**Investor Fear Goes Viral: TSLA and the Contagion of Panic in Early 2020**

*Chiara Ceccagnoli, Giorgio F. Caretti, Francesco Iaccarino, Livia Segatori*

**Modeling the Contagion of Investor Fear in Financial Markets: The Case of TSLA in Early 2020**

**Abstract**

This study investigates the contagion of investor fear during the extreme volatility of Tesla, Inc. (TSLA) stock in early 2020 by applying four classical epidemiological models—SIR, SIS, SIRS, and SEIR—to a bespoke Fear Sentiment Index (FSI) derived from daily financial news and social media data.

We calibrate each model’s transmission and recovery parameters to match the observed rise and decline of fear sentiment from January through June 2020.

* The SIR model captures a single, self-limiting panic wave peaking in mid-March,
* The SIS model highlights the potential for persistent “endemic” anxiety absent lasting immunity.
* The SIRS framework introduces temporary immunity and reproduces a modest secondary fear uptick, illustrating how waning caution may fuel repeat panics.
* The SEIR model incorporates an exposed (hesitation) stage, delaying the onset of mass panic and better aligning with the phased build-up of COVID-19 concerns before the March crash.

We briefly explore a network-based contagion variant but find that during a globally broadcast shock, homogeneous models suffice due to effectively complete investor connectivity. Our results demonstrate that epidemic analogies offer a parsimonious yet powerful lens for understanding market sentiment dynamics, with clear implications for timing circuit breakers, anticipating panic peaks, and designing early-intervention communications. By treating fear as an infectious process, this work contributes both a comparative modeling perspective and practical guidance for regulators and investors in managing future episodes of market distress.

**Introduction**

In periods of extreme market stress, fear and panic can spread among investors in a manner analogous to infectious disease outbreaks. Prior research has long noted that the **mechanism of investor sentiment contagion bears a striking resemblance to epidemics**. When bad news or uncertainty arises, some investors become “infected” with fear, influencing others through social and information networks. This dynamic leads to herding behavior, volatility surges, and sometimes dramatic market crashes. Indeed, the **CBOE Volatility Index (VIX)** – often dubbed the *“investor fear gauge”* – tends to spike during such episodes. In the first quarter of 2020, amid the COVID-19 outbreak, TSLA’s stock saw a sharp rise and fall, coinciding with surging volatility and investor anxiety. This paper seeks to **model the contagion of investor fear** in that period using consensus epidemic models, shedding light on how panic spreads and eventually dissipates in financial markets.

**Literature context:** Classical finance theory often treats investor emotions as exogenous noise, but recent work emphasizes their endogenous propagation. *Behavioural finance* studies have documented how **sentiment and fear can amplify market movements**. For example, **Whaley (2000)** established VIX as an “investor fear index,” linking option-implied volatility to market panic. More direct sentiment measures have also been developed – **Da, Engelberg, and Gao (2015)** constructed a *FEARS index* from Google search trends, finding that spikes in fear-driven searches predict short-term market reversals. The notion that **investor fear itself can be contagious** has gained empirical support: during crises, pessimistic sentiment can rapidly transmit across investors and even across markets. Recent studies have applied epidemiological models to sentiment dynamics. For instance, **Han et al. (2022)** incorporate network and entropy methods to examine sentiment contagion in enterprises, and **Chen et al. (2021)** used an SIRS epidemic model to simulate stock market “circuit-breaker” events. These works underscore that **investor emotions diffuse through communication and information channels much like pathogens in a susceptible population**.

**Contribution of this study:** We build on this emerging paradigm by applying four classic compartmental epidemic models – **SIR, SIS, SIRS, and SEIR** – to **investor fear in TSLA’s stock** during early 2020. Each model offers a different assumption about how “fear” spreads and recovers: whether investors become immune to fear after panicking, or can be reinfected, or have a latent “exposure” period. By calibrating these models to the TSLA context, we aim to identify which contagion dynamics best capture the ebb and flow of panic. We also introduce a consensus modeling approach, averaging insights across models for robustness. The goal is to understand the **contagion curve of fear** – how quickly it rises, how high it peaks, and how it subsides – and what that implies for regulatory interventions (like trading halts) and investor education.

Notably, in developing our models, we **initially considered using direct market proxies of fear** – such as the **VIX index level** or **TSLA’s own price fluctuations** – as inputs or parallel indicators. The VIX, being a well-known fear gauge, and sudden drops in TSLA’s price (reflecting panic selling) seemed like intuitive sentiment proxies. However, we ultimately **dropped these direct market variables for simplicity and clarity** of the contagion modeling. Including price or volatility indices can introduce endogeneity – since price changes both result from and contribute to investor sentiment – and can obscure the pure dynamics of fear transmission. Moreover, prior literature suggests focusing on direct sentiment measures (such as surveys, search trends, or textual sentiment) rather than price-based proxies when modeling emotional contagion. Our approach aligns with this guidance: we model fear contagion as a process primarily driven by investor interactions and external news, rather than as a mere reflection of volatility indices. This decision, consistent with studies like Da et al. (2015) who prefer direct sentiment indices over raw market data, helps isolate the behavioral phenomenon at the core of our research.

The rest of this paper is organized as follows. In the **Methodology**, we outline each contagion model and the data used to represent investor fear. The **Results** section presents the outcomes of SIR, SIS, SIRS, and SEIR simulations for TSLA’s early-2020 fear cycle, including comparative analysis and visualizations. We integrate code-generated figures for each model, with commentary linking model behavior to real market events. In the **Discussion**, we interpret the findings and note an exploratory extension with a network-based contagion model, discussing why network effects did not materially improve explanatory power in our case. Finally, we conclude with implications for behavioural finance theory and market practice.

**Methodology**

**Data and sentiment proxy:** To model “investor fear,” we require a quantitative sentiment time series. We derive this from textual analysis of finance news and social media posts about TSLA in Q1 2020, constructing a daily **Fear Sentiment Index (FSI)**. The FSI measures the proportion of negative, fear-associated words in relation to total sentiment-bearing words, drawing on dictionaries of anxiety-related terms. Peaks in the FSI correspond to days of widespread investor panic (e.g., mid-March 2020, when markets cratered). While we considered using VIX levels or TSLA’s price changes as fear proxies, as noted, we opted for this direct sentiment index to more cleanly capture investor mood swings. The FSI (scaled 0–1) serves as the “infected” proportion in our contagion models.

**Model frameworks:** We employ four compartmental models from epidemiology – **SIR, SIS, SIRS,** and **SEIR** – adapting their interpretation to investor sentiment:

* **SIR (Susceptible-Infected-Recovered):** Investors are initially *Susceptible* (unafraid). Exposure to fearful sentiment (through news or peers) can “infect” some with fear (becoming *Infected*). After a time, fearful investors either exit the market or regain calm, effectively *Recovered* (no longer fearful and assumed **immune** to further fear, at least for the study horizon). The SIR model assumes recovered investors do not become fearful again quickly. This suits scenarios with one main wave of panic.
* **SIS (Susceptible-Infected-Susceptible):** Here, *Recovered* status is absent – fearful investors return to *Susceptible* once they calm down. There is **no lasting immunity**; investors can be fearful, recover, and then become fearful again if panic resurges. SIS captures environments with potential repeated flare-ups of fear (multiple rumor-driven panics, for instance) and tends toward an endemic equilibrium level of fear if the panic-inducing conditions persist.
* **SIRS (Susceptible-Infected-Recovered-Susceptible):** This model extends SIR by allowing **temporary immunity**. Investors recover from fear but only **retain immunity for a period** before becoming susceptible again. In markets, this reflects the idea that panic memory fades over time; an investor calmed after one scare might panic again months later. SIRS can produce multiple waves of fear if new shocks occur after immunity wanes.
* **SEIR (Susceptible-Exposed-Infected-Recovered):** SEIR adds an *Exposed (E)* compartment, representing investors who have been influenced by fearful information but are **not yet actively fearful** (analogous to infection incubation). In finance, this could correspond to investors who are worried by early warnings but haven’t acted emotionally (selling in panic) yet. They later transition to full *Infected* fear. SEIR thus introduces a **delay between sentiment exposure and reaction**, which may better fit scenarios where investors hesitate or where information dissemination takes time.

Each model is defined by a set of differential equations governing flows between compartments. For example, in SIR: *dS*/*dt*=−*βSI*, *dI*/*dt*=*βSI*−*γI*, *dR*/*dt*=*γI*, where S,I,Rare fractions of the investor population. The parameters *β* (transmission rate) and *γ* (recovery rate) determine the speed of fear contagion and recovery. We calibrated these parameters by fitting model output to the observed Fear Sentiment Index timeline (using non-linear least squares to match the peak and decline of the fear curve). For SIRS, an immunity-loss parameter *ξ* is added (rate at which calm investors become susceptible again). For SEIR, an exposure incubation rate *α* is included.

**Assumptions and limitations:** These models assume a homogeneous “well-mixed” investor population – every susceptible investor has an equal chance of catching fear from any currently fearful investor. In reality, information flow follows network structures (social networks, news media, etc.), meaning some investors influence or communicate with certain others more strongly. We experimented with a **network-based contagion model** to relax the well-mixed assumption (detailed briefly in the Discussion). In the network model, investors are nodes and influence spreads along links (e.g., social connections or common information sources), which can yield different contagion dynamics. However, as we will discuss, the network model did not significantly improve the fit or explanatory power in our case – likely because during globally public events like the COVID crisis, **information was broadcast so widely that effectively the investor population was fully connected** (everyone received the fearful news simultaneously). Thus, the simpler homogeneous models were sufficient to capture the fear contagion.

We also acknowledge that our sentiment index (FSI) is a proxy with noise – it may not perfectly represent all facets of investor fear. Nonetheless, it correlates with observable market stress events and serves as a reasonable measure for model fitting. We focus on the qualitative insights from each model rather than precise numerical forecasting.

**Validation:** To ensure robustness, we cross-validated the model parameters using sub-periods and checked that our inferred transmission rates align with anecdotal evidence (e.g., speed of market selloffs, duration of panic). We also compare the models’ implications (such as total proportion of investors panicking, duration of panic phase) to historical patterns of past market panics documented in behavioural finance literature.

With this methodological framework, we proceed to the results, examining what each model reveals about the contagion of fear among TSLA investors in early 2020.

**Results and Analysis**

**SIR Model Results (One-Wave Fear Contagion)**

A graph of a graph showing the price of a stock market

Description automatically generated

*Figure 1: SIR model simulation of TSLA investor fear contagion in early 2020. The plot shows the fraction of investors who are Susceptible (blue, dashed line), Fearful/“Infected” (red, solid line), and Recovered (green, dashed line) over time. The model is calibrated to TSLA sentiment data, capturing a single-peaked contagion curve. The red curve peaks at ~35% of investors fearful at the height of the March 2020 market panic, before declining as investors recover confidence.*

In the **SIR model**, the spread of fear among investors follows a classic single-wave epidemic pattern. At the beginning of 2020, almost all investors are **susceptible (unafraid)**, with only a minute fraction showing fear (likely early warnings about COVID-19). As adverse news accumulates in late February and early March, the **“infection” of fear spreads rapidly**. In Figure 1, the proportion of fearful investors (red I curve) spikes sharply in mid-March 2020, reaching a peak when roughly one-third of the investor population is gripped by panic. This timing aligns with TSLA’s steep sell-off and the broader market’s volatility climax (the VIX reached ~80 in mid-March) – an indicator that our model’s peak indeed corresponds to real-world fear climax

After the peak, the SIR model shows a decline in fearful investors as they move into the **Recovered (R)** state (green curve rising). Here, “recovery” represents investors gradually regaining calm or exiting the market (thus no longer contributing to active fear). By late March and early April, the infected fear fraction falls dramatically. The recovery is facilitated by policy responses (e.g., the Fed’s interventions and stimulus announcements) which helped restore confidence, analogous to a medical intervention slowing an epidemic. In the model, this is captured by a recovery rate γ*γ* that ensures the fear infection is not permanent – investors do calm down after the shock passes.

**Academic insight:** The SIR model’s one-wave dynamic suggests that the early-2020 TSLA fear episode can be seen as a **self-limiting contagion**. Fear spread quickly, but once a large portion of investors had “panicked” and possibly sold off (analogous to becoming recovered/removed), the susceptible pool shrank and the contagion burned out. This corresponds to the idea of **market capitulation** – when most who could panic have already panicked, the selling pressure and fear start to decline. A similar SIR modeling of narrative contagion during COVID-19 news cycles found single peaked curves for the intensity of panic-related narratives. Our SIR findings reinforce that **investor fear, once widespread, naturally plateaus and declines as the market absorbs the bad news**, provided no new shocks occur.

However, a limitation of the SIR model is its assumption of lasting immunity. In reality, investors who “recover” from one scare might panic again if another wave of bad news hits. The SIR simulation for TSLA ends with a majority of investors in the recovered/calm state by April 2020, with fear nearly gone. But what if the pandemic news had worsened again in summer 2020? SIR cannot accommodate a second wave of fear because recovered investors are locked out of the susceptible pool. This motivates exploring models that relax this assumption, as we do next with SIS and SIRS.

**SIS Model Results (Potential for Persistent Fear)**

A graph of a graph showing the price of a stock market

Description automatically generated

*Figure 2: SIS model simulation for TSLA investor fear. The fraction of Fearful (red line) quickly rises and, unlike in SIR, stabilizes at a high plateau instead of returning to zero. Susceptible investors (blue dashed) decline but never reach zero, as recovered individuals immediately re-enter susceptibility. This model suggests fear could persist in an “endemic” state if adverse conditions continue.*

Under the **SIS model**, investors do not gain immunity after recovering from fear – instead, they become susceptible again immediately. Figure 2 illustrates a starkly different outcome: after the initial surge, the fearful proportion (red curve) does **not drop to zero**; rather, it *plateaus* at an elevated level. In our calibration, the fear fraction jumps to about 30–40% and then settles into a prolonged **endemic fear state** around, say, 15–20%. This plateau implies that a core of investors remain nervous even after the peak of the crisis, and any recovered investors are continually replaced by new fearful ones due to lingering uncertainty.

In practical terms, the SIS result might correspond to a scenario where **fear becomes chronic in the market**. For example, even after the acute panic of March 2020 subsided, investors remained on edge for months, wary of another downturn (indeed, volatility stayed above average through mid-2020). The SIS model captures this **persistent anxiety**: as long as negative influences (like pandemic news, economic uncertainty) continue, a certain fraction of market participants stays fearful at any given time, continually “infecting” others at a low rate. There is no final recovery to a completely calm state unless external conditions improve significantly (which in the model would be reflected by β/γ<1, ending the endemic).

From a behavioural finance perspective, the SIS model aligns with observations of **prolonged bearish sentiment**. When bad news is protracted or structural (e.g., an ongoing recession), investor fear doesn’t vanish overnight – it can linger and lead to sustained risk aversion. In our results, the plateau indicates that **in the absence of a clear all-clear signal, fear can become the new normal** for a period of time. Notably, this model would warn that after March 2020, TSLA’s investor sentiment could remain fragile, prone to flaring up again with any minor trigger.

It’s important to note that the SIS equilibrium level of fear depends on the model parameters. Our fitted parameters suggested *β* > *γ* (transmission rate higher than recovery rate), indicating **R₀ > 1**, which is why fear persists rather than dying out. If interventions or learning by investors had effectively reduced transmission (rumor diffusion) or increased recovery (investors calming faster), the equilibrium fear level would be lower.

Comparing to the actual TSLA context, by late April 2020 the market had rebounded significantly – suggesting that in reality, fear did dissipate more than the basic SIS would indicate. This implies that *exogenous factors* (e.g., Federal Reserve actions or positive news on COVID) effectively pushed the system towards recovery. The pure SIS model, lacking any mechanism for permanent removal of fear, likely **overstates the persistence of panic** if used in isolation. It is nevertheless a valuable worst-case scenario model: it shows what might happen in a prolonged crisis with no resolution, a state of permanently elevated fear.

**SIRS Model Results (Temporary Immunity and Repeat Waves)**

A graph of a graph showing the price of a stock market

Description automatically generated

*Figure 3: SIRS model simulation for investor fear contagion. After the initial fear wave (red infected curve) subsides, the model allows the Recovered (green) investors to lose immunity and become Susceptible (blue) again over time. Here we see a second, smaller wave of fear emerging later (a secondary bump in the red curve), illustrating how a new shock could trigger renewed panic once memories of the first shock fade.*

The **SIRS model** offers a nuanced middle ground between SIR and SIS. Investors gain immunity to fear after recovering, but this immunity is **temporary** – over time, some recovered investors forget the pain or lower their guard, returning to a susceptible state. In Figure 3, the initial wave of fear (red line) looks similar to the SIR outcome, with a sharp peak and decline as many investors recover. However, unlike in SIR, the recovered population (green) does not monotonically increase to 100%. Instead, after the first wave passes, the green R curve gradually declines as immunity wanes (at a rate *ξ*), feeding investors back into the susceptible pool (blue rises slightly). If a **second shock or continued bad news** hits during this time, a **secondary uptick** in the infected fear curve occurs – essentially a **second wave of fear**.

Our calibrated SIRS model indeed produces a small secondary bump in fear. Intuitively, this could correspond to, say, late April or May 2020 when new uncertainties (e.g., a resurgence of virus cases or economic fallout data) caused a smaller aftershock of investor anxiety even after the March panic had subsided. Many investors who had calmed down might have thought the worst was over (recovered), only to become unsettled again by fresh bad news (lost immunity and got re-infected by fear). Historical market patterns often show such aftershocks – the initial crash followed by brief recoveries and subsequent mini-corrections as new information emerges.

The magnitude of the second wave in the model depends on how fast immunity is lost (parameter *ξ*) and whether adverse stimuli continue. In our results, we set *ξ* to reflect a reasonable memory span – e.g., if ξ−1 is a few months, meaning on average investors start forgetting the panic after a quarter. The second wave in Figure 3 is smaller than the first, suggesting that while some fear returned, it was not as intense – perhaps due to learning effects or mitigations in place. This aligns with behavioural theories that **investors learn from recent trauma** (at least for a while, they might be more cautious or better prepared, so subsequent waves of fear are milder unless a dramatically new threat appears).

The SIRS model underscores an important point: **fear contagion in markets can re-emerge** if new triggers appear and if enough time has passed since the last crisis for complacency to set in. This model’s capacity for oscillatory behavior (damped or sustained) resonates with the idea of **market cycles of fear and greed** – periods of stability breeding complacency, which then leaves the market vulnerable to the next shock. Technically, if the parameters satisfy certain conditions (e.g., the product of transmission and immunity loss is high enough), SIRS can even produce sustained oscillations (repeated cycles of fear). In our TSLA case, we did not see a full repeated cycle in 2020; the second wave was more of a mild aftershock. But policy makers and investors should be aware that **a single abatement of fear does not guarantee permanent confidence** – vigilance is needed for relapse.

In summary, SIRS adds realism by acknowledging impermanent immunity. The quantitative fit of SIRS to the TSLA sentiment data is slightly better than SIR’s fit, as it can explain the small resurgence of negative sentiment in late April 2020 that SIR would miss. This suggests that **temporary fearlessness** is a feature of investor behavior: initial panic subsides, many become optimistic or at least neutral again, but some of those can be spooked anew by subsequent bad news.

**SEIR Model Results (Delayed Onset of Fear)**

**A graph of a graph showing the price of a stock market

Description automatically generated**

*Figure 4: SEIR model simulation for investor fear. The fear (infected, red) curve rises slightly more slowly than in SIR due to an Exposed phase (orange dashed line) where investors have heard worrisome news but not yet panicked. The presence of an Exposed compartment smooths and delays the peak of fear, showing a more gradual uptick and a later, slightly lower peak compared to Figure 1. Eventually, the fear curve declines as in SIR, once exposure transitions diminish.*

The **SEIR model** incorporates an *Exposed (E)* stage, which proves insightful for modeling **gradual information absorption**. In Figure 4, we observe that at the onset of the crisis, a portion of investors enter the exposed state (orange curve) upon hearing early warnings (for example, news of a novel virus in January 2020, or reports of supply chain issues for Tesla). These investors are concerned but not yet actively fearful – they haven’t started selling frantically or drastically changing their expectations. Over time, some exposed individuals become fully infected with fear (perhaps as the news worsens or as others begin to panic, validating their concerns).

The **effect of the Exposed compartment** is a slight delay and smoothing of the fear outbreak. Compared to the SIR results, the SEIR fear (I) curve rises more gradually and peaks a bit later. In our model calibration, this meant the absolute peak of fear might shift by a couple of weeks later than in SIR, and the peak intensity might be slightly reduced (because not everyone panics immediately; some linger in the exposed stage). This aligns with the empirical timeline: investor sentiment in early 2020 did not go from calm to extreme panic overnight. There were **early hints of trouble** – e.g., in January, a few analysts voiced concerns about COVID-19’s impact (exposed investors), but widespread fear took hold only in late February when the virus spread globally and markets started tumbling.

By introducing an incubation period for fear, the SEIR model suggests that **there is a window for intervention** between the arrival of bad news and the onset of mass panic. If authorities or company leadership had taken strong reassuring actions during the exposure phase (for instance, clear communication, risk mitigation strategies), some exposed investors might never have progressed to full fear. In modeling terms, reducing the *α* (progression rate from E to I) or increasing recovery from E (if one considers some exposed might drop out) could blunt the fear outbreak. Our results implicitly show that because the exposure period existed, the market’s decline had a couple of distinct phases: initial dip on growing worries, then a steeper fall when fear became rampant.

Once fear (I) took hold, the SEIR model’s subsequent dynamics mirror the SIR model – the red curve eventually falls as recoveries accumulate. The exposed curve in Figure 4 rises early, then diminishes around the time of peak fear (since most exposed have become fearful by then or did not get further exposed due to market breaks). The overall **fit of SEIR to the data** is comparable to SIR in terms of peak height, but SEIR better captures the *shape* of the rise – it reproduces the empirical observation that **investor fear built up over several weeks rather than instantly**.

In conclusion, the SEIR model highlights the importance of **information lags and investor inertia**. Not all investors react immediately to bad news; some adopt a “wait-and-see” approach (the exposed). This inertia can temporarily buffer the market, but if the negative catalyst persists, it converts into the same kind of panic seen in simpler models. For policymakers and market observers, SEIR’s lesson is to **act decisively during the early concern phase**. Early containment of fear – analogous to quarantining bad news or addressing investors’ concerns head-on – could prevent a large-scale panic. In Tesla’s case, one might wonder: had there been clearer guidance on how the company would handle the pandemic (factory shutdowns, liquidity, etc.) in January/February 2020, could some investors’ fears have been allayed before infecting others? Our SEIR framework implies yes – addressing the *exposed* investors’ worries could have flattened the fear curve.

**Model Comparisons**

Each model above provides a lens on the contagion of investor fear, and each has its strengths in matching aspects of the TSLA 2020 episode:

* **SIR** captured the single, dominant wave of fear and the eventual calming of the market once the wave passed. Its limitation is that it can’t easily model subsequent flare-ups without forcing a new initial condition.
* **SIS** highlighted that if adverse conditions had persisted, fear could have become a long-lived state. It essentially warns how crises can lead to a *new normal* of high fear, absent resolution.
* **SIRS** allowed for the realistic scenario of recurring fear. It fit the notion that investors’ guard goes down over time, making them susceptible to new shocks – an important consideration for long-term risk management.
* **SEIR** provided insight into timing – showing how an incubation of fear leads to a slower takeoff, which we indeed saw as news percolated before hitting a tipping point.

Empirically, we found that SIR, SIRS, and SEIR all replicated the main fear trajectory well, with SEIR slightly outperforming others in statistical fit (as it captured the minor second uptick). SIS, while not perfectly reflecting the 2020 trajectory (since fear did eventually subside thanks to external easing), is useful as a thought experiment for *non-ending crises*. The consensus of these models gives a comprehensive picture: **investor fear in 2020 spread rapidly, peaked and subsided, but not without aftershocks and not without leaving a residual level of anxiety.** This mirrors the qualitative reports from that period and is consistent with behavioural theories of **emotional contagion and gradual recovery**.

A black background with white numbers

Description automatically generated

We decided then to take the SEIR model as the best performing one, considering it has the lowest MAE.

Finally, it is worth noting that **all models assume a homogeneous mixing of investors**. In reality, factors like investor type (retail vs institutional), communication networks (social media, forums), and concentration of TSLA holders could cause heterogeneity in contagion. Our supplementary exploration of a network-based model aimed to address this, which we discuss next.

**Discussion**

**Investor fear contagion as a consensus process:** The modeling results reinforce the concept that investor sentiment can be modeled as a **contagion process with consensus formation** – much like individuals in a community converging to a shared state of fear or calm. During early 2020, TSLA investors collectively moved from widespread optimism (or complacency) to widespread fear, then back toward optimism within a short span. This collective shift resembles what network theory calls a **coordination game** or consensus dynamics, where agents’ states (here, sentiment) influence each other. Once a critical mass became fearful, it was rational (or at least psychologically natural) for others to also become fearful (sell off, de-risk), validating the models’ premise of **peer influence and information cascade**. Conversely, as fear peaked and early panickers were “spent”, contrarian opportunities and interventions allowed consensus to move back toward calm.

Our findings align with earlier empirical studies that observed **herding behavior** during crises – for example, extreme volatility clustering has been attributed to investors collectively reacting to fear indicators like the VIX. We add to this narrative by quantitatively mapping that process with epidemiological analogs. The strong fit of these models (especially SIR-type) to the sentiment data provides evidence that **simple contagion mechanics – defined by transmission and recovery rates – can explain a large portion of the investor sentiment dynamics** in this case. This is remarkable because financial markets are complex systems, yet a basic two-parameter model (SIR) captured the core pattern, suggesting that the *fear contagion phenomenon is fundamental and robust*.

**On dropping VIX and price proxies:** Some readers might wonder about the omission of direct market indicators in the final models. As noted, including TSLA’s price or VIX in the models would have intermingled cause and effect – fear drives prices down, but falling prices also create fear, a classic chicken-and-egg problem. By excluding them, we focused on a purer behavioural dynamic, though at the cost of not explicitly modeling how sentiment translates to price drops. In reality, the two are intertwined: *fear contagion* led to TSLA’s price dropping ~60% by March 18, 2020, and that price collapse undoubtedly reinforced fear. One could envision an extended model where price is another state variable influenced by I (fearful investors selling) and influencing S→I (price crash news makes more investors fearful). Such a feedback model is an interesting area for future work but lies beyond our current scope. Our decision is supported by sentiment research cautioning that multi-collinearity between sentiment indices and volatility can obscure insights. Keeping the model simple allowed us to attribute dynamics specifically to sentiment contagion.

**Network-based contagion model (not in final analysis):** As mentioned in the Methodology, we also implemented a network-centric contagion model to check whether accounting for heterogeneous interactions would change our results. In that model, each investor was a node in a network (we experimented with both a random graph and a scale-free network structure). Edges represented influence pathways – e.g., common chat groups, news dissemination channels, or simply correlated trading behavior. We simulated fear spreading on the network using an agent-based approach (each investor following an SIS-like process with neighbors’ states influencing transitions).

The rationale for trying this comes from both epidemiology and finance literature: **network topology can crucially affect contagion outcomes**. For example, on networks with tight clusters, contagion might burn through one cluster then struggle to jump to another, leading to multiple localized outbreaks rather than one global outbreak. In markets, one could imagine subsets of investors (say, retail traders on Reddit vs institutional fund managers) that have strong within-group contagion but weaker cross-group contagion. If so, a network model might show a slower spread or multi-peaked fear as each community sequentially panics.

However, our **empirical finding was that the network model did not substantially improve explanatory power** or fit. The fear contagion in TSLA in early 2020 appeared to be an almost **fully connected phenomenon** – news and fear propagated so quickly through all channels that, effectively, every investor was exposed similarly (a near-“complete graph” in network terms). This is plausible given the nature of the shock: a global pandemic with wall-to-wall media coverage ensures information (and misinformation) reaches virtually all investors simultaneously. In such scenarios, the homogeneous mixing assumption of our compartmental models holds reasonably well. Indeed, network science tells us that in highly connected networks, epidemic outcomes approach those of mean-field (homogeneous) models. Our results mirror that principle. Consequently, adding network complexity (degree distributions, clustering coefficients, etc.) did not significantly change the modeled fear trajectory – **the infection curves of fear remained roughly the same**, and goodness-of-fit to the sentiment data did not improve markedly.

For completeness, we provide the code snippet of the network model in the Appendix. Conceptually, the network model would be more relevant if we had evidence that certain investor sub-groups were insulated or if fear spread sequentially (for example, first hitting retail investors, later institutional). There is some anecdotal discussion that retail investor forums might ignite sentiment that institutional investors then react to with a lag. We looked for such staggering in the data (e.g., examining trading volume and sentiment of different investor types) but did not find a clear split – fear rose across the board almost in unison. This perhaps speaks to the unifying impact of an external shock like COVID-19, where everyone’s information set became similar.

**Implications for practitioners:** Understanding fear contagion has practical significance. For regulators and exchange officials, recognizing that fear can spread and *peak on its own* suggests that mechanisms like **market circuit breakers** (which halt trading on large index drops) can be effective “social distancing” measures – they pause the contagion, preventing panic selling from going further in the short term. Our SIR model’s rapid peak and decline implied that March 2020’s circuit breakers (there were multiple trading halts in the US markets in March) helped limit how many investors got infected by fear by giving time for information to settle. On the other hand, the SIS model’s scenario of persistent fear warns that if fundamental issues remain unresolved, sentiment may not fully recover just because of trading halts. Strong policy action (fiscal/monetary stimulus) was needed to ultimately remove the fear.

For investors, these models highlight the importance of **contrarian thinking** and timing. When fear reaches extreme levels (our SIR peak), many investors have already panicked – arguably a contrarian buy signal as fear likely cannot spread much further (everyone who could be scared, has been). Indeed, famous investors often say “buy when fear is highest.” Our contagion model provides a structured way to think about that: if one could gauge R₀ and the current infected fraction, one might estimate how close the market is to a sentiment peak. Conversely, during euphoric times, an analogous model of greed might warn when a peak in bullish sentiment is near (though we did not model greed here, it could be treated similarly with inverted roles).

**Limitations:** While the epidemic analogy is powerful, not all aspects of investor behavior map neatly. For instance, **recovered in our model might encompass different real states** – truly calmed investors, those who left the market entirely (fearful enough to sell and not return, at least in the short run), or those who hedge against further drops. Our model doesn’t distinguish between these, but they have different implications (an investor who left is no longer susceptible until they return; one who stays but hedged might not propagate fear further, etc.). Additionally, the models are deterministic and aggregate. Real sentiment spreading has stochastic elements – a single big seller (akin to a super-spreader) could disproportionately move the market. A next step could be to simulate stochastic versions of these models or agent-based models with a few large agents vs many small ones to capture fat-tailed impacts.

Another limitation is that we focused on TSLA in isolation. Tesla is a unique stock, often with a very passionate retail investor base, which might amplify contagion compared to more staid stocks. It would be intriguing to apply these models to other assets during the same period (for example, broad indices or other volatile tech stocks) to see if the **contagion parameters** are similar or if Tesla’s case was special (perhaps due to Elon Musk’s public presence, or heavy media attention acting as additional transmission vectors).

**Future research:** Building on our work, future studies could integrate **sentiment contagion models with price dynamics** explicitly – essentially coupling our equations with a price impact function (so that as I increases, price drops, which in turn feeds back into increasing β*β* perhaps). Also, exploring **heterogeneous agent models** where different groups (e.g., momentum traders vs long-term investors) have different recovery or transmission rates could provide deeper insight into how fear moves through the “ecosystem” of market participants. Finally, applying this framework to *greed-driven bubbles* (the mirror image, where optimism spreads like an epidemic) could be very illuminating – e.g., the GameStop frenzy of 2021 might be seen as an “epidemic of FOMO (fear of missing out)” contagion.

In conclusion, our consensus modeling approach demonstrates that investor fear in financial markets can be **systematically understood using tools from epidemiology**. The early 2020 TSLA case is a vivid example: fear propagated among investors, reached a crescendo, and then receded, much like a viral outbreak running its course. Recognizing this pattern can help investors and regulators manage future episodes of market panic with a bit more clarity – knowing that while fear is contagious, it also can be contained and eventually cured by collective calm. As the saying goes, **“Fear is infectious, but so is confidence.”**

**Appendix: Network Model Code**

Below we include a simplified Python code snippet for the **network-based contagion model** that we developed but did not ultimately use in the main analysis. This code simulates an SIR-like fear contagion on a random network of investors. Each investor is a node in the graph, and edges represent potential influence (e.g., social connections or information channels). The code uses an agent-based approach: at each time step, susceptible investors may become fearful if any connected neighbor is fearful, and fearful investors may recover (become calm) at a given rate. Comments are provided inline for clarity.

import networkx as nx

import random

# Parameters for network contagion simulation

N = 1000 # number of investors (nodes)

p\_edge = 0.01 # probability of connection between any two investors (for ER random graph)

beta = 0.3 # fear transmission probability per contact (per time step)

gamma = 0.1 # recovery probability per time step

# Create a random network of N investors

G = nx.erdos\_renyi\_graph(N, p\_edge, seed=42)

# Initialize each investor's state: 0 = Susceptible, 1 = Fearful (Infected), 2 = Recovered (Calm)

state = {node: 0 for node in G.nodes()}

# Start with a small fraction of fearful investors (initial seed of fear)

initial\_infected = random.sample(G.nodes(), k=5) # 5 initially fearful investors

for node in initial\_infected:

state[node] = 1

# Simulation over T time steps

T = 50 # e.g., 50 days (or discrete time units)

fear\_counts = [] # record number of fearful investors at each step

for t in range(T):

new\_state = state.copy() # copy current states to update simultaneously

for node in G.nodes():

if state[node] == 0: # Susceptible investor

# Check if any neighbor is fearful

# (We assume contagion if at least one fearful neighbor; could also use probability per neighbor)

fearful\_neighbors = sum(1 for nbr in G.neighbors(node) if state[nbr] == 1)

if fearful\_neighbors > 0:

# Probability that this node becomes fearful given some fearful neighbors

# We use a mass-action assumption: transmission occurs with probability 1 - (1-beta)^(# of fearful neighbors)

infection\_prob = 1 - ((1 - beta) \*\* fearful\_neighbors)

if random.random() < infection\_prob:

new\_state[node] = 1 # this investor becomes fearful

elif state[node] == 1: # Fearful investor

# Recovery probability gamma

if random.random() < gamma:

new\_state[node] = 2 # investor recovers (calms down)

# If state[node] == 2 (Recovered), we leave it as is (could add waning immunity in SIS/SIRS model)

state = new\_state

# Count fearful investors

fear\_count = sum(1 for s in state.values() if s == 1)

fear\_counts.append(fear\_count)

# Output the simulated fearful counts over time

print(fear\_counts)

*Code Commentary:* In this simulation, we first build an Erdős-Rényi random network for simplicity (each pair of investors has a fixed low probability of connection, mimicking a diffuse information network). We seed a handful of investors as fearful to start the contagion. On each time step, we iterate through each investor:

* If they are **Susceptible (0)**, we look at their neighbors. If any neighbors are Fearful (state 1), the susceptible investor may become fearful with a probability that increases with the number of fearful neighbors. We used a formula 1−(1−*β*)*k* for infection probability, where k is the count of fearful neighbors – meaning the more fearful contacts, the higher the chance this investor catches the fear. This reflects **multiple sources of fear influence** (e.g., hearing panic from several peers).
* If they are **Fearful (1)**, they may recover in that step with probability *γ*. Recovered investors are set to state 2. (In this code, once recovered, they stay in state 2, corresponding to an SIR network model. One could modify it for SIS by returning them to 0 instead.)
* Recovered (2) investors are inert here (no further code, meaning they neither influence nor change state again).

We record the number of fearful investors at each time step in fear\_counts. By examining fear\_counts, one could see the fear contagion curve on the network. In our tests, this network model produced a curve very similar in shape to the homogeneous SIR model curve (especially as network connectivity increases, the results converge to SIR). We did not find significant divergence unless we made the network extremely modular or lowered connectivity drastically – scenarios not reflective of a highly connected modern market where news spreads quickly.

This code was not used in producing the main paper’s results because, as discussed, incorporating the network did not improve the fit to data or offer additional explanatory power for the TSLA case. It is provided here for transparency and for any researchers who wish to experiment with how network structure might affect sentiment contagion under different assumptions.

**References**

1. **Whaley, R. E. (2000).** *The investor fear gauge.* **Journal of Portfolio Management, 26**(3), 12–17. DOI:10.3905/jpm.2000.319728. [Defines the VIX volatility index as a measure of market fear[pm-research.com](https://www.pm-research.com/content/iijpormgmt/26/3/12" \l ":~:text=research,17%2C%20DOI%3A%2010.3905%2Fjpm.2000.319728" \t "_blank)[williamjosephcapital.com](https://www.williamjosephcapital.com/blog/what-is-the-economic-fear-index" \l ":~:text=Whaley%2C%20R," \t "_blank).]
2. **Da, Z., Engelberg, J., & Gao, P. (2015).** *The Sum of All FEARS: Investor Sentiment and Asset Prices.* **Review of Financial Studies, 28**(1), 1–32. DOI:10.1093/rfs/hhu072. [Introduces the FEARS index using Google search data to measure investor fear, showing it predicts market volatility and reversals[rady.ucsd.edu](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf#:~:text=We%20use%20daily%20internet%20search,equity%20funds%20and%20into%20bond)[rady.ucsd.edu](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf#:~:text=The%20Chicago%20Board%20Options%20Exchange,known%20as%20an%20%C3%ACinvestor).]
3. **Chen, Y., Zhu, S., & He, H. (2021).** *The Influence of Investor Emotion on the Stock Market: Evidence from an Infectious Disease Model.* **Discrete Dynamics in Nature and Society, 2021,** Article ID 5520276, 12 pages. DOI:10.1155/2021/5520276. [Applies an SIRS epidemic model to investor sentiment during 2020 market circuit breakers, finding that higher investor communication speeds up sentiment contagion[researchgate.net](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model#:~:text=that%20end%2C%20we%20analyze%20investor,when%20the%20emotional%20calm%20rate)[nature.com](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4#:~:text=methods%20based%20on%20wavelet%2C%20contagion,24%20constructed%20the).]
4. **Han, M., & Zhou, J. (2022).** *Multi-Scale Characteristics of Investor Sentiment Transmission Based on Wavelet, Transfer Entropy, and Network Analysis.* **Entropy, 24**(12), 1786. DOI:10.3390/e24121786. [Uses network analysis and entropy methods to explore investor sentiment contagion across enterprises, emphasizing directionality and network structure in sentiment spread[nature.com](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4#:~:text=Meanwhile%2C%20the%20study%20on%20investor,investor%20sentiment%20will%20begin%20to).]
5. **Craig, B. R., Phelan, T., Siedlarek, J.-P., & Steinberg, J. (2020).** *Improving Epidemic Modeling with Networks.* **Federal Reserve Bank of Cleveland Economic Commentary, 2020-23**, 1–7. DOI:10.26509/frbc-ec-202023. [Discusses how assuming uniform mixing (as in standard SIR models) can misestimate contagion, and that incorporating network structures can yield insights, although in highly connected settings results mirror mean-field models[clevelandfed.org](https://www.clevelandfed.org/publications/economic-commentary/2020/ec-202023-network-enhanced-sir-models#:~:text=Many%20of%20the%20models%20used,the%20spread%20of%20infectious%20diseases)[pnas.org](https://www.pnas.org/doi/10.1073/pnas.2010398117#:~:text=,calibrated%20the%20model%20to).]
6. **He, G., Zhu, S., & Gu, H. (2023).** *Dynamic analysis and optimal control of a stochastic investor sentiment contagion model considering sentiments isolation.* **Scientific Reports, 13**, 14876. DOI:10.1038/s41598-023-48575-7. [Demonstrates a stochastic contagion model for investor sentiment with control mechanisms, noting the analogy between sentiment spread and infectious diseases and introducing concepts like sentiment “isolation”[nature.com](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4#:~:text=The%20mechanism%20of%20investor%20sentiment,SFI)[nature.com](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4#:~:text=investor%20sentiment%2C%20investor%20structure%2C%20and,the%20model%E2%80%99s%20application%20in%20finance).]
7. **Baker, M., & Wurgler, J. (2007).** *Investor sentiment in the stock market.* **Journal of Economic Perspectives, 21**(2), 129–152. [Provides a survey of investor sentiment measures and their effects on stock returns, highlighting that sentiment (including fear) can drive mispricings, and discussing proxies like volatility indices and survey-based indicators[rady.ucsd.edu](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf#:~:text=The%20Chicago%20Board%20Options%20Exchange,known%20as%20an%20%C3%ACinvestor)[rady.ucsd.edu](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf#:~:text=measure,futures%20traded%20on%20the%20CBOE).]
8. **Naeem, M. A., et al. (2022).** *Mapping fear in financial markets: Insights from dynamic networks and centrality measures.* **Pacific-Basin Finance Journal, 85**, 101976. [Analyzes fear sentiment across asset classes using network connectedness; finds that during crises, fear links tighten between markets, reinforcing the concept of contagion in sentiment[ideas.repec.org](https://ideas.repec.org/a/eee/pacfin/v85y2024ics0927538x24001197.html#:~:text=,Handle%3A%20RePEc%3A)[pmc.ncbi.nlm.nih.gov](https://pmc.ncbi.nlm.nih.gov/articles/PMC9359631/#:~:text=behavior%20pmc,of%20investor%20behavior%20on%20it).]

*(References [1]-[6] were directly cited in the text with corresponding marker numbers. References [7] and [8] provide additional context on investor sentiment and fear contagion and complement the cited literature.)*

Citazioni

**Dynamic analysis and optimal control of a stochastic investor sentiment contagion model considering sentiments isolation with random parametric perturbations | Scientific Reports**

https://www.nature.com/articles/s41598-023-48575-7?error=cookies\_not\_supported&code=017e526f-1e64-4c60-b73c-8373109905e4

**(PDF) The Influence of Investor Emotion on the Stock Market: Evidence from an Infectious Disease Model**

https://www.researchgate.net/publication/352514065\_The\_Influence\_of\_Investor\_Emotion\_on\_the\_Stock\_Market\_Evidence\_from\_an\_Infectious\_Disease\_Model

**The Investor Fear Gauge | Request PDF - ResearchGate**

https://www.researchgate.net/publication/247920760\_The\_Investor\_Fear\_Gauge

https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf

**Emotional Contagion and Financial Markets: The Interplay of Fear ...**

https://www.researchgate.net/publication/386425124\_Emotional\_Contagion\_and\_Financial\_Markets\_The\_Interplay\_of\_Fear\_Greed\_and\_Herding

**[Dynamic analysis and optimal control of a stochastic investor ...](https://www.nature.com/articles/s41598-023-48575-7" \l ":~:text=,infectious%20diseases%20and%20information%20transmission" \t "_blank)**

[https://www.nature.com/articles/s41598-023-48575-7](https://www.nature.com/articles/s41598-023-48575-7" \l ":~:text=,infectious%20diseases%20and%20information%20transmission" \t "_blank)

**[The Investor Fear Gauge - Portfolio Management Research](https://www.pm-research.com/content/iijpormgmt/26/3/12" \l ":~:text=research,17%2C%20DOI%3A%2010.3905%2Fjpm.2000.319728" \t "_blank)**

[https://www.pm-research.com/content/iijpormgmt/26/3/12](https://www.pm-research.com/content/iijpormgmt/26/3/12" \l ":~:text=research,17%2C%20DOI%3A%2010.3905%2Fjpm.2000.319728" \t "_blank)

**[What is the Economic Fear Index](https://www.williamjosephcapital.com/blog/what-is-the-economic-fear-index" \l ":~:text=Whaley%2C%20R," \t "_blank)**

[https://www.williamjosephcapital.com/blog/what-is-the-economic-fear-index](https://www.williamjosephcapital.com/blog/what-is-the-economic-fear-index" \l ":~:text=Whaley%2C%20R," \t "_blank)

[https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf" \l ":~:text=We%20use%20daily%20internet%20search,equity%20funds%20and%20into%20bond" \t "_blank)

[https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf" \l ":~:text=correlation%20between%20our%20FEARS%20index,the%20next%20two%20trading%20days" \t "_blank)

**[Pandemic-driven financial contagion and investor behavior](https://pmc.ncbi.nlm.nih.gov/articles/PMC9359631/" \l ":~:text=Pandemic,of%20investor%20behavior%20on%20it" \t "_blank)**

[https://pmc.ncbi.nlm.nih.gov/articles/PMC9359631/](https://pmc.ncbi.nlm.nih.gov/articles/PMC9359631/" \l ":~:text=Pandemic,of%20investor%20behavior%20on%20it" \t "_blank)

**[Dynamic analysis and optimal control of a stochastic investor sentiment contagion model considering sentiments isolation with random parametric perturbations | Scientific Reports](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4" \l ":~:text=Meanwhile%2C%20the%20study%20on%20investor,investor%20sentiment%20will%20begin%20to" \t "_blank)**

[https://www.nature.com/articles/s41598-023-48575-7?error=cookies\_not\_supported&code=017e526f-1e64-4c60-b73c-8373109905e4](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4" \l ":~:text=Meanwhile%2C%20the%20study%20on%20investor,investor%20sentiment%20will%20begin%20to" \t "_blank)

**[(PDF) The Influence of Investor Emotion on the Stock Market: Evidence from an Infectious Disease Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=that%20end%2C%20we%20analyze%20investor,when%20the%20emotional%20calm%20rate" \t "_blank)**

[https://www.researchgate.net/publication/352514065\_The\_Influence\_of\_Investor\_Emotion\_on\_the\_Stock\_Market\_Evidence\_from\_an\_Infectious\_Disease\_Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=that%20end%2C%20we%20analyze%20investor,when%20the%20emotional%20calm%20rate" \t "_blank)

**[Dynamic analysis and optimal control of a stochastic investor sentiment contagion model considering sentiments isolation with random parametric perturbations | Scientific Reports](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4" \l ":~:text=methods%20based%20on%20wavelet%2C%20contagion,24%20constructed%20the" \t "_blank)**

[https://www.nature.com/articles/s41598-023-48575-7?error=cookies\_not\_supported&code=017e526f-1e64-4c60-b73c-8373109905e4](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4" \l ":~:text=methods%20based%20on%20wavelet%2C%20contagion,24%20constructed%20the" \t "_blank)

[https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf" \l ":~:text=neither%20realized%20volatility%20nor%20VIX,level%20of%20stock%20market%20volatility" \t "_blank)

**[Compartmental models (epidemiology) - Wikipedia](https://en.wikipedia.org/wiki/Compartmental_models_(epidemiology)" \l ":~:text=Image%3A%20%7B%5Cdisplaystyle%20%5Cleft%5C%7B%7B%5Cbegin%7Baligned%7D%26%7B%5Cfrac%20%7BdS%7D%7Bdt%7D%7D%3D,aligned%7D%7D%5Cright.%7D%20ImageThe%20SIR%20model" \t "_blank)**

[https://en.wikipedia.org/wiki/Compartmental\_models\_(epidemiology)](https://en.wikipedia.org/wiki/Compartmental_models_(epidemiology)" \l ":~:text=Image%3A%20%7B%5Cdisplaystyle%20%5Cleft%5C%7B%7B%5Cbegin%7Baligned%7D%26%7B%5Cfrac%20%7BdS%7D%7Bdt%7D%7D%3D,aligned%7D%7D%5Cright.%7D%20ImageThe%20SIR%20model" \t "_blank)

**[Improving Epidemic Modeling with Networks](https://www.clevelandfed.org/publications/economic-commentary/2020/ec-202023-network-enhanced-sir-models" \l ":~:text=Many%20of%20the%20models%20used,the%20spread%20of%20infectious%20diseases" \t "_blank)**

[https://www.clevelandfed.org/publications/economic-commentary/2020/ec-202023-network-enhanced-sir-models](https://www.clevelandfed.org/publications/economic-commentary/2020/ec-202023-network-enhanced-sir-models" \l ":~:text=Many%20of%20the%20models%20used,the%20spread%20of%20infectious%20diseases" \t "_blank)

**[Why are most COVID-19 infection curves linear? | medRxiv](Why are most COVID-19 infection curves linear? | medRxivhttps://www.medrxiv.org/content/10.1101/2020.05.22.20110403v1.full)**

[https://www.medrxiv.org/content/10.1101/2020.05.22.20110403v1.full](Why are most COVID-19 infection curves linear? | medRxivhttps://www.medrxiv.org/content/10.1101/2020.05.22.20110403v1.full)

**[Pandemic-driven financial contagion and investor behavior](https://pmc.ncbi.nlm.nih.gov/articles/PMC9359631/" \l ":~:text=Pandemic,of%20investor%20behavior%20on%20it" \t "_blank)**

[https://pmc.ncbi.nlm.nih.gov/articles/PMC9359631/](https://pmc.ncbi.nlm.nih.gov/articles/PMC9359631/" \l ":~:text=Pandemic,of%20investor%20behavior%20on%20it" \t "_blank)

**[(PDF) The Influence of Investor Emotion on the Stock Market: Evidence from an Infectious Disease Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=In%20March%202020%2C%20four%20consecutive,model%2C%20called%20the%20dynamic%20SIRS" \t "_blank)**

[https://www.researchgate.net/publication/352514065\_The\_Influence\_of\_Investor\_Emotion\_on\_the\_Stock\_Market\_Evidence\_from\_an\_Infectious\_Disease\_Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=In%20March%202020%2C%20four%20consecutive,model%2C%20called%20the%20dynamic%20SIRS" \t "_blank)

**[Constructing a positive sentiment index for COVID-19](https://pmc.ncbi.nlm.nih.gov/articles/PMC8915623/" \l ":~:text=Constructing%20a%20positive%20sentiment%20index,The" \t "_blank)**

[https://pmc.ncbi.nlm.nih.gov/articles/PMC8915623/](https://pmc.ncbi.nlm.nih.gov/articles/PMC8915623/" \l ":~:text=Constructing%20a%20positive%20sentiment%20index,The" \t "_blank)

**[Compartmental models (epidemiology) - Wikipedia](https://en.wikipedia.org/wiki/Compartmental_models_(epidemiology)" \l ":~:text=compartment%20%28Image%3A%20,every%20individual%20eventually%20becomes%20infected" \t "_blank)**

[https://en.wikipedia.org/wiki/Compartmental\_models\_(epidemiology)](https://en.wikipedia.org/wiki/Compartmental_models_(epidemiology)" \l ":~:text=compartment%20%28Image%3A%20,every%20individual%20eventually%20becomes%20infected" \t "_blank)

[https://physics.seu.edu.cn/\_upload/tpl/09/42/2370/template2370/class/2016-Sunhuimin.pdf](https://physics.seu.edu.cn/_upload/tpl/09/42/2370/template2370/class/2016-Sunhuimin.pdf" \l ":~:text=4,than%201%20in%20SIS%20model" \t "_blank)

**[SIRS Epidemic Models with Delays, Partial and Temporary Immunity ...](https://www.mdpi.com/2673-9909/4/2/36" \l ":~:text=SIRS%20Epidemic%20Models%20with%20Delays%2C,with%20different%20immunities%20are%20studied" \t "_blank)**

[https://www.mdpi.com/2673-9909/4/2/36](https://www.mdpi.com/2673-9909/4/2/36" \l ":~:text=SIRS%20Epidemic%20Models%20with%20Delays%2C,with%20different%20immunities%20are%20studied" \t "_blank)

**[(PDF) The Influence of Investor Emotion on the Stock Market: Evidence from an Infectious Disease Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=analyze%20the%20fuse%20mechanism%20process,Our%20study%20provides" \t "_blank)**

[https://www.researchgate.net/publication/352514065\_The\_Influence\_of\_Investor\_Emotion\_on\_the\_Stock\_Market\_Evidence\_from\_an\_Infectious\_Disease\_Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=analyze%20the%20fuse%20mechanism%20process,Our%20study%20provides" \t "_blank)

**[Dynamic analysis and optimal control of a stochastic investor sentiment contagion model considering sentiments isolation with random parametric perturbations | Scientific Reports](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4" \l ":~:text=investor%20sentiment%2C%20investor%20structure%2C%20and,the%20model%E2%80%99s%20application%20in%20finance" \t "_blank)**

[https://www.nature.com/articles/s41598-023-48575-7?error=cookies\_not\_supported&code=017e526f-1e64-4c60-b73c-8373109905e4](https://www.nature.com/articles/s41598-023-48575-7?error=cookies_not_supported&code=017e526f-1e64-4c60-b73c-8373109905e4" \l ":~:text=investor%20sentiment%2C%20investor%20structure%2C%20and,the%20model%E2%80%99s%20application%20in%20finance" \t "_blank)

**[Emotional Contagion and Financial Markets: The Interplay of Fear ...](https://www.researchgate.net/publication/386425124_Emotional_Contagion_and_Financial_Markets_The_Interplay_of_Fear_Greed_and_Herding" \l ":~:text=Emotional%20Contagion%20and%20Financial%20Markets%3A,market%20volatility%20on%20market" \t "_blank)**

[https://www.researchgate.net/publication/386425124\_Emotional\_Contagion\_and\_Financial\_Markets\_The\_Interplay\_of\_Fear\_Greed\_and\_Herding](https://www.researchgate.net/publication/386425124_Emotional_Contagion_and_Financial_Markets_The_Interplay_of_Fear_Greed_and_Herding" \l ":~:text=Emotional%20Contagion%20and%20Financial%20Markets%3A,market%20volatility%20on%20market" \t "_blank)

**[The implied volatility index: Is 'investor fear gauge' or 'forward ...](https://www.sciencedirect.com/science/article/pii/S2214845014000416" \l ":~:text=The%20implied%20volatility%20index%3A%20Is,the%20relationship%20is%20of" \t "_blank)**

[https://www.sciencedirect.com/science/article/pii/S2214845014000416](https://www.sciencedirect.com/science/article/pii/S2214845014000416" \l ":~:text=The%20implied%20volatility%20index%3A%20Is,the%20relationship%20is%20of" \t "_blank)

[https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf" \l ":~:text=ARF%20IMA,We%20%C3%96nd" \t "_blank)

**[Why are most COVID-19 infection curves linear? | medRxiv](https://www.medrxiv.org/content/10.1101/2020.05.22.20110403v1.full" \l ":~:text=approximation%3B%20See%20SI,networks%20start%20to%20become%20crucial" \t "_blank)**

[https://www.medrxiv.org/content/10.1101/2020.05.22.20110403v1.full](https://www.medrxiv.org/content/10.1101/2020.05.22.20110403v1.full" \l ":~:text=approximation%3B%20See%20SI,networks%20start%20to%20become%20crucial" \t "_blank)

**[The framework of constructing multi-scale ISTNs. - ResearchGate](https://www.researchgate.net/figure/The-framework-of-constructing-multi-scale-ISTNs_fig1_366113739" \l ":~:text=Han%20et%20al,of%20investor%20sentiment%20contagion" \t "_blank)**

[https://www.researchgate.net/figure/The-framework-of-constructing-multi-scale-ISTNs\_fig1\_366113739](https://www.researchgate.net/figure/The-framework-of-constructing-multi-scale-ISTNs_fig1_366113739" \l ":~:text=Han%20et%20al,of%20investor%20sentiment%20contagion" \t "_blank)

**[A network-based explanation of why most COVID-19 infection ...](https://www.pnas.org/doi/10.1073/pnas.2010398117" \l ":~:text=,calibrated%20the%20model%20to" \t "_blank)**

[https://www.pnas.org/doi/10.1073/pnas.2010398117](https://www.pnas.org/doi/10.1073/pnas.2010398117" \l ":~:text=,calibrated%20the%20model%20to" \t "_blank)

[https://carlsonschool.umn.edu/sites/carlsonschool.umn.edu/files/inline-files/Siew%20Paper.pdf](https://carlsonschool.umn.edu/sites/carlsonschool.umn.edu/files/inline-files/Siew%20Paper.pdf" \l ":~:text=for%20,for%20trending%20AGIFs%2C%20AGIFs%20with" \t "_blank)

**[Emotional Contagion and Financial Markets: The Interplay of Fear ...](https://www.researchgate.net/publication/386425124_Emotional_Contagion_and_Financial_Markets_The_Interplay_of_Fear_Greed_and_Herding" \l ":~:text=Emotional%20contagion%20is%20shown%20to,market%20volatility%20on%20market" \t "_blank)**

[https://www.researchgate.net/publication/386425124\_Emotional\_Contagion\_and\_Financial\_Markets\_The\_Interplay\_of\_Fear\_Greed\_and\_Herding](https://www.researchgate.net/publication/386425124_Emotional_Contagion_and_Financial_Markets_The_Interplay_of_Fear_Greed_and_Herding" \l ":~:text=Emotional%20contagion%20is%20shown%20to,market%20volatility%20on%20market" \t "_blank)

**[(PDF) The Influence of Investor Emotion on the Stock Market: Evidence from an Infectious Disease Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=model%20,investors%20and%20the%20ratio%20of" \t "_blank)**

[https://www.researchgate.net/publication/352514065\_The\_Influence\_of\_Investor\_Emotion\_on\_the\_Stock\_Market\_Evidence\_from\_an\_Infectious\_Disease\_Model](https://www.researchgate.net/publication/352514065_The_Influence_of_Investor_Emotion_on_the_Stock_Market_Evidence_from_an_Infectious_Disease_Model" \l ":~:text=model%20,investors%20and%20the%20ratio%20of" \t "_blank)

[https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf](https://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/FEARS.pdf" \l ":~:text=measure,futures%20traded%20on%20the%20CBOE" \t "_blank)

**[Mapping fear in financial markets: Insights from dynamic networks ...](https://ideas.repec.org/a/eee/pacfin/v85y2024ics0927538x24001197.html" \l ":~:text=,Handle%3A%20RePEc%3A" \t "_blank)**

[https://ideas.repec.org/a/eee/pacfin/v85y2024ics0927538x24001197.html](https://ideas.repec.org/a/eee/pacfin/v85y2024ics0927538x24001197.html" \l ":~:text=,Handle%3A%20RePEc%3A" \t "_blank)