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Authors(s)	Kelly, Morgan
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Contagion.

Morgan Kelly.

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The power of the metaphor of contagion—that beliefs, actions, and strategies spread among economic agents like pathogens among biological organisms—causes it to recur in disparate areas of economics. This article focusses on four applications of contagion to economics: social influence or memoryless learning; Bayesian social learning; strategy choice in coordination games; and the spread of crises in international financial markets.

Social Influence.

The metaphor of contagion is central to the early studies of crowd psychology of Mackay (1841), Tarde (1900) and LeBon (1895); and classical early models of disease diffusion were applied to financial markets by Shiller (1984).

The modern analysis of social influence starts with Allport and Postman (1946-47) who studied the spread of wartime rumor. They identified four circumstances that facilitate the spread of rumor: two are characteristics of the rumor, two of the population: The topic of the rumor should be important to people and the rumor should be hard to verify individually; while individuals should be credulous, and going through a time of unusual stress.

Motivations for neglecting formal Bayesian learning differ between economics and sociology. Sociology emphasises situations that do not lend themselves to Bayesian updating either through lack of time (is a bank about to fail?), or the nature of the question (what is the one true religion?). Economics, by contrast, emphasises computational simplicity: rules of thumb make fewer cognitive demands on agents than formal updating algorithms.

Kirman (1993) analyzes a simple model of influence, motivated by the foraging behavior of ants, but applicable, he argues, to the behavior of stock market investors. Faced with a choice between two identical piles of food, ants switch periodically from one pile to the other. Kirman supposes that there are N ants and that each switches randomly between piles with probability ε (this prevents the system getting stuck with all at one pile or the other), and imitates a randomly chosen other ant with probability δ .

By the ergodic theorem of Markov chains, there is a unique steady state distribution of ants between piles, and Kirman shows by simulation that the shape of the distribution depends on the relative magnitudes of the imitation parameter δ and the mutation parameter ε . With weak imitation and strong mutation there is a single peak at $\frac{1}{2}$, with equal numbers of ants at each pile. With stronger imitation and weaker mutation, the steady state distribution has two peaks at 0 and N : most ants concentrate on a single pile and switch periodically to the other; the behavior observed among real ants and possibly stock market participants. In contrast to Bayesian learning models, the absence of martingale convergence allows society continually to flip between beliefs.

The independent work of Weidlich and Haag (1983) in quantitative sociology presents an analogous model in continuous time. Agents switch states with a logistic probability that again depends on the relative social popularity of each choice, but Weidlich and Haag also allow agents to have a personal preference for one of the choices. Again, for sufficiently strong imitative behavior there is a steady state distribution with two peaks, but now the relative magnitude of the peaks depends on how much agents prefer each choice. Society spends most time at the choice preferred by each agent, but will spend time at the choice that is less popular with everyone, as a consequence of social influence.

Ellison and Fudenberg (1993) look at the role of popularity weighting in choosing between a superior and an inferior technology. They observe that popularity can be a useful summary of the relative past performances of the two technologies—the better technology should be more popular—but that the amount of information conveyed by popularity is diluted the more people rely on it. They therefore look at the likelihood that the better technology is adopted, allowing a fixed fraction of the population to change its choice each period, when the relative weights put on

the popularity of the technology versus its performance last period are allowed to vary.

Ellison and Fudenberg (1993) show that there is an optimal popularity weighting that causes the system to converge to everyone's using the better technology. If popularity weighting exceeds this optimum, the system converges to a steady state where everyone uses one technology, but which technology depends on the starting number of users of each. With under-weighting of popularity, the inefficient alternative can survive indefinitely.

The competitive exclusion principle, proved in the context of ordinary differential equations by Levin (1970), states that the number of co-existing species cannot exceed the number of resources they compete for. Here, there are two competing species or technologies competing for one resource, being used by people, so if the technological choice problem is recast as one of biological competition we know that only one technology will survive. This is done by Juang (2001), who uses an evolutionary selection argument to show how an Ellison-Fudenberg society can reach the optimum when different groups of agents have sufficiently different popularity weightings. In periods when the inferior technology is excessively popular, agents putting low weight on popularity receive higher payoffs and increase in number, while agents who put high weight on popularity do better in periods when the superior technology is popular.

In the popularity weighting models of Kirman (1993), Weidlich and Haag (1983), and Ellison and Fudenberg (1993), every person is equally influenced by every other member of society. In many situations however, we are influenced more by individuals that we know and have learned to trust than by strangers. To model the greater social influence of neighbors, the individual is put into some mathematical space, being more likely to interact with individuals close to him than far away. Durlauf (1997) looks at the behavior of agents in an Ising model (originally developed to model the flipping of magnetic poles of atoms in a crystal) where agents live on a lattice and change between two actions at a rate which depends logarithmically on the state of their nearest neighbors.

If the influence of neighbors lies above a critical value, the system has two steady state distributions (there are an infinite number of agents so the ergodic theorem of Markov chains does not apply) with all agents either in one state or the

other. If agents have a preference for one state over the other (the physical analogue is an external magnetic field) however, the system has only one steady state with all choosing the preferred action.

In Durlauf's model, agents in each state influence each other symmetrically, affecting only their nearest neighbors. Durrett and Levin (1998) analyze a system where agents of different types can affect others over different distances. While biologically motivated—Durrett and Levin (1998) are interested in how slow growing trees can out-compete rapidly growing grasses—this analysis suggests how propaganda and advertising can be used to cause bad ideas to drive out good.

Suppose that type 0 dominates type 1: an agent of type 0 converts a type 1 neighbor at rate 1, whereas a type 1 agent converts a type 0 only at rate $\delta < 1$. If both types have the same radius of influence then, so long as the dominant type 0 avoids getting wiped out by an unlucky run at the start, it will take over. However, Durrett and Levin (1998) show that if the dominant type affects only neighbors in a radius of 1, whereas the dominated type affects neighbors over a large radius R , there is a critical value of the conversion rate $\delta_c < 1$, above which the dominated type 1 takes over.

It is straightforward to demonstrate the existence of social influence empirically when individuals observe the overall popularity in society rather than among neighbors. The influence of best-seller lists on book buying is sufficiently well known for publishers to seek to manipulate them by buying books in stores known to be tracked by the lists, and a variety of examples of imitative behavior are given by Bikchandani, Hirshleifer and Welch (1992) and Chamley (2004, pp59–60).

Testing for the influence of neighbors is more difficult because neighborhood choice is frequently endogenous: you must make sure that the behavior you are attributing to the influence of neighbors is not due to some individual factor that led the person to choose this neighborhood over others in the first place.

The classic Ryan and Gross (1943) study, which found that the main factor influencing farmers to adopt hybrid corn was the number of nearby farmers who had adopted it, passes the exogeneity test: it is unlikely that farmers chose farms to be near other innovative farmers. Sacerdote (2001) uses the random allocation of roommates to incoming Dartmouth University students to show how roommates influence each other's behavior, finding that roommates have an effect on indi-

vidual academic performance, while dormitory effects influence decisions to join fraternities. Kelly and O Grada (2000) look at the behavior of Irish immigrants, mostly housemaids and day laborers, in 1850s New York during two bank runs. As immigrants it is possible to identify their social network from their place of origin in their home country: newly arrived immigrants tend to associate with people they knew at home. Kelly and O Grada (2000) found that immigrants from one set of counties in Ireland tended to close their accounts during the panics, while otherwise identical immigrants from other counties stayed put.

Bayesian Learning.

Bayesian models of social learning allow individuals to infer the information of other agents from their observed actions in an optimal manner rather than through ad hoc imitation. Bayesian social learning can exhibit pathologies. After the first few agents have chosen, subsequent actions convey little new information and are dominated by idiosyncratic noise. Society converges slowly to the optimal action and, in some circumstances, may become stuck on the sub-optimal action. A useful textbook discussion of the literature is given by Chamley (2004).

In Bikchandani, Hirshleifer and Welch (1992) and Banerjee (1992), the world can be in either state σ_0 or σ_1 . Each agent receives a signal s_0 or s_1 with symmetric precisions $P(s_0|\sigma_0) = P(s_1|\sigma_1) = p$ and must choose whether to invest or not. Agents choose in a fixed order and, before receiving his private signal, the agent investing in period t observes the history of past investments and uses this to determine their prior probability π_{1t} that the state is 1.

Bikchandani, Hirshleifer and Welch (1992) start with the case where the cost of investment is $\frac{1}{2}$, the payoff in state 1 is 1, and 0 otherwise. Their expected payoff is $p\pi_{1t}/(p\pi_{1t} + (1-p)(1-\pi_{1t}))$. After a number of moves there will be a sufficient difference between the number who have invested and those who have not for the agent's action to be determined solely by his prior belief, irrespective of his signal. Specifically, if the first agent gets a good signal, the second invests if he gets a good signal, and all subsequent agents will then invest irrespective of their signals. If the second gets a bad signal he is indifferent about investing and is assumed to invest, so the third investor again invests regardless of signal, and so on. Once there are

two more investors than non-investors, the excess of positive signals outweighs any negative signal an agent might have. Everyone invests regardless of signal, leading to a cascade.

An unlucky series of wrong signals at the start of the game can lead society to fix on the wrong equilibrium. Bikchandani, Hirshleifer and Welch (1992) observe that this wrong equilibrium is fragile, being based on the observations of a handful of early agents, and vulnerable to being overturned by public information available to all agents.

A frequent criticism of cascade models is their reliance on finite signals: all signals are equal and there is no way for a huge negative signal to counter-act a series of positive ones. However the important lesson of the cascade literature is not that society can get stuck at the wrong equilibrium—which does require signals that are finite—but that Bayesian social learning with individual signals are observed imperfectly is very slow to converge to the true equilibrium. Vives (1993) shows how adding noise to a Gaussian model slows down its convergence from rate t to rate $t^{1/3}$: 1000 noisy observations are equivalent to 10 clean ones.

The basic intuition of cascades models that imperfectly observed individual information is poorly incorporated into social beliefs is the basis of several other models. Bulow and Klemperer (1994) model rational frenzies in auctions where participants reveal their valuations by bidding. Bidders with high valuations are willing to pay just under the Walrasian clearing price and, being usually infra-marginal, all face similar optimization problems. A bid by one agent therefore sets off a chain of bidding by other agents, leading to a pattern of booms and crashes. Caplin and Leahy (1994) look at investment where individuals have Gaussian signals. If the true state is bad, individuals continue to invest, driven by the dominating effect of past actions. Eventually, however, because signals are Gaussian, a few agents get sufficiently bad signals to induce them to stop investing, causing priors rapidly to move to a belief that the state is bad, leading to a market crash and “wisdom after the fact”.

While the essence of the cascade literature is that agents transmit a noisy signal of their information, Avery and Zemsky (1998) observe that this is not the case for markets obeying the efficient markets hypothesis where price reflects all publicly available information. In such markets, assuming risk neutral agents, the price of

an asset worth 1 in the good state and 0 in the bad is the Bayesian prior π_{1t} , causing agents always to trade according to their private signal. They show that cascades can still occur if extra dimensions of uncertainty are added: specifically if there is event uncertainty—agents know that something important has happened by not whether it is good or bad—or compositional uncertainty—agents are uncertain how many informed traders are active in the market.

Underlying Bayesian models of cascades is the obvious but strong assumption that people are Bayesians. Probability is difficult for most people, and conditional probability especially so. Even with trivial problems of the form “a family has two children, one of whom is a daughter: what is the probability that the other child is a son?” most will incorrectly answer $\frac{1}{2}$ rather than $\frac{2}{3}$. Similarly, when asked “one percent of the population has a disease. A test detects the disease in 95% of patients when it is present, and generates 10% false positives when it is absent. What is the probability that someone who tests positive has the disease?”, most will give answers slightly below 95% rather than the correct 1.05%.

In other words, people appear to ignore base rates, assuming that the probability of a state given a signal equals the probability of the signal given the state $P(\sigma_i|s_i) = P(s_i|\sigma_i)$ even when the probability of the state is considerably lower than the probability of the signal. Agents show overconfidence, focusing excessively on their own signal, rather than the history of signals of other agents contained in the prior.

If people neglect priors like this, cascades cannot occur when private signals are uncorrelated. However, if the signal is common, cascades can still occur. For instance if agents view market price as the signal, a run of rising prices induced by improving fundamentals (such as the good macroeconomic conditions and loose credit that Kindleberger (1978) saw as the preconditions for speculative bubbles) are treated by agents as a positive signal inducing them to buy, driving up price and inducing others to buy and so on.

Strategies in Coordination Games.

Kandori, Mailath and Rob (1993) considered the strategies of players in a coordination game with payoffs

	L	R
L	a,a	b,c
R	c,b	d,d

where $a > c, d > b$ and $(a - c) > (d - b)$ so (L, L) and (R, R) are Nash equilibria and (L, L) is the risk dominant one. With myopic, best-response play, they show that a small probability of mutation suffices for the risk dominant equilibrium to be chosen.

Ellison (1993) observed that this convergence is slow, requiring many simultaneous mutations, and showed instead that if there is local interaction of players along a line, the $\frac{1}{2}$ -dominant strategy (the best response if half your neighbors adopt it) spreads rapidly, but not in two dimensions. Blume (1995) shows that non-trivial mixed long run equilibria exist in two dimensional interaction but not in one, while Morris (2000) examines the characteristics of arbitrary networks that permit the risk dominant strategy to spread. Lee and Valentinyi (2000) look at a game without mutation but where initial strategy choice is random and show that myopic best response to strategies played by immediate neighbors on the lattice causes large populations to coordinate on the risk dominant equilibrium.

International Market Contagion.

Large falls in asset values in one country are sometimes followed rapidly by falls in other countries. To the extent that these falls are too great to be explained by interdependence in trade or exposure to common macroeconomic factors, the process is called contagion.

Two main sources of contagion have been proposed: financial fragility and common financial linkages; and pathologies in the diffusion of information. The empirical study of Kaminsky, Reinhart and Vegh (2003) argues that three sources of fragility underlie international contagion: rapid inflows of capital; macroeconomic shocks that occur too rapidly for gradual portfolio re-balancing; and a leveraged common creditor. Allen and Gale (2000) show that if banks in different regions have claims on each other, a fall in asset values in one region can bring banks in other regions under pressure and lead to falls in asset values in those regions. In

Kyle and Xiong (2001) losses suffered by traders who arbitrage between markets dominated by fundamentalists and markets dominated by noise traders cause them to reduce their positions in both markets, causing returns to become more volatile and more correlated.

Models of contagion as information transmission abstract away from agents who revise excessively optimistic forecasts of returns in all markets after a fall in one market, and concentrate on rational actors instead. Calvo and Mendoza (2000) show that if there are fixed costs to gathering and processing information specific to one country and limits to short selling in each country, the benefits of acquiring information about each country in one's portfolio fall as the portfolio expands. Agents put more weight on the behavior of other investors, making portfolio allocation more sensitive to realized returns in each market. In Kodres and Pritsker (2002), portfolio re-balancing by informed investors can set off panics among the uninformed who misinterpret it as negative information about the market.

The empirical literature on testing for contagion has focused on increases in the correlation of returns between markets during periods of crisis. Forbes and Rigobon (2002) show the elementary weakness of simple correlation tests: with an unchanged regression coefficient, a rise in the variance of the explanatory variable reduces the coefficient standard error causing a rise in the correlation of a regression.

The regression underlying contagion tests is of the form

$$y_{it} = \delta'_i \mathbf{z}_t + \alpha'_i \mathbf{x}_{it} + \beta_i I(y_j - c_j) + \varepsilon_{it}$$

where y_i is asset return in country i , \mathbf{z} are common macroeconomic factors, \mathbf{x}_i are country specific factors, and I is an indicator of a period of crisis in the originating economy j . As Pesaran and Pick (2007) observe, this is a difficult system to estimate econometrically. To disentangle contagion from interaction effects, county specific variables have to be used to instrument foreign returns. Choosing the crisis period introduces sample selection bias, and it has to be assumed that crisis periods are sufficiently long to allow correlations to be reliably estimated. In consequence, there appears to be no strong consensus in the empirical literature as to whether contagion occurs between markets or how strong it is.

References

- Allen, Franklin and Douglas M. Gale. 2000. "Financial Contagion." *Journal of Political Economy* 108:1–33.
- Allport, Gordon W. and Leo Postman. 1946-47. "An Analysis of Rumor." *Public Opinion Quarterly* 10:501–517.
- Avery, Christopher and Peter Zemsky. 1998. "Multidimensional Uncertainty and Herd Behavior in Financial Markets." *American Economic Review* 88:724–748.
- Banerjee, Abhijit V. 1992. "A Simple Model of Herd Behaviour." *Quarterly Journal of Economics* 107:797–817.
- Bikchandani, Sushil, David Hirshleifer and Ivo Welch. 1992. "A Theory of Fads, Custom, and Cultural Change as Informational Cascades." *Journal of Political Economy* 100:992–1026.
- Blume, Lawrence. 1995. "The Statistical Mechanics of Best-Response Strategy Revision." *Games and Economic Behavior* 11:111–145.
- Bulow, Jeremy and Paul Klemperer. 1994. "Rational Frenzies and Crashes." *Journal of Political Economy* 102:1–23.
- Calvo, Guillermo A. and Enrique G Mendoza. 2000. "Rational Contagion and the Globalization of Security Markets." *Journal of International Economics* 51:79–113.
- Caplin, Andrew and John Leahy. 1994. "Business as Usual, Market Crashes, and Wisdom after the Fact." *American Economic Review* 84:548–565.
- Chamley, Christophe. 2004. *Rational Herds: Economic Models of Social Learning*. Cambridge: Cambridge University Press.
- Durlauf, Steven N. 1997. Statistical Mechanics Approaches to Socioeconomic Behavior. In *The Economy as an Evolving Complex System II*, ed. Arthur B., S. Durlauf and D. Lane. Reading, Mass: Addison-Wesley.

- Durrett, Rick and Simon Levin. 1998. "Spatial Aspects of Interspecific Competition." *Theoretical Population Biology* 53:30–43.
- Ellison, Glenn. 1993. "Learning, Local Interaction, and Coordination." *Econometrica* 61:1047–1071.
- Ellison, Glenn and Drew Fudenberg. 1993. "Rules of Thumb for Social Learning." *Journal of Political Economy* 101:612–643.
- Forbes, Kristin J. and Roberto Rigobon. 2002. "No Contagion, Only Interdependence: Measuring Stock Market Comovements." *Journal of Finance* 57:2223–2261.
- Juang, Wei-Torng. 2001. "Learning from Popularity." *Econometrica* 69:735–747.
- Kaminsky, Graciela L., Carmen M. Reinhart and Carlos A Vegh. 2003. "The Unholy Trinity of Financial Contagion." *Journal of Economic Perspectives* 17:51–74.
- Kandori, Michihiro, George J. Mailath and Rafael Rob. 1993. "Learning, Mutation, and Long Run Equilibria in Games." *Econometrica* 61:29–56.
- Kelly, Morgan and Cormac O Grada. 2000. "Market Contagion: Evidence from the Panics of 1854 and 1857." *American Economic Review* 90:1110–1125.
- Kindleberger, Charles. 1978. *Manias, Panics, and Crashes*. New York: Basic Books.
- Kirman, Alan. 1993. "Ants, Rationality, and Recruitment." *Quarterly Journal of Economics* 108:137–156.
- Kodres, Laura and Matthew Pritsker. 2002. "A Rational Expectations Model of Financial Contagion." *Journal of Finance* 57:769–800.
- Kyle, Albert and Wei Xiong. 2001. "Contagion as a Wealth Effect." *Journal of Finance* 56:1401–1440.
- LeBon, Gustave. 1895. *Psychologie des Foules*. Translation: "The Crowd: A Study of the Popular Mind", 1960, New York: Viking.

- Lee, In Ho and Akos Valentinyi. 2000. "Noisy Contagion without Mutation." *Review of Economic Studies* 67:47–56.
- Levin, Simon A. 1970. "Community Equilibria and Stability, and an Extension of the Competitive Exclusion Principle." *American Naturalist* 104:413–423.
- Mackay, Charles. 1841. *Extraordinary Popular Delusions and the Madness of Crowds*. London: Bentley.
- Morris, Stephen. 2000. "Contagion." *Review of Economic Studies* 67:57–78.
- Pesaran, M. Hashem and Andreas Pick. 2007. "Econometric Issues in the Analysis of Contagion." *Journal of Economic Dynamics and Control* .
- Ryan, Bryce and Neal C. Gross. 1943. "The Diffusion of Hybrid Seed Corn in Two Iowa Communities." *Rural Sociology* 8:15–24.
- Sacerdote, Bruce. 2001. "Peer Effects with Random Assignment: Results for Dartmouth Roommates." *Quarterly Journal of Economics* 116:681–704.
- Shiller, Robert J. 1984. "Stock Prices and Social Dynamics." *Brookings Papers on Economic Activity* 2:457–498.
- Tarde, Gabriel. 1900. *Les Lois de l'Imitation*. Translation "The Laws of Imitation" 1962, Gloucester, MA: Peter Smith.
- Vives, Xavier. 1993. "'How Fast do Agents Learn?'" *Review of Economic Studies* 60:329–347.
- Weidlich, Wolfgang and Gunther Haag. 1983. *Concepts and Models of Quantitative Sociology*. New York: Springer.