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Why Does Fake News Always Win? An Econometric Modelling of Misinformation as a Market Equilibrium On Digital Platforms Using the Principle of Attention Scarcity

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ABSTRACT

This paper develops an econometric framework to replicate the behaviour of misinformation on digital platforms and model it as an economic market. Through formalising attention as a scarce resource, attention is able to function as the price. The prevalence of fake news acts as the quantity. These two factors outline the structure within which the market is able to operate. The demand-side of the market is driven by the concept of rational inattention as well as cognitive capabilities, bias, and verification costs. Alternatively, the supply-side of the market is influenced by algorithmic factors such as affinity, moderation, recency, engagement, and baseline platform architectures. Once the model for both demand and supply is found, a comparative statics is done to examine the effect of each parameter on the equilibrium prevalence. Utilising the findings from the comparative statics of each variable, recommendations as to how to limit the spread of misinformation are derived. Finally, a 10,000-run monte carlo simulation is employed to illustrate the market dynamics more clearly and test the stability of the model.

Key Words: Attention as a Price Signal, Algorithmic Supply, Demand for Misinformation, Misinformation Equilibrium, Prevalence

INTRODUCTION

The World Economic Forum deems fake news to be a major risk plaguing society today (World Economic Forum, 2025). A Pew Research Centre study conducted in 2022 found that 74% of social media users in the US have seen information labelled as false (Rainie, Lee, et al., 2022). Social media platforms have taken steps to curtail the diffusion of misinformation. However, despite efforts by suppliers[1], consumers[2] still find it challenging.

A YouGov survey showed that 29% of people aged 18 to 29; 36% of people aged 30 to 44; 55% of people aged 45 to 64; and 59% of people aged 65+ in the US report being exposed to false information (Statista Research Department, 2025).

For clarity, misinformation is defined as unintentionally sharing inaccurate or misleading information. Misinformation should not be confused with disinformation. Disinformation is the deliberate dissemination of false or inaccurate information (Cuny, 2026).

To understand the spread of misinformation, this paper takes a behavioural economics approach and asks whether misinformation can be modelled using supply and demand functions, wherein attention serves as a price signal, and the prevalence of misinformation serves as quantity.

Approach: Functions are first derived from theory. Then synthetic data has been used to prove the functions derived.
Structure: First, the paper outlines why attention can serve as a price signal. We outline the metrics for attention and give an equation to measure the factors that affect attention allocation. Then, we model both the demand-side and the supply-side angles, using which, we analyse the equilibrium.

METHODOLOGY

The paper builds a theoretical economic model wherein the consumer's Flow Attention is interpreted as the price and a fraction of news items that are false corresponds to the quantity. The steps to be followed are: (a) analysing relevant information pertaining to attention economics, factors of human psychology that relate to information processing, and the dynamics of online recommendation algorithms. (b) building an econometric model conducting a series of comparative statics in. (c) using synthetic data to illustrate the theorised graphs.

The aim is to outline an equilibrium level of misinformation and to describe how changes in platform and consumer parameters affect this. The use of synthetic data is appropriate to help justify the theories due to the lack of available empirical information to draw conclusions.

Developing the Model

Definition of variables: The level of attention over a period of time is defined as the price P; 'Prevalence' is used as in (Cisternas & Vásquez) report where $v \in [0,1]$. Demand parameters include the processing constant β, the belief congruence B and the verification cost C_v; α represents the elasticity of demand. On the other hand, the supply parameters include the algorithmic resistance θ (which is divided into the baseline, θ_0; the affinity, γ; the engagement weights, E; the recentness, R; and the moderation, M) and the virality exponent λ.

Clarification: It should be noted that these assumptions are core to the model and cannot be altered: the assumption of a uniform limit of flow attention (24h) across all users (Assumption 1), the assumption that all platforms have the same monetisation value per user attention (Assumption 2), any value of prevalence greater than 1 results in a corner solution and these instances are capped at 1 (Assumption 3) and the negligible monetary marginal cost of algorithmic distribution, as well as the non-inclusion of peer-to-peer sharing in the supply function.

Analytical Methodology

Since the actual values of the parameters are empirically impossible to observe or quantify, this study adopts a method based on synthetic data creation to test the validity of the mathematical model.

A robust sample of a market environment was created via a Monte Carlo simulation of 10,000 runs. In the process of creating 10,000 distinct market settings, random samples were selected for all nine parameters of a market: four on the demand side and five on the supply side. Human behavioral characteristics, like the Confirmation Bias parameter (B), and Verification Cost (Cv), were randomly sampled from log-normal distribution because of the skewness observed in social media online polarization dynamics. However, algorithmic parameters, such as moderation strictness (M) and algorithmic engagement factor (E), were uniformly sampled to account for diverse policy implementations. Each sample of the market environment was then analyzed through the log-linearization of the Master Equation and calculation of equilibrium polarization v*.

REVIEW ON LITERATURE

Attention As A Price Signal

Daniel Kahneman defines attention as the selective allocation of scarce mental resources to process certain tasks and exclude others. In his *capacity theory of attention*, he portrays attention not only as a filter but as a finite mental resource that can be allocated selectively across tasks (Attention and Effort, Kahneman, 1973). This theory was taken forward by Herbert Simmons. His philosophy of a *scarcity of attention* forms the basis of attention being used as a price signal (Simmons, 2006).

Attention can be classified into two brackets: Flow Attention and Calcified Attention (Maxi Heitmayer, 2024). The amount of flow attention is constant for every individual: 24-hours. The value of flow attention is derived from what users choose to spend it on. Attention allocated to reading must be weighed against attention for exercise. Calcified Attention is recorded attention. In today's online ecosystem, Suppliers seek to capture users' Flow Attention by converting them to calcified attention metrics through views, likes, shares, comments, and other forms of engagement.

In "The Second Wave of Attention Economics", Hetimayer modelled how users provide Flow Attention to "Mediating Structures" and how these structures record it to calcified attention, using this to gain money from economic systems and power from political systems by selling data on consumer preferences. (See Figure 3.1).

Suppliers can monetise attention as online platforms are two sided markets. A two sided market is where a platform serves two groups (Rochet, et al, 2003). The benefit to both groups depends on the number of users on each side. For example, on social media platforms there are advertisers and consumers. The more consumers provide their flow attention, the more value the platform has for advertisers.

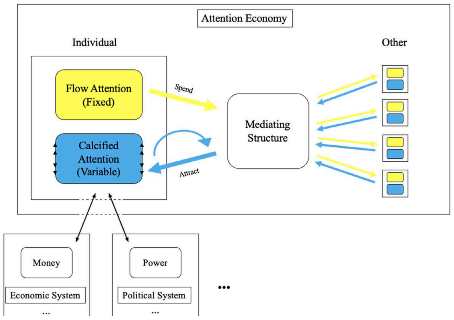

Figure 3.1

This diagram was taken directly from Maxi Heitmayer's 2024 paper The Second Wave of Attention Economics to illustrate how mediating structures leverage the flow and calcified attention received to gain money and power.

Finally, attention is a store of value. 'Popularity cues' are a known concept in psychology. In their paper: "Popularity cues in online media", Haim, et al. define popularity cues as metric information about users' behaviour or their evaluations of entities. Put plainly, consumers are likely to have their judgement swayed to fit societal norms and beliefs. Calcified attention metrics (likes, shares, comments) are quantified popularity cues. Because attention signifies importance, it serves as an indication of value, making it a suitable price signal.

Demand-Side

Loewenstein and Wojtowicz's paper, "The Economics of Attention", refers to the concept of rational inattention: "agents select among informative signals by weighing the expected utility benefits of enriching decision making against a presumed cost of deploying attention to refine their beliefs about the world" (Loewenstein, 2023). So, in order to gather and process information, agents pay a cost that is proportional to how much these activities reduce their uncertainty of the true state of the world. Lowenstein calls this attention based utility.

Attention based utility is the benefit that a consumer derives from allocating scarce mental resources to a specific piece of information, independent of the material payoff that the information may generate (Torreblance, Edika, et al., 2020). Attention based utility is also influenced by biases, specifically confirmation or learning biases (Loewenstein, Wojtowicz, 2023).

"Confirmation bias, as the term is typically used in psychological literature, connotes the seeking or interpreting of evidence in ways that are partial to existing beliefs, expectations, or a hypothesis in hand." (Nickerson, 1998). A learning bias - also referred to as an attractiveness bias- is when people prefer to focus on more attractive results rather than less attractive results (Azzopardi, 2021; Loewenstein, Wojtowicz, 2023).

Consumers have finite information processing capacity as they cannot perfectly observe all relevant variables. They must compress, code, and filter information. Acquiring precision in one dimension reduces precision elsewhere. Verification costs therefore arise from the scarcity of processing bandwidth (Sims, 2003). However, multiple factors can influence verification costs: (1) The time delay of outcome: In the short run costs are low as information pertaining to short-run events can be easily observed. If the news forecasts rain in an hour, it is easily verified by whether or not it rains in the next hour. On the other hand, the long-run poses high costs. Predictions that gold prices will rise over the next decade cannot be fact-checked with the same ease. (2) Observability of the true state: If a piece of information has been widely touched upon, it is easier to verify whether such information is true. However, if there is very low coverage on a topic, verification becomes harder. (3) Competition in the information market: With many private information producers, it is hard to find one true source of information (Gentzkow, et al, 2005).

Supply-Side

Online models use recommendation algorithms to spread information to users. Such recommendation algorithms learn from past user behaviour through implicit feedback (Pathak, et al, 2023). As a result, personalisation of the information that a consumer receives is the goal, not the spread of true information to all users on a platform (Epstein, et al., 2020).

It is important to underline the various algorithmic families: (a) Popularity based recommendation; (b) Collaborative filtering: Recommending items that users similar to you interact with; (c) Social Network: Recommending items that people who you follow and those who follow you like (Pathak, et al, 2023). To fully gauge consumer preferences, algorithms also have rankings. Affinity is possibly the most crucial factor, and refers to the strength of connection between the user and content creator; user and topic; or the user and the network that a piece of information reaches. Factors of engagement also weigh in. For example: commenting on a post has a greater weightage than liking a post. Finally, newer content is ranked higher than old content (Zimmer et al., 2019).

Furthermore, algorithms are neutral and cannot differentiate between true and false information (Zimmer et al., 2019). An algorithm is also unable to distinguish between bots, trolls, and true users. Hence, misinformation shared by bots and trolls is algorithmically amplified with minimal safeguards (Etter, Albu, 2020). Algorithms can also unintentionally exaggerate misinformation diffusion. A consumer engages with something out of disbelief, the system records attention allocated to this, similar items are recommended, crowding out true information, exposure narrows, reinforcing the pattern (Pathak, et al, 2023).

Another aspect to consider are the effects of echo chambers. This is one of the main reasons why misinformation spreads as rapidly as it does (Törnberg, 2018). Echo chambers start as a cluster of biased individuals in a network. Among this group, a specific piece of misinformation is generally regarded highly and given high levels of engagement and attention. The algorithm records this as interest in such posts. The cluster forms a critical mass for misinformation to gain traction and once enough momentum is built, the algorithm recommends such misinformation to others on the platform leading to a cascade of misinformation (Törnberg, 2018).

Finally, it is vital to consider that there are little to no marginal costs for algorithms to spread such misinformation; the spread of fake news is monetarily costless (Cisternas, et al, 2020).

RESEARCH GAP

Existing economic models position human creators as the main suppliers and social media platforms as neutral. Cisternas and Vasquez (2020), and Gravino et al. (2024, 2022) treat the supply of fake news as human driven and passive. However, on most networks, human publishers simply write content while the algorithm actively proliferates it. Current literature does not model the algorithm as the main provider, therefore, it ignores the designed mechanics that enable global virality.

Moreover, existing literature fails to establish measures of the internal microeconomic currency of this market and usually depends on external proxies to measure cost and demand. Other methods determine demand externally, for example, through the volumes of search-engine queries (Gravino et al, 2024). These models do not reflect the passive (but highly elastic) cognitive effort the user puts into scrolling.

The paper reorganises the market model into one that presents the actualities of algorithmic distribution. Instead of the emphasis being on human creation and external verification costs, the set up suggested makes the recommendation algorithm the explicit supplier of virality and user cognitive attention the literal market-clearing price. The model proves that the prevalence of misinformation is an engineered phenomenon by mathematically encoding the parameters of the structural platform into the supply curve, which includes engagement weights, recency bias, or network affinity barriers. It ascertains that mathematical friction of the algorithmic supply curve has a similar force controlling market equilibrium as the human confirmation bias.

PROPOSED MODEL

Theory

Attention serving as price: As *attention* becomes scarcer, the opportunity cost for users allocating their attention becomes greater (Simmon, 2006). Moreover, the two-sided market dynamic gives *attention* derived value as it is a form of pre-monetary capital. Without value there is no incentive for consumers or suppliers to provide or receive this resource. These properties make attention an effective and valuable price signal . Furthermore, the idea of a consumer being able to give valuable *attention* to a platform in return for information, indicates that attention has the ability to be "spendable".

Demand-Side: The concept of rational inattention leads to a downward sloping demand curve. A new piece of information requires more attention. From this we derive that information that challenges pre-existing beliefs or notions will require more attention to process and, hence, the quantity of information that can be consumed reduces. The same logic can be applied to viewing information that is in accordance with a consumer's existing knowledge of the world. As the uncertainty of the true state of the world is not relatively decreasing by much, the consumer allocates less attention and, as a result, consumes a higher quantity of such information. These two relationships establish a downward sloping demand curve. The marginal attention-based utility decreases as exposure to misinformation increases. The relative decrease in uncertainty of the true state of the world decreases with every extra piece of information consumed.

Supply-Side: For supply, this paper focuses only on the effect of recommendation algorithms in providing consumers with misinformation. Peer to peer sharing between consumers are not factored. Algorithms are structured to maximise the proliferation of information that receives the greatest amount of attention from consumers. High engagement signals public sentiment, driving the algorithm to push the information to even more consumers leading to an exponential growth of the spread of misinformation. This is known as a power law. This is the same logic that applies to the effect of echo-chambers that was explored in 3.3. Exponential growth is what gives the upward sloping supply curve an increasing gradient.As the monetary cost of sharing information for algorithms is near zero, we assume that the marginal cost is also zero and has no effect on the supply curve (Cisternas, Gonzalo, Vásquez, 2020).

Establishing the Axes

Consider attention as a fraction of cognitive space where $A \in [0, 1]$ where 1 shows that all cognitive processes are being allocated towards that specific task. As all cognitive processes can not be dedicated towards a specific task we can assume that $0 \leq A < 1$ for any piece of misinformation.

Assumption 1: *Flow attention is restricted to twenty four hours a day. The quantum of twenty four hours is also considered to be homogenous across consumers, ignoring influence.*

Due to this assumption, allocating a fraction of cognitive space(A) to misinformation displaces the ability to consume truthful information. Thus creating an opportunity cost between the two and giving value to the attention a consumer allocates to a piece of misinformation. Such value can be used to define the price of consuming misinformation(P) not as a monetary value but rather a scalar index of cognitive load. The cognitive load spent on processing misinformation is a scarce resource being exhausted, effectively creating a zero-sum environment where cognitive load functions as a market clearing price.

The price (P) is bound by the limits of human processing capabilities. Hence, $0 \le P \le P_{max}$ where P_{max} represents a state of complete mental exhaustion. The value of P can not drop to below 0 as attention can not drop below 0 (as defined earlier).

On the x $axis$, parallel to Gonzalo Cisternas' and Jorge Vásquez's paper "Fake News in Social Media: A Supply and Demand Approach" and their article "Breaking Down the Market for Misinformation", prevalence of misinformation shall be present on the x $axis$. In their paper they refer to prevalence as v where $v \in [0, 1]$ and is "a fraction of news items that are false".

Assumption 2: *Any value of prevalence calculated that exceeds 1 ($v > 1$) results in a corner solution. It is to be assumed that such instances are capped at 1 and represent total market saturation.*

Demand

We define demand as the ability and willingness of a consumer to purchase a good at a specific price in a given period of time (Alfred Marshall, 1890). However, in this model, assuming that we are only viewing flow attention, everyone has the ability to process tasks as everyone has the same twenty four hours a day.

This re-defines our demand function as the willingness of a consumer to process misinformation using their scarce mental resources to focus on one task and exclude others in a given period of time.

To model the demand for misinformation, first take a variable k where $k = \beta \cdot B \cdot C_v$ to represent the demand shifter, where β is a constant representing a consumer's processing power, B is the belief congruence (bias), and C_v is the verification cost. The direct demand function to determine the prevalence at a given price can be represented by:

$$v(P) = k \cdot P^{-\alpha} \tag{1}$$

Where $\alpha > 0$ represents the constant elasticity parameter. This equation answers how much misinformation a user is willing to consume, given a cognitive cost P.

Using this equation it is clear that shifts in demand are caused by changes in belief congruence(B) to the misinformation. An increase in belief congruence would lead to a rightward shift of the demand curve. This is because belief congruence, or confirmation bias, is a utility multiplier. The consumer gains higher utility from consuming misinformation that feeds into their bias.

Additionally, the verification costs(C_v) are also directly proportional to the demand. When misinformation is extremely difficult to fact-check the curve shifts to the right. The high cognitive load of checking information leads to a consumer abandoning the verification process and defaults into acceptance especially if the bias is high. Therefore, to verify information effectively has higher demand.

Finally, an increase in processing capacity(β) allows for a lower proportion of cognitive capabilities to be used to process information. If a consumer has an increased capability to absorb a higher amount of misinformation at lower conscious effort, their demand would increase.

We can also rearrange this equation to give the inverse demand function:

$$P(v) = k^{\frac{1}{\alpha}} \cdot v^{\frac{-1}{\alpha}} \tag{2}$$

This equation shows the maximum amount of attention a consumer is willing to pay in order to secure a specific amount of information. In this equation, the utility parameter $\frac{1}{\alpha}$ determines the rate of diminishing marginal attention-based utility. This makes the curve convex to the origin.

The inverse demand equation can be used to prove that the demand curve will be downward sloping. To confirm this, we must take the first derivative of the inverse demand curve with respect to v:

$$\frac{dP}{dv} = \frac{-1}{\alpha} k^{\frac{1}{\alpha}} \cdot v^{-\left(\frac{1}{\alpha}+1\right)} \tag{3}$$

As the demand driver (k), the elasticity(α), and the prevalence(v) are all strictly positive, the first derivative of the inverse demand function will always be negative$\left(\frac{dP}{dv} < 0\right)$ for all $v > 0$. This shows that as the prevalence of misinformation increases, the marginal cognitive price a user is willing to pay decreases.

To confirm that the shape of the demand curve is convex to the origin, we take the second derivative:

$$\frac{d^2P}{dv^2} = \frac{1}{\alpha}\left(\frac{1}{\alpha} + 1\right) k^{\frac{1}{\alpha}} \cdot v^{-\left(\frac{1}{\alpha}+2\right)} \tag{4}$$

Again, as all parameters are strictly positive, the second derivative will remain positive$\left(\frac{d^2P}{dv^2} > 0\right)$ for all values of $v > 0$. This proves that the inverse demand curve is strictly convex to the origin, reflecting the diminishing marginal utility of attention.

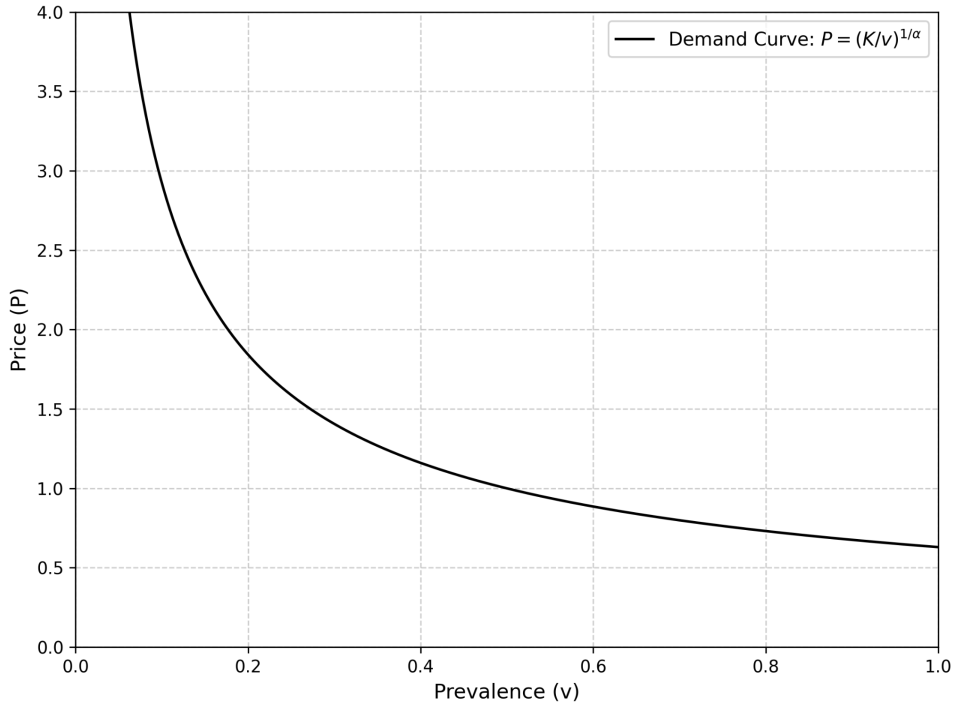

Figure 5.1

The above graph is a visualisation of the inverse demand curve.
The parameter values used to plot this graph are: $k = 0.5$ and $\alpha = 1.5$

It is also important to establish that the price elasticity of demand (ϵ) remains constant.

Step 1: Using the standard elasticity definition on the direct demand function

$$\epsilon = \left| \frac{dv}{dP} \cdot \frac{P}{v} \right| \tag{5}$$

Step 2: Substituting the direct demand function and its derivative

$$\epsilon = \left| -\alpha k P^{-\alpha-1} \cdot \frac{P}{kP^{-\alpha}} \right| \tag{6}$$

Step 3: Simplify to get

$$\epsilon = \left| -\alpha \cdot \frac{kP^{-\alpha}}{kP^{-\alpha}} \right| = \alpha \tag{7}$$

Hence, $\epsilon = \alpha$.

As α is constant, the elasticity remains constant.

Now, if the elasticity is high ($\alpha > 1$), it indicates that the user is sensitive to cognitive effort. They stop paying attention at the slightest instance of friction. They are highly sensitive to the cognitive attention they give out. As they do not give out much attention, they consume small amounts of misinformation at a time. Their satisfaction remains high with every new piece of misinformation consumed as they barely engage, hence there is a lower decay for their marginal utility.

On the other hand, if the elasticity is low ($\alpha < 1$), it shows that a user is insensitive to cognitive effort. They will continue to provide attention and gain misinformation even if it means that they will go through extra steps to get there. However, due to the vast amount of misinformation being consumed they reach a saturation or exhaustion point fast. This leads to a high decay of their marginal utility.

Supply

In this model, the cost to a supplier is not monetary in value. Rather it is the opportunity cost of what to show users and what not to show them. The algorithm has finite slots in user feeds. To justify showing misinformation to a wider, skeptical audience (high prevalence), the engagement signal must be higher.

Previously, it was established that power laws give the supply curve a constantly increasing gradient. Considering the way in which an algorithm works, attention acts as a signal that leads to exponential growth. Hence, a small change in P_t will result in a disproportionately larger increase in v_t. This can be modelled by the power function:

$$v(P) = \left(\frac{P}{\theta}\right)^{\frac{1}{\lambda}} \tag{8}$$

The inverse function for this would be:

$$P(v) = \theta \cdot v^{\lambda} \tag{9}$$

Where:
P is the price (How much cognitive effort a user will give)
v is the prevalence (Fraction of news items that are false)
θ is the algorithmic resistance
λ is the virality exponent

Assumption 3: *In the two-sided market system for online platforms, the value of information that a platform receives when a user gives attention is uniform regardless of power, influence, or wealth.*

The algorithmic resistance (θ) refers to how easily misinformation is spread across a platform. In 3.3, multiple factors affecting the spread of misinformation on a platform are explored. They are: Affinity(γ), engagement weightings(E), and recency(R). These are all factors that play a role in algorithmic resistance.

Hence, θ can be represented as:

$$\theta = \theta_0 \cdot \frac{\gamma}{E \cdot R \cdot (1-M)} \tag{10}$$

In this θ_0 is the baseline architecture. This accounts for the fundamental code structure of a platform. This is a constant greater than zero and sets a baseline before the variables are applied. Before any user interaction, affinity, or moderation is added, θ_0 shows the lowest level of friction that a piece of content will face just by being on the platform. It measures the platform's basic design philosophy. $\theta_0 < 1$ refers to a platform that is designed for viral broadcast while $\theta_0 > 1$ indicated high structural friction wherein users must actively seek the information.

The affinity γ is always greater than or equal to 1 where 1 shows no affinity needed while anything greater shows some level of affinity is required for a platform to supply misinformation to a user (Zimmer et al., 2019). Affinity functions as friction to algorithm supply. By strictly enforcing the boundaries of social demographics that a specific piece of misinformation is circulated around, misinformation is generally trapped in local clusters known as echo-chambers. To achieve a global cascade and widespread diffusion, the content must generate high attention signals among unconnected groups. Hence, if affinity is 1, all content will be restricted to a specific group and the market will be safe from the spread of misinformation.

Additionally, M is the moderating strictness where $M \in [0, 1]$. This refers to an algorithm's ability to filter out misinformation. In this, $M = 0$ shows that the algorithm is completely neutral while $M = 1$ depicts perfect recognition. This is not to be confused with θ_0 as M is the algorithm actively intervening to block misinformation while θ_0 is passive structural friction that exists for all types of information on the platform.

When $M = 1$, θ approaches infinity. This makes the supply equation:

$$v(P) = \left(\frac{P}{\infty}\right)^{\frac{1}{\lambda}} \tag{11}$$

Therefore, $v(P) = 0$ and no misinformation is supplied.

Finally, engagement weight E refers to the importance of the calcified attention metrics a platform uses to track user attention (Eg. Commenting or Liking). This is not to be confused with the price signal P which also refers to attention. E refers to the way an algorithm categorises and values the attention given. This concept reflects Zimmer et al. and their work on how certain calcified attention metrics are more valuable than others (Eg. Commenting is valued higher than liking).

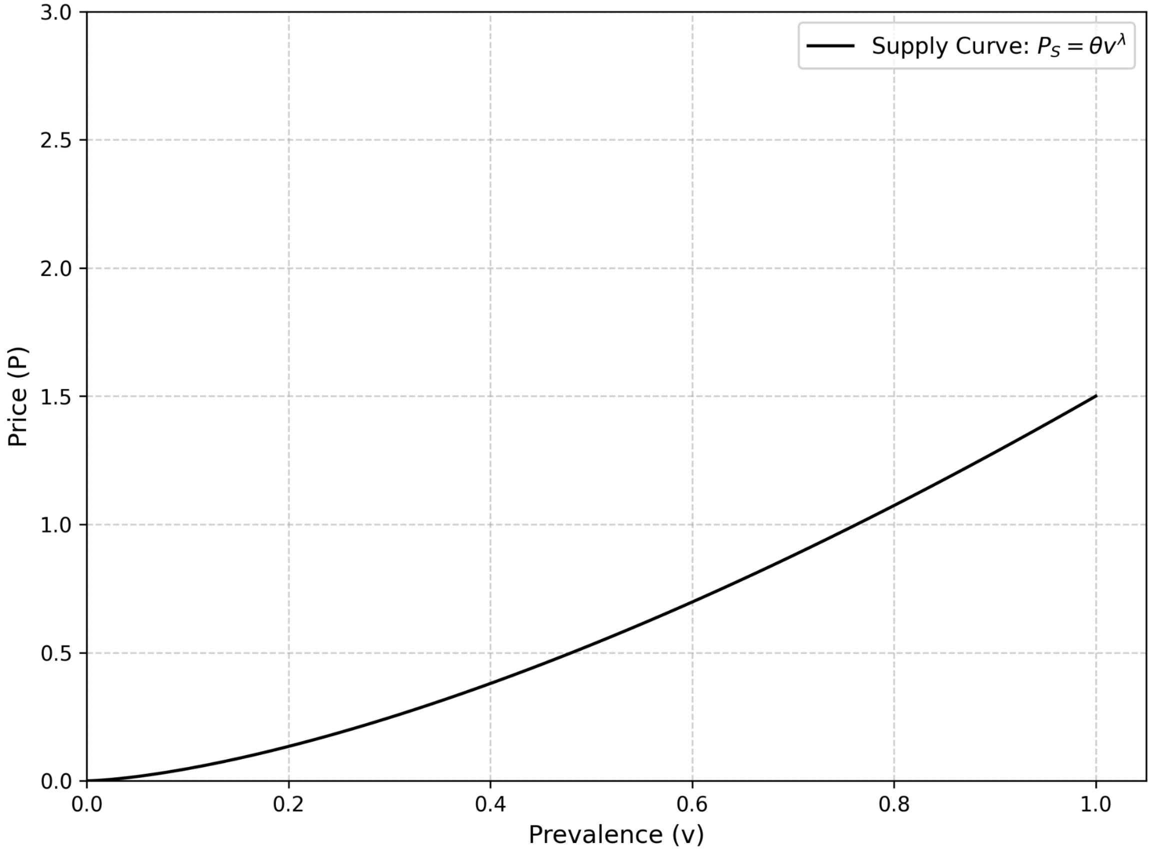

Figure 5.2
The above graph is a visualisation of the inverse supply curve.
The parameter values used to plot the graph are: $\theta = 1.5$ and $\lambda = 1.5$.

Furthermore, algorithmic supply function is permanently pinned at two absolute boundaries: the origin ($v = 0$, since $0^\lambda = 0$) and total market saturation ($v = 1$, since $1^\lambda = 1$). As a result, the market-clearing prevalence (v) must occur between these two fixed points and increasing λ cannot pivot the curve. Instead, it strictly forces the interior of the curve to act as a jump rope between the two points.

Finally, it is critical to consider what the price elasticity of supply (PES) would be for such a graph and its importance.

Step 1: Establish the formula to calculate PES

$$PES = \frac{dv}{dP} \cdot \frac{P}{v} \tag{12}$$

Step 2: Differentiate v with respect to P to get

$$\frac{dv}{dP} = \frac{1}{\lambda}\theta^{-\frac{1}{\lambda}} \cdot P^{-\frac{1}{\lambda}-1} \tag{13}$$

Step 3: Substitute the formula obtained in step 2 back into the PES formula

$$PES = \left(\frac{1}{\lambda}\theta^{-\frac{1}{\lambda}} \cdot P^{-\frac{1}{\lambda}-1}\right) \cdot \frac{P}{\theta^{-\frac{1}{\lambda}}P^{\frac{1}{\lambda}}} \tag{14}$$

Simplify the terms to get: $PES = \frac{1}{\lambda}$

COMPARATIVE STATICS

In order to start the comparative statics, we transform the master equation (Appendix A) into a simpler format, to give a clearer idea of how each factor affects the equilibrium.

Step 1: Take the natural logarithm of each side of the equation to get

$$ln(v^*) = \frac{1}{\alpha\lambda + 1}\left[ln(\beta) + ln(B) + ln(C_v)\right] + \frac{\alpha}{\alpha\lambda + 1}\left[ln(E_c) + ln(R) + ln(1 - M) - ln(\theta_0) - ln(\gamma)\right]$$

In this equation the demand-side factors and the supply-side factors are being split into separate troupes in order to ease our analysis of the changes in the equilibrium.

Step 2: Use the standard rule for logarithmic differentiation

$$\frac{\partial ln(v_t^*)}{\partial x} = \frac{1}{v_t^*} \cdot \frac{\partial v_t^*}{\partial x} \equiv \frac{\partial v_t^*}{\partial x} = \frac{\partial ln(v_t^*)}{\partial x} \cdot v_t^*$$

Parameter	Economic Description	Market Side	Partial Derivative ($\partial v^* / \partial x$)	Market Effect (When Increased)
B	Confirmation Bias	Demand	>0	Accelerant (Shifts Demand Outward)
C_v	Verification Cost	Demand	>0	Accelerant (Shifts Demand Outward)
β	Processing Capacity	Demand	>0	Accelerant (Shifts Demand Outward)
M	Moderation Strictness	Supply	<0	Friction (Shifts Supply Inward)
E	Engagement Weight	Supply	>0	Accelerant (Shifts Supply Outward)
λ	Virality Exponent	Supply	>0	Accelerant (Shifts Supply Outward)
R	Recency Bias	Supply	>0	Accelerant (Shifts Supply Outward)
γ	Network Affinity	Supply	<0	Friction (Shifts Supply Inward)
θ_0	Baseline Resistance	Supply	<0	Friction (Shifts Supply Inward)
α	Price Elasticity exponent	Structural	Ambiguous	Shape Parameter (Alters Curve Convexity)

Figure 6.1

Demand Side Parameters

Let any demand side parameter be represented by x. This is the general form for the partial derivative of a demand-side parameter:

$$\frac{\partial ln(v^*)}{\partial x} = \frac{1}{\alpha\lambda + 1} \cdot \frac{1}{x} \equiv \frac{\partial v^*}{\partial x} = \frac{v^*}{x(\alpha\lambda + 1)} \tag{15}$$

An increase in cognitive bias

$$\frac{\partial v^*}{\partial B} = \frac{v^*}{B(\alpha\lambda + 1)} \tag{16}$$

Suppose there is a polarising event that occurs. This increases user bias to a certain type of misinformation. Since all the variables in the above equation are strictly positive. The partial derivative is, therefore, greater than 0.

Hence, the model predicts that during periods of high social polarisation, the market equilibrium prevalence and price will both expand. This is troubling for policymakers whose goal is to restrict the spread of fake news. Programs to “educate” users during such a period will likely fail as users would prefer bias-confirming misinformation to those that challenge their pre-existing beliefs. So, in such a situation policymakers should suppress the market through using supply-side measures rather than demand-side measures.

An increase in processing capacity

$$\frac{\partial v^*}{\partial \beta} = \frac{v^*}{\beta(\alpha\lambda + 1)} \tag{17}$$

Similar to the partial derivative of v * to Bias(B), as all the variables are strictly positive, the partial derivative of v * to Processing Capacity(β) will also be greater than 0. When a user has a larger cognitive bandwidth to consume information, the absolute demand for that consumer will increase as the marginal cost of each piece of new information is less as compared to before, shifting the demand curve outwards. β can be influenced by factors such as education, age (older consumers may find it easier to process new information), or even the platform itself (“high brow” media would be tougher to process that “pop media”)

As higher processing capacity(β) directly drives up the equilibrium prevalence (v *), introducing “speed bumps” may force users to slow the rate at which they consume misinformation. For example, the use of adverts containing true information would help break the flow and educate consumers before they go further down the path of misinformation. However, this could also lead to a lower demand for an information platform as a whole, making this policy hard to implement.

An Increase in Verification Costs

$$\frac{\partial v^*}{\partial C_v} = \frac{v^*}{C_v(\alpha\lambda + 1)} \tag{18}$$

Economically, as the "price" of finding the truth increases, users shift their demand to cheap, readily available fake news, pushing the demand curve outward and driving the equilibrium price (P) and prevalence (v^*) up. This logic is reflected in the strictly positive partial derivative of v^* to C_v.

If a platform wants to restrict the demand for misinformation without reducing demand for the platform, they should embed frictionless one-click fact-checking straight into the feed. This will push the demand curve leftwards, although it may come with an initial setup cost.

Supply Side Parameters

An Increase in Engagement weight

$$\frac{\partial v^*}{\partial E} = \frac{v^* \cdot \alpha}{E(\alpha\lambda + 1)} \tag{19}$$

Suppose a platform heavily prioritises interactions with a piece of information as a way to judge whether or not the information should be spread further on their platform via recommendations and suggestions. Again, all the variables are positive, hence the derivative is greater than 0. This indicates that an increase to the supply factors E and R will lead to an outward shift in the supply curve causing v^* to increase and P to decrease.

The model predicts that algorithmic architectures optimized solely for engagement facilitate the spread of misinformation. This highlights a critical structural market failure: in a two-sided market, platforms with a financial incentive to maintain high engagement weights for ad revenue are mathematically disincentivized from solving the misinformation crisis.

An Increase in Moderation

$$\frac{\partial v^*}{\partial M} = \frac{-v^* \cdot \alpha}{(1-M)(\alpha\lambda + 1)} \tag{20}$$

The partial derivative of v^* with respect to $1 - M$ is negative at all times. Effectively moderation is an algorithmic tax. It artificially raises the marginal cost to the platform of providing misinformation, strictly shifting the supply curve inward, reducing the equilibrium price(P^*) and equilibrium prevalence (v^*).

According to the model, moderation is the most dominant supply-side friction. Even in a market with highly inelastic human demand for misinformation an increase in algorithmic moderation is mathematically sufficient to push the equilibrium prevalence (v^*) down. This means regulatory frameworks need to focus on structural supply-side interventions because platforms have the unilateral mathematical ability to choke the market. For instance, a platform can introduce itself into the market and use AI classifiers or human moderators to identify unverified claims, and restrict their dissemination, raising the moderation strictness parameter (M).

An Increase in The Virality Exponent
Mathematically, the virality exponent (λ) represents the inverse of the Price Elasticity of Supply ($PES = 1/\lambda$). While elasticity variables typically alter the shape of the curve itself, λ functions as a market accelerant because of how the supply curve is structurally anchored at $v = 0$ and $v = 1$.
The demand elasticity parameter (α) causes the demand curve to ambiguously "seesaw" around a floating interior anchor point ($v = k$, representing baseline demand). The demand curve cannot mathematically anchor at the market boundaries: as prevalence approaches zero ($v \to 0$), the cognitive price asymptotes to infinity, and at total saturation ($v = 1$), the price remains highly sensitive to any change in α.

This shows that algorithmic virality serves as a pure market accelerator. As the platform refines its algorithm to favor more virality, it reduces its Price Elasticity of Supply, making it structurally indifferent to cognitive prices and significantly reducing the marginal cost of producing misinformation. Since the supply curve is made to bow downwards, the algorithmically guaranteed outcome is an increased equilibrium level of fake news. Therefore, the regulator needs to see the virality algorithm as a driver of market failure on the supply side (See Appendix B for the Derivation of the Partial Derivative of v^* with respect to λ).

USING SYNTHETIC DATA TO ILLUSTRATE MARKET DYNAMICS

The synthetic data was generated from a randomised simulator. The synthetic data was generated programmatically using Python’s NumPy and SciPy libraries. To organically plot the supply and demand curves without forcing an equilibrium, the simulation was divided into supply and demand shocks ($n = 10,000$ for each) in a monte carlo simulation. In supply-side shocks the supply variables were subjected to high variance while the demand-side variables had low variance. For demand-side shocks the demand factors had high variance and the supply-side factors had low variance.

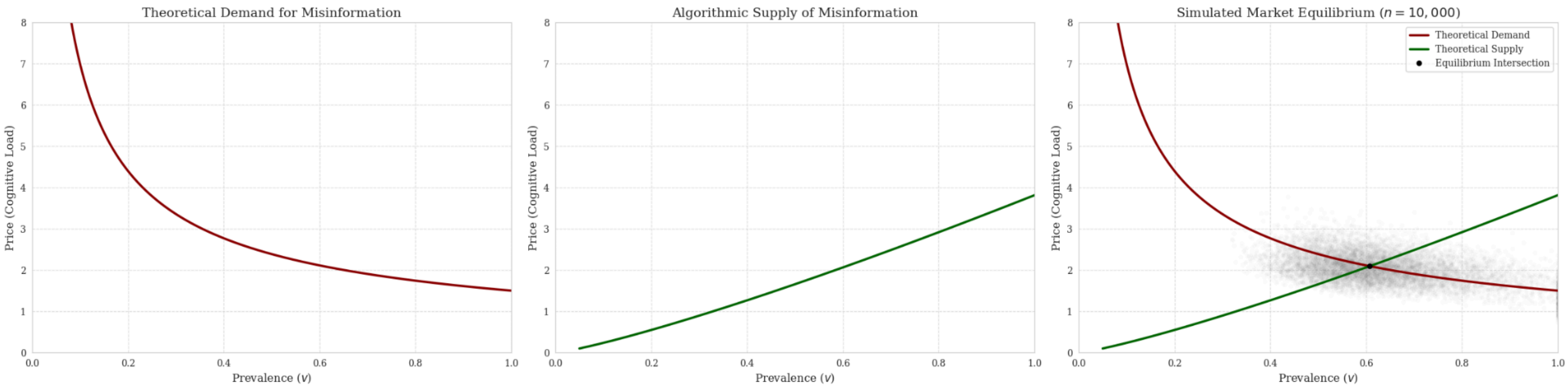

Figure 7.1

The first panel depicts the demand graph drawn from the synthetic data, the send panel shows the supply curve derived from the synthetic data, and panel three overlays the two graphs onto a low-opacity density distribution to show where the equilibrium is formed. The low-opacity density distribution visualisation ensures that the equilibrium of the two graphs has formed at a point where the density of equilibrium points from the simulation is the highest, illustrating the stability of the proposed model.

In Figure 7.1, the first two graphs were drawn by substituting the mean values of each demand-side and supply-side variable into each inverse demand and supply functions respectively. The panels above illustrate that the functions behave according to standard microeconomic laws when populated with baseline parameters. The demand curve slopes downwards and the supply curve slopes upwards with respect to prevalence. Furthermore, the third panel combines both curves and overlays it onto a low-opacity density distribution. The overlay illustrates the stability of the equilibrium. Despite all the variables being subject to high variance (Refer to Figure 7.3 and Figure 7.4), the curves were able to intersect at an equilibrium point on the graph where there was a high density of the 10,000 individual market-clearing coordinates.

Additionally, parameter boundaries were deliberately constrained to reflect realistic cognitive and algorithmic constraints. Figure 7.3 and 7.4 outline the distribution and constraints used for the demand-side and supply-side parameters respectively. The demand-side parameters were subjected to a normal distribution in order to normal distributions in order to represent standard population clustering around a mean point. On the other hand, most of the supply-side parameters were drawn from uniform distributions as every value within the platform's practical limits is equally probable due to the fact that it is being developed. The mean, standard deviation, minimum, and maximum values of each variable are outlined in Figure 7.2.

	β	B	C_v	α	θ_0	γ	E	R	M	λ	v *	P *
count	10000	10000	10000	10000	10000	10000	10000	10000	10000	10000	10000	10000
mean	0.999893	1.416571	1.303026	1.499621	1.000746	3.30172	1.150218	0.999638	0.223432	1.200387	0.637547	2.050309
std	0.050173	0.276661	0.187542	0.050224	0.114878	0.903302	0.08625	0.087316	0.100929	0.057801	0.148423	0.361831

min	0.80388	1.000000	1.000000	1.27672	0.800003	1.000000	1.000039	0.85003	0.05001	1.100006	0.319254	0.74014
25%	0.96637	1.201397	1.15997	1.465269	0.903458	2.690977	1.074772	0.922988	0.13535	1.149908	0.536275	1.8089
50%	0.99987	1.404754	1.298846	1.499481	1.000926	3.309164	1.151766	1.000651	0.22405	1.200192	0.613086	2.036049
75%	1.033554	1.608159	1.432779	1.533952	1.100413	3.914859	1.225068	1.076014	0.309859	1.251149	0.710427	2.282075
max	1.196312	2.500000	2.038325	1.686392	1.199976	6.000000	1.29996	1.149998	0.399992	1.299955	1.685303	3.776774

Figure 7.2

Demand-Side Parameters			
Processing Capacity	β	*Normal* $\mathcal{N}(1.0, 0.05)$	*Unbounded*
Confirmation Bias	B	*Normal* $\mathcal{N}(1.4, 0.3)$	$[1.0, 2.5]$
Verification Cost	C_v	*Normal* $\mathcal{N}(1.3, 0.2)$	$[1.0, 2.5]$
Elasticity Parameter	α	*Normal* $\mathcal{N}(1.5, 0.05)$	*Unbounded*

Figure 7.3

Supply-Side Parameters			
Baseline Resistance	θ_0	*Uniform* $\mathcal{U}(0.8,\ 1.2)$	$[0.8, 1.2]$
Network Affinity	γ	*Normal* $\mathcal{N}(3.3, 0.9)$	$[1.0, 6.0]$
Engagement Weights	E	*Uniform* $\mathcal{U}(1.0,\ 1.3)$	$[1.0, 1.3]$
Recency Bias	R	*Uniform* $\mathcal{U}(0.85,\ 1.15)$	$[0.85, 1.15]$
Moderation Strictness	M	*Uniform* $\mathcal{U}(0.05,\ 0.40)$	$[0.05, 0.40]$
Virality Exponent	λ	*Uniform* $\mathcal{U}(1.1,\ 1.3)$	$[1.1, 1.3]$

Figure 7.4

Simulation Outcomes		
Mean Equilibrium Prevalence	v^*	0.634
Mean Equilibrium Price	P^*	2.05
Corner Solutions	$v^* > 1.0$	2.60%

Figure 7.5

Even though the 10,000-run Monte Carlo simulation successfully verifies the stability of the model, there are three empirical limitations with such a synthetic approach. First, due to the fact that both algorithmic engagement (E) and virality exponents (λ) remain proprietary, the simulation fails to validate the findings through external validation to derive exact parameter values. Thus, the results of the simulation can be viewed only as an illustration of the mechanism rather than any accurate prediction. Second, the model makes use of conventional distributions for behavioral parameters such as Confirmation Bias (B) and

Verification Cost (C_v). Even though it helps in keeping things mathematically simple, this approach could underestimate the speed of misinformation in cases of black-swan events when the distribution of the number of shares follows a heavy-tailed power law. Finally, the simulation makes an assumption that all parameters are independent from each. However, in reality, such parameters are interdependent, and prolonged exposure to, say, high algorithmic moderation (M) might influence users' cognitive biases.

CONCLUSION

The spread of misinformation is not a technological mishap or a pure psychological failing, it is a quantifiable market equilibrium where human demand and algorithmic supply meet. However, it is also a clearly defined social ill that continues to influence politics, health, and social fabric.

In this paper, we find that the main accelerants for the spread of misinformation are: biases, verification costs, cognitive capability to process information, engagement on platforms, and the recency of the misinformation. Likewise, the main brakes on the spread are: moderation and the importance of affinity.

The master equation in the paper allows for a deeper understanding of the factors that drive the propagation of misinformation, thereby highlighting those levers that can be pulled by policymakers and platforms to prevent its spread.

To have real-world impact, however, the practicality in controlling each identified lever needs to be appreciated. Clearly, factors such as the strength of bias, cognitive capacity, engagement, and recency are hard to influence. However, determinants like verification costs and the moderation strictness can be addressed through the use of AI machine learning models to track content related to misinformation that may be stuck within an echo-chamber and remove such misinformation before it spreads further. Another solution is for platforms to use AI to recognise the types of misinformation that are widely popular, and promote content that explains why such information is false. This reduces verification costs and reduces demand for pieces of misinformation.

Limitations: A main limitation is that the model assumes a constant elasticity of attention, whereas real human capacity for providing attention may fluctuate throughout the day. One more limitation is the lack of empirical data used to perfectly calculate factors such as the strength of bias, the virality exponent, cognitive capabilities, and more.

However, indexes can be made along these lines to track user behaviour and quantify these factors. By enumerating these indicators, the model can be applied to real-world scenarios.

Finally, it is important to consider that as long as platforms treat human attention and engagement as extractable resources to use for their gain, the market for misinformation will always remain at a high prevalence.

Attempts to curtail or influence this would almost certainly run against the grain of the "invisible hand" but may be necessary if the spread of certain misinformation constitutes a potential social crisis. It is up to policy makers to decide where to draw the line and push platforms to install the requisite guardrails, even if that means diminished engagement.

The commoditisation of attention is a dangerous reality. As long as engagement-hungry algorithms dictate the supply, markets for misinformation will clear at the equilibrium where truth is the cheapest to abandon and false information is easiest to extract.

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APPENDIX A:

Derivation for the Final Equilibrium Formula

The definition for the equilibrium is: At a prevalence (v *), the attention signal that consumers provide(P_{demand}) is equal to the attention signal that an algorithm requires (P_{supply}) to keep the content at that exact level of spread. Similarly, v_{demand} must equal v_{supply}.

For an equilibrium price (P *) to form, $P * = P_{demand} = P_{demand}$ and for an equilibrium prevalence to form, $v * = v_{demand} = v_{supply}$.

Step 1:Equate the inverse demand function to the inverse supply function

$$\left(\frac{\beta \cdot B \cdot C_v}{v}\right)^{\frac{1}{\alpha}} = \theta \cdot v^{\lambda} \tag{A.1}$$

Step 2: Isolate v in the equation

$$v^{\lambda + \frac{1}{\alpha}} = \frac{\left(\beta \cdot B \cdot C_v\right)^{\frac{1}{\alpha}}}{\theta} \tag{A.2}$$

Step 3: Raise both sides by $\frac{\alpha}{\alpha\lambda + 1}$ to isolate v_t to get v_t *

$$v * = \left(\frac{\left(\beta \cdot B \cdot C_v\right)^{\frac{1}{\alpha}}}{\theta}\right)^{\frac{\alpha}{\alpha\lambda + 1}} \tag{A.3}$$

Step 4: Expand the algorithmic resistance to get the final function of v_t *

$$v * = \left(\frac{\left(\beta \cdot B \cdot C_v\right)^{\frac{1}{\alpha}} \cdot E \cdot R \cdot (1 - M)}{\theta_0 \cdot \gamma}\right)^{\frac{\alpha}{\alpha\lambda + 1}} \tag{A.4}$$

This master equation, with the assumptions set previously defines the rate at which misinformation is supplied and consumed on online platforms. However, why does an equilibrium exist in the first place?

To start, take a situation where $v_{t_{supply}} > v_{t_{demand}}$ meaning that consumers are being exposed to a greater fraction of news items that are false than they would prefer to. Soon, the marginal utility of the consumer drops as the consumer's increase in the understanding of the true state of the world is decreasing; hence, the willingness to supply attention falls as well. In this situation we assume that the consumer does not know it is misinformation, but rather just another piece of information.

Similarly, when $v_{t_{demand}} > v_{t_{supply}}$ it indicates that a consumer wants to be exposed to a greater fraction of news items that are false than they are currently being exposed to. As a result, they give more attention to the posts related to the piece of misinformation due to the fact that their marginal utility is high. The algorithm will then record such activity as interest and increase the share of this piece of misinformation in comparison to all other posts to collect more attention from the consumer.

APPENDIX B:

Deriving the Partial Derivative of the Equilibrium Prevalence to the Virality Exponent

Step1: Compress the Equation Constants

Let Y_D represent the demand-side constraints $(ln(\beta) + ln(B) + ln(C_v))$

Let Y_S represent the supply-side constraints $(ln(E) + ln(r) + ln(1 - M) - ln(\theta_0) - ln(\gamma))$

We can re-write the master equation as:

$$ln(v\ *) = \frac{Y_D + \alpha Y_s}{\alpha\lambda + 1} \qquad \text{(B.1)}$$

Step 2: Apply the Chain Rule

Let $Y_D + \alpha Y_s$ equal to C. The equation becomes $ln(v\ *) = C(\alpha\lambda + 1)^{-1}$.

Take the derivative with respect to λ:

$$\frac{\partial ln(v^*)}{\partial\lambda} = -C(\alpha\lambda + 1)^{-2} \cdot \alpha \qquad \text{(B.2)}$$

$$\frac{\partial ln(v^*)}{\partial\lambda} = \frac{-C \cdot \alpha}{(\alpha\lambda+1)^2} \qquad \text{(B.3)}$$

Step 3: Substitution of C

If $ln(v\ *) = C(\alpha\lambda + 1)^{-1}$ then $C = (\alpha\lambda + 1) \cdot ln(v\ *)$, and we can substitute this back into the numerator to get:

$$\frac{\partial ln(v^*)}{\partial\lambda} = \frac{-\alpha \cdot (\alpha\lambda+1) \cdot ln(v^*))}{(\alpha\lambda+1)^2} \qquad \text{(B.4)}$$

$$\frac{\partial ln(v^*)}{\partial\lambda} = \frac{-\alpha \cdot ln(v^*))}{(\alpha\lambda+1)} \qquad \text{(B.5)}$$

Step 4: Isolate the Partial Derivative Using the Standard Rule for Logarithmic Differentiation

$$\frac{\partial ln(v^*)}{\partial\lambda} = \frac{1}{v^*} \cdot \frac{\partial v^*}{\partial\lambda} \qquad \text{(B.6)}$$

Hence:

$$\frac{1}{v^*} \cdot \frac{\partial v^*}{\partial \lambda} = \frac{-\alpha \cdot ln(v^*)}{(\alpha\lambda+1)} \quad \text{(B.7)}$$

$$\frac{\partial v^*}{\partial \lambda} = \frac{-\alpha \cdot v^* \cdot ln(v^*)}{(\alpha\lambda+1)} \quad \text{(B.8)}$$

As prevalence is the fraction of news items that are false, $ln(v\ ^*) < 0$ for all values of $v\ ^*$. As α, $v\ ^*$, and λ are all positive, multiplying the negative value of $ln(v\ ^*)$ with the negative sign at the front of the front will yield a positive partial derivative.

$$\frac{\partial v^*}{\partial \lambda} > 0$$