price increases under decreasing demand. In *Do Price Increases While Demand Is Falling Indicate Collusion?* (2011), the authors discuss the logic of the Supreme Court's decision in *American Tobacco v. United States*, where the Court concluded that price increases by cigarette manufacturers during the Great Depression could be considered evidence of collusion.⁶ The authors note that "the tobacco industry has witnessed a decrease in demand but, at the same time, cigarette price has increased noticeably."⁷ They remark that colluding firms may raise prices when demand is falling, but also recognize that decreases in demand may result in changes in "customer mix," which could also result in higher prices without collusion:

[H]owever, care must be exercised [in inferring collusion from higher prices under decreasing demand]. Social promotional activities such as antismoking campaigns designed to discourage fringe consumers may result in a quantity that is only slightly less than before. The remaining hardcore consumers, being more addicted to the product, generally have more difficulty kicking the habit, and demand becomes more inelastic at higher prices.⁸

⁶ Yang, et al., "Do Price Increases While Demand Is Falling Indicate Collusion?", *Journal of Competition Law & Economics*, 7(2), 481-495; *Am. Tobacco Co. v. United States*, 328 U.S. 781 (1946) at 805.

As the authors note, the Court's logic was disputed by Judge Posner of the seventh circuit in his book *Antitrust Law: An Economic Perspective* (1976).

⁷ Yang, et al., p. 495. According to publicly available statistics, the price of a pack of cigarettes net of taxes increased at a rate of 7.1% per year between 1970 and 2013. See "Trends in State and Federal Cigarette Tax and Retail Price—United States, 1970–2013," <http://www.cdc.gov/tobacco/data_statistics/tables/economics/infographics/index.htm> and "The Tax Burden on Tobacco," Volume 49, 2014.

⁸ Yang, et al., p. 495.

In other words, if demand is decreasing because “fringe” consumers are exiting the market, leaving only “core” consumers, then sellers may unilaterally increase prices.

Holiday sales are an example of this general economic phenomenon (though in reverse). The holiday shopping season is a period of relatively high demand, because customers enter the market seeking to buy gifts and other items they do not purchase year-round. The plaintiffs’ argument would imply that manufacturers and retailers should raise prices during this period. But, as we all know, the opposite happens – sellers often advertise significant price reductions during the holidays. Because holiday wish lists are long and gift-givers (uncertain of what gift to buy) often view many different products as good substitutes for one another, their demand for any single product is relatively price sensitive. Manufacturers and retailers respond to the influx of relatively price-sensitive customers by lowering prices (e.g., Black Friday and Cyber Monday). Thus, despite strong market demand, prices decline.

Nevo and Hatzitaskos (2006) provide a similar example, noting that the average price of tuna falls during Lent, a period when many Catholics choose to eat fish instead of meat, driving up demand for fish. The authors interpret their finding in two ways. First, some of the price reduction reflects an influx of customers to the market for tuna who are relatively more price sensitive. Second, some of the price reduction reflects a composition effect, in which brand preferences of existing customers shift toward less-expensive products. Again, the simple model offered by some plaintiffs would imply the opposite pattern: higher demand should increase prices. Yet, a key takeaway from Nevo and Hatzitaskos (2006) is that “one has to be careful in using prices paid by customers to make inferences about supply side behavior. The observed prices might be driven, at least in part, by customer behavior and not by pricing.”⁹

⁹ Aviv Nevo and Konstantinos Hatzitaskos, “Why Does the Average Price Paid Fall During High Demand Periods?” *Working Paper*, July 2006.

3.2. Price Discrimination

Economic theory posits that a seller with market power may try to engage in price discrimination. Price discrimination is rooted in the idea that different customers are willing to pay different amounts for products. Customer A may be willing to pay \$10 for a product, whereas Customer B may be willing to pay only \$8. Ideally, the seller would set a price of \$10 for Customer A and a price of \$8 for Customer B. But because sellers may not directly observe customers' willingness to pay, it is often not possible for sellers to set customer-specific prices (usually because, for example, Customer A could easily pretend to be Customer B).

Although sellers generally cannot perfectly price discriminate, they can devise price-discrimination mechanisms. In a car dealership, for example, sellers frequently post list prices and then negotiate off list prices with customers who request discounts. Customers who are relatively price sensitive may be willing to invest time and energy negotiating a lower price, whereas the customers who are less price sensitive will simply pay the posted price. Similarly, sellers may use coupons as a means of charging different customers different prices. Customers who are relatively price sensitive may be more willing to search for coupons to obtain discounts; customers who are relatively less price sensitive may be more willing to simply pay the posted price.

Sellers' use of price discrimination also has implications with respect to the appropriateness of an attempt to infer collusion from the observation of higher prices during periods of weak demand. As discussed above, during an industry downturn or recession, the composition of customers may change, which, in turn, may affect the prices that are paid, even if sellers do not actually change their price offers. For example, if the customers who were more likely to use coupons exit the market, the remaining customers will pay higher prices, and average prices paid may be higher.

Sellers can also engage in price discrimination through what economists refer to as "quantity-dependent pricing," in which lower prices are charged for larger quantities. For example, a customer might pay \$10 per

unit when purchasing fewer than 1,000 units, \$9 per unit when purchasing 1,000–3,000 units, and \$8 per unit when purchasing more than 3,000 units.

Quantity-dependent pricing relates to the plaintiffs' attempts to infer collusion from higher prices during periods of weak demand precisely because customers may be purchasing smaller quantities and therefore receiving fewer quantity discounts from sellers during periods of weak demand. As in the example studied by Nevo and Hatzitaskos, it is important to understand if demand-side substitution among differentiated brands or quantity-priced purchases has affected the market prices paid.

4. Summary

Plaintiffs sometimes allege that defendants increased prices during periods of weak demand (e.g., during an industry downturn) and assert that such price increases are evidence of collusion. The plaintiffs' argument is straightforward: absent collusion, prices should fall when demand gets weaker; thus, higher prices during periods of weak demand are evidence of collusion. We have explained in this article that this logic is based on an oversimplified economic model of perfect competition. In the real world, most markets are not perfect. Rather, most sellers attempt to differentiate their goods from their competitors' goods in some way. In so doing, the seller is able to have some control of the price that it charges. In markets in which differentiated products are sold, changes in demand can cause prices to go up or down. In particular, prices may decline during periods of strong demand or increase during periods of weak demand. Importantly, in contrast to plaintiffs' allegations in numerous cases, the mere observation that prices were relatively high during a period of weak demand is an insufficient basis on which to infer collusion.

A Primer on Spurious Statistical Significance in Time Series Regressions

Ai Deng¹

Regression analysis is an important tool in antitrust litigation: it's a formal way to establish an empirical relationship among variables such as prices, quantities, and supply and demand factors. Regression models are commonly used by economic experts to estimate the impact of cartel conduct in price-fixing cases and to investigate competitive effects in merger cases. Proper uses of regression models have been accepted by the courts and have met Daubert standards. But in relying on regressions, economic consultants, as well as attorneys, need to be aware of the possibility of “spurious statistical significance.”

Imagine, for instance, that an economic expert decides to use a regression analysis to formalize and test the theory of harm. The expert finds that the regression results in a high R squared (R^2) and produces statistically significant coefficients. In the expert report, the expert explains (1) that a high R^2 shows the model fits the data very well and (2) that the statistically significant coefficients are consistent with a meaningful impact. But then the rebuttal expert report comes back and alleges that the expert's regression produced a false positive—i.e., the coefficient is in fact not significant and the high R^2 is not indicative of a meaningful relationship.²

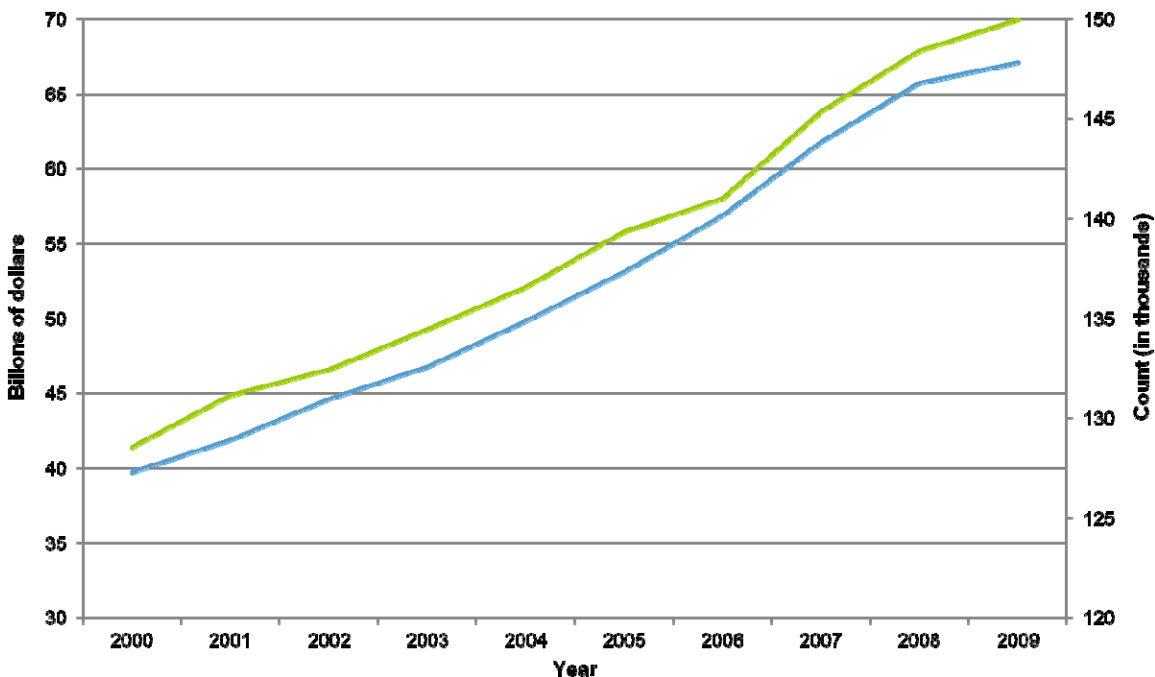
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² It is important to keep in mind the fact that statistical significance also depends on the sample size, a factor that an economist might not have full control over in a litigation context. This is an issue we will not address in this article.

In this article, we take a closer look at the problem of false positives. We focus on a common type of economic data that are observed over time, known as *time series*. Such data are routinely processed and analyzed by expert witnesses in litigation matters. Examples include monthly prices and sales of the products in question. In this context, we provide a non-technical discussion about when spurious statistical significance might arise and what measures can be taken to avoid the problem.

Let's now consider a concrete example. Figure 1 shows two variables and their values over time (i.e., a time series). The correlation between the two variables is 0.99 and highly statistically significant.³ A regression gives similar statistically significant results. These statistical results “confirm” what our eyes see—that the trend lines move in concert over time. It turns out that the blue line shows the amount of money spent on pets in the United

Figure 1: An example of a spurious relationship



³ The correlation or the correlation coefficient between two variables is a number between -1 and 1. If the correlation is 1 (-1), we say that the two variables are perfectly positively (negatively) correlated.

States and that the green line shows the number of lawyers in California.⁴ It is therefore highly unlikely that the 99% correlation is “real.”

In another example, Professor David Hendry, in his 1980 article “Econometrics: Alchemy or Science,” reported on a regression that used a measure of the UK government’s money supply and the cumulative rainfall in the United Kingdom. This regression fitted the data quite well and the relationship was highly statistically significant.⁵

The problem is not new. In 1926, Yule, asked “Why Do We Sometimes Get Nonsense Correlations?”⁶ Since then, econometricians have come a long way in understanding the problem and in learning how to avoid it. Understanding what produces these unreliable results would allow attorneys and economic experts to (1) ensure that they don’t run into the problem themselves and (2) develop appropriate challenges to opposing sides’ analysis/arguments.

Intuitively, a statistical regression “looks at” the empirical patterns of how variables move and then infers their relationship. With the two trending variables shown in Figure 1, the regression is “tricked” into believing that there is a true meaningful relationship between the variables. While this example, especially the almost perfect parallel movements, may appear rather contrived, the econometric research has found that spurious statistical

⁴ This example is taken from http://www.tylervigen.com/view_correlation?id=2956, accessed Nov. 21, 2014. This website, maintained by Tyler Vigen, contains many other examples of potentially spurious correlations. Some of my personal favorites are “US spending on science, space, and technology and Suicides by hanging, strangulation and suffocation” (correlation of 0.99); “number of lawyers in North Carolina and Suicides by hanging, strangulation and suffocation” (correlation of 0.99); and on a sweeter and happier note, “honey producing bee colonies (US) and marriage rate in Vermont” (correlation of 0.94).

⁵ David Hendry, “Econometrics: Alchemy or Science,” *Economica* 47, no. 188 (1980): 387–406. To be precise, Hendry regressed the money supply on both the cumulative rainfall and the squared cumulative rainfall.

⁶ George U. Yule, “Why Do We Sometimes Get Nonsense-Correlations between Time-Series?—A Study in Sampling and the Nature of Time-Series,” *Journal of the Royal Statistical Society* 89, no. 1 (1926): 1–63.

significance can arise in more subtle ways—as a simulation exercise below will demonstrate, variables certainly do not need to move in parallel as those in our example are made to appear for there to be a risk of spurious statistical significance. Furthermore, extensive research tells us that spurious results such as those in the examples above are *not* mere statistical coincidence.

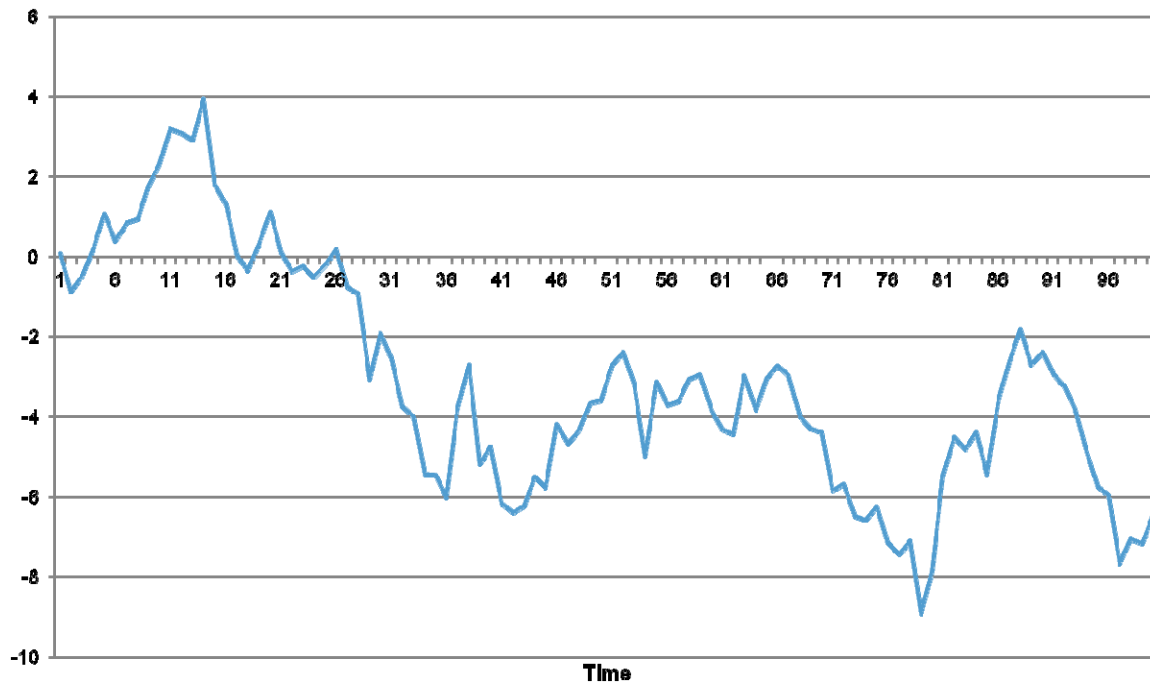
To understand what is going on, it is helpful to know that different types of variables “behave” differently in a statistical analysis including a regression or correlation analysis. Intuitively, trending, slowly moving (nonstationary) variables carry more information content than nontrending (stationary) variables.⁷ What do we mean by “more information content”? The following heuristic example will illustrate.

Suppose we want to figure out, by observing the behavior of two colleagues over a number of days, whether those two colleagues are friends. Assume that these two are friends, but that we don’t know that. In scenario 1, we see them texting each other, hanging out, and having lunch on many occasions. From those observations we can deduce with a high degree of confidence that they are friends. In scenario 2, we observe that the two have no contact at all (perhaps because they are extremely busy). In the latter case, we can’t really know much from what we observe. In scenario 1, there are a lot of activities or “variations” in our observations. These are precisely the types of information that statistical techniques such as correlations or regressions try to exploit. It turns out that nonstationary or trending variables behave similarly to the data in scenario 1. And they typically carry more information than stationary variables.

⁷ The technical definitions of stationary and nonstationary variables are related to the constancy and invariance of the mean and (co)variances of the variables. For details, see, for example, James D. Hamilton, *Time Series Analysis* (Princeton, NJ: Princeton University Press, 1994).

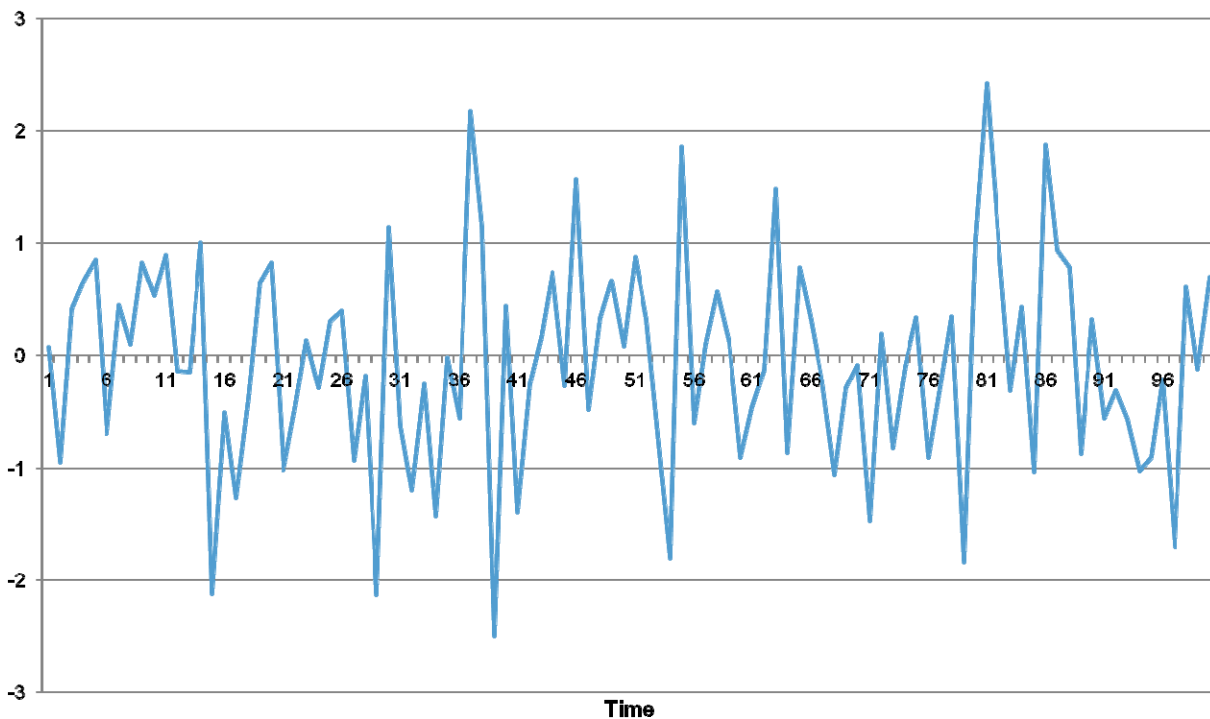
Research has shown that the strong information content in nonstationary variables is a double-edged sword. One type of “nonstationarity” that is well known to be capable of creating problems in regressions is the so-called stochastic trend. Loosely speaking, this is a time trend with variable slopes (i.e., slopes that do not always head in the same direction as a “deterministic” trend would). Such data are also called “integrated” in the econometrics literature. In their 1972 seminal paper, Granger and Newbold found that if two variables both have a stochastic trend, then regressions would (more often than not) indicate a statistically significant relationship between them, even when they are completely

Figure 2: A simulated example of a random walk



independent from each other!⁸ A classical example of a stochastic trend is the so-called random walk. Figure 2 shows a simulated example. In contrast, Figure 3 shows a simulated example of a particular type of stationary variable: “white noise.” The visual difference is striking.⁹

Figure 3: A simulated example of a white noise



To illustrate the type of problem that Granger and Newbold called our attention to, I replicated a small simulation exercise from their study. In this exercise, I used a computer program to generate a large number of independent random walks and tested the statistical significance of the relationship between pairs of these independent time series. Had there been

⁸ Clive W. J. Granger and Paul Newbold, “Spurious Regression in Econometrics,” *Journal of Econometrics* 2 (1974): 111–20. Their study was later extended by other researchers. Phillips provided a mathematical theory to explain these simulation results. Peter C. B. Phillips, “Understanding Spurious Regressions in Econometrics,” *Journal of Econometrics* 33 (1986): 311–40.

⁹ In practice, the difference between stationary and nonstationary time series is often far from clear-cut.

no spurious statistical significance, we should find statistical *insignificant* relationship between the majority of the pairs, simply because they are generated as entirely independent variables. It turned out, however, that out of the 2,000 pairs of *independent* random walks that I generated, the relationship between over 1,500 pairs or 76% are found to be statistically significant by the commonly used two-sided *t*-test.¹⁰

So trends, deterministic or stochastic, can do the “trick”; but can other “shapes” of the data also do the “trick?” Yes, they can. Seasonality is one such “trickster.” One interesting and well-known example of seasonality producing spuriousness is a regression/correlation analysis on the amount of ice cream sold and the number of deaths caused by drowning.¹¹ The occurrence of these events in the summer season is the only thing that produces a high correlation and similar patterns in both variables.¹² Another data feature that can result in spurious statistical significance is structural breaks such as level or slope shifts in the data.¹³

Trends, seasonality, and structural breaks are all part of a low-frequency component in that they are all somewhat smooth, slow moving,

¹⁰ Among those 1,500 pairs, roughly half of them appear to be positively related and the other half negatively related.

¹¹ See, e.g., Robert B. Johnson and Larry B. Christensen, *Educational Research: Quantitative, Qualitative, and Mixed Approaches* (Thousand Oaks, CA: SAGE Publications, 2013), Table 11.2.

¹² The issue here is that both variables are affected by a common factor. So in this sense, this example is different from the spurious regression between independent stochastic trends. It is more related to a broader definition of spurious correlation/causation mentioned in the end of the article.

¹³ Antonio E. Noriega and Daniel Ventosa-Santaulària, “Spurious Regression under Broken Trend Stationarity,” *Journal of Time Series Analysis* 27, no. 5 (2006): 671–84.

and/or long lasting. Economists, and attorneys, need to be careful when these components are in the data.¹⁴

In fact, high correlations between trending variables have been treated cautiously by the courts. An example can be found in Judge Seeborg's recent Order in *In re Optical Disk Drive Antitrust Litigation*. After discussing how the plaintiffs' economic expert offered a correlation analysis to "show that supra-competitive prices paid by Dell and HP as a result of bid-rigging affected prices paid by other purchasers," Judge Seeborg, citing economic experts from both sides, commented: "There appears to be little dispute, however, that strong correlations would arise from the long term price declines and the competitive market forces in any event."¹⁵ The "long term price declines" refer specifically to the downward trend in the optical disk drive prices. What is interesting here is that, unlike our previous heuristic and somewhat extreme examples (money supply vs. cumulative rainfall, or money spent on pets vs. the number of lawyers), the price data being analyzed in this case are at least conceptually related. So the strong statistical correlation might actually reflect a true economic relationship, hence not spurious. But how does one go about trying to resolve this question in practice? The most obvious approach is to examine *additional* economic/econometric evidence to see if they either corroborate or refute the conclusion of a meaningful relationship. For example, economic experts may consider performing a formal cointegration analysis, which will be briefly discussed below, to see if the high correlation is in fact spurious in a statistical sense. Also important are an analysis of the economics of the relevant market and the associated empirical analysis. A detailed discussion is beyond the scope of this article.

Going back to the type of spurious significance problem discussed above, a natural question is how it can be avoided. Earlier economists would simply remove the trend (through a so-called detrending process), and then

¹⁴ To precisely define trends, however, is actually quite challenging. See Halbert White and Clive W. J. Granger, "Consideration of Trends in Time Series," *Journal of Time Series Econometrics* 3, no. 1 (2011): 1-38.

¹⁵ Order Denying Motions for Class Certification, *In re Optical Disk Drive Antitrust Litig.*, No. 3:10-md-2143 RS (N.D. Cal. Oct. 3, 2014).

they would analyze these “detrended” data.¹⁶ In other words, nonstationary variables were often detrended to be turned into stationary variables. Usually, proper detrending can take care of the problem, but detrending can also lead to other issues. In fact, the particular issues related to detrending variables with stochastic trends were the basis for the research that garnered Professor Clive Granger (University of California, San Diego) the 2003 Nobel Prize in economics.

Prior to Granger’s groundbreaking work, Professor David Hendry commented that a regression between variables with stochastic trends need not produce spurious statistical relationship. Granger, who conducted the simulation study discussed above to illuminate the danger of spurious regression between variables with stochastic trends, set out to prove Hendry wrong; but instead Granger proved Hendry right. That effort led to the Nobel Prize-winning “theory of cointegration.”

Cointegration refers to the situation where there is a true relationship between two, or more, variables with stochastic trends.¹⁷ Intuitively, when such variables are cointegrated, the regression/correlation is not spurious in the sense discussed above. An oft-cited heuristic example of a cointegration relationship is that of a drunkard and his leashed dog walking on the street.¹⁸ The drunkard’s path may resemble a random walk (hence nonstationary) and so does the path of his dog. But obviously they will not “deviate” too far from each other. One economic example of a plausible cointegrated relationship is

¹⁶ Depending on the type of trends, one could detrend data by estimating a regression such as $x_t = a + bt + \epsilon_t$, where a and b are estimated coefficients and t is the time trend. The detrended data is simply ϵ_t . Or in the case of a stochastic trend, take the first difference, i.e., $\Delta x_t = x_t - x_{t-1}$.

¹⁷ In an anecdote, when two young economists, both of whom studied stochastic trends or integrated data, told Granger that they were getting married, Granger said without even thinking: “So then you guys are cointegrated.” (Personal communications with Pierre Perron).

¹⁸ Michael Murray, “A Drunk and Her Dog: An Illustration of Cointegration and Error Correction,” *American Statistician*, 48, no. 1 (1994): 37–39.

that of aggregate consumption and income.¹⁹ Although both variables tend to increase over time, the pertinent economic theory nevertheless suggests a meaningful underlying relationship between them.

Importantly, Engle and Granger, in their Nobel Prize-winning article published in 1987, proved mathematically that if the variables are actually cointegrated, not only will there be no problem with analyzing the correlation or regression of the variables (without detrending) but doing so will be precisely the *correct* thing to do.²⁰ Why is that? Because, as explained intuitively above, nonstationary variables carry more information than stationary variables; and as a result their relationships are more accurately estimated by regressions.²¹ Detrending would have eliminated the most informative component, i.e., the stochastic trend, from the nonstationary variables. In other words, the very reason that nonstationary variables can cause statistics to go astray is also the very reason that one should not ignore them in a cointegrated regression! But how do we know if the variables are cointegrated in practice? In that same paper, Engle and Granger developed a statistical test to help us answer this question empirically, thus, at least conceptually, giving us a way to properly handle data with stochastic trends.

¹⁹ There is evidence that both consumption and income contain a stochastic trend and that they are cointegrated. See J. E. H. Davidson, D. F. Hendry, Frank Srba, and Stephen Yeo, "Econometric Modelling of the Aggregate Time-Series Relationship between Consumers' Expenditure and Income in the United Kingdom," *Economic Journal*, 88, no. 352 (1978): 661–92.

²⁰ Clive W. J. Granger, Robert Engle, "Co-Integration and Error Correction: Representation, Estimation, and Testing," *Econometrica*, 55, no. 2 (1987): 251–76. See also, Søren Johansen, "Correlation, Regression, and Cointegration of Nonstationary Economic Time Series," *Bulletin of the ISI LXII* 2007, 2008, 19–26.

²¹ In technical terms, it has been shown that the regression estimates between cointegrated nonstationary variables are "super-consistent." A statistical estimate is said to be consistent if it approaches (or "converges") the true (but unknown) value as the sample size gets larger. When econometricians talk about consistency, they often associate it with a "rate," i.e., how fast the convergence is. In regressions of stationary variables, the rate of convergence is usually the square root of the sample size. But if the nonstationary variables are "cointegrated," the rate of convergence turns out to be the sample size, which is a much "faster" rate than in the "stationary" case. Consequently, these estimates are called "super-consistent."

There has been an explosion of academic research on cointegration in the past 30 years. And because many, if not most, economic data (prices, in particular) are nonstationary, cointegration has become an indispensable tool in the economist's toolkit.^{22, 23}

To avoid the most basic problem of spurious statistical significance when analyzing time series data, the first line of defense is and should always be the pertinent economic theory. Questions such as does the economic theory support a plausible relationship among these variables should always be asked before any actual regression analysis is undertaken. When the theory is not sufficient or strong enough to convince a careful economist, further diagnostic analysis will be needed. For example, it is often helpful to plot the data to spot trends and to examine the regression residuals (i.e., the variations in the variable of interest that are not explained by the other variables in the regression) for nonstationary behavior. When a formal test is justified and necessary, the economist can apply it to check for evidence of cointegration.

A final caution: while this article focuses on a particular type of statistical illusion, especially with regard to variables with stochastic trends, the word "spurious" as in "spurious regression" and "spurious correlation" is sometimes also used to describe any situation where a false positive is found

²² For a nontechnical introduction and a historical perspective of cointegration, see Granger's 2003 Nobel Prize lecture. Clive W. Granger, "Time Series Analysis, Cointegration, and Applications," Nobel Lecture, Dec. 8, 2003, available at http://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2003/granger-lecture.pdf. For more technical details, see, for example, James D. Hamilton, *Time Series Analysis* (Princeton, NJ: Princeton University Press, 1994).

²³ With our improved understanding of the related issues, some no longer think that spurious regression is a problem, *as long as we take the effort to properly handle it*. McCallum even goes as far as asking "Is the Spurious Regression Problem Spurious?" See Bennett, McCallum, "Is the Spurious Regression Problem Spurious?" *Economics Letters* 107, no. 3 (2010): 321–23. Others have commented that the problem may not appear as easily solvable as McCallum believed. See Berenice Martínez-Rivera and Daniel Ventosa-Santaulària, "A Comment on 'Is the Spurious Regression Problem Spurious?'" *Economics Letters* 115, no. 2 (2012): 229–31.

or where there is a more subtle case of “spurious causation.”²⁴ On the topic of causation, it is worth pointing out that similar to correlation, the presence of cointegration *by itself* in general does not imply causation. These issues are beyond the scope of this article. Interested readers can learn more about cointegration by following the references cited in this article.²⁵

²⁴ For example, in the Opinion and Order in the discrimination case *Borden v. Walsh Group*, No. 06 C 4104 (N.D. Ill. Mar. 30, 2012), Judge Lefkow cited the book *The Statistics of Discrimination* to generically define spurious correlation in this way.

²⁵ The issue discussed in this paper is also distinct from the well-known multiple testing problem in statistics. The multiple testing problem is related to the fact that in the framework of standard (frequentist) hypothesis testing, when a test is applied multiple times (usually over multiple data sets), the (same) null hypothesis may be rejected in some of the applications. But such instances of rejection are not necessarily evidence against the null hypothesis. The interested reader is referred to the vast and still active literature on this important statistical topic for details.

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