THE RELATIONSHIP BETWEEN COMPLEXITY AND BEHAVIORAL BIAS

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ABSTRACT

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In the corporate workplace employees are routinely asked to do analysis of impacts, outcomes, demographics, and economic opportunities just to name a few. While these projects vary greatly in regard to their subject matter, they also vary in terms of complexity. Some are straight forward with few moving parts while others entail dozens of confounding variables and noise. Knowing that humans are not able to treat problems systematically and without bias, we propose the question: how do complexity and behavioral biases interact? Using case studies from analysis done at an eCommerce company located in the Mountain West, this research found that different levels of complexity lend themselves to different behavioral biases. Complex problems create an environment where employees are more susceptible to creative interpretation, social pressure, and incentives. Less complex problems leave less room for creative interpretation but create situations where assumptions and findings are overstated.

Research Setting

The following research took place at Puzzle Inc.[1] found in the Mountain West. Puzzle supplies a variety of services including eCommerce management, distribution optimization, and marketing consulting. Puzzle started out as a company called weServe in 2013 which grew until it acquired Practical in 2018, an international consultancy firm. In November of 2018 weServe was rebranded into Puzzle and is now a top 5 third party seller on Amazon. Currently it has offices in the United States, London, Dubai, Hong Kong, China, and Australia and over 200 employees. Puzzle uses multiple eCommerce platforms including eBay, Amazon, and Jet. Yet, Amazon is Puzzle's main focus as it hosts about 75 percent of the United States online sales. Puzzle partners with approximately 50 brands to sell through online marketplaces and improve their products, marketing, and distribution.

Specifically, the observations for this research were taken during projects including measuring the impact of certain promotions, campaigns, and company processes, and projects including estimated brand growth and value through historical sales and volume estimates. Through these projects, observations were made about the biases and potential biases which analysts, advertisers, brand managers, and managers were exposed to. This real-world setting helped expose the uncertainty and messiness involved in analytics and their contribution to behavioral biases. Though the real-world setting deterred from the ability to control confounding variables, this research greatly benefited from the proximity to human behavior outside of the laboratory setting.

Organizational Structure

Puzzle generates revenue by managing several brands' online sales. They buy products from over 50 assorted brands and then resell these products, mainly through Amazon, at marked-up prices. They work closely with these brands to help them maintain positive brand image, regulate minimum

[1] Company name change to protect privacy

advertised prices, increase advertising, improve marketing, and consult on product strategy. To facilitate this process Puzzle has a complex organizational structure.

One of the most client facing roles within Puzzle are the brand managers. They are the liaison between Puzzle and the brand. They help communicate to brands Puzzle's decisions and strategies about their brand's online presence, advertising etc. They help explain why sales volumes have risen or decreased and communicate to the brands Puzzle's findings about how their products compete with other products and how they could improve their reviews/ services.

The advertising and marketing teams work closely to increase the sales of products through improving awareness, increasing product ratings, optimizing prices, running ad campaigns, and finding the right channels to promote brands' products. The creative team works with the advertising and marketing teams to create the best content for image stacks and ads, and for marketing Puzzle's services. The sales team uses this content and success stories from brand managers to promote Puzzle's services and negotiate with potential clients. They are instrumental in helping potential clients know the benefits of selling through Puzzle and onboarding them to the system.

The development team works hand in hand with all the teams by building out the technology and interfaces needed to support their processes. They create and support the website, build report interfaces, improve data collection and storage, and respond to various other technologically related requests. Other supporting functions common to any corporation include the finance and accounting teams, I.T., warehouse and transportation, and human resources.

Management oversees the entire process and helps make strategic decisions regarding Puzzle's trajectory and growth. They oversee their specific departments and weigh in on large decisions such as acquisitions and hiring. They are essential in determining which brands are sold through Puzzle and which brands are not. Most brands that want Puzzle’s services are turned away for various reasons including lack of potential growth, incompatible products, and company size incompatibilities.

Research Question

Puzzle, and eCommerce in general, is a perfect environment to study behavioral biases because of its large amounts of data, rapidly changing marketing and advertising campaigns, and an overarching goal to influence consumer behavior. Yet, even though it is in companies’ best interest to influence consumers through behavioral biases, one can see behavioral biases also influence those in the workforce, specifically those doing analytics in complex environments. By complexity, which could also be defined as noise, we are referring to the many moving parts in corporations and the economy at large. Unlike controlled lab experiments, analysis of corporation data often involves dozens of uncontrolled variables, and potential confounding factors. This is especially true when initiatives are not implemented using an experimental design strategy such as the A-B method. Therefore, this research strives to better understand the relationship between complexity and behavioral bias in the workforce. With added complexity we predict that there is greater room for behavioral biases such as self-serving attribution bias and confirmation bias.

Literature Review

Complexity is a complex subject. Depending on the field, whether it be computer science or biology, complexity has a different meaning. Yet, there are overlapping similarities which we draw upon for this paper. For example, Adami (2002) describes complexity as the amount of information an organism stores in its genome. Applied to inanimate data analysis, one could say that the complexity of a given analysis is the measure of sources of information, or independent variables, that the data contains.

Complex data is often referred to as noisy. The noise being the data included in the analysis that does not reflect the desired signal. In engineering there is a ratio called the signal-to-noise ratio (SNR) which is used to determine how much signal there is compared to the noise (Johnson, 2006). In analytics for Puzzle, this would be comparable to the signal from the independent variable of interest and the competing noise from other variable changes, measurement error, seasonality, and random chance. Though this research does not contain a specific signal to noise ratio, we choose to classify our observations according to their levels of competing noise.

Behavioral bias spans a large domain of possible behaviors. As such, specifically for observing bias in different situations as will be done in this analysis, it becomes important to classify behavioral biases collectively. In classifying behavioral biases, I use the framework as developed by DellaVigna (2009) and laid out by Guhl et. Al (2017). This framework classifies behavioral biases into three categories, (1) Non-standard preferences, (2) Non-standard beliefs, and (3) Non-standard decision-making. These groups help categorize the decisions that people make which depart from what classical economic theory would predict. Neoclassical economic theory treats people as rational who make decisions to maximize their utility. Included in its assumptions, Rabin (2002) states that people:

- "are Bayesian information processors;"
- "have well-defined and stable preferences;"
- "maximize their expected utility;"
- "exponentially discount future well-being;"
- "are self-interested; narrowly defined;"
- "have preferences over final outcomes; not changes;"
- "have only "instrumental"/functional taste for beliefs and information"

However, we know that people often depart from these assumptions in systematic ways as are categorized below by DellaVigna (2009) and Gahul (2017).

1. Non-standard preferences

    1.1. Non-standard preferences refer to human preferences which do not conform to the rational assumptions in the neoclassical economic model laid out by Rabin (2002) such as having "stable preferences" and being only "self-interested" (Guhl et. Al, 2017). For example, conflicting these rational assumptions, Rabin (1993) finds that people are not only self-interested because they care about the social outcomes of others. They look to help those who are helping and hurt those who are hurting. Furthermore, people often use hyperbolic discounting (Liabson,1997). Hyperbolic discounting states that perceived value decreases rapidly in the short term and more slowly in the long term. For example, people might prefer 100 dollars today than 105 dollars tomorrow because they must wait an extra day to get more money. But if given the choice between $100 in 100 days or $105 in 101 days, they are more likely to wait an extra day for the larger check. This has large repercussions for the workplace. How many people decide not to work on a report only to wish they would have worked on it when their meeting comes? Or how many CEO's seek short term economic benefits at the long-term detriment of their company?

2. Non-standard beliefs

    2.1. Non-standard beliefs refer to the systematic biases that are prevalent in human judgement and interpretation of information (Guhl et. Al, 2017). For example, people are overconfident in their own skills and abilities. An experiment by Svenson (1981) revealed that around 90% of US drivers thought themselves to be above average in safety. Extrapolating to the workplace, most employees think they are more skilled than their counterparts and their decision have a larger impact on the company than they actually do. Another example is human's tendency to over extrapolate from a few sample data points (Tversky and Kahneman, 1971). People mistakenly believe that small samples are representative of larger populations. For instance, someone who meets a mean stranger in NYC might mistakenly believe that most strangers in NYC are mean. Or in a professional environment, one might believe that sales data from a given month are representative of the entire year neglecting seasonality, price and advertising changes, and other economic factors.

3. Non-standard decision-making

3.1. Non-standard decision making refers to the fact that people are not reference or setting independent in their decisions (Guhl et. Al, 2017). One example of this is social influence. Bicchieri and Xiao (2009) find that people act following what they believe others will do. People's beliefs about the people in their environment affect their choices. Therefore, if one believes that their co-workers cheat or slack off at work, it is easier for them to do the same. Similarly, reference points impact peoples' decision (Kahneman & Tversky, 1981). For example, a $4 medium sized soda does not look as expensive next to the $10 large soda but looks expensive compared to the $0.50 small soda.

Methodology

To study the effects of complexity on behavioral biases we use a case study approach. We choose three analytics related projects, classified as low, medium, or high complexity, for which we observe behavioral biases. To measure complexity, we count the number of, what we refer to as, "moving parts" within the analysis. These "moving parts" could be anything from number of confounding factors to the messiness of the data. For example, analyzing the impact of Fourth of July on a company's performance is more complex than analyzing which gender buys more of a company's products. The Fourth of July analysis would involve a lot of human interpretation, historical figures, economic data, sales numbers etc., and result in an estimation instead of a clear-cut answer. The gender analysis would only require sales data and could result in a concrete answer.

After describing the complexity of the cases, we address the behavioral biases that arose in performing these analyses. The behavioral biases that we describe were either observed in or brainstormed as potential biases that could arise specifically related to that case. Therefore, this analysis relies on qualitative methods with some quantitative aspects. Admittedly, this type of study is subjective personal bias as there is no clear objective measurement of behavioral bias or complexity. However, we find that this research to be helpful in generating further research ideas in this area.

The three cases which I use have real life data and events. Therefore, we withhold the names of the companies involved in these analyses to protect their privacy.

CASE STUDY 1: Automation Analysis

Stan's Supplements, founded about 30 years ago, uses Puzzle to sell a variety of health, detox, and athletic supplements. Puzzle has been selling Stan's Supplements through Amazon since 2015. Part of Puzzle's appeal to Stan's Supplements is its ability to use advertising and paid search through Amazon to increase product sales. In early 2019 Puzzle implemented an automated advertising campaign to Stan's Supplements products selling through Amazon. Normally, requiring daily monitoring and bidding, advertising through Amazon took a tremendous amount of human interaction. On the other hand, the new advertising automation system reduced the human interaction time, automatically changing bids according to an algorithm built to optimize advertising sales. Transitioning from its previous advertising method took from mid-January to early February. Naturally, Puzzle is interested in knowing the effects of this transition and the effectiveness of automated advertising campaigns.

Complexity

From the surface level Stan's Supplement automation analysis doesn't look too complex. However, upon further investigation, it becomes clear that there are a lot of moving parts, both specific to this example and in analyzing the impact of advertising in general. We rate this analysis as high complexity.

Part of this complexity is to the many changes Stan's Supplements went through in 2018 and 2019. First, Stan's supplements rebranded in early 2019, completely changing their logo and public image. This caused inventory and other transition issues which impacted sales, advertising, and clientele. How the new brand effected the sales is difficult to know. Parsing out whether changes in sales were due to the new brand, new advertising, or something else is nearly impossible to do. Additionally, Puzzle hired a new advertising manager in mid-2018 who started to manage Stan's Supplements' Amazon advertising portfolio. The changes she made to Stan's advertisements are yet another addition to changing variables during this period.

Taking a more global perspective, there is usually seasonality in supplement sales. It is thought that people are most likely to buy supplements at the beginning of the year when they set their New Year's resolutions and start going to the gym again, and least likely to buy supplements in the summer months. This seasonality in sales happened around the same time that the advertising automation was implemented. Furthermore, the economy at large experiences large swings in productivity. Stocks experienced at least three significant dips in 2018 and 2019 potentially impacting consumer buying behavior.

To make matters even more complex, the implementation of the advertising automation sprawled two months. There was no clear start and stop date, especially because advertising campaigns take days or weeks to gain tractions and effectiveness on Amazon. This means that there is lagged effects of the implementation, and changes in sales reflect both taking away old campaigns and adding in new ones. One could hypothesize dozens of other changing variables which make this analysis complex. There is enough noise in the data to make it very difficult to suggest causal impact of any one variable. For all these reasons, we consider this analysis to be of high complexity.

Behavioral Biases

In the complexity of Stan's Supplement analysis, we noticed several biases or opportunities for bias. For this, and the following case studies, we organize the biases according to the framework presented in the literature and created by Rabin (2002). As will be explained below, the many moving parts of Stan's Supplement analysis created opportunity for creative interpretation and bias in a way unlike the simpler analyses.

Non-Standard Preferences

Reciprocity- Reciprocity is the tendency for people to reciprocate behavior according to how others treat them. One of the employees charged with exploring this project had been recently hired. After receiving a job from Puzzle, it is likely that they wanted to reciprocate and find positive things related to the company in the data. In the complexity of Stan's Supplements this tendency became more evident as this employee had freedom to creatively interpret the multifaceted data. For example, as shown in Figure 1, a slight change a trend line can lead to a significantly different outcome. Depending on the dates chosen for the trend in Oct 2017 leads to different outcomes when comparing it to Oct 2018. Given free reign over simple choices such as trendlines or independent variables, can lead to reciprocal behavior.

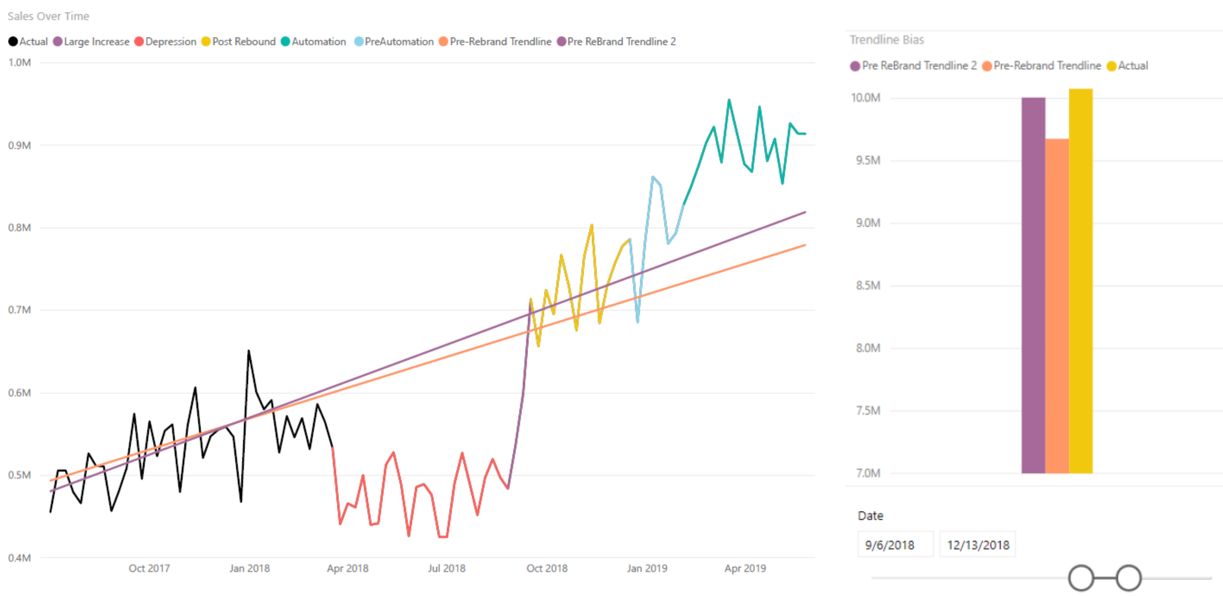

Figure 1 A slight change a trend line can lead to a significantly different outcome when analyzing post-depression sales data compared to pre-depression trends.

Non-Standard Beliefs

Confirmation Bias: Confirmation bias is "the tendency to interpret new evidence as confirming one's existing beliefs or theories." As you will notice in the Figure 2, there was a significant increase in sales around October 2018 (shown in purple). When asked what caused the increase in sales, some employees mentioned that another employee had started working around that time and her advertising tactics must have increased sales. Yet, in a separate conversation a VP brand manager stated that the large increase was just Stan's Supplements returning to normal sales after going through a depression caused by rebranding problems. Lastly, Stan's Supplements brand manager said the data did not look accurate to her. Three different interpretations of the same data. They all had some truth but were also all biased by their experience. When looking at historical data it is hard not to confirm your prior beliefs in your interpretation of causality. This is particularly true when employees are emotionally attached to the outcome. For example, in looking at the impact of the automation time period, it was tempting for employees to confirm beliefs that the automation process improved sales.

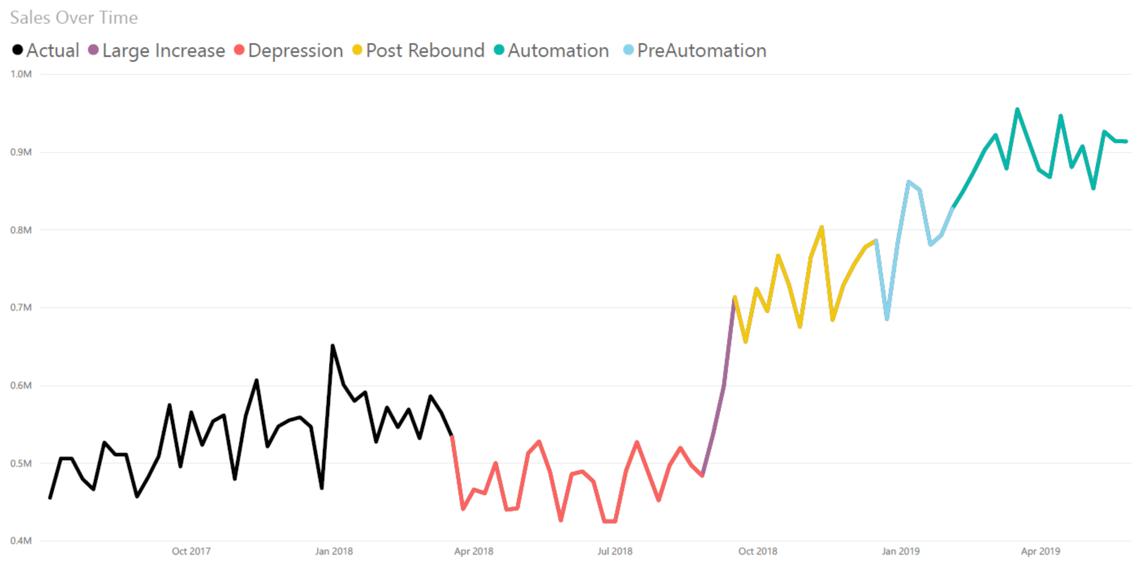

Figure 2 Post depression rebound sales, shown in purple, were attributed to wrong data, a quality employee, and natural recovery

Self-Serving Attribution Bias- The Self-serving attribution bias is the tendency to accept responsibility for positive outcomes and blame outside sources for negative outcomes. Within the example of confirmation bias, we can see effects of self-serving attribution bias. The depression in sales was blamed on a source outside of the company, rebranding by Stan's Supplements, and the increase in sales was attributed to a source inside the company, a new employee.

Overconfidence: Overconfidence is when people have much stronger beliefs in their own abilities than they rationally should have. Relating to confirmation bias, in the interpretation of Stan's Supplements, an overconfidence in one's ability to interpret complex data was observable as employees offered simple answers to the multifaceted reasons behind the movements in sales. Additionally, employees tended to be overconfident in their own company's/ coworkers' abilities and the abilities of the automation process. This made it difficult to approach the problem without preconceived ideas of what the findings would be.

Availability Bias-Availability bias is the tendency to believe things that come easier to mind than what is representative of the real world. In the analysis, there was a belief that the new branding increased sales. It was easier to imagine the beautiful new images increasing sales than decreasing sales. However, in some regression analysis, it appeared as if the brand change did in fact decrease sales. Employees are biased by the easily imagined scenario of a new brand boosting sales.

Gambler Fallacy- Gambler Fallacy is the tendency for people to believe that unrelated events are interrelated. With so many moving parts it was tempting to start assigning meaning to potentially random noise within the historical data.

Non-standard Decision Making

Social Pressure- Social pressure is the pressure we feel to behave or act in a certain way due to what the actions we see others take or our beliefs about what they think we should do. We noticed that with such a complex problem it was tempting to want to find something that would please management. Because complex problems do not have clear answers, it is easy to look for data that conforms with social pressures. Less complex problems on the other hand, make it harder to conform to social pressure because doing so feels more dishonest.

Case Study 2: Prime Day

Once a year Amazon launches a huge promotional sale called Prime Day. Prime Day is full of large discounts and hot deals for Prime Members. In 2018 Amazon sold approximately $4.2 billion worth of products within a 36-hour period. Members love the discounts and businesses love the increased traffic on their advertisements and sales. Naturally, Puzzle is interested in knowing more about Prime Day. To appeal to consumers of its blog, Puzzle wanted to write a piece analyzing if Prime Day offers better prices than other yearly low prices.

Complexity

We rate the complexity of this analysis as low. While the task of finding data on millions of products is large, the analysis with regards to the collected data is straight forward. Either the product is more expensive, or it isn't. Additionally, this analysis is not subject to confounding factors as seen in the Automation Analysis because Puzzle wasn't looking for a casual relationship. It was simply interested in knowing when prices were the lowest outside of prime day and if they were lower than Prime Day prices.

The complexity of this analysis was found mainly in choosing which products to analyze, which Amazon price to use, and how to categorize the findings. Admittedly, price history data can be slightly complex. As seen in the Figure 3 below, from Keepa.com, price histories can include list price, new and used prices, and Amazon prices if Amazon sells the product.

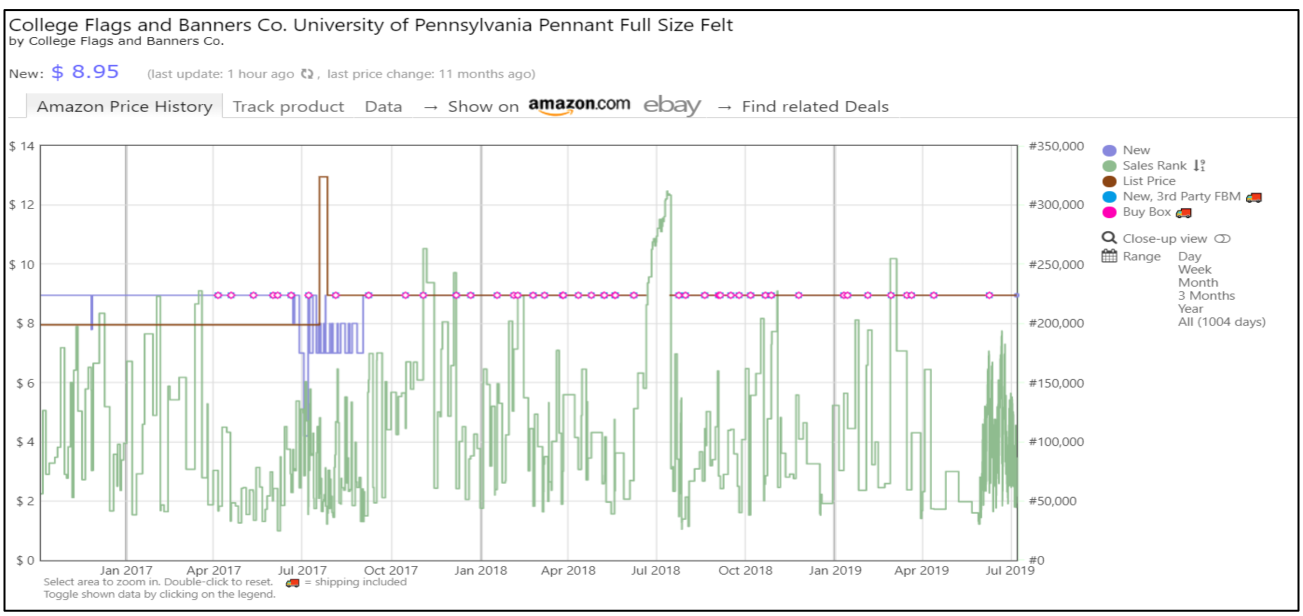

Figure 3 Historical sales, rank, and price history example of an Amazon product.

Behavioral Biases

Non-Standard Preferences

Hyperbolic Discounting- Hyperbolic discounting is the bias in which people discount the near future at a greater rate than the distant future. This makes it so that people routinely choose a smaller reward now than wait for a larger reward later. After doing the Prime Day analysis one employee wished that they would have spent more time on it, making it more robust and interesting to a reader. However, in the moment the analysis felt too straight forward and simple to give much time to.

Non-Standard Beliefs

Law of Small Numbers- The law of small numbers is a bias in people to take the findings of a small sample and believe that they pertain to the whole population. During the Amazon Prime analysis, items were grouped according to product category. Within each category the Amazon Prime Day prices and the other yearly low prices were added together and compared, see Figure 4 below. Some of the samples had as few as 4 products yet, the findings were projected from these small populations onto the whole population of products. Though employees may have statistically understood that these sample sizes were not large enough in some cases to prove statistical differences, it was difficult not to believe the findings pertained to the whole population.

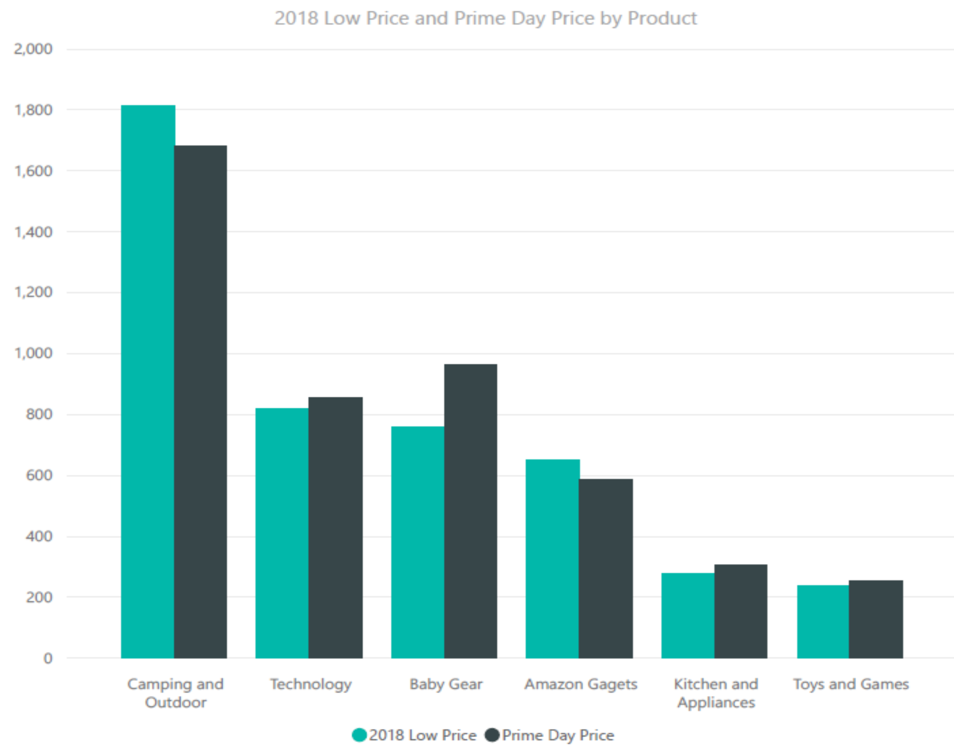

Figure 4 Graph comparing Prime Day and 2018 Low prices for different product categories

Availability Bias-Availability bias is the tendency to belief things that come easier to mind than what is representative of the real world. After doing the Prime Day analysis on 65 products, the lead analyst realized that their analysis didn't include beauty products. Being something that they were not interested in, this likely influenced their choice of analysis. Though the categories came from a separate article, we hypothesize that if the lead researcher was someone who loved beauty products, beauty products might have been included in the analysis.

Non-Standard Decision-Making

Framing- The bias that causes us to interpret the same material differently depending on how it is presented is referred to as framing. After creating an excel sheet that measured whether a products prime day's prices were lower or not, we observed that depending on how the data was displayed, it would be telling two different stories. If one just measured lower or not lower for the Prime Day price, they wouldn't capture the whole picture of lower and same price products. Though it had the same information, the story told by the data was much different depending on how it was framed. With a little different framing, shown in Figure 5, it became clear that a lot of the products had equally low prices on Prime day as the other yearly low price.

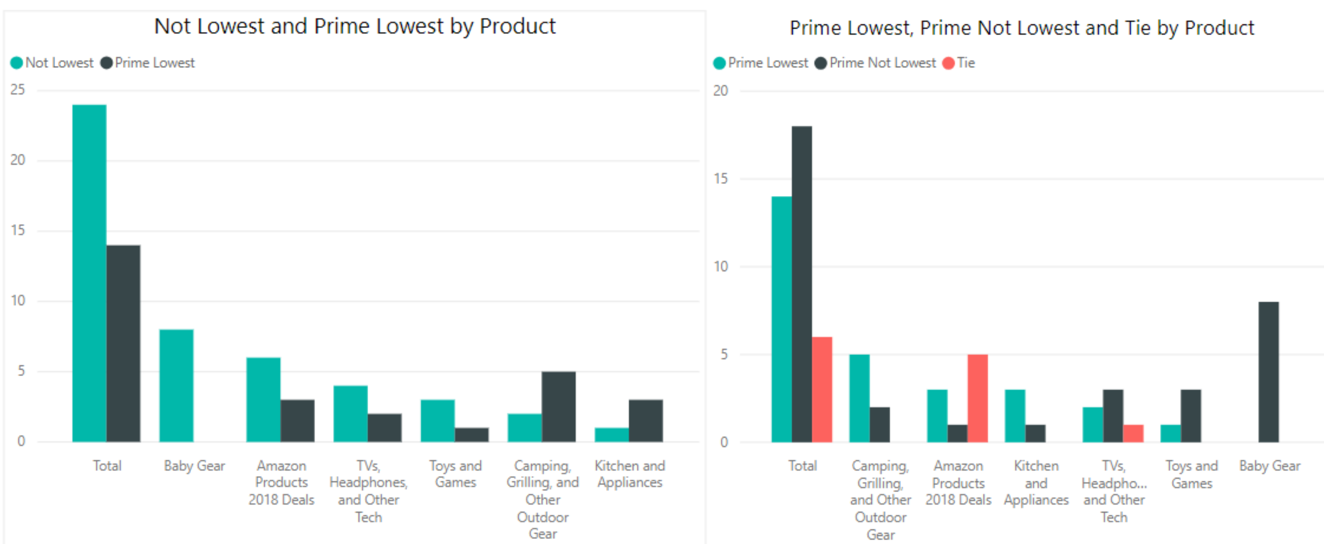

Figure 5 Prime day lowest price comparisons by category appear differently depending on if they are framed with tied prices or not

Case Study 3: Publicity Impact

One company that sells through Puzzle, called Miracle Skin, produces a variety of skincare products. Miracle Skin has existed since 1997 and Puzzle has been selling their products since January of 2019. On March 25th Yahoo released an article promoting the product as being able to miraculously cure a specific skin issue. The product started trending on google and Amazon sales spiked to an unprecedented level. After the event, it became of interest to know what the effect of the Yahoo article was on sales.

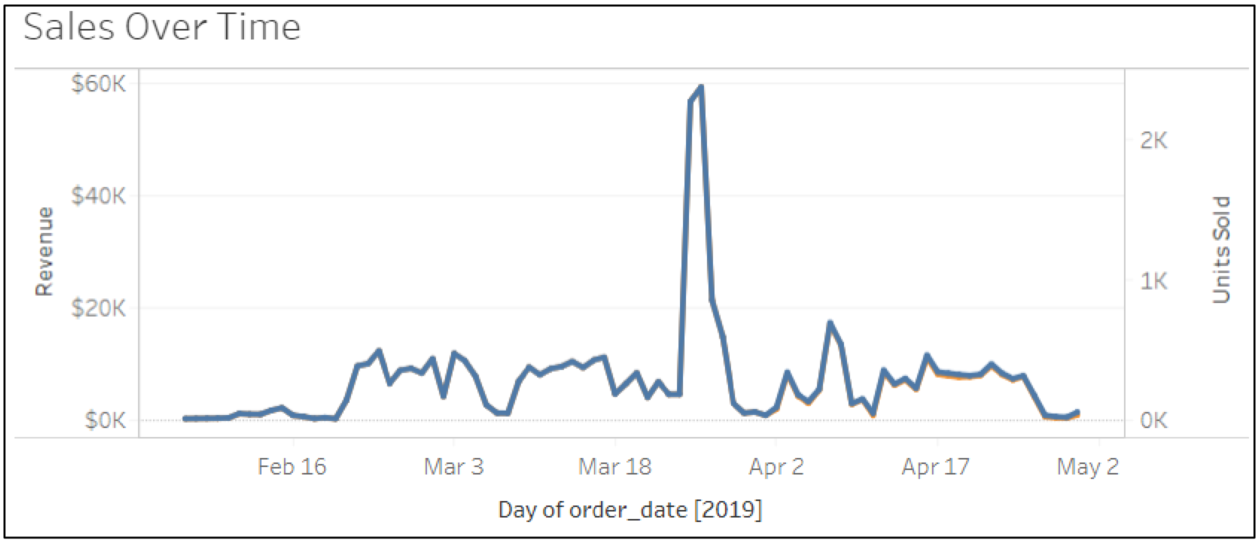

Figure 6 Miracle Skin shows a spike in sales at the end of March in 2019

Complexity

We rate the complexity of this analysis as low to medium. Like Stan's Supplements, this analysis relies heavily on comparing actual sales to an alternative hypothetical situation in which a given event didn't happen. However, unlike Stan's Supplements, the event of interest in this analysis was clearly implemented and easier to imagine an alternative reality. Additionally, unless a significant unknown variable was involved, abnormal sales can be traced back to this event because other known variables were, as far as we know, stable. See Figure 6 above to see the clear spike in sales. What is less clear, is the resulting impact on sales in the following days or months to come. Did the news article cannibalize future sales, increase returning customers, bring negative reviews to Amazon? These are unknowns and complex questions.

Due to the short time horizon of this analysis, the potential confounding influences of seasonality and global economic factors were of less concern. This made this analysis less problematic than Stan's Supplements which incorporated seasonality and other confounding factors. On the other hand, due to the lack of historical sales data for Miracle Skin, assumptions were made about the limited data that we had.

Behavioral Biases

Non-Standard Preferences

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Non-Standard Beliefs

Law of Small Numbers- The law of small numbers is a bias to take the findings of a small sample and believe that they pertain to the whole population. Interestingly Miracle Skin has only been selling through Puzzle for a few months. Therefore, we only have a small sample of what its yearly sales look like. Because of this, in analyzing the impact of the yahoo article, we projected this sample into the unknown. Perhaps spikes in sales are common throughout the year. Maybe a business bought a lot of miracle skin product at the same time as the yahoo article came out. Though seemingly straight forward, this analysis projected a small sample onto the whole population.

Confirmation Bias- Confirmation bias is "the tendency to interpret new evidence as confirming one's existing beliefs or theories." The employee who was given this assignment was handed the data about Miracle Skin and the article that was thought to cause the spike. With this type of introduction to the analysis, it is likely that the employee did not dive as deeply into the data as they could have looking for alternative causes to the spike in sales. Therefore, much of their analysis was confirming their prior belief that they inherited from another team member.

Non-Standard Decision-Making

Social Pressure- Social pressure is the pressure we feel to behave or act in a certain way due to what the actions we see others take or our beliefs about what they think we should do. Part of analysts' responsibilities is to find events of interest. As such it becomes appealing to find large results that would be intriguing for brand managers and management to read. For example, in Figure 7 we show three different hypothetical sales situations. Social Pressure biases analysts to choose the alternative which shows sale increasing the most due to the article.

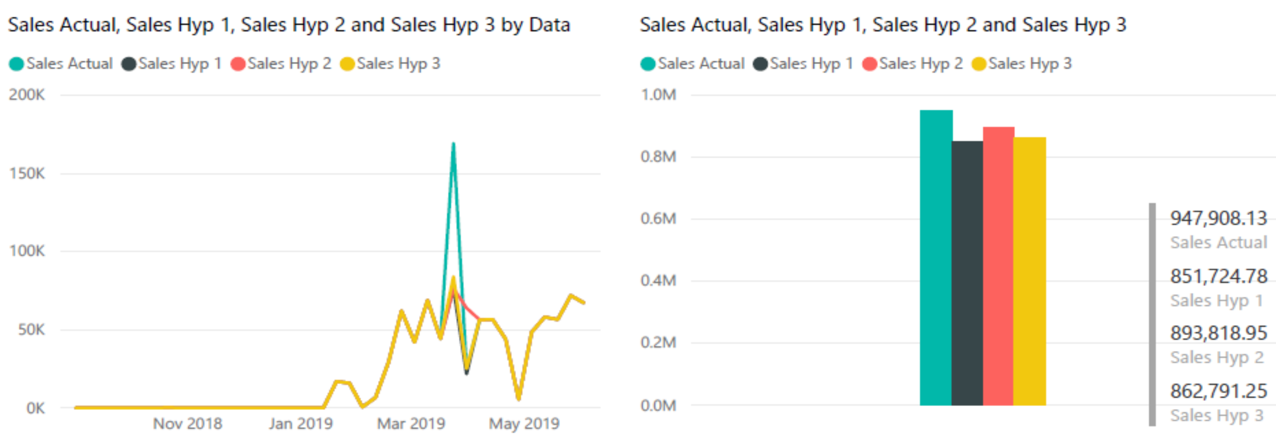

Figure 7 Three different hypothetical alternatives to the actual sales (green) and their respective total sales

Conclusion

Though not conclusive evidence, after completing the above case studies, it appears as if different levels of complexity lend themselves to different behavioral biases. See the Table 1 for a summary of our findings. Complex problems have a lot of grey area without clear answers. This grey area acts as a blank canvas for the mind, allowing it to see what it wants to see, or be influenced by incentives and social pressures. For example, self-serving attribution bias, social norms, and self-serving attribution bias. These types of bias seem more creative than the biases which we observed in the simpler analyses.

Simpler solutions, we noticed, lead to simple assumptions about the population or dataset. In solving these analyses, we did not notice as much creative interpretation biased by internal or external pressures. Instead, the simpler solutions were subject to oversimplification of the data and problem at large. The simpler analyses lead to larger assumptions about the data and overstating the findings through projections of a small sample.

		Biases		
Project	**Complexity**	**Non-Standard Preferences**	**Non-Standard Beliefs**	**Non-Standard Decision Making**
Automation Analysis	High Complexity	Reciprocity	Self-Serving Attribution Bias Overconfidence Availability Bias Gambler Fallacy	Social Pressure
Publicity Impact	Low-Medium		Law of Small Numbers Confirmation Bias	Social Pressure
Prime Day	Low	Hyperbolic Discounting	Law of Small Numbers Availability Bias	Framing

Table 1 Summary of the case studies done at Puzzle, their complexity levels, and observed behavioral biases.

As discussed by Briscoe and Feldman (2011), when modeling data there is often a bias/variance tradeoff. Either the data is overfit with a high variance or underfit with a high bias. The same phenomenon happens with behavioral biases and complex problems. With complex problems we tend to consciously and unconsciously fit the data with our prior beliefs and incentives. This leads to solutions that are “over fit” and highly variant in their solutions due to multiple biases. It is as if the complexity of the problem allows for creativity in the solution. This freedom can lead to solutions that are informed by human bias. Simpler problems, on the other hand, give less leeway to creativity. However, with simpler problems it is easy to underfit the data with simple assumptions. This leads to inaccurate beliefs about the population.

Corporate Behavioral Bias Prevention Recommendations

We offer this section of recommendation to employers as a means to help employees avoid behavioral biases in their analysis.

Use Blind Analysis in Impact Measurement

One way to help employees avoid being biased by prior beliefs, peer pressure, etc. is to leave them out of the loop as to what event is being analyzed until after the research is done. This will allow the employee to focus on the number without worrying about what outcome they "should" be finding.

Encourage Exploration

Employees should not feel pressure to find specific results. This can be done by encouraging employees to find both positive and negative stories surrounding the data. Through exploring potential outcomes and reporting them they and you will be more likely to catch unidentified biases.

Separate Analysis and Personal Connections

Employees doing analysis should not have emotional or incentivized connections to the project that they are working on. For example, the person who implements a new marketing tactic should neither be the one who does the analysis or to whom the analysis is reported.

Avoid Giving Preconceived Beliefs

When assigning tasks to employees it is important to allow them to come to their own conclusions. Instead of assigning a task to see how much the new advertisement increased sales, one should ask how much the new advertisement increased or decreased sales. Being careful in language when assigning tasks will help avoid analysts being tainted by preconceived ideas.

Ask if Findings are Population Representative

With tasks of lower levels of complexity always ask if the sample being studied was representative of the population. This could include considering simple demographics, sample size, and where the data was pulled from.

Assign Two Analysts the Same Task

Assigning two analysts the same task, when the bandwidth is available, helps mitigate the risk of behavioral bias.

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