CHAPTER

Epidemiological Expectations[1]

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ABSTRACT
'Epidemiological' models of belief formation put social interactions at their core; such models are the main (almost, the only) kind of 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 recently converged in ways that may make epidemiological expectations (EE) modeling more feasible and appealing than in the past.

[1] Thanks to the participants in the *Handbook of Economic Expectations* Conference for insightful comments, and the editors for comments that substantially improved the paper. Thanks also to Sebastian Benthall, Francesco Bianchi, Jennifer Manning, and Adrian Monninger for feedback on earlier drafts, and special thanks to Mridul Seth for help in using the `NDLib` and `NetworkX` python libraries to produce our SIR Model Notebook.

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]

1.1 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, debates are rarely about whether social interactions are fundamental; the question is which particular models for capturing social interactions are most suitable for understanding the prevalence 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 approaches would be a standard part of the economist's toolkit for modeling expectations — unless there were good reason to suppose that economic ideas are immune to social influence.

[1] See Rasmussen [2017].

But evidence for social transmission of economic ideas is plentiful – see Section 1.4.4. 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 – a conventional off-the-shelf alternative, say, to a 'rational expectations' ('RE') approach, the 'Rational Inattention' ('RI') approach advocated by Sims [2003], the 'diagnostic expectations' model of Bordalo et al. [2018], or a number of bounded rationality approaches (e.g., Gabaix [2020] or Ilut and Valchev [2020]).

This is perhaps because nowhere has any focused attempt been made to define what would constitute an EE treatment of an economic question. For the purposes of this survey, we will think of a full-fledged EE treatment 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 implications for an observable outcome (often, prices, quantities, or market values) that is the primary subject of the economic analysis.

We have identified three fields in economics – technological diffusion (section 1.4.1), financial markets (section 1.4.2), and macroeconomics (section 1.4.3), with sets of papers that satisfy all these criteria – even if in some cases the work has not mainly been thought of as 'epidemiological' until now. In addition, we survey the proliferating evidence that social interactions drive expectations and corresponding behaviors (section 1.4.4); draw connections between the EE approach and a separate literature on financial contagion (section 1.4.5); and present a selection of research on the spreading of news and rumors, scientific ideas, and online content (section 1.4.6).

1.2 BACKGROUND AND MOTIVATION

1.2.1 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."

Since then, 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 et al. [2016]).

But few 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) – though disagreements on such subjects are rife and people make choices that correspond to their expressed beliefs (Giglio et al. [2021]).[2]

Partly, the failure to incorporate expectational heterogeneity reflects the fact that until recently there was not widespread awareness among macroeconomists that measurable expectation differences have 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). The commissioning of this *Handbook*, and the proliferation of new research summarized herein, are among the many indications of a sea-change in the profession's attitudes.

The proliferation of new data on expectations, and new evidence that they explain differences in behavior, seem likely to tempt economists to produce models to fit the facts. Our guess is that epidemiological models may be one of the primary methods of accomplishing this goal.

1.2.2 EPIDEMIOLOGICAL MODELS

We will use the word 'classical' to refer to epidemiological models that descend from the work of Kermack et al. [1927], who formulated the problem as one of tracking the size of 'compartments' of the population in different disease states ('Susceptible' to infection, 'Infected,' or 'Recovered'; S, I, and R for short) 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 formulation of the problem as a set of nonlinear differential equations.

A newer literature uses the tools of 'network theory' to study models in which the 'nodes' in a graph are people and the 'edges' are social links between nodes. Erdos 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 the 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.[3]

While the classical and the network-theory approaches seem quite different, it turns out that a 'random graph' network can be configured to produce an arbitrarily close approximation to the classical problem, by assuming that at any date t each node is in one of the three $\{S, I, R\}$ states, and that the 'edges' are the link by which

[2] 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.

[3] A standard reference for economists is the textbook by Jackson [2010].

an infection can pass from an infected to a susceptible person (see our example in Section 1.3.2 below; see Newman [2002] for an early analysis of epidemics on networks).

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 particularly interesting result is the "Small World" effect explained by Watts and Strogatz [1998], who show that even when a network's '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, 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.[4]

Moore and Newman [2000] demonstrate that the patterns of the spread of diseases on 'small worlds' networks can be quite similar to those of the classical SIR model - under certain assumptions about the nature of the interactions that occur over the links. But a subsequent literature has shown that, even in a network whose link structure satisfies the 'small worlds' requirements, the ultimate outcome depends sensitively not only on the structure of the network but also on the exact assumptions about the nature of the interactions. Even in a fully connected world, it is easy to construct models in which disagreement persists indefinitely (Acemoğlu et al. [2013]) and subpopulations converge to different beliefs (Sikder et al. [2020]).

1.2.3 EXPECTATIONAL TRIBES

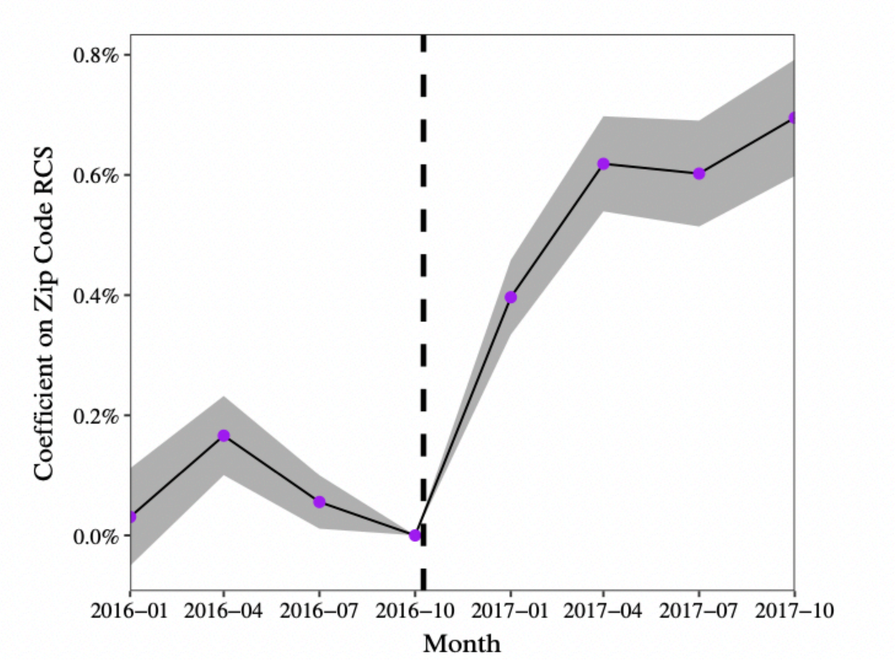
If there were no evidence that persistent differences of opinion could matter for important economic decisions, the case for using the epidemiological modeling toolkit would be weaker. We therefore conclude this section on 'background and motivation' by presenting some evidence of a recent clear failure of 'identical beliefs' with consequences for measured choices in an area core to both micro and macro modeling: financial risk-taking.

Meeuwis et al. [2021], using data on millions of retirement investors, 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 1.1.) These choices occurred at exactly the same time that consumer sentiment surveys showed that self-

[4] 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.

identified Republicans had suddenly become more optimistic, and Democrats more pessimistic, about the economy's prospects over the next few years.[5]

Figure 1.1 Portfolio responses to 2016 U.S. election



Note: Reproduced from Meeuwis et al. [2021], this figure reports the baseline regression coefficients of equity share on zip-code level campaign contribution share to Republican candidates for the three quarters prior to the election and the four quarters following the election.

1.3 WHAT INSIGHTS CAN THE EPIDEMIOLOGICAL FRAMEWORK OFFER?

1.3.1 WHAT IS AN EPIDEMIOLOGICAL FRAMEWORK?

We will say that ideas, beliefs, 'narratives,' or other mental states that affect behavior (henceforth, 'expectations') result from an "epidemiological" process whenever they

[5] The New York Fed blog post *"Political Polarization in Consumer Expectations"* also finds partisan differences in consumer expectations.

are modeled as resulting from some social interaction.

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

But transmission need not be person-to-person; it can reflect exposure to a "common source." For example, cosmic radiation can cause diseases like cancer. In the context of beliefs, a natural interpretation of such a "common source" is news media (a point to which we return below).

The simplest epidemiological model is a 'common source SI model': A continuous population is divided into compartment 'I' containing persons who have been infected (and can never recover), and compartment 'S' containing people who are not yet infected. The 'common source' assumption is 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 1.1, with the obvious implication that as n approaches infinity the entire population eventually becomes infected.

Table 1.1 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	$(1-p)^n$	$1-(1-p)^n$

This framework can be extended in many directions. The usual next step is for the disease be transmitted by 'random mixing' in which each susceptible person who encounters an infected person becomes infected with a fixed probability in each period. Then in discrete time, given a non-zero initial infected fraction I_0, the fraction infected and susceptible evolve as described in Table 1.2.

Table 1.2 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	$S_{n-1} - \beta S_{n-1} I_{n-1}$	$I_{n-1} + \beta S_{n-1} I_{n-1}$

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

The SIR framework has rich and interesting implications, such as the potential for 'herd immunity' which comes about when a high enough proportion of the population has either Recovered or otherwise been Removed (say, by vaccination) from the pool susceptible to infection.

Options proliferate from there.[6] 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.

1.3.1.1 Adapting the Disease Metaphor to Expectations

Basic epidemiological models usually study 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.

An advantage of network-theory models is that the framework can easily accommodate ways in which an economic application may call for such modifications. It is trivial to represent as many competing 'diseases' (e.g., 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 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].[7]

1.3.2 ONE EXAMPLE

Here, we provide a first example of an economic question formulated in a thoroughgoing epidemiological way. Our present purpose is not to extract economic insights

[6] 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 et al. [1927], Bailey et al. [1975], Anderson et al. [1992], Hethcote [2000], Brauer [2017].

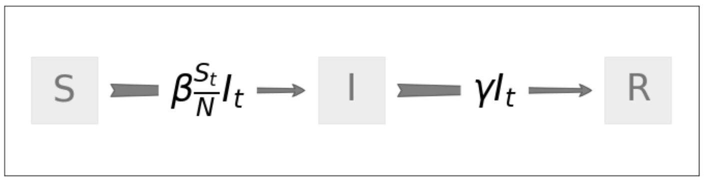
[7] See the interesting discussion of such 'threshold models' in Glasserman and Young [2016].

– we do that in section 1.4.2 below – but simply to illustrate how the epidemiological toolkit works.

Shiller and Pound [1989][8] use an SIR model to capture how the interest in particular stocks spreads in a population; we examine a model almost identical to theirs.

At any date t, a large population of investors of size N is divided into three "compartments." (See Figure 1.2). 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.[9]

Figure 1.2 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].

Under 'random mixing,' each person is expected to have contact with χ others, randomly selected from the entire population. The only kind of contact with any consequence is between an infected and a susceptible person: Such an encounter has a probability τ of causing the susceptible person to become infected.

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:[10]

$$\beta = \tau\chi. \tag{1.1}$$

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

[8] This paper builds on the earlier work comparing the efficient market hypothesis of stock prices and an alternative model incorporating social dynamics [Shiller et al., 1984].

[9] 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.

[10] See Newman [2002] and Jackson [2010] for the results from an SIR model augmented with various social networks.

number of newly generated infections per infected person will be $\tau \times \chi \times (S_t/N)$.

The 'infected' population also changes because 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

$$\begin{aligned}\Delta S_{t+1} &= -\beta I_t (S_t/N)\\ \Delta I_{t+1} &= \beta \frac{S_t}{N} I_t - \gamma I_t\\ \Delta R_{t+1} &= \gamma I_t.\end{aligned} \tag{1.2}$$

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 1.3.1. 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, we configure it with four combinations of parameter values taken from Shiller and Pound [1989], characterizing two different kinds of investors and two categories of stocks.

We calculate the quantitative implications using one of the best of the many computational toolkits for analyzing such models that have proliferated in recent years: NDlib lets users specify an arbitrary network structure on which a disease might spread. We exploit the fact that a random-mixing SIR model can be approximated with an *ex-ante* generated random graph 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 1.1).[11]

In Figure 1.4 the vertical axis measures the proportions of Susceptible (dashed line), Infected (dash-dot line), and Recovered (solid line) investors; elapsed time since the initial date of infection is on the horizontal axis. Also plotted is the limiting size of the recovered compartment.

Two common patterns emerge. 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 people have cycled through infection and recovery. 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'

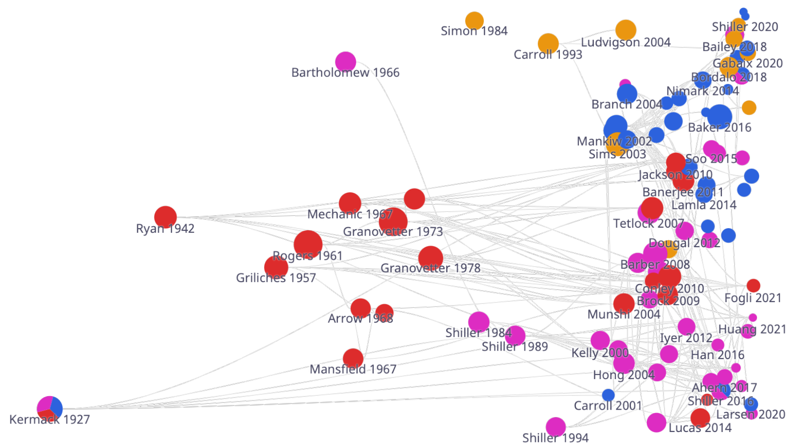
[11] See the companion Jupyter Notebook of this paper for our implementation.

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, see our discussion of the model’s economic content in Section 1.4.2).

1.4 LITERATURE

Figure 1.3 Literature map of cited papers



Note: This graph includes papers we have identified a strong epidemiological flavor in three literatures in economics: technological diffusion (red), asset market investment (purple), and macroeconomic expectations (blue). Papers in yellow have no epidemiological content but contain results relate may be of interest to EE modelers. See here for an interactive version.

The bulk of this section discusses the literatures mentioned in the introduction as having examples of full-fledged EE modeling (see Figure 1.3 for a citation map of all three literatures). The remainder addresses a miscellany of topics that did not fit elsewhere.

1.4.1 DIFFUSION OF TECHNOLOGY

Arrow [1969] argues that the process of knowledge diffusion may account for international differences in both levels and dynamics of income per capita. He conjectures that 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 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 that what spreads is the 'expectation' that adoption of the technology will yield higher productivity (See Banerjee et al. [2013], discussed below, for survey evidence confirming that people adopt a technology when they expect it to be beneficial).

In closely related work, Rogers et al. [1962] popularized a theory of the "diffusion of innovations" based on a meta-analysis of studies of the spread of ideas in academic disciplines.[12] 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 to which populations are "exposed" to the idea, and many of the other elements of epidemiological models.

Young [2009] is a broad 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.[13]

The aforementioned paper by Banerjee et al. [2013] estimates an epidemiological model based on the real-world network and pattern of the diffusion of microfinance in a number of Indian villages, providing direct evidence for word-of-mouth diffusion of beliefs through a social network.

Lucas and Moll [2014] construct an economy containing agents with a distribution of levels of productivity, and consider the dynamics of aggregate productivity under several alternative assumptions about how agents with lower productivity 'learn' from agents with higher productivity. Agents solve an optimization problem to determine the intensity of their search effort, which affects the likelihood of encountering an agent with a learnable "better technology."

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 struc-

[12] 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.

[13] 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.

ture 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 et al. [1960]: ‘degree,’ ‘clustering,’ and ‘sprinkling’ (see the discussion in section 1.2.2). Both productivity and disease spread through these connections, and as a result the dynamics of productivity and disease are connected. The model highlights a trade-off between the speed of technological diffusion and disease spreading, both of which affect economic growth outcomes (in opposite directions).

1.4.2 FINANCIAL MARKETS

Academic models of financial markets traditionally assume 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 account 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 popular emphasis on the importance of social interactions has continued to the present: Michael Lewis [2011]’s bestselling book about the financial crisis of 2008-09 goes so far as to suggest that one of the reasons a particular analyst was able to perceive the housing bubble early was his temperamental indifference to other people’s opinions.

The academic tide seems now to be turning in a popular direction. 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,” and argues that such models may be able to make sense of patterns that are 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; they 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. Now we interpret its content as an economic model. Shiller and Pound [1989] surveyed individual active investors to understand the sources of information that generated the investors’ initial interest in the stock they had most recently purchased (which they designate as ‘randomly selected’ – `RAND`), and in a set of stocks they identify as “rapidly rising.” (‘`RPI`’). Separately, they surveyed institutional investors using a different methodology to designate `RAND` and `RPI` stocks.

Their survey-based estimates of the epidemiological model for both individual

('IND') and institutional ('INS') investors reveal considerable heterogeneity in infection rates both within and between the groups. They also suggest that infectiousness differs between a randomly selected stock RAND and a rapidly rising stock RPI. Interestingly, the RAND category is more (interpersonally) "infectious" than the rapidly rising stock; the authors propose, plausibly, that public news sources will already have widely covered the rapidly rising stocks, so that interpersonal communications are unnecessary to draw attention to them.

Figure 1.4 shows compartmental dynamics 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.

The epidemiological parameters are estimated on a sample of highly interested and motivated investors – which is why it is not as surprising or implausible as it might seem that all parameterizations were ones in which R (the proportion of investors who would eventually become interested in a stock) was high.

The results can now also be interpreted in temporal terms. The authors note 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.

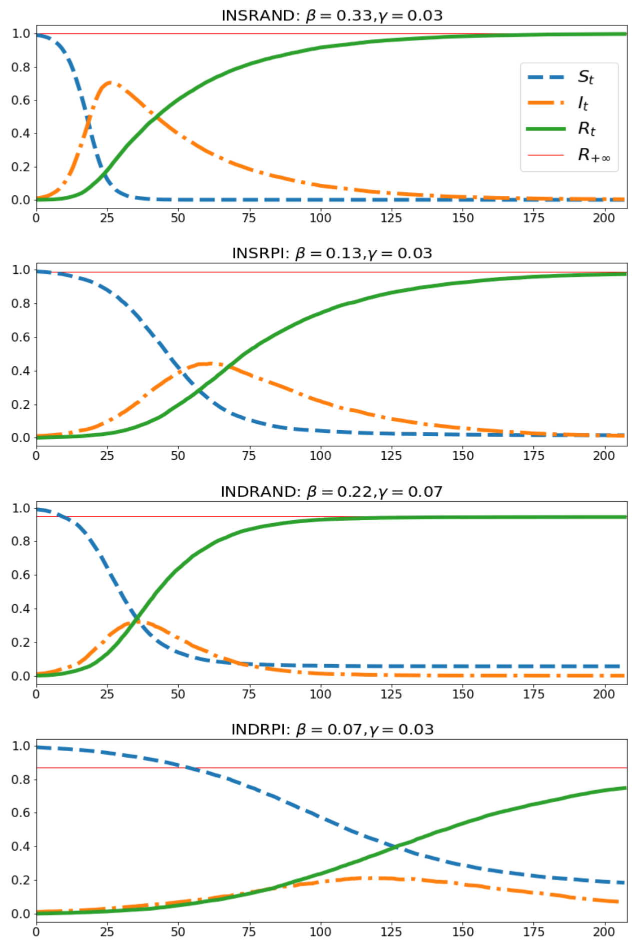
The paper also argues that in a special case where the infection rate is close to the removal rate, and the size of the pool of interested investors is driven by serially uncorrelated shocks, stock prices could follow a random walk, because under those assumptions the change in the level of 'interest' is nearly unforecastable.[14] This is another example of an economic consequence flowing from the pattern of spread of an infection.

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

A likely reason for this lack of followup is the nonexistence, until quite recently, of direct data on either of the two key components of the model: beliefs (about, say, stock prices); and social connections – and no data at all about how *changes* of beliefs reflect the structure of a measured social network. Shiller and Pound [1989] had to make heroic assumptions to quantify their model. Few subsequent scholars 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

[14] Shiller et al. [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.

Figure 1.4 Simulated dynamics from a SIR model of stock investors



Simulated paths of populations in different compartments in a SIR model of stock investors, as described in Shiller and Pound [1989]. We plot 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.

using its downstream implications for things we can observe."

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

Shive [2010] uses an SI ('susceptible-infected') model to figure out how to construct a reduced-form regressor that aims to capture social influences among investors. 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 standard variables (demographics, news sources, price dynamics, and others), the author estimates the β coefficient in Equation (1.2). The estimated β is highly statistically significant, indicating at a minimum that there is some local dynamic pattern to stock purchases not captured by the controlled-for standard variables from finance theory, but which is captured by 'proportion locally infected last period' (corresponding to S_t/N in our equation (1.2)).

Second is Huang et al. [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. 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. The authors also find stronger transmission between investors of the same characteristics (age, income category, and gender), confirming the usual presumption of homophily (people trust others with similar backgrounds); and between senders and receivers with high past performance, the natural interpretation of which is that you are more likely to boast about your investment in a winner than admit to having invested in a loser.

A final contribution that satisfies all our criteria is an impressive model of housing market fluctuations by Burnside et al. [2016], which shows how incorporating social interactions can generate booms and busts. A foundational assumption is that agents differ in their beliefs (optimistic or skeptical) about the fundamental value of housing. Although it is a random-mixing model, the paper has a mechanism similar in its implications to the simplest epidemiological model of 'super-spreaders' that obtains when some agents have many more social connections than others: Agents 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. Their most interesting result is that whether a housing boom is followed by a bust can depend on which opinion (optimistic or skeptical) turns out to be closer to the true fundamental value: 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 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 this work as exploring epidemiological models of expectations of asset prices, 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 partly because there are a number of excellent surveys already available, and partly because it has not mainly interpreted itself as modeling the dynamics of expectations (and has mostly not tested its models with data on expectations).

1.4.3 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.[15]

1.4.3.1 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:

$$M_t[\pi_{t+1}] = (1-\lambda)M_{t-1}[\pi_t] + \lambda\mathbb{E}_t[\pi_{t+1}] \tag{1.3}$$

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 1.1.[16] 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[17]
2. All consumers are susceptible to infection with probability λ
3. Infection means that the consumer adopts the view in the media
4. 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 previously 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

[15] See Chapter 7, Inflation Expectations, and Chapter 25, Bayesian Learning, for non-social models of macroeconomic expectations formation.
[16] See Easaw and Mossay [2015] for a version that adds social learning between households.
[17] Carroll [2003] quotes news stories quoting professionals, and subsequent research by Lamla and Lein [2014] has confirmed the point.

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 1.2: It collapses to the rational expectations model as the parameter λ approaches 1, making it easy to examine the consequences of the epidemiological deviation from RE. 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.[18]

Another implication – inflation expectations are a result of the degree of exposure to news stories – leads to a straightforward prediction: 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 et al. [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 Carroll [2003] and published a year earlier, Mankiw and Reis [2002] simply assume that the dynamics of inflation expectations are given by a process like (1.3); they call this a 'sticky information' assumption,[19] 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.[20]

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 a microfoundation for their 'sticky information' equation. (Conveniently, however, their baseline calibration of the model was $\lambda = 0.25$, while Carroll's empirical estimate of the parameter was 0.27.)[21]

[18] It is perhaps 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.

[19] See Chapter 25, Bayesian Learningfor a potential microfoundation.

[20] 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.

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

1.4.3.2 Sticky Consumption

A number of recent papers including Carroll et al. [2020] and Auclert et al. [2020] have applied the same epidemiological model used in Carroll [2003] to model the behavior of consumers whose attention to macroeconomic news may be spotty even if they are very well informed about their own idiosyncratic circumstances. The consequence is that aggregate consumption exhibits 'excess smoothness' in a way that matches macro data 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.

1.4.3.3 Sentiment and the Business Cycle

Section 1.4.4 summarizes empirical evidence on the macroeconomic effects of consumer sentiment or "animal spirits." Angeletos and La'O [2013] rationalizes such sentiment-driven business cycle fluctuations with a theoretical model with a strong epidemiological flavor. The paper defines the "sentiment shocks" as extrinsic shocks to beliefs that neither affect fundamentals (such as technology and preferences) nor the beliefs about these fundamentals and shows that these shocks still drive equilibrium outcomes of the economy under the critical assumption that imperfect communication prevents agents from achieving common knowledge. The paper explores aggregate belief and output dynamics after an exogenous sentiment shock hits a fraction of the agents in the economy and gradually spreads via random mixing. The paper computes population flows between what an epidemiologist would describe as three 'compartments' (uninformed, informed, and fully informed about productivity). Such dynamics induce "fad-like" or boom-bust dynamics of both aggregate beliefs and realized outputs.

1.4.3.4 Social Learning of Macroeconomic Equilibria

Arifovic et al. [2018] examine an economy with agents who have different macroeconomic forecasting rules. Its dynamics evolve as agents discard their own rules when they encounter others whose rules have proven more effective. Another way of describing this would be to say that more effective rules are more infectious. 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; it seems likely that almost all of that literature could 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 have 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 literature (and especially the work of Hommes).

1.4.4 NONSTRUCTURAL EMPIRICAL EVIDENCE

1.4.4.1 Background

Above we cite efforts to calibrate structural parameters of epidemiological models to data. Here, we touch upon literatures that collect evidence in ways not targeted to estimating such parameters, but that may nevertheless be useful in guiding the construction of epidemiological models. 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 channels 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 is 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 such questions.

1.4.4.2 Directly Measured Social Networks

In a world with ubiquitous social networks, the set of people who can influence expectations is not limited to peers who are physically nearby. Bailey et al. [2018, 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.[22] 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. Research using such data is a promising path to the estimation of explicit epidemiological models.

[22] See Chapter 8, Housing Market Expectations, for a discussion of various drivers of housing price expectations.

1.4.4.3 Papers Using Proxies for Social Connections

In the absence (until very recently) of direct evidence about the nature and frequency of social contacts between people, economists have naturally used proxies. For instance, Hong et al. [2005] found that fund managers tend to buy similar stocks to other fund managers in the same city. Hvide and Östberg [2015] found that a person's stock market investment decisions are positively correlated with those of coworkers. Cohen et al. [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 et al. [2004], Brown et al. [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 suggests epidemiological mechanisms as a way to model the channels of transmission, is Bayer et al. [2021], which shows that novice investors were more likely to enter the market (in speculative ways) after seeing that their immediate neighbors had invested.

Finally, there is a large literature finding 'peer effects' on people's financial choices; a natural interpretation is that in many cases such effects likely reflect epidemiological transmission of beliefs. But much of this literature has been content to document the existence of such correlations while remaining mute on the mechanism. (See Kuchler and Stroebel [2021] for a comprehensive survey).

1.4.4.4 Public Media

News media are not the only 'broadcast' (one-to-many) way in which ideas are transmitted. We use the term 'Public Media' to encompass all such sources (e.g., websites; podcasts; books; ...) whose natural interpretation is as a 'common source' of infection.

Finance. Rather than attempting to summarize the diffuse literature on the relationship between public 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 et al. [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. 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. Choi [2022] proposes that systematic deviations of household financial choices from the normative advice offered by optimizing models may reflect decisionmakers' infection with ideas common in personal finance books. (He surveys 50 such books and finds a host of systematic deviations of their advice from the recommendations made by standard rational optimizing models.)

Macroeconomics. A substantial literature (mostly outside of economics, cf. Soroka et al. [2015]; Damstra and Boukes [2021]) characterizes the nature of news coverage of macroeconomic developments (see Bybee et al. [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 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.[23]

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 et al. [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.[24]

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 et al. [2016], who use news 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 to make sense of this finding is unclear; the authors' interpretation seems to be mainly that they are measuring a fundamental fact about the world (the policymaking process inherently and unavoidably generates uncertainty).

But the uncertainty the authors measure might be 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 changes in the epidemiological landscape (say, the rise of Fox News) have consequences for economic outcomes by changing the degree or dynamics 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 to our next topic.

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[23] See also Chahrour et al. [2021] provide evidence that coverage about newsworthy events that affect particular sectors but are unrepresentative of broader developments can affect broader hiring decisions.

[24] 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.

1.4.4.5 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]).

After presenting a popular (and sometimes very persuasive) case for the idea in Akerlof and Shiller [2010]), he has recently returned to the theme; 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 et al. [2021] and the references therein.)

Larsen and Thorsrud [2019] take up the challenge of quantifying media narratives, deriving virality indexes, and conducting Granger causality tests to determine the extent to which viral narratives can predict or explain 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 et al. [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 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,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.

1.4.4.6 Animal Culture

A large literature (Whiten [2021]), with roots going back to Aristotle (Laland et al. [2009]) and Darwin (Heyes and Galef Jr [1996]), documents many examples of the social transmission of ideas in animal populations. Recent work in cognitive science (Kendal et al. [2018]) argues that biological mechanisms of "social learning" are common across species and between humans and animals. Results from this literature could be useful because animal populations are easier to experiment on; so, for example, uncovering the role of potential neurological mechanisms of transmission (e.g., "mirror neurons") may be more feasible for animals than in humans (Carcea and Froemke [2019]). Results have the potential to discipline economists' choices of plausible mechanisms of social transmission of ideas among humans.

1.4.5 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 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.

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, causing it to fail; 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 about 'contagion' is of this kind – that is, about multiple equilibria without any testable description of transmission or dynamics (much less measurement of expectations).

Nothing intrinsic to the questions this literature addresses prohibits construction of genuinely epidemiological models – 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 possible 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 1.1) of 3.6 percent via social network connections (approximated by 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 take for someone interested in advancing the EE agenda.)

One branch of the 'financial contagion' literature that developed after the panic following the collapse of Lehmann Brothers in 2008 explores the idea that markets can be vulnerable to the failure of entities that are 'too interconnected to fail.' This literature has 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. But what has been 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 such flows. Despite the overarching "contagion" metaphor, the low-level elements of the transmission process generally do not have interpretations corresponding to epidemiological primitives like 'infectiousness,' and the literature does not mainly aim to model the transmission of expectations at either the micro or the aggregated level. (See Glasserman and Young [2016] for a summary of this literature and Cabrales et al. [2015] for a deep dive).

Some (most?) 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 (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 will be undertaken by others who want to bring the insights from that literature to a new audience.

1.4.6 NON-ECONOMIC APPLICATIONS

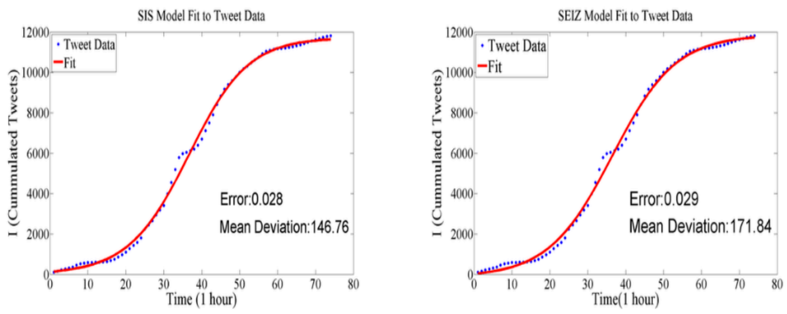
This section highlights elements of epidemiological modeling in other fields that might be of most value to economists. We focus on the following three areas:

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

Daley and Kendall [1964]'s work proposing that rumors spread like diseases spurred a literature exploring variants of the classical epidemiological model. A highly cited example (Jin et al. [2013]) estimates a model using the diffusion patterns of news about eight real events among Twitter users, including the Boston Marathon Bombings, the resignation of Pope Benedict, and rumors such as the Mayan Doomsday. In each case, the model matches the dynamics reasonably well. (See Figure 1.5).

Vosoughi et al. [2018] found that falsehood spreads on the internet faster than the truth, possibly because of such content's capacity to produce emotional arousal. Similarly, Berger and Milkman [2012] found that "content that evokes high-arousal

Figure 1.5 Spreading of news and rumors: Jin et al (2013)



(a) SIS (b) SEIZ

Note: This graph is reproduced from Jin et al. [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.

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." Zannettou et al. [2018] found that content of memes affect their virality: racist and political memes are particularly viral.

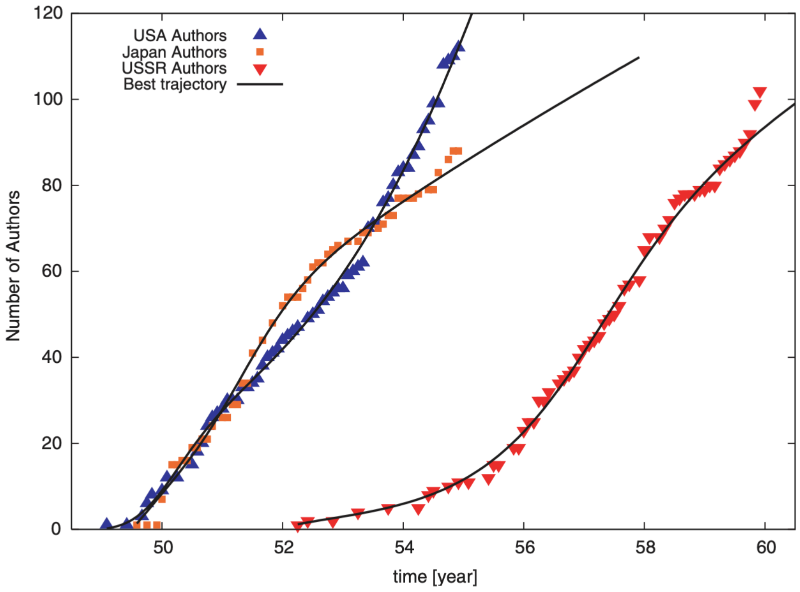
Kohlhas and Walther [2021] attempt to explain evidence that people seem to underreact to events that are not very surprising, but overreact to surprising events. The authors attempt to capture this using a combination of ideas from Sims's rational inattention framework and the Bordalo-Shleifer diagnostic expectations model, but to the extent that surprising events elicit emotional arousal, this paper may also be connected to the noneconomic literature.

Allcott and Gentzkow [2017] used a post-2016 election survey of 1200 U.S. adults to analyze the importance of social media for fake news consumption, exposure to fake news, and partisan composition. The paper models profit-maximizing entities who supply fake news in order to appeal to consumers subject to confirmation bias. This seems a natural extension of standard epidemiological models to incorporate the production side of the content – "infectiousness" of certain ideas in subpopulations is an incentive for the production of content that will become "viral" because of a high reproductive number in the targeted subpopulation.

Another potential determinant of the degree to which ideas spread is explored in Acemoğlu et al. [2010], who show show that the presence of "forceful" agents (who are immune to others' opinions) may lead to the persistence of misinformation. The key insight 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 the spread of scientific ideas. Bettencourt et al. [2006] finds that epidemiological models perform well in explaining the the spread of Feynman diagrams through theoretical physics communities (see Figure 1.6).

Figure 1.6 Diffusion of scientific ideas: Bettencourt et al (2006)



Note: This graph is reproduced from Bettencourt et al. [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.

Internet memes are a favorite topic of non-economist modelers. Bauckhage [2011] shows that epidemiological models do a good job capturing the growth and decay of some famous memes. Wang and Wood [2011] finds that a modified SIR model allowing for the reinfection of the “recovered” fits the propagation dynamics of various viral memes well.

1.4.7 FUTURE DIRECTIONS

Common tools from epidemiological practice could usefully be imported into expectational surveys – particularly the tools that epidemiologists use to track the source of an infection (‘contact tracing’ being the most straightforward). 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]." 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."[25]

Above, we mentioned evidence that information from some sources, or of some kinds, was more infectious; other evidence indicated that certain recipients are more 'susceptible.' 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.

1.4.8 LITERATURE SUMMATION

Similar themes have emerged independently from scholarly communities who seem largely unaware of each others' existence. Different terminology has developed for ideas that are close cousins; this likely has hindered the ability of participants in distant fields to recognize commonalities in their work.

For example, the work on "social learning" in macroeconomics involves the propagation of competing forecasting rules in a population. Interpreting rules as the consequence of beliefs, 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, embody ideas that are more infectious. But authors in this literature often do not describe their models in explicitly epidemiological terms, nor do they typically propose testing their models by querying simulated agents about their simulated expectations, and comparing simulated expectations data to actual expectations data.

Nor does this work take much notice of Shiller's longstanding view that economic dynamics reflect the competition of 'narratives' that 'go viral.' "Social learning" models' 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 'tournaments' are a good candidate for a computational representation of the consequences of what might be meant by the claim that 'narratives' can 'go viral.'

One of our ambitions is for this survey to infect scholars with the idea that it is useful to describe their models 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.

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[25] Arrondel et al. [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.

1.5 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 key mechanisms of the social transmission of ideas – as has already been done in a few cases of economic models (and many 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 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 with structural models of expectational heterogeneity calibrated to match empirically measured expectations. While there are other mechanisms for generating such heterogeneity, epidemiological modeling is a promising candidate.

An epidemiological expectations modeling approach is by no means applicable only to macroeconomic questions – expectations are at the heart of all sorts of economic questions. But available tools allow economists to expand their imagination far beyond the limited 'classical' epidemiological models. 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 scholars have done since time immemorial.

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