Debt Diffusion, and Infection: The Hard Science of Economics

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Abstract

In an effort to better understand the mechanisms underlying finance and economics, this investigation simplifies an economy to its most basic form –an economic space of assets consisting of atomic equity and debt. By applying the concept of diffusion to debt, the corresponding behaviour of equity was investigated. The findings reveal that debt and equity cannot both diffuse or concentrate simultaneously at the macroscopic scale of a market-driven economy, and that equity only concentrates in an economy experiencing robust economic growth. Additionally, if diffusion is a required assumption for homogenous mixing, and debt transforms into equity with some probability, then an economic system can be modelled as a system of competing viral infections within a susceptible population, or market. It is shown how parameters of infection correspond to measures of sales and marketing, suggesting that the product/business lifecycle curve is very likely an infection curve. This Economic Infection model provides a unified framework that can incorporate metrics used in sales and marketing –such as convserion rate, churn rate, engagement rate, etc– to forecast revenue and market share growth for market competitors whose values can be estimated. Also, a preliminary decomposition of Price Elasticity of Demand within this economic infection framework reveals multiple contributing elasticities (including the Price Elasticity of Supply) which producers and retailers can manipulate to shift PED more positive or negative. These decomposed elasticities align with several known pricing strategies aimed at driving sales quantities, with one particular elasticity identified as a possible driver of demand-pull inflation.

Table of Contents

Introduction - The Economic Macrostate

In the world of Statistical Mechanics, the heat equation describes how the distribution of a concentration of energy changes through time. It features prominently in the world of financial risk modelling and relies heavily on the assumption of Brownian motion on equity. ie. The random walk. However, there are many issues with this application of the Brownian motion assumption. First of all, Brownian motion is not an assumption that exists alone. It *itself* is a conclusion that arises from far more fundamental assumptions. Second of all, in a system of Brownian motion, there is no mechanism for any accumulation to persist. If capital flows resulting from economic transactions were Brownian in nature there would be no mechanism for sustained wealth and capital concentration over time. Something is obviously missing but it’s not clear what.

This is a deep dive into how the heat equation is derived, and one of its more fundamental assumptions in particular –the assumption of increasing entropy. It will be apparent why applying diffusion and Brownian motion to equity in macroeconomic and financial systems may be fundamentally incorrect, and how a simple correction can lead to a more accurate description of equity flows without contradicting what is observed in reality.

Financial and Economic Microstates

Asset weightings in a portfolio of assets is implemented in the real world through the use of equity and debt. So an abstract collection of asset weights that look like this:

Figure 1: This portfolio's weights have been scaled down such that the absolute value of the weights sum to 1 to correspond to "full investment"

... is actually implemented in the real world like this:

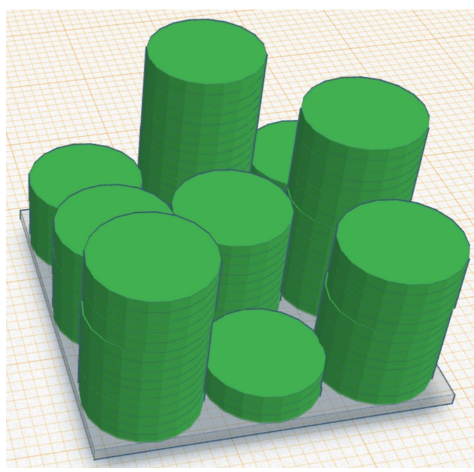


Figure 2: An all-equity allocation of Figure 1

Each potential investable asset creates a spot on an abstract grid where equity can be allocated to. Each green disc in Figure 2 represents a "unit of value" that is free to move to any spot on this grid without restriction, at the discretion of its owner. It's easy to see how an extremely large number of arrangements are possible from even a small collection of investable assets and a moderate quantity of investable equity. Each possible arrangement is known as a *microstate*, or *portfolio*.

When considering a system with an *extremely large* number of these possible microstates, the average/expected state is considered and is referred to as a *macrostate*.

Levered Systems

At the simplest level, an economic or financial system can be described as collection of economic or financial assets (an apartment building, a shoe factory, a stock portfolio, etc) that have varying quantities of equity and debt allocated to them.

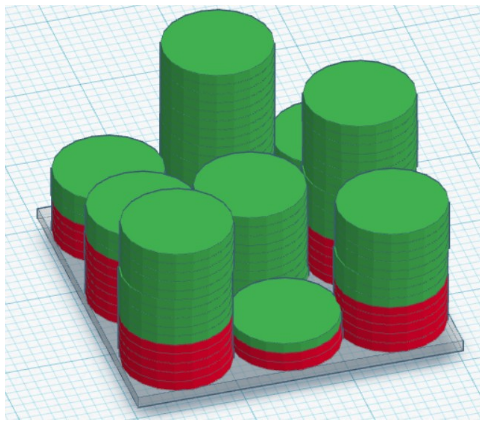


Figure 3: Allocations of equity (green) and debt (red) onto financial assets (squares)

For the sake of simplicity, the assumption that equity and debt can move freely and independently of each other will be made here (in reality, most scenarios of debt allocation requires some minimum allocation of equity to function as collateral). If equity and debt are assumed to move freely and independently of each other, then which of the two can the assumption of diffusion (Brownian motion) be applied? The Black-Scholes options formula is a popular tool used to model risk/volatility in equity prices over time, and one of its core assumptions is that prices follow geometric Brownian motion (GBM). This assumes that the equity of the $Assets = Equity + Debt$ equation is the entity performing the random walk. However, one anomaly appears in financial systems in the tails of the distribution of measured returns –they are much fatter than they would be if equity followed a pure diffusion process. Also, if equity underwent a pure diffusion process, high concentrations –prices– would simply radiate randomly into its environment and stock prices would decline. An additional issue is the anecdotal observation of “momentum” and “trends” in price behaviour through time. This flies in the face of a required assumption for Brownian motion, that changes in equity prices/levels are independent and identically distributed.

In macroeconomic systems, incredible concentrations of wealth and profit should almost be impossible to create if the diffusion assumption were applied to equity, since increases in equity levels “should” increase the rate of its “radiation” back out into its economic environment. Despite these and other contradictions, the assumption of the diffusion process on equity is still widely used and accepted. The assumption appears to “still work” to some degree, but seems to do so with some big caveats. So, as unconventional as it may sound, maybe the diffusion assumption shouldn’t be applied to equity.

So what happens if it’s applied to debt instead?

What is Debt?

Debt is something, typically money, that is owed –*an obligation to pay*.

A simple debt transaction is as follows:

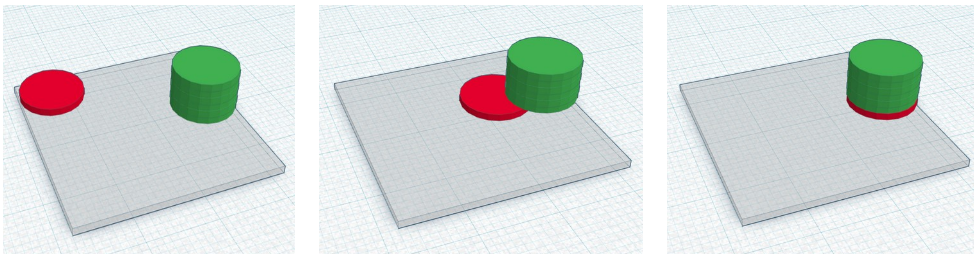


Figure 4: (Left) An obligation to pay is directed at an entity with some equity (green). (Centre) The entity absorbs the obligation to pay (red). (Right) The entity has absorbed the payment obligation and is in a "levered state".

An entity absorbs a payment obligation D from somewhere, and exists in a levered state for some period of time. At some time in the future, the payment obligation disappears when a unit of equity E travels to the origin of the obligation, returning the entity to an un-levered state. From the perspective of the entity, not only does $D=-E$ but $\vec{D}=-\vec{E}$ as well.

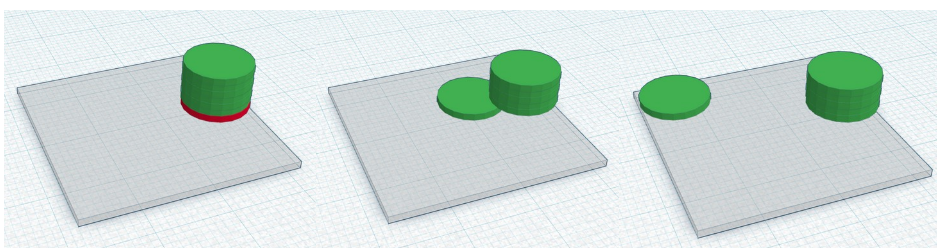


Figure 5: Eventually, a payment obligation causes equity to travel back to the obligation's source.

This is a simple description of a debt transaction. However, what this transaction represents, and the time spanned by this sequence, is ambiguous. These sequence of events could be an accurate depiction of the creation of any loan and a subsequent payment (a student loan, a mortgage, or even a smartphone bought with a credit card). However, the explicit creation of a loan is not the only way to create a "payment obligation". These sequence of events are equally applicable if the red unit in Figure 4 were an advertisement that induced the purchase of a movie ticket, or a pair or shoes taken off a shelf at a store, or even a sandwich. In this extremely fundamental picture of "debt", it becomes clear that it is indistinguishable from the abstract concept of "demand". The only difference between a mortgage and a sandwich would be the length of time a system of equity remains in a levered state (years vs minutes or seconds). The *mere decision to consume* creates an obligation to pay. In this way, it may be more accurate to describe "debt" as simply "demand". Or more precisely, "demand still in-progress".

Diffusion of Debt and Demand

If debt is simply "demand", then it may be reasonable to assume that market economy participants are strongly incentivized to spread (diffuse) "payment obligations" than "equity" throughout their economic system. Applying the diffusion process and all its baked-in assumptions onto the debt instead of equity may seem like a strange idea, but this would be an incredibly desirable situation from the point of view of the entity creating/issuing that obligation. In fact, entire industries have grown and evolved to spread "obligations to pay" efficiently. eg. Shipping/transport, distribution and warehousing, advertising, etc.

The most critical assumption of diffusion is the assumption of increasing entropy. That is, "things that can be arranged" will eventually be found in arrangements that maximize the number of ways they can be arranged. ie. High concentrations evolve over time to spread –or radiate– to low concentrations. At this point, randomly radiating "payment obligations" into an economic system makes more sense than randomly radiating "equity".

Applying diffusion[1] to debt *D*, gives

$$\frac{dT_D}{dt} = \frac{dT_D}{dD}\frac{dD}{dt}$$
$$\frac{dT_D}{dt} = c_D^2 k_D \frac{d^2 T_D}{dx^2}$$

Since $D = -E$,

$$\frac{dT_E}{dt} = \frac{dT_E}{dE}\frac{dE}{dt}$$
$$= c_E^2 \left(\frac{dE}{dD}\frac{dD}{dt}\right)$$
$$\frac{dT_E}{dt} = -c_E^2 \frac{dD}{dt}$$

Which gives

$$\frac{dT_E}{dt} = -c_E^2 k_D \frac{d^2 T_D}{dx^2}$$

T_D Debt temperature (tendency for an entity to radiate "debt" into its economic environment).

1 See Appendix for diffusion derivation via maximization of entropy

D Total debt level, or "payment obligations" (PQ_{total} for price and total quantity P and Q_{total}).

c_D Specific heat of debt $c_D^2 = \frac{dT_D}{dD}$ –how changes in debt levels affect the tendency for debt to spread.

k_D Debt conductivity (speed with which debt can diffuse into its environment via distribution logistics, advertising, etc).

T_E Equity temperature (tendency for an entity to radiate equity into its economic environment).

E Total level of equity (equity exchanged for total debt/demand).

c_E Specific heat of equity $c_E^2 = \frac{dT_E}{dE}$ –how changes in equity levels affect the tendency for equity to spread.

x Economic environment.

As long as demand spreads, equity will concentrate over time –the *opposite* of regular Brownian motion. This is likely the fundamental mechanism behind the economic phenomenon of wealth concentration that is not possible if the diffusion assumption were applied to equity.

A particular solution to the diffusion equation $\frac{dT_D}{dt} = c_D^2 k_D \frac{d^2 T_D}{dx^2}$ is,

$$T_D(x,t) = \frac{1}{\sqrt{4\pi c_D^2 k_D t}} e^{\left(\frac{-x^2}{4 c_D^2 k_D t}\right)}$$

For the simplicity of illustration, assume $c_D, c_E, k_D, k_E = 1$.

Consider a supplier located at $x = 0$ with a large concentration of goods at time $t = 0.2$. This is shown in the following example as $T_D(x,t) = \frac{1}{\sqrt{4\pi\sigma^2 c_D^2 k_D t}} e^{\left(\frac{-x^2}{4\sigma^2 c_D^2 k_D t}\right)}$ with $\sigma^2 = 0.02$ used to create the initial high concentration near $t = 0$.

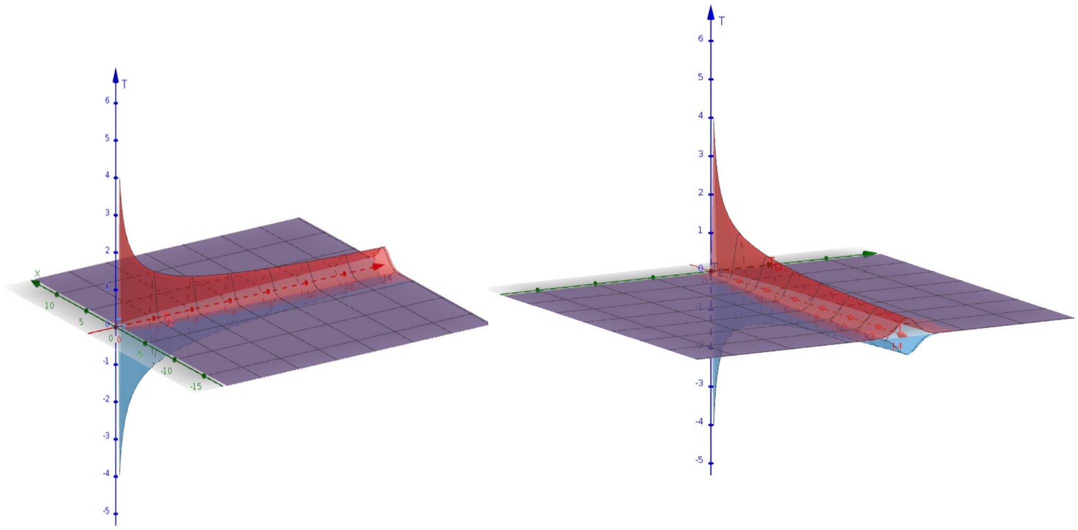


Figure 6: Temperature (z-axis) vs x and time. Tendency to attract units of equity (revenue) is highest when equity temperature (blue) T_E is lowest. The built-up demand D (red) diffuses through its economic neighbours over time, while equity temperature T_E, rises over time, slowing the rate of revenue attraction.

Since $\frac{dE}{dt} \propto \frac{dT_E}{dt}$, the supplier's equity grows with the rise of its equity temperature T_E , and equity/wealth therefore concentrates at $x = 0$ over time.

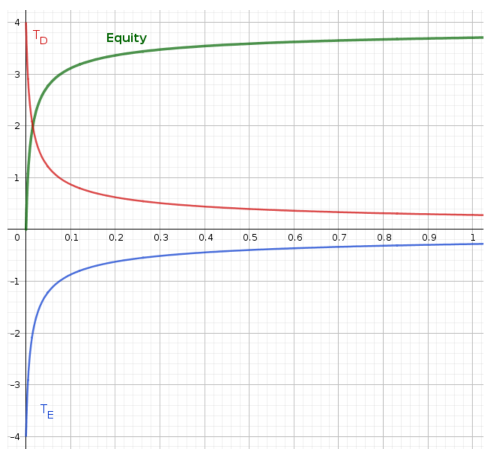


Figure 7: Cross section of Figure 6, temperature (y-axis) vs time (x-axis) for supplier at x = 0. Rising equity temperature T_E drives the concentration of equity and wealth at macro-economic scales.

This description of equity flow has several consequences. At the macro-economic scale, 1) equity concentrates as demand spreads over time (to the surprise of nobody), and 2) "normal" diffusion can only happen to either debt/demand or equity, *but never both at the same time*.

At a high level, the overall picture of a healthy growing economy can be visualized as a system that experiences millions upon millions of debt-diffusion events that are followed by "implosions" of equity. Debt is hot and radiates; equity is cold and concentrates.

Payment Plans and Equity Temperature

Recall that leverage is simply an incomplete transaction, extended through time.

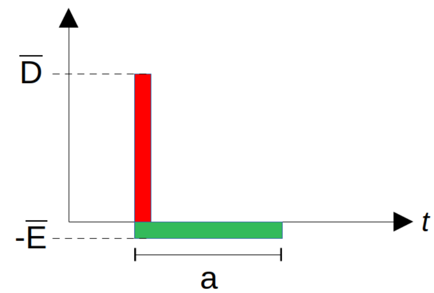


Figure 8: Mean debt $\overline{D}$ split into equal payments over period 'a'.

If payment for demand level D is spread uniformly over period a, then $-\frac{dE}{dt} = \frac{1}{a}\frac{dD}{dt}$.

Then

$$\frac{dT_E}{dt} = \frac{dT_E}{dE}\left(\frac{dE}{dt}\right)$$

$$\frac{dT_E}{dt} = \frac{dT_E}{dE}\left(\frac{-1}{a}\frac{dD}{dt}\right) \qquad \text{with} \quad k_E = \frac{1}{a}$$

$$\frac{dT_E}{dt} = -k_E \frac{dT_E}{dE}\left(k_D \frac{d^2 T_D}{dx^2}\right)$$

Allowing payments to be split and paid over time slows the rate at which T_E rises, keeping it cooler for longer, extending the time the entity can absorb equity from its environment (Figure 9).

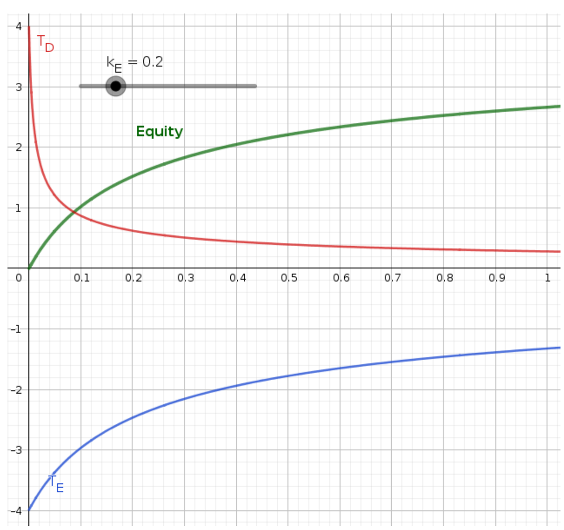


Figure 9: Same system as Figure 7, but with k_E = 0.2 while k_D = 1.
The rate at which equity temperature T_E rises is reduced.

Final Thoughts

Applying the diffusion process to debt may be strange at first, but makes sense when debt is reduced to its most fundamental description as a simple “payment obligation”. Potential payment obligations can take the form of a pair of running shoes, a sandwich, a haircut, or anything that meets the economic concept of “supply”. “Demand” transforms these potential debts into real payments –transfers of equity. Debt, demand, decision to consume, and desire to consume, could all be considered conceptually equivalent to “debt” in the context that they all impact equity negatively.

It may very well be the case that equity and profit simply *indicate* when and where “debt” was consumed during its random walk, much like how footprints in sand indicate the presence of a pair of feet on a beach, but the footprints themselves do not spread. As a consequence, the distribution of equity can only be sampled from the distribution of debt and demand. This diffusion of payment obligations is what drives the phenomenon of macroeconomic wealth concentration –essentially diffusion in reverse. Debt/demand being “negative equity” also guarantees that equity and debt/demand cannot both spread at the same time at the macroscopic level; when one radiates, the other *must* concentrate.

What’s Next

With numerous market competitors spreading “units of potential debt” throughout an economic system, consumption of these payment obligations is not guaranteed, nor is it infinite. Economic demand can be satiated, and potential payment obligations do not convert into equity with 100% probability whenever it comes into contact with a potential customer; it is typically much lower. This diffusion of debt and demand into a finite system, and probabilistic transition between two states (“potential debt” into “equity”), lays the groundwork that permits debt and demand in a market economy to be modelled as a viral infection within a susceptible population.

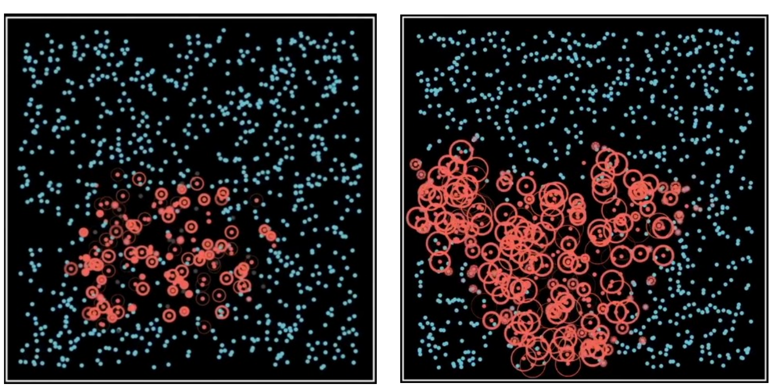


Figure 10: A simulation of a viral infection diffusing through a population.
Source: 3Blue1Brown https://www.youtube.com/watch?v=gxAaO2rsdIs

Appendix

From Microstates to Macrostate – Temperature, Specific Heat, and Diffusion

A "microstate" is a unique arrangement of "things" at some moment in time. Each possible microstate can have a quantity of "things" E_i in some arrangement within the system. The total number of possible arrangements possible with quantity E_i is denoted as n_i .

The total number of possible microstates N would then be,

$$n_1 + n_2 + \ldots + n_i + \ldots = \sum_i n_i = N$$

And the total quantity of things from each possible microstate is,

$$n_1 E_1 + n_2 E_2 + \ldots + n_i E_i + \ldots = \sum_i n_i E_i = N \bar{E}$$

Where $\bar{E}$ is the average quantity in each microstate.

To illustrate this, consider a system with three cells. Each cell can either hold one "thing" or be empty. An empty cell is indicated with a "0", and an occupied cell is indicated with a "1".

Microstate	i	E_i
000	1	0
001	2	1
010	2	1
011	3	2
100	2	1
101	3	2
110	3	2
111	4	3

The levels given by $E_1 = 0,\ E_2 = 1,\ E_3 = 2,\ E_4 = 3$ produce $n_1 = 1,\ n_2 = 3,\ n_3 = 3,\ n_4 = 1$

The total number of possible arrangements being $N = 8$, and $N\bar{E} = 12$, gives $\bar{E} = 1.5$.

Temperature

A very important assumption introduced here is the statement that *a system at equilibrium is evenly distributed over all microstates accessible to it at a fixed total level* E_i .

Using the previous example as an illustration, if a system had two things in it, $E_i = 2$, it would have access to the three microstates 011, 101, 110 with equal probability. This assumption gives rise to the consequence of *increasing entropy*. If nothing were known about the total level E_i of the system, then the microstates of the system are assumed to have a uniform probability distribution, and thus each equally likely. Thus, the group of microstates contained by the largest n_i will be the group with the largest number of possible arrangements –and thus have the highest entropy– and will be the set of microstates that the system will most likely be found in at equilibrium.

With this, the probability of the system having a given total level is,

$$p_i = \frac{n_i}{N}$$

Maximizing entropy S should produce the most likely microstates a system can be found in. However, this maximization has two constraints. First, $\sum_i p_i = 1$; and second, the average total quantities $\overline{E}$ do not change, so $\sum_i p_i E_i = \overline{E}$.

Maximizing entropy subject to these two constraints gives

$$\underset{p_i}{\text{argmax}} \; S(p_i) = -\sum_i p_i \ln(p_i) - \alpha\left(\sum_i p_i - 1\right) - \beta\left(\sum_i p_i E_i - \overline{E}\right)$$

where α and β are Lagrange multipliers.

Maximizing with respect to the probabilities gives

$$\begin{aligned} \frac{dS}{dp_i} &= -\ln(p_i) - 1 - \alpha - \beta E_i \\ 0 &= -\ln(p_i) - 1 - \alpha - \beta E_i \\ \ln(p_i) &= -(1+\alpha) - \beta E_i \\ p_i &= e^{-(1+\alpha)-\beta E_i} \end{aligned}$$

A new variable $Z = e^{(1+\alpha)}$ can be defined in order to simplify the expression, so we’re left with

$$p_i = \frac{1}{Z} e^{-\beta E_i}$$

So if $\sum_i p_i = 1$ then,

$$\sum_i \frac{1}{Z} e^{-\beta E_i} = 1$$
$$\frac{1}{Z} \sum_i e^{-\beta E_i} = 1$$
$$Z = \sum_i e^{-\beta E_i}$$

In statistical mechanics, this Z is called the partition function. It serves as a normalizing expression for probabilities to sum to 1.

When Z is differentiated with respect to β

$$\frac{dZ}{d\beta} = -\sum_i E_i e^{-\beta E_i}$$

Dividing both sides by Z gives

$$\begin{aligned}
\frac{1}{Z}\frac{dZ}{d\beta} &= -\frac{1}{Z}\sum_i E_i e^{-\beta E_i} \\
&= -\sum_i p_i E_i \\
&= -\overline{E} \\
\frac{-d\ln Z}{d\beta} &= \overline{E}
\end{aligned}$$

Armed with these equalities that deliver maximum entropy, they can be applied to the entropy equation to see what the maximum entropy (its description at equilibrium) actually is.

$$\begin{aligned}
S(p_i) &= -\sum_i p_i \ln(p_i) \\
&= -\sum_i p_i \ln\left(\frac{1}{Z} e^{-\beta E_i}\right) \\
&= \sum_i p_i (\beta E_i + lnZ) \\
&= \beta \sum_i p_i E_i + \frac{1}{Z} lnZ \left(\sum_i e^{-\beta E_i}\right) \\
&= \beta \overline{E} + \frac{1}{Z} \ln Z (Z) \\
&= \beta \overline{E} + lnZ
\end{aligned}$$

So,

$$
\begin{aligned}
dS &= \overline{E}\,d\beta + \beta d\,\overline{E} + d\,lnZ \\
&= \overline{E}\;d\beta + \beta\,d\overline{E} + \frac{\partial\,lnZ}{\partial\beta}\;d\beta \\
&= \overline{E}\,d\beta + \beta\,d\,\overline{E} + \left(-\overline{E}\right)d\beta \\
&= \beta\,d\overline{E}
\end{aligned}
$$

But it is more commonly recognized as $\frac{d\,S}{d\,\overline{E}} = \frac{1}{T}$ where $\beta = \frac{1}{T}$.

This statistical mechanical derivation shows that the thermodynamic property of temperature does not require any concepts like pressure, energy, or volume to exist. The only requirements are 1) there must be entropy, and 2) that it increases in the average case. It doesn't matter if the "arrangeable things" are particles, energy, checkerboard game pieces, or a basket of french fries. If french fries in a basket can be anywhere else (has entropy), then the basket of fries will have a "french fry temperature" that is unrelated to its thermal temperature. This french fry temperature determines the rate at which the fries in the basket will "radiate out" from its location of high concentration (the basket) to places of lower concentration (like in the mouths of hungry people who like french fries).

So in layman's terms, if a system can things that can be arranged, then it has entropy; if a system has entropy, then it has a temperature.

Temperature is simply a parameter (lagrange multiplier) that quantifies the tendency for a system to spontaneously emit "stuff".

Specific Heat

Specific heat can be understood to be the quantity of "things" required to change the temperature by 1 unit. This idea is one that we're familiar with in the physical world. Adding and removing energy to things increases and lowers their temperatures; and some things heat up and cool down faster than others. This macroscopic property can be derived by simply assuming that $\overline{E}$ (average "stuff" per state) has variance, or uncertainty, in its measurement.

$$Var(E) = \overline{(\Delta E)^2}$$

Then, with $\overline{E} = -\frac{1}{Z}\frac{dZ}{d\beta}$

$$\begin{aligned} Var(E) &= \overline{E^2} - (\overline{E})^2 \\ &= \sum_i \frac{1}{Z} e^{-\beta E_i} E_i^2 - \left(\frac{-1}{Z}\frac{dZ}{d\beta}\right)^2 \\ &= \frac{1}{Z}\frac{d^2 Z}{d\beta^2} - \frac{1}{Z^2}\left(\frac{dZ}{d\beta}\right)^2 \end{aligned}$$

since

$$\begin{aligned} \sum_i \frac{1}{Z_E} e^{-\beta E_i} E_i^2 &= -\frac{d}{d\beta}\left(\sum_i \frac{1}{Z} e^{-\beta E_i} E_i\right) \\ &= -\frac{d^2}{d\beta^2}\left(\sum_i \frac{1}{Z} e^{-\beta E_i}\right) \\ &= \frac{1}{Z}\frac{d^2}{d\beta^2}(Z) \end{aligned}$$

Then,

$$\begin{aligned} &= \frac{1}{Z}\frac{d^2 Z}{d\beta^2} + \frac{\partial}{\partial Z}\left(\frac{1}{Z}\right)\frac{dZ}{d\beta}\left(\frac{dZ}{d\beta}\right) \\ &= -\frac{d}{d\beta}\left(\frac{-1}{Z}\frac{dZ}{d\beta}\right) \\ &= -\frac{d\overline{E}}{d\beta} \end{aligned}$$

So with

$$\begin{aligned} \beta &= \frac{1}{T} \\ \frac{d\beta}{dT} &= -\frac{1}{T^2} \end{aligned}$$

we have

$$\begin{aligned} Var(E) &= -\frac{d\overline{E}}{d\beta} \\ &= -\frac{\partial \overline{E}}{\partial T}\frac{dT}{d\beta} \\ &= -\frac{\partial \overline{E}}{\partial T}(-T^2) \\ \frac{\partial \overline{E}}{\partial T} &= \frac{\overline{(\Delta E)^2}}{T^2} \end{aligned}$$

There are two things to note here.

First, the concept of “specific heat” requires only one more assumption than the assumptions that went into the derivation of temperature –the assumption of variance. If the average “stuff” per state has any variance or uncertainty in its measurement, then the system will have the property of “specific heat”. So, like temperature, the concept of specific heat is not tied to being anything “physical” like a gas, liquid, or solid. It only requires that a system have a “number of arrangements” and uncertainty of the quantities of “stuff” in those arrangements.

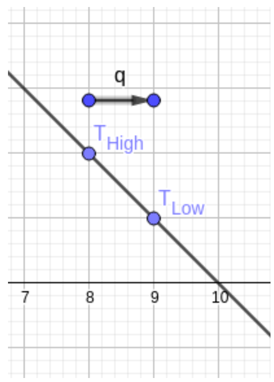
Second, the squared term ensures the specific heat is always positive. This means if the amount of “stuff” increases/decreases, then its temperature increases/decreases. This concept should be familiar. ie. If energy is added to a cup of coffee, its temperature will rise and will be more likely to emit energy. If energy is taken away, its temperature will fall and be more likely to absorb energy. This property ensures that two systems with different temperatures will reach a stable equilibrium after some time, if brought together.

Direction of Flow

This description is in regard to the direction of flow of arrangeable things, and it moves from systems with high temperature to systems of low temperature. In the world we're all familiar with, that thing is energy, and it moves the same way. The rate at which energy is transmitted depends on the medium's conductivity *k*. The larger *k* is, the higher the rate of flow.

$$q = -k\frac{dT}{dx}$$

For example, consider the temperature at a single point on the x-axis. If the temperature at that point is cooler then the point immediately to its left, then the slope between those two points, $\frac{dT}{dx}$, will be negative, making *q* positive, indicating energy will flow to the right along the x-axis. Thus, energy/heat flows from hot to cold regions.



The temporal change in "arrangeable energy" over time is proportional to the second derivative of the temperature with respect to *x*.

$$\frac{dE}{dt} = -\frac{d}{dx}\left(\frac{dq}{dx}\right)$$
$$\frac{dE}{dt} = k\frac{d^2T}{dx^2}$$

When the temperature at *x* is higher than the average temperature of its immediate environment , $\frac{d^2T}{dx^2} < 0$, some quantity of *E* (on average) will be emitted away from point *x*, and its temperature change will also be negative, leading to a temperature decrease. If *x* is colder than its immediate environment $\frac{d^2T}{dx^2} > 0$, then some quantity of *E* will be absorbed leading to a positive increase in temperature.

All Together

So, if 1) a system has “things” like energy, and 2) those things can be arranged (have entropy), 3) there is error/variance in its energy level, 4) the system evolves to increase entropy, then it is a system that A) has temperature, and B) the evolution of temperature over time can be modelled with the full heat equation, which is

$$\frac{dT}{dt} = \frac{\partial T}{\partial \overline{E}} \frac{d\overline{E}}{dt}$$

$$\frac{dT}{dt} = \frac{T^2}{\overline{(\Delta E)^2}} k \frac{d^2 T}{d x^2}$$

which is your basic heat equation, with thermal conductivity *k*.

This equation describes how temperature evolves through a system that has everything held constant – the number of states, and the total energy (or any other “arrangeable” thing) of the system. A collection of particles interact with other particles and exchange energy via positive specific heat. Any concentrations will diffuse through a system and reach an equilibrium.

From Debt Diffusion to Demand Infection

Maximizing capital growth by maximizing the spread of payment obligations should come as no surprise. The role of an economic competitor in a market-driven economy is simple: To create products and services that are high in demand, diffusing those "payment obligations" as aggressively as possible through an economic system (distribution, advertising, social media, word-of-mouth, etc), and maximizing the probability of converting as many "non-customers" that interacted with this diffused debt/demand into "customers".

The combination of the two assumptions of 1) increasing entropy (giving homogeneous mixing), and 2) transformation between two states ("non-customer" and "customer") places debt/demand diffusion firmly within the realm of disease modelling –Epidemiology. Modelling the spread of debt and its conversion into equity within an economic system as a contagious viral infection that changes a "susceptible" population into an "infected" one should not only be appropriate, but its consequences should also be consistent with current ideas and observations in micro and macro economic systems in incredibly fundamental ways.

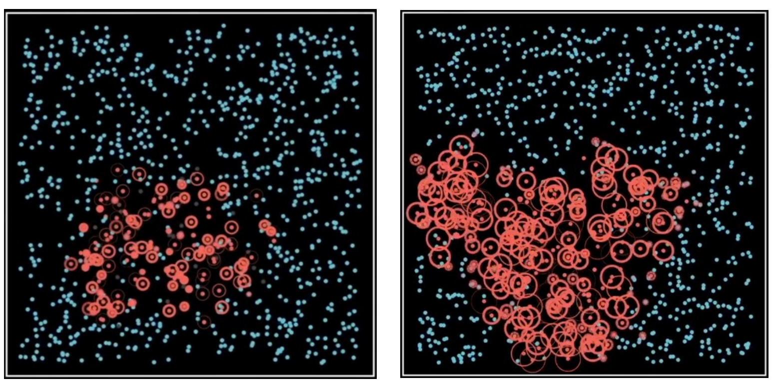


Figure 11: A simulation of a viral infection diffusing through a population.
Source: 3Blue1Brown https://www.youtube.com/watch?v=gxAaO2rsdIs

The Basic Dynamics of Infection – The SI Model

The SI model of infection is one of the most basic models for describing the progression of an infectious disease in a population over time. People are assigned one of two states, *susceptible* and *infected*, and they transition from the susceptible state to the infected state. One of the key assumptions required by this and related models is the assumption of homogeneous mixing of susceptible and infected people. That is, concentrations of infected people spread out within in the population to areas where infections are less common. This assumption is essentially a re-wording of the assumption of "increasing entropy" requirement of temperature and diffusion. Arriving here makes sense intuitively when the initial objective was to maximize growth.

Starting with a population of ***N*** people, the number of susceptible people *S(t)*, and infected people *I(t)*,

$$S + I = N$$

Working with fractions of the total population, the susceptible and infected fractions s and i are,

$$s = \frac{S}{N} \quad \text{and} \quad i = \frac{I}{N} \quad \text{, so} \quad s + i = 1$$

New infections develop with probability β when a susceptible person interacts with an infected person. So the change in the fraction of the population that are infected will be,

$$\frac{di}{dt} = \beta i\, s$$

Likewise, the change in the fraction of the population that are susceptible will be,

$$\frac{ds}{dt} = -\beta i\, s$$

A stable state (equilibrium) is reached when the infection rate does not change with time, $\frac{di}{dt} = 0$.

Since $\frac{di}{dt} = -\frac{ds}{dt}$, this can only happen when either $\beta = 0$, or $i = 0$, or $s = 0$.

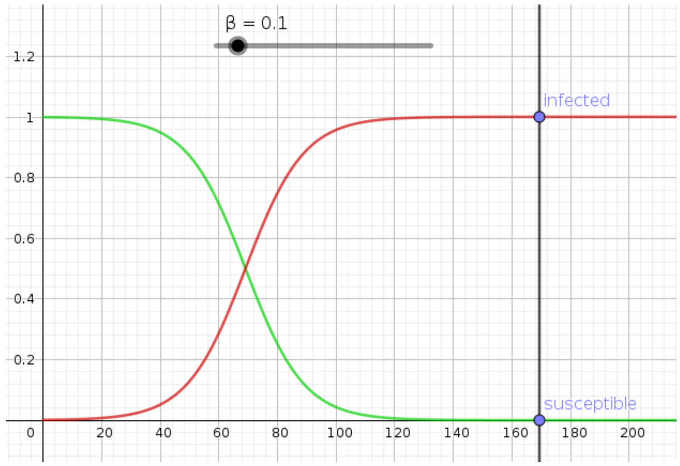


Figure 12: A numerically-computed solution with s(0) = 0.001 shows the susceptible fraction of the population inevitably falling to zero.

The transition from “susceptible” to “infected” is not unlike the transition from “non-customer” to “customer”. They are both simply changes of state. The statistical mechanical assumptions of “demand diffusion” are identical to the base assumptions of the SI model of infection –homogeneous mixing that comes with diffusion, and a probabilistic change of state upon an interaction. So, there is a possibility that an economic system may very well be, at its most fundamental level, a system of infection.

Economic “Infection”?

Employing the idea of viral growth is not meant to suggest or imply anything negative towards economic systems. It is simply a system of things that has increasing entropy that have a probability of changing states. In a system with viral infection, the virus is the thing with increasing entropy, and the two states are ***susceptible*** and ***infected***. An economic system would have demand as the entity with increasing entropy, with the two states being ***susceptible*** and ***customer***. People who become “infected” convert a company’s diffused “demand” into “equity”. In this way, each percent of infected population has a worth to the company $\frac{dE}{di}$ so $\frac{dE}{dt}=\frac{dE}{di}\frac{di}{dt}$ where $\frac{di}{dt}=\beta i s$.

Biological organisms that become infected by a viral or bacterial disease often become contagious themselves and transmit their infection to other organisms. This is the reasoning behind $\beta i s$; the *infected* and *susceptible* have to interact. While word-of-mouth advertising would be the closest analogue to biological viral spread (“organic growth”), media outlets like television, online advertising, and social media would be major drivers for the diffusion of demand via advertising.

Figure 12 illustrates the progression of market share if every susceptible entity transitioned to the *customer* state with a 10% probability after interacting with “infectious demand” that was diffused through this economic system (through a long-lasting advertising campaign perhaps). Realistically, it is only a matter of time before market share growth slows so dramatically that diminishing marginal market share gains fall below the costs of maintaining that constant rate of diffusion (advertising).

It’s important to note that the “infection probability” β would encapsulate many factors involved with the probability of state transition: The appeal of the ads shared via social media, the popularity/effectiveness of media events or trade shows, transition/conversion rates after word-of-mouth exposure, even the transition rates acquired through deceptive business practices and fraud, etc.

In sales, this probability is known as the “close rate”. This metric that measures the effectiveness of converting leads or prospects into paying customers. Under this infection model, these prospects would have been the susceptible population who have been made aware of –or exposed to– the product or service.

SIS Model of Infection

Losing Market Share

Products and services usually have a shelf-life. If a customer's purchase only lasted a certain amount of time, they would again be "susceptible" to being convinced to make a subsequent purchase. In the SIS (Susceptible – Infected – Susceptible) model of infection a recovery term $0 \leq \gamma \leq 1$ is introduced and reflects the probability that an infected person will again be susceptible to infection. The recovery rate can be thought of as $\gamma = \frac{1}{D}$ where $D = E[\textit{infected periods}]$, the average duration of infection. The fraction of the infected population that is expected to recover from infection at any point in time is then γi .

Starting with,

$$s + i = 1 \quad \text{where} \quad s = \frac{S}{N} \quad \text{and} \quad i = \frac{I}{N}$$

The change in the fraction of the infected and susceptible populations with recovery term γ becomes,

$$\frac{di}{dt} = \beta\, i\, s - \gamma\, i \quad \text{and} \quad \frac{ds}{dt} = -\beta\, i\, s + \gamma\, i$$

The infected fraction of the population won't change at equilibrium $\frac{di}{dt} = 0$, so

$$0 = i_E \left(\beta \left(1 - i_E\right) - \gamma\right)$$
$$i_E = 1 - \frac{\gamma}{\beta}$$

where i_E is the infected fraction of the population at equilibrium.

This means at steady-state (in the long run), either nobody's infected $i_E = 0$, or a fraction of the population will always be infected, $i_E > 0$, and that fraction will converge at $i_E = 1 - \frac{\gamma}{\beta}$, leaving the susceptible fraction at equilibrium as $s_E = \frac{\gamma}{\beta}$.

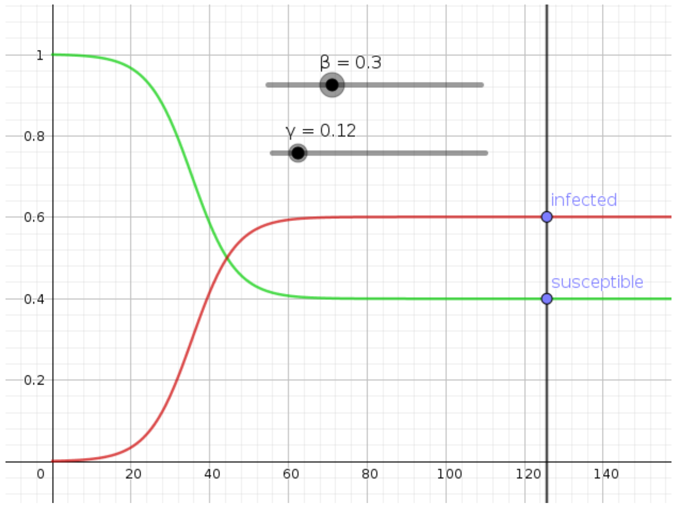


Figure 13: Infected fraction vs time. 1 – 0.12/0.3 = 60% infected population at steady-state.

For certain companies that sell long-lived products (cars, washing machines, etc), the recovery rate γ will be a small number because a reasonably long period of time will pass before their customers become susceptible again to buying a product of the same type again. The duration may likely depend on things like product durability, customer satisfaction, obsolescence, degree of customer lock-in, etc. Companies that sell relatively short-lived products and services like streaming media subscriptions and smart phones will have relatively shorter recovery times, and therefore larger γ .

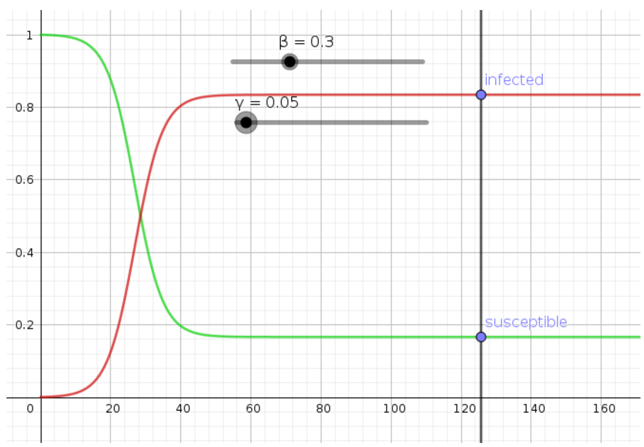


Figure 14: A lower recovery rate (0.05 from 0.12) increases steady-state market share to 1 – 0.05/0.3 ≈ 83%.

Reducing the recovery rate from 0.12 to 0.05 while leaving the infection rate unchanged increases market share to 1 – 0.05/0.3 = ~83% at steady-state.

The stability of a system with multiple competing strains under the SIS model of infection has been studied in depth. In the study of epidemiology, the term $R_0 = \frac{\beta}{\gamma}$ is known as the "basic reproduction number". An infectious equilibrium $i_E > 0$ will be reached if a strain has $R_0 > 1$, or will eventually die out $i_E = 0$ if $R_0 < 1$.

Competition and Market Share Stability

Opportunities for a company to grow and expand as the sole provider of a particular good/service demand in a capitalist economy are fairly rare. Many economic systems consist of multiple companies competing with each other over the same finite resource of potential market size. Infection modelling of a system consisting of multiple strains can be used to illustrate the dynamics of economic competition.

With ***n*** number of competing infectious strains, and assuming a susceptible person can be infected by one strain at a time, then the susceptible and infected fractions of the entire population are:

$$s + i_1 + i_2 + i_3 + \dots + i_n = 1$$

The change in the fraction of the susceptible population becomes,

$$\frac{ds}{dt} = -\frac{di_1}{dt} - \frac{di_2}{dt} - \frac{di_3}{dt} - \dots - \frac{di_n}{dt}$$

Using the SIS model of infection (Susceptible – Infected – Susceptible) where each strain has their own infection and recovery rates β_k and γ_k, we have the following

$$\frac{ds}{dt} = -(\beta_1 s + \gamma_1) i_1 - (\beta_2 s + \gamma_2) i_2 + \dots - (\beta_n s + \gamma_n) i_n$$

$$\frac{di_1}{dt} = (\beta_1 s - \gamma_1) i_1$$

$$\frac{di_2}{dt} = (\beta_2 s - \gamma_2) i_2$$

$$\dots$$

$$\frac{di_n}{dt} = (\beta_n s - \gamma_n) i_n$$

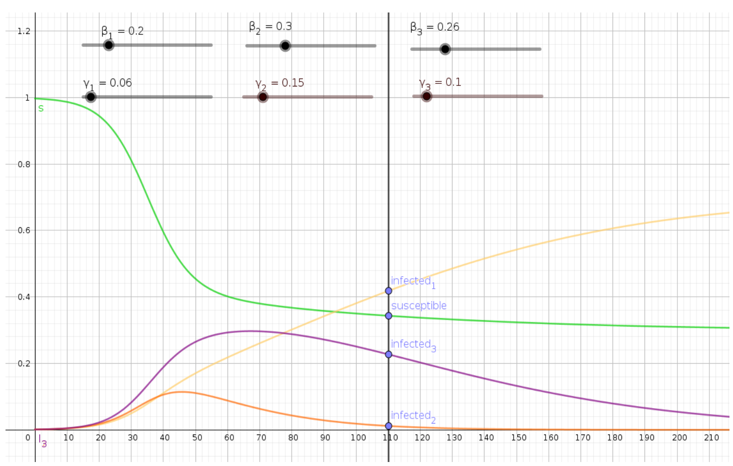


Figure 15: A system with three infectious strains, each with different infectiousness and rates of recovery. The strain with the largest R_0 will eventually dominate in finite time.

It is not at all obvious at first what values transmission and recovery parameters need to be in order for infections to coexist successfully with one another. Even with all parameters held constant, strains with the highest growth *initially* do not necessarily become the dominant strain in the long run. In fact, their demise may already be guaranteed despite having characteristics of transmission and recovery that achieve the strongest growth in the early phases of competition.

Others have shown that infectious strains with the largest R_0 will eventually dominate, and all other strains with lower R_0 will become extinct in finite time. However, there are scenarios where multiple competing strains can coexist at equilibrium (the long run).

Given the total infected fraction of the population is

$$i = i_1 + i_2 + \ldots + i_k + \ldots + i_n$$

Which means

$$\frac{di}{dt} = (\beta_1 s - \gamma_1) i_1 + (\beta_2 s - \gamma_2) i_2 + \ldots + (\beta_k s - \gamma_k) i_k + \ldots + (\beta_n s - \gamma_n) i_n$$

Then if all k infectious strains are to coexist $i_k > 0$ at equilibrium, then $(\beta_k s - \gamma_k) = 0$ for all strains. This can only happen if $\frac{\gamma_1}{\beta_1} = \frac{\gamma_2}{\beta_2} = \ldots = \frac{\gamma_n}{\beta_n}$, or in other words $\frac{1}{R_{0,1}} = \frac{1}{R_{0,2}} = \ldots = \frac{1}{R_{0,k}} = \ldots = \frac{1}{R_{0,n}}$.

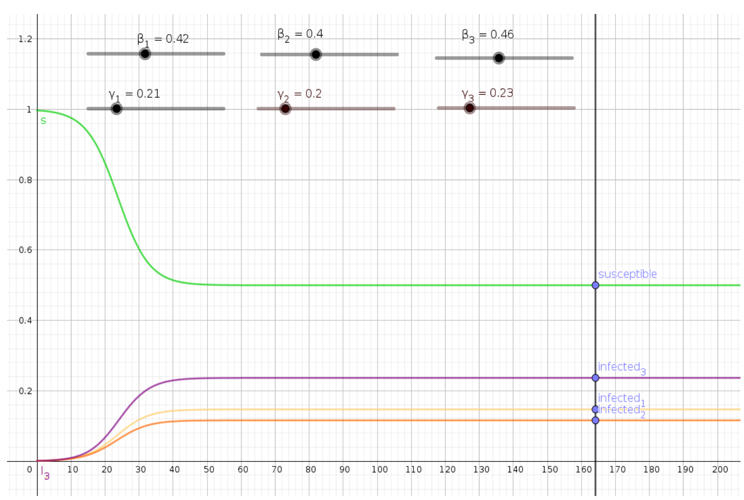


Figure 16: A system (infected fraction vs time) with three infectious strains, each with identical R_0 and initial values of $i_k(0) = 0.001$.

Within the context of an economic system, long-term market share stability can be achieved if economic participants design and price their products and services so their market share gain and loss rates converge on the same $\frac{\gamma}{\beta}$, which we can represent as $\frac{1}{R_{0,E}} = \frac{\gamma_E}{\beta_E}$ with $R_{0,E}$ being the reproduction number that all strains must share to coexist at equilibrium.

If a strain *k* suddenly achieves a higher reproduction number $R^*_{0,k}$ than all other strains in the system $R^*_{0,k} > R_{0,E}$, then strain *k* will eventually dominate the system and all other strains will eventually become extinct if their parameters of infection remain constant. Namely, $i_j \rightarrow 0$ in finite time for all other *j* strains where $R^*_{0,k} > R_{0,j}$.

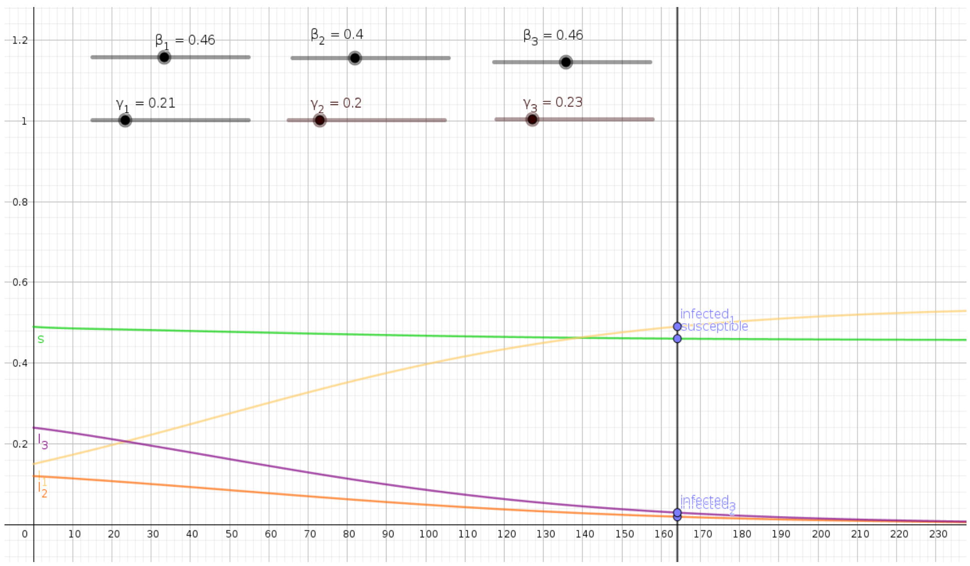


Figure 17: Using steady-state infection rates in Figure 16 as starting points, a small increase in $R_{0,1}$ leads to dramatic growth in market share.

Economically, this incentivizes smaller and/or less innovative market participants to simply copy features of products with the most aggressive market share growth in order to acquire the same, or higher $R^*_{0,k}$.

SIS Economic Model with Periodic Infection

Investigations into the SIS model of competing strains of demand so far have applied the probability of transmission β on the assumption of constant instantaneous homogeneous mixing of the infected and susceptible fractions of the population $i\,s$. However, assuming periodic mixing isn't an unreasonable assumption to make. A virus that is infectious to humans has a greater opportunity of achieving homogeneous mixing during daylight hours than overnight, when the majority of people are at home and asleep. In an economic system, many products and services are seasonal, manufacturing plants have production cycles, inputs need to be acquired, inventories take time to build up, transport and distribution of finished products are not instantaneous, advertising campaigns take time to plan and execute, and these sales cycles come to an end. Additionally, economic participants have strong incentive to synchronize these economic phases as much as possible to avoid costly inefficiencies that result from delays.

So, a new periodic probability function $p(t)=\sin^2\left(\frac{1}{C}\pi\,t\right)$ will be defined to capture the oscillation of demand that diffuses through an economic system, with ***C*** being the average duration of one complete cycle. The function $\sin^2(x)$ provides a convenient method for obtaining a sine curve such that $0\leq p(t)\leq 1$.

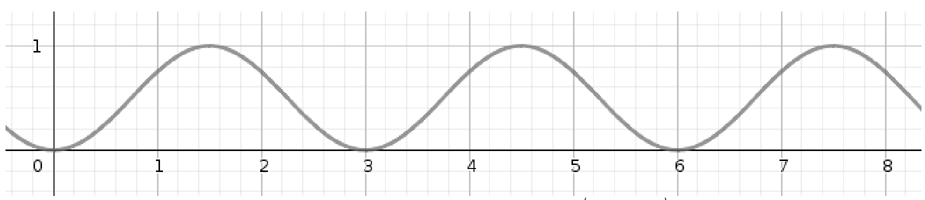


Figure 18: Probability function $p(t)=\sin^2\left(\frac{1}{C}\pi\,t\right)$ *with C = 3*

Starting with the same fractions of the infected and susceptible populations over time $\frac{di}{dt}=i(p\beta s-\gamma)$ and $\frac{ds}{dt}=-i(p\beta s+\gamma)$, an infectious equilibrium is reached when $\frac{di}{dt}=0$. If a fraction of the population remains infected at equilibrium, then $i>0$. The periodicity of $\sin^2(x)$ means the actual infected fraction *i* will vary around the average value of $\sin^2(\pi x)$. Then, maybe considering the *expected* infected fraction $E\left[\frac{di}{dt}\right]$ to zero would reveal the state of the system at equilibrium.

Beginning with the definition of expectation,

$$E[f(x)] = \frac{1}{T}\int_0^T f(x)dt$$

We have

$$E\left[\frac{di}{dt}\right] = \frac{1}{T}\int_0^T i(p(t)\beta s - \gamma)dt$$

Due to the periodic nature of $p(t) = \sin^2(\pi x)$, only the interval between 0 and 1 is needed since that is the interval of one complete period.

$$\begin{aligned} E\left[\frac{di}{dt}\right] &= i\frac{1}{T}\int_0^1 (\sin^2(\frac{1}{C}\pi t)\beta s - \gamma)dt \\ 0 &= i\left[\left(\frac{1}{2}t - \frac{C}{4\pi}\sin(\frac{1}{C}2\pi t)\right)\beta s - \gamma t\right]\Bigg|_0^1 \\ &= i\left(\frac{1}{2}\beta s - \gamma\right) \end{aligned}$$

So, if $i > 0$ at equilibrium, the expected infected fraction i will be

$$\begin{aligned} 0 &= \frac{1}{2}\beta(1-i) - \gamma \\ i &= 1 - \frac{2\gamma}{\beta} \end{aligned}$$

The recovery rate is effectively doubled, halving the strain's oscillation-free R_0 .

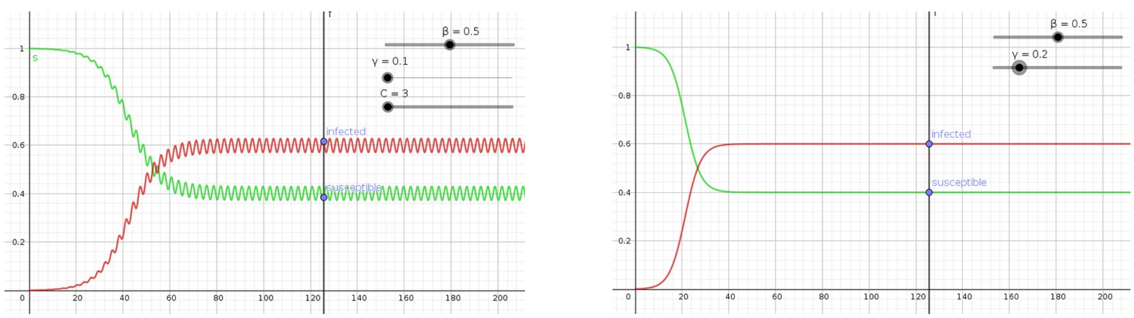


Figure 19: Periodic infection at equilibrium (Left), vs constant infection rate with double

Competitive Market Share Stability of Periodic Demand Infectiousness

Multiple competitive strains can reach a stable equilibrium of coexistence if the duration of their infectiousness cycle are of the same length C and synchronized to be in-phase with each other.

Starting with the SIS model with multiple competing strains, we have

$$\frac{di_{total}}{dt} = (p_1(t)\beta_1 s-\gamma_1)i_1 + (p_2(t)\beta_2 s-\gamma_2)i_2 + \ldots + (p_n(t)\beta_n s-\gamma_n)i_n$$
$$where\ s = 1-i_1-i_2-\ldots-i_n$$

It was shown earlier it was possible for competing strains to coexist in equilibrium if each strain shared the same R_0. One obvious equilibrium of coexistence would be where $p_k(t) = p_1(t)$, making $\sin^2\left(\frac{1}{C_k}\pi t\right) = \sin^2\left(\frac{1}{C_1}\pi t\right)$ for each strain *k*.

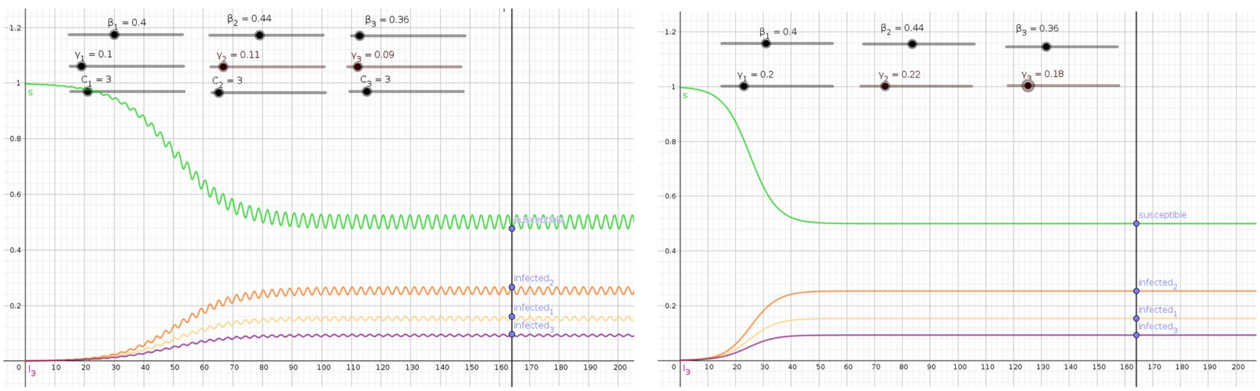


Figure 20: With $C_K = C_1$, i_k and s will converge to, and oscillate around, the same equilibrium as an identical non-periodic system with all recovery rates doubled.

Within the context of economic systems, periodic infectiousness can result in market share stability of multiple competitors in the long run if all cycles involved (production, distribution, advertising, etc) share the same duration, start and end at the same time, and the same R_0.

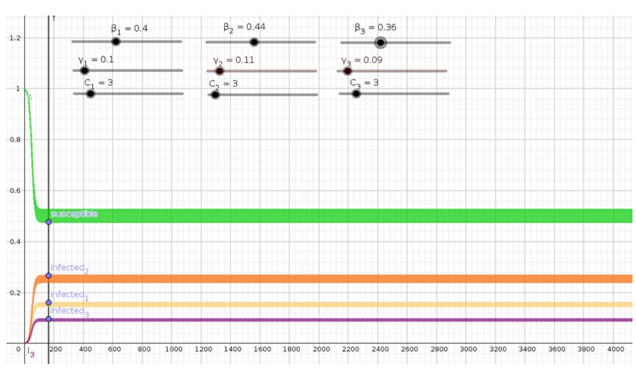


Figure 21: Long-run stability of synchronized periodic demand infectiousness

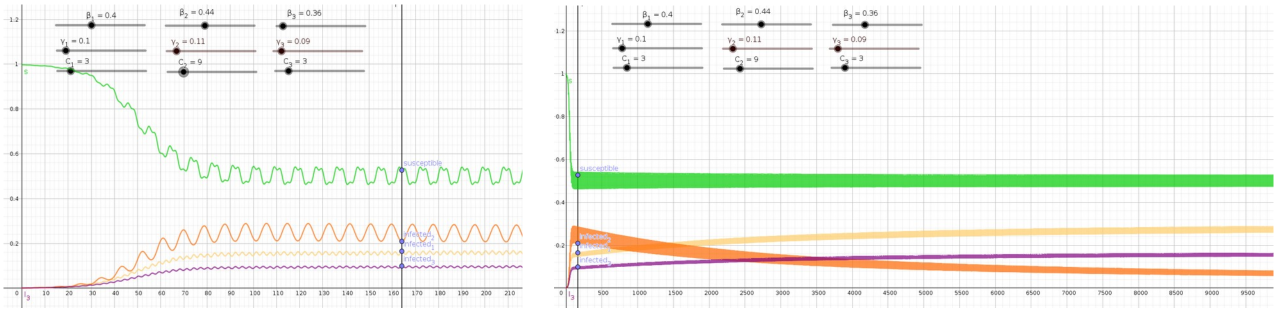


Figure 22: Increasing cycle duration C_k of strain k leads to a reduction of the infected fraction i_k at equilibrium.

A competitive strain k having a longer duration for their demand cycle C_k of a competitive economic participant exposes its “recovering” customers to infection by their competition at a relatively higher frequency. Ultimately, this drives market share i_k lower over the long run.

This should incentivize market competitors to shorten the duration of their demand cycle (production, distribution, advertising, etc).

Competitive Market Share Stability with Shifted Periodic Infection Rates

A market with periodic demand that reaches an equilibrium of coexistence in a market economy may be an indication of a non-competitive market. Similar products with very similar pricing may offer no meaningful differences in their products’ infection and recovery rates β and γ in the eyes of the susceptible consumers. However, even if all participants share the same reproduction number at equilibrium $R_{0,E}$, a competitor can still disrupt this equilibrium and grow their market share.

A parameter *d* will be introduced that indicates the fraction of a cycle to lead by.

$$p(t) = \sin^2\left(\left(\frac{1}{C}t + d\right)\pi\right) \quad \text{, where} \quad 0 \leq d \leq 1$$

Consider two market competitors *k* and *j* at a periodic infectious equilibrium $R_{0,k} = R_{0,j} = R_{0,E}$, both with cycle length $C_k = C_j = 1$. Market competitor *k* can achieve a *temporary* higher effective infection rate $p_k(t)\beta_E > p_E(t)\beta_E$ than the rest of the stable market that shares the same $R_{0,E}$ and period lengths, by shifting their own periodic demand forward such that $0 < d_k < \frac{1}{2}$.

Figure 23: $p_k(t) = \sin^2\left((t+0.2)\pi\right)$ *(red) vs* $p_E(t) = \sin^2(t\pi)$ *(blue)*
Green area denotes range of d_k where competitor k (red) gains a relative advantage.

While this advantage is temporary, competitors with the same $R_{0,E}$ will have their own infectiousness apply over a now-smaller susceptible population. Therefore, it will be impossible for all other competitors to reclaim market share lost to competitor *k* due to their periodic shift of $0 < d_k < \frac{1}{2}$ if their parameters of infection do not change.

Maximizing the difference between $R_{0,k}$ and $R_{0,E}$ with all other infection parameters held constant can be done by maximizing the difference between $\sin^2\left((t+d)\pi\right)$ and $\sin^2(t\pi)$ over the interval $0 \le t \le \frac{1}{2}$.

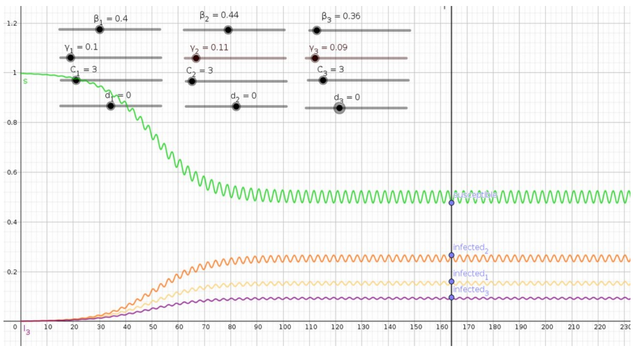
$$
\begin{aligned}
G(t,d) &= \int_0^{0.5} \sin^2\left[\left((t+d)\pi\right) - \sin^2(t\pi)\right] dt \\
&= \left. \frac{-\sin[2\pi(t+d)] + 2\pi d + \sin(2\pi t)}{4\pi} \right|_0^{0.5} \\
&= \frac{\sin(2\pi d) - \sin[2\pi(d+0.5)]}{4\pi}
\end{aligned}
$$

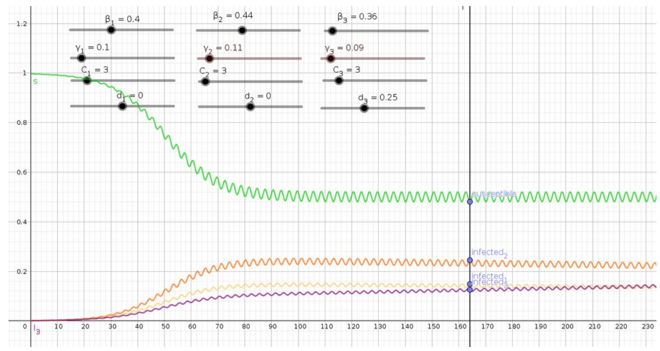
Maximizing the difference with respect to phase shift *d*,

$$
\begin{aligned}
\frac{dG}{dd} &= \frac{1}{2}\left[\cos(2\pi d) - \cos(2\pi d + \pi)\right] \\
0 &= \cos(2\pi d) - \cos(2\pi d + \pi) \\
0 &= 2\cos(2\pi d) \\
d &= \ldots, -\frac{3}{4}, -\frac{1}{4}, \frac{1}{4}, \frac{3}{4}, \ldots
\end{aligned}
$$

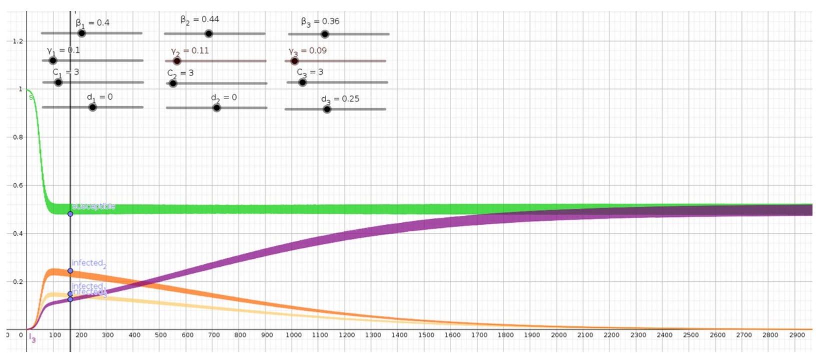
Ensuring $\frac{d^2G}{dd^2} = -2\pi\sin(2\pi d) < 0$ gives $d = \ldots, -\frac{3}{4}, \frac{1}{4}, \frac{5}{4}\ldots$

So, a market competitor *k* could maximally disrupt a non-competitive economic system at equilibrium with periodic demand cycles by consistently starting their own demand cycle 1/4th of a period earlier than other participants (if their demand cycles are periodic) if all other parameters of infection are held constant.





a) A competitive viral system at equilibrium, i vs t. *b) The same viral system as a), but with shift d_3 = 1/4*



c) Long-run view of b)

Figure 24: Shifting a periodic demand infectiousness curve forward by 1/4 cycle creates a larger effective R_0, even when all other parameters of infection necessary for market share stability are identical (equivalent R_0 and C).

Recalling that the strain with the largest R_0 will eventually dominate and drive all other strains to extinction, this advantage due to timing may not last in reality if competitors also advance the timing of their demand cycles to match in response. (Anecdotally, this could explain why retailers appear to put holiday-related goods out for sale earlier and earlier).

Comments

While the SIS model of infection is fairly understood in the field of epidemiology, its application as a model for competitive market economies does not appear to be a common idea. The use of SIS is a reasonable choice given that companies not only acquire, but lose customers as well. Further investigation is required to validate whether infection models align with economic realities for macroeconomic and financial forecasting. What follows is a list of potential areas for testing the validity of the economic infection model, which arises from the assumption of debt and demand diffusion.

Business and Product Life Cycles, and Their Inference

The product life cycle curve is very likely a simple infection curve. Concepts such as innovation diffusion[2], exponential growth, maturity, product evolution, and survival of the fittest already evoke ideas of biological processes and viral spread. The SIS model of infection is a fundamentally-derived analytical description for the anecdotally-observed product/business life cycle[3], and unifies several disconnected concepts under a single economic theory of debt/demand diffusion.

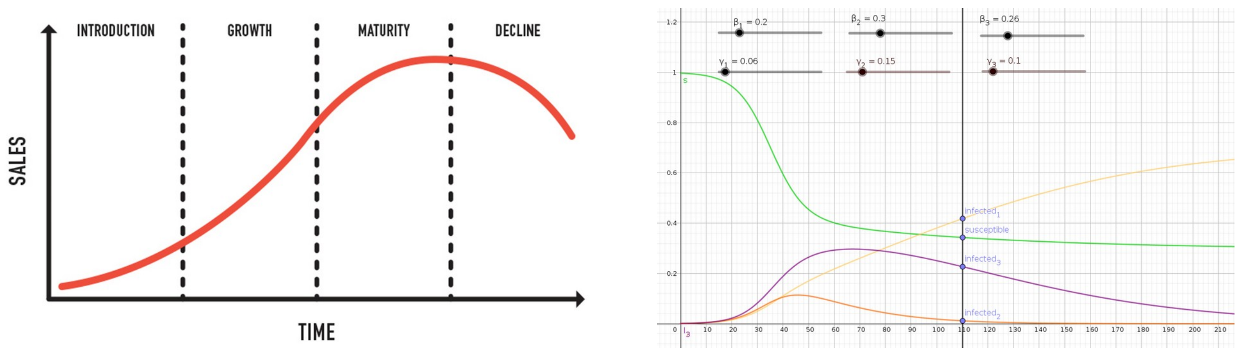


Figure 25: A simple visualization of the four stages of the product life cycle (left), vs infection curve over time (right).
https://commons.wikimedia.org/wiki/File:Product_Life_Cycle_Management.png
Image author: Tres West. Used, unmodified, under the Creative Commons Attribution-Share Alike 4.0 International license [https://creativecommons.org/licenses/by-sa/4.0/deed.en]

Verification of the SIS infection model as an economic model should be possible with industry sales and marketing data that will most likely be proprietary and confidential. It should not only be possible to model and validate the sales performance of industry competitors, but it should also be possible to infer the aggregate performance of competitors whose data are not publicly disclosed (privately owned companies). This may be complicated by several factors. First, the low frequency of such data may put a floor on the resolution of measurements and forecasts. Second, β and γ of competitors may evolve over time in a way that may be less than predictable.

2 https://en.wikipedia.org/wiki/Diffusion_of_innovations
3 https://en.wikipedia.org/wiki/Product_life-cycle_management_(marketing)

Marketing and Epidemiology – Direct and Viral Advertising

Companies engage in direct advertising in order to communicate information about a product or service directly to consumers. This is in contrast with viral marketing, which communicates information through the word-of-mouth interactions of customers. In the economic model of infection, direct advertising (flyers, television commercials, billboards, etc) can be though of as a constant source of infection.

If an entire population receives a constant source of exposure ‘c’, then the total fraction of the population that has been exposed ‘a’ will be $a = c \cup i$.

The infection model then becomes $\frac{di}{dt} = \beta a s - i\gamma$ and $\frac{ds}{dt} = -[\beta a s - i\gamma]$ with $s = 1 - i$.

With this modification, companies should be able to fit their market share growth profile to this model and determine the parameters of infection of their products, or company as a whole. The increased exposure has a theoretical limit on its effect on market share, and thus a theoretical maximum on the number of sales that can be expected over a set period of time. This model can then be used to further optimize their product planning, pricing, and marketing strategies and budgets.

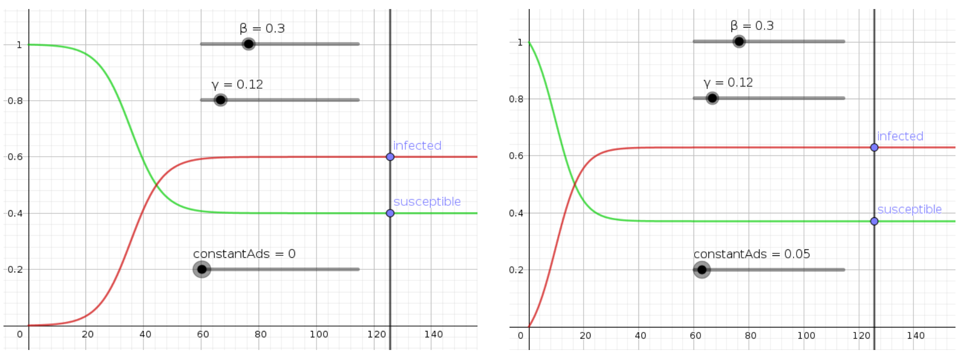


Figure 26: Numerically-computed solutions with i(t=0) = 0.001, and their given infection and recovery parameters. Ads constantly shown to 0% of a population (Left) vs 5% of a population (Right).

Extending this model to estimate the outcome of direct and viral marketing campaigns among multiple economic competitive strains should be fairly straightforward. The variables and metrics associated with “viral advertising” ought to align those used in viral disease modelling. So, marketers should be capable of identifying quantitative methods for measuring, tracking, and forecasting the performance of marketing strategies within the field of epidemiology.

Non-Competitive Markets

Market share stability is achieved when R_0 (and frequency and phase shift, in the case of periodic demand cycles) are identical across all market participants. Any change by any single competitor would be enough to break this stability if allowed to persist. Achieving market share stability is obviously easier to do when 1) there are few dominant market participants, and/or 2) market participants collude on price. Collusion allows dominant participants to maximize revenue while reducing costs –customer acquisition costs, advertising, R&D, etc. However, collusion or cooperation are not required to form a non-competitive market. Participants simply need to strive for “good enough”, and poseess no desire to gain market share by advancing their periodic demand cycle either.

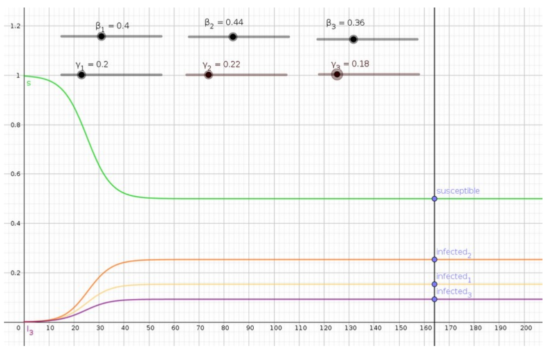


Figure 27: Market share in a non-competitive market

However, market share stability at equilibrium appears fragile on short time horizons. It only takes one competitor *k* to break stability by increasing their own β_k , or decreasing their customer “recovery” rate γ_k , or advancing the phase shift d_k (if their demand is periodic). If any competitor *k* establishes a higher basic reproduction number $R^*_{0,k}$ than the rest of the market at equilibrium $R^*_{0,k} > R_{0,E}$, this will be enough for market share gains $\frac{di_k}{dt} > \frac{di_j}{dt}$, and eventual market share dominance, if all other *j* competitors fail to respond by:

1. Improving their own infection and recovery rates to match via sales discounts and marketing, such that $R_{0,j} = R^*_{0,k}$
2. Absorbing the competitor to eliminate its higher $R^*_{0,k}$ from the market, re-establishing stability at $R_{0,E}$.
3. Absorbing the competitor, or establishing licensing agreements, to gain the innovations and efficiencies and higher $R_{0,j} = R^*_{0,k}$ quickly.

Under this economic infection model, it may be argued that the mere presence of market share stability, or highly correlated non-seasonal marketing, could be an indicator of a non-competitive market. Restricting mergers in markets with stable market share may help ensure a competitive market economy by effectively transforming market share stability into an economic prison for all large competitors, from which innovation is the only means of escape.

Price Elasticity of Demand and Supply

This competitive infection model can easily assimilate the concept of price elasticity of demand (PED) for any number of competitors, and determine its effects on market share of all other competitors at the same time.

Price Elasticity of Demand

Elasticity of demand is typically negative. With most products, consumers will purchase fewer quantities when their prices rise. Values near zero mean quantities purchased does not change meaningfully with substantial changes in price.

Beginning with the definition $PED = \frac{dQ}{dP}\frac{P}{Q}$, where Q is the expected transacted quantity at expected price P , PED is the average percent change in quantity transacted per average percent change in price.

The expected transacted quantity Q can be expressed as

$$Q = p_{transaction} Q_{total}$$

where Q_{total} is the total quantity available or offered for sale. Or simply, total inventory, or total supply. The probability of transaction is then the fraction of the population that are non-customers s , that become exposed to advertising broadcast to a fraction of the population a , which then in turn decide to engage in a transaction with probability β (the “conversion rate”). This gives $p_{\mathrm{transaction}} = \beta a s$. This probability of infection also represents the increase in newly-infected over time $\frac{di}{dt} = \beta a s$, under this infection model of economics.

$$\begin{aligned} Q &= p_{transaction} Q_{total} \\ Q &= \frac{di}{dt} Q_{total} \\ Q &= \beta a s Q_{total} \end{aligned}$$

Taking the derivative relative to price gives,

$$\frac{dQ}{dP} = \frac{d\beta}{dP} a s Q_{total} + \frac{da}{dP}\beta s Q_{total} + \frac{ds}{dP}\beta a Q_{total} + \frac{dQ_{total}}{dP}\beta a s$$

Price elasticity of demand becomes,

$$\begin{aligned} \frac{dQ}{dP}\frac{P}{Q} &= \left(\frac{d\beta}{dP} a s Q_{total} + \frac{da}{dP}\beta s Q_{total} + \frac{ds}{dP}\beta a Q_{total} + \frac{dQ_{total}}{dP}\beta a s\right)\frac{P}{Q} \\ &= \frac{d\beta}{dP}\frac{P}{\beta} + \frac{da}{dP}\frac{P}{a} + \frac{ds}{dP}\frac{P}{s} + \frac{dQ_{total}}{dP}\frac{P}{Q_{\mathrm{total}}} \end{aligned}$$

The exposed fraction of the population ***a*** can be composed of a) viral exposure from existing customers i, and b) a fraction who are exposed to direct/constant media advertising c. Some exposed to constant/direct advertising will also be exposed to viral advertising, so this overlap ic will have to be taken into account to avoid double-counting.

This gives $a = c \cup i = c + i - ci$, or $a = 1 + s(c-1)$ since $s + i = 1$.

Price elasticity of demand is then,

$$\begin{aligned}
\frac{dQ}{dP}\frac{P}{Q} &= \frac{d\beta}{dP}\frac{P}{\beta} + \left(\frac{da}{dc}\frac{dc}{dP} + \frac{da}{ds}\frac{ds}{dP}\right)\frac{P}{a} + \frac{ds}{dP}\frac{P}{s} + \frac{dQ_{total}}{dP}\frac{P}{Q_{\text{total}}} \\
&= \frac{d\beta}{dP}\frac{P}{\beta} + s\frac{dc}{dP}\frac{P}{a} + \left(\frac{da}{ds}\frac{s}{a}\right)\frac{ds}{dP}\frac{P}{s} + \frac{ds}{dP}\frac{P}{s} + \frac{dQ_{total}}{dP}\frac{P}{Q_{\text{total}}} \\
&= \frac{d\beta}{dP}\frac{P}{\beta} + s\frac{dc}{dP}\frac{P}{a} + \frac{ds}{dP}\frac{P}{s}\left(\frac{da}{ds}\frac{s}{a} + 1\right) + \frac{dQ_{total}}{dP}\frac{P}{Q_{\text{total}}}
\end{aligned}$$

Therefore, PED can be decomposed conceptually as,

$$\begin{matrix} Price\ Elasticity \\ of\ Demand \end{matrix} = \begin{matrix} Price\ Elasticity \\ of\ Conversion \end{matrix} + s\begin{pmatrix} Price\ Elasticity \\ of\ Direct \\ Exposure \end{pmatrix} + \begin{matrix} Price\ Elasticity \\ of\ Market\,, \\ Exposure\ Adjusted \end{matrix} + \begin{matrix} Price\ Elasticity \\ of\ Supply \end{matrix}$$

The implication here is that PED can be influenced positively or negatively by manipulating these decomposed elasticities.

Price Elasticity of Conversion (PEC) $\frac{d\beta}{dP}\frac{P}{\beta}$

This is typically negative for a broad range of goods and services –the probability of an exposed person making a purchase falls when prices rise (in most cases). This reflects the desirability of a product or service.

Price Elasticity of Direct Exposure (PEDE) $\frac{dc}{dP}\frac{P}{a}$

Retailers will be motivated to keep this value as large as possible, because increasing a product's exposure/advertising alongside increases in price should ultimately increase quantities demanded, which in turn would lessen the impact of a negative PEC. Note that the percent-change of direct exposure is relative to *all* exposure $\frac{\Delta c}{a} = \frac{\Delta c}{c \cup i}$, and scaled by the fraction of susceptible population within the definition of PED, giving $s\frac{dc}{dP}\frac{P}{a}$. This follows intuition where advertising has decreasing marginal impact on sales of products when it has dominant market share.

Price Elasticity of Market (PEM) $\frac{ds}{dP}\frac{P}{s}$

This term quantifies how changes in price affect the sizes of the susceptible population. This term could conventially be negative, where a decline in price usually makes a product or service more accessible to a larger population, and an increase in price reduces the size of the available market. This relationship contributes negatively to PED, but a retailer who wishes to combat negative PED through this parameter can ensure that PEM is positive by increasing availability along-side higher prices (like offering delivery with slightly higher prices/spending), or offering lower prices with decreased availability (like walk-in/in-person discounts).

Market Elasticity of Exposure (MEE) $\frac{da}{ds}\frac{s}{a}$

This term measures the efficiency of exposure, by quantifying the percent change in market share per percent change in exposure. This elasticity will always be negative, since increasing exposure ***a*** will lead to increasing market share ***i*** and therefore decreasing ***s***. This term ranges from $-\infty$ when the susceptible fraction of the population is 100% (no market share, first-mover advantage) and approaches the asymptotic limit of 0 as the susceptible fraction approaches 0%, indicating market dominance/monopoly. This term’s rapid approach towards zero captures the dimishing returns of advertising and exposure for companies that have already captured and exposed a large portion of the market.

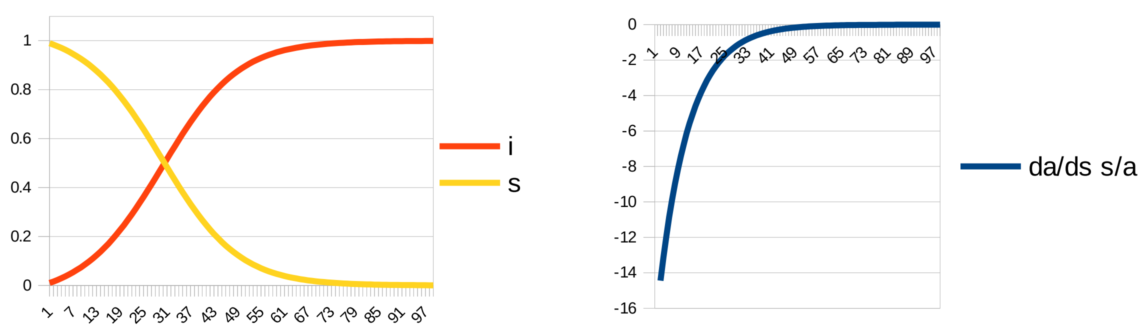


Figure 28: Market share 'i' and susceptible market 's' vs time (left) for a single market participant, and corresponding Market Elasticity of Exposure vs time (right)

Market Elasticity of Exposure Adjustment (MEE-A) $\left(\frac{da}{ds}\frac{s}{a}+1\right)$

In contrast to MEE, this term is positive when the susceptible fraction of the population falls below the point at which MEE-A is inelastic, which is when

$$\frac{da}{ds}\frac{s}{a}+1=0$$
$$\frac{da}{ds}=-\frac{a}{s}$$
$$c-1=-\frac{a}{s}$$
$$s=\frac{a}{1-c}$$

Substituting this into the definition of ***a*** made earlier $a=1+s(c-1)$, gives

$$a=1+\left(\frac{a}{1-c}\right)(c-1)$$
$$a=1-a$$
$$a=\frac{1}{2}$$

Therefore, MEE-A becomes inelastic when the total exposed population $a=c\cup i=50\%$, for a market with a single competitor.

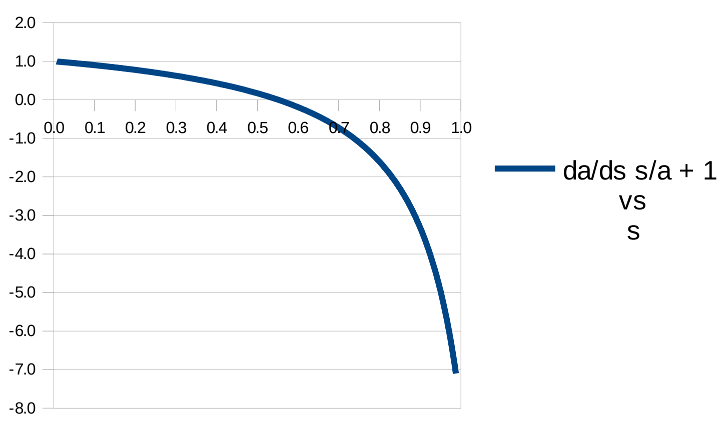


Figure 29: Market Elasticity of Exposure vs Susceptible 's' of a single market participant, using a constant exposure c = 0.1. MEE is inelastic when (market share ∪ *exposure) = 50%, which occurs here when s ~= 55.6%, and is negative in a largely untapped susceptible market.*

Price Elasticity of Market, Exposure-Adjusted (PEM-EA) $\frac{ds}{dP}\frac{P}{s}\left(\frac{da}{ds}\frac{s}{a}+1\right)$

This term contributes to PED in a way that captures market elasticities with market share and exposure. If PEM is negative $\frac{ds}{dP}\frac{P}{s}<0$ (falling prices increases susceptible market, and rising prices reduces susceptible market) and MEE-A is negative $\left(\frac{da}{ds}\frac{s}{a}+1\right)<0$, then PEM-EA will be positive $\frac{ds}{dP}\frac{P}{s}\left(\frac{da}{ds}\frac{s}{a}+1\right)>0$ and will contribute positively to PED when the exposed population is less than 50% $a<c \cup i=50\%$ for a market with a single competitor. In fact, PEM-EA can force PED to be extremely positive during the initial exponential growth phase, when prices increase alongside rising quantities sold. If there were any time for retailers to raise prices with minimal impact to sales quantities, this growth phase would be the environment to raise them.

With this in mind, this term appears to be a potential candidate for the fundamental mechanism behind the economic phenomenon observed as ***demand-pull inflation***. This type of price inflation appears to be common among new products that experience viral demand.

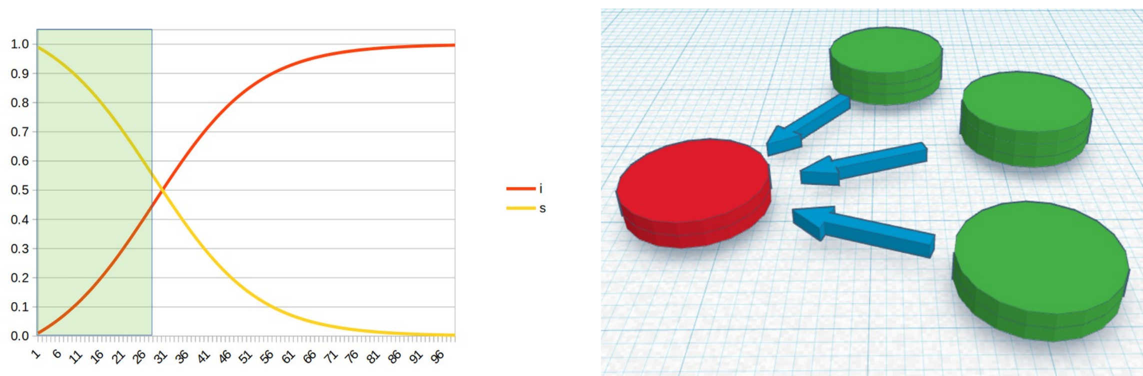


Figure 30: Left: Market share 'i', and susceptible population 's' vs time for a market with a single competitor. With constant exposure, c = 10%, and a typical economy where Price Elasticity to Market (PEM) is negative, PEM-EA contributes positively to PED in the green shaded area which ends at s ~= 55.6%. PEM-EA has the potential to contribute large positive values to PED in the early stages of market share growth, which could be the source of "demand pull inflation". Right: Demand-pull inflation requires plenty of susceptible equity (green) per "payment obligation" (red) for exposure and subsequent infection/convsersion.

However, $\left(\frac{da}{ds}\frac{s}{a}+1<0 \quad when\ a>50\%\right)$ in the case of a single market competitor, and PEE-A approaches the asympotic limit of 1, as shown in Figure 29. So, PEM-EA has the potential to contribute negatively to PED during this phase of a product or company's lifecycle. This phase may represent a company or product's "mature phase", where the market is saturated, growth opportunities are limited, and revenues are steady. However, retailers can influence PEM-EA to take on a positive value again by ensuring that the PEM $\frac{ds}{dP}\frac{P}{s}$ remains positive with the suggestions mentioned previously in "Price Elasticity of Market (PEM) " (offering in-person discounts, etc).

Price Elasticity of Supply $\frac{dQ_{total}}{dP}\frac{P}{Q_{\mathrm{total}}}$

Seeing price elasticity of supply in the same expression as price elasticity of demand may appear strange. This equivalence suggests that producers and retailers can manipulate price elasticity of demand more in their favour –less negative, and maybe even push PED into being positive– simply by ensuring their price elasticity of supply is a large positive number.

Large positive PES values can be achieved if small increases in price are accompanied by larger increases in quantities offered. These pricing strategies are observed in the style of "buy one, get one for 50% off" by retailers, or by producers who sell products in "wholesale" quantities at slightly higher prices (eg. Costco, Sam's Club, "party/family size" food packages, etc). Retailers who reduce offered quantities with incrementally higher prices (eg. "shrinkflation") may actually be acting against their own interests, since such pricing strategies will drive PES negative and push PED more into negative territory, making demanded quantities even more sensitive to price changes.

Large positive PES values can also be achieved by making reductions in offered quantities alongside smaller reductions in prices. Instead of offering "wholesale" product sizes at relatively higher prices, offering "convenience" product sizes at slightly lower prices should also drive PED more positive. Retailers that implement this pricing strategy would be similar to convenience stores and "dollar" discount stores. This could also be the most common response among producers to cost-push inflation.

Note that the objective of pricing strategies mentioned here is to increase quantities sold, and thereby improve market share; not to maximize profit. Other considerations like marginal costs, fixed costs, variable costs, etc, are required to find the optimal pricing strategy that maximizes revenue.

Countering the Negative PED of Consumer Demand via Viral Exposure

The price elasticity of demand (PED) for consumer goods is generally negative and elastic, meaning that as market prices rise, the quantity demanded tends to decrease. However, by isolating the factors of infection, brands can formulate a strategy to influence PED positively. These strategies include increased exposure (direct and viral marketing), increasing accessibility by having an online presence and increasing the range of distribution, offering discounts for fractions of the population that are “close”.

Viral marketing is often preferred over direct marketing because it tends to be more cost-effective when diffusing demand into an economic system. As shown above, a product has the best chance of achieving inelastic demand, or even positive PED, during the early stages of viral growth. Social media’s proficiency in this diffusion makes it a valuable tool for smaller economic competitors in a capitalist system under this infection model of economics.

PED Prediction vs Measurement

This economic infection framework enables the preemptive calculation of PED using data and statistics from marketing campaigns, sales, and market analyses. This approach allows for PED to be determined before actual changes occur, rather than measuring it retrospectively. Consequently, economists and market regulators might find this decomposition of PED useful as a tool to assess the economic competitiveness or anti-competitiveness of a product, company, or market.

Regional Monopolies

Due to the relationship between price elasticity of demand and market share, it should be clear why companies are incentivized to establish market share dominance in smaller regional markets. This dominance results in a lower price elasticity of demand (PED), which, in turn, allows them to increase prices with less risk of losing customers. This can lead to the consequence of monopolistic pricing across an entire economy even if no national-level monopolies exist. For instance, consider a scenario where a country accommodates five prominent mobile service providers, each commanding a 20% market share nationwide. If their service areas were segmented into five distinct regions (areas of exposure), each provider could potentially hold a monopolistic market share within their respective geographical areas. The price elasticity of demand for these mobile service providers would be extremely inelastic, despite having only 20% market share each nationally. Thus, this economic infection framework could possibly reveal uncompetitive markets by quantifying factors like exposure and market share elasticities.

Predatory Pricing

This factorization of price elasticity of demand reveals the mechanism by which the strategy of predatory pricing works. Predatory pricing occurs when a market competitor initially sets prices at very low levels to quickly gain market share. But, once other market competitors have been forced out of the market, or the predatory firm has acquired a sufficient market share, prices are often raised to levels higher than their initial pricing by that dominant firm.

In a market where susceptible customers are geographically bound to a certain location, and exposed to only one large grocer and retailer, the components of PED would be the following:

$\frac{d\beta}{dP}\frac{P}{\beta}$	Price elasticity of conversion will be very close to zero, if the goods sold are essential, like food, energy, and medication. A high sales conversion rate means any changes to this rate due to changes in price will be relatively small.
$s\frac{dc}{dP}\frac{P}{a}$	Price elasticity of direct exposure would be close to zero and therefore inelastic. Change in exposure can be close to zero for retailers who have a constant presence in its geographical area, and the susceptible population having no other options geographically. This term's impact on PED is scaled lower even further by the fraction of the remaining susceptible population who remains non-customers.
$\frac{ds}{dP}\frac{P}{s}\left(\frac{da}{ds}\frac{s}{a}+1\right)$	PEM-EA will usually be negative, but also close to zero if the susceptible population faces obstacles in leaving the area, preventing any increases or descreases to ***s*** in with changes in price. With dominant market share, increases or decreases in exposure do not meaningfully change the fraction of the population that remain susceptible.
$\frac{dQ_{total}}{dP}\frac{P}{Q_{\mathrm{total}}}$	With all other elasticities close to zero, and sales quantities all but guaranteed, producers are incentivized to increase prices with very little changes to offered quantities (if any). Consequently, this elasticity is also close to zero.

This decomposition of PED may be useful in determining the driving factors and indicators of (un)competitive markets and (anti-)competitive businesses practices.

Market Consolidation and Monetary Interest Rate Adjustments

Central banks use interest rate adjustment as a monetary policy tool to influence aggregate demand, which is the total spending in an economy. When central banks raise borrowing costs by increasing interest rates, they do so with the expectation that higher interest rates will discourage borrowing and, as a result, lead to a decrease in actual spending. However, such adjustments to interest rates should exhibit reduced effectiveness if the true drivers of PED are less sensitive to interest rate-driven causes. For instance, if PED can be made inelastic due to an oligopolistic market. This implies that if certain industries with low levels of competition are identified as being major drivers of inflation, interest rate adjustments must be more substantial than standard changes to achieve equivalent results, compared to smaller interest rate adjustments in industries with more competitive markets.

This outcome only adds to the complexities and challenges associated with managing monetary policy using the limited tools available to central banks, especially when dealing with markets characterized by limited competition.

Price Elasticity of Attrition (PEA)

While PED can be expressed in terms of infectiousness β and price, there does not appear to be an equivalent metric for customer attrition γ. Customer loss due to changes in price is something that definitely exists in business (known as “Churn Rate”), but its importance and impact on market share in the long run may not have been clearly understood before. Because long-term market dominance depends on achieving a superior R_0, price sensitivity of γ cannot be overlooked, especially in a highly competitive economic system, and especially when subscription-based revenue models are becoming more and more popular among businesses.

So, the concept of Price Elasticity of Attrition can be defined as,

$$PEA = \frac{d\gamma}{dP}\frac{P}{\gamma}$$

The relationship between changes in price and customer turnover would not be difficult to measure among large companies (especially companies that depend on recurring revenue) like subscription-based businesses and suppliers of consumable products and services. Incorporating such a concept into this economic infection model should be fairly simple to do, and to verify.

Planned Obsolescence vs Lasting Products

This framework of economic infection should allow for analysis of product strategies when it comes to increasing frequency of revenue, and operating cash flow. Planned obsolescence may seem like a good idea to improve recurring revenue and cash flow, but it effectively increases the recovery rate γ by shortening the mean duration of their customers' infection, and leaving their ex-customers susceptible to be infected by competitors. This makes planned obsolescence a double-edged sword if implemented in markets where innovation is high (ie. consumer electronics) and market participants are constantly driving the infectiousness β of their own products higher. A company producing long-lived products may pass up revenue that comes with repeat purchases, but those long-lived products also deny market share and revenue from competitors. Such companies should be more likely to survive by in the long-run by having a larger addressable market to compensate for the relative lack of recurring revenue that comes with having a low γ . ie. Companies that produce long-lived high quality products may be more likely to have a global presence, simply because such expansion may be necessary for survival.

New Product Requirements and Performance Tracking

Feature Replication

Being the first to bring a product to market provides an enormous advantage in gaining market share. However, not all companies can enjoy the benefit of being first and must resort to creating similar products in order to gain market share instead. Replicating product features is essentially an attempt at matching a market leader's β . However, what is just as important as replicating infectiousness (and probably under-estimated) is the impact of factors that drive rates of customer loss γ . Poor quality, inadequate customer service, bad customer experience, etc, will almost guarantee long term extinction of a product or service even if features of the market leading product are matched.

This may also shed some light on the failures of the Google+ social media site to gain traction, as well as the extinction of Google's many attempted mobile chat applications. While Google may have attracted many users to their social media platform Google+ initially, a high recovery rate would have driven their lower relative to other social media platforms, which would have doomed Google+'s market share for user attention.

Anecdotally, this dynamic should be observed among social media companies as they compete for the finite attention of their users. Social media platforms are almost forced to replicate each others' features to avoid their users "recovering" from their own service and become "infected" by competing services (Instagram copying Snapchat with the introduction of "Instagram Stories", YouTube copying TikTok with "YouTube Shorts", Meta copying TikTok's serving of seemingly random videos beyond users' social circles).

Premature Discontinuation of Products and Services

This framework should also provide an additional method of gauging the success of new products. Metrics like user-growth and total-users don't tell the full story. A product, service, or company could have the weakest growth rate in the industry and still be destined for market domination if nothing were changed. The introduction of a new parameter like R_0 as a performance metric would give companies new insight into the long-term growth and survivability of new products and services and may even prevent them from being discontinued prematurely.

Modelling Monetary Policy Outcomes and Response Times

Predicting the impact of monetary policy interest rate decisions on aggregate consumer demand should be possible under this model of economic infection. In this scenario, the "susceptible population" are the dollars a household earns as income each month. Debt diffuses through the economy, exposing and infecting these dollars, which then become expenses. Housing, food, energy, discretionary spending, and other categories of spending are different viral strains competing to infect a portion of the total susceptible dollars of income, each with their own estimates of β and γ .

An increase in interest rates would be akin to an increase in the infectiousness of the "interest rate virus". This would naturally alter the fractions of income that other "demand strains" occupy at equilibrium. By modelling these changes numerically, it should be possible to estimate the rate at which these changes would achieve a desired economic outcome. These models could be created for all income brackets or geographical regions, enabling policy-makers to determine which changes will lead to the most desirable outcomes, how these changes will interact, and how long it will take for these changes to propagate through the economy to reach their desired outcomes.

Factors for Long-term Growth

Growing revenue is challenging when a market is saturated with strong competitors. Growing revenue may be possible through inflation, but such strategies may simply drive customers away and reduce market share.

An investigation can be done on industries/companies/products to determine if any relationship exists between their decomposed PED values (PEC, PEDE, PEM-EA, PES) and their market longevity, revenue outcomes, and share price.

Based on this decomposition of PED, the keys to success and longevity appear to be:

1. Constant expansion into new markets through the creation of new strains of products and services and releasing them in as many different markets as possible (Apple Inc, Samsung Group, Johnson & Johnson, Procter & Gamble, would be examples of such companies). Doing so keeps the susceptible fraction $\boldsymbol{s}$ of the population high, thus providing the best chance of achieving a positive PED via a large positive PEM-EA.

2. Achieving an inelastic PED, not through exploitation of market share afforded by geographical or technological boundaries, but through the use of effective pricing strategies that force each component of PED to be as positive as possible to counter the negative price elasticity of closure (PEC).
3. Targeting, and achieving a high R_0 through the design and production of highly desirable products and services with high rates of infection and low rates of attrition. A customer retaining a long-lived product still denies a competitor of that customer.

Equity and Debt Valuations of Companies With Lasting Products

If Present Value is the discounted sum of future cash flows, then special considerations can be made to create a more precise valuations of the equity and debt of companies that produce last-lasting products with very low recovery rate γ (eg. Instant Pot pressure cookers, Peleton stationary bikes, etc). Sales, and thus future cash flows, will not be constant through time. In these cases, better estimates of future cash flows may be possible through the use of a sigmoidal sales profile through time instead.

Corporate Financial Forecasting

This simple economic infection model allows companies to incorporate the decomposed elasticities of PED to optimize product development, pricing, and marketing. By doing so, companies can maximize revenue and market share growth while considering all market competitors simultaneously. This model should also expose, and help companies avoid self-destructive strategies that could harm their long-term survival.

Aside from improving and validating corporate forecasts, investment professionals should also be able to use this framework to identify companies with lower rates of growth that are on paths to strong market positions in the long run. Such companies might be overlooked and potentially undervalued when compared to the outcomes generated by other financial and economic models.

What's Ultimately Best for Shareholders

This economic infection framework provides an additional perspective when considering what is ultimately best for the shareholder. Shareholders demand growth and long-term success, but it doesn't take much to show that strong growth does not imply long-term market dominance, or even survival.

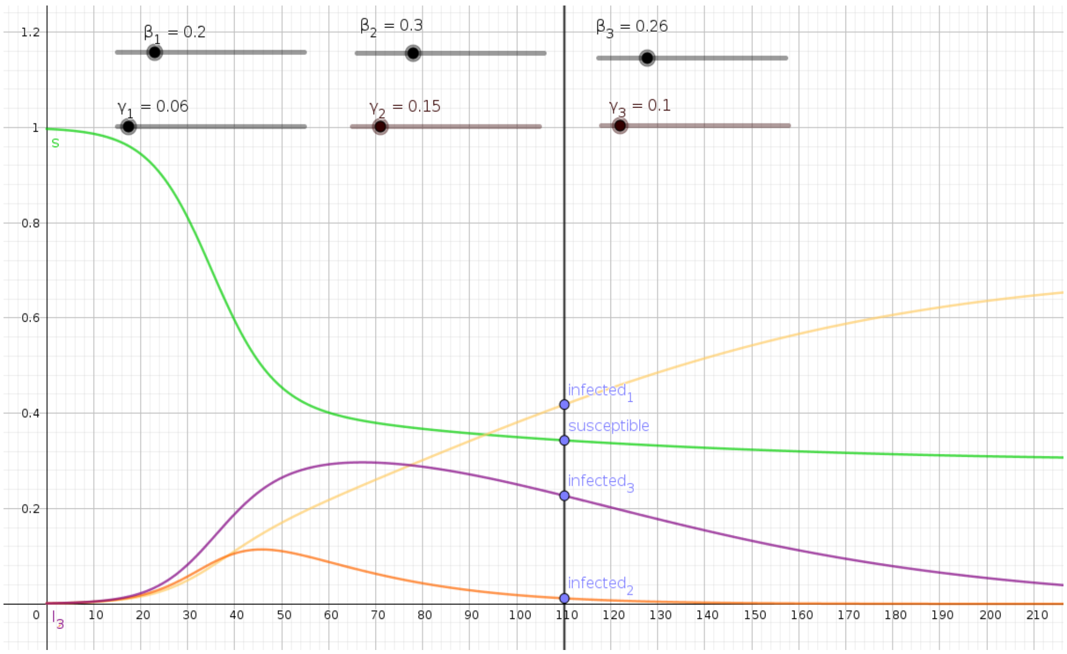


Figure 31: Eventual extinction can be mathematically guaranteed by the same parameters that created initial dominant growth.

Many companies tie executive salaries and bonuses to metrics like revenue growth and share price. However, shareholders may benefit by including a metric like R_0 to incentivize managers and executives to adopt business strategies that enhance long-term survival.

The decomposition of price elasticity of demand under this economic infection model should provide companies with interesting insights into the consequences that different pricing and marketing strategies have on revenue and market share growth, and help their managers avoid the self-destructive inflationary pricing strategies that boost short-term revenue but jeopardize their own future existence.

Final Thoughts

The economic infection model presented here is highly simplified, and this paper hasn't covered all possible economic complexities. For example, only market share has been discussed, not revenue or cash flow, and not all consumed goods are mutually exclusive. The decomposition of PED performed here doesn't factor in customer attrition, other market competitors, or the a "viral scaling factor" (realistically, only a fraction of customers tell people they know about their purchases). Furthermore, it's important to note that the size of an addressable market can change over time. Despite all this, the economic infection model offers significant potential for capturing and modeling these nuances of economic realities. These aspects, among others, can be easily integrated into the framework with minor adjustments. In general, the economic infection model appears relevant to any system characterized by competitive demand –such as demand for capital, household spending, labor, transportation, social media engagement, political votes, etc. Assuming the fundamental conditions hold true, –specifically, that 1) debt's entropy increases over time, and 2) it converts into equity with some probability– it is entirely plausible that both micro and macroeconomics are grounded in the fields of statistical mechanics, viral eipidemiology, and viral ecology. Consequently, this bottom-up re-evaluation of economic systems could potentially shift the study of economics from being classified as a social science into being recognized –at least partially– as a hard science.

What's Next

From here, a progression from economic systems to financial systems can be made. While goods and services are demanded in economic systems, financial returns are demanded in financial systems. This does not change the initial assumptions of debt/demand diffusion. Just as the advertising and distribution industries work to diffuse demand into an economic system, the financial industry also has mechanisms to disseminate information and drive trading demand in financial markets. With a susceptible population of investors and traders, 'buy' and 'sell' demand can be thought of as competing strains of viral infections, constantly mutating and spreading various strains of "reasons to buy" and "reasons to sell". This welcomes the possibility for the theory of Debt/Demand Diffusion and Economic Infection to be an adequate foundation on which to model and predict the distribution of financial returns, as financial market participants compete to be the first to react to propagating waves of viral demand for buying and selling. This theory may not only explain the observed phenomenon known as 'momentum' in price behaviour, but it might also *require* momentum to exist across *all* time scales.