PROGRAMMATIC LEMON MARKET GAME

Pricing Ad Quality Uncertainty Into A Competitive Bidding Advantage

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"Nobody counts the number of ads you run; they just remember the impression you make."

– Bill Bernbach

ABSTRACT

This methodology paper is ultimately about the absence of programmatic ad quality information in the advertiser's decision-making process. A solution to this problem is proposed as a model to approach programmatic as a game. The game is won or lost based on a marketer's ability to correctly price the quality of ad impressions sold in programmatic auctions. The model introduces the notion of *intrinsic price* strategy. If the *price paid* for an ad impression is greater than the intrinsic value of the impression, and if this outcome occurs too often, then the marketer is involved in a lemon market. When such a situation is identified, steps can be taken to correct the course and turn the game outcome in the marketer's favor, thus creating a competitive advantage.

1. PROGRAMMATIC ADVERTISING PRESENTED AS A GAME

Let us consider programmatic as a lemon market game where, more often than not, the price a buyer pays for an ad impression is greater than what the ad impression is actually worth. The game only has three rules:

Rule #1: A certain amount of advertising budget must be spent, by a specified point in time, to buy banner and video ad impressions (e.g. spend $1 million by June 1, 2020).

Rule #2: The ad impressions that the marketer bids on and buys in programmatic auctions are supplied by publishers. Since many publishers are unable to sell 100% of their available impressions under pre-sold, guaranteed conditions, they seek incremental revenue by selling the unsold portion to the highest bidder.[1]

Rule #3: Both the advertiser and the publisher, and any supply chain agent in between, believe the purpose of buying, selling, and serving ads is to expose consumers to a visual experience. Doing so is believed to have a positive incremental effect on business outcomes (e.g. sales, subscriptions, user profile generation, content consumption, etc.).

As a consequence of Rule #2, there must exist some level of buyer uncertainty over the quality of ad impressions sold in programmatic auctions compared to the alternative of buying ad impressions with certain contractual guarantees (e.g. 100% viewable ad guarantee).[2] Given some level of uncertainty over programmatic ad quality, the game is won or lost based on a marketer's ability to correctly price the quality of ad impressions sold in programmatic auctions. In other words, the marketer wins the game by minimizing the error rate between the price paid and the *intrinsic price* of ad quality received.

After having spent the entire ad budget, the marketer will have paid some average price and received an average ad quality level. Therefore, when a relatively high price is paid, the marketer should expect to receive proportionally higher ad quality. Conversely, when a below-average price is paid, the marketer should expect to receive below-average ad quality.

While this may sound logical for other goods bought and sold in normalized commodities markets, the reality in programmatic is often not so logical. Given rule #3, one should expect to see at least some correlation between the price paid for an ad impression and the resulting ad quality. However, what routinely appears in the data is a "spray & pray" scattergram illustrated in Figure 1 below indicating a market failure where prices are unhinged from the rational expectations that a marketer should have with respect to ad quality.

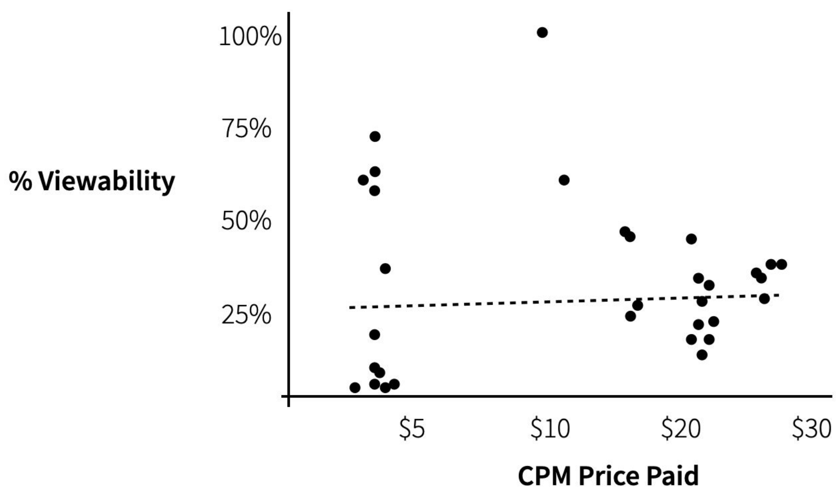
[1] Even in the case of header bidding, which comes with similar guarantees but transacted through programmatic pipes, some amount of impressions will remain unsold and funneled to an open auction or other biddable mechanisms such as private marketplace deals. See "The Beginner's Guide To Header Bidding" by Ratko Vidakovic.

[2] While pricing information is directly available in buying technology platforms such as Demand-Side Platforms (DSPs), information about ad quality is more difficult to access and assess given certain programmatic supply chain limitations and incentives. However, the concept of ad viewability and the technology to measure viewability is made directly available to any analyst, thus serving as a reasonable proxy to quantify ad quality.

Spray and Pray buying strategies inspire the notion that marketers might be involved in a lemon market when participating in programmatic auctions. Perhaps more concerning is a common justification heard from supply chain practitioners who justify pricing disparity by explaining programmatic auctions as **"special".** When buying programmatically, the conventional thinking sold to marketers becomes a neat story where sometimes you pay high prices for low ad quality, but many other times you pay low prices for high ad quality. This commonly accepted thinking goes on to assume that programmatic works as intended because the end result is positive for marketers. In other words, all's well that ends well because the good will eventually outweigh the bad after enough buying cycles. However, the data often indicates a deviation from the story and routine campaign reporting results.

Figure 1

"Spray and Pray"

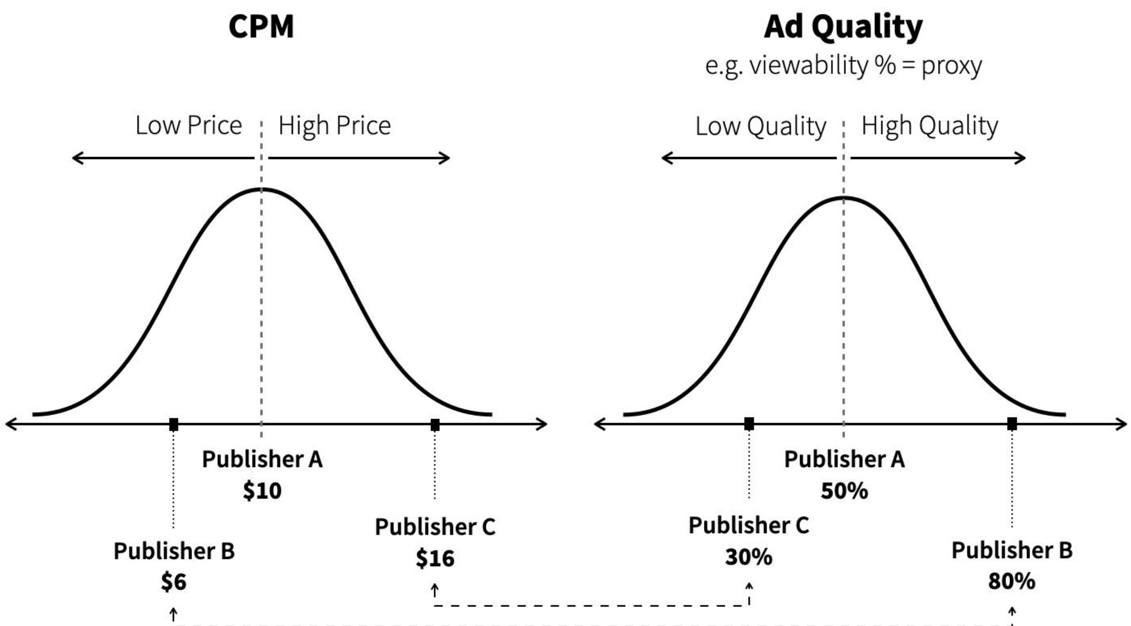


What the marketer should expect to see after having gone through many auction learning cycles is a "tightening" of price paid relative to ad quality received. As such, a limited set of scenarios are possible in a matrix constrained by the price paid for an ad impression and the ad quality received in exchange.

Consider Figure 2 below and assume a marketer spends budget to buy auctioned ads from a number of publishers.[3] Assuming the average CPM (cost per mille) paid is $10 in return for an average ad quality of 50% viewability, the marketer has revealed an *intrinsic* willingness or expectation of achieving a certain ad quality (measured in terms of ad placement viewability) in exchange for a certain price ($10).

[3] Note that a typical programmatic campaign will buy inventory from hundreds if not thousands of individual publishers. It is not uncommon to buy ad inventory from hundreds of thousands of individual publishers. Moreover, it is also important to note that hundreds and even thousands of individual webpage URLs can be bought from a single publisher.

Figure 2
Price-Value Parity



Importantly, the price paid for Publisher A's impressions is exactly equal to the average price across all other publishers, while the viewability received is also exactly equal to average viewability. Publisher B's inventory costs less than the average price but delivers higher than average ad quality in terms of viewability. In this case, the marketer gets a bargain by buying ad impressions worth $16 (e.g. the intrinsic price) for just $6, thus creating $10 of value.

Publisher C illustrates the opposite, lemon market result. Ad quality is below average while the price paid is well above average resulting in a bad deal. In this case, the marketer buys ad impressions worth $6 but pays $16, thus destroying $10 of value. If the marketer over-allocates too much ad budget to Publisher C, then the game will be lost once all the ad budget is spent. And in all three cases, various supply chain actors will earn a percentage fee on each of the $10, $6 and $16 transactions, respectively.

While Rules #1 and #2 are satisfied, Rule #3 is not. Conversely, if the marketer manages to recognize the game layout and consequently buys only from Publishers A and B — and either minimizes or avoids buying inventory from Publisher C — then value will be created and the game outcome will flip into a win.

Game Outcomes

When programmatic advertising is examined as a lemon market game, value creation (or destruction) is constrained to just two criteria, thus creating four possible outcomes generalized in Figure 3 below.

1. The *Price Paid* for an impression(s)
2. The *Ad Quality* of an impression(s)

The *price paid* for an impression is classified as either a high price or a low price such that high versus low is distinguished by deviation from the average price paid. Similarly, the *quality* of an ad impression is classified as either high or low, where high (peach impressions) versus low (lemon impressions) are distinguished by deviation from average quality.

Figure 3
Generalized Payoffs

		Price Paid: **Low**	Price Paid: **High**
Ad Quality	**Low (Lemon)**	I. Good, Bad or Neutral	II. Value Destructive "Winner's Curse"
Ad Quality	**High (Peach)**	III. Value Creative "Diamonds in the Rough"	IV. Good, Bad or Neutral

Quadrant I: Pay Low Price for Lemon Quality

An ad impression is classified as a lemon when ad quality is below average. Lemon impressions are not necessarily good or bad. It simply depends on the difference between the intrinsic price and price paid, which could result in a zero-sum, positive-sum, or negative-sum outcome.

- Low Price–Low Quality (zero-sum): When the intrinsic price is equal to the price paid, the game outcome is zero-sum, so value is neither created nor destroyed.[4]
- Low Price–Relatively High Quality (positive-sum): When the intrinsic price is greater than the price paid, the game outcome is positive-sum, meaning value is created. Even though the impressions might be low quality, at least an appropriate market price is paid.
- Low Price–Relatively Low Quality (negative-sum): When the intrinsic price is less than the price paid, the game outcome is negative-sum and economic value is destroyed. In this case, the advertiser not only buys below-average ad quality but also pays a price that is disproportionately too high.

Quadrant II: Pay High Price for Lemon Quality (Winner's Curse)

This particular bucket is the essence of a programmatic lemon market because the price paid is *always* higher than the intrinsic price resulting in a negative-sum outcome. In other words, buying low-quality lemon impressions at disproportionately high prices is a value-destructive practice.

Impressions that fall into this bucket suffer the consequences of *winner's curse* — a tendency for the winning bid in an auction to exceed the intrinsic value or true worth of the item of interest.[5] When this

[4] In all likelihood, when marketers run lemon market analysis, they will find that zero-sum outcomes are extremely rare.
[5] "Competitive Bidding in High-Risk Situations", Capen; Clap; Campbell (June 1971). Journal of Petroleum Technology. Society of Petroleum Engineers. 23 (6): 641 to 643. "In competitive bidding, the winner tends to be the player who most overestimates the true value."

outcome occurs and is identified, the concept of *buyer's remorse* should set in and motivate the marketer to change buying strategies toward a more favorable outcome.[6]

Quadrant III: Pay Low Price for Peach Quality

Quadrant III is the opposite of winner's curse. This is the best possible scenario because the marketer is able to buy impressions with better than average ad quality for a below-average price. This favorable outcome is *always* positive-sum as the intrinsic price is always greater than the price paid. Any time a marketer is able to cut through ad quality uncertainty and find a high-value impression is like finding a peach in a basket of lemons. This particular outcome not only describes the promise of programmatic sales pitches, but it also chronicles the power of establishing belief systems in the busy marketer's mind.

Quadrant IV: Pay High Price for Peach Quality

An ad impression is classified as a peach when ad quality is above average. Similar to lemon impressions in Quadrant I, peach impressions are not necessarily good or bad. Again, it depends on the difference between the intrinsic price and price paid, which could result in a zero-sum, positive-sum, or negative-sum outcome.

- High Price–High Quality (zero-sum): When the intrinsic price is equal to the price paid, the game outcome is zero-sum, so value is neither created nor destroyed. In other words, a fair price is paid for commensurately high ad quality.
- High Price-Relatively High Quality (positive-sum): When the intrinsic price for a relatively high-quality impression is greater than the price paid, the outcome is positive-sum and value is created.
- High Price–Relative Low Quality (negative-sum): When the intrinsic price is less than the price paid, the game outcome is still negative-sum and value is destroyed. In this case, the advertiser manages to buy above-average ad quality but still pays a price that is disproportionately too high. Similar to Quadrant III, the advertiser is mesmerized into a mirage while the supply chain that processes the transaction always earns a percentage fee.

2. BACKGROUND

The Market for Lemons: Quality Uncertainty and the Market Mechanism

The concept of a lemon market was first discussed in a 1970 paper by economist George Akerlof, "The Market for Lemons: Quality Uncertainty and the Market Mechanism".[7] For example, suppose an advertiser cannot distinguish between a high-quality impression (e.g. viewable 'peaches') and a poor quality impression (e.g. nonviewable 'lemons') during a programmatic auction where the bid request-response transaction takes place in a few hundred milliseconds. If the marketer is unable to distinguish between high and low quality prior to calculating a bid response value, the tendency might be to overbid and thus

[6] Buyer's Remorse, Oxford Dictionary, "a feeling of regret experienced after making a purchase, typically one regarded as unnecessary or extravagant".
[7] The Quarterly Journal of Economics, Volume 84, Issue 3, (Aug 1970), 488-500.

overpay. In other words, if the marketer ends up buying non-viewable lemon impressions for relatively high prices, then value is destroyed with respect to the intended purpose of advertising (e.g. rule #3 exposing consumers to visual ad experiences). Consequently, the advertiser suffers the winner's curse when such a negative auction outcome occurs.

In situations where sellers — along with the associated supply chain that processes programmatic auctions — take advantage of information asymmetry by either misrepresenting lemon impressions as peach impressions or not declaring an accurate assessment of quality in general, then it stands to reason that the chances of achieving a positive-sum result are not likely in the marketer's favor.[8] To compound matters, if the marketer is unaware of such negative outcomes, then he/she has no opportunity to experience buyer's remorse. For example, if a marketer buys lemon impressions, but is led to believe they are peachy, and is unable or unwilling to inspect the quality, then there exists no opportunity for remorse to set in as a trigger for future buying behavior. When such an opportunity is unknowingly missed in perpetuity over millions and even billions of auction opportunities, and tens to hundreds of millions of ad dollars, then the game is tilted against the marketer.[9]

Buying More Peaches and Fewer Lemons

To improve price-value parity and bring more balance into programmatic transactions, the marketer can apply lemon market analysis using The Key Value Formula discussed in this paper. The Key Value Formula not only quantifies lemon market outcomes with precision, but also allows marketers to make appropriate adjustments in future auction cycles. The methodology model herein illustrates how specific changes to buying strategy can correct buyer-seller information imbalance and create new circumstances to approach programmatic strategy with more competitiveness as well as tighten the link between advertising and business outcomes.

Establishing Programmatic As A Lemon Market

Brand marketers spend billions of dollars in programmatic advertising auctions to expose their products to customers.[10] Unfortunately, marketers often don't know if they are winning or losing in the programmatic game. Due to a complex supply chain through which these ad dollars move — along with some level of uncertainty over ad quality, data integrity and data availability — it is difficult for marketers to know if participation in programmatic auctions creates or destroys value.

Brand marketers also buy display ads (e.g. banner and video ad impressions served on dynamic web pages) in order to create a visual experience hoping to connect consumers with their products.[11] If the ad inventory happens to be poor quality, and buyers do not possess, or are not provided, enough

[8] It should be noted that asymmetric information issues are also present with pre-sold, guaranteed inventory.
[9] In some cases, a marketer might have natural incentives, certain constraints and/or observable cognitive biases (e.g. success bias, confirmation bias, availability bias) such that ad quality is misinterpreted in order to prove that ad campaigns are performing as promised.
[10] According to Zenith, global programmatic ad spend will exceed US$125 billion in 2020. Zenith, Nov 25, 2019. Considering that spending on programmatic auctions began approximately in 2007, total straight-line cumulative spend over the 14 year period is approximately $700B. Given expected growth rates over the foreseeable future, cumulative programmatic ad spend will likely surpass $1 trillion in 2023.
[11] A dynamic web page is a web page that displays different content each time it's viewed based on user interaction with the web page, such as a mouse or keyboard action.

information to assess ad quality prior to buying, then undesirable outcomes might prevail more often than not.

Publishers, who create online ad inventory, sit on the other side of the trade. When the publisher's sales team is unable to pre-sell all of its available inventory in advance, which contain certain quality guarantees provided in a contract, the publisher is left with what is referred to as remnant inventory. This unsold inventory ends up in programmatic auctions hoping to fetch a satisfactory price. Therefore, it stands to reason that the origin of ad inventory sent to programmatic auctions creates the circumstances for lemon market outcomes.[12]

A lemon market is one in which the quality of goods traded in a market (e.g. viewable ad impressions) can degrade in the presence of information asymmetry between buyers and sellers, leaving only "lemons" behind.[13] For instance, when sellers — along with a host of advertising technology ("ad tech") companies that mechanize the supply chain such as Demand-Side Platforms (DSPs), Supply-Side Platforms (SSPs) and publishers ranging from large media brands to millions of long-tail sites — possess all the information about ad inventory quality and have little-to-no incentive to share it with buyers, then buyers ultimately suffer the consequences of information asymmetry.[14] The consequence of buyer-seller information imbalance can be quite severe for buyers. Without enough accurate information on ad quality, marketers will likely overpay time after time while all the disintermediating agents in between still collect fees independent of outcomes.

A handful of market observers have described programmatic as a lemon market. For example, Andrew Shebbeare, co-founder of Essence Digital, a major digital advertising agency owned by WPP, said in 2016: [15]

> *The market for ad impressions is a lot like the market for used cars. Think of lemons, where the buyer of the used car knows a lot less about what's inside it than the seller. Information asymmetry creates a real problem when there is a lack of transparency, or what we call in economics a moral hazard*.

Nico Neumann, Assistant Professor at the Melbourne Business School, echoed a similar view in 2017:[16]

> *The lack of transparency and ability to evaluate media quality properly from the demand side creates a significant information asymmetry between sellers and buyers. Economists refer to such a phenomenon as a "market for lemons"*.

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[12] In American slang, a lemon is a car that is found to be defective only after it has been bought.
[13] Asymmetric information, also known as "information failure," occurs when one party to an economic transaction possesses greater material knowledge than the other party. This typically manifests when the seller of a good or service possesses greater knowledge than the buyer; however, the reverse dynamic is also possible. Almost all economic transactions involve information asymmetries.
[14] A Demand-Side Platform (DSP) is buy-side technology that processes information sent by a Supply-Side Platform (SSP) in the form of a bid request. An SSP is a sell-side technology that processes and represents unsold publisher inventory in programmatic ad auctions. Advertisers use DSP technology to calculate bid responses and send it back to the SSP auction. Interactive Advertising Bureau (See IAB tutorial, "How an Ad is Served with Real Time Bidding (RTB) - IAB Digital Simplified").
[15] Change Or Die? Essence's Co-Founder On Why The Ad Industry Needs To Re-Evaluate Its Priorities, AdExchanger, May, 2016.
[16] Lemon Markets And Marketplace Crashes: Lessons For Programmatic, AdExchanger, Oct 2017.

More recently, Mohammad Akbarpour (Stanford economist), and Shengwu Li (Harvard economist) concluded the following in their 2019 research paper on programmatic auction data:[17]

> *One view might be that if you give bidders very little information, maybe you can trick them into bidding more. But mature markets don't work like that.*

Lemon-like Origins of Programmatic Ad Inventory

Online publishers range from big media brands such as Yahoo and Forbes to millions of long-tail and niche publishers such as golfadvisor.com or blogs such as yogabycandace.com. No matter the size or brand name appeal, they all try to execute a common sales strategy in order to sell available inventory. Given that publisher revenue is a function of quantity sold (ad impressions) and price (expressed as CPM), their goal like any other business is to sell an optimal mix of quantity and price such that profits are maximized.

The quantity of ad inventory available for sale by any publisher is a function of content consumption and the size of the audience that consumes the publisher's content. Therefore, the primary production parameters of ad inventory for any given publisher are unique visitors (human or bot) over some time period, page views per visitor, and ad units available per page. For example, let's say CNET has nearly 100M unique visitors per month generating three page views per visitor and each page contains three ad units.[18] CNET would then have over one billion ad impressions available for sale every month.

Whether a publisher has a single impression or 1 billion impressions to sell, the sales objective is no different from any other profit-seeking business in that the publisher wants to sell the necessary number of impressions in order to generate a total revenue outcome that maximizes profits. Given this profit-seeking objective, there is no requirement for a publisher to sell 100% of the available inventory. A given publisher can sell 1%, 100% or any amount in between in order to meet the profit objective highlighted in Rule #2.

The typical publisher does, however, have two broad sales levers at its disposal.[19] The top priority is to pre-sell ad inventory that will be delivered on a future date, on a guaranteed basis, where the price, ad placements, and the number of impressions must be served within certain campaign dates as specified by a contract (e.g. insertion order) between the publisher and the advertiser.[20] Publishers generally prefer to maximize these pre-sold "premium" inventory deals because they tend to fetch the highest price in exchange for the specified guarantees.[21] Pre-sold contracts also tend to be a predictable revenue source for publishers compared to advertisers who tend to put a premium on quality guarantees. In essence, the

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[17] "Credible Mechanisms", Mohammad Akbarpour and Shengwu Li, July 21, 2019.
[18] SimilarWeb, CNET.
[19] Line item types and priorities, Google.
[20] An Insertion Order (IO) is a forward contract agreement between the publisher and advertiser to run an ad campaign on the publisher's inventory. Once an insertion order is signed by both parties, the publisher must run the ads for a specified amount of time and ad impressions. An insertion order contains campaign start date, end date, ad unit dimensions and placements on specific webpages, desired target audience, number of impressions to be served, pricing structure, and total cost to run the campaign.
[21] "For marketers, premium ad inventory means knowing your ad is connected to a highly valuable audience and connected to content or an experience that's important to consumers. For publishers, it means giving marketers a great platform to connect with audiences", DigiDay, Nov 7, 2012.

two parties are making a trade to mutually reduce each other's uncertainty — publishers prefer certain revenue over uncertain revenue while advertisers prefer quality guarantees over ad quality uncertainty.

The generalized distinction between large brand name publishers and smaller, long-tail publishers is by how much or how little they pull the two sales levers. Larger publishers tend to have more resources in the form of salespeople, operations staff and capital expenditure on technology. Smaller publishers possess less of these resources so they tend to sell a larger share or all of their ad inventory in programmatic auctions. Therefore, when advertisers buy guaranteed "premium" ad inventory, they do so because they know with probability *p* that the inventory has some certainty of guaranteed quality (e.g. peaches). This is observed in the fact that chief marketing officers (CMO), and their downstream marketing organization, have a public history of articulating a demand for human, brand-safe and viewable ad inventory.[22]

A key factor with advertisements on dynamic web pages (and certain connected TV video environments) is publishers having to contend with a relatively short shelf life, which is an inherently important consideration to any sales strategy. As soon as that instant passes, the ad opportunity vanishes.

For instance, let's say a publisher has 50 unique users per day visiting a cooking recipe site. Let's also imagine this site has just one page with just two ad units — one at the top of the page and another at the very bottom. The top unit always achieves 100% viewability while the bottom unit averages 50% viewability. Every morning, the publisher posts a new recipe hoping that both old and new users visit the site. With 50 unique visitors, one page and two ad units the total available inventory for sale is 100 ad units. Since the recipe publisher prefers predictable revenue over unpredictable revenue, it contracts a guaranteed deal with a spice company that only wants to buy the top ad unit, thus leaving 50% of the inventory unsold. This particular publisher also prefers to keep the website aesthetically pleasing and avoids serving pages with empty ad spaces, so it will serve either "house ads" promoting its own content and/or serve a charity ad (e.g. Unicef, Red Cross, etc.) thus earning a tax write-off.[23]

Ideally, the recipe publisher would like to sell the remaining ad inventory so long as the price received works toward maximizing profits. However, the unsold inventory is effectively worth zero until an advertiser bids a price greater than zero. With the advent of programmatic auctions, the publisher can package up the leftover inventory — which has some probability between 0% and 100% of being a lemon — and set a price floor (aka reserve price) hoping to fetch the highest price possible from competing advertisers thus generating incremental revenue.

Since only the publisher knows the true quality of the unsold inventory, any bidding advertiser must assume the probability of buying above average quality in a basket of unguaranteed inventory is lower than the probability of buying the same quality level on a guaranteed basis. It is only *after* buying these auctioned impressions and getting a post hoc viewability measurement that the marketer can form a

[22] "Marc Pritchard: 2017 Is The Year the Bloom Came Off The Rose for Digital Media", Marketing Week, Sept 14, 2017. "The fog has begun to clear and what we are finding is illuminating".

[23] A house ad refers to a self-promotional ad that a company runs on its own Web site or Network of Websites to use space left from the unsold inventory. Webopedia. With respect to charity ads, the inventory donated to the charity is valued at some price for the publisher to establish a basis for the tax write-off.

more precise idea about ad quality and thus assign a new probability about whether future impressions will be a lemon or a peach.[24]

Although it may seem clear that the post-hoc estimate would be more accurate than the pre-auction estimate, it is not observable today that such a price-value mechanism, or the related strategic thinking, exists within the typical programmatic marketer's organization or mindset. This missing link may perhaps explain much of the angst various CMOs have articulated with respect to quantifying the uncertainty of ad quality prior to participating in programmatic auctions.

As proposed by G. Akerlof's example with used cars versus new cars, suppose for clarity that there are just four kinds of online ad inventory. There are guaranteed (pre-sold) impressions and what remains as unsold impressions, and either one could be a peach or lemon as per Figure 4 below.

Figure 4

		Guaranteed	Unsold
Ad Quality	**Peach**	p_{peach}	$p_{peach\ guaranteed} > p_{peach\ unsold}$
	Lemon	$p_{lemon\ guaranteed} = 1 - p_{peach}$	p_{lemon}
		= 100%	**= 100%**

When the marketer contracts guaranteed inventory, it is expressly done based on some perceived certainty of expected ad quality. Let's say the marketer is 90% certain that the quality will materialize as agreed in the publisher contract, so p_{peach} equals 90%.[25] With 90% certainty of buying peaches on a guaranteed basis, the marketer implies a $1 - p_{peach}$ chance of getting lemons in the guaranteed deal, so $p_{lemon\ guaranteed}$ must equal 10%.

When it comes to unsold inventory, the certainty of getting a peach in an auction full of unsold inventory must be less than the certainty of getting a peach on a guaranteed basis. While this key probability might go generally unknown with conventional reporting, it can be solved with lemon market analysis.[26] For example, assume the game is played and the marketer uses the Key Value methodology finding that 40% of the outcomes include below-average lemon impressions, therefore p_{lemon} is 40% and $p_{peach\ unsold}$ is 60%.

With these probabilities in hand, the marketer can now more accurately enhance pricing strategy. For instance, imagine a marketer is willing to pay CNN a $100 CPM for guaranteed ad placements with a 90% probability and now knows that the probability of finding peach impressions in an auction made of unsold inventory is 60%. The expected value and willingness to pay for a peach in the unsold inventory auction is now $60 ($100 CPM x 60% chance).

Lastly, it should be apparent that an unsold ad impression bought at auction cannot have the same valuation as a guaranteed impression — if it did have the same valuation, it would clearly be

[24] "An asymmetry in available information has developed: for the sellers now have more knowledge about the quality [of a car] than the buyers", The Quarterly Journal of Economics, Volume 84, Issue 3, (Aug 1970), 489.

[25] While this paper focuses on programmatic data, similar data is available to assess and calculate the probability of buying various ad quality gradients on guaranteed deals.

[26] By classifying and counting impressions against the standard distribution curves of ad quality and price, the probability of getting a lemon (or peach) in a remnant impression auction falls out as a residual value.

advantageous for advertisers (or agents of the advertiser) to buy lemons in an auction market and then immediately re-sell them as guaranteed peaches for a much higher price. If such a complex practice took place at scale, and trusting buyers were unaware of such *moral hazard* taking place, then one might also imagine the importance of protecting such a profitable trade for as long as possible.[27]

3. CONDITIONS FOR SCORING THE PROGRAMMATIC LEMON MARKET GAME

Scoring the programmatic lemon market game requires three conditions: A) a data set that contains information on ad quality and prices; B) a mechanism to quantify ad quality; and C) a mechanism to convert prices into value (The Key Value Formula).

A. Data Set That Contains Information On Ad Quality And Prices

Applying the Key Value Formula requires a conveniently simple data set available to any marketing analyst by logging into any DSP's reporting platform. Simply select a date range and pull just four data fields (spreadsheet columns):[28]

1. Buying Event such as sites, placement, etc. (column 1, represents all the rows in the data set)[29]
2. Total Ad Spend (column 2, typically referred to as "media cost" in DSP platforms)
3. CPM Paid (column 3)
4. Percentage Viewability (column 4)

While additional columns or attributes can be appended for deeper analysis, these four data fields represent the minimal viable data required to initiate lemon market analysis. Table 1 below shows an example data set consisting of five generic sites representing a typical campaign where a $1 million budget buys 100 million ad impressions for an average $10 CPM with average viewability of 50%.

Table 1

Publisher	Budget	CPM	Viewability	Budget Allocation
Publisher A	$100,000	$10.00	50.00%	10%
Publisher B	$100,000	$12.00	60.00%	10%
Publisher C	$500,000	$12.00	40.00%	50%
Publisher D	$100,000	$8.00	60.00%	10%
Publisher E	$200,000	$8.00	40.00%	20%
	$1,000,000	**$10.00**	**50.00%**	**100%**
	↑	↑	↑	↑
	Total	*Average*	*Average*	*Total*

[27] Moral Hazard is the concept that individuals have incentives to alter their behavior when their risk or bad-decision making is borne by others, economicshelp.org, Nov 2019.
[28] Depending on the date range and dollar size of the selected campaign, the analyst can expect a data set with just a few hundred row events to several thousand row events.
[29] A "buying event" could be all the sites bought on a campaign. More granular views could include additional parameters such as ad type (banner or video), ad environment (desktop, mobile, CTV), auction exchange and several other event types.

Given these descriptive statistics, the advertiser can be observed as having *an intrinsic willingness to pay $10, on average, in exchange for 50% average viewability*.[30] If the marketer pays more than $10, then the expectation should be to get more than 50% ad viewability in exchange. Conversely, paying less than $10 should get less than 50% ad viewability in exchange. The marketer is “in the money” any time $10 or less fetches 50% or more viewability.[31]

For instance, an ad impression with 0% viewability must have zero dollar value for an advertiser interested in maximizing the visual experience of targeted consumers (Rule #3). Conversely, an impression that is 100% viewable must be worth not only more than $0, but it could also represent the highest price the advertiser is willing to pay for a given publisher’s ad inventory. Therefore, the notion of *intrinsic price* is revealed within the expectation a buyer has with respect to achieving a certain viewability in exchange for a certain price.

For example, if Proctor and Gamble (the world’s largest advertiser) buys impressions on CNN for $100, but pays an average of $10 in exchange for 50% average viewability across all other sites bought during the course of a typical ad campaign, then P&G should certainly expect to get much more viewability in exchange for $100 compared to the $10 average price. For such a relatively high price, P&G should expect to get 100% viewability in return. Any result short of 100% viewability means P&G will experience a value-destructive advertising outcome.

B. Viewability Data As A Mechanism To Quantify Ad Quality

As previously discussed, pricing information is made directly available in DSP platforms. However, the quantification of ad quality is not as straightforward. While there exist a handful of potentially useful metrics to address ad quality such as “attention metrics”, viewability data is not only available and plentiful within DSP and verification platform reporting tools, but also aligns well with the accepted logic and purpose of advertising defined by Rule #3.[32] Nevertheless, any reasonable metric used to address ad quality will still contain descriptive statistics (such as average, standard deviation, etc.) and thus can be used as a replacement for viewability.[33]

Seven fundamental principles become apparent when using viewability as a reasonable proxy for ad quality to study programmatic as a lemon market game:

Principle 1: Viewable ad impressions are worth more than non-viewable ad impressions.

Principle 2: The viewability of an impression is a function of passing a binary test consisting of at least two criteria defined by the advertiser:[34]

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[30] While a five site generic example campaign case is used throughout this section for simplicity sake, a typical programmatic campaign will buy inventory from hundreds if not thousands of individual publishers.
[31] “In the money” refers to paying a price below the intrinsic value.
[32] “How Brands Can Use Attention Metrics to Find Value and Possibly Fix the Web”, MTA MarTech Advisor, Oct, 9, 2019. Attention Metrics are promising new metrics that when utilized in lemon market analysis might provide increased accuracy and enhance buying strategies. Attention metrics not only include viewability but also other information such as statistical exposure times, types of exposure experiences, ad clutter on the page and other relevant elements.
[33] “There are many markets in which buyers use some market statistic to judge the quality of prospective purchases,” The Quarterly Journal of Economics, Volume 84, Issue 3, (Aug 1970), 488.
[34] MRC Viewable Ad Impression Measurement Guidelines, June 2014, MRC Standard requires that 1) the percentage of pixels that render in the viewport of the webpage must be greater than 50% for banners and 100% for video; AND 2) the ad impressions must

1. The percentage of pixels between 0% and 100% that render on a browser page (or other screen types), in the viewport of the user's browser.[35]

2. The amount of time, in seconds, that the downloaded ad is present in the viewport of the user's browser.[36]

Principle 3: When an advertiser bids on and wins an ad impression in a programmatic auction, and the ad is subsequently downloaded to a browser page, it could be served to a real human user or a bot.

Principle 4: When an ad impression is bid and won in an auction, and subsequently served on a browser page, it could be downloaded in a brand-safe or brand unsafe environment, as determined by the individual marketer's risk tolerance for brand safety.[37]

Principle 5: If an ad impression is served to a human in a brand-safe environment, then the resulting ad viewability becomes an observable data point and reasonable proxy for ad quality.

Principle 6: The accuracy of viewability measurement performed by a verification measurement provider is of paramount importance.[38] Any error rate or defect in viewability measurement will diminish the results of lemon market analysis.

Principle 7: When a verification vendor's tag fires after a DSP has bought and served an impression, it might be measurable or unmeasurable (e.g. iframe issues). Current MRC standards assume the viewability of measured impressions equals the presumed viewability of unmeasurable impressions. However, regression models show, for example, that viewability of unmeasured impressions is magnitudes lower than measured viewability. Accounting and normalizing for such a wide difference is important to get better results from lemon market analysis.

The seven principles together form a logical decision tree that, in theory, a DSP follows during the algorithmic buying process illustrated in Figure 5 and explained below.

---

be in-view in the viewport for at least 1 second for banners and 2 seconds for video. For example, imagine an advertiser buys 1000 banner ad impressions on Yahoo. After the impressions are served the advertiser gets a report from its verification vendor that says the measured viewability of the 1000 impressions was 70%. This means that 700 out of 1000 impressions passed the two-criteria test.

[35] A viewport represents a polygonal (normally rectangular) area in computer graphics that is currently being viewed. In web browser terms, it refers to the part of the document you're viewing, which is currently visible in its window (or the screen, if the document is being viewed in full-screen mode). Mozilla Developer.

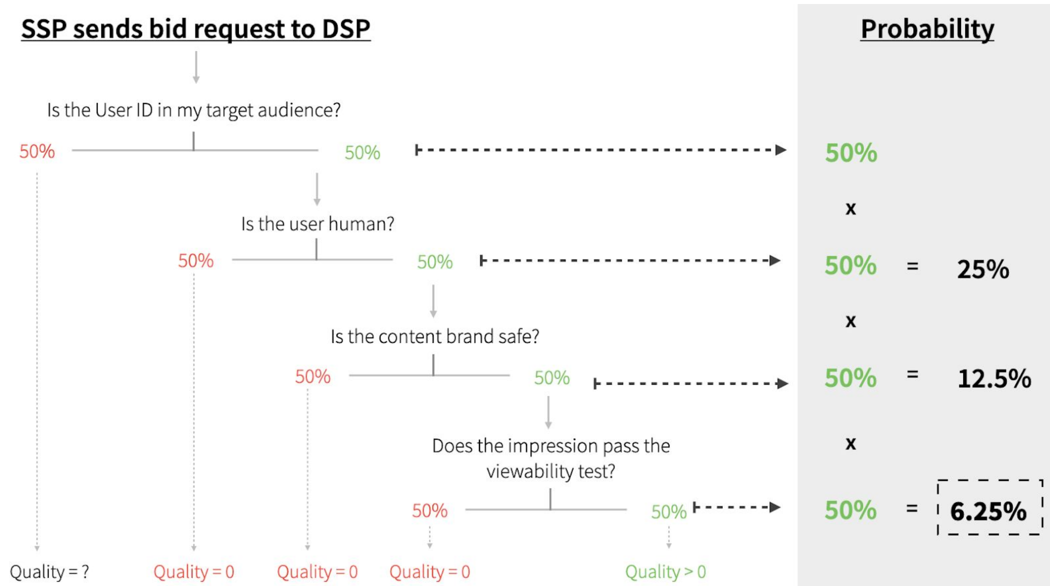
[36] "IntersectionObserver Coming into View", Google Developers Guide.

[37] For example, an advertiser might want to filter the word "dead" in order to avoid placing an ad on news content that discusses deaths in a terrorist attack, but it probably would not want to block content containing "Greatful Dead" or terms such as "knock'em dead", "dead-on", etc.

[38] Several verification vendors are used by advertisers and ad agencies. For example, Moat (owned by Oracle), Integral Ad Science, DoubleVerify, and ActiveView (Google product). It is also possible for more advanced in-house marketers to run their own javascript tag using open source code based on Intersection Observer.

Figure 5

Generalized DSP Algorithmic Decision Tree



When a user visits an ad-supported website, the user's browser not only loads the website content but also initiates the auction process by sending an "ad call" to an SSP. The SSP then syndicates the ad request to one or more DSPs. Since the overall objective of programmatic is to only serve ads to a predefined target audience, the first criteria for the DSP is to decide if the particular user ID is in the target audience. If so, the DSP then processes various deterministic and/or probabilistic data sources to decide if the user that generated the ad call is human or non-human.[39] If the user is determined to be non-human then the resulting ad quality is nil. With an on-target human user in play, the DSP will process other deterministic and/ or probabilistic data sources to ensure that the environment in which the ad is about to be served is brand-safe and bid on the ad impression.[40] If the marketer's DSP wins, the ad is served and loads in the user's browser. At this point — and only this point in time — post-hoc viewability is determined by processing various deterministic and/ or probabilistic data sources.

From a planning and buying strategy perspective, the objective is to create game circumstances such that the highest probabilities prevail. As per Figure 5 above, there are five possible outcomes. Only one results in some level of ad quality greater than nil, three result in ads with no opportunity to create value and one where ad quality cannot be undetermined.

For instance, imagine a marketer is willing to pay a $10 CPM for the "ideal ad placement", which is 100% human and brand-safe, and 100% viewable. Assuming a cascading series of the four 50% probabilities occur at each branch, there is a just 6.25% chance of serving an ad with a quality score greater than nil. In such a case the intrinsic or probability-based value of the impression is just $0.625. If these probabilities occur, then paying $10 for an ad impression only worth $0.625 is unlikely to result in a good advertising

[39] "How Much of the Internet Is Fake? Turns Out, a Lot of It, Actually," Max Read, NY Magazine, Intelligencer, Dec 26, 2018.
[40] The concept of brand safety is based on certain criteria and a varying degree of risk tolerance set by the marketer.

outcome. If the probability-based value formed the bid price instead of the ideal price of $10, the marketer would be indifferent between winning and losing the auction.

C. The Key Value Formula: A Mechanism To Convert Prices Into Value

When programmatic is approached as a game consisting of thousands of advertisers competing for billions of impressions supplied by millions of publishers, there could be a mix of winners and losers in terms of value creation. In the case where no buyer is able to generate a winning outcome, the only potential winner would be the supply chain that supports and administers the game in exchange for fees earned independently of the advertising outcome.[41]

The Key Value Formula discussed in the following sections is intended for the individual marketer to learn, and leverage, if participating in programmatic auctions results in a lemon market outcome and how to change buying strategies toward better outcomes. Application of the Key Value Formula allows marketers to know if they are winning or losing, pinpoints the strategic buying changes to turn losing outcomes into winning outcomes, and balances the information asymmetry problem by embedding value-based pricing into buying strategy.

Based on George Akerlof's 1970 paper — "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism"— the Key Value Formula teases out standard statistics from the same data that marketers already use for other purposes. Beyond the primary benefit of correcting information imbalance, the model also provides marketers a significant advantage with respect to competitors who remain unaware of their particular lemon market predicament. For instance, given the relative scarcity of high-quality ad impressions, if three Competitors A, B and C all suffer lemon market outcomes when participating in programmatic auctions, and if only Competitor A corrects the problem, then not only will Competitor A be positioned to buy the best impressions at value-generating prices, but Competitors B and C will be left with higher-priced and lower quality impressions. Assuming Competitors B and C eventually catch on and correct their information imbalance, the lemon impression problem will, in theory, get squeezed out of the market to the benefit of all advertisers.

One could also imagine a scenario where the marketing organizations of Competitors A, B, and C are characterized by various biases such as escalation of commitment, confirmation bias, cognitive dissonance, availability bias, fundamental attribution error, etc. When Competitor A recognizes the disadvantage of these biases through lemon market analysis and translates this mental shift into probability-based bidding, it gains a bidding advantage over Competitors B and C.

[41] "eMarketer's New Ad Tech Tax Estimates Show One-Third of Spending Goes to Intermediaries", eMarketer, Aug 5, 2019. "ISBA/PwC Programmatic Supply Chain Transparency Study" ,Incorporated Society of British Advertisers, May 2020.

Simply put, the Key Value Formula is the *intrinsic price* of an individual impression less the *actual price paid* across the sum of all impressions bought by the advertiser:

Equation 1

Key Value Formula

$$V = \sum_{imp} (P_i - P_r)$$

- V is the value of the ad impression(s).
- P_r is the real, post-transaction price paid for the ad impression(s).
- P_i is the intrinsic price of the ad impression(s).

For instance, imagine Proctor and Gamble pays a $100 CPM for 1000 banner ad impressions on CNN. After the impressions are served, P&G gets a report from its viewability measurement vendor showing that viewability across the 1000 impressions was 70%.[42] An analyst at P&G then applies the Key Value Formula calculating an $80 *intrinsic price* resulting in a negative outcome of -$20. In this case, $100 is spent in a programmatic auction game resulting in a –$20 outcome. In other words, it costs P&G $100 to buy just $80 of value.

$$Value = \sum_{1000} (\$80_i - \$100_r) = -\$20$$

Given these observations revealed from the data, the calculation of *intrinsic price* (P_i) is the key feature of programmatic lemon market analysis:

Equation 2

Intrinsic Price

$$P_i = (P_r \, x \, V_r / V_e)$$

- V_r is the real, post-hoc viewability expressed as a percentage, provided by the advertiser's verification vendor.
- V_e is the *expected viewability* expressed as a percentage, which is a function of relative price paid compared to the average and standard deviation of viewability.
- The term V_r/V_e is the Viewability Ratio, which is the ratio of actual, post-hoc viewability divided by expected viewability.[43]

[42] 70% viewability means that 700 out of 1000 impressions passed the test described in Principle 2.
[43] In essence, the Viewability Ratio is a key performance indicator missing from the typical marketer's programmatic strategy. The Viewability Ratio is simply the proportional price a buyer would have paid based on the actual viewability of the ad impression compared to the expected viewability as a reflection of the price paid.

By substituting the intrinsic price formula (Equation 2) into the Key Value Formula (Equation 1), the fully expressed Key Value Formula is:[44]

Equation 3

Key Value Formula Fully Expressed

$$Value = \sum_{imp} \left((P_r \, x \, V_r / V_e) - P_r \right)$$

Of the three variables in the formula, two are explicitly known and one is unknown. The actual price paid (P_r) and post-hoc viewability (V_r) are known, but the key variable of interest — *expected viewability* (V_e) — is unknown. Expected viewability drives programmatic value creation (or destruction) and is derived using a conversion process consisting of four sequential steps starting with Table 3b below.

Table 2

Publisher	CPM	Z-Score CPM	Actual Viewability		Expected Viewability
Publisher A	\$10	0.0x	50%	=	50.00%
Publisher B	\$12	1.0x	60%	=	60.00%
Publisher C	\$12	1.0x	40%	<	60.00%
Publisher D	\$8	-1.0x	60%	>	40.00%
Publisher E	\$8	-1.0x	40%	=	40.00%
	\$10.00				
	↑				
	Average				

Step 1: Calculate the average and standard deviation of price paid, which are \$10 and \$2, respectively.[45]

Step 2: With the average and standard deviation of CPM tabulated, calculate the Z-Score of price paid for each site as illustrated in Table 2. The Z-Score is like an "Expected Viewability Index" because values less than zero mean the price paid for the particular site is less than the average price paid and values greater than zero mean the price paid is greater than the average price paid. For example, an Expected Viewability Index of 1.0x for Publisher C means the \$12 price tag is 1.0 standard deviations from the \$10 average CPM.

[44] If other measures of ad quality used in lieu of the viewability proxy, such as an overall ad quality scoring system comprising invalid traffic, brand-safety, viewability or additional approaches such as attention metrics, the Intrinsic Price formula in Equation 2 can be expressed more generally as $P_i = (P_r \times A_r / A_v)$.

[45] The example case used in this paper is based on impression-level data aggregated and processed at the site level. However, lemon market analysis allows for a wide creative analysis with respect to a wide range of data categories that can be analyzed. For example, the analyst can also examine data aggregated by ad unit type (banner, video); ad placement (above or below the fold); ad environment (e.g. desktop, mobile, OTV); ad size; line item tactic; site category; SSP inventory source and several other parameters all the way down to the individual impression-level. In addition, and depending on the data set, average CPM and viewability (or any other ad quality metric) can also be calculated as weighted averages with budget allocation as the weights.

Step 3: Translate the Z-Score of price paid into Expected Viewability by applying it to the average and standard deviation of post-hoc viewability, which are 50% and 10%, respectively.

Equation 4

Expected Viewability

$$V_e = (Z\ Score\ Price\ Paid\ x\ Standard\ Deviation\ of\ Viewability\ ) + \ Average\ Viewability$$

Take Publisher A, for example. The $10 price paid indexes at exactly zero standard deviations, which is equal to the $10 average price paid. Therefore, in a possible viewability range of 0% to 100%, $10 falls exactly in the middle of the standard distribution for viewability, which is 50%. In other words, when the buyer pays the average CPM for any given site, the buyer should also expect to achieve an average post-hoc viewability as a reflection of that price. Publisher E, on the other hand, is priced at $8 which is 1.0 standard deviation below the average, so the expected viewability is 40%, or 10% lower than the 50% average.

$$V_e^{Publisher\ E} = (-\ 1.0\ x\ 10\%)\ +\ 50\%\ =\ 40\%$$

Step 4: With Expected Viewability now calculated, the final step is to calculate the *Intrinsic Price* for each publisher in Table 3 below, which is the price that the advertiser *should pay* in exchange for the actual viewability (e.g. ad quality) received.

Table 3

Publisher	CPM		Intrinsic Price	Value Gain or (Loss)
Publisher A	$10	=	$10.00	$ -
Publisher B	$12	=	$12.00	$ -
Publisher C	$12	>	$8.00	$ (4.00)
Publisher D	$8	<	$12.00	$ 4.00
Publisher E	$8	=	$8.00	$ -

For example, the intrinsic price of Publisher C is $8, but the marketer paid $12 due to misjudging the anticipated ad quality. For a $12 price tag, the marketer intrinsically expected to get 60% viewability but only received 40% viewability, thus losing $4.00 in the process.

$$P_i^{Publisher\ C}\ =\ (\$12\ x\ 40\%/60\%) = \$8$$

Publisher D is the opposite because the marketer intrinsically expected to get 40% viewability by paying \$8 but ended up getting 60% viewability, thus earning a \$4.00 spread.

$$P_i^{Publisher\ D} = (\$8\ x\ 60\%/40\%) = \$12$$

Table 4 below illustrates the final result of the Key Value Formula across Publishers A to E. Given the lopsided budget allocation going to Publisher C, where the intrinsic price was less than the cost for those impressions, the total game outcome is –\$117K (rounded).

Table 4

Publisher	CPM	Budget Allocation	Budget	Value Gain or (Loss)		Total Value Gain or (Loss)	Impressions
Publisher A	\$10.00	10%	\$100,000	\$ -	=	\$ -	10,000,000
Publisher B	\$12.00	10%	\$100,000	\$ -	=	\$ -	8,000,000
Publisher C	\$12.00	50%	\$500,000	\$ (4.00)	=	\$ (166,667)	42,000,000
Publisher D	\$8.00	10%	\$100,000	\$ 4.00	=	\$ 50,000	13,000,000
Publisher E	\$8.00	20%	\$200,000	\$ -	=	\$ -	25,000,000
		100%	**\$1,000,000**			**\$ (116,667)**	
		↑	↑			↑	
		Total	*Total*			*Total*	

With this new information in hand, one can better analyze \$1M the marketer placed into programmatic auctions. The marketer bought 100 million impressions from five different publishers and achieved mixed results in terms of actual and expected viewability outcomes. However, half of the budget was spent on Publisher C resulting in a value destructive outcome.

Publisher A, for example, costs \$10 with an intrinsic price also equal to \$10 resulting in a zero-sum outcome. Since 10% or \$100K of the \$1M campaign budget was allocated to Publisher A at a \$10 CPM, the marketer bought ten million impressions (Total Impressions =[Budget Allocation ÷ CPM x 1000) and achieved perfect value-price parity between the actual viewability received and the expected viewability embedded in the \$10 price tag.

$$Value^{Publisher\ A} = \sum_{10M} (\$10_i - \$10_r) = \$0$$

Publisher C, on the other hand, costs \$12 but is only worth an \$8 intrinsic price resulting in –\$4 negative-sum outcome. Given the 50% budget allocation, a total of \$167K in value destruction accrued across 42M impressions.

$$Value^{Publisher\ C} = \sum_{42M} (\$8_i - \$12_r) = –\$167,000$$

Publisher D highlights the raison d’être of participating in programmatic auctions. In this case, peach inventory was found at a lemon price (diamond in the rough). The \$8 cost is worth a \$12 intrinsic price resulting in a $4 positive-sum outcome, but unfortunately, only 10% of the total budget was allocated to Publisher D resulting in a $50K gain.

$$Value^{Publisher\ D} = \sum_{13M} (\$12_i - \$8_r) = \$50,000$$

Table 5 below illustrates how each of the five example publishers are classified across Ad Quality (high or low) and Price Paid (high or low).

Table 5

Publisher	**Actual Viewability**	**CPM**	**Ad Quality Classification**	**Price Paid Classification**
Publisher A	50%	$10	average	average
Publisher B	60%	$12	high	high
Publisher C	40%	$12	low	high
Publisher D	60%	$8	high	low
Publisher E	40%	$8	low	low
	50%	**$10**		
	↑	↑		
	Average	*Average*		

Recall that the distinction between high and low is based on how each site performs with respect to being above or below average viewability and the average price paid, respectively. With these classifications now countable, programmatic game outcomes can be visualized as illustrated below in Table 6.

While the results appear to be balanced with one publisher occupying each of the four possible buckets, the lopsided budget allocation going to Publisher C drives a negative-sum monetary payoff for the advertiser.

Table 6

		Price Paid		
		Low	**High**	**Total**
Ad Quality	**Low**	1	1	**2**
	High	1	1	**2**
	Total	**2**	**2**	**4**

	Price Paid		
	Low	**High**	**Total**
Low	$ -	$ (167,000)	**$ (167,000)**
High	$ 50,000	$ -	**$ 50,000**
Total	**$ 50,000**	**$ (167,000)**	**$ (117,000)**

Note: It is not necessary to count Publisher A in the outcome table. Since Publisher A price and viewability were exactly equal to the overall averages it is treated as an unclassified outcome by virtue of reaching perfect price-value parity.

Armed with clear game outcomes, the marketer can now make appropriate adjustments to buying strategy, rerun the analysis, and judge the impact. By first recognizing outcomes and then flipping budget allocation from Publisher D to C, the revised post-optimization outcome turns into a $217K positive-sum game illustrated in Table 7 below.

Table 7

Ad Quality	Price Paid			
		Low	High	Total
	Low	1	1	**2**
	High	1	1	**2**
	Total	**2**	**2**	**4**

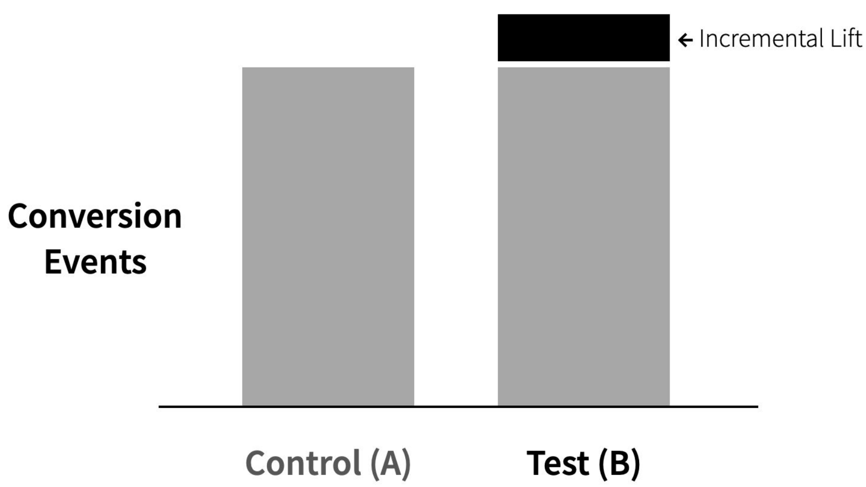
	Price Paid		
	Low	High	Total
Low	$ -	$ (33,000)	**$ (33,000)**
High	$ 250,000	$ -	**$ 250,000**
Total	**$ 250,000**	**$ (33,000)**	**$ 217,000**

4. VIEWABILITY AND CONVERSION OUTCOMES OF INTEREST

Running lemon market analysis has important applications beyond bringing balance to the information asymmetry problem in the programmatic supply chain. Given the fact that only viewable ads can be clicked by human users mixed with the concept of view-through attribution[46] as an optimization metric aiming to drive incremental conversions (e.g. product sales, content downloads, landing page visitation, user email collection, etc.), running a lemon market optimization approach and gearing ad buys toward an intrinsic pricing strategy will likely drive incremental demand generation in the right direction.[47]

Using the generic example outlined in Figure 4 below, one can see a generalized picture of what a causal incrementality A/B test might look like. The concept is straightforward: Expose the test group to ads and suppress the control from getting ads, then check for relative lift by calculating the conversion probability and incremental conversion probability in both test and control groups.[48]

Figure 6



[46] View-through Attribution: The counting of human users who did not click on an ad impression, but nonetheless were served a viewable ad impression and then took some desired action within some defined time period.
[47] “New Study Draws a Direct Connection Between Viewability and Success in Direct-Marketing Campaigns”, AdWeek, Nov 8, 2017.
[48] “Incrementality Bidding & Attribution”, Lewis and Wong, Mar 12, 2018.

A big "what if" for marketers to consider is how ad quality in general, or viewability specifically, matters as a key driver of incremental conversions. For instance, what if ad impressions that are 100% in view for at least 3 seconds are the best predictor of incremental conversions?[49] What if ad quality in general or top quartile attention metrics drive nearly all incremental lift?[50] And what if minimizing the variation between intrinsic price and price paid turns out to be an accurate predictor of incremental gain? Finally, if running causal incrementality analysis is often too complex for marketers and lemon market analysis is not, but both squeeze out the bad in favor of the good, then ends will justify the means.

For example, Tables 4a and 4b illustrate the intuitiveness of lemon market analysis. In all likelihood, buying high-quality ads will generate the lion's share of incremental conversions and also minimize other financial objectives such as cost per acquisition (CPA) in line with Rule #3.

Table 8

		Conversions Price Paid			CPA Price Paid		
		Low	**High**	**Total**	**Low**	**High**	**Total**
Ad Quality	**Low**	250	420	**670**	$800	$1,190	**$1,045**
	High	1,950	1,200	**3,150**	$51	$83	**$63**
	Total	**2,200**	**1,620**	**3,820**	**$136**	**$370**	**$236**

Even in cases where marketers only care about clicks and subsequent conversions, the results will show only the most viewable and highest quality ad inventory generates the most clicks and conversions. In more advances where a marketer is proficient with causal incrementality statistics, the results will show a high correlation between lemon market-based optimization and incrementality-based decisioning.

5. WINNING THE GAME

When a marketer buys programmatic ads tied to a hard budget constraint (Rule #1) aiming to expose consumers to visual ad experiences (Rule #3), and when publishers sell ad impressions with varying degrees of ad quality in programmatic auctions (Rule #2), the marketer wins the game by minimizing the error rate between price paid and the *intrinsic price* of ad quality received.

This notion of winning is illustrated in the following example that shows how a typical ad campaign is progressed through three optimization cycles. While the optimization tactics discussed in Sections 3 and 4 are based on rearranging budget allocation, a more precise illustration in Table 9 shows what happens when *probability-based optimization is used by changing bid prices as a reflection of intrinsic value*, which indirectly alters budget allocation as a consequence of auction win rates.

[49] "Incrementality Bidding & Attribution", Lewis and Wong, Mar 12, 2018, Page 28.
[50] Attention metrics and attention units can reveal the quality of programmatic media and reduce viewability-optimized waste, AdelaideLift.

For example, assume a marketer is informed by lemon market analysis and adjusts for expected ad quality by raising or lowering prices. Lower bid prices decrease the chances of winning an auction for a particular publisher's inventory, which in turn decreases the amount of budget that flows to that publisher. The opposite is true when raising bid prices. *Therefore, when a marketer bids the intrinsic price, he/she becomes indifferent to winning or losing because both outcomes generate value, albeit in different ways.*

Optimization Cycle 1

		Budget Allocation	CPM	Viewability	Expected Viewability	Intrinsic Price	Total Value Gain / (Loss)	
big bet →	Publisher A	50%	$14.00	50.00%	82.65%	$8.47	–$ 198,000	*← bad deal*
	Publisher B	20%	$12.00	60.00%	76.32%	$9.43	–$ 43,000	
	Publisher C	15%	$10.00	70.00%	70.00%	$10.00	$ -	
small bet →	Publisher D	10%	$8.00	80.00%	63.68%	$10.05	$ 26,000	*← good deal*
	Publisher E	5%	$6.00	70.00%	57.35%	$7.32	$ 11,000	
	Average		***$10.00***	***66.00%***	***70.00%***	***$9.06***		
	Deviation		***$3.16***	***11.40%***	***10.00%***	***$1.16***		
low accuracy →	***Pricing Error***	***15.97%***					**–$ 204,000**	*← losing outcome*

Cycle #1 shows a campaign with five publishers and a $1 million ad budget. For the sake of this example, assume the goal is to maximize viewable impressions.[51] At some point in time after launching the campaign (e.g. typically a few days to a few weeks), the marketer runs the data through lemon market analysis and sees the average price paid is $10 in exchange for 66% average viewability. The marketer also finds the average $9.06 intrinsic price is less than the $10 average price paid, resulting in –$204,000 outcome. The marketer should also hone in on a key barometer called *pricing error*, which is 15.97%. The pricing error is an efficiency score that shows how well the marketer is pricing (or mispricing) the resulting ad quality received.[52]

Optimization Cycle 2

		Budget Allocation	CPM	Viewability	Expected Viewability	Intrinsic Price	Total Value Gain / (Loss)	
budget decrease →	Publisher A	30%	$12.00	60.00%	78.16%	$9.21	–$ 70,000	*← improved deal*
	Publisher B	20%	$12.00	60.00%	78.16%	$9.21	–$ 46,000	
	Publisher C	15%	$10.00	70.00%	70.00%	$10.00	$ -	
budget increase →	Publisher D	30%	$10.00	80.00%	70.00%	$11.43	$ 43,000	*← better deal*
	Publisher E	5%	$6.00	70.00%	53.67%	$7.83	$ 15,000	
	Average		***$10.00***	***68.00%***	***70.00%***	***$9.54***		
	Deviation		***$2.45***	***8.37%***	***10.00%***	***$1.32***		
tighter correlation →	***Pricing Error***	***7.51%***					**–$ 58,000**	*← fewer losses*

[51] Another goal might be to maximize clicks, view-through conversions or true incremental conversions where the conversion could be "soft" (e.g. visits to a landing page, content consumption, etc.) or "hard" (e.g. product purchase, subscription, etc.).
[52] Pricing error is similar to other prediction error rates such as root mean squared error (RMSE) where a lower rate means more accurate pricing.

In Cycle #2, the marketer decides to decrease the CPM paid on Publisher A and increase the CPM for Publishers B's inventory hoping to get more viewability. After a few days, the marketer reruns the analysis and sees improved results. The lower CPM on Publisher A translates into less competitiveness for relatively low viewability, hence less budget flows to Publisher A due to a lower auction win rate.

Publisher D realizes a better fate as the marketer places a bigger bet by offering a higher price for relatively high viewability. While the overall game outcome is still negative-sum at –$58,000, the pricing error rate dramatically decreases to 7.51% and average viewability increases to 68%. Importantly, it should also be noted that the standard deviation of price and viewability also tightened in line with the decreased pricing error.

Optimization Cycle 3

		Budget Allocation	**CPM**	**Viewability**	**Expected Viewability**	**Intrinsic Price**	**Total Value Gain / (Loss)**	
budget decrease →	Publisher A	10%	$10.00	70.00%	77.30%	$9.06	–$ 9,000	← *damage control*
	Publisher B	20%	$10.00	80.00%	77.30%	$10.35	$ 7,000	
budget decrease →	Publisher C	10%	$8.00	70.00%	59.05%	$9.48	$ 19,000	
optimized →	Publisher D	20%	$10.00	90.00%	77.30%	$11.64	$ 33,000	← *good deal*
budget increase →	Publisher E	40%	$8.00	80.00%	59.05%	$10.84	$ 142,000	
	Average		***$9.20***	***78.00%***	***70.00%***	***$10.27***		
	Deviation		***$1.10***	***8.37%***	***10.00%***	***$1.04***		
favorable error rated →	***Pricing Error***	***5.78%***					**$ 192,000**	← *winning outcome*

What started as a lemon market outcome starts to turn into a competitive advantage. With updated information in hand, the marketer decides to run a third cycle with additional buying strategy changes. The CPM for Publisher A decreases further while viewability continues to improve toward the expected average. By using intrinsic pricing information as a new auction tool, Publisher A is now more incentivized to increase the ad quality that it sends to auctions. The bigger change is increasing the CPM on Publisher E and also getting more viewability out of Publisher D without increasing the CPM any further, resulting in $192,000 of value creation and a campaign win. Most importantly, the analysis and subsequent strategy changes bring the pricing error down to 5.78% while the *average intrinsic price* ($10.27) moves higher than the *average price paid* ($9.20).

5. CONCLUSION

The worst-case scenario for the individual advertiser is to be unknowingly locked into a lemon market yet carry on. There is little hope of achieving a positive return in such a scenario. The second worst case is knowing about it and doing nothing. In either case, inaction ultimately relegates programmatic into an exercise where spending advertising budget (Rule #1) becomes the end game instead of using programmatic data and tools as a means to a more worthwhile objective (Rule #3). Even in cases where the outcome is a positive-sum game, there is still room for improvement in terms of tightening price-value parity and bringing it to bear with probability-based bidding strategies.

Ultimately, an individual marketer should want to know whether or not to remain in the programmatic game or to exit until better prepared to play with more competitiveness. Remaining in the game means evolving from lemon market analysis toward a systematic execution of intrinsic price bid strategy. This missing practice is perhaps the greatest unrealized benefit of programmatic auctions. It is also the most pragmatic approach available to correct whatever information asymmetry exists, thus clearing the market of lemon impressions and leaving behind only what is useful for advertisers.

By translating readily available data and adjusting bid prices into intrinsic-based pricing strategies, marketers can elevate themselves into a state of indifference with respect to winning or losing the auction. For it is better to lose an auction than to overpay, and better to win an auction when the price paid is less than the intrinsic value of the ad impression. In the case where no ad inventory can be won by bidding the intrinsic price, then the marketer will know with total certainty that lemon market outcomes are the only outcome and should thus pause or exit the game.

Lastly, while this paper focuses on the multi-billion dollar programmatic marketplace for banner and video ads placed in dynamic webpage environments, a growing emphasis should be placed on how TV advertising for which an increasing amount is shifting toward audience targeting and programmatic trading mechanisms on connected TV (CTV) ad inventory. Given the growing importance that marketers place in connected TV advertising within the overall advertising mix, and how programmatic is increasingly creeping up as the new buyer-seller norm, usage of lemon market analysis and intrinsic pricing strategy should also grow in importance and urgency.