CHAPTER

Epidemiological Expectations[1]

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ABSTRACT
'Epidemiological' models of belief formation put social interactions at their core; such models are widely used by scholars who are not economists to study the dynamics of beliefs in populations. We survey the 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 internet memes. A main theme of the paper is that a number of independent developments have recently converged to make epidemiological expectations ('EE') modeling more feasible and appealing than in the past.

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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]

1.1 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 about how to model belief dynamics are largely about which particular models of social communication are most suitable for understanding the spread of which kinds of ideas.[2]

"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 believe that economic ideas are immune to social influence. But evidence for social transmission of economic ideas is plentiful – see Section 1.4.4.

[1] See Rasmussen [2017].

[2] A recent article in *Nature Scientific Reports* begins "Opinion formation cannot be modeled solely as an ideological deduction from a set of principles; rather, repeated social interactions ... are consequential in the construct of belief systems." (Nedić et al. [2019]).

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], the overconfidence model of Daniel et al. [1998], or a number of bounded rationality approaches (e.g., Gabaix [2020], Ilut and Valchev [2020]).[3]

This is perhaps because nowhere has a 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 incorporating the following elements:

1. **a mechanism:** An explicit and rigorous mathematical description of a process by which ideas are communicated between 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), asset pricing (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 selected examples of research outside of economics that might be particularly interesting for economists (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*

[3] See Hommes [2021] for a wide-ranging summary of other non-RE approaches – but does not include Epidemiological Expectations.

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]).[4]

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 behavior. 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). The commissioning of this *Handbook*, and the proliferation of new research summarized herein, are among the many other indications of a sea-change in the profession's attitudes.

1.2.2 EPIDEMIOLOGICAL MODELS

We will use the word 'classical' to refer to epidemiological models that descend from Kermack and McKendrick [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. These assumptions 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 network 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.[5]

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 states $\{S, I, R\}$, and that 'edges' are the links by which an infection can pass from an infected to a susceptible person (our SIR model in Section 1.3.2 is constructed in exactly this way; see Newman [2002] and Jackson [2010] for canonical analyses of epidemics on networks, and Easley and Kleinberg

[4] One example is Velásquez-Giraldo [2022], who shows that household portfolio choice models yield much more reasonable results when the model is calibrated with survey respondents' self-reported stock market expectations than when calibrated with beliefs like the empirical history of stock returns.

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

[2010] for a textbook focused on markets).

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. 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 - they have 'six degrees of separation'.[6]

Moore and Newman [2000] examine the spread of diseases on 'small worlds' networks; if the 'clustering coefficient' is small enough, results can be quite similar to those of the classical SIR model. But Allard et al. [2020] show that incorporating directionality of infection in an otherwise-standard SIS model substantially changes the results. And even in a fully connected world without clustering or directionality, there is no guarantee of 'the wisdom of crowds' (opinions will converge to the truth). Using the DeGroot model DeGroot [1974] (in which agents' opinions are a wegihted average of the views of their neighbors), Golub and Jackson [2010] show that crowds are wise only if the aggregate weight of the most influential nodes is asymptotically negligible. Alternatively, if some agents are 'stubborn' (Acemoğlu et al. [2013]) or prone to confirmation bias (Sikder et al. [2020]), different subpopulations can converge to different beliefs.

Matters become even more interesting if ideas can change as they pass from one person to another. The direct epidemiological term for this, of course, is mutation, which has in fact been used in some papers. (Shiller [2020]; Hachem and Wu [2017]).

1.2.3 EXPECTATIONAL TRIBES

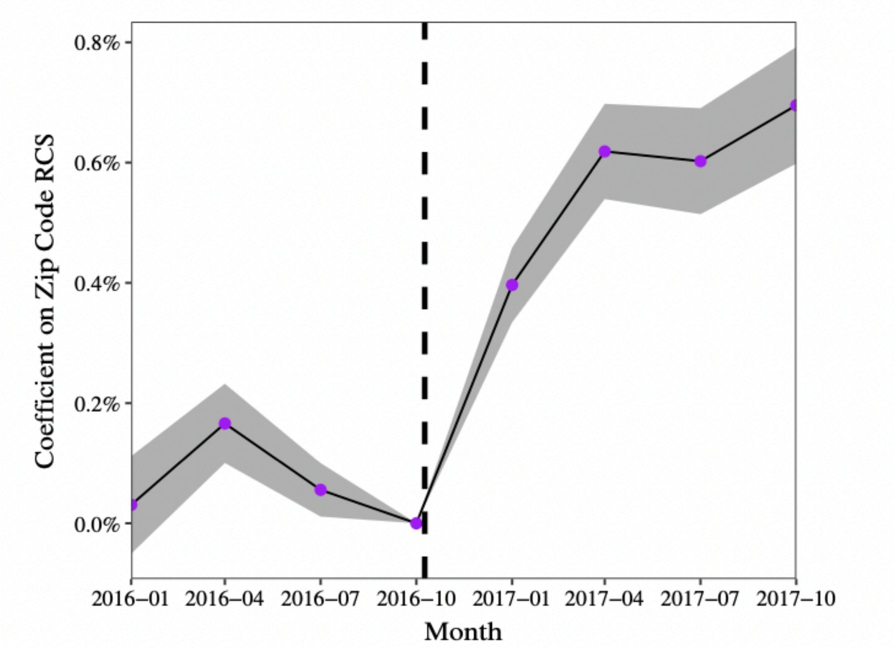
If there were no evidence that such differences of opinion matter for important economic decisions, the case for epidemiological modeling would be weaker. We therefore conclude this 'background and motivation' with some evidence of a recent clear failure of 'identical beliefs' with consequences for measured 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,

[6] 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.

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-identified Republicans had suddenly become more optimistic, and Democrats more pessimistic, about the economy's prospects over the next few years.[7]

Figure 1.1 Portfolio Responses to the 2016 U.S. Election



Note: Reproduced from Meeuwis et al. [2021], this figure reports regression coefficients of equity share on zip-code-level campaign contribution share to Republican candidates over an interval spanning the election.

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

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 are modeled as resulting from some social interaction.

Transmission need not be person-to-person; it can reflect exposure to a "common source." (Cosmic radiation to which everyone is exposed 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).

In the simplest epidemiological model, a continuous population is partitioned among infected people I and those who are susceptible S but not yet infected, and the infectiousness of the 'common source' is time-independent at probability p. For a population at discrete date zero with a susceptible population of size 1, the dynamics of such a common-source SI model 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 to be transmitted as a result of 'random mixing' where each susceptible person who encounters an infected person becomes infected with a fixed probability. Given a non-zero initial infected fraction I_0, the fraction infected and susceptible evolve per Table 1.2.

The best-known epidemiological framework adds an 'R' state that can designate either recovery or 'removal' (via, say, death), yielding the 'classical' SIR models. 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 Susceptible compartment.

Options proliferate from there.[8] A framework in which there are two possible

[8] For a general introduction to these model basics, we refer the reader to this Wikipedia page. Promi-

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

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 tools is that they 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].[9]

1.3.2 ONE EXAMPLE

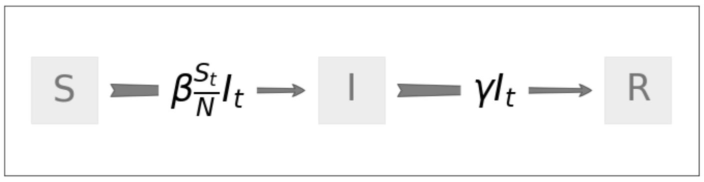
Here, we provide a specific example of an economic question formulated in a thoroughgoing epidemiological way. Our present purpose is not to extract economic insights – we do that in section 1.4.2 below – but simply to illustrate how the epidemiological toolkit works.

nent examples include Bailey et al. [1975], Anderson et al. [1992], Hethcote [2000], Brauer [2017].

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

Shiller and Pound [1989] use an SIR model to capture how interest in particular stocks spreads;[10] we examine a model almost identical to theirs. At date t, a large population of investors measured by the real number N is divided into three "compartments." (See Figure 1.2). I_t investors are currently "infected" with interest in a certain stock; S_t investors are not infected but are "susceptible" to becoming interested; and R_t measures investors who have been "infected" but have "recovered" from the infection.[11]

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 contact, τ:

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

The expected number of new infections generated in period t (corresponding to the decline in the number of susceptible persons) can now be calculated: 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 '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 com-

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

[11] For our purposes here, we do not need to define the exact consequences of 'recovery.' See below (or see the original paper) for further discussion.

partments 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 above-mentioned 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).[12]

In Figure 1.3 the vertical axis measures the populations of S, I, and R investors; 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' 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 a discussion of the model's economic (as distinct from epidemiological) content see Section 1.4.2).

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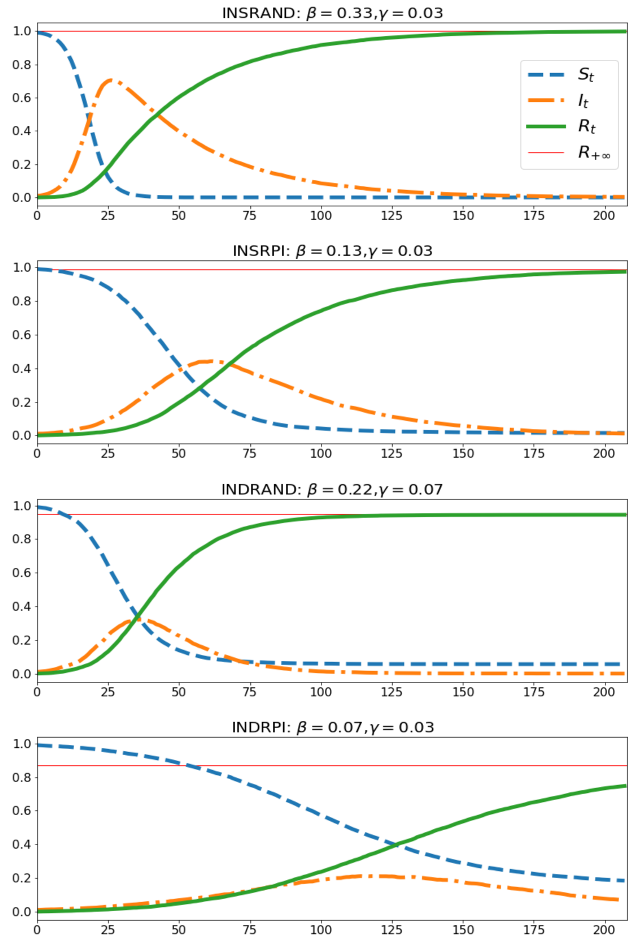
[12] See the companion Jupyter Notebook of this paper for our implementation.

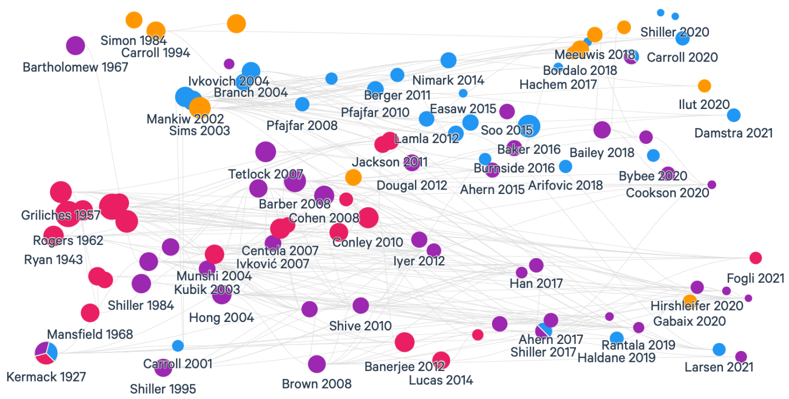
Figure 1.3 Simulated dynamics from a SIR model of stock investors



The four figures respectively simulate an SIR model under calibrations corresponding to Shiller and Pound [1989]’s parameter estimates for (1) institutional investors for a randomly selected stock (INSRAND); (2) institutional investors for a rapidly rising stock (INSRPI); (3) individual investors for a random stock (INDRAND); and (4) individual investors for a rapidly rising stock (INDRPI). The susceptible population S is dashed; dash-dot shows the size of the I compartment, and the recovered population R is solid. The horizontal thin solid line corresponds to the limiting size of compartment of R in the long run. To reproduce these figures, see the companion Jupyter Notebook.

1.4 LITERATURE

Figure 1.4 Literature map of cited papers



Papers we have identified as having a strong epidemiological flavor in three literatures in economics: technological diffusion (red), asset markets (purple), and macroeconomic expectations (blue). Papers in yellow have no epidemiological content but are cited in the text as having content that may be interesting to EE modelers. See here for an interactive version. (Articles are represented by dots; citations are represented by lines between dots; x axis orders papers by publication date; y axis orders papers into citation clusters).

Figure 1.4 provides a citation map of papers in the literatures we discuss here; the thin lines represent a citation from the later paper to the linked earlier one.

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 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.[13] 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] presents a broad survey of how alternative epidemiological models generate different shapes of "adoption curves" with consequent effects on the path of economic growth. He shows how the shape of diffusion curves differs in models of 'inertia' (a SI common-source model), 'social influence' (a threshold model), 'contagion' (a transmissible SI model), and 'social learning,' where learning is based on observed actions of others.[14]

The aforementioned Banerjee et al. [2013] estimates an epidemiological model based on the real-world network and pattern of diffusion of microfinance in 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 structure of the networks connecting people ('nodes') allows the authors to explore the roles of the three dimensions central to the network theory literature that has developed since Erdos et al. [1960]: 'degree,' 'clustering,' and 'sprinkling' (see section 1.2.2). Both productivity and disease spread through these connections, so the dynamics of productivity and disease are connected. The model highlights a trade-off between the speed of technological diffusion and disease spreading, which affect economic growth outcomes in opposite directions.

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[13] 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.

[14] 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.

1.4.2 FINANCIAL MARKETS

Academic models of financial markets traditionally assume investors choose stocks based on self-generated 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 [1852]'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 bestseller 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 this 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. Akçay and Hirshleifer [2021] make a broad argument that there are important biases in the transmission of ideas from one person to another which 'shape market outcomes.' Hirshleifer [2015], Hirshleifer [2020] and Kuchler and Stroebel [2021] propose 'social finance' as the name for a field that would study the role of social interactions, and argue that new data and new methods could advance the field quickly.

These are by no means the first academics to propose a role for social transmission of financial ideas. But 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 Shiller and Pound [1989], used in Section 1.3.2 to delineate the elements of the generic SIR 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 their initial interest in the stock they had most recently purchased (which they designate as 'randomly selected' – `RAND`), and in a set of stocks that have been "rapidly rising." ('`RPI`'). Their separate survey of institutional investors used a different methodology to designate `RAND` and `RPI` stocks.

Their survey-based estimates of the epidemiological parameters for both individual ('`IND`') and institutional ('`INS`') investors indicate considerable heterogeneity in infection rates both within and between the groups. The estimates also suggest that infectiousness differs between `RAND` and a `RPI` stocks. Interestingly, the `RAND` category is more (interpersonally) "infectious" than the rapidly rising category; the authors speculate that public news sources will already have widely covered rapidly rising stocks, so that interpersonal communications are unnecessary to attract attention.

Figure 1.3 shows compartmental dynamics under their median estimates (of infection and removal rates) for individual and for institutional investors, and for randomly selected versus rising stocks, respectively.

The epidemiological parameters are estimated from a sample of highly interested and motivated investors – which is why it is not surprising that all parameterizations were ones in which R (the proportion of investors who would eventually become interested in a stock) converges to a high value.

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 spikes in trading volume should immediately follow news events, while 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. 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 the change in the level of 'interest' would be nearly unforecastable.[15]

Remarkably little of the large literature citing Shiller and Pound [1989] has involved meaningful epidemiological modeling; most has either been nonstructurally empirical, or has used a modeling framework that cannot really be characterized as 'epidemiological.' A likely reason for this lack of followup is the nonexistence of direct data on either of the two key components of the model: beliefs (about, say, stock prices); and social connections. We have found only two subsequent papers that 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 empirical regressor that aims to capture social influences among investors ($I_t S_t / N$ in our equation (1.2)). The author assumes that the key social infection channels are at the municipal level, and estimates the time-series dynamics of ownership within municipalities. 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 which is captured by 'proportion locally infected last period' (S_t/N in our equation (1.2)).

The second example is Huang et al. [2021], which estimates an epidemiologi-

[15] Shiller [1984] elaborates on this logic by allowing the presence of both rational investors ("smart money") and social-dynamics driven investors. The presence of unforecastable social dynamics undermines the conclusion that a random walk implies full rationality.

cal 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 $(\beta S_t/N)/\gamma$ in the SIR model above). 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 the kind of 'transmission bias' modeled by Han et al. [2022], in which people are more likely to boast about their investments in winners than to mention their losing bets.

A final example of an EE model in asset markets is an impressive model of housing price 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 (and the model collapses to a Rational Expectations equilibrium under some simple alternative assumptions). Although it is a random-mixing model, the paper has a mechanism with implications similar to those of the simplest epidemiological model of 'super-spreaders' (in which some agents have many more social connections than others): Their 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. Because it is calibrated using survey data on house price expectations, the model satisfies all our criteria for a full-fledged EE model.

Another two strands of literature that deserves brief mention are the "evolutionary approach" of the financial markets (Lo [2004], Brennan and Lo [2011]) and 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 this literature partly because there are a number of excellent surveys already available, and partly because the literature 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.[16]

1.4.3.1 Sticky Expectations

Carroll [2003] presents an epidemiological model in which the dynamics of aggregate consumer inflation expectations 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.

This 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 we presented in table 1.1.[17] The idea is that consumers' expectations of inflation stem from exposure to (common) news media sources. 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. The model 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.

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 professionals' expectations will depend on the intensity of news coverage of inflation. Carroll [2003] found some support for this; Lamla and Lein [2014] and Larsen et al. [2021] find further evidence that a greater intensity of news coverage of inflation leads to more accurate expectations in the population.

The SI model provides a plausible (and testable) microfoundataion for the work of Mankiw and Reis [2002], who simply assume that the dynamics of inflation expectations are given by a process like (1.3); they call this a 'sticky information' assumption,[18] 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. 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.

An example closely related to the overtly epidemiological work on inflation expectations is Branch [2004], who considers a model in which agents who have different inflation forecasting rules meet each other and the rules that work better are

[16] See Chapter 7, Inflation Expectations, and Chapter 25, Bayesian Learning, for non-social models of macroeconomic expectations formation.
[17] See Easaw and Mossay [2015] for a version that adds social learning between households.
[18] See Chapter 25, Bayesian Learningfor an alternative potential microfoundation.

adopted.

A number of recent papers including Shibata et al. [2019], Carroll et al. [2020], and Auclert et al. [2020] have applied the same SI 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.

1.4.3.2 Sentiment and the Business Cycle

Section 1.4.4 summarizes evidence of macroeconomic effects of consumer sentiment or "animal spirits." Most of the theoretical work in this area[19] resembles the theoretical work in on financial contagion: It examines questions like existence of an equilibrium (or multiple equilibria), but does not focus on understanding social interaction mechanisms by which the equilibrium could come about, and does not use expectations data to test the model.

Angeletos and La'O [2013] is an exception. It rationalizes sentiment-driven business cycle fluctuations with a theoretical model with an explicit epidemiological mechanism. The paper defines the "sentiment shocks" as extrinsic belief shocks that neither affect fundamentals (such as technology and preferences) nor the beliefs about these fundamentals and shows that these shocks still drive equilibrium outcomes 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 agents 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.

1.4.3.3 Learning of Macroeconomic Equilibria

Brock and Hommes [1997] model the dynamics of beliefs using a model in which there is a population of forecasting rules that agents can adopt, and in which the agents periodically construct a predictor by choosing combinatoins of forecasting rules whose performance has been better. The dynamics in the model are described as reflecting the 'survival of the fittest.' Arifovic et al. [2018] also examine an economy with agents who have different macroeconomic forecasting rules. Aggregate dynamics evolve as agents discard their own rules when they encounter other agents 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 po-

[19] For example, Angeletos and La'o [2010], Benhabib et al. [2015], Angeletos et al. [2018].

tential 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.'

These papers are examples of an 'agent-based modeling' approach, which Tesfatsion [2006] has argued has application to many subfields of economics. Haldane and Turrell [2019] make a strong case for a broad reinterpretation of these kinds of models as epidemiological, particularly in the macroeconomic context. Though most such models do not use expectations data to test their implications (an exception is the work of Hommes [2006]; see also Branch [2004]), it is a short leap from the assumption that successful decision rules spread to an interpretation that what spreads is a set of expectations that would induce the decision rule that is spreading.

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]). 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

Above we cite efforts to construct and calibrate structural models of epidemiological models. Here, we touch upon literatures that collect evidence in ways not targeted to constructing structural models, but that may nevertheless be useful in guiding the construction of structural EE models.

1.4.4.1 Directly Measured Social Networks

Direct data on social interactions have only very recently become available to researchers. One of the first papers to use such data is Allen et al. [2018], who use data from peer-to-peer (P2P) FinTech platforms to examine effects of social connections on consumer and small business loans. They find that P2P loan demand in a given locale increases faster it has previously been growing in its socially connected locales, even when they are geographically distant. Cookson and Niessner [2020] use data from a social media investing platform to examine sources of disagreement across investors who are in direct communication with each other. Cookson et al. [2022] shows how network formation on social investing platforms leads to information flows that are more likely to support investors' pre-existing beliefs, leading to the creation of "echo chambers".

Several papers have used data from Facebook. Bailey et al. [2018a, 2019], using data on individual users' social networks, show 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.[20]

Bailey et al. [2018b] constructed an aggregated social-connectedness-index (SCI)

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

using the universe of Facebook users, which calculates the Facebook connections between any two zip codes in the U.S., as well as the connections of each zip with foreign countries. There is already a burgeoning literature using these data (much of it outside of economics). Among selected early results in economics, Makridis [2019] shows that a rise in a locality's sentiment caused by events in socially connected areas has a substantial effect on nondurables spending. 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 places to which that county had especially dense social ties – even when those places were geographically distant. Ratnadiwakara [2021] shows that individuals who are socially connected to someone affected by Hurricane Harvey are more likely to purchase flood insurance policies after the event.

1.4.4.2 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. 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] show that fund managers place larger bets (that perform better) on firms to whose employees they are socially connected. Social interaction also affects stock market participation and stock choices (Hong et al. [2004]; Brown et al. [2008]; 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.[21]

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).

1.4.4.3 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 re-

[21] Kaustia and Knüpfer [2012] finds evidence for similar mechanisms in stock market entry decisions.

lationship 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.

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.[22]

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 has predictive power for economic outcomes (Ludvigson [2004], Carroll et al. [1994]). One example is a clever paper by Doms and Morin [2004] who show that consumer sentiment is driven by news coverage by finding episodes where other news events have crowded out economic news.[23]

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 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 . 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.[24]

[22] 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.
[23] 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.
[24] See Eliaz and Spiegler [2020] for a model of such mechanisms.

That leads us to our next topic.

1.4.4.4 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 case for the idea in Akerlof and Shiller [2010], he has recently returned to the theme; our opening quote from him makes it clear that he thinks narratives spread by “going viral.” See Shiller [2017, 2019] for extended treatments.

There are formidable obstacles to turning Shiller’s plausible idea 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 combing historical news archives and internet search records, he identified six economic narratives that have circulated since 2009, which he labeled as “Great Depression,” “secular stagnation,” “sustainability,” “housing bubble,” “strong economy,” and “save more.” (See also Ash et al. [2021] and Andre et al. [2022] 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. The authors find episodes in which their methodology identifies ‘narratives’ that have ‘gone viral,’ with measured economic consequences.

1.4.4.5 Social Communication in Animals

A large literature (Whiten [2021]) documents many examples of the social transmission of behaviors and ‘ideas’ in populations of animals, and argues that the epidemiological mechanisms by which novel ideas spread are similar to those in human populations (Whiten et al. [2016]). Results from this literature could be useful because animal populations are easier to experiment on. For example, in one such experiment, Kendal et al. [2015] find that ideas are more likely to spread from dominant chimpanzees to subordinate ones than vice-versa.

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 (Carcea and Froemke [2019]). Again, laboratory experiments to uncover the role of potential neurological mechanisms of transmission (e.g., “mirror neurons”) may be more feasible in animals than in humans.

Results from these literatures have the potential to shape economists’ perceptions of the most 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. Most 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 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 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.)

Another branch of the 'financial contagion' literature that has aimed to understand the panic occasioned by the 2008 collapse of Lehmann Brothers 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) described above. 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 models 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 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).

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 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 proposal 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 and the resignation of Pope Benedict, and rumors such as the Mayan doomsday. In each case, the model matches the dynamics reasonably well.

Vosoughi et al. [2018] found that falsehood spreads on the internet faster than the truth, possibly because the interesting falsehoods have a greater capacity to produce emotional arousal. Similarly, Berger and Milkman [2012] claim 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." Zannettou et al. [2018] found that the content of a meme affects its 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 model 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 U.S. survey to analyze the importance of social media for fake news consumption, exposure to fake news, and partisan composition. The paper models profit-maximizing firms 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 effectively used to study the spread of scientific ideas. For example, Bettencourt et al. [2006] find that epidemiological models perform well in explaining the the spread of Feynman diagrams through theoretical physics communities.

Internet memes (Dawkins [1978]) 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. A large literature has followed their work.

1.4.7 FUTURE DIRECTIONS

1.4.7.1 New Tests of Competing Models

One attractive aspect of the EE modeling approach is that it opens the possibility of testing competing models of an aggregate outcome using patterns in the cross-section and panel dynamics of microeconomic expectations. Since there are often many competing models that are able to fit aggregate patterns roughly equally well (stock price dynamics, say) it should be possible to winnow down the field of plausible contenders using their different predictions about microeconomic expectations data.[25]

1.4.7.2 New Kinds of Survey Data

Common tools from epidemiological practice could usefully be imported into expectational surveys – particularly tools that epidemiologists use to track the source of an infection (e.g., 'contact tracing'). 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 the respondent might have a useful response: "A friend told me" or "I read it in the newspaper" or "I did some research on the internet."[26]

Several times we have mentioned evidence that information from certain sources, or of some kinds, was more infectious; other evidence indicated that certain recipients are more susceptible to infection. 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 assumptions for our models.

[25] A few such exercises have already been performed: Carroll [2001] shows that the time-series dynamics of micro-level *disagreement* in inflation expectations matches reasonably well the predictions of his baseline SI/sticky expectations model. Coibion and Gorodnichenko [2012] compare the implications of sticky expectations to those of a Kalman filter, and conclude that the dynamics of the cross section indicate substantial rigidity in beliefs whichever framework is used.

[26] Arrondel et al. [2020] provide an example of this approach. They not only elicited survey 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.

1.4.7.3 New and Big Data

There is also a rapidly expanding body of work that tries to answer economic questions by analyzing 'big data' on textual/conversational information using natural language processing (NLP). (See Gentzkow et al. [2019] for an overview). As those tools get more sophisticated, they might become usable for creating 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 will be possible to train AI algorithms 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 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.

1.4.8 LITERATURE SUMMATION

Ideas that we would term 'epidemiological' have emerged independently in scholarly fields that (ironically) seem largely unaware of each others' existence. Different terminology and methodological tools have developed for ideas that are close cousins; this likely has hindered the ability of participants in distant fields to recognize deep commonalities in their work.

For example, the work on "social learning" in macroeconomics studies the propagation of competing forecasting rules via agent interactions in simulated populations. If it were couched as being about the spread of beliefs in the efficacy of the rules, this work would have satisfied our criteria that it addressed a substantive economic question using a mechanism by which beliefs were transmitted by social interaction. 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 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, mutation, and so on (in place of miscellaneous other words that in practice are synonymous with the epidemiological term).

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 (surveyed) 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 more cases outside of economics).

Other work based on measures of 'clustering' like geographical proximity or shared workplaces has found robust evidence of social transmission of ideas, while another strand of research has explored the ways in which each news outlet 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 incorporating measurable 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 heterogeneity, given the copious evidence of epidemiological transmission of beliefs and the rich toolkits for epidemiological modeling, 'EE' modeling seems a natural choice.

An EE approach is by no means applicable only to macroeconomic questions; expectations are at the heart of all sorts of economic questions. Available tools allow economists to expand their imagination far beyond the limits of '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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