Epidemiological Expectations

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Abstract

'Epidemiological' models of belief formation put social interactions at their core; such models are the main (almost, the only) tool used by non-economists to study the dynamics of beliefs in populations. We survey the (comparatively) small literature in which economists attempting to model the consequences of beliefs about the future – 'expectations' – have employed a full-fledged epidemiological approach to explore an economic question. We draw connections to related work on 'contagion,' narrative economics, news/rumor spreading, and the spread of online content. We conclude by arguing that a number of independent developments have converged in ways that may make epidemiological expectations (EE) modeling more feasible and appealing than in the past.

Keywords Economic Expectations, Epidemiological Expectations, Social interactions, Social dynamics, Information diffusion, Economic Narratives

JEL codes D84, D91, E71, G41

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    REMARK:  https://econ-ark.org/materials/epiexp
 Dashboard:  Click 'Launch Dashboard' Button
      html:  https://llorracc.github.io/BufferStockTheory/
       PDF:  EpiExp.pdf
    Slides:  EpiExp-Slides.pdf
    GitHub:  https://github.com/llorracc/EpiExp
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While mass media play a major role in alerting individuals to the possibility of an innovation, it seems to be personal contact that is most relevant in leading to its adoption. Thus, the diffusion of an innovation becomes a process formally akin to the spread of an infectious disease.

– Arrow (1969)

A very natural next step for economics is to maintain expectations in the strategic position they have come to occupy, but to build an empirically validated theory of how attention is in fact directed within a social system, and how expectations are, in fact, formed.

– Simon (1984)

If we want to know why an unusually large economic event happened, we need to list the seemingly unrelated narratives that all happened to be going viral at around the same time and affecting the economy in the same direction.

– Shiller (2017)

An idea is like a virus. Resilient. Highly contagious. And even the smallest seed of an idea can grow. –Cobb

– The movie *Inception* [2010]

1 Introduction

It is a commonplace, in academia and popular culture, that ideas spread like diseases: they can be "infectious" or "go viral." The proposition is hardly new; as Shiller (2017) points out, it can be found at least as far back as Hume (1748), whose ideas thoroughly infected the work of his friend Smith (1776).[1] Indeed, in fields other than economics, the debates are rarely about whether social interactions are fundamental; the main question is which particular models for capturing social interactions are most suitable for understanding the spread of which kinds of ideas.

"Expectations" are just a category of ideas. So upon being told that expectations play a critical role in structural economic modeling, a scholar who was not an economist might suppose that epidemiological models of expectations would be a standard part of the economist's modeling toolkit — unless there were good reason to suppose that economic ideas are immune to social influence.

But evidence for social transmission of economic ideas is plentiful and has recently been growing by leaps and bounds – see Section 4.4. Still, it would not be accurate to say that an 'epidemiological expectations' ('EE') approach is a standard way of constructing formal models of economic phenomena – as a conventional off-the-shelf

[1] See Rasmussen (2017).

alternative, say, to a 'rational expectations' ('RE') approach, the 'Rational Inattention' ('RI') approach advocated by Sims (2003), or even to the 'diagnostic expectations' model of Bordalo, Gennaioli, and Shleifer (2018), or a number of bounded rationality approaches (e.g., Gabaix (2020) or Ilut and Valchev (2020)).

This is perhaps because nowhere has any careful attempt been made to define what would constitute a full-fledged EE treatment of an economic question.[2] Despite this handicap, there have been some notable examples of what we would describe as full-fledged EE approaches, which we define as requiring the following elements:

1. a mechanism: An explicit and rigorous mathematical description of a social interaction process by which ideas are transmitted among agents ...
2. implying expectational dynamics: ... that generates observable expectation dynamics at the level of individuals or populations ...
3. with economic consequences: ... and those expectations have knock-on consequences for an observable outcome (often, prices, quantities, or market values) that is the primary subject of the economic analysis.

These criteria whittle down a vast number of invocations, or partial discussions, of the proposition that ideas spread through social interaction to the surprisingly small number of papers on which we primarily focus here. (The last criterion allows us to neglect enormous literatures on public opinion, politics, musical tastes, internet memes, and other topics).

We have identified three fields in economics – technological diffusion (section 4.1), financial markets (section 4.2), and macroeconomics (section 4.3), in which there is a set of papers that satisfy all these criteria – even if in some cases the work has not been mainly thought of as 'epidemiological' until now.[3] In addition, we survey the proliferating work providing evidence that social interactions drive expectations and corresponding behaviors (section 4.4); draw the connection between the EE approach and a separate yet related literature on financial contagion (section 4.5); and present a selection of research on the spreading of news and rumors, scientific ideas and online content, most of which has been performed by scholars outside of economics (section 4.6).[4]

[2]A methodology in cultural economics called 'the epidemiological approach' seeks to identify cultural variations in the same way epidemiologists sometimes identify latent disease risks: By a person's place of origin, or other observable exogenous traits that might be markers of cultural attitudes. Since this approach does not aim to study the transmission of expectations by social interactions, we see little danger of its being confused with what we define as EE modeling.

[3]Ironically, these literatures claiming that ideas succeed by contagion have developed largely in isolation, judging at least by the almost complete independence of the citation networks connecting them (see our figure 3). The only paper that is cited by all three of the literatures is the foundational paper by Kermack, McKendrick, and Walker (1927).

[4]Since the outbreak of the COVID-19 pandemic, a large literature has sprung up in which economists have directly modeled COVID itself as a disease, or modeled the economic consequences of the disease; this work of course does meet our criteria, but some of it – e.g. Gourieroux and Jasiak (2020) – contains interesting techniques for modeling the spread of the disease which could potentially be repurposed for modeling the spread of ideas.

2 Background and Motivation

2.1 Expectational Heterogeneity

In their introduction to the *Handbook of Microeconomics*, Browning, Heckman, and Hansen [1999], wrote that the most universal lesson of micro economics is that "people are different in ways that importantly affect their economic behavior."

Over the subsequent two decades, a great deal of the progress in macro economics has come from incorporating microeconomic heterogeneity "in ways that importantly affect" macroeconomic behavior. (See "Macroeconomics and Heterogeneity" in the latest *Handbook of Macroeconomics*, Krueger, Mitman, and Perri (2016)). In particular, Heterogeneous Agent ('HA-Macro') models that match the distributions of income and wealth have now provided rigorous microfoundations for Keynesian macroeconomics by capturing measured heterogeneity in (and a large average value for) the marginal propensity to consume – see Violante (2021)'s Laffont lecture.

But only a few structural models in the HA-Macro literature have allowed for differences in agents' expectations about variables like stock returns (where everyone's realized outcome will be identical) – even though disagreements on such subjects are rife and people make choices that correspond to their expressed beliefs (Giglio, Maggiori, Stroebel, and Utkus (2021)).[5]

Partly, the failure of modelers to incorporate expectational heterogeneity may reflect the fact that until recently there was not widespread awareness among macroeconomists that measurable expectation differences have considerable power to explain observable microeconomic behavioral differences. Evidence of the recent change in attitudes can be seen in the published discussions in the 2017 *NBER Macroeconomics Annual* of Manski (2017)'s paper surveying the literature on the measurement of expectations (in which Manski himself has been the leading figure, and until recently something of a lone voice crying in the wilderness). Other signs of the profession's new interest in the measurement of expectations are developments like the commissioning of this *Handbook*, the creation of the *Survey of Consumer Expectations* by the Federal Reserve Bank of New York in 2014 (and several similar surveys or pilots in Canada, Europe, and elsewhere (see Bruine de Bruin, Chin, Jeff, and Van Der Klaauw (2022) for a list of such surveys), and the fact that expectational questions have begun to be added to existing surveys like the ones used for calibrating HA-Macro models.

But EE modeling approaches may be particularly appealing now as a result of the emergence of new *kinds* of data. In particular, for the first time ever, it is now becoming possible to directly observe economic expectations spreading over social networks – as in the papers we describe below by Bailey, Cao, Kuchler, and Stroebel (2018); Bailey, Dávila, Kuchler, and Stroebel (2019).

[5] One of the few examples is Velásquez-Giraldo (2022), who shows that household portfolio choice models yield much more reasonable results when the model is calibrated with survey respondents' actual measured stock market expectations than when calibrated, as usual, under the assumption that all households hold beliefs identical to those that economists have estimated in scholarly literature.

2.2 Epistemology and Epidemiology

One aspect of the EE approach that seems to trouble economists more than scholars from other fields is the requirement to specify a source for the idea(s) whose spread is being modeled.

The Rational Expectations approach gets around this problem by making some rather bold assumptions (there is only one 'true' model of the world; everyone believes the same true model; everyone observes an identical set of facts and draws the same conclusions from them; everyone *knows* that everyone believes ... ; and so on).

An appealing way to move forward is for epidemiological models to be built to be 'tunable' in the degree to which they differ from better-understood models. This should not be hard: If the only 'source' of ideas is an agent who believes in the rational expectations solution, and the infection rate is 100 percent, the solution will be the rational expectations solution. It will then be possible to pin down, step by step, the reasons for any deviation between the EE and the corresponding RE model.

In fact, most of the examples of EE models we highlight below are of this kind: There is some parameter or set of parameters which can be set to zero (or some other specific value), causing the model to collapse to an off-the-shelf rational expectations model.

2.3 Epidemiology on Networks

For short, we use the word 'classical' to refer to epidemiological models that descend from the work of Kermack, McKendrick, and Walker (1927), who formulated the problem as one of tracking the size of 'compartments' of the population in different disease states (like susceptible or infected) under a 'random mixing' assumption in which all members of the population were equally likely to encounter each other in a time interval. Along with the use of continuous time and real numbers for the compartment sizes, the random mixing assumption allowed the problem to be described by a set of differential equations that could be solved numerically even in 1927.

A newer literature also examines the social transmission of beliefs and satisfies any reasonable interpretation of an 'epidemiological' approach: A large body of work using the tools of 'network theory' studies models in which the 'nodes' in a graph are interpreted as people and the 'edges' are social connections between nodes. Erdos, Rényi, et al. (1960) originated this literature with a model in which connections among agents were a 'random graph' (the analog of the 'random mixing' assumption), so the only parameter was 'degree': the number of connections each agent had. Subsequent work relaxed random graph assumption, allowing meaningful definition of an agent's 'neighbors,' and showed that a 'clustering coefficient' is a useful measurement of the extent to which a person's neighbors know each other. These tools allow the researcher to consider any measurable type of connection – not restricted to geography or workplace or any other narrow category.[6]

While the classical and the network-theory approaches seem quite different, it turns out that network theory tools can be configured to produce an arbitrarily close approx-

[6] A standard reference for economists is the textbook by Jackson (2010).

imation to the classical problem (see our example in Section 3.2 below). But networks can also be used to study a great many other essentially epidemiological questions that could not even be formulated in the classical setup.

One well-known network-theory result that (to some extent) helps bridge the classical and the network approaches is the "Small World" effect explained by Watts and Strogatz (1998), who show that even when the 'clustering coefficient' is high, a small sprinkling of random links to 'distant' nodes has remarkable power to make a network 'completely connected' (or nearly so). Barabási et al. (2016)'s summary is that when network models are calibrated to match facts about human connections (or, for that matter, internet links), the "interconnectedness" phenomenon is extremely robust.

This provides a satisfying explanation for a phenomenon first documented by Milgram (1967), who famously found that, on average, any two randomly selected people in the U.S. population were able to identify intermediate links of personal friends and friends-of-friends (and so on) by which they were connected, with the typical length of the chain involving only six people.[7] For our purposes, the interesting insight is that the "Small Worlds" phenomenon may suggest that the 'random mixing' assumption in classical epidemiological models may not be as problematic as it might seem at first.

The 'small worlds' phenomenon also provides a plausible mathematical explanation for the 'strength of weak ties' phenomenon (Granovetter (1973)) according to which jobfinding through a social network most often happens through a distantly connected person. The key feature of such 'weak ties' is that they connect the job-seeker to many opportunities not known to those in the job-seeker's immediate 'cluster.'

A distinct advantage of the 'network' approach over the classical epidemiological approach is the extent to which, especially with modern computational tools, a network modeler can examine the consequences of almost arbitrarily rich assumptions about the exact nature of interactions between agents. A key theme of the network literature is that even in a fully connected world, it is easy to construct models in which disagreement persists indefinitely (Acemoğlu, Como, Fagnani, and Ozdaglar (2013)) and subpopulations converge to different beliefs (Sikder, Smith, Vivo, and Livan (2020)).

2.4 Expectational Tribes

The fact that epidemiological models can easily imply that subgroups can settle into permanently different points of view is inconvenient from a modeling perspective. If there were no evidence that persistent differences of opinion could matter for important economic decisions, the case for using the epidemiological modeling toolkit would be weaker. We therefore conclude this section on 'background and motivation' by presenting some evidence of a recent clear failure of 'identical beliefs' with consequences for measured choices in an area core to both micro and macro modeling: financial risk-taking.

[7] This provides another example of crossover appeal in popular culture, having spawned John Guare (1990)'s play 'Six Degrees of Separation' a movie adaptation, a popular parlor game, and other byproducts like calculators for the degrees of separation between academics).

Meeuwis, Parker, Schoar, and Simester (2021), using a dataset on millions of retirement investors from a large financial institution, show that after Donald Trump's surprise victory in the U.S. 2016 Presidential election, investors likely to be affiliated with Republican Party (inferred from campaign donations at the zip code level) increased the equity share in their portfolio, while (likely) Democrats rebalanced into safe assets. (See Figure 1.) These choices occurred at exactly the same time that consumer sentiment surveys showed that self-identified Republicans had suddenly become more optimistic, and Democrats more pessimistic, about the economy's prospects over the next few years.[8,9]

3 What insights can the epidemiological framework offer?

3.1 What Is an Epidemiological Framework?

We will say that ideas, beliefs, 'narratives,' or other mental states that can affect behavior (henceforth, 'expectations' are shorthand for all of these) result from an "epidemiological" process whenever they are modeled as resulting from some social interaction.

This is a slightly narrower scope than the mechanisms encompassed in textbook definitions of epidemiology, which can include the study of diseases that develop without any identifiable external influence. The category of epidemiological models we are interested in is those for "transmissible" diseases.

But the transmission need not be person-to-person. "Common source" diseases do not involve any one-on-one contact; for example, cosmic radiation to which everyone is exposed can cause diseases like cancer. In the context of expectation formation a natural interpretation of such a "common source" is news media (a point to which we return below).

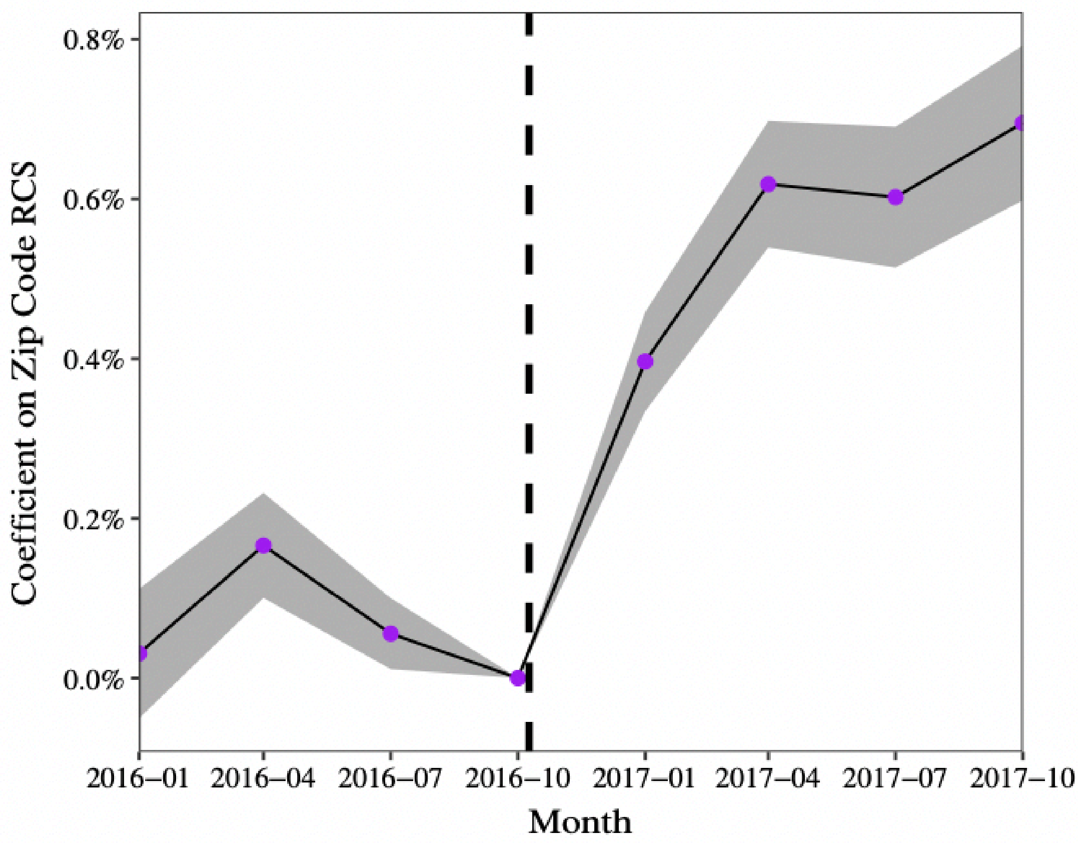
Probably the simplest epidemiological model is a 'common source SI model.' In this case a continuous population is divided into two 'compartments': Persons in compartment 'I' have been infected with the disease (and can never recover), while persons in compartment 'S' are not yet infected. The mathematical expression of the 'common source' assumption is simply that the probability that any particular susceptible person will become infected is time-independent.

For a population that begins at discrete date zero with a susceptible population of size 1, the dynamics are given by Table 1, with the obvious implication that as n approaches infinity the entire population eventually becomes infected.

[8]The New York Fed blog post *"Political Polarization in Consumer Expectations"* also provides evidence for partisan differences in consumer expectations.

[9]Of course as is the case in many settings, the cause of changes in beliefs, here the election outcome, is also a potential cause of changes in objective economic circumstances. The paper makes use of its rich data to provide strong evidence that differences in circumstances such as local economic conditions or hedging needs are not driving the results. In particular, investment behavior differs by political affiliation even among people living in the same county and working at the same firm, and after controlling for many other individual-level characteristics.

Figure 1 Portfolio responses to 2016 U.S. election



Note: reproduced from Meeuwis, Parker, Schoar, and Simester (2021), this figure reports the baseline regression coefficients of equity share on zip-code level campaign contribution share to Republican candidate for the three quarters prior to the election and the four quarters following the election, relative to allocations just before the election.

This modeling framework can be extended in many directions. The usual next step is to have the disease be transmitted from agent to agent by 'random mixing' which leads to the most familiar subclass of the SI modeling family, in which each susceptible person who encounters an infected person becomes infected at a rate β in each period. Then in the discrete-time formulation, given a non-zero initial infected fraction I_0, the fraction infected and susceptible evolve as described in Table 2.

The best-known epidemiological framework adds one more potential state to "susceptible" and "infected": 'R' can be used to designate either recovery or 'removal' (via, say, death); this yields the rich set of 'SIR' models first proposed by Kermack, McKendrick, and Walker (1927), who formulated the transition equations as a system of continuous-time nonlinear differential equations.

The SIR model has rich and interesting implications, such as the potential for 'herd immunity' which comes about when a high enough proportion of the population has

Table 1 Common Source SI Model

Date t	Susceptible$_t$	Infected$_t$
0	1	0
1	$(1-p)$	$1-(1-p)$
2	$(1-p)^2$	$1-(1-p)^2$
$\vdots$	$\vdots$	$\vdots$
n	$(1-p)^n$	$1-(1-p)^n$

Table 2 Transmissible SI Model

Date t	Susceptible$_t$	Infected$_t$
0	S_0	I_0
1	$S_0 - \beta S_0 I_0$	$I_0 + \beta S_0 I_0$
2	$S_1 - \beta S_1 I_1$	$I_1 + \beta S_1 I_1$
$\vdots$	$\vdots$	$\vdots$
n	$S_{n-1} - \beta S_{n-1} I_{n-1}$	$I_{n-1} + \beta S_{n-1} I_{n-1}$

either Recovered or otherwise been Removed (say, by vaccination) from the pool of those susceptible to infection.

Unfortunately, the model's equations do not have finite closed-form analytical solutions,[10] so implications must be obtained using numerical computational procedures – though with current computational technologies such computations for the original Kermack, McKendrick, and Walker (1927) model have negligible cost.

Potential modeling choices proliferate from there.[11] A framework in which there are two possible outcomes of the infection, recovery or death, receives the acronym SIRD. If the disease is one in which it is necessary to track the proportion who have been Exposed but are not yet (and may never become) infected, the result is an SEIR model – and so on.

One standard assumption for all of these models is that agents are *ex-ante* homogeneous, but the classical framework can be extended to permit various kinds of heterogeneity – at the considerable cost of adding whole new systems of nonlinear differential equations. An advantage of the network approach is that since it is solved by simulation, modifications of the model are much easier to make because they do not add new systems of simultaneous differential equations to be solved.

[10] Miller (2012) and Harko, Lobo, and Mak (2014) produce alternative formulations of what they call analytical solutions – see this Wikipedia page – but both involve an integral that can only be calculated numerically, so neither is available in closed form. These amount to convenient modern restatements of the original Kermack, McKendrick, and Walker (1927) model.

[11] For a general introduction to these model basics, we refer the reader to this Wikipedia page. Epidemiologists use the term 'compartmental models' refer to models in which people transition between states like susceptible and infected. References to such models include Kermack, McKendrick, and Walker (1927), Bailey et al. (1975), Anderson, Anderson, and May (1992), Hethcote (2000), Brauer (2017).

3.1.1 Adapting the Disease Metaphor to Expectations

Epidemiologists are usually interested in studying the dynamics of a single disease in a population, with a natural terminal stage like recovery or death. Economists will often be interested in keeping track of how expectations change about an aggregate variable like stock prices, which does not have a terminal point and in which many competing opinions may infect different people at the same time.

Another advantage of the network theory formulation of epidemiological models is that it can easily accommodate dimensions in which an economic application may call for such modifications. It is a trivial matter to represent as many competing 'diseases' (theories of stock prices) as desired, and there is no need to specify a 'recovery' state.

To take a more complex example, in classical epidemiological models it would be painful (though possible) to capture dynamics of a disease in which people become 'more infected' after repeated contact with other infected people. But in a network model, it is easy to capture the proposition that a person may need to be exposed to an idea more than a certain number of times, or from more than a given number of sources, before they will adopt it – as proposed in Granovetter (1978), and as implemented in Jackson and Yariv (2007). [12]

3.2 One Example

Here, we provide a first example of an economic question formulated in a thoroughgoing epidemiological way. Our purpose, here, is not to extract economic insights – we do that in section 4.2 below – but simply to illustrate how the epidemiological toolkit works.

Shiller and Pound (1989)[13] use an SIR model to capture how the interest in particular stocks spreads in a population; we examine a model almost identical to theirs.[14]

At any date t, a large population of investors of size N is divided into three "compartments." (See Figure 2). I_t represents investors who are currently "infected" with interest in a certain stock, S_t corresponds to investors who are not infected but are "susceptible" to becoming interested in the stock, and R_t are investors who have been "infected" but have "recovered" from the infection.[15]

In each period, each person is expected to have contact with χ others, randomly selected from the entire population (this is the 'random mixing' assumption mentioned above). In the SIR framework, the only kind of contact with any consequence is between an infected person and a susceptible person: Such an encounter has a probability τ of causing the susceptible person to become infected.

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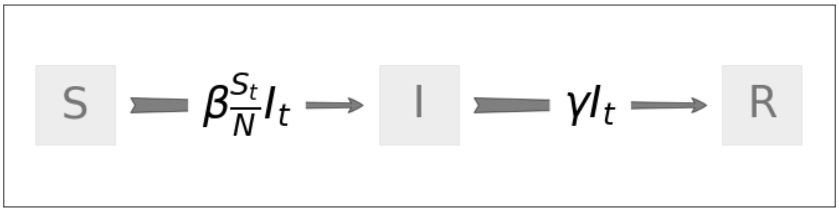
[12] See the interesting discussion of such 'threshold models' in Glasserman and Young (2016).

[13] This paper builds on the earlier work comparing the efficient market hypothesis of stock prices and an alternative model incorporating social dynamics (Shiller, Fischer, and Friedman, 1984).

[14] Our treatment makes two inconsequential modifications. First, in order to be able to instantiate the model using the `NDLib` computational toolkit described below, we rewrite the originally continuous-time model in a discrete-time form. Second, the original paper described an additional stochastic shock to the change in I_t meant to capture a potential "change in the 'source' of the infection or the nature of the contagion." Because that shock was not actually used for any results in the paper, we neglect it in our exposition.

[15] The "recovery" compartment contains investors who have lost interest in the stock. For our purposes here, we do not need to define the exact consequences of 'recovery' – like, whether it means that the person sells the stock. See the original paper for further exposition.

Figure 2 A SIR model of stock investors



Note: This graph plots the transitions between different compartments in the SIR model of stock investors described in Shiller and Pound (1989).

Epidemiological models typically define a parameter β that combines consequences of the rate of social contact χ and the rate of transmission upon such a contact, τ:[16]

$$\beta = \tau\chi. \tag{1}$$

The expected number of new infections generated in period t (corresponding to the decline in the number of susceptible persons) can now be calculated transparently: A fraction S_t/N of an infected person's contacts will be susceptible, so the number of newly generated infections per infected person will be $\tau \times \chi \times (S_t/N)$.

The population of infected persons also changes: Every infected person recovers with a probability of γ per period. Putting these elements together, the changes in the population in different compartments are given by

$$\begin{aligned} \Delta S_{t+1} &= -\beta I_t (S_t/N) \\ \Delta I_{t+1} &= \beta \frac{S_t}{N} I_t - \gamma I_t \\ \Delta \mathsf{R}_{t+1} &= \gamma I_t \end{aligned} \tag{2}$$

The simplest special case of the SIR model is one with a recovery rate of $\gamma = 0$, in which case the model reduces to the transmissible SI model discussed in Section 3.1. Another straightforward case is $\beta < \gamma$, in which from any starting point the population of infected persons I gradually dies down to zero.

The interesting cases emerge when the 'basic reproduction ratio' $\mathcal{R}(0) = (\beta/\gamma)$ exceeds one (this $\mathcal{R}(0)$ is unrelated to the R used elsewhere to measure the recovered population), because $\mathcal{R}(0) > 1$ guarantees that an initial arbitrarily small infection will grow, at least for a while (assuming that at the beginning everyone is susceptible, $S_0/N = 1$).

To illustrate the model's implications in such a setting, we configure the model with

[16] In any extended SIR model embedding an explicitly defined connection network by which the "disease" spreads, the value of β is equal to the product of the average number of connected nodes ("degree" in the terminology of network theory), and the infection probability conditional on the contact. For instance, in a random graph (Erdos, Rényi, et al. (1960)) with connection probability p and the size of network N, the average contacts every agent has is $(N-1)p$. See Newman (2002) and Jackson (2010) for the results from an SIR model augmented with various social networks.

four combinations of parameter values taken from Shiller and Pound (1989), characterizing two different kinds of investors and two categories of stocks.

We explore the quantitative implications using one of the many computational toolkits for analyzing such models that have proliferated in recent years.[17] The toolkit lets users specify explicitly the network structure on which the disease spreads. We exploit the fact that a random-mixing SIR model can be approximated with a SIR model residing on an *ex-ante* generated random graph (Erdos, Rényi, et al. (1960)) when the transmission probability τ and the average number of connections χ in the graph are configured such that their product is equal to the calibrated infection rate β (see Equation 1).[18]

In Figure 6 the vertical axis measures the proportions of Susceptible (dashed line), Infected (dash-dot line), and Recovered (solid line) investors, and elapsed time since the initial date of infection is on the horizontal axis. Also plotted is the limiting size of the recovered compartment, for which an analytical solution exists.[19]

Two common patterns emerge from the simulation under these four sets of parameters of infection and recovery rates. First, since in all four cases the basic reproduction ratio $\mathcal{R}(0)$ is greater than 1, in all four cases there is an outbreak. The size of the infected population first expands to its maximum value and then gradually levels off to zero, exhibiting a hump-shaped "viral curve" characteristic of SIR models. Second, in all scenarios, the system ultimately converges to a steady-state where most of the people have cycled through infection and recovery, with a small proportion remaining susceptible. Even in the case with the smallest reproduction ratio, the proportion who cycle through the process of Infection and Recovery is almost 85 percent, implying a high degree of infectiousness. Under other configurations, the limiting size of the infected-then-recovered 'compartment' R is close to 100 percent.

The main difference in the parameterizations is the speed with which these eventualities play themselves out, which varies considerably. (For the substantive interpretation of the model, see our discussion of its economic content in Section 4.2).

4 Literature

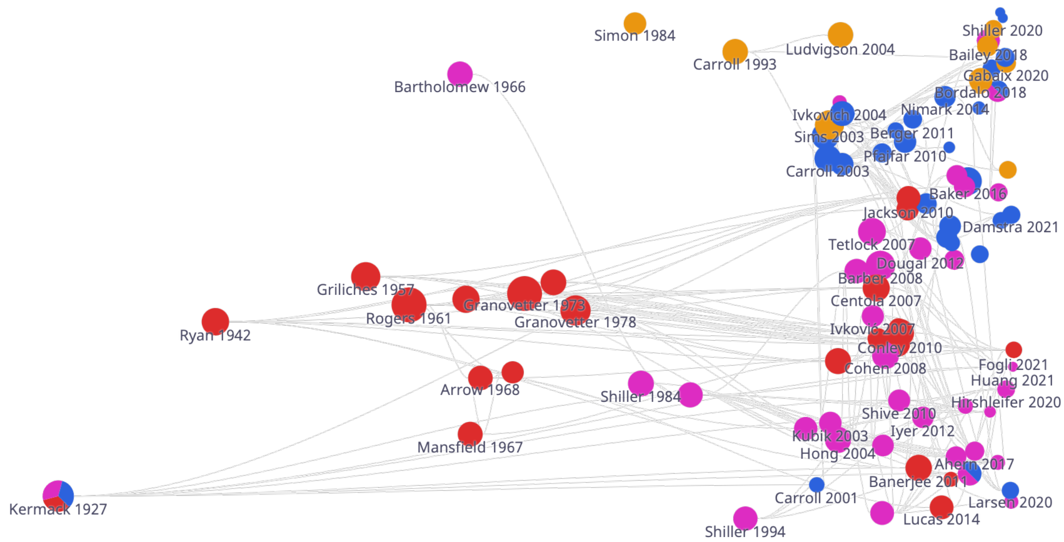
The bulk of this section discusses the three literatures mentioned in the introduction as having examples of full-fledged EE modeling (a map of all three literatures is in Figure 3). In the remainder we address a miscellany of topics including some interesting evidence for the epidemiological mechanisms of the transmission of economic expectations; the relationship of epidemiology to what are called models of 'contagion' in economics and

[17] Specifically, we use the Python library NDlib (Rossetti, Milli, Rinzivillo, Sîrbu, Pedreschi, and Giannotti (2018)) for the simulation of the SIR model here. The library builds upon another Python library called NetworkX (Hagberg, Swart, and S Chult (2008)), a toolkit for analyzing complex networks.

[18] See the companion Jupyter Notebook of this paper for detailed implementation.

[19] Given a constant basic reproduction ratio β/γ that is strictly greater than 1, and an initial fraction S_0/N close to 1, the limiting fraction of R, denoted as $\mathsf{r}_{+\infty} = \mathsf{R}_{+\infty}/N$, is the solution to the implicit equation: $e^{-\frac{\beta}{\gamma}r_{+\infty}} = 1 - r_{+\infty}$. See this Wikipedia page, Harko, Lobo, and Mak (2014), Kröger and Schlickeiser (2020), Okabe and Shudo (2021) for details of the results.

Figure 3 Literature map of cited papers



Note: This graph includes papers we have identified a strong epidemiological flavor in three literatures in economics: technological diffusion, asset market investment, and macroeconomic expectations. It also contains papers we have cited because they have content that may be of interest to EE modelers. See here for an interactive version.

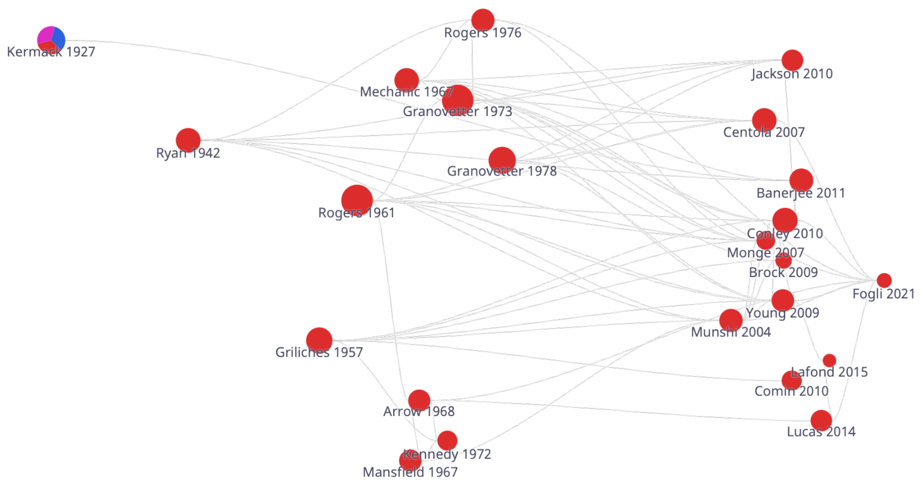
finance; and the highlights of the application of epidemiological models to the spread of information outside economics.

4.1 Diffusion of Technology

Arrow (1969) draws an explicit analogy between the diffusion of ideas and the spread of disease. (His paper is one of the earlier contributions from the economics literature captured in Figure 4; see Section 4.6 for work outside of economics on the diffusion of scientific knowledge.)

Arrow puts interpersonal communication at the center of knowledge diffusion and the consequent economic growth, and argues that the speed of knowledge diffusion may account for international differences in both levels and dynamics of income per capita. He conjectures that the speed of knowledge diffusion is influenced by factors that he explicitly compares to those that influence the spread of disease including (1) the perceived reliability of the sender (which affects infectiousness); (2) socioeconomic

Figure 4 Literature map of EE models of technological diffusion



Note: This graph includes selected papers under the topic of epidemiological modeling of technological/innovation diffusion in economics and closely related literature from other fields. See here for an interactive version.

traits (which affect exposure and susceptibility); (3) the understandability of information by the receiver (degree of immunity); and so on.

Arrow's interpretation is the step that puts technological diffusion squarely in the realm of EE modeling, under the mild further assumption articulated above: That what spreads is the 'expectation' that adoption of the technology will yield higher productivity (expectations were not explicitly modeled because Arrow's seminal research predated the era when expectations were solicited on surveys; but expectational questions of exactly this kind have been asked in more recent work on diffusion, see Banerjee, Chandrasekhar, Duflo, and Jackson (2013), and unsurprisingly confirm that people adopt a technology when they expect it to be beneficial).

Closely related to Arrow's work on technological progress is work by Rogers et al. (1962), who popularized a theory of the "diffusion of innovations" based on a meta-analysis of early studies of the spread of ideas within many academic disciplines.[20] The factors that this literature identifies as determinants of the dynamics of diffusion are directly interpretable as corresponding to the "infectiousness" of the idea, the degree

[20]Though Rogers was a sociologist, we include his work in the discussion here because it has had such a strong impact on the subsequent economics literature.

to which populations are "exposed" to the idea, and many of the other elements of the epidemiological frameworks sketched below.

Young (2009) is a broader survey of how alternative epidemiological models of technological diffusion generate different shapes of "adoption curves" with consequent effects on the path of economic growth. He shows that how the shape of diffusion curves differs in models of 'inertia' (a SI common-source model), 'social influence' (a threshold model), 'contagion' (a standard transmissible SI model), and 'social learning,' where learning is based on observed actions of others.[21]

Banerjee, Chandrasekhar, Duflo, and Jackson (2013) estimates an epidemiological model based on the real-world network and pattern of the diffusion of microfinance in a number of Indian villages. The paper provides direct evidence for word-of-mouth diffusion of beliefs through a social network. The model differentiates between agents who simply adopt the technology because they have heard about it from others (an 'information passing mechanism') and those who have adopted due to others' participation (an 'endorsement mechanism'). This is an example of how standard epidemiological models can be extended to incorporate alternative infection rules to accommodate more sophisticated applications.

Lucas and Moll (2014) construct a model economy containing agents with a distribution of levels of productivity, and consider the dynamics of aggregate productivity under several alternative assumptions about the ways in which agents with lower productivity can 'learn' from agents with higher productivity. ('Learning' in their model just means that, in an encounter between two agents, the agent with lower productivity adopts the other agent's technology).

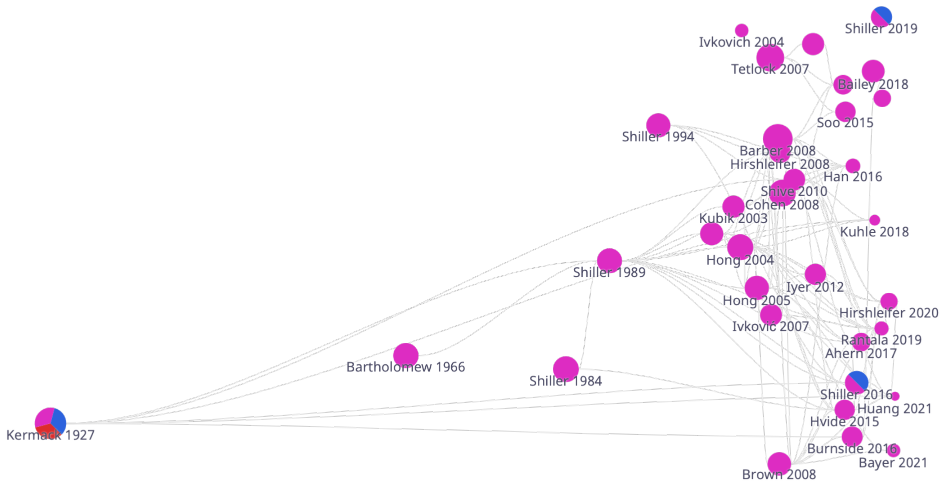
A particularly interesting feature of this model is that the agents solve an optimization problem to determine the intensity of their search effort, which affects the likelihood of encountering "better technology." This is likely to be a common direction in which economists may take epidemiological models: Incorporation of purposive behaviors by agents. While some work in epidemiology also allows agents to take actions to reduce the probability of infection, models in that literature have rarely been formulated with an eye to creating a structure where an explicit analytical optimization problem can be stated and solved.

Not only are mechanisms of the spread of technology and disease comparable, they may interact. Fogli and Veldkamp (2021) develop a model in which the structure of the networks connecting people ('nodes') allows the authors to explore the roles of the three dimensions that have emerged in as central to the network theory literature that has developed since Erdos, Rényi, et al. (1960): 'degree,' 'clustering,' and 'sprinkling' (see the discussion in section 2.3). Both productivity and disease spread through these connections, and as a result the dynamics of productivity and disease are connected. The model highlights a central trade-off between the speed of technological diffusion and disease spreading, both of which affect economic growth outcomes (but in opposite directions).

[21] We do not survey a large parallel literature on technology/innovation diffusion in economics that features the role of social learning, as this work is not explicitly built upon epidemiological frameworks. Examples include Munshi (2004), Comin and Hobijn (2010) and so on.

4.2 Financial Markets

Figure 5 Literature map of EE models of stock/housing market investment



Note: This graph includes selected papers related to epidemiological models of expectations in asset markets, and studies of the role of news media in financial markets. See here for an interactive version.

Academic models of financial markets have traditionally assumed that investors choose stocks based on well-informed rational beliefs about future returns. But popular treatments have emphasized social communication, and ideas with a distinctly epidemiological flavor, since the first published description of the first publicly traded securities (De La Vega (1688)'s discussion of the trading of shares of the East India company on the Amsterdam stock exchange). MacKay (1850)'s vivid prose has made his (thoroughly epidemiological) descriptions of the Dutch Tulip mania and other financial episodes of "The Madness of Crowds" a classic of English literature. This theme has continued to the present: Michael Lewis (2011)'s bestselling book about the Great Financial Crisis goes so far as to suggest that one of the reasons a particular analyst was able to perceive the housing bubble early was his psychological indifference to other people's opinions.

The academic tide seems now to be turning toward an acknowledgment that there is some truth in the popular view. Hirshleifer (2020)'s Presidential Address to the American Finance Association urged the profession take up the study of the social transmission of ideas as "[a] key but underexploited intellectual building block of social economics and finance." Hirshleifer specifically points out the potential for epidemiological models to make sense of patterns that have been difficult to understand with traditional models. Kuchler and Stroebel (2021) propose 'social finance' as the name for a field that would study such social interactions, and make a powerful case that new sources of data and new modeling techniques offer great promise.

These are by no means the first academic authors to propose a role for social transmission of financial ideas. But, as we explained above, the proportion of efforts that could be described as constituting a full-fledged EE analysis, as opposed to piecemeal evidence or provocative theoretical exercises, is small.

An early example of such a comprehensive approach is the paper by Shiller and Pound (1989) used above to delineate the elements of a standard epidemiological model. Shiller and Pound (1989) constructed survey questions designed to understand the sources of information that motivated investors' initial interest in the stock that they had most recently purchased (which they designate as 'randomly selected' – `RAND`). About a third indicated that their interest in that stock originated with "a person who is not an investment professional." The authors identify another category of stocks owned by their survey respondents as "rapidly rising" and for those they find that roughly half of the initial interest in the stock originated with nonprofessionals. Using a different methodology to designate 'rapidly rising' – '`RPI`' – stocks for institutional investors, they find that 10 percent and 30 percent of their initial interest originated from 'nonprofessionals.'

The survey-based estimates of their epidemiological model for both individual ('`IND`') and institutional ('`INS`') investors reveal considerable heterogeneity in infection rates both within and between the two groups. They also suggest that the infectiousness differs between a randomly selected stock `RAND` and a rapidly rising stock `RPI`. Interestingly, they find that the `RAND` category is more (interpersonally) "infectious" than the rapidly rising stock; they propose, plausibly, that public news sources will already have widely covered the rapidly rising stocks, so that interpersonal communications are unnecessary to bring attention to them.

Our Figure 6 shows the compositional changes of investors under the paper's median estimates (of infection and removal rates) for individual and for institutional investors, and for randomly selected versus for rising stocks, respectively.[22,23]

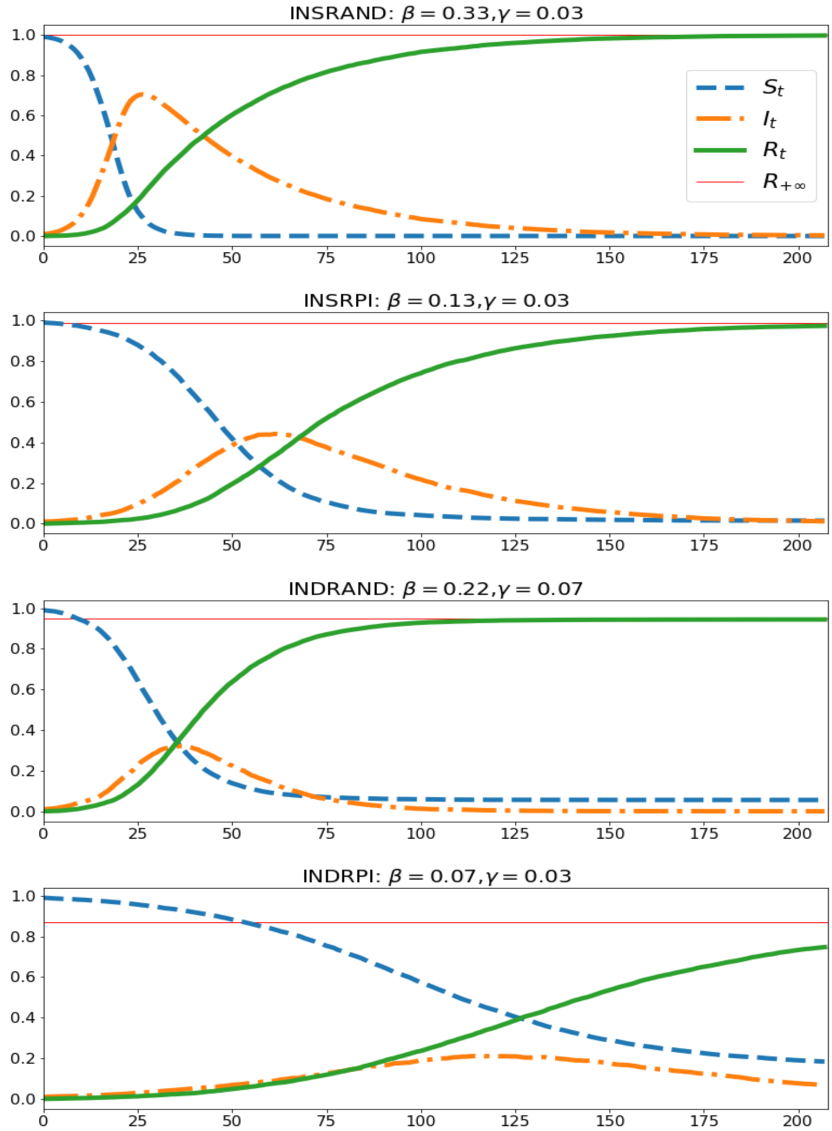
The epidemiological analysis above is for parameters that characterize a sample of highly interested and motivated investors. There is no sense in which these parameters can be thought of as characterizing the whole population – which is why it is not as surprising or implausible as it might seem that all the parameterizations of the models were ones in which R (the proportion of investors who would eventually become interested in a stock) was high.

The economic analysis can now also be interpreted in temporal terms. The authors

[22]We convert all the continuous-time rates into discrete-time and from annual to weekly frequency. For instance, the recovery rate estimated from the decaying pattern of the time spent on studying a given stock for INSRPI is $g = 1.39$ (a half-life of $ln(2)/g = 0.50$ years). In discrete-time and at weekly frequency, this is equivalent to a probability of recovery $\gamma = 1 - \exp^{-g/52} = 0.02$. For the removal rate, under the assumption made by the paper that the fraction of susceptible is close to 1 despite being time-varying, the estimated median removal rate of INSRPI is $b = 2.02$. It is converted to a weekly probability of $\beta = 1 - \exp^{-b/52} = 0.038$.

[23]We set the initial fraction of the infected to be 1 percent.

Figure 6 Simulated dynamics from a SIR model of stock investors



Note: This graph plots the simulated paths of populations in different compartments in a SIR model of stock investors, as described in Shiller and Pound (1989). We use the median estimates of the infection rate β and recovery rate γ for four samples: institutional investors for a randomly selected stock (INSRAND), institutional investors for a rapidly rising stock (INSRPI), individual investors for a random stock (INDRAND), and individual investors for a rapidly rising stock (INDRPI). The horizontal thin solid line corresponds to the limiting size of compartment of R in the long run. The simulation is done with the Python library "NDlib", for details, see the companion Jupyter Notebook.

point out that a fully rational model with no private information would imply that trading volume should be heavily concentrated around identifiable dates of news events, but the epidemiological model is consistent with long and variable lags. It takes around half a year for the interest of institutional investors in the randomly selected stocks to reach its peak and a little more than a year for a rapidly rising stock. As for individual investors, the population interested in `RAND` reaches its peak after 40 weeks, while interest in `RPI` takes 2.5 years to peak.

The paper also argues that in a special case where the infection rate is close to the removal rate, and the size of the pool of interested investors is driven by serially uncorrelated shocks, stock prices could follow a random walk, because under those assumptions the change in the level of 'interest' is nearly unforecastable.[24] This is another example of an economic consequence flowing from the pattern of spread of an infection. Furthermore, the pool of investors is potentially measurable, so it is an implication that can be tested.

Remarkably little of the extensive literature citing Shiller and Pound (1989) has involved meaningful epidemiological modeling; almost all of it has either been empirical, or has used a modeling framework that cannot be characterized as 'epidemiological' as we are interpreting the term.

A potential reason for this lack of followup is the nonexistence, until quite recently, of much direct data on either of the two key components of the model: beliefs (about, say, stock prices), or social connections – and no data at all about the *changes* of beliefs as a function of the structure of a measured social network. Shiller and Pound (1989) had to make heroic assumptions in order to quantify their model. Few subsequent scholars seem to have been willing to go so far in employing what might today be termed an 'indirect inference' approach: "Assuming the epidemiological model is right, let's calibrate it using its downstream implications for things we can observe."

However, we have found two good exceptions, both of which estimate parameters of structural epidemiological model of stock investors using microdata.

The first is Shive (2010), which uses an SI ('susceptible-infected') model to inform the structure of a reduced-form regressor that aims to capture social influences among investors. Using nearly the universe of ownership data for Finnish stocks between 1994 and 2004, the author assumes that the key social infection channels are at the municipal level, and estimates the time-series dynamics of ownership within municipalities.

Specifically, controlling for all of the variables (demographic variables, news sources, price dynamics, and others) that standard models might suggest could affect ownership patterns, the author estimates an equation that can be interpreted as measuring the β coefficient in Equation (2). The estimated β coefficient is highly statistically significant, indicating at a minimum that there is some local dynamic pattern to stock purchases not captured by the usual finance and economic models, but which is captured by 'proportion locally infected last period' (corresponding to S_t/N in Equation (2)).

[24] Shiller, Fischer, and Friedman (1984) presents an elaboration on this logic by allowing the presence of both rational investors ("smart money") and social-dynamics driven investors. The presence of unforecastable social dynamics weakens the statistical power of the random-walk test of rationality of stock market.

The second example is Huang, Hwang, and Lou (2021), which estimates an epidemiological model of diffusion of financial news among geographical neighbors. The paper reports a time-average estimate of the reproduction ratio $\mathcal{R}$ between 0.3 to 0.4 (equivalent to $\frac{\beta S_t/N}{\gamma}$ in an SIR model); that is, each stock trade that the authors identify as exogenous (see the paper for the mechanism) resulted in a total of 0.3∼0.4 trades among that person's neighbors, aggregated over all neighbors and all time.

The authors also find stronger transmission between investors of the same characteristics (age, income category, and gender), confirming the usual presumption of homophily (people tend to trust others with similar backgrounds). The paper found stronger transmission between senders and receivers with high past performance, suggesting that conversations between neighbors were more likely when past performance has been high. The natural interpretation – consistent with common findings in behavioral finance – is that you are more likely to boast about your investment in a winner than admit to having invested in a loser.

Their estimate that $\mathcal{R}$ is positive and highly statistically significant is consistent with the presence of neighborly social influence, and they work hard to rule out plausible alternatives. But since the estimated reproduction ratio is below 1, their results imply that news of this kind does not lead to an epidemic of stock trading. This is in contrast with Shiller and Pound (1989), whose corresponding reproduction ratios far exceeded one. This difference highlights the extent to which epidemiological models must be interpreted with care; even if similar phenomena (stock trading) are being studied, and even if there is evidence of social communication, the estimated nature and size of the epidemiological consequences can vary greatly depending on the exact experiment.

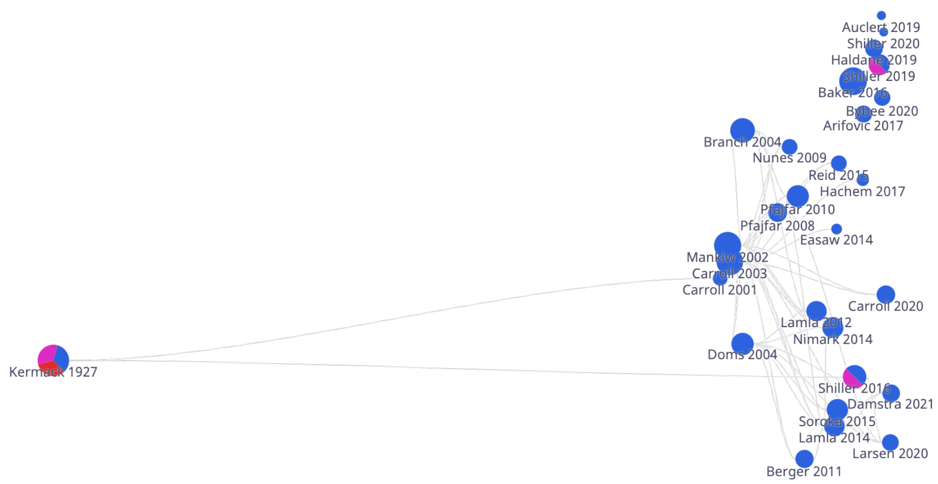
A final, and very impressive, contribution that satisfies all our criteria is a model of housing market fluctuations by Burnside, Eichenbaum, and Rebelo (2016), which shows how incorporating social interactions can generate booms and busts. In the model, agents differ in their beliefs (optimistic or skeptical) about the fundamental value of housing. Although it is a random-mixing model, paper has a mechanism similar in its implications to the simplest epidemiological model of 'super-spreaders' which occurs when some agents have many more social connections than others: The agents in this model differ in the degree of confidence they have in their opinions (whether optimistic or pessimistic) and those with greater confidence are more likely to convert those who have less confidence. Defining a 'boom' as a period in which house prices rise rapidly as the result of a spread in optimism, and a 'bust' as a rapid decline in prices caused by rising proportion of skepticism, their most interesting result is that whether a boom is followed by a bust can depend on whose opinion (optimists or skeptics) turns out to be closer to the true fundamental value. Specifically, busts happen when the skeptics turn out to be right about the fundamentals, while booms caused by optimists who happen to be right are not followed by busts.

One further literature that deserves a brief mention is the work on "Agent Based Computational Finance" (see the survey of that title by LeBaron (2006)). It would be straightforward to reinterpret much of the work in that literature as exploring epidemiological models of expectations of asset prices and financial market outcomes, and epidemiological terminology is sometimes explicitly invoked in the literature. Economists interested in constructing formal EE models would do well to delve into that literature for ideas that could be reinterpreted (or relabeled) to purpose. We have chosen not to survey that literature here partly because there are a number of excellent surveys already available, and in part because that literature has not mainly interpreted itself as modeling the dynamics of expectations.

4.3 Macroeconomic Expectations

We have identified only a few papers in macroeconomics (excluding finance; see above) that either constitute full-fledged EE modeling exercises or are closely related to such models. Figure 7 depicts the network of citation connections between those papers.[25]

Figure 7 Literature map of EE models of macroeconomic expectations



Note: This graph includes selected papers related to epidemiological models of macroeconomic expectations, and research on the interaction between news media and macroeconomic expectations. See here for its interactive version.

[25] See D'Acunto, Malmendier, and Weber (2022), and Baley and Veldkamp (2022), for non-social models of macroeconomic expectations formation.

4.3.1 Sticky Expectations

Carroll (2003) presents an epidemiological model in which the dynamics of aggregate consumer inflation expectations can be shown to follow a 'sticky expectations' equation:

$$M_t[\pi_{t+1}] = (1-\lambda)M_{t-1}[\pi_t] + \lambda\mathbb{E}_t[\pi_{t+1}] \tag{3}$$

where $M_t[\pi_{t+1}]$ reflects mean consumer expectations at date t for inflation at date $t+1$, and $\mathbb{E}_t[\pi_{t+1}]$ is a 'rational' expectation with which an individual consumer might be infected.

An analytical solution for aggregate dynamics of expectations is possible because the paper employs the simplest tool in the epidemiological toolkit: the common-source susceptible-infected (SI) model whose dynamics were traced out in table 1.[26] The idea is that consumers' expectations of inflation stem from exposure to (common) news media sources. The elements of the framework are:

1. All news outlets report professional forecasters' consensus views[27]
2. Consumers and forecasters believe the same 'true' inflation stochastic process
3. All consumers are susceptible to infection with probability λ
4. Infection means that the consumer adopts the view in the media
5. The consumer retains that view until next infected

The consequence is a population distribution of beliefs in which a proportion of the population $(1-\lambda)^n$ holds the belief that was held by professional forecasters n periods in the past. Not only does this yield testable predictions about the distribution of beliefs in the microeconomic cross-section, it yields implications about the dynamics of the cross section, both of which are tested in the companion paper Carroll (2001). The possibility of testing a macroeconomic model using the dynamics of microeconomic cross-sectional expectations highlights a virtue of the approach: measurable heterogeneity in expectations can provide a new kind of discipline for microfounded macroeconomic models.

The model was also constructed in the manner suggested in Section 2: It collapses to the rational expectations model as the parameter λ approaches 1, so that it is straightforward to examine the consequences of the epidemiological deviation from RE. In fact, the model can also be interpreted as nesting the 'Rational Inattention' framework, to the extent that one further assumption seems plausible: Beliefs about inflation derive from exposure to news coverage because the 'reading the newspaper' method of becoming informed is almost infinitely easier than solving (yourself) the full-fledged Rational Inattention macroeconomic model.[28]

[26] See Easaw and Mossay (2015) for a version that adds social learning between households.

[27] Carroll (2003) quotes news stories quoting professionals, and subsequent research by Lamla and Lein (2014) has confirmed the point.

[28] It is more plausible to model the professional forecasters themselves as having the skills and time and motivation to solve the full Rational Inattention model - or, alternatively, an EE model.

Another implication that flows from the model – inflation expectations are a result of the degree of exposure to news stories – leads to a straightforward implication: The speed at which inflation expectations move toward the rational expectation will depend on the intensity of news coverage of inflation. Carroll (2003) found some support for this implication; Lamla and Lein (2014) and Larsen, Thorsrud, and Zhulanova (2021) find further evidence that greater intensity of news coverage of inflation leads to more accurate expectations in the population.

In a paper written independently of and published before Carroll (2003), Mankiw and Reis (2002) simply assume that the dynamics of inflation expectations are given by a process like (3); they call this a 'sticky information' assumption,[29] and argue that the macroeconomic implications of a New Keynesian model in which expectations work this way match a variety of facts (most notably, the sluggishness of inflation dynamics) that standard NK models cannot capture.

The combination of their paper with that of Carroll (2003) is closer to constituting a full-fledged EE approach to macroeconomic modeling than either paper is alone: Carroll's paper did not examine the consequences of his model of inflation expectations for anything else, while Mankiw and Reis (2002) did not provide an epidemiological motivation for their 'sticky information' equation. (Conveniently, however, their baseline calibration of the model was to set $\lambda = 0.25$, while Carroll's empirical estimate of the parameter was 0.27.)[30]

Mankiw and Reis (2007) extend the analysis of their earlier paper to a general equilibrium context with goods, labor, and financial markets, and point out explicitly that the stickiness that drives the core results in their new model can be motivated by an epidemiological model.

4.3.2 Effectiveness of Monetary Policy

Heterogeneous expectations have important implications for the effectiveness of central bank communication. To capture this point, Hachem and Wu (2017) construct a model in which monopolistically competitive firms hold heterogeneous inflation expectations due to different forecasting rules. One group of firms simply expect inflation to remain stable ("Random Walkers"), and the other group makes forecasts based on central bank announcements ("Fed Watchers"). The fraction of Fed Watchers summarizes the credibility of the central bank. The model's epidemiological content comes from the transmission of beliefs about which strategies to pursue: firms meet each other and potentially switch forecasting rules based on relative performance. The paper shows that for the central bank, a period of gradual announcements helps build credibility and achieves target inflation, while an abrupt change in the target leads to undershooting.

[29] See Baley and Veldkamp (2022)for a potential microfoundation.

[30] A number of subsequent papers have estimated similar equations in a variety of countries, generally finding roughly similar results.

4.3.3 Sticky Consumption

A number of recent papers including Carroll, Crawley, Slacalek, Tokuoka, and White (2020) and Auclert, Rognlie, and Straub (2020) have applied the same epidemiological model used in Carroll (2003) to the problem of consumers whose attention to the macroeconomic news relevant for their consumption decisions may be spotty even if they are very well informed about their own idiosyncratic circumstances. The consequence turns out to be that aggregate consumption exhibits 'excess smoothness' in a way that matches data dynamics well, while at the same time predictions about microeconomic behavior are consistent with the micro facts that have been used to discipline the new generation of HA-Macro models.

4.3.4 Social Learning of Macroeconomic Equilibria

As we noted earlier, many approaches to economic questions can be described using the language of epidemiological modeling even though that terminology is not how the authors described their own work. This is true, for example, of work on "social learning" in macroeconomics. For example, in Arifovic, Schmitt-Grohé, and Uribe (2018), an economy with agents who have different macroeconomic forecasting rules evolves as agents discard their own rules when they encounter others whose rules have proven more effective. Another way of describing this process would be to say that the more effective rules are more infectious. Indeed, the parallel to the biological process is deeper: As diseases can do, the rules can mutate into more (or less) effective forms. The paper also discusses the potential role of professional forecasters and the extent to which their views can spread to the population at large – in our terminology, because their views are more 'viral.'

Tesfatsion (2006) has made a sustained case that agent based modeling has application to many subfields of economics, but it seems likely that almost all of that literature could also be reinterpreted as being about the transmission of expectations (when it is not already explicitly formulated in those terms, as in Hommes (2006)). An example closely related to the explicitly epidemiological work on inflation expectations is Branch (2004), who considers a model in which agents with different inflation forecasting rules compete and the rules that work better are adopted. Haldane and Turrell (2019) make a strong case for a broad interpretation (or reinterpretation) of these kinds of models as epidemiological, particularly in the macroeconomic context. As with the work on agent based modeling in finance, we chose not to attempt a summary of this literature because excellent comprehensive surveys already exist (see, e.g., Dawid and Gatti (2018)), and because little of the literature focuses explicitly on the dynamics of measured expectations. But readers interested in these subjects would do well to absorb this work (and especially the work of Hommes).

4.4 Nonstructural Empirical Evidence

4.4.1 Background

Above we cite efforts to calibrate structural parameters of specific epidemiological models to data. Here, we summarize literature that collects evidence in ways not targeted to estimating parameters, but that may nevertheless be useful in guiding the construction of epidemiological models. In principle, such work could help answer questions like

1. When do socially transmitted beliefs cause consequential economic decisions?
2. What are characteristics of sources and recipients of expectational infection?
3. Through which media are expectations mostly transmitted?
4. What kinds of information/expectations are more infectious?
5. How can Manski (1993)'s reflection problem be addressed?

Among the reasons epidemiological modeling has been slow to spread, one is surely that every one of these questions has been difficult to answer using traditional data sources. But new data, particularly the burgeoning "social network" data, offer rich opportunities for profoundly improving our ability to answer these questions.

4.4.2 Papers Using Proxies for Social Connections

In the absence of direct evidence about the nature and frequency of social contacts between people, the economics literature has naturally relied upon plausible proxies. For instance, Hong, Kubik, and Stein (2005) found that fund managers tend to buy similar stocks to other fund managers in the same city. Hvide and Östberg (2015) found that stock market investment decisions of individuals are positively correlated with those of coworkers. Cohen, Frazzini, and Malloy (2008) shows that fund managers place larger bets (that perform better) on firms to whose employees they are socially connected. In addition, social interaction also affects stock market participation and stock choices, as shown in Hong, Kubik, and Stein (2004), Brown, Ivković, Smith, and Weisbenner (2008), and Ivković and Weisbenner (2007).

In the context of housing market investment, one paper that explicitly emphasizes the transmission of information or beliefs by social contacts, and specifically mentions epidemiological mechanisms as potential channels of transmission, is Bayer, Mangum, and Roberts (2021), which shows that novice investors were more likely to enter the market (in speculative ways) after seeing that their immediate neighbors had invested.

A small literature provides direct evidence for social dynamics during bank run episodes, as we described in section 4.5. Iyer and Puri (2012) study the dynamics of an actual bank run using high-frequency data on deposit withdrawals among persons connected in a social network. Kelly and O'Grada (2000) showed that depositors who learned bad news about a bank from acquaintances were the first to close their accounts.

There is a also large literature that finds evidence for 'peer effects' on people's financial choices; a natural interpretation of such effects is that in many cases they likely reflect epidemiological transmission of beliefs, but much of this literature has been content to document the existence of the effect while remaining mute on the mechanism. (See Kuchler and Stroebel (2021) for a comprehensive survey of the substantial literature on peer effects on financial behaviors).

4.4.3 Directly Measured Social Networks

In a world with ubiquitous social networks, the set of people who can influence economic expectations is not limited to peers who are physically nearby. Bailey, Cao, Kuchler, and Stroebel (2018); Bailey, Dávila, Kuchler, and Stroebel (2019) show, essentially, that people who happen randomly to have social-network friends in distant cities where home prices have increased are more optimistic about their local housing market, and more likely to buy, than people whose remote friends happen to live in places where house prices declined.[31] Using Facebook data, Makridis and Wang (2020) find that during the COVID-19 crisis, the severity of the decline in consumption in a county was partly explained by the severity of the epidemic in the locales to which that county had especially dense social ties – even when those locales were geographically distant.

4.4.4 News Media

Social communication not only takes the form of conversations within direct social circles but also via mass media.

Financial Markets. Rather than attempting a broad discussion of the diffuse literature on the relationship between the media and financial markets, we refer the reader to "The Role of Media in Finance" by Tetlock (2015). Here we highlight just a few contributions that are particularly noteworthy for our purposes. Dougal, Engelberg, Garcia, and Parsons (2012) attempt to measure the impact of the opinions of individual *Wall Street Journal* columnists on market outcomes; this is a particularly clear example of a result with a straightforward interpretation using a 'common source' epidemiological model. Ahern and Sosyura (2015) found that younger and more inexperienced journalists tended to write more sensational and ambiguous news reports about corporate mergers, so that the youth and inexperience of the journalist had predictive power for the market impact of merger stories. Soo (2015) used news sources to construct an index of "animal spirits" in the housing market and argued that this index had predictive power for housing prices.

Macroeconomics. There is a substantial literature on the nature of news media coverage of macroeconomic developments (mostly outside of economics, cf. Soroka, Stecula, and Wlezien (2015); Damstra and Boukes (2021); see Bybee, Kelly, Manela, and Xiu (2020) for recent work by economists), but the slow-moving nature of macroeconomic outcomes makes it difficult to distinctly identify consequences of the nature of the coverage from the consequences of the economic events themselves. Nimark (2014) is

[31] See Kuchler, Piazzesi, and Stroebel (2022), for a discussion of various drivers of housing price expectations.

nevertheless able to show that particularly surprising events seem to have identifiable macroeconomic consequences out of proportion to what might be judged to be their appropriate impact.[32]

An indirect approach is to attempt to measure the effect of news coverage on consumer sentiment, and then to rely upon a separate literature that has found that consumer sentiment seems to have predictive power for economic outcomes (Ludvigson (2004), Carroll, Fuhrer, and Wilcox (1994)). One example is a clever paper by Doms and Morin (2004) showing that consumer sentiment is driven by news coverage even during periods in which coverage is inconsistent with economic conditions.[33]

New ways of pursuing these kinds of ideas may be feasible using data like Google Trends search queries, which Choi and Varian (2012) have shown can predict sentiment data well and can serve as a real-time measure of the degree of internet users' interest in economic topics.

Perhaps the most notable recent work relating media to macroeconomics has been that of Baker, Bloom, and Davis (2016), who use media sources to construct an index of "economic policy uncertainty" and find that it has predictive power for macroeconomic outcomes beyond what can be extracted from the usual indicators. The extent to which an epidemiological mechanism is necessary in making sense of this finding is unclear; the authors' own interpretation seems to be mainly that they are measuring a fundamental fact about the world (the policymaking process inherently and unavoidably generates uncertainty.)

It is possible, however, that the degree of uncertainty the authors measure is affected by the structure of interactions in the media ecosystem; the extensive literature on "fake news" (see Allcott and Gentzkow (2017) discussed elsewhere) and the incentives faced by suppliers of commentary would surely admit the possibility that uncertainty might be introduced or amplified by epidemiological mechanisms, in which case analysis of those mechanisms might yield some insight into whether epidemiological factors (say, the rise of Fox News) have consequences for economic outcomes by changing the degree of economic policy uncertainty.

One way to test for the epidemiological alternative might be consider alternative scenarios for the policies that might be manifested as competing 'narratives' about how policymakers will behave; the uncertainty would then be about which narrative would turn out to be correct. That leads us naturally to our next topic.

4.4.5 Epidemiology and 'Narrative Economics'

Robert Shiller has repeatedly speculated that the driving force in aggregate fluctuations, both for asset markets and for macroeconomies, is the varying prevalence of alternative 'narratives' that people believe capture the key 'story' of how the economy is working (his earliest statement of this view seems to be Shiller (1995)).

[32] See also Chahrour, Nimark, and Pitschner (2021) provide evidence that coverage about newsworthy events that affect particular sectors but are unrepresentative of broader developments can affect broader hiring decisions.

[33] For further evidence that news coverage is a key source of people's views, see Lamla and Maag (2012), though see Pfajfar and Santoro (2013) for a skeptical view.

He has returned to this theme more recently, and our opening quote from him makes it clear that he thinks narratives spread by "going viral." See Shiller [2017; 2019] for more extended treatments.

There are formidable obstacles to turning Shiller's plausible argument into a quantitative modeling tool. One is the difficulty of identifying the alternative narratives competing at any time, and reliably measuring their prevalence. Shiller (2020) made an initial effort at this. By reading over historical news archives and internet search records, he identified six major economic narratives that have circulated during the economic expansion since 2009, including "Great Depression," "secular stagnation," "sustainability," "housing bubble," "strong economy," and "save more." (See also Ash, Gauthier, and Widmer (2021) and the references therein.)

Larsen and Thorsrud (2019) have recently taken up the challenge of quantifying media narratives, deriving virality indexes, and conducting Granger causality tests to determine the extent to which viral narratives have predictive power for economic outcomes, in the U.S., Japan, and Europe. The authors do find episodes in which their methodology identifies 'narratives' that have 'gone viral.' This is early work, but the authors identify apparent connections between the intensity and valence of discussion of some topics and subsequent economic outcomes.

There is also a rapidly expanding body of work that tries to answer economic questions by analyzing a large volume of textual/conversational information using the developing technique of natural language processing (NLP). (See Gentzkow, Kelly, and Taddy (2019) for an overview).

As those tools get more sophisticated, they might become usable for creating more sophisticated and nuanced and reliable methods for tracking the content of narratives in the manner required to turn Shiller's 'narrative economics' ideas into practical tools of current analysis.

Separately, it is not beyond imagining that at some point, and to the extent that corporate interests and privacy considerations permit, it might be possible to train AI tools to comb through the vast amount of information contained in social network communications to identify economic narratives, and to measure the ways in which they spread. Because such a source would have direct measures of the social connections between agents, at that point it might be possible to construct a thoroughly satisfactory epidemiological model of Shiller's narrative theory of economic fluctuations – and to see how effective it is. But that date is still some distance in the future.

4.5 Contagion

In the epidemiology literature and in ordinary usage the word "contagion" means essentially 'epidemic of a transmissible disease.' Large literatures in economics and finance describe themselves as investigating the phenomenon of economic or financial 'contagion.' But for reasons we articulate here, most of this work is quite different from what we define as an EE modeling approach.

4.5.1 Multiple Equilibrium

Diamond and Dybvig (1983)'s canonical model of 'bank runs' has two RE (self-fulfilling) equilibria. In one, all depositors attempt to withdraw their savings from the bank and it fails; in the other nobody wants to withdraw their savings and the bank remains sound. But the paper's model fails our first criterion for an EE model: There is no dynamic process by which ideas 'spread' so it has no testable implications for measured expectational dynamics at either the micro or the macro level.

Much of the theoretical work that describes itself as being about 'contagion' is of this kind – that is, about multiple equilibria without any testable description of transmission or dynamics (much less measurement of expectations).

There is nothing intrinsic about such questions that prohibits the construction of what we would call a genuinely epidemiological model – indeed, work by Iyer and Puri (2012) makes an excellent start by collecting data on detailed dynamics of bank withdrawals among members of a social network during a bank run episode. The authors write: "we want to understand ... contagion in bank runs. In order to model this, we draw on a long, time honored literature on contagion of infectious diseases in the epidemiology literature." (Note the explicit invocation of the meaning of 'contagion' from the epidemiology literature, presumably to head off any confusion with whatever might be meant by 'financial contagion.')

They proceed to note that "the parallel [to infection] in bank runs is the probability of running as a result of contact with a person who has already run." The paper reports an estimated transmission probability (corresponding to τ in Equation 1) of 3.6 percent via social network connections (approximated by the account referrals) and of 6 percent through neighborhood connections. Despite the straightforward structural implications of these estimates, the authors stop without using them to parameterize and simulate an SI model of the bank run they study. These would be interesting steps to pursue for someone interested in advancing the EE agenda.

But one branch of the 'financial contagion' literature that developed after the panic that followed the collapse of Lehmann Brothers in 2008 explores the idea that markets can be vulnerable to the sudden disappearance of entities that are 'too interconnected to fail.' This interpretation led to a literature that examined datasets on the interconnections between financial institutions, using many of the same tools (network theory, random graphs, etc) that have elsewhere been used to model the transmission of ideas across social networks.

In this work, what is modeled as being transmitted along the network connections is usually financial flows (rather than ideas or expectations), because financial flows are what the datasets measure. The modeled mechanisms of contagion therefore involve assumed mechanical consequences of disruptions to those flows. Despite the overarching "contagion" metaphor, the low-level elements of the transmission process generally do not have immediate interpretations corresponding to epidemiological primitives like 'infectiousness,' and the literature does not mainly aim to model the dynamics of expectations at either the micro or the aggregated level. (See Glasserman and Young

(2016) for a summary of this literature and Cabrales, Gale, and Gottardi (2015) for a deep dive).

It is possible that some of this work could be reinterpreted to fit into our definition of EE modeling, in the same way that the work on technology diffusion clearly fits our definitions and has a straightforward epidemiological interpretation (already articulated by Arrow (1969)). But the literature is so vast and complex, and the reinterpretation would have to be so thorough, that this is a task we hope might be undertaken by others who want to bring the insights from that literature to a new audience.

4.6 Non-economic Applications

This section highlights elements of epidemiological modeling in other fields that might be of most value to economists. (See Figure 8)

We focus on the following three areas:

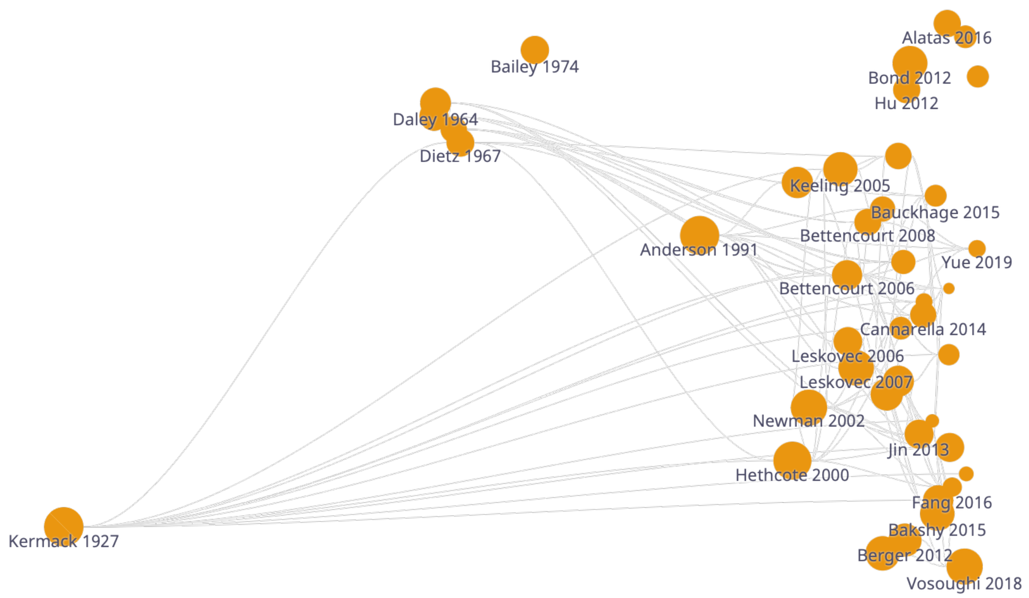
1. the spread of news, fake news, and rumors
2. the diffusion of scientific ideas
3. the dissemination pattern of internet content such as memes

The first epidemiological model we have been able to find in which rumors spread like disease is by Daley and Kendall (1964), whose work spurred a subsequent literature that explored variants of the standard epidemiological model allowing for different 'compartments.' A highly cited example is a paper by Jin, Dougherty, Saraf, Cao, and Ramakrishnan (2013) that augments the usual three compartments of Susceptible, Infected, and Exposed with another compartment of skeptics, and estimates the model with a diffusion pattern of eight real events among Twitter users, including actual news events such as the Boston Marathon Bombings, the resignation of Pope Benedict, and rumors such as the Mayan Doomsday, an injury to President Obama, etc. In each case, the augmented model with estimated parameters matches the dynamics of both news and rumors reasonably well. (See Figure 9)

Other empirical studies on news dynamics may provide useful modeling insights. For instance, Vosoughi, Roy, and Aral (2018) found that falsehood spreads faster than the truth possibly because of its novelty and emotional arousal. Similarly, Berger and Milkman (2012) found that "content that evokes high-arousal positive (awe) or negative (anger or anxiety) emotions is more viral. Content that evokes low-arousal, or deactivating, emotions (e.g., sadness) is less viral." Moreover, Zannettou, Caulfield, Blackburn, De Cristofaro, Sirivianos, Stringhini, and Suarez-Tangil (2018) found that content of memes affect their virality: racist and political memes are the most common type of viral content.

It is possible that these points are related to the results from Kohlhas and Walther (2021), who attempt to explain evidence that people seem to underreact to events that are not very surprising, but overreact to surprising events. While the authors attempt to capture this using a combination of ideas from Sims's rational inattention framework

Figure 8 Other fields related to epidemiological models

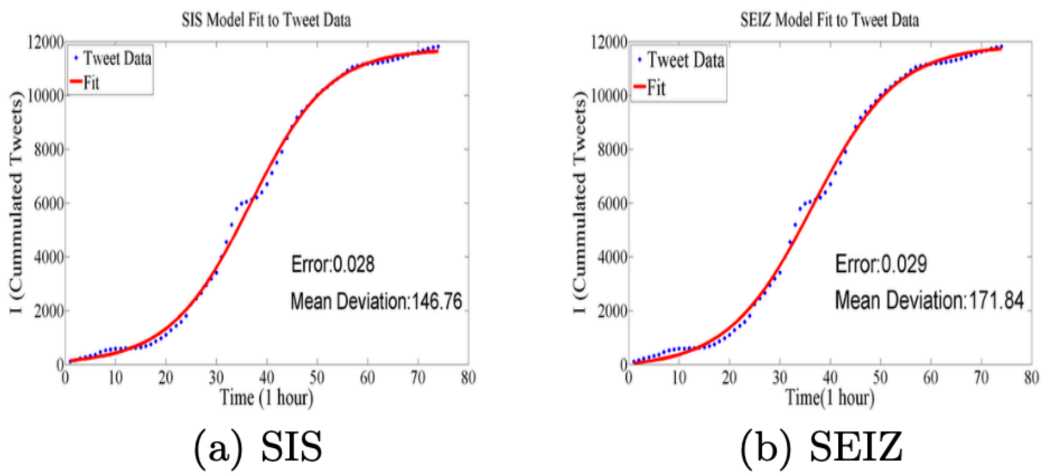


Note: This graph includes selective non-economic research surveyed in this chapter, including epidemiological models of rumor/news/online content/scientific ideas. See here for its interactive version.

and the Bordalo-Shleifer diagnostic expectations framework, to the extent that surprising events elicit emotional arousal, this paper may also be connected to the noneconomic literature just mentioned.

Some research in economics studies the spread of fake news and misinformation in a 'market for news' framework. Allcott and Gentzkow (2017) used a post-2016 election survey of 1200 U.S. adults to analyze the importance of social media on fake news consumption, exposure to fake news, and partisan composition. The paper highlights social media as one of the important (but not dominant) channels for the diffusion of fake news. The paper constructs a model with a supply side of fake news provided by profit-maximizing entities appealing to consumers subject to confirmation bias. This seems a natural extension of standard epidemiological models to incorporate the production side of the content – exploiting the "infectiousness" of certain ideas in subpopulations as an incentive for the production of content that the producers know will become "viral" because of a high reproductive number in the subpopulation.

Figure 9 Spreading of news and rumors: Jin et al (2013)



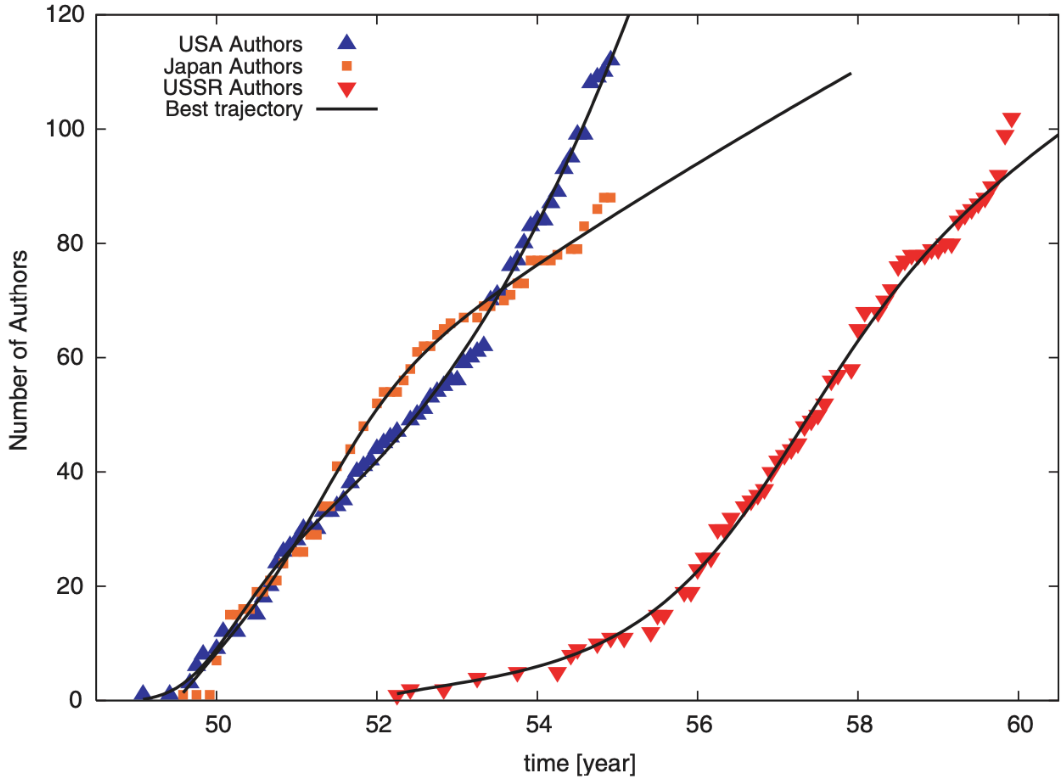
Note: This graph is reproduced from Jin, Dougherty, Saraf, Cao, and Ramakrishnan (2013), showing their fitted SIS and SEIZ model of the counts of Twitter posts related to the "Mayan Doomsday" rumor, which was widely circulated before December 21, 2012.

Another potential determinant of the degree to which ideas spread is explored in Acemoglu, Ozdaglar, and ParandehGheibi (2010), which builds a model of social learning with "forceful" agents who disregard information from other agents in the network. The presence of such agents may lead to the persistence of misinformation in equilibrium. The insight for epidemiological modeling is that heterogeneity in infectiousness can reflect characteristics of the sender ('forcefulness') as well as the receiver.

Epidemiological models have also been used to study patterns in the spread of scientific ideas, in a separate literature outside of economics but closely related to the economic research on the diffusion of technology. Bettencourt, Cintrón-Arias, Kaiser, and Castillo-Chávez (2006) estimates an epidemiological model of the spread of Feynman diagrams through theoretical physics communities. (See Figure 10.) That paper uses an SEIR model where E represents the exposed state, and a SEIZ model where Z represents skeptics (mutually exclusive with being infected) who held competing ideas. Introducing skeptics generates an additional steady state of the model where competing ideas coexist. This differs from two-compartment and three-compartment models, in which typically the system converges to a single state.

Internet memes have been another favorite topic of epidemiological modelers outside of economics. Bauckhage (2011) shows that epidemiological models do a good job of capturing the growth and decay of famous internet memes (See Figure 11). Wang and Wood (2011) finds that a modified SIR model allowing for the reinfection of the "recovered"(those who lose interest in the meme) fits the propagation dynamics of

Figure 10 Diffusion of scientific ideas: Bettencourt et al (2006)



Note: This graph is reproduced from Bettencourt, Cintrón-Arias, Kaiser, and Castillo-Chávez (2006), showing their fitted SEIZ model to the diffusion dynamics of Feynman diagrams in three theoretical physics communities, measured by the cumulative number of authors using the Feynman diagrams.

various viral memes well. In addition, Kucharski (2016) fits an epidemiological model to outbreaks of a number of notable internet contagions such as the "ice bucket challenge" and "no-makeup selfies," suggesting an initial reproduction ratio in the range of 1.9 to 2.5.

4.7 Future Directions

Many suggestions for future work are contained in the foregoing. Here, we mention a few further points that did not neatly fit above.

First, common tools from epidemiological practice could usefully be imported into expectational surveys – particularly the deliberate efforts that epidemiologists make to determine the source of an infection ('contact tracing' being the most straightforward) – usually by asking direct questions. We would argue that, after a person's expectations have been elicited, at least a small amount of extra time should sometimes be allocated to asking "why do you believe [x]." The respondent may not be able to give an answer, but in many cases they might have a useful response: “A friend told me” or “I read it in the newspaper” or “I did some research on the internet” or “I learned that from my parents when I was growing up.”[34] Any of these answers (or potentially others) might prove very helpful in narrowing the set of models that are plausible for explaining any particular set of beliefs. Direct questions could also help distinguish between different kinds of information: A job seeker might learn from friends that job prospects have improved, which causes improved expectations. These same friends might also tell the job-seeker about a specific current vacancy. If job seekers were directly asked separate questions about expectations and vacancy tips, it would be much easier to distinguish a mechanism in which optimistic job-seekers work harder to find jobs from a mechanism in which job vacancy tips are more frequent in periods when optimism is greater.

Above, we made mention of several kinds of evidence that information from some sources, or of some kinds, was more infectious. The literature on homophily, for example, suggests that ideas spread more readily among persons who have more in common. And even among social connections with otherwise-similar characteristics, some are likely to be more credible than others. Direct survey questions asking respondents which sources of information they find most persuasive, and why, might prove very helpful in thinking about the most appropriate structure for our models (and potentially even addressing problems like the Manski’s reflection problem.)

Epidemiological ideas might also prove to be useful in understanding how to interpret results like those in Galesic, de Bruin, Dumas, Kapteyn, Darling, and Meijer (2018), who find that election surveys that ask participants about the voting intentions of their social contacts proved more accurate in predicting voting outcomes than surveys asking people how they themselves would vote, and other results that suggest that it is easier to elicit prevalence of socially stigmatized behaviors or attitudes by asking respondents about prevalence among members of their social circles rather than asking the respondent about themselves. (“Are you a racist” does not elicit useful responses - and may even result in the termination of the survey; “how many of your friends would you say might be racist” seems to generate much more revealing responses; cf Radas and Prelec (2021).)

4.8 Literature Summation

We have barely scratched the surface of the scholarly literature with interesting evidence about the ways in which social interactions shape population beliefs. Even within economics, where the topic has received less attention than might be expected, there is so much material that we are confident that we have missed some content that should have been included, for which we hereby preemptively apologize to readers (and authors).

One unifying point is that similar themes seem to have emerged independently using a number of different approaches and from scholarly communities who seem largely unaware of each others’ existence and results. Often quite different terminology has

[34] Arrondel, Calvo Pardo, Giannitsarou, and Haliassos (2020) provides an example of this approach. In a survey of French households, they not only elicited respondents’ stock market expectations, but also the size and financial expertise of the social circles within which they discuss financial matters. The paper finds that social interactions affect stock market beliefs mostly through information channels, instead of social preferences.

developed for ideas that are close cousins, and this may have hindered the ability of participants in ostensibly distant fields to recognize the common elements of their work.

For example, the work cited above on "social learning" in macroeconomics involved the propagation of competing ideas (forecasting rules) in a population. This work satisfied our criteria that it addressed a substantive economic question using a mechanism by which beliefs were transmitted by explicit social interaction: The rules that work better, basically, are more infectious. But the authors in this literature typically do not cast their models in epidemiological terms, nor do they typically propose testing the models by querying simulated agents about their simulated expectations, and comparing simulated expectations data to actual expectations data. Doing so would not be a large leap.

Nor does this work take much notice of Shiller's longstanding view that economic dynamics reflect the competition of 'narratives' that 'go viral.' The "social learning" model's forecasting rules are arguably exactly how one might want to make a computational representation of what Shiller calls a narrative, and the economic dynamics that result from the increasing prevalence of the rules that succeed in the 'tournaments' are a good candidate for a rigorous computational representation of the consequences of what might be meant by the claim that 'narratives' can 'go viral.'

Reciprocally, it does not seem that scholars interested in the "narrative approach" have embraced "social learning in macroeconomics" literature – perhaps because papers in that literature usually do not describe the decisions the agents make as being a consequence of the "narratives" they have adopted to understand the world.

One of our ambitions for this survey is for it to infect scholars with the idea that it is useful to express the mechanisms of their models, as much as possible, in a common language drawn as much as possible from the familiar domains of epidemiological modeling and network theory: Infectiousness, susceptibility, transmissibility, exposure, immunity, mixing, homophily, reproduction rates, degree distributions, clustering, and so on, in addition to whatever domain-specific terminology may be natural to their particular topic.

5 Conclusion

Many of the obstacles, real and perceived, to the construction of what we call full-fledged Epidemiological Expectations models have lessened over the last two decades.

A large body of evidence now finds that opinions on economic questions are sharply heterogeneous, and that people's choices are related to their opinions.

Data from social networks now provide the possibility of directly observing the operation of the key mechanisms of the social transmission of ideas – as has already been done in a few cases of economic models (and many more cases outside of economics). Other work, based not on social network data but on measures like geographical proximity or shared workplaces or common places of origin, has found further evidence of social transmission of ideas, while another strand of research has explored the ways in which news outlets can be modeled as a source of heterogeneity in beliefs if news stories have degrees of either exposure or infectiousness less than 100 percent.

The recent successes achieved by the HA-Macro literature from the incorporation of realistic heterogeneity in non-expectational variables seem likely to tempt scholars to see what more can be accomplished by modeling expectational heterogeneity in ways based on empirically measured expectations.

An epidemiological expectations modeling approach is by no means applicable only to macroeconomic questions – the formation and consequences of expectations are at the heart of economic questions across the discipline. A particularly attractive direction that any literature written by economists is likely to take is to apply the discipline's sophisticated tools for analyzing purposive behavior, as is done for example in the paper by Lucas and Moll (2014) whose agents optimally expose themselves to the possibility of infection with new ideas in the hopes of improving their productivity – something that scholars have done since time immemorial.

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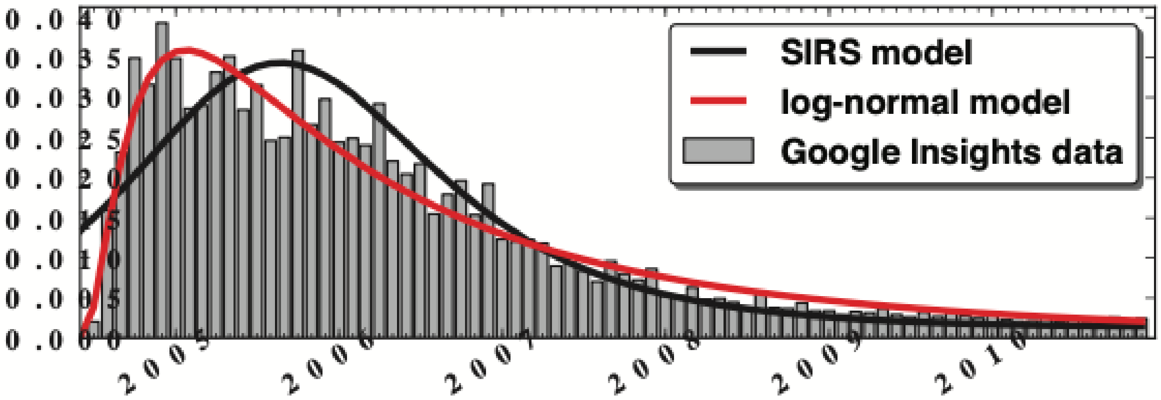
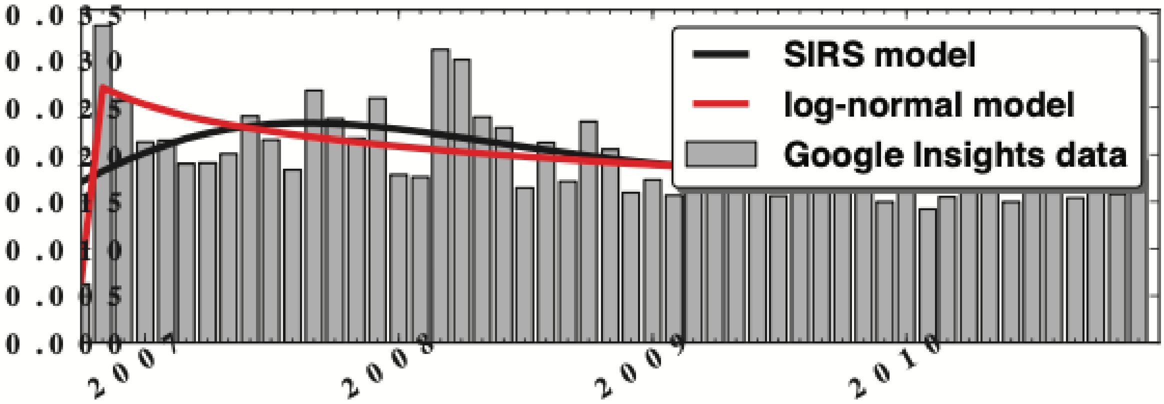
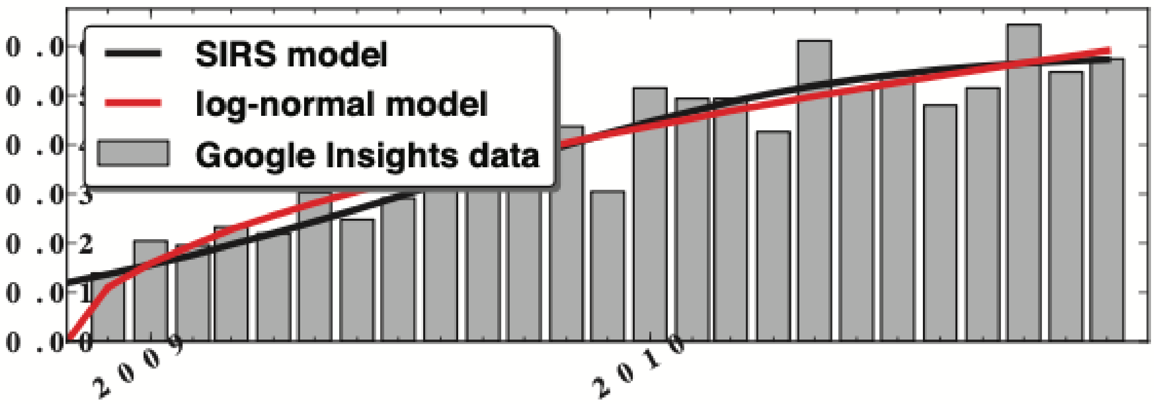
Figure 11 Virality of internet memes: Bauckhage (2011)



(a) "salad fingers"



(b) "laughing baby"



(c) "so much win"

Note: This graph reproduces the SIRS model fit and log-normal fits to Google insights time series measuring the interest in six viral memes, as shown in Bauckhage (2011).