Social Interactions and Macroeconomics

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Abstract

This essay discusses how the growing literature on social interactions can be used in macroeconomics. This new literature represents a systematic effort to introduce sociological reasoning into economic contexts. Theoretical and empirical analyses of social interactions have proven valuable in understanding a range of aspects of individual decisionmaking and have been useful in understanding aggregate phenomena such as inequality. We describe the basic ideas underlying social interactions models and speculate on how macroeconomics might benefit from incorporating this perspective.

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> Political economy…finds the laws underlying a mass of contingent occurrences. It is an interesting spectacle to observe here how all of the interconnections have repercussions on others, how the particular spheres fall into groups, influence others, and are helped or hindered by these. This interaction, which at first sight seems incredible since everything seems to depend on the arbitrary will of the individual, is particularly worthy of note...
>
> G. W. F. Hegel, *Elements of the Philosophy of Right*

I. Introduction

Within economics, social interactions research constitutes a growing area of study. This research represents a good faith attempt to introduce substantive sociological factors into economic modeling. As such, this work represents a significant departure from the sorts of market-mediated interdependences between individuals that one finds in general equilibrium theory. While the substantive ideas underlying this work may be found in now classic papers such as Loury (1977), the modern social interactions literature is quite young. Despite this, there are now an impressive range of applications of social interactions models in microeconomic contexts. Examples of phenomena where empirical evidence of social interactions has been found include 1) crime (Glaeser, Sacerdote, and Scheinkman (1996), Sirakaya (2003)), 2) welfare and public assistance use (Aizer and Currie (2004), Bertrand, Luttmer, and Mullainathan (2000)) 3) fertility (Brooks-Gunn et al (1993), Rivkin (2001)), 4) housing demand and urban development (Irwin and Bockstaed, (2002), Ioannides and Zabel (2003a,b)), 5) contract determination (Young and Burke (2001,2003)), 6) employment (Oomes (2003), Topa (2001), Weinberg, Reagan, and Yankow, (2004)), 7) cigarette smoking (Krauth (2003), Nakajima (2003)), 8) school performance (Boozer and Cacciola (2001), Graham (2005)) and even 9) medical techniques (Burke, Fournier, and Prasad (2004)).

While the importance of social interactions has been argued for a range of interesting behaviors, far less attention has been paid to the role of social interactions in aggregate phenomena. The one partial exception to this claim is the use of social interactions to study inequality and the aggregate cross-section income distribution and/or dynamics of inequality (Bénabou (1996), Durlauf (1996)). There has yet to be any systematic examination of whether social interactions may help explain the standard macroeconomic phenomena: growth and fluctuations, although elements of the existing literature may be connected to social interactions.

In this paper, we attempt to accomplish two things. First, we review some of the theory and econometrics of social interactions. This part of the paper will represent a brief synthesis of a large literature; more extensive surveys include Brock and Durlauf (2001b) and Durlauf (2004). Second, we consider how this body of work may be related to macroeconomics. This discussion is necessarily speculative. Our objective is to stimulate further work on social interactions that moves the field towards the consideration of aggregate phenomena.

2. Social interactions: theory

i. A baseline model

We first describe the general structure of social interactions models. We follow the approach we have taken in previous work (Brock and Durlauf (2001a,b,2004a,b)). Consider a group of I individuals who are members of a common group *g*. Individual *i* makes a choice ω_i. The description of the decision problem facing agent *i* is used to construct a conditional probability measure for ω_i in which the conditioning variables reflect different individual and social influences on the choice. The conditional probability measures that describe individual choice embody the microfoundations of the model. The set of conditional probability measures for each individual is then used to construct a conditional probability measure for the vector of choices of all the members of the group, which we denote as ω_g. Equilibrium in a social interactions model may be understood as the consistency between the individual-level probability measures and the joint probability measure.

In modeling individual decisions, there are four distinct factors that determine individual and, hence, group behavior. Distinguishing between these factors is important both in terms of the development of the theory as well as its econometric implementation. These factors are:

X_i: deterministic (to the modeler) individual-specific characteristics associated with individual i,

ε_i: random individual-specific characteristics associated with i,

Y_g: predetermined (with respect to ω_g) group-level characteristics, and

$\mu_i^e\left(\omega_{g,-i}\right)$: a subjective probability measure that captures the beliefs individual i possesses about behaviors of others in his group.

Two of these factors, Y_g and $\mu_i^e\left(\omega_{g,-i}\right)$, capture how membership in a group affects an individual. Following Manski (1993), Y_g measures what are known as contextual effects and $\mu_i^e\left(\omega_{g,-i}\right)$ captures what are known as endogenous effects; the key difference between the two is that endogenous effects capture how the behaviors of others in a group affect an individual whereas contextual effects capture how the characteristics of others in a group affect him. The endogenous effect is typically determined by the equilibrium of the model whereas contextual effects are typically modeled as predetermined. A typical endogenous effect is the expected average behavior of others whereas a typical contextual effect is the average of some individual characteristics of others such as age. We model endogenous effects as beliefs rather than as outcomes, i.e. individuals are affected by what they think others will do rather than what they actually do. By allowing beliefs to mediate endogenous effects, substantial analytical convenience is achieved. The appropriateness of this assumption will depend on context; presumably for small groups such as friendship trios individuals know the actual behavior of others whereas for larger groups, such as ethnicity, beliefs about behavior are what matters.

While this abstract description of social interactions as either contextual or endogenous effects is useful for formal modeling, we should note that it obscures the actual mechanisms by which social interactions may occur. Within the social interactions literature there has been interest in peer effects (in which individuals imitate others due to a direct utility benefit), information effects (in which the behavior of others provides information on the payoffs to a person's choices), role model effects (in which the previous behavior of some individuals affects the current choices of group members), social norms (the emergence of rules by which individuals are punished by others for certain behaviors), etc. There has yet to be much integration of these types of direct sources of interdependences in decisions into formal social interactions models; such integration would be quite valuable, particularly for questions such as counterfactual evaluation of policy.

In our baseline model, individual decisions follow standard microeconomic analysis in that they represent those choices that maximize an individual payoff function $V(\cdot)$, which, given the factors we have described means that each individual choice ω_i is defined by

$$\omega_i = \arg\max_{\omega \in \Omega_i} V\left(\omega, X_i, \varepsilon_i, Y_g, \mu_i^e\left(\omega_{g,-i}\right)\right). \tag{1}$$

The solution to this problem for all members of the group produces a set of conditional probability measures

$$\mu\left(\omega_i \middle| X_i, Y_g, \mu_i^e\left(\omega_{g,-i}\right)\right) \tag{2}$$

which describes how observable (to the econometrician) individual-specific and contextual effects as well as unobservable (to the econometrician) beliefs influence the likelihood of the possible choices.

Under our assumptions, moving from the specification of individuals to group behavior is straightforward. Since the errors are independent, the joint probability measure of decisions will equal the product of the conditional probability measures

$$\mu\left(\omega_g \left| Y_g, X_1, \mu_1^e\left(\omega_{g,-1}\right), \ldots, X_I, \mu_I^e\left(\omega_{g,-I}\right)\right.\right) = \prod_i \mu\left(\omega_i \left| X_i, Y_g, \mu_i^e\left(\omega_{g,-i}\right)\right.\right). \qquad (3)$$

In order to complete this model, it is necessary to specify how beliefs are formed. The benchmark in the literature is that the beliefs are rational in the sense that the subjective beliefs an individual possesses about others corresponds to the actual probability measure that describes those behaviors given the information available to the individual. We assume that this information set is comprised of the deterministic characteristics and beliefs of others X_j and $\mu_j^e\left(\omega_{-j}\right)$, so that subjective beliefs obey

$$\mu_i^e\left(\omega_{g,-i}\right) = \mu\left(\omega_{g,-i} \left| Y_g, X_1, \mu_1^e\left(\omega_{g,-1}\right), \ldots, X_I, \mu_I^e\left(\omega_{g,-I}\right)\right.\right). \qquad (4)$$

While recent developments in behavioral economics suggest the importance of moving beyond this notion of rationality in describing beliefs, the self-consistency embedded in (4) is a key baseline in understanding the properties of social interactions models.

Together, eqs. (1)-(4) represent a complete description of behavior within a group. The main technical issues that arise in the study of such models is the demonstration that a joint probability measure exists which satisfies (3) and (4); the mathematical techniques for developing such proofs are discussed in Blume (1993), Brock (1993), Durlauf (1993) and Bisin, Horst and Ozgur (2004) and Horst and Scheinkman (2004). One should also note early work by Föllmer (1974) and Allen (1982) which anticipated the modern social interactions approach. These early papers are useful in making clear the links between social interactions models and models of statistical mechanics that appear in physics and models of random fields that appear in probability theory.

ii. properties

The interesting properties of social interactions models occur when these models exhibit strategic complementarities in behavior. The key idea underlying the notion of complementarity is that incentives exist to behave similarly to others. Formally, let μ^{high} and μ^{low} denote two probability measures such that for any fixed vector $\bar{\omega}$, $\mu^{high}\left(\omega_{-i,g} \geq \bar{\omega}\right) \geq \mu^{low}\left(\omega_{-i,g} \geq \bar{\omega}\right)$; this condition means that higher values of $\omega_{-i,g}$ are more likely under μ^{high} than μ^{low}. Let $\omega^{high} > \omega^{low}$ denote two possible levels of ω_i. The payoff function V exhibits strategic complementarities if

$$\begin{gathered} V\left(\omega^{high}, \varepsilon_i, X_i, Y_g, \mu^{high}\right) - V\left(\omega^{low}, \varepsilon_i, X_i, Y_g, \mu^{high}\right) > \\ V\left(\omega^{high}, \varepsilon_i, X_i, Y_g, \mu^{low}\right) - V\left(\omega^{low}, \varepsilon_i, X_i, Y_g, \mu^{low}\right). \end{gathered} \tag{5}$$

Eq. (5) captures the idea that when others are expected to make relatively high choices, the relative attractiveness of a high choice is increased for each individual.

Complementarity in individual payoffs has important implications for the aggregate equilibrium in social interactions models. The following properties are among those found in social interactions models.[1]

Multiple equilibria. When complementarities are sufficiently strong, multiple equilibria can exist. What this means is that more than one joint probability measure for the vector of choices ω_g is compatible with the conditional probabilities that describe the individual choices. Intuitively, complementarities mean that each individual has incentives to behave similarly to others, i.e. conformity effects are present. When this conformity effect is sufficiently large relative to other influences, this introduces a degree of freedom in aggregate behavior: individuals in equilibrium behave similarly to one another, but this does not uniquely determine what they will do.

Phase transition. Phase transitions exist when small changes in a parameter of a system can induce qualitative changes in the system's equilibrium. Phase transitions are common in physical contexts. A standard example in physics concerns the relationship between the state of water and its temperature. When the temperature of water moves

[1] This discussion borrows from Durlauf (2001).

from slightly above 32° F to below 32° F, the water undergoes a transition from liquid to solid. In social interactions models, phase transitions occur via the interplay of endogenous social interactions and other influences. Suppose there is a parameter that measures the strength of endogenous social interactions; this is the case in Brock and Durlauf (2001a,b,2004a), for example. When this parameter is zero, then the equilibrium is unique. Suppose that when this parameter is infinity, all agents behave the same as one another, as the payoff loss from not doing so is unbounded, inducing multiple equilibria. Then as this parameter is increased from 0 to infinity, at some point the number of equilibria will change. A phase transition occurs when this change is discontinuous.

Social Multipliers. Regardless of the number of equilibria, social interactions models will typically exhibit social multipliers, which means that the equilibrium effect of a change in Y_g on individual m_g increases with the level of complementarity in the system. The basic idea is that when there are complementarities in behavior, a change in Y_g both affects each person directly as in (2) as well as indirectly, via the effect of the change in Y_g on the behavior of others, i.e. $\mu^e\left(\omega_{g,-i}\right)$, as captured in (4).

These properties are not necessarily present in social interactions models, but typically arise depending on the level of the complementarities embedded in the individual payoff functions.

3. Social interactions: econometrics

In this section we briefly review some of the econometric issues that arise in trying to bring social interactions models to data. Our focus will be on identification problems, i.e. the extent to which socioeconomic data can provide evidence of social interactions given alternate explanations for individual outcomes. As such, we will review the main econometric work that has been accomplished for the study of social interactions. It is important to note that many outstanding issues remain, such as how to account for the lack of prior knowledge about the identity of the group which affects individuals in a given data set or how to allow for different strengths of interactions across members of a given group. Manski (2000) discusses many such issues.

i. identification and the reflection problem

The first difficulty in identifying social interactions concerns the distinction between contextual and endogenous effects. Manski (1993), in a classic analysis, indicates how it may be impossible to disentangle these different effects in a linear model.

To see why this is so, consider the linear-in-means model of social interactions which Manski studied:

$$\omega_i = k + cX_i + dY_g + Jm_g^e + \varepsilon_i \tag{6}$$

where m_g^e denotes the subjective expected value of the average choice in group g. Relative to the general formulation above, this model assumes all endogenous effects work through this average. For now, we assume that $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right) = 0$, so that the model residuals are uncorrelated with the model regressors and that no self-selection effects are present.

As discussed earlier, under self-consistency, the subjective expected average equals the actual expected average, m_g, which is defined by

$$m_g = \frac{k + cX_g + dY_g}{1-J} = \frac{k + dY_g}{1-J} + \frac{cX_g}{1-J} \tag{7}$$

where X_g is the average of X_i across members of group g. Comparing (6) and (7), it is easy to see why an identification problem can arise. Unless $\frac{cX_g}{1-J}$ is linearly independent from Y_g, then one cannot distinguish between endogenous and contextual effects. Put differently, endogenous social interactions are linearly dependent on the contextual effects; this is what is meant by the reflection problem. The reflection problem indicates the importance of prior information for identification in linear models. For example, suppose that one does not have any basis for distinguishing individual and contextual variables, in other words, that a researcher has no basis for arguing that for certain elements of X_i the corresponding values in the group average X_g are not elements of Y_g. Then, this would imply that $X_g = Y_g$, so identification fails. This is precisely Manski's insight.

The reflection problem is specific to linear regressions. To see this, following Brock and Durlauf (2001b), consider the nonlinear model

$$\omega_i = k + cX_i + dY_g + J\lambda\left(m_g^e\right) + \varepsilon_i \tag{8}$$

where $\lambda(\cdot)$ is an invertible function with $\lambda'' \neq 0$, i.e. the second derivative of the function is nonzero. Defining $\psi(\cdot) = 1 - J\lambda(\cdot)$, the self-consistent expected average choice equals

$$m_g = \psi^{-1}\left(k + cX_g + dY_g\right). \tag{9}$$

Even if $X_g = Y_g$, (9) indicates that m_g cannot be linearly dependent on Y_g, so long as Y_g has a large enough support.

Similar reasoning indicates why the reflection problem does not arise in discrete choice or duration data models, see Brock and Durlauf (2001b,2004a,b) for formal proofs. This is straightforward to see for a discrete choice model where the expected percentage of individuals in a group that make a particular choice is the measure of endogenous effects associated with the choice. Because these percentages must lie between 0 and 1, they cannot be linear functions of Y_g.

Relatively little work has been done on the estimation of nonlinear social interactions models; exceptions include Bisin, Moro and Topa (2002), Krauth (2004), and

Sirakaya (2003). This is an important area for future analysis if the identification results for such models are to be useful in practice and is ready to proceed given the results on identification that are now available.

ii. self-selection

The assumption that $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right) = 0$ is unappealing in contexts where group memberships are endogenous, as occurs in cases such as residential neighborhoods. Following Heckman's classic (1979) formulation, one can think of self-selection as an omitted variables problem, in the sense that the appropriate linear regression model in the presence of self-selection is

$$\omega_i = cX_i + dY_g + Jm_g + E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right) + \xi_i \,. \tag{10}$$

It is easy to see why failing to account for self-selection can induce spurious evidence of social interactions. Consider the question of identifying social interaction effects on academic performance of students. If relatively ambitious parents self-select into neighborhoods with higher student achievement, the failing to account for this self-selection can lead one to the appearance of social interactions effects when none are in fact present. The potential importance of self-selection is indicated by Evans, Oates, and Schwab (1992), who show that instrumental variables estimates of social interactions, designed to overcome self-selection, can eliminate statistically significant evidence of social interactions. Rivkin (2001), using similar instruments, produces an analysis in which the instrumental variables produce much larger evidence of social interactions than when instruments are not used. We concur with Rivkin's interpretation that his results show that it is problematic to identify valid instruments in social interactions contexts; Brock and Durlauf (2001c), while discussing a very different issue (economic growth) provide some general reasons why finding persuasive instrumental variables is extremely hard for theories (such as social interactions) which are "openended" i.e. theories whose internal logic does not exclude alternative theories of behavior from operating simultaneously.

This is one reason why we prefer the explicit modeling of self-selection when analyzing social interactions. Self-selection does not represent an insuperable problem in drawing inferences on social interactions; as is well understood in the microeconometrics literature, consistent model estimates can be achieved in a variety of circumstances so long as self-selection is accounted for.

From the perspective of social interactions work, the new idea that emerges when accounting for self-selection, and our second reason for advocating explicit modeling of self-selection, is that self-selection can help with identification. Specifically, Brock and Durlauf (2001b) show that if one can model the self-selection correction, self-selection can contribute to identification by addressing aspects of the reflection problem.

To understand why this is so, consider the original linear-in-means model. Suppose that $X_g = Y_g$ so that if $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right) = 0$ identification fails because of the reflection problem. As shown in Brock and Durlauf (2001b), self-selection may allow identification for this same linear-in-means model for two distinct reasons, depending on the structure of $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right) = 0$. First, if $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right) = \phi\left(m_g\right)$, i.e. self-selection is determined by the expected average behavior of the neighborhood, then the selection correction induces nonlinearity into the model, thereby eliminating the possibility of a reflection problem outside of hairline cases.

Alternatively, if $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right) = \phi\left(X_i\right)$, then the selection correction is an example of an individual-specific variable whose group level analogue does not appear in the Y_g variables. The average of $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right)$ within g will function as an additional X_g variable that is not an element of Y_g; the average value of $E\left(\varepsilon_i \middle| X_i, Y_g, i \in g\right)$ does not appear as a contextual effect in the model specification. Intuitively, self-selection provides additional information on an agent's behavior which may be used to uncover the role that social interactions may have in influencing his decisions.

While Brock and Durlauf (2001b) develop this general argument in the context of self-selection with respect to a binary choice, this idea can be generalized to multiple groups, as in Brock and Durlauf (2004a) and Ioannides and Zabel (2003b). The potential for using self-selection to facilitate the identification of social interactions is illustrated in Ioannides and Zabel (2003b) who use selection corrections for residential neighborhoods to identify interdependences in housing demand.

So far, analyses of self-selection corrections as facilitators of identification have all employed parametric corrections, i.e. strong assumptions are made on the error distributions in both the selection equation and the behavioral model. An important next step in this work is the analysis of semiparametric selection corrections. Another useful extension is the linking of this approach to identification with hedonic modeling, in which prices for group memberships such as residential housing presumably contain information on social interactions. Methods to extract such information may be found in Ekeland, Heckman, and Nesheim (2002,2004) and Nesheim (2002).

iii. unobserved group effects

A second important issue in social interactions models concerns the possibility of unobserved group effects. Suppose that the correct behavioral model is

$$\omega_i = k + cX_i + dY_g + Jm_g + \alpha_g + \xi_i \tag{11}$$

where α_g is a fixed effect. Without any restrictions on α_g, it is obvious that (11) is not identified, since for a given model one can always rewrite this original equation with $\alpha_g^* = \alpha_g + dY_g + Jm_g \quad d = 0$, $J = 0$ and perfectly replicate the behavior of ω_i. As in the case of self-selection, it is easy to identify cases where unobserved group effects are likely to matter, so that ignoring them will lead to noncredible inferences. For example, if one wants to identify endogenous social interactions in a classroom, one needs to account for unobserved differences in teacher quality.

Unobserved group effects appear to be somewhat more difficult to address than self-selection since there is no natural way to model the effects using economic theory. One possible solution is to employ panel data and eliminate the fixed effects through differencing; this approach is suggested in Brock and Durlauf (2001b) and pursued in detail by Graham and Hahn (2004). While differencing can solve the fixed effects problem in principle, it is not clear that the sorts of fixed effects associated with groups are necessarily time invariant. For example, teacher quality may vary across time due to changes in experience, health, etc. Another route to achieving identification for this model is to assume that α_g may be modeled as a random effect; this approach is developed in Graham (2005). This assumption is relatively appealing in contexts such as random assignment of teachers to classrooms, as is studied by Graham.

For nonlinear models, it is possible to achieve partial identification even in cross-sections. This is shown for binary choice models in Brock and Durlauf (2004b). The basic idea of this approach is to ask whether there are shape restrictions one may place on the cross-group distribution function for α_g, F_α, that would allow for the data to reveal the presence of social interaction effects. What Brock and Durlauf (2004b) show is that for binary choice models where the endogenous social interactions parameter is large enough to induce multiple equilibria across groups, such shape restrictions exist. While the specific arguments are complicated, the basic ideas are relatively intuitive. For example, one version of this approach is to identify restrictions on F_α that imply that m_g (as before, the expected average choice in a group) is monotonically increasing in Y_g when $J = 0$. One can then derive evidence by comparing expected average choices between pairs of groups, g and g'. If one then observes cases where $m_g > m_{g'}$ whereas $Y_g < Y_{g'}$, this can only be explained by g and g' coordinating at equilibria that allow such a "pattern reversal." Another version of this approach involves exploiting the role of multiple equilibria in producing bimodality of the conditional distribution of m_g given Y_g, which extends and makes rigorous ideas that appear in Glaeser, Sacerdote, and Scheinkman (1996). Pattern reversal findings of this type represent a form of partial identification (Manski (2003)) in that their presence does not provide an estimate of the value of J, but rather implies that it is non-negative and large enough to induce multiple equilibria.

4. Macroeconomic applications

In this section, we consider some possible uses of social interactions models in macroeconomic contexts. To some extent, the arguments here will echo previous analyses that have claimed an important role for complementarities in aggregate analysis; Cooper (1999) provides a valuable survey of this perspective. One feature that distinguishes our discussion is the emphasis on complementaries as a manifestation of social forces. Further, our probabilistic formulation of social interactions creates a natural way to move from theory to empirical work, since the equilibrium joint probability measures in our social interactions models may be interpreted as likelihood functions from the econometric perspective.

i. economic growth

One area where we believe social interactions may have important aggregate consequences is in terms of long term economic growth. Within growth economics, there is a small but growing body of work that has focused on the role of "culture" in explaining cross-country growth differences. On the empirical side, work of this type has focused on factors that range from trust (Knack and Keefer (1997)) to religious views (Barro and McCleary (2003)). These papers are suggestive, but suffer from complicated identification problems (Brock and Durlauf (2001c), Durlauf, Johnson, and Temple (2004)). In essence, these findings are difficult to interpret because of the model uncertainty that plagues cross-country growth regressions with respect to the choice of variables and the measurement of social factors. We believe that aggregate studies of this type are a useful starting point, but feel they need to be supplemented with studies using disaggregated data that permits a resolution of these types of problems. We therefore interpret these aggregate studies as indicating that more careful analysis of social forces and growth is warranted.

A second source of evidence on the role of social factors in growth derives from economic history. Landes (1998) provides a broad argument in favor of this perspective with many suggestive examples. Other studies represent careful empirical delineations of particular historical episodes or comparisons. Important evidence of a role for social interactions in growth has been developed in Clark (1987); additional findings of this type appear in Wolcott and Clark (1999). This paper compares productivity differences between cotton mills in New England versus those in Great Britain, Greece, Germany, Japan, India, and China for the period around 1910. This comparison is especially interesting as the technology for cotton weaving did not differ across these countries and so one can engage in relatively straightforward comparisons of factories. Clark finds immense productivity differences between textile workers; around 1910, output per textile worker in New England was 1.5 times greater than in Great Britain, 2.3 times greater than in Germany, and 6 times greater than in Japan.

How can one interpret such a finding? One possibility, which is the basis of Clark's analysis, relates to social norms and effort. Clark is able to argue persuasively that these differences are not due to managerial or worker quality, but are due to what he calls "local culture." This type of analysis is a natural candidate for a formal social interactions type analysis. Work such as Lindbeck, Nyberg, and Weibull (1999), which provides a model of social norms and welfare/work decisions, could be readily adapted to this. More generally, we see social interactions as providing an underpinning for efforts to formally model culture. For example, it seems reasonable to suppose that culture is to some extent a manifestation of how individuals define their identities, in the sense of Akerlof and Kranton (2000) or Fang and Loury (2004). To the extent that social interactions-type phenomena such as peer influences or conformity effects help determine which identities become salient in a population, social interactions can play a role in producing cultural differences. Social interactions approaches would be of particular interest if one could identify substantial within-country variation in productivity, so that the cultural differences identified by Clark are in fact generated locally.

Moving to new growth theory, one can identify a number of models which have social interactions components. One class of models focuses on the formation of trading networks that link different economic actors and the concomitant implications for industrialization and development. By way of background, Kirman (1983) was the first to show that small differences in the process by which direct bilateral connections between economic actors form can produce, when markets represent groups of actors that are directly or indirectly linked, either economy-wide markets or many groups of small markets; the implications of these different market sizes for macroeconomic outcomes such as overall levels of risk sharing are explored in Ioannides (1990). These ideas have proven useful in understanding the expansion of market size and its implications for economic development. A particularly interesting analysis is due to Kelly (1997) who models the takeoff to industrialization as a type of phase transition. Alternatively, one can use social interactions-type models to understand how local spillover effects can affect growth. This approach is taken in Durlauf (1993), where sector-specific spillovers can produce a phase transition from underdevelopment to industrialization in response to small increases in productivity.

In considering the roles of social norms and trading networks as mechanisms explaining industrialization and growth, we are led to conjecture that one can develop a vision of the development process in which social or cultural norms and preferences diffuse because of trading relationships and eventually dominate a population. To be clear, one needs to be careful about what this process encumbers. De Vries (1994) has argued that, in understanding the Industrial Revolution, one needs to account for the "industrious revolution" by which labor supply dramatically increased in England beginning in the 1600's. De Vries' claim has been challenged by Voth (1998) who finds that increases in hours worked occurred in the middle 1700's rather than earlier and by Clark and van der Werf (1998) who find little evidence of increased work rates in England before 1850. We are sympathetic with Clark's focus on effort while working as opposed to hours worked per se. But for either measure, one can envision the diffusion of new work attitudes and behaviors as a dynamic social interaction process. And we regard the debates over the industrious revolution as indicative of a role for more formal identification analysis in disentangling different types of social interactions that may be present. While we of course have no reason to think that there exist historical data sets that would allow estimation of the models we have described, the identification results provide clues as to what sort of evidence could help in resolving disagreements. In fact, we believe that the development of a complete evaluation of evidence for social interactions may well require considerable attention to evidence sources such as historical ones that are not amenable to full econometric analysis; of which Clark's work is an outstanding example.

ii. fluctuations

At first glance, it is less clear how social interactions approaches can influence the study of economic fluctuations. One perhaps trivial reason for this is that the primary body of dynamic stochastic general equilibrium (DSGE) models that are used in current macroeconomic theory have not been developed in ways in which there are natural routes for embodying social interactions. While recent work on DSGE models has made important advances in modeling individual heterogeneity, Krusell and Smith (1998) is an exemplar, DSGE models have not generally developed in directions where social interactions are a natural addition to existing microfoundations.

That being said, there are important strands of the modern macroeconomic literature where social interactions models may prove to be useful. As well reviewed in Cooper (1999), there has been considerable work in macroeconomics that has attempted to use the idea of complementarities in a range of contexts. One strand concerns the role of increasing returns to scale in propagating aggregate fluctuations. As developed for example in Benhabib and Farmer (1994), increasing returns to scale may lead to indeterminacy in the equilibrium paths of macroeconomic aggregates, this means that a given specification of the microeconomic structure of the economy, while leading to a unique balanced growth path, is consistent with multiple paths for output, consumption, etc. One important implication of increasing returns and indeterminacy is that business cycle fluctuations may be induced by self-fulfilling expectations. Focusing specifically on the "animal spirits" of investors, Farmer and Guo (1994), engage in a number of calibration exercises to demonstrate that these effects can capture a number of observed dynamic relationships in the US economy.

We conjecture that the introductions of social interactions into some aspects of business cycle models can strengthen the microfoundations for these types of results. At one level, we would argue that social interactions models can help to elucidate the microfoundations that have already been identified. For example, suppose there are social interactions in the labor force participation decision. If so, then the potential for phase transition in social interactions models can induce nonconvexities in the aggregate supply schedule.

Alternatively, to the extent that one wishes to understand animal spirits of investors, work such as Brock (1993) suggests that a natural way to understand shifts in investor beliefs is via the interdependences in these beliefs; formal mechanisms for this are described in Brock and Hommes (1997). In our view, understanding waves of optimism and pessimism in the macroeconomy is critical in understanding short term and medium term fluctuations. We further believe that interdependence of beliefs play an essential role in generating these waves. Put differently, phenomena such as "irrational exuberance," to employ Robert Shiller's (2001) term, emerge, we would argue, precisely because individual beliefs are highly interdependent, so that small outside changes can be magnified up into large fluctuations on average.

Indeed the whole literature on "sunspot" effects (i.e. effects of "extrinsic uncertainty") could benefit from the introduction of social interactions. A problem with the sunspots literature is that while one can demonstrate theoretically that sunspot effects can have macro level effects, existing sunspot models do not demonstrate why a cross sectional form of the law of large numbers might not apply to "wash out" the effects of such sunspots at the macro level. To put it another way, if there do not exist social interactions linking individual beliefs, there seems to be no reason why each individual micro agent would condition on the same sunspot variable when there is no intrinsic fundamental reason why that particular variable should matter. But methods such as Brock (1993) and Brock and Durlauf (2001a,b,2004a) should be adaptable to produce tractable macro models where the cross sectional law of large numbers breaks down and where tiny outside effects cause explosive shifts in macro aggregates. We believe, for example, that this could be one way to give plausible microfoundations to the emergence of lock-in to one particular sunspot variable even though there is no intrinsic fundamental reason that particular sunspot variable should command economy-wide attention. It could also be a useful way to model the emergence and persistence of irrational exuberance.

The potential for social interactions to induce correlated behaviors in a population suggests a second area where the approach may have value in understanding business cycles: the role of individual-specific shocks in affecting aggregate outcomes. The possibility that interdependences in individual decisions can convert individual shocks into aggregate fluctuations was originally studied in Jovanovic (1987), who identified the key role of complementarities in such a transformation, but this idea has not been nearly as much developed as we think is appropriate. Horvath (1998,2000), using log linear models of the type pioneered by Long and Plosser (1983), extended this type of analysis by focusing on input/output-type relationships between sectors of the economy and showed how it is possible for sector-specific shocks to affect aggregate output; calibration evidence showed this approach can match various moments of aggregate US data. The marginal value of this approach in understanding fluctuations has been criticized by Dupor (1999) who provides a number of observational equivalence theorems between one sector and multi-sector models of fluctuations.

We see a role for social interaction in elucidating the aggregate implications of sector-specific shocks. Social interactions can provide mechanisms by which individual sectors are interrelated. We would imagine that animal spirits are subject to various intersectoral dependences that mimic the technological interdependences that lie at the heart of Horvath's analysis. Further, the social interactions models we have described have the important feature that they are intrinsically nonlinear. Nonlinearities should, we believe, break the observational equivalence that Dupor has identified and as such may lead to sector-specific shocks generating aggregate fluctuations quite different from their aggregate shock counterparts. Of course, it may be that nonlinear single sector models can reestablish Dupor's observational equivalence result.

Recent work on the aggregation of idiosyncratic shocks is close to our vision of how research of this type might proceed. In a very interesting paper, Gabaix (2004) shows that in a world of fat-tailed firm size distributions, idiosyncratic firm-level shocks can aggregate up to non-trivial aggregate fluctuations at the GDP level, whereas in a world of thin-tailed firm size distributions, this can not happen. He argues that idiosyncratic shocks to the 100 largest firms account for about 40% of US output volatility. Gabaix uses the statistical theory behind fat-tailed distributions to get a factor of $1/\log N$ for the scaling of aggregate volatility rather than the usual scaling of $1/N^{1/2}$. One can see that $1/\log N$ "diversifies away" idiosyncratic fluctuations at a much slower rate than does $1/N^{1/2}$. While this is very speculative, we conjecture that it may be fruitful for future research in macroeconomics to couple a mechanism like Gabaix's with the presence of social interactions at various levels in the macroeconomy in order to get a more complete understanding of how idiosyncratic shocks can aggregate to macroeconomic volatility via the emergence of fat-tailed distributions at various levels of disaggregation. For example, intrafirm shocks may, via intrafirm social interactions, produce the fat tails needed for Gabaix's interfirm analysis. We believe this research route may be promising because we have already shown how social interactions can magnify very small shocks into large ones (Brock (1993), Brock and Durlauf (2001a,b); see also Glaeser, Sacerdote, and Scheinkman (1996) who describe links between social interactions and excess volatility of averages) and so regard social interactions as a natural source for fat-tailed distributions.

Third, we see a potential role for social interactions in understanding what is still the major business cycle event of the modern economy – the Great Depression. While the idea of the Great Depression as a bad equilibrium has longstanding lineage, beautifully analyzed in Leijonhufvud (1968), with a few exceptions, notably Cooper and Ejarque (1995) and Dagsvik and Jovanovic (1994), this interpretation has fallen out of current macroeconomic discourse. The state-of-the art analysis of the Great Depression is arguably Cole and Ohanian (2004) which focuses on the role of bad government policies in generating persistence in the Depression; coordination failure/multiple equilibrium issues do not arise in their treatment. We believe that social interactions models, by providing a rigorous mathematical foundation for modeling how heterogeneous populations can exhibit phase transitions into locally stable, collectively undesirable equilibia, can help develop an approach to understanding the Great Depression in line with the Leijonhufvud vision. Whether this vision is empirically viable, of course, remains to be seen. For our purposes, what matters is that there has yet to be a quantitative delineation of the coordination failure view that can be compared to approaches such as Cole and Ohanian. The formal statistical mechanical models that have appeared in the social interactions literature provide a possible way of producing such a comparison and perhaps even an integration of these differing perspectives.

Finally, we would observe that social interactions have a role to play in understanding the interactions of business cycles and income distribution and as such can contribute to the research program developed in Krusell and Smith (1998) and elsewhere. One case where this seems plausible concerns the distribution of unemployment across different groups. As shown in theoretical work such as Montgomery (1990) and Oomes (2003), group heterogeneity will emerge in unemployment rates via network effects; the empirical importance of these effects is shown in Topa (2001). In this regard, Conley and Topa (2002) is of particular interest in its efforts to empirically compare different types of groups – spatial, ethnic, etc. – as the relevant group in which social interactions are created.

More generally, we think the sorts of factors that underlie social interactions models – peer effects, information spillovers, social norms, etc. – are an important complement to the imperfect risk sharing that is generally at the heart of macroeconomic models of income inequality. There is a dichotomy between macroeconomic models of inequality, with their emphasis on complete modeling of the evolution of the income distribution with relatively narrow views of the determinants of individual decisionmaking, and microeconomic models of inequality which contain richer conceptions of individual choice, but do so at the expense of less developed ways of modeling populations. The mathematical models underlying social interactions analysis have the potential to combine these two perspectives.

5. Conclusions

While we have great confidence in the importance of social interactions in explaining a range of socioeconomic phenomena, we wish to reemphasize that this case has yet to be established by a consensus of empirical evidence. The empirical literature on social interactions is young and has not fully incorporated the insights of the relevant econometric literature. So one cannot make overly strong empirical claims for the importance of social interactions even in the microeconomic contexts in which social interactions seem most plausible.

Still, we strongly believe that in many macroeconomic contexts, social interactions plausibly matter and can affect how one thinks about the generative mechanisms underlying both long run and short run macroeconomic outcomes. At this stage, our claims are, to repeat, essentially speculative. Whether this belief is correct can only be resolved through new research. What we have tried to argue here is that expected payoff from this research warrants its undertaking.

Bibliography

Aizer, A. and J. Currie, (2004), “Networks or Neighborhood? Correlations in the Use of Publicly-Funded Maternity Care in California,” *Journal of Public Economics*, 88, 12, 2573-2585.

Akerlof, G. and R. Kranton, (2000), “Economics and Identity, *Quarterly Journal of Economics*, 115, 3, 715-753.

Allen, B., (1982), “Some Stochastic Processes Exhibiting Externalities Among Adopters,” *International Economic Review*, 23, 3, 595-608.

Barro, R. and R. McCleary (2003), “Religion and Economic Growth Across Countries,” *American Sociological Review*, 68, 5, 760-781.

Benhabib, J. and R. Farmer, (1994), “Indeterminacy and Increasing Returns,” *Journal of Economic Theory*, 63, 19-41.

Bénabou, R., (1996), “Equity and Efficiency in Human Capital Investment: The Local Connection,” *Review of Economic Studies*, 63, 2, 237-264.

Bertrand, M., E. Luttmer, and S. Mullainathan, (2000), “Network Effects and Welfare Cultures,” *Quarterly Journal of Economics,* 115, 3, 1019-1055.

Bisin, A., U. Horst, and O. Ozgur, (2004), “Rational Expectations Equilibria of Economies with Local Interactions,” mimeo, New York University.

Bisin, A., A. Moro, and G. Topa, (2002), “The Empirical Content of Models with Multiple Equilibria,” mimeo, New York University.

Blume, L, (1993), “The Statistical Mechanics of Strategic Interaction,” *Games and Economic Behavior*, 5, 3, 387-424.

Boozer, M. and S. Cacciola, (2001), “Inside the Black Box of Project Star: Estimation of Peer Effects Using Experimental Data,” *Yale University Economic Growth Center Discussion Paper no. 832.*

Brock, W., (1993), “Pathways to Randomness in the Economy: Emergent Nonlinearity and Chaos in Economics and Finance,” *Estudios Economicos*, 8, 3-55.

Brock, W. and S. Durlauf, (2001a), “Discrete Choice with Social Interactions,” *Review of Economic Studies*, 68, 2, 235-260.

Brock, W. and S. Durlauf, (2001b), “Interactions-Based Models,” in *Handbook of Econometrics, Vol. 5,* J. Heckman and E. Leamer, eds., Amsterdam: North Holland.

Brock, W. and S. Durlauf, (2001c), “Growth Empirics and Reality,” *World Bank Economic Review*, 15, 229-272.

Brock, W. and S. Durlauf, (2004a), “A Multinomial Choice Model with Social Interactions,” *The Economy as an Evolving Complex System III*, L. Blume and S. Durlauf, eds., Oxford University Press, forthcoming.

Brock, W. and S. Durlauf, (2004b), “Identification of Binary Choice Models with Social Interactions,” mimeo, University of Wisconsin.

Brock, W. and C. Hommes, (1997), “A Rational Route to Randomness,” *Econometrica*, 65, 5, 1059-1096.

Brooks-Gunn, J., G. Duncan, P. Klebanov, and N. Sealand, (1993), "Do Neighborhoods Affect Child and Adolescent Development?," *American Journal of Sociology*, 99, 2, 353-395.

Burke, M., G. Fournier, and K. Prasad, (2004), “Physician Social Networks and Geographical Variation in Medical Care,” mimeo, Florida State University.

Clark. G., (1987), “Why Isn’t the Whole World Developed?,” *Journal of Economic History*, XLVII, 1, 141-173.

Clark, G. and Y. van der Werf, (1998), “Work in Progress? The Industrious Revolution,” *Journal of Economic History*, 58, 3, 830-843.

Cole, H. and L. Ohanian, (2004), “New Deal Policies and the Persistence of the Great Depression,” *Journal of Political Economy*, 112, 4, 119-816.

Conley, T. and G. Topa, (2002), “Socio-Economic Distance and Spatial Patterns in Unemployment,” *Journal of Applied Econometrics*, 17, 4, 303-327.

Cooper, R., (1999), *Coordination Games*, New York: Cambridge University Press.

Cooper, R. and J. Ejarque, (1995), “Financial Intermediation and the Great Depression,” A Multiple Equilibrium Intepretation,” *Carnegie-Rochester Series on Public Policy*, 43, 285-323.

Dagsvik, J. and B. Jovanovic, (1994), “Was the Great Depression a Low-Level Equilibrium?,” *European Economic Review,* 38, 9, 1711-1729.

De Vries, J., (1994), “The Industrial Revolution and the Industrious Revolution,” *Journal of Economic History*, 54, 2, 249-270.

Dupor, W., (1999), “Aggregation and Irrelevance in Multi-Sector Models,” *Journal of Monetary Economics*, 43, 391-409.

Durlauf, S., (1993), “Nonergodic Economic Growth,” *Review of Economic Studies*, 60, 2, 349-366.

Durlauf S., (1996), “A Theory of Persistent Income Inequality,” *Journal of Economic Growth*, 1, 1, 75-93.

Durlauf, S., (2001), “A Framework for the Study of Individual Behavior and Social Interactions,” *Sociological Methodology*, 31, 47-87.

Durlauf, S., (2004), “Neighborhood Effects,” in *Handbook of Regional and Urban Economics*, vol. 4, J. V. Henderson and J.-F. Thisse, eds., Amsterdam: North Holland

Durlauf, S., P. Johnson, and J. Temple, (2004), “Growth Econometrics,” forthcoming, *Handbook of Economic Growth*, P. Aghion and S. Durlauf, eds., Amsterdam, North-Holland.

Ekeland, I., J. Heckman and L. Nesheim, (2002), “Identifying Hedonic Models,” *American Economic Review*, 92, 2, 304-309.

Ekeland, I. J. Heckman and L. Nesheim, (2004), “Identification and Estimation of Hedonic Models,” *Journal of Political Economy*, 112, S1, S60-S109.

Evans, W., W. Oates, and R. Schwab, (1992), “Measuring Peer Group Effects: A Study of Teenage Behavior,” *Journal of Political Economy*, 100, 5, 966-991.

Fang, H. and G. Loury, (2004), “Toward an Economic Theory of Cultural Identity,” mimeo, Yale University.

Farmer, R. and J.-T. Guo, (1994), “Real Business Cycles and the Animal Spirits Hypothesis,” *Journal of Economic Theory*, 63, 2, 42-72.

Föllmer, H., (1974), “Random Economies with Many Interacting Agents,” *Journal of Mathematical Economics*, 1, 1, 41-62.

Gabaix, X., (2004), “The Granular Origins of Aggregate Fluctuations,” mimeo, MIT.

Glaeser, E., B. Sacerdote, and J. Scheinkman, (1996), “Crime and Social Interactions,” *Quarterly Journal of Economics*, 111, 2, 507-548.

Graham. B. and J. Hahn, (2004), “Identification and Estimation of Linear-in-Means Model of Social Interactions,” mimeo, Department of Economics, Harvard University.

Graham, B., (2005), “Identifying Social Interactions through Excess Variance Contrasts,” mimeo, Harvard University

Heckman, J., (1979), “Sample Selection Bias as a Specification Error,” *Econometrica*, 47, 1, 153-161.

Horst, U. and J. Scheinkman, (2004), “Equilibria in Systems of Social Interactions,” mimeo, Princeton University.

Horvath, M., (1998), “Cyclicality and Sectoral Linkages: Aggregate Fluctuations from Independent Sectoral Shocks,” *Review of Economics Dynamics*, 1, 781-808.

Horvath, M., (2000), “Sectoral Shocks and Aggregate Fluctuations,” *Journal of Monetary Economics*, 45, 69-106.

Ioannides, Y., (1990), “Trading Uncertainty and Market Form,” *International Economic Review*, 31, 3, 619-638.

Ioannides, Y. and J. Zabel, (2003a), “Neighborhood Effects and Housing Demand,” *Journal of Applied Econometrics*, 18, 563-584.

Ioannides, Y. and J. Zabel, (2003b), “Interactions, Neighborhood Selection, and Housing Demand,” mimeo, Department of Economics, Tufts University.

Jovanovic, B., (1987), “Micro Shocks and Aggregate Risk,” *Quarterly Journal of Economics*, 102, 395-409.

Irwin, E. and N. Bockstaed, (2002), “Interacting Agents, Spatial Externalities, and the Evolution of Residential Land Use Patterns,” *Journal of Economic Geography*, 2, 31-54.

Kelly, M., (1997), “The Dynamics of Smithian Growth,” *Quarterly Journal of Economics*, 112, 3, 939-964.

Kirman, A. (1983), “Communication in Markets: A Suggested Approach,” *Economic Letters*, 12, 2, 101-108.

Knack, S. and P. Keefer, (1997), “Does Social Capital Have an Economic Payoff? A Cross-Country Investigation,” *Quarterly Journal of Economics*, 112, 4, 1251-1288.

Krauth, B., (2003), “Peer Effects and Selection Effects on Youth Smoking in California,” mimeo, Simon Fraser University.

Krauth, B., (2004),”Simulation-Based Estimation of Peer Effects,” mimeo, Simon Fraser University.

Krusell, P. and A. Smith, (1998), “Income and Wealth Heterogeneity in the Macroeconomy,” *Journal of Political Economy*, 106, 5, 867-896.

Landes, D., (1998), *The Wealth and Poverty of Nations*, New York: W. W. Norton.

Leijonhufvud, A., (1968), *On Keynesian Economics and the Economics of Keynes*, New York: Oxford University Press.

Lindbeck, A., S. Nyberg, and J. Weibull, (1999), "Social Norms and Economic Incentives in the Welfare State," *Quarterly Journal of Economics*, 114, 1, 1-35.

Long, J. and C. Plosser, (1983), "Real Business Cycles," *Journal of Political Economy*, 91, 39-69.

Loury, G. (1977), "A Dynamic Theory of Racial Income Differences," in *Women, Minorities, and Employment Discrimination*, P. Wallace and A. Lamond, eds., Lexington, Massachusetts: Lexington Books.

Manski, C., (1993), "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies*, 60, 3, 531-542.

Manski, C., (2000), "Economic Analysis of Social Interactions," *Jorunal of Economic Perspectives*, 14, 3, 115- 136.

Manski, C., (2003), *Partial Identification of Probability Distributions*, New York: Springer-Verlag.

Montgomery, J. (1990), "Social Networks and Persistent Inequality in the Labor Market, mimeo, Department of Economics, Northwestern University.

Nakajima, R., (2003), "Measureing Peer Effects in Youth Smoking Behavior," mimeo, University of Osaka.

Nesheim, L., (2002), "Equilibrium Sorting of Heterogeneous Consumers Across Locations: Theory and Implications," *Centre for Microdata Methods and Practice Working paper no. CWP08/02.*

Oomes, N., (2003), "Local Network Trades and Spatially Persistent Unemployment," *Journal of Economic Dynamics and Control*, 27, 11-12, 2115-2149.

Rivkin, S., (2001), "Tiebout Sorting, Aggregation, and the Estimation of Peer Group Effects," *Economics of Education Review*, 20, 201-209.

Shiller, R., (2001), *Irrational Exuberance*, Princeton: Princeton University Press.

Sirakaya, S., (2003), "Recidivism and Social Interactions," mimeo, Department of Economics, University of Washington.

Topa, G., (2001), "Social Interactions, Local Spillovers, and Unemployment, *Review of Economic Studies*, 68, 2, 261-295.

Voth, H.-J., (1998), "Time and Work in Eighteenth Century London," *Journal of Economic History*, 58, 1, 29-58.

Weinberg, B., P. Reagan, and J. Yankow, (2004), "Do Neighborhoods Affect Hours Worked? Evidence from Longitudinal Data," *Journal of Labor Economics*, forthcoming.

Wolcott, S. and G. Clark, (1999), "Why Nations Fail: Managerial Decisions and Performance in Indian Cotton Textiles, 1890-1938," *Journal of Economic History*, 59, 2, 397-423.

Young, H. P. and M. Burke, (2001), "Competition and Custom in Economic Contracts: A Case Study of Illinois Agriculture," *American Economic Review*, 91, 3, 559-573.

Young, H. P. and M. Burke, (2003), "On the Distributional Effects of Contractual Norms: The Case of Cropshare Contracts," mimeo, Department of Economics, Johns Hopkins University.