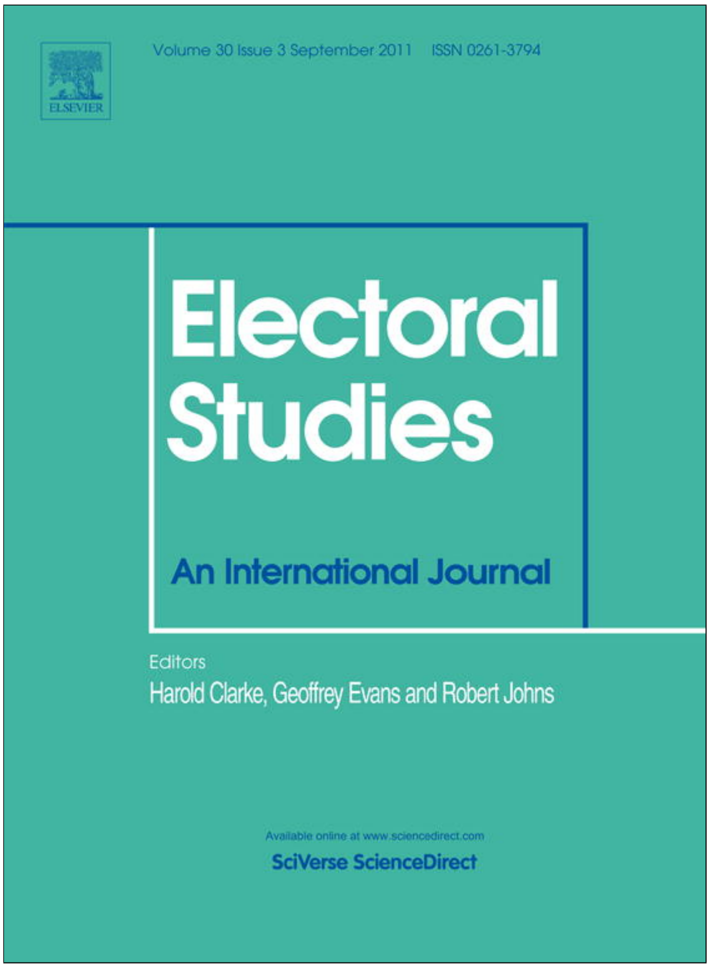
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Modeling and testing the diffusion of expectations: An EITM approach

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A B S T R A C T

This paper uses the empirical implications of theoretical models (EITM) framework to examine the consequences of the asymmetric diffusion of expectations. In the spirit of the traditional two-step flow model of communication, less-informed agents learn the expectations of more-informed agents. We find that when there is misinterpretation in the information acquisition process, a boomerang effect exists. In this equilibrium the less-informed agents' forecasts confound those of more-informed agents. We apply the EITM approach to a key economic variable known to have a relation to economic fluctuations – inflation expectations. Using surveyed inflation expectations data for the period, 1978–2000, we find the boomerang effect exists. One implication of this finding pertains to economic policy and economic volatility: because policymakers have more information than the public, the boomerang effect can lead policymakers to make inaccurate forecasts of economic conditions and conduct erroneous policies which contribute to economic instability.

1. Introduction

How can decentralized political and economic systems, with uneven agent information levels, exhibit coherent behavior? Considerable research, debate, and even some common sense, suggest it is fantasy. This skepticism is not new. A chief obstacle is that agents lack the information necessary for accurate predictions. After all, good forecasts – accurate expectations – require useful information.[1]And while agents do have specific knowledge of the political and economic information in their immediate setting this familiarity is confounded by their imperfect knowledge, and sometimes lack of interest, of their more general surroundings. On its face, coordinating these two types of information – specific and general – is a formidable challenge.[2] Yet, there are ways to minimize this knowledge and forecast deficit. One way is through formal and informal social interaction where agents, who pay more attention and have better information, pass on their information and expectations to less attentive agents (Granato and Krause, 2000). In the limit, after a good deal of learning occurs, the less attentive agents can forecast as if they are the highly attentive agents. Accurate articulation on political and economic matters, through increasingly accurate predictions by all agents, is achieved with the passage of time.

It should come as no surprise that expectation formation and information diffusion are an important research focus for social scientists.[3] Research topics such as economic

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[1] We use the terms forecast(s) and expectation(s) interchangeably in this paper.

[2] Research also suggests that agents do not interpret public information in an identical manner (see Kandel and Zilberfarb, 1999).

[3] While political scientists have been working on information diffusion processes for many decades (see Lazarsfeld et al., 1944), there is also a very robust tradition in economics (see Chamley, 2004). For example, financial economists have studied explanations for herding behavior, in which rational investors demonstrate some degree of behavioral convergence (Devenow and Welch, 1996). Most recently studies in monetary economics are exploring how information diffusion influences economic forecasting behavior. Carlson and Valev (2001) show in theory that the proportion of agents who form rational expectations can affect the speed and the overall performance of a disinflation policy. They argue that a central bank would have an incentive to choose how much information to disseminate since this choice can ultimately determine the effectiveness of a disinflation policy by affecting the number of informed agents in the economy.

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voting, in its modern form in particular, give expectation formation over key economic variables a prominent role (Clarke and Stewart, 1994; Alesina and Rosenthal, 1995; Duch and Stevenson, 2010).[4] On the other hand, information diffusion, as it pertains to the formation and distribution of expectations, specifically over economic variables such as inflation, have also been examined. Granato and Krause (2000), for example, investigated the possibility of inflation expectations diffusion within the electorate. Using educational differences as a proxy for information heterogeneity, they find the forecasts of the more educated influence the less educated group's forecasts and that the relation is asymmetric. The study of inflation expectations has also been of particular importance since its stability is related to output stability (see Granato and Wong, 2006) which also ties back to the economic voting literature.

In this paper, we use an EITM framework to explore forecasting behavior within an information diffusion process where a less-informed group interacts with a more-informed group. We extend the applied statistical work of Granato and Krause (2000) and incorporate the attributes of the EITM framework to lead to new equilibrium predictions about behavior. The attribute of the EITM approach is that it allows for an investigation of a boomerang effect, which we define as a situation in which the inaccurate forecasts of a less-informed group confound a more-informed group's forecasts. We investigate whether the boomerang effect exists using quarterly surveyed inflation expectations from the Survey Research Center (SRC) at the University of Michigan.[5] Our results indicate that the boomerang effect exists.

The paper is organized as follows. Section 2 presents the EITM framework. Section 3 applies the EITM framework to a model that links information diffusion and learning to forecast error. In this EITM linkage we show a boomerang effect is an equilibrium outcome. In Section 4 we outline the data and tests. We then report the evidence for the existence of a boomerang effect. Section 5 discusses the conclusions and implications of the EITM framework and the result.

2. The EITM framework

The purpose of EITM is to provide a framework that demonstrates how to unify formal and empirical analysis. This framework takes advantage of the mutually reinforcing properties of formal and empirical analysis. EITM also places emphasis on finding ways to model human behavior and action and, thereby, it assists in creating realistic representations that improve upon simple socio-economic categorization. Application of EITM does not guarantee that a model is correct. Rather, it provides analytical transparency to support cumulative scientific practice. In more concrete terms we use the EITM framework for purposes of attaining valid inference and prediction when we specify, say, a relation between two variables, *X* and *Y*.

For this particular research question involving the diffusion of expectations (information) we show how the argument fits in an EITM framework. The three-step EITM framework can be summarized as follows (see Granato, 2005; Granato et al., 2010a,b).

2.1. Unify theoretical concepts and applied statistical concepts

Given that human beings are the agents of action, concepts reflect overarching social and behavioral processes. Examples include (but are not limited to):

- decision making
- bargaining
- expectations
- learning
- social interaction.

It is also important to find an appropriate statistical concept to match with the theoretical concept. Examples of applied statistical concepts include (but are not limited to):

- persistence
- measurement error
- forecast error
- nominal choice
- simultaneity.

For our particular research question the behavioral/theoretical concepts will be *expectations*, *learning*, and *social interaction*. The applied statistical concept will be *forecast error*.

2.2. Develop behavioral (formal) and applied statistical analogues

To link concepts with tests, we need analogues. An analogue is a device in which a concept is represented by continuously variable – and measurable – quantities. Examples of analogues for the behavioral (formal) concepts such as decision making, expectations, and learning include (but are not limited to):

- decision theory (e.g., utility maximization)
- conditional expectations (forecasting) procedures
- adaptive and Bayesian learning (information updating) procedures.

Examples of applied statistical analogues for the applied statistical concepts of persistence, measurement error, nominal choice, and simultaneity include (respectively):

- autoregressive estimation
- error-in-variables regression
- discrete choice modeling
- multi-stage estimation (e.g., two-stage least squares).

The behavioral/theoretical analogues we use are *conditional expectations* and *adaptive learning*. We also specify

[4] Alesina and Rosenthal (1995), for example, employ a retrospective voting model with rational expectations (RE) to depict how voters deal with the uncertainty in assigning blame or credit toward incumbents for good or bad economic conditions. Similarly, Lohmann (2003) investigates political business cycles based on RE over inflation.

[5] The period of analysis is 1978: I through 2000: II.

the model so that social interaction and information diffusion occur between the *less-* and *more-informed* groups. The applied statistical analogue we use will be *the mean square error of the forecasts*.

2.3. Unify and evaluate the analogues

The third step takes purchase of the mutually reinforcing properties of the formal and empirical analogues and unifies them. There are various ways to establish the linkage. In this example the linkage will be established by taking the formal model parameters that have a behavioral interpretation, and linking them directly to the mean square error metric.

3. Applying the EITM framework

3.1. Step 1: relating expectations, information diffusion, and learning to forecast error

We first relate the behavioral concepts to the applied statistical concepts. Recall that our argument is that less informed agents can receive information from more informed agents for the purpose of enhancing their forecast accuracy. Further, the relation is not simply one group informing another. We take the relation between less- and more-informed agents – information diffusion and social interaction – and incorporate expectations and learning as well. When we incorporate these behavioral traits with forecast accuracy, we seek distinctive predictions that these behavioral concepts would give us independent of a passive transfer and acceptance of information (see Granato and Krause, 2000).

3.2. Step 2: develop behavioral (formal) and applied statistical analogues

Since information diffusion centers on inflation expectations, we build a formal model for inflation's behavior. We link a standard Lucas aggregate supply model (Lucas, 1973) with an aggregate demand function. (Evans and Honkapohja, 2001).

3.2.1. The expectations analogue: conditional expectations

The aggregate supply function and demand function, respectively, are:

$$y_t = \bar{y} + \theta\left(p_t - E^*_{t-1}p_t\right) + \epsilon_t, \tag{1}$$

where $\theta > 0$, and:

$$m_t + v_t = p_t + y_t. \tag{2}$$

The variables are as follows: p_t and y_t are the price and output level at time t, respectively, $\bar{y}$ is the natural rate of output level, $E^*_{t-1}p_t$ is the expectation (may not be rational) of the price level at time t, formed at time $t-1$ m_t is the money supply, and v_t is a velocity shock. If agents form expectations rationally, it implies that people use all the available information to make the best possible forecasts of the economic variables which are relevant to them (Lucas, 1972). In more technical terms, rational expectations (RE) is an equilibrium condition where the subjective expectations of some variable of interest is equivalent to the objective mathematical expectations conditional on all available information at the time the expectation is formed.[6]

Similar to Evans and Honkapohja (2009), we assume that velocity depends on some exogenous observables, w_{t-1}:

$$v_t = \kappa + \lambda w_{t-1} + \varepsilon_t, \tag{3}$$

where $\lambda > 0$ and the money supply (m_t) is determined by the following policy rule:

$$m_t = \overline{m} + p_{t-1} + \phi w_{t-1} + \xi_t, \tag{4}$$

where $\phi > 0$, $\overline{m}$ is a constant money stock, and $\epsilon_t, \varepsilon_t$, and ξ_t are iid stochastic shocks.

Using Eqs. (1) through (4) and defining $\pi_t = p_t - p_{t-1}$ and $E^*_{t-1}\pi_t = E^*_{t-1}p_t - p_{t-1}$, we can derive the dynamic model of inflation:

$$\pi_t = \alpha + \beta E^*_{t-1}\pi_t + \gamma w_{t-1} + \eta_t, \tag{5}$$

where:

$$\alpha = (1+\theta)^{-1}(\kappa + \overline{m} - \bar{y}),$$

$$\beta = \theta(1+\theta)^{-1} \in (0,1),$$

$$\gamma = (1+\theta)^{-1}(\phi + \lambda),$$

and

$$\eta_t = (1+\theta)^{-1}(\epsilon_t + \varepsilon_t + \xi_t).$$

Eq. (5) is a self-referential model where inflation depends on its expectations ($E^*_{t-1}\pi_t$), exogenous variables (w_{t-1}), and the stochastic shocks (η_t). If we assume RE, we can solve for the unique rational expectations equilibrium (REE) as:

$$\pi = \bar{a}^{REE} + \bar{b}^{REE} w_{t-1} + \eta_t, \tag{6}$$

where $\bar{a}^{REE} = \alpha/(1-\beta)$, and $\bar{b}^{REE} = \gamma/(1-\beta)$. From the equilibrium (6), agents can make rational forecasts $E_{t-1}\pi_t$ if they have the full information set w_{t-1} at time $t-1$ such that:

$$E_{t-1}\pi_t = \bar{a}^{REE} + \bar{b}^{REE} w_{t-1}. \tag{7}$$

3.2.2. The information diffusion analogue

Research suggests forecast accuracy is associated with education, a common proxy for information levels (w_{t-1}) (Granato and Krause, 2000; Carlson and Valev, 2001). Agents who possess more education have more accurate forecasts. One extension of this finding is a second finding

[6] Evans and Honkapohja (2001) argue that the assumption of RE is rather strong. They suggest the assumption can be relaxed by allowing agents to "learn" or update their conditional forecasts over time to obtain RE in the long run. This is called the adaptive learning approach which will be introduced later.

relating to information diffusion: more-informed agent forecasts and expectations (e.g., with higher education levels) influence less-informed agent forecasts and expectations (Granato and Krause, 2000).

With these findings in mind we take Eq. (5) and partition the information set w_{t-1} into two parts: $w_{t-1} = (x_{t-1}, z_{t-1})$, where x_{t-1} is "common" information, and z_{t-1} represents the "advanced" information:

$$\pi_t = \alpha + \beta E^*_{t-1}\pi_t + \gamma_1 x_{t-1} + \gamma_2 z_{t-1} + \eta_t, \tag{8}$$

where $\gamma = (\gamma_1, \gamma_2)$. We follow Granato et al. (2008) by separating the population into two groups of agents. In the spirit of the two-step flow model (Lazarsfeld et al., 1944), the groups are separated by the amount of information and interest they possess. We define Group L as the less-informed group. These agents are assumed to be less current on political and economic events. Members of the second group, Group H, are opinion leaders (e.g., issue publics) who are generally up-to-date on political and economic events. They are generally better informed. These opinion leaders are key in any information diffusion process since they are recognized by the less-informed group to have superior information.

It follows that these two groups possess different information sets (x_{t-1}, w_{t-1}). Group H has the complete information set of $w_{t-1} \equiv (x_{t-1}, z_{t-1})$, while Group L only obtains the common information set x_{t-1}. We further assume that there is a continuum of agents located on the unit interval [0,1] of which a proportion of, $1-\mu$, where $\mu \in [0,1)$, are agents in Group H who and more informed when forecasting inflation.

Agents are interactive. Group L observes Group H's expectations to make its forecasts (but not vice versa).[7] However, the less-informed agents may interpret (or even misinterpret) the more-informed agents' forecasts differently or may not be able to obtain the exact information from the more-informed agents. Granato et al. (2008) introduce a distribution of observational errors, e_{t-1}, for Group L during the process of information diffusion.[8] Therefore, Group L's forecasting model is:

$$\pi_t = a_L + b_L x_{t-1} + c_L \hat{\pi}_{t-1} + v_t, \tag{9}$$

and

$$\hat{\pi}_{t-1} = E^*_{H,t-1}\pi_t + e_{t-1}, \tag{10}$$

where $e_{t-1} \sim iid(0, \sigma_e^2)$ represents the observational errors which are uncorrelated with v_t and w_{t-1}, and $\hat{\pi}_{t-1}$ is the observed information that Group L gets from Group H, $E^*_{H,t-1}\pi_t$ (see Eq. (12)) with observational error (e_{t-1}) at time $t-1$. Since Group L obtains the observed information after Group H forms its expectations, Group L treats the observed information as a predetermined variable.

The forecasting model for Group H is different since this group possesses the full information set to forecast inflation:

$$\pi_t = a_H + b_{1H} x_{t-1} + b_{2H} z_{t-1} + v_t. \tag{11}$$

3.2.3. *The learning analogue: adaptive learning*

In this model, we assume that Group L and Group H do not directly obtain RE. Instead, we assume that Group L and Group H forecast following the process of Eqs. (9) and (11), respectively, and that they have data on the political economic system from periods $t_i = T_i, \ldots, t-1$, where $i \in \{L, H\}$. The time $t-1$ information set for the less-informed group, Group L, is $\{\pi_i, x_i, \hat{\pi}_i\}_{i=T_L}^{t-1}$, but the information set for Group H at time $t-1$ is $\{\pi_i, w_i\}_{i=T_H}^{t-1}$.

With analogues for expectations and information diffusion established, we now derive the analogue for learning (see Evans and Honkapohja, 2001; Granato et al., 2008). Based on the adaptive learning method, agents attempt to learn the stochastic process by updating their forecasts (expectations) as new information becomes available. Both groups use (12) for their perceived law of motion (PLM) when they forecast the variable of interest (inflation rate):

$$E^*_{i,t-1}\pi_t = \varphi_i' q_{i,t-1}, \tag{12}$$

where $i \in \{L, H\}$, $q'_{L,t-1} \equiv (1, x_{t-1}, \hat{\pi}_{t-1})$, $q'_{H,t-1} \equiv (1, x_{t-1}, z_{t-1})$, $\varphi'_L \equiv (a_L, b_L, c_L)$ and $\varphi'_H \equiv (a_H, b_{1H}, b_{2H})$. The inflation expectations, $E^*_{t-1}\pi_t$, in the society can be calculated as the weighted average of the expectations from both groups:

$$E^*_{t-1}\pi_t = \mu E^*_{L,t-1}\pi_t + (1-\mu) E^*_{H,t-1}\pi_t. \tag{13}$$

Using Eqs. (8)–(11) and (13), we can derive the actual law of motion (ALM):

$$\pi_t = \Omega_\alpha + \Omega_x x_{t-1} + \Omega_z z_{t-1} + \Omega_e e_{t-1} + \eta_t, \tag{14}$$

where:

$$\Omega_\alpha = \alpha + \beta\mu a_L + \beta(1-\mu) a_H,$$

$$\Omega_x = \beta\mu b_L + [\beta\mu c_L + \beta(1-\mu)] b_{1H} + \gamma_1,$$

$$\Omega_z = [\beta\mu c_L + \beta(1-\mu)] b_{2H} + \gamma_2,$$

and

$$\Omega_e = \beta\mu c_L.$$

Eqs. (5), (12), and (14) represent a system that now incorporates adaptive learning. Both Group H and Group L

[7] Bomfim (2001) suggests an opposite assumption. He uses a dynamic real business cycle model in which there are sophisticated or rule-of-thumb agents in an economy. He assumes that the sophisticated agents form their expectations by forecasting the decisions of the less sophisticated rule-of-thumb agents. His results indicate that the aggregate properties of the economy are influenced by the rule-of-thumb agents.

[8] This assumption can also be supported by Kandel and Zilberfarb (1999). They find that people do not interpret the existing information in an identical way. Using Israeli inflation forecast data, they show that the hypothesis of identical-information interpretation is rejected. In other words, less-informed agents could experience some difficulty in understanding these expectations, and they may interpret the more-informed agents' information differently themselves. It is also intuitively reasonable to believe agents are not able to obtain the exact information from others. Therefore, we impose a distribution of observational errors, e_{t-1}, to indicate the degree of misinterpretation of others' actions.

use their PLM's (i.e., Eq. (12)) to update their forecasts of inflation ($E^*_{i,t-1}\pi_t$, in Eq. (5)) based on information, $q_{i,t-1}$.

Evans (1989) and Evans and Honkapohja (1992) show that mapping the PLM to the ALM is generally consistent with the convergence to REE under least square learning. Further, assuming that agents have a choice of using one of several forecasting models and that there are equilibrium predictions in these models, Guse (2005, 2010) refers to a resulting stochastic equilibrium as a "mixed expectations equilibrium" (MEE).[9]

By computing the linear projections on Eqs. (8), (12) and (13), the MEE coefficients are the following[10]:

$$\bar{\varphi}_L = \begin{pmatrix} \bar{a}_L \\ \bar{b}_L \\ \bar{c}_L \end{pmatrix} = \begin{pmatrix} \frac{\alpha}{1-\beta}(1-\bar{c}_L) \\ \frac{\gamma_1}{1-\beta}(1-\bar{c}_L) \\ \frac{\bar{b}^2_{2H}\sigma^2_z}{\bar{b}^2_{2H}\sigma^2_z+(1-\beta\mu)\sigma^2_e} \end{pmatrix} \tag{15}$$

and

$$\bar{\varphi}_H = \begin{pmatrix} \bar{a}_H \\ \bar{b}_{1H} \\ \bar{b}_{2H} \end{pmatrix} = \begin{pmatrix} \frac{\alpha}{1-\beta} \\ \frac{\gamma_1}{1-\beta} \\ \frac{\gamma_2}{1-\beta+\beta\mu(1-c_L)} \end{pmatrix}, \tag{16}$$

where $\gamma \equiv (\gamma_1, \gamma_2)$.

The MEE (15) and (16) is the equilibrium of the forecasting models for Group L and Group H, respectively. Recall equation (6) that the REE is $\bar{a}^{REE} = \alpha/(1-\beta)$ and $\bar{b}^{REE} = \gamma/(1-\beta)$. Both groups can obtain the REE if they are able to receive the same complete information. However, because of the process of information diffusion, Groups L and H fail to obtain the REE.

The observational error e_{t-1} plays a very important role in the model. Whether Group L uses the observed information from Group H depends on how accurately the less-informed group understands information (the expectations) from the more-informed group. The accuracy is represented by the variance of the observational error, σ^2_e.

Eq. (15) implies that $0 < \bar{c}_L \le 1$ for $\beta < 1/\mu$. If Group L can fully understand and make use of Group H's expectations (i.e., $\sigma^2_e \to 0$), then we can see that $\bar{c}_L = 1$ (by solving Eqs. (15) and (16) with $\sigma^2_e = 0$). In addition, $\bar{c}_L \to 0$ as $\sigma^2_e \to \infty$ and the values of $\bar{c}_L$ affect $\bar{a}_L$ and $\bar{b}_L$. If $\bar{c}_L \to 0$, $\bar{a}_L \to \alpha/1-\beta$ and $\bar{b}_L \to \gamma_1/1-\beta$, and both $\bar{a}_L, \bar{b}_L \to 0$ if $\bar{c}_L \to 1$.

In the case of Group H, under the assumption that the covariance between x_t and $w_{2,t}$ is zero, $\bar{c}_L$ does not affect $\bar{a}_H$ and $\bar{b}_{1H}$ at all. Both will approach the REE,[11] $(\bar{a}_H, \bar{b}_{1H}) \to (\alpha/1-\beta, \gamma_1/1-\beta)$. However, Eq. (16) shows that $\bar{b}_{2H}$ is affected by $\bar{c}_L$, where $|\bar{b}_{2H}| \in (|\gamma_2|/1-\beta(1-\mu), |\gamma_2|/1-\beta)$ for $\beta \in [0,1)$ and $|\bar{b}_{2H}| \in (|\gamma_2|/1-\beta, |\gamma_2|/1-\beta(1-\mu))$ for $\beta \in (-\infty, 0)$. This latter relation is evidence of what we call the boomerang effect on expectations: the observational error of the less-informed group biases the parameter(s) of the highly informed group's forecasting rule.[12]

3.2.4. The forecast error analogue: mean square error

The applied statistical analogue we use for forecast error is the mean square error (MSE). For the inflation forecast error the mean square error is represented by the following formula:

$$MSE_i \equiv E\left(\pi_t - E^*_{i,t-1}\pi_t\right)^2,$$

for $i \in \{L, H\}$.

3.3. Step 3: unify and evaluate the analogues

In the formal model we demonstrate that Group L places weight on the observed information from Group H. Group L makes use of Group H's expectations (i.e., higher $\bar{c}_L$) as long as Group L does not face large variation in observation error in interpreting Group H's information (i.e., lower σ^2_e). Here we link the formal and applied statistical analogues for purposes of creating transparency between model and test and show how expectations, information diffusion, and learning create interesting and testable dynamics.

To show this, we calculate the mean squared error (MSE) for the forecasts of Groups L and H, respectively[13]:

$$MSE_L = \left[\frac{\gamma_2(1-\bar{c}_L)}{1-\beta+\beta(1-\bar{c}_L)\mu}\right]^2 \sigma^2_z + (1-\beta\mu)^2\bar{c}^2_L\sigma^2_e + \sigma^2_\eta \tag{17}$$

$$MSE_H = (\beta\mu\bar{c}_L)^2\sigma^2_e + \sigma^2_\eta \tag{18}$$

where $MSE_i \equiv E(\pi_t - E^*_{i,t-1}\pi_t)^2$ for $i \in \{L, H\}$.

Eq. (17), which uses different values of σ^2_e, depicts the accuracy of the less-informed group's predictions. If Group L is able to fully understand the expectations from Group H (i.e., without any observation errors $\sigma^2_e = 0$), the result is that Group L obtains the minimum MSE ($MSE_L = \sigma^2_\eta$). Otherwise, the finite σ^2_e reduces the less-informed agents' predictive accuracy where $MSE_L > \sigma^2_\eta$.

More importantly, due to the information diffusion, Group H fails to obtain the most accurate forecast. If there is no information diffusion process, then both groups form their forecasts independently, Group H obtains the minimum forecast error, $MSE_H = \sigma^2_\eta$. However, when information diffusion exists, with a finite σ^2_e, Group H has higher forecast errors: $MSE_H = (\beta\mu\bar{c}_L)^2\sigma^2_e + \sigma^2_\eta > \sigma^2_\eta$ in Eq. (18). This result is called the boomerang effect on the MSE (see Proposition 4 in Granato et al., 2008: 360–361).

The results for Group H indicate that only the two limit points of the variance of the observation errors ($\sigma^2_e = 0$ or

[9] In this model, agents have a choice to be either in Group H or in Group L when they form their forecasting models.

[10] To obtain MEE, one can solve for the orthogonality condition (OC) using the ALM (14) and the PLM (12). For Group H, the OC is $E(\pi_t - E^*_{H,t-1}\pi_t)(1, x_{t-1}, z_{t-1}) = 0$. For Group L, the OC is: $E(\pi_t - E^*_{L,t-1}\pi_t)(1, x_{t-1}, \tilde{\pi}_{t-1}) = 0$.

[11] If the $cov(x_t, w_{2,t}) \neq 0$, then $\bar{b}_{1H}$ can also be affected by the less-informed group's forecast errors.

[12] See Granato et al. (2008: 358–360) for details.

[13] For comparison, we also calculate the MSE's for situations in which both groups have the same (full) information set and learn independently. Both groups' MSE's are at a minimum when $MSE_L = MSE_H = \sigma^2_\eta$.

$\sigma_e^2 \to \infty$) produce the most efficient outcome. When $\sigma_e^2 = 0$, $\bar{c}_L = 1$. In other words, Group L uses the expectations from the highly informed group. It implies that Group L's expectations become exactly the same as those of Group H. As a result, both groups can forecast efficiently. However, if $\sigma_e^2 \to \infty$, $\bar{c}_L = 0$. In this case, Group L is not able to interpret Group H's expectations at all and eventually discards them. Both groups learn independently. The boomerang effect does not occur.

4. EITM and the boomerang effect

The attributes of EITM can now be seen. When we take the analogues that characterize expectations, learning, and information diffusion, we can examine how the parameters and variables create distinct predictions. This provides a refinement in prediction that is superior to, say, a purely applied statistical approach (see Granato and Krause, 2000). In this particular case, the boomerang effect is one such refinement.

We use surveyed inflation expectations from the SRC at the University of Michigan to test the dynamics embedded in (5). Our tests are directed at two things. First, our theoretical model assumes that information diffusion is asymmetric: the expectations of Group H influence the expectations of Group L. The first test serves as a necessary condition for the second test. The second test examines whether the boomerang effect exists. This test involves examining if larger observation errors made by Group L agents (σ_e^2) result in greater the inaccuracy in inflation predictions by Group H agents (MSE_H).

4.1. Data: the SRC inflation expectations survey

Inflation expectations surveys are conducted by the SRC at the University of Michigan and the results are published in the Survey of Consumer Attitudes. Since 1978 the center has conducted monthly telephone interviews from a sample of at least 500 households randomly selected to represent all American households, excluding those in Alaska and Hawaii. Each monthly sample is drawn as an independent cross-section sample of households. Respondents selected in the drawing are interviewed once and then re-interviewed six months later. This rotating process creates a total sample made up of 60% new respondents and 40% prior respondents.

Survey respondents are asked approximately 50 core questions that cover three broad areas of consumer opinions: personal finances, business conditions, and buying conditions. In this paper, we consider the following questions that relate to measuring inflation expectations:

1. During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?
2. By about what percent do you expect prices to go (up/down), on the average, during the next 12 months?

If respondents expect the price level will go up (or down) on question 1, they are asked in the second question to provide the exact percent the price level will increase (or decrease), otherwise the second question is coded as zero percent.[14]

We divide our inflation expectation survey data into different educational categories. To be consistent with our theory, we consider the respondents with college or graduate degrees as the highly informed group (Group H) and those without college degree as the less-informed group (Group L). Based on the unique characteristics of our data set, we are able to separate Group L in two distinct levels: (1) high school diploma or some college (denoted as "L1"); and (2) less than high school or no high school diploma (denoted as "L2").[15]

4.2. Testing for the asymmetric diffusion of inflation expectations

Panels A and B of Fig. 1 graph inflation forecasting data and inflation forecast error, respectively. We note that the inflation forecasts and forecast errors share similar movements in the long run, although Group H expects lower inflation and also are more accurate than the less-educated groups.

Following Granato and Krause (2000), we examine the direction of information diffusion by means of Granger causality tests in a vector autoregression (VAR). Since there is evidence that the data possess a unit root, we use first differences for all classes of inflation forecasts. The Akaike information criterion (AIC) and Lagrange multiplier (LM) test statistics suggest the VAR system with lag order of seven is preferable on the basis of a minimum AIC with no serial correlation or heteroskedasticity in the residuals.[16]

Table 1 reports results of the Granger causality tests. The null hypothesis that Group H does not Granger-cause Group L2 is rejected (p-value equals 0.030). However, Group H does not Granger-cause Group L1 (p-value equals 0.122). We also note that Group L1 Granger causes Group L2 (p-value equals 0.047). In contrast, Groups L1 and L2 do not Granger-cause Group H. We also find that Group L2 does not Granger-cause Group L1's forecasts. Overall, the testing results in Table 1 clearly indicate that there is an asymmetric information diffusion: the inflation forecasts of the more-educated group(s) affect the less-educated groups.

Using these findings, Fig. 2 depicts the dynamic responses of inflation forecasts from a less educated group from an

[14] Some respondents may confuse the concepts of "change in level" and "change in rate." To account for this confusion, respondents who answer "stay the same" on question 1 are asked the following to eliminate any confusion: "Do you mean that prices will go up at the same rate as now, or that prices in general will not go up during the next 12 months?" For more details on the surveying procedures, see http://www.sca.isr.umich.edu/.

[15] Since the survey sample is randomly selected every month, the number of respondents in different educational categories will vary. These variations can create insufficient monthly data for respective education categories. To account for this sampling challenge, we convert the monthly data into quarterly data (1978: I to 2000: II).

[16] Our unit root test results are based on both the augmented Dickey and Fuller (1979) test, and the Elliott et al. (1996) test. The results of the unit root tests and of the lag order selection for the VAR are available from the authors on request.

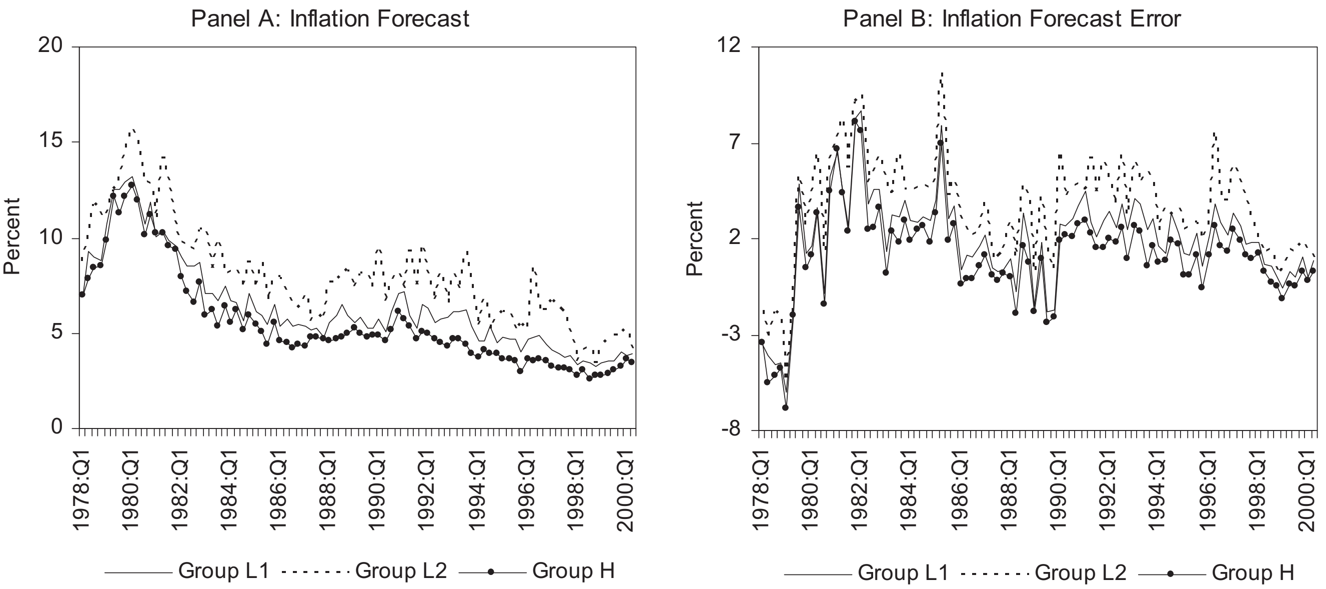

Fig. 1. Inflation forecasts and forecast errors for agents in three educational categories. Note: Group L1 represents agents with a high school diploma or some college. Group L2 represents agents with less than or no high School diploma. Group H represents agents with a college degree or graduate degree. The data source is the SRC at the University of Michigan.

innovation in a more educated group's inflation expectations. The results show that the less-educated agents do mimic agents with higher education level in a "positive" manner in revising their inflation expectations. The result supports the precondition of the boomerang effect.

4.3. Testing for the boomerang effect

To test for the evidence of a boomerang effect we examine if a "positive" relation exists between the size of observation errors of less-informed agents and the size of forecast inaccuracy of more-informed agents. We measure the size of observation error (e_t) by its variance (σ_e^2), and the size of the mean square error of Group H's forecasts (MSE_H).

Using Eqs. (9) and (10), we construct the following regression model:

$$E^*_{Lj}\pi_t = a_{Lj} + b_{Lj}x_{t-1} + c_{Lj}\left(E^*_{H,t-1}\pi_t + e_{Lj,t-1}\right), \tag{19}$$

where $E^*_{Lj,t-1}\pi_t$ and $E^*_{H,t-1}\pi_t$ represent the inflation forecasts of less and more-informed groups, respectively, $j \in \{1,2\}$ and x_t is the information set for inflation forecasts for Group L, which includes the current and lagged federal funds rate, the current inflation rate, and oil prices.[17] We construct the series, $\sigma^2_{e_{Lj}}$, using a rolling regression technique in which we fix the regression window of (19) at 12 years and move it forward every quarter.[18]

The observation error generated from Eq. (19) for the less-informed groups is:

$$e_{Lj,t-1} = \frac{E^*_{Lj,t-1}\pi_t - a_{Lj} - b_{Lj}x_{t-1} - c_{Lj}E^*_{H,t-1}\pi_t}{c_{Lj}}.$$

This result follows that the variances of the observation error ($\sigma^2_{e_{Lj},t}$) for the less-informed groups are:

$$\sigma^2_{e_{Lj},t} = \frac{\sum_t^{t+s} e^2_{Lj,t}}{s-1}, \forall t$$

where s represents the number of quarters in rolling windows.

We adopt the same rolling regression technique to estimate the mean square error for Group H:

$$MSE_{H,t} = \frac{\sum_t^{t+s}\left(\pi_t - E^*_{H,t-1}\pi_t\right)^2}{s}, \forall t.$$

Table 1
VAR pairwise Granger causality test: the direction of information diffusion across Group H, Group L1 and Group L2.

Null hypothesis	Chi-sq statistics *P*-value
If forecasts of the *higher* educated group Granger-cause those of the *less* educated group?	
a. Group H does not Granger-cause Group L1	11.401 [0.122]
b. Group H does not Granger-cause Group L2	15.522[a] [0.030]
c. Group L1 does not Granger-cause Group L2	14.253[a] [0.047]
If forecasts of the *less* educated group Granger-cause those of the *higher* educated group?	
d. Group L1 does not Granger-cause Group H	3.897 [0.792]
e. Group L2 does not Granger-cause Group H	7.583 [0.371]
f. Group L2 does not Granger-cause Group L1	2.603 [0.919]

[a] Indicates statistical significance at 5%.

[17] The data are from the FRED database provided by the Federal Reserve Bank of St. Louis.

[18] We alter the size of the rolling windows to check if the empirical results are robust. We use 15-year and 10-year rolling regression windows in our empirical analysis. However, results from using different choices of regression windows do not show any substantive or statistical difference, indicating the robustness of empirical findings presented in the paper. Results based on alternative rolling regression windows are available on request.

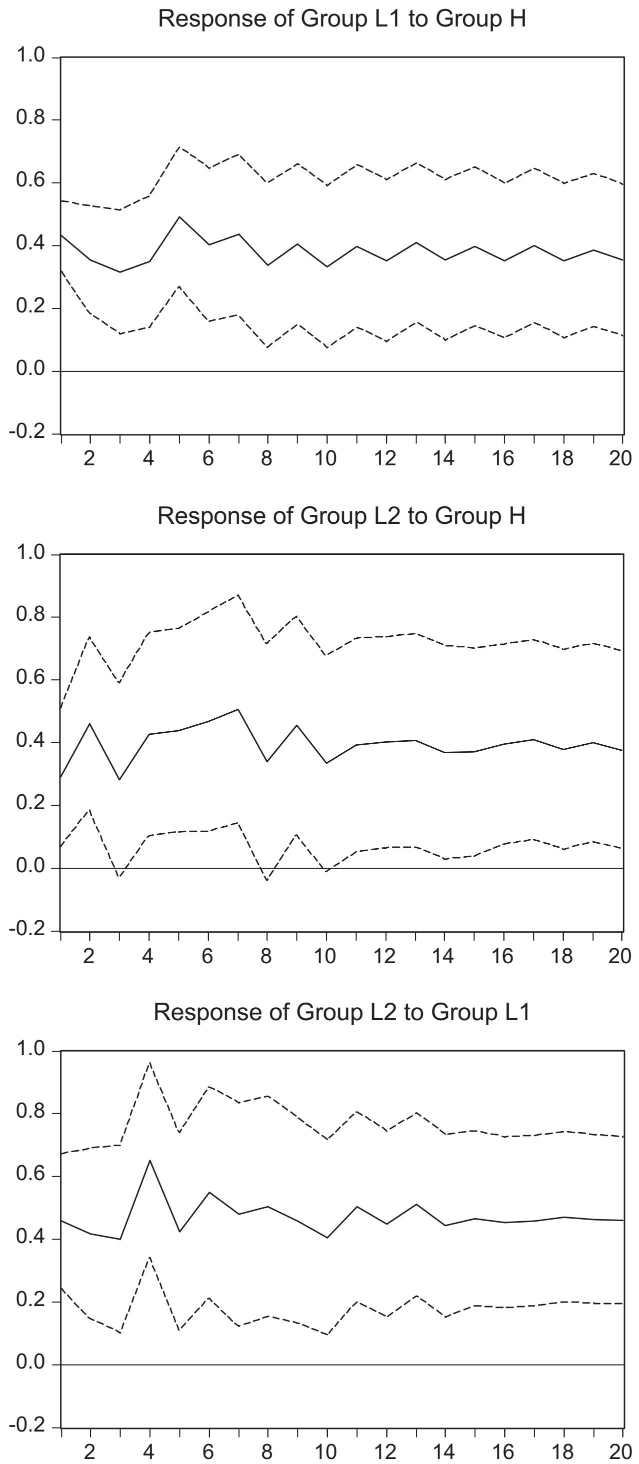

Fig. 2. Accumulated response to one S.D. innovations ± 2 S.E. Note: dashed lines denote 95% confidence intervals. Group L1 represents agents with a high school diploma or some college. Group L2 represents agents with less than or no high school diploma. Group H represents agents with a college degree or graduate degree. The data source is the SRC at the University of Michigan.

Our primary concern is the long-run (inter-)relation between MSE_H and $\sigma^2_{e_{Lj}}$ and whether a larger value of $\sigma^2_{e_{Lj}}$ causes MSE_H to increase. This result would support the boomerang effect hypothesis. To obtain consistent estimates of the unknown parameters entering the system consisting of MSE_{H}, $\sigma^2_{e_{L1}}$, and $\sigma^2_{e_{L2}}$, we first characterize the stochastic properties of these underlying variables.

Table 2 presents the augmented Dickey and Fuller (1979) and Elliott et al. (1996) test results. We find that MSE_{H}, $\sigma^2_{e_{L1}}$, and $\sigma^2_{e_{L2}}$ all contain a unit root. With test results indicating that we have all non-stationary variables in the system, the cointegration methodology is useful for exploring the long-run (inter-)relation among the variables. We use the Johansen test for this particular task.

4.3.1. The cointegration test on the boomerang effect

Panel A in Table 3 reports the results of the cointegration tests of the long-run relation between MSE_H and $\sigma^2_{e_{Lj}}$. Columns 1 and 2 in Panel A summarize the results of cointegrating relations for two pairs of variables, $(MSE_H, \sigma^2_{e_{L1}})$ and $(MSE_H, \sigma^2_{e_{L2}})$. Both the maximum eigenvalues and trace statistics indicate that there are long-run equilibrium relations for both. Using the Johansen cointegration procedure, we find the cointegrating vectors of $(MSE_H, \sigma^2_{e_{Lj}})$ are $(1, -29.58)$ and $(1, -21.54)$ for $j \in \{1, 2\}$.

These results show a positive long-run equilibrium relation with the existence of the boomerang effect between MSE_H and σ^2_e. It suggests that the mean square error on inflation forecasts for the respondents who hold a college degree or above (MSE_H) are positively related with the measurement errors resulting from the non-degree-holding respondents (σ^2_e).

The results in column (3), where the cointegrating system consists of all three variables of MSE_{H}, $\sigma^2_{e_{L1}}$, and $\sigma^2_{e_{L2}}$, provides further evidence to support the boomerang effect found in columns (1) and (2). With an estimated cointegrating vector of $(MSE_{H}, \sigma^2_{e_{L1}}, \sigma^2_{e_{L2}}) = (1, -20.52, -0.79)$, this robustness check shows that both $\sigma^2_{e_{L1}}$ and $\sigma^2_{e_{L2}}$ are positively related with MSE_H in the long run; that is, $MSE_H = 20.52\sigma^2_{e_{L1}} + 0.79\sigma^2_{e_{L2}}$. The results in column (4) also show that the robust cointegrating vector among the three variables is solely the result of the boomerang effect since the variances of the measurement errors in the two levels of Group L are not cointegrated.

Furthermore, we examine if the boomerang effect is robust when both levels of Group L are combined. We examine this case by averaging the inflation expectations from Groups L1 and L2 to obtain σ^2_e. The cointegration estimation (not shown here) indicates that the boomerang effect is still robust where σ^2_e is positively related with MSE_{H}.

4.3.2. A robustness check

Additional support for a boomerang effect occurs if we see that the direction of causality runs from σ^2_e to MSE_H (but not vice versa). Panel B of Table 3 gives the results of the Granger-causality tests using a vector error correction model (VECM). The results from systems (1) and (2) indicate that we can reject the null hypotheses that $\sigma^2_{e_{Lj}}$ does not Granger causes MSE_{H}, for $j \in \{1, 2\}$. The respective test statistics are equal to 14.36 and 19.43 and are significant at the 0.05 level. On the other hand, we cannot reject the null hypothesis for reverse causation. Column (3) in Panel B report associated results which are highly consistent with findings in columns (1) and (2).

Table 2
Unit root test results: the integration properties of MSE_H, $\sigma^2_{e_{L1}}$, and $\sigma^2_{e_{L2}}$.

Variable	Augmented Dickey–Fuller test		Elliott–Rothenberg–Stock test			Conclusion
	DF_μ [a]	DF_τ [b]	Optimal lag	$DF-GLS_\mu$ [c]	$DF-GLS_\tau$ [c]	
A. Data in levels						
MSE_H	−2.222	−0.661	3	−0.305	−1.690	I(1)
$\sigma^2_{e_{L1}}$	−0.826	−2.797	3	−0.531	−2.638	I(1)
$\sigma^2_{e_{L2}}$	−1.896	−3.327*	6	−0.743	−3.327**	I(1)
B. Data in first differences						
MSE_H	−4.536***	−4.966***	2	−2.041*	−2.371**	I(0)
$\sigma^2_{e_{L1}}$	−7.616***	−7.588***	2	−2.957***	−2.973*	I(0)
$\sigma^2_{e_{L2}}$	−7.002***	−6.926***	7	−3.367***	−3.440**	I(0)

***, **, and * indicate statistical significance at 1, 5 and 10%, respectively.
[a] Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary. Fuller (1976) 1 and 5% critical values for a sample size of 41 equal −3.597 and −2.934, respectively.
[b] Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary. Fuller (1976) 1 and 5% critical values for a sample size of 41 equal −4.196 and −3.522, respectively.
[c] Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary. The critical values, not reported here, are calculated from the response surface estimates of Table 1, Cheung and Lai (1995).

Table 3
Johansen cointegration tests and Granger causality tests in VECM: the (inter-)relation among MSE_H, $\sigma^2_{e_{L1}}$, and $\sigma^2_{e_{L2}}$.

Null hypothesis	Variables in the system							
	$MSE_H, \sigma^2_{e_{L1}}$ [a] (1)		$MSE_H, \sigma^2_{e_{L2}}$ [b] (2)		$MSE_H, \sigma^2_{e_{L1}}, \sigma^2_{e_{L2}}$ [c] (3)		$\sigma^2_{e_{L1}}, \sigma^2_{e_{L2}}$ [d] (4)	
	$\widehat{\lambda}_{max}$	Trace	$\widehat{\lambda}_{max}$	Trace	$\widehat{\lambda}_{max}$	Trace	$\widehat{\lambda}_{max}$	Trace
A: Rank test and cointegrating relation								
No rank	12.82** [11.44]	15.22** [12.53]	8.00 [11.44]	12.20* [12.53]	48.60*** [22.00]	87.52*** [34.91]	6.52 [11.44]	8.80 [12.53]
At most 1 rank	2.40 [3.84]	2.40 [3.84]	4.20 [3.84]	4.20 [3.84]	32.65*** [15.67]	38.92*** [19.96]	2.28 [3.84]	2.28 [3.84]
At most 2 ranks	–	–	–	–	6.27 9.24]	6.27 9.24]	–	–
Conclusion	1 cointegrating relation		1 cointegrating relation		2 cointegrating relations		None	
Estimated cointegration vector	$(MSE_H, \sigma^2_{e_{L1}} = (1, -29.58))$		$((MSE_H, \sigma^2_{e_{L2}}) = (1, -21.54))$		$(MSE_H, \sigma^2_{e_{L1}}, \sigma^2_{e_{L2}}) = (1, -20.52, -0.79))$		None	

Null hypothesis	Variables in the system			
	$MSE_H, \sigma^2_{e_{L1}}$ [a] (1)	$MSE_H, \sigma^2_{e_{L2}}$ [b] (2)	$MSE_H, \sigma^2_{e_{L1}}, \sigma^2_{e_{L2}}$ [c] (3)	$\sigma^2_{e_{L1}}, \sigma^2_{e_{L2}}$ [d] (4)
	Chi-sq statistics *p*-value	Chi-sq statistics *p*-value	Chi-sq statistics *p*-value	Chi-sq statistics *p*-value
B: The direction of causality in VECM				
$\sigma^2_{e_{L1}}$ does not cause MSE_H	14.36*** [0.006]	–	21.04*** [0.007]	–
MSE_H does not cause $\sigma^2_{e_{L1}}$	3.82 [0.430]	–	5.68 [0.682]	–
$\sigma^2_{e_{L2}}$ does not cause MSE_H	–	19.43*** [0.000]	30.87*** [0.000]	–
MSE_H does not cause $\sigma^2_{e_{L2}}$	–	4.72 [0.194]	7.15 [0.521]	–

***, **, and * indicate statistical significance at 1, 5 and 10%, respectively. We use the AIC criterion to choose the optimal number of lags to be included in each empirical model. Five percent critical values, from Osterwald-Lenum (1992), for rank tests are in parentheses.
[a] Test allows for a constant but no trend in the data space and 4 lags are included in the system.
[b] Test allows for a constant but no trend in the data space and 3 lags are included in the system.
[c] Test allows for a constant but no trend in the cointegration space and 8 lags are included in the system.
[d] Test allows for a constant but no trend in the data space and 4 lags are included in the system.

5. Conclusion

In this paper, we use an EITM framework to explore forecasting behavior within an information diffusion process. The information diffusion process is in the same spirit of the two-step flow of communication: a less-informed group interacts with a more-informed group. We extend the applied statistical work of Granato and Krause (2000) and incorporate the attributes of the EITM framework to lead to new equilibrium predictions about behavior. The attributes of the EITM approach allows for an investigation of the boomerang effect, which we define as a situation in which the inaccurate forecasts of a less-informed group confound a more-informed group's forecasts.

We use the Survey Research Center (SRC) inflation expectations data to test the existence of asymmetric information diffusion and the boomerang effect. The quarterly survey data, divided along different educational groups, covers 1978 through 2000. To test for the existence of the boomerang effect, we use a cointegration test to estimate the long run relation between the variance of observational errors from the less educated group and the mean square error of the more educated group's expectations. We find a long-run positive relation and evidence of a boomerang effect.

This paper also has implications for economic stability. Since the equilibrium forecasts in an economy are aggregations of agents' forecasts, a large boomerang effect can cause policymakers themselves to make inaccurate forecasts of economic conditions. The inaccurate forecasts can eventually cause additional economic volatility and failed stabilization policies.[19] To alleviate the boomerang effect, one normative policy suggestion is that policymakers should be more transparent about policy information. Transparency will make it possible for the less-informed citizens to better understand how the policy will work and hence make more accurate use of others with more information.[20] With more precision in information acquisition, the less-informed citizens will confound a more-informed group's forecasts less and it can reduce the boomerang effect, improve policy effectiveness, and help with overall economic performance.

References

Alesina, A., Rosenthal, H., 1995. Partisan Politics, Divided Government, and the Economy. Cambridge University Press, New York.

Bernanke, B., Laubach, T., Mishkin, F., Posen, A., 2001. Inflation Targeting: Lessons from the International Experience. Princeton University Press, Princeton, NJ.

Bomfim, A.N., 2001. Heterogeneous forecasts and aggregate dynamics. Journal of Monetary Economics 47, 145–161.

Carlson, J., Valev, N., 2001. Credibility of a new monetary regime: the currency board in Bulgaria. Journal of Monetary Economics 47, 581–594.

Chamley, C.P., 2004. Rational Herds: Economic Models of Social Learning. Cambridge University Press, New York.

Cheung, Y.W., Lai, K.S., 1995. Lag order and critical values of the augmented Dickey-Fuller test. Journal of Business and Economic Statistics 13, 277–280.

Clarke, H.D., Stewart, M.C., 1994. Prospections, retrospections, and rationality: the `Bankers' model of presidential approval reconsidered. American Journal of Political Science 38, 1104–1123.

Devenow, A., Welch, I., 1996. Rational herding in financial economics. European Economic Review 40, 603–615.

Dickey, D., Fuller, W., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 366, 427–431.

Duch, R.M., Stevenson, R., 2010. The global economy, competency, and the economic vote. The Journal of Politics 72, 105–123.

Elliott, G., Rothenberg, T., Stock, H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64, 813–836.

Evans, G.W., 1989. The fragility of sunspots and bubbles. Journal of Monetary Economics 23, 297–313.

Evans, G.W., Honkapohja, S., 1992. On the robustness of bubbles in linear RE models. International Economic Review 33, 1–14.

Evans, G.W., Honkapohja, S., 2001. Learning and Expectations in Macroeconomics. Princeton University Press, Princeton, NJ.

Evans, G.W., Honkapohja, S., 2009. Learning and macroeconomics. The Annual Review of Economics 1, 421–449.

Fuller, W.A., 1976. Introduction to Statistical Time Series. John Wiley, New York.

Granato, J., 2005. Scientific progress in quantitative political economy. The Political Economist 12, 11–13.

Granato, J., Guse, E.A., Wong, M.C.S., 2008. Learning from the expectations of others. Macroeconomic Dynamics 12, 345–377.

Granato, J., Krause, G., 2000. Information diffusion within the electorate: the asymmetric transmission of political-economic information. Electoral Studies 19, 519–537.

Granato, J., Lo, M., Wong, M.C.S., 2010a. The empirical implications of theoretical models (EITM): a framework for methodological unification. Políitica y gobierno 17, 25–57.

Granato, J., Lo, M., Wong, M.C.S., 2010b. A framework for unifying formal and empirical analysis. American Journal of Political Science 54, 783–797.

Granato, J., Wong, M.C.S., 2006. The Role Policymakers in Business Cycle Fluctuations. Cambridge University Press, New York.

Guse, E.A., 2005. Stability properties for learning with heterogeneous expectations and multiple equilibria. Journal of Economic Dynamics and Control 29, 1623–1642.

Guse, E.A., 2010. Heterogeneous expectations, adaptive learning, and evolutionary dynamics. Journal of Economic Behavior & Organization 74, 42–57.

Kandel, E., Zilberfarb, B., 1999. Differential interpretation of information in inflation forecasts. Review of Economics and Statistics 81, 217–226.

Lazarsfeld, P.F., Berelson, B., Gaudet, H., 1944. The People's Choice: How the Voter Makes Up His Mind in a Presidential Campaign. Columbia University Press, New York.

Lohmann, S., 2003. Representative government and special interest politics: (we have met the enemy and he is us). Journal of Theoretical Politics 15, 299–319.

Lucas Jr., R.E., 1972. Expectations and the neutrality of money. Journal of Economic Theory 4, 103–124.

Lucas Jr., R.E., 1973. Some international evidence on output-inflation tradeoffs. American Economic Review 63, 326–334.

Osterwald-Lenum, M., 1992. A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. Oxford Bulletin of Economics and Statistics 54, 461–472.

[19] A similar implication is also suggested by Bomfim (2001). See Footnote 7.

[20] There is research supporting this common-sense suggestion. Bernanke et al. (2001) notes that when information about the plans, objectives, or decisions of the monetary authorities are carefully explained, the public can more easily understand the contents of a policy announcement.