Positive feedback trading and diffusion of asset price changes: Evidence from housing transactions

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Received February 1992, final version received August 1992

Abstract

The positive feedback hypothesis states that good news (bad news) engenders positive (negative) attitudes that accentuate the impact of the news on asset prices. It is a special case of the representativeness heuristic which states that there is a general tendency to overemphasize the most recent evidence. This paper tests a form of the positive feedback hypothesis where recent rates of change in asset prices become important information used by decision-makers. If this is the case, housing price changes will tend to diffuse throughout a metropolitan area. Evidence from Hartford, Connecticut supports this hypothesis and the evidence is inconsistent with alternative explanations.

Key words: Positive feedback; Representativeness heuristic; Efficient markets hypothesis; Real estate price indices
JEL classification: D83; G14; R31

1. Introduction

The search for an alternative framework for explaining movements in asset prices has been stimulated by mounting evidence against the market efficiency (EMH) paradigm (Shiller, 1979; LeRoy, 1989). A common alternative to EMH postulates that asset prices are characterized by positive

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** We are grateful to Stephen LeRoy, Robert Shiller, two anonymous referees and Larry Summers for helpful suggestions and to the Center for Real Estate and Urban Economic Studies (The University of Connecticut) for financial support. An extended version of this paper can be obtained from the authors upon request.

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SSDI 0167-2681(93)E0030-4
feedback. That is, good news (bad news) engenders positive (negative) attitudes that accentuate the impact of the news on asset prices (DeLong et al., 1990; Shiller, 1990; Cutler, Poterba, and Summers, 1990). The assumption of positive feedback is consistent with several broad classes of models, including overreactions (DeBondt and Thaler, 1985); mean reversion (Summers, 1986; Fama and French, 1988); fads (Shiller, 1984; Shiller and Pound, 1989) and rational bubbles (Blanchard and Watson, 1982).

The representativeness heuristic provides a foundation for the positive feedback postulate. The representativeness heuristic is a more general hypothesis which states that there is a tendency to overemphasize present (i.e., most recent) evidence, to use stereotypes, and to ignore the quality (e.g., sample size) of this evidence (Arrow, 1982, especially p. 5; Grether, 1992, pp. 32–33). Tversky and Kahneman (1974) have used laboratory experiments to provide considerable evidence (covering investment decisions as well as other decisions and judgments) in favor of the representativeness heuristic. The survey research of Shiller and Pound supports investor behavior (diffusion of beliefs) consistent with the representativeness heuristic.

A heuristic decision rule is used when the 'optimal' decision rule is too costly. Arrow (1986) argues that incomplete markets may cause decision makers to use heuristic devices. Grossman (1989) points out that it is rational for uninformed investors to use price levels and price movements as indicative of information available to informed investors. Thus, the representativeness heuristic – and, therefore, the positive feedback postulate – is not inconsistent with the principles of rationality.

The purpose of this paper is to empirically test a specific form of the positive feedback postulate. This form says that there is diffusion of information through personal contact. Furthermore, it asserts that the most important piece of information conveyed is about recent rates of change in asset prices: i.e., people interpret current price change data as conveying information about the underlying value of the asset. Thus, the question addressed here is a specialization of the one addressed by Shiller and Pound, 'is contagion of interest important in financial markets?' (1989, page 47).

The representativeness heuristic is consistent with positive serial correlation over periods as long as one year in stock prices (Shiller, 1990) as well as in bonds, foreign exchange, gold, houses, and collectibles (Cutler, Poterba, and Summers, 1990). However, this small positive correlation could also be consistent with the gradual unfolding of fundamental information. For example, news about the business cycle, gradually revealed, would be consistent with these empirical results. Similarly, the diffusion of price movements through world-wide stock markets might be explained by the fundamental linkages among economies (see King and Wadhwani, 1990). Similar problems bedevil tests using closed-end mutual fund discounts (Lee, Shleifer, and Thaler, 1991) and insider trading (Seyhun, 1990). As argued by
Lee, Shleifer, and Thaler, shifts in investor sentiment might explain these results; overreaction to recent past price changes or to any news item have not been proven.

This paper departs from previous tests of the same hypotheses by using data on the rate of change in housing market prices (transactions prices) for a group of neighboring towns in a single metropolitan area (Hartford, CT). Prices in these towns should have a common response to events influencing the entire metropolitan area (e.g., national and international economic events). Thus, one would generally expect parallel town price movements. It will be argued that any diffusion of price change from one town to another is consistent with positive feedback (and, therefore, with the representativeness heuristic) and not with alternative theories.

Housing is an ideal asset for testing the representativeness heuristic. Housing markets have no centralized source of information on price levels or price movements, and transactions costs are high. Furthermore, these markets are thin with few buyers and sellers relative to stock markets. These frictions imply that we will be able to observe any reactions to recent past price changes; in fact, evidence consistent with this hypothesis has been found by Case and Shiller (1989, 1990), and by Tirtiroglu (1991).

1.1. Comparison of EMH to the representativeness heuristic

The efficient markets hypothesis provides a point of departure for this study. EMH is widely accepted as a paradigm for real estate markets. (See Case and Shiller 1989, 1990; Gau 1984, 1985). This paper uses EMH as a simple paradigm that produces testable hypotheses that can be contrasted with empirical implications of the representativeness heuristic.

There are several reasons why real estate markets should not be as efficient as stock markets. Most importantly, participants in a real estate transaction have invested substantial amounts of time and money that are ‘sunk.’ These costs arise from information that must be collected on differences across neighborhoods and properties; monopolistic markets develop whenever sunk costs are important.

There are two implications of monopolistic markets. One is thin markets where prices reflect the information obtained by a few participants in the transaction who have paid the sunk costs. Most importantly, transactions

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1 An alternative point of view holds that these frictions rob EMH of meaning when it is applied to real estate markets. If so, then it is unclear what alternative hypothesis can be contrasted with positive feedback. (We are grateful to Stephen LeRoy for pointing this out.) The point of departure here is a body of literature maintaining that house prices rapidly reflect available information (see Case and Shiller, 1989, for a summary of this literature). For example, relatively few buyers and sellers with low transactions costs (because they would have to move anyway) may keep housing prices close to a competitive market equilibrium.
prices reflect bilateral negotiations between seller and buyer. Secondly, there are high transactions costs that have to be paid to the real estate professionals facilitating the sale. Both of these factors stem from the frictions associated with space. Both limit the ability of real estate prices to reflect information available to all market participants, not just those who have incurred transaction costs.

Gau (1987) squarely addresses the 'paradox' of assuming EMH when the frictions associated with space suggest that a monopolistic model would work better. Gau finds EMH useful because:
1. The evidence supports weak form market efficiency for real estate markets;
2. EMH produces useful empirical implications;
3. He judges market efficiency to be an adequate approximation for many empirical studies.

EMH is particularly useful for this study because we use changes over time for a price index representing a typical constant-quality house in each neighborhood (i.e., town) in the Hartford area. Each town used in this study has at least 10,000 people and the number of housing transactions used to construct the constant-quality price index are in the tens of thousands. Thus, models of bilateral monopoly at the individual transaction level are not appropriate for the price variable used in this study.

The next section develops the representativeness heuristic and shows how it applies in housing markets. The following section develops an estimating equation designed to test the representativeness heuristic by isolating positive feedback and diffusion of house price information. The discussion of results explores alternative theories (the Tiebout (1956) hypothesis, accessibility theory, and the 'prisoners dilemma' hypothesis) to determine if these are consistent with the evidence.

2. Theory of the representativeness heuristic

Arrow (1982) evaluates the rationality principle critically and asserts that evidence of excess volatility is incompatible with it. He notes:

an individual judges the likelihood of a future event by the similarity of the present evidence to it. There is a tendency to ignore both prior information and the quality of the present evidence . . . .

This typifies very precisely the excessive reaction to current information which seems to characterize all the securities and futures markets. It is a plausible hypothesis that individuals are unable to recognize that there will be many surprises in the future; in short, as much other evidence tends to confirm, there is a tendency to underestimate uncertainties. (p. 5).

Arrow suggests the 'representativeness heuristic' of cognitive psychology as
an alternative to global rationality (i.e., with complete information from complete markets) and as a behavioral model consistent with the evidence of excess volatility.

Tversky and Kahneman (1974, 1981) have been two of the leading cognitive psychologists in developing and testing alternative models of human judgment and behavior. They take the expected utility hypothesis (hence, rationality) as the refutable null hypothesis in their work and demonstrate through laboratory experiments that individuals use some behavioral heuristics to simplify their decision-making under uncertainty.

2.1. Factors which lead to systematic errors in asset pricing

Misconceptions of regression and chance occur when people do not understand causal mechanisms (See Clapp and Tirtiroglu, 1992, for details). For example, misconceptions of regression occur when people identify poor outcomes with one causal factor while positive outcomes are identified with another causal factor. In reality, the differences in the outcomes are a characteristic of the random process as the regression toward the mean rule states. Insensitivity to sample size causes people to draw conclusions from a few observations. A few stories regarding price appreciations of neighboring houses thus seem sufficient for people to use change in prices as present evidence. The following section uses this idea to develop testable hypotheses.

3. Estimation of housing price indices

Under the null hypothesis of market efficiency, the change in house prices within a given town (i.e., a townwide price index) can be decomposed as follows:

\[ \Delta P_i = \Delta P_M + \Delta P_{LP} + \Delta P_{LA} + E_i, \]  

(1)

where

\( \Delta P_i \) = Percent change in single-family house prices in town i,

\( \Delta P_M \) = Metropolitan area (MSA) price change, common to all towns in the MSA,

\( \Delta P_{LP} \) = Percent change due to pure local influences (e.g., local taxes and public services) in town i,

\( \Delta P_{LA} \) = Percent change due to local accessibility characteristics (e.g., job change, major highway improvement) in town i,

\( E_i \) = A mean zero iid error term for town i.

Metropolitan-wide price (\( \Delta P_M \)) change follows from international, national,
and regional influences on the metropolitan area. Any changes in the macro economy that influence local real estate prices are reflected in this term. The pure local influences ($\Delta P_{lp}$) are felt only within the boundaries of a given town. These 'Tiebout' influences include local public services and local taxes. Local accessibility effects ($\Delta P_{la}$) are changes within a given town that influence surrounding towns. For example, a change in employment opportunities or a major change in highways may make access to the given town more valuable. Therefore, surrounding towns will be influenced as indicated by the new urban economics model of housing prices and accessibility.

In the model developed below, $\Delta P_m$ is controlled by subtracting it from $\Delta P_l$. This detrends local house prices ($\Delta P_l$), effectively controlling for the time series properties of the data.\(^2\) It is possible that pure local influences ($\Delta P_{lp}$) and/or changes in local accessibility characteristics ($\Delta P_{la}$) might explain any observed cross-correlation in price changes. This possibility will be examined after the empirical evidence has been presented.

There are several steps involved in estimating a model based on equation (1). First, we have to estimate housing price indices by town because there is nothing analogous to the S&P500 for real estate markets. A next step is to form excess returns, eliminate returns due to general metropolitan wide influences ($\Delta P_m$ in equation 1), and, finally, estimate a model designed to test the diffusion hypothesis.

3.1. Estimating price indices by town

We use the assessed value (AV) methodology recently developed by Clapp (1990) and by Clapp and Giaccotto (1992). The AV method reduces the property and locational characteristics to a single variable, assessed value. Since the hedonic variable controls for heterogeneous property and locational characteristics, the time trend can be estimated by adding quarterly time dummies:

$$\ln P_{jt} = c \ln A_{j0} + c_{11} Q_{1j} + c_{12} Q_{2j} + \ldots + c_{1T} Q_{Tj} - cz_{j0} + e_{jt}, \quad (2)$$

where

- $P_{jt}$ = the arm's-length transaction price for property $j$ in town $i$ at time $t$, $j = 1, \ldots, n_j$, and $t = 1, \ldots, T$.
- $A_{j0}$ = assessed value for property $j$ at time zero.
- $Q_{tj}$ = a time dummy with values of 1 if the $j$th house sold in period $t$, zero otherwise, and

\(^2\) We are grateful to Larry Summers for pointing out that this is the best way to isolate spatial diffusion from the serial correlation observed by Case and Shiller (1989, 1990).
A separate regression for each town produces town price indices, $\hat{c}_{it}$.

Assessed value is not a constant proportion of true market value, so measurement error must be taken into account. Clapp and Giaccotto derived the following relationship:

$$\text{plim}(\hat{c}_t - \hat{c}_{t-1}) = c_t - c_{t-1} + \left(\frac{\sigma_{\mu}^2}{\sigma_e^2}\right)(\bar{V}_t - \bar{V}_{t-1}),$$

(3)

where $\bar{V}_t = (1/n_t)\sum_{i=1}^{n_t} \ln V_{it}$, the average of (log) true market value, as of time zero, for the sample of properties that sold during period $t$; $\sigma_{\mu}^2$ is the variance of the log of assessed value. For a given population, the only reason a non-zero value for the last term in parenthesis is sampling variability, so measurement error will tend to zero.

Empirical tests based on equation (3) show that measurement error is insignificant for the Hartford data (see Clapp and Giaccotto, 1992). Thus, the reduction of hedonic characteristics to the single assessed value variable is effective with this sample.

3.2. Deriving annual excess returns

The first difference of the log price index given by equation (2) is the continuously compounded quarterly rate of percentage change in house prices in the given town. But, quarterly percentage changes are subject to seasonal movement and to measurement error. (Note that the price indices are the estimated coefficients on the quarterly time dummy. These estimated values are random variables.) In order to eliminate seasonality and attenuate measurement error, annual rates of change (fourth differences) will be used for this paper:

$$\Delta P_{it} = \hat{c}_{it} - \hat{c}_{it-4} = (\hat{c}_{it} - \hat{c}_{it-1}) + (\hat{c}_{it-1} - \hat{c}_{it-2}) + (\hat{c}_{it-2} - \hat{c}_{it-3}) + (\hat{c}_{it-3} - \hat{c}_{it-4}),$$

(4)

where the $\hat{c}_{it}$s are the estimated coefficients (townwide price indices) from equation (2). Note that these fourth differences could be viewed as the sum of four quarterly rates of change (first differences).

The annual rates of change overlap with those for the previous three quarters. In fact, the rate of change for quarter $t$ overlaps by three quarters with the one for $t-1$, by two quarters with the one for $t-2$, etc. Thus, the
annual rates of change are not independently distributed, requiring estimation by a method of moments.

We define excess returns as being those returns over and above returns for the entire metropolitan area. Metropolitan area returns are defined as

$$\Delta P_{Mt} = \frac{1}{N} \sum_{i=1}^{N} \Delta P_{i,t}$$

(5)

where $N$ = the number of towns in the metropolitan area. Thus, we form annual excess returns as follows:

$$\Delta PE_{it} = \Delta P_{it} - \Delta P_{Mt}.$$  

(6)

This controls for the $\Delta P_M$ term in equation (1), so it should have no influence on the diffusion model developed next. Equation (6) has the effect of detrending the data.

4. The diffusion model with the Hansen-Hodrick (1980) correction

The diffusion hypothesis derived from the representativeness heuristic can be tested by regressing change for the price index in a given town on lagged changes in neighboring towns:

$$\Delta PE_{it} = \beta_0 + \beta_1 \Delta PE_{n,t-4} + \epsilon_{it}$$  

(7)

where $n$ indicates neighboring towns, and $t = 6, \ldots , T$. Here $\beta_1$ is a $(1 \times 4)$ row vector and $\Delta PE_{n,t-4}$ is a $(4 \times 1)$ column vector since there are four neighboring towns. The hypothesis is $\beta_1 > 0$, a positive diffusion across space. The one-year lag worked well in a nonspatial context for Case and Shiller; it is designed to eliminate seasonality.

A 'control group' can be set up by randomly selecting non-neighboring towns and using them as explanatory variables:

$$\Delta PE_{it} = \gamma_0 + \gamma_1 \Delta PE_{nn,t-4} + \epsilon_{it}.$$  

(8)

where $nn$ indicates randomly selected non-neighboring towns, and $t = 6, \ldots , T$. Here $\gamma_1$ is a $(1 \times 4)$ row vector and $\Delta PE_{nn,t-4}$ is a $(4 \times 1)$ column vector since there are four non-neighboring towns. Since the diffusion hypothesis applies only to neighboring towns, it implies zero coefficients ($\gamma_1 = 0$) in equation (8).

We did extend equations (7) and (8) by including the dependent variable lagged four quarters. Because of spurious negative correlation (see Case and Shiller, 1989), we do not expect the coefficient on the own-town lag to be significantly positive. But, we want to find out whether the coefficients on neighboring towns are statistically significant only because they are serving
as proxy for the own-town. Therefore, the issue is whether the coefficients on neighboring town price change remain significant after including own-town price change, where all explanatory variables are lagged by four quarters.

To increase the power of the tests of models (7) and (8), the data for the N towns are stacked. This is consistent with the representativeness heuristic, a general rule which states that there is no reason to believe that the rate of diffusion, \( \beta_1 \), differs by town.

The stacked models are:

\[
\Delta P_E = \beta_0 + \beta_1 \Delta P_{E_n} + \epsilon, \quad (9)
\]

\[
\Delta P_E = \gamma_0 + \gamma_1 \Delta P_{E_{nn}} + \epsilon, \quad (10)
\]

where all variables are \( N \times (T-4) \) column vectors with \( T-4 \) observations over time (after subtracting the four observations lost due to lagged explanatory variables) for the ith town stacked under those for town \( i-1, i=2, \ldots, N \). In some of the empirical work, we expand the explanatory vectors to matrices with four columns, one for each of four towns (neighboring or non-neighboring).

It is desirable to estimate (9) and (10) by OLS because the null hypothesis of market efficiency assumes no knowledge of future prices. But the overlap generated by equation (4) means that successive disturbances are not independent. Following Case and Shiller (1990, pp. 264–265), we use a method of moments estimator. (See Clapp and Tirtiroglu (1992) for further details.)

\[
\text{Cov}(\hat{\beta}_1) = (\Delta P'E \Delta P)^{-1} \Delta P' S \Delta P (\Delta P'E \Delta P)^{-1}, \quad (11)
\]

\[
S = V \otimes Z, \quad (12)
\]

\[
V = \begin{bmatrix}
  v_{11} & v_{12} & \cdots & v_{1N} \\
  v_{21} & v_{22} & \cdots & v_{2N} \\
  \vdots & \vdots & \ddots & \vdots \\
  v_{NI} & \cdots & v_{NN}
\end{bmatrix}, \quad (13)
\]

\[
Z = \begin{bmatrix}
  1 & 0.75 & 0.5 & 0.25 & 0 & \cdots & 0 \\
  0.75 & 1 & 0.75 & 0.5 & 0.25 & \cdots & 0 \\
  0.5 & 0.75 & 1 & 0.75 & 0.5 & \cdots & 0 \\
  \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
  0 & \cdots & 0 & \cdots & 1
\end{bmatrix}, \quad (14)
\]

\[3\] Note that we have already dealt with this issue by subtracting the average area price change from each variable.
where $v_{ij}$ is the variance ($i=j$) of disturbances for town $i$ or covariance between $i$ and $j$. $Z$ is a $(T-4) \times (T-4)$ square matrix and $k=n$ or $nn$ indexes the model (the $k$ subscript has been suppressed on the $\Delta P E$ matrices). Equation (13) generalizes Case and Shiller, since they forced all the on-diagonal elements to have the same value. To estimate (11), we estimate $V$ from the OLS residuals from (9) or (10).

5. The data

The data for the empirical part of this study are obtained from the Office of Policy and Management (OPM), State of Connecticut. This state agency collects, classifies, verifies, and electronically stores data for all real estate sales transactions, for all Connecticut towns. Arm's-length transactions (used here) are separated from intrafamily transactions and those involving personal property. Thus, OPM cleans the data from many possible sources of noise, and maintains high standards for its database and data collection.

There are four subcategories of usable transactions. If the transaction pertains to residential real estate, its code is $R$; vacant land code is $V$; industrial property code is $I$; and commercial and utilities property code is $C$. The data used in this research are all usable residential sales transactions. Condominium units are eliminated from the data set. Therefore, the data set includes only transactions for the 1- to 3-family residential homes, hereafter designated 'single family' (SFR).

The data are available from October 1, 1981 to September 30, 1988. The available series is not as long as the Case-Shiller study series. But, the idea behind the empirical test of the efficient markets hypothesis is not a time-series approach. Therefore, relatively short series does not pose a serious problem.

Data on 19 neighboring towns ($N=19$) are extracted from the database of 169 Connecticut towns. Three criteria are used in selecting the towns:

1. each town has a population of more than 10,000,
2. the towns should have a common border with at least one other sample town,
3. the towns should be in the Hartford-Bristol-New Britain-Middletown metropolitan area.

The first criterion increases the chances of obtaining enough data (i.e.,

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4 We had 19 quarters of data after allowing for annual percentage change (equation 14) and one year lags (equations 7 and 8).
observations of sales transactions), because some towns have as little as 500 residents. Thus, the number of transactions are often very limited in these towns. The second and third criteria ensure that physical proximity is incorporated into the research design.

The 19 towns in the sample were divided into four groups to reduce the computational burdens associated with equations (11)-(13). Group 1 is all five towns East of the Connecticut river. Groups 2 and 3 are mutually exclusive groups of five towns (randomly assigned) West of the Connecticut river. Group 4 is the remaining four towns, all West of the river. Thus, there are 95 observations for groups 1–3 (5 towns times 19 quarters) and 76 observations for group (4 times 19 quarters).

Most towns had four neighboring towns, but some had as few as two neighbors and some had as many as six neighbors. These neighbors were ranked by distance from downtown, with neighbor one being closest. Non-neighboring towns were randomly assigned from the group of towns remaining after eliminating neighbors.

6. The results

Table 1 describes the data. As expected from a simple model where $\Delta P_{LP} = \Delta P_{LA} = 0$ (equation 1), the subtraction of the metropolitan area mean produces near zero means on all variables. This is because percentage price increases over the seven-year period were nearly equal for all towns. Thus, a prediction of EMH, that differences in price changes for substitute assets will be arbitraged away, holds if all years are taken as one observation. An important implication of Table 1 is that pure local effects ($\Delta P_{LP}$) and local accessibility effects ($\Delta P_{LA}$) are not important over the time period: i.e., a major change in these variables should cause substantial differences in the time series means for some groups of towns.

Table 1 is also consistent with the diffusion hypothesis. Under that hypothesis, a price change in any one town will influence neighboring towns. This process continues until price changes are equal for all towns. Thus, Table 1 does not allow discrimination between EMH and the diffusion hypothesis.

Table 2 reports the results obtained from estimating equations (9) and (10). The estimated coefficients are added to find the cumulative amount of diffusion of percentage change in house prices. The variable SUM is used to report these totals. (See Clapp and Tirtiroglu, 1992, for details).

For group 1, the most spatially homogeneous group, three of the

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5 Similar tests were conducted for all neighboring towns averaged together, as well as the average randomly selected town. The results strongly confirm those reported here, where four explanatory towns are used.
Table 1
Means and standard deviations of variables

<table>
<thead>
<tr>
<th></th>
<th>Group 1</th>
<th></th>
<th>Group 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Neighboring</td>
<td>Nonneighboring</td>
<td>Neighboring</td>
</tr>
<tr>
<td>Dep. Var.</td>
<td>0.00469 (0.03087)</td>
<td>-0.00288 (0.04397)</td>
<td></td>
</tr>
<tr>
<td>Ind. Var. 1</td>
<td>-0.00357 (0.03374)</td>
<td>-0.01221 (0.04803)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.00501 (0.03726)</td>
<td>-0.00091 (0.05526)</td>
<td></td>
</tr>
<tr>
<td>Ind. Var. 3</td>
<td>-0.00586 (0.03959)</td>
<td>0.00096 (0.04925)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.00003 (0.03100)</td>
<td>-0.00508 (0.03512)</td>
<td></td>
</tr>
<tr>
<td>Ind. Var. 4</td>
<td>-0.00764 (0.04562)</td>
<td>-0.00339 (0.04576)</td>
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<tr>
<td></td>
<td>0.00242 (0.04238)</td>
<td>-0.00122 (0.04397)</td>
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<table>
<thead>
<tr>
<th></th>
<th>Group 3</th>
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<tr>
<td></td>
<td>Neighboring</td>
<td>Nonneighboring</td>
<td>Neighboring</td>
</tr>
<tr>
<td>Dep. Var.</td>
<td>-0.00125 (0.05017)</td>
<td>-0.00030 (0.04427)</td>
<td></td>
</tr>
<tr>
<td>Ind. Var. 1</td>
<td>-0.00976 (0.05171)</td>
<td>-0.00523 (0.03842)</td>
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<tr>
<td></td>
<td>-0.00491 (0.04625)</td>
<td>-0.00514 (0.03835)</td>
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<tr>
<td>Ind. Var. 3</td>
<td>-0.01247 (0.04785)</td>
<td>0.00062 (0.04238)</td>
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<tr>
<td></td>
<td>-0.00102 (0.03113)</td>
<td>0.001267 (0.04494)</td>
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<tr>
<td>Ind. Var. 4</td>
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<td>-0.00643 (0.05382)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.00080 (0.03264)</td>
<td>0.00080 (0.04288)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Numbers in parentheses are standard deviations.

neighboring towns have diffusion coefficients above 0.1. Two of these coefficients are statistically significant at the 5% level after considering the Hansen–Hodrick corrections, equations (11)–(14). The sum of diffusion effects for neighboring towns is large and statistically significant. Non-neighboring towns have a much smaller and marginally significant sum, and none of the individual towns has a significant diffusion coefficient.

Likewise, the results for groups 2 and 3 are strongly supportive of diffusion and, therefore, of the type of positive feedback considered here. Both neighboring sums are strongly positive, as are several individual coefficients. By way of contrast, non-neighboring towns show no coefficients that are economically important or statistically significant.

The results for group 4 are mixed. Both neighboring and non-neighboring towns have one positive and significant coefficient. While neither of the sum variables is significant, the sum for non-neighboring towns is large.

Word-of-mouth diffusion of price information suggests a reasonably smooth function for the influence over time of neighboring price changes. Estimation of a distributed lag model shows that neighboring towns do
Table 2
SFR price appreciation on appreciation for neighboring and non-neighboring towns (estimation of equations (9) and (10))

<table>
<thead>
<tr>
<th>GROUP 1</th>
<th>GROUP 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta P_{E_{nn,l-4}}$</td>
<td>$\Delta P_{E_{nn,l-4}}$</td>
</tr>
<tr>
<td>(n \text{ or } nn=1)</td>
<td>-0.0022</td>
</tr>
<tr>
<td>(n \text{ or } nn=2)</td>
<td>0.1534</td>
</tr>
<tr>
<td>(n \text{ or } nn=3)</td>
<td>0.1782</td>
</tr>
<tr>
<td>(n \text{ or } nn=4)</td>
<td>0.1274</td>
</tr>
<tr>
<td>SUM</td>
<td>0.4570</td>
</tr>
<tr>
<td>R-SQUARE</td>
<td>0.1500</td>
</tr>
<tr>
<td>ADJ R-SQ</td>
<td>0.1122</td>
</tr>
<tr>
<td>NUM</td>
<td>95</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GROUP 3</th>
<th>GROUP 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta P_{E_{nn,l-4}}$</td>
<td>$\Delta P_{E_{nn,l-4}}$</td>
</tr>
<tr>
<td>(n \text{ or } nn=1)</td>
<td>-0.0814</td>
</tr>
<tr>
<td>(n \text{ or } nn=2)</td>
<td>-0.8143</td>
</tr>
<tr>
<td>(n \text{ or } nn=3)</td>
<td>0.0179</td>
</tr>
<tr>
<td>(n \text{ or } nn=4)</td>
<td>0.1254</td>
</tr>
<tr>
<td>SUM</td>
<td>0.2950</td>
</tr>
<tr>
<td>R-SQUARE</td>
<td>0.1683</td>
</tr>
<tr>
<td>ADJ R-SQ</td>
<td>0.1122</td>
</tr>
<tr>
<td>NUM</td>
<td>95</td>
</tr>
</tbody>
</table>

Note: * and ** indicate that the estimate is significant at 5% and 10%, respectively. The values in parentheses are t-statistics. NUM indicates number of observations.

follow a concave pattern peaking at the fourth lag (See Clapp and Tirtiroglu, 1992).

6.1. Results including own lags

Table 3 reports results including the dependent variable lagged four quarters (own lags) as an explanatory variable. Table 3 can easily be compared to Table 2 because the two are the same except for the first row of each group which is the own lag in Table 3.
Table 3
SFR price appreciation for own town neighboring and non-neighboring towns

<table>
<thead>
<tr>
<th>GROUP 1</th>
<th>GROUP 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔP_{n-4}</td>
<td>ΔP_{nn-4}</td>
</tr>
<tr>
<td>own town</td>
<td>-0.3851</td>
</tr>
<tr>
<td></td>
<td>(-3.0147)*</td>
</tr>
<tr>
<td>n or nn=1</td>
<td>-0.0026</td>
</tr>
<tr>
<td></td>
<td>(0.0309)</td>
</tr>
<tr>
<td>n or nn=2</td>
<td>0.1878</td>
</tr>
<tr>
<td></td>
<td>(2.8109)*</td>
</tr>
<tr>
<td>nn or nn=3</td>
<td>0.1084</td>
</tr>
<tr>
<td></td>
<td>(1.4647)</td>
</tr>
<tr>
<td>nn or nn=4</td>
<td>0.1803</td>
</tr>
<tr>
<td>SUM</td>
<td>(2.3704)*</td>
</tr>
<tr>
<td>R-SQUARE</td>
<td>0.3247</td>
</tr>
<tr>
<td>ADJ R-SQ</td>
<td>0.2792</td>
</tr>
<tr>
<td>NUM</td>
<td>95</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GROUP 3</th>
<th>GROUP 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔP_{n-4}</td>
<td>ΔP_{nn-4}</td>
</tr>
<tr>
<td>own town</td>
<td>-0.1638</td>
</tr>
<tr>
<td></td>
<td>(-1.2052)</td>
</tr>
<tr>
<td>n or nn=1</td>
<td>-0.0931</td>
</tr>
<tr>
<td></td>
<td>(-1.0181)</td>
</tr>
<tr>
<td>n or nn=2</td>
<td>0.0077</td>
</tr>
<tr>
<td></td>
<td>(0.0572)</td>
</tr>
<tr>
<td>n or nn=3</td>
<td>0.2855</td>
</tr>
<tr>
<td></td>
<td>(2.4043)*</td>
</tr>
<tr>
<td>n or nn=4</td>
<td>0.1548</td>
</tr>
<tr>
<td>SUM</td>
<td>(0.7703)</td>
</tr>
<tr>
<td>R-SQUARE</td>
<td>0.3550</td>
</tr>
<tr>
<td>ADJ R-SQ</td>
<td>0.1119</td>
</tr>
<tr>
<td>NUM</td>
<td>95</td>
</tr>
</tbody>
</table>

NOTE: * and ** indicate that the estimate is significant at 5% and 10%, respectively. The values in parentheses are t-statistics. Neighboring towns are indexed by n, and non-neighboring by nn. Neighboring towns are ordered by increasing distance from the central business district. The own town row is the dependent variable lagged four quarters. SUM does not include the own town coefficient. NUM indicates the number of observations.

The results for neighboring and non-neighboring towns are substantially the same in the two tables. This is true whether one looks at each coefficient individually or at the SUM of all neighboring or non-neighboring coefficients (the SUM row of the two tables). Thus, including the own-town variable does not cause important modifications of the conclusions of Table 2.
Negative coefficients on the own-town variable result from measurement errors causing spurious negative correlation. The results in Tables 2 and 3 are not consistent with EMH. Towns within a metropolitan area are substitutable, so that information causing price changes in one town should be reflected by all prices in the area, provided that the information has general implications for the area (see the discussion below of the Tiebout hypothesis). Thus, non-neighboring towns should be influenced as much as neighboring towns.

7. Alternative explanations of the results

An intuitively plausible notion is that towns within a metropolitan area are substitutable. Thus, ‘a local shock, such as the closing of a big factory, should be expected to induce cross-sectional as well as time-series correlation in housing prices.’ While this certainly is true, the purpose of this section is to point out that substitutability does not imply the pattern of lagged positive correlations with neighboring towns observed in our data.

7.1. The Tiebout hypothesis

The Connecticut towns, the unit of observation for this study, have autonomous governments, each with its own bundle of services, regulations, and taxes. According to the Tiebout model, any changes in these bundles should be reflected in housing prices, the $\Delta P_{LP}$ term in equation (1). In essence, households ‘vote with their feet,’ moving towards towns with attractive bundles (away from those with less attractive bundles); this bids up (down) the price of land in those towns. Mills and Oates (1975) point out that the local public services considered in the Tiebout model can be consumed only by local residents. Thus, the bundle of services, regulations, and taxes should have no direct influence outside the boundaries of the town.

In an open economy (utility is fixed throughout the metropolitan area), there should be no association between $\Delta P_{LP}$ terms for any pair of towns. Migration into or out of the metropolitan area will cause changes in house prices to compensate for changes in local taxes and local public services (i.e., in the efficiency of local government operation) in any one town. After migration, utility in the town with the changed bundle will be the same as

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6 Shorter time lags show much larger positive coefficients for neighboring towns: 1–3 quarter lags for all 19 towns stacked together give coefficients of 0.69, 0.54 and 0.36, respectively. All coefficients are statistically significant.

before the bundle changed. Other towns, with no changes in their bundles, will have no changes in utility or in property values.

In a closed economy (no migration into or out of the metropolitan area) there will be a negative association: people move away from towns with no change (or negative changes) in their bundles (and, by implication, zero or negative changes in local government efficiency) and into towns with positive changes.

We found significant positive association between neighboring towns, contrary to the zero or negative predictions from the Tiebout hypothesis.

7.2. Changes in the price gradient due to local accessibility

Price changes may be due to improvements in accessibility (e.g., job growth or highway improvement), the \( \Delta P_{LA} \) term in equation (1). The 'new urban economics (NUE)' theory says that the cross-sectional price gradient is:

\[
\frac{\delta P}{\delta d_i} = -\frac{q}{S'(d_i)},
\]

where \( d_i \) is distance from town \( i \), which is a center of employment, \( q \) is transportation cost per unit distance, and \( S' \) is the compensated demand (\$ expenditure) for housing at distance \( d_i \).

Any change in employment, income, or accessibility will cause the entire gradient to shift, producing \( \Delta P_i \) (changes over time) in each town (see Mills and Hamilton, 1984). Can these changes be related across neighboring towns so as to produce the observed positive values for \( \beta_1 \) (equation 9)?

Since Hartford is a monocentric city, any change over time in the price gradient in equation (15) would make the gradient steeper (Case 1) or leave it unchanged or flatter (Case 2). The second case is more likely (see Mills and Hamilton, 1984, p. 102). But, in either case, the results from equation (9) will not be symmetrical. In Case 2 (Case 1) towns farther (closer) to the center will have \( \Delta P \) greater than their neighboring town. This implies \( \beta_1 > 1 \) in equation (9), whereas \( \beta_1 < 1 \) for the neighbor on the other side (e.g., closer to the center in Case 2).

In Table 2, neighboring towns were arranged by distance from the center of Hartford: \( n=1 \) is closer to the center than \( n=2 \), etc. But no spatial pattern was observed for \( \beta \) as a function of \( n \). More importantly, we did not observe any results indicating \( \beta > 1 \) (or even close to one), contrary to predictions from the NUE model.

A review of newspaper articles and other information sources indicates no major changes in the price gradient for Hartford during our sample period. There were no major changes in transportation arteries or employment centers. Employment growth was small and it was concentrated in the center.
of the metropolitan area. Thus, as suggested by Table 1, $\Delta P_{LA}$ does not play an important role in equation (1).

7.3. **Explanations based on neighborhood effects**

Davis and Whinston (1973) proposed the application of game theory to explain spatial interdependencies associated with urban blight and gentrification. Their model is based on the notion that the value of a given property is partly determined by investment and maintenance decisions made by neighboring properties. Could changes over time in blight and gentrification explain the diffusion of price movements observed in the Hartford data?

Detailed analysis of newspaper articles indicates gentrification and blight were largely confined to the town of Hartford. But Hartford is not in the sample of towns used for this study. The town of Bloomfield, adjacent to the North end of Hartford, did experience substantial racial change from White to Black during the sample period. However, Bloomfield is a dependent variable in Group 4 where the results were not strongly supportive of the diffusion hypothesis. Thus, urban blight and gentrification were not of sufficient magnitude to explain the results reported in Table 2.

8. **Conclusions**

The representativeness heuristic is a general behavioral principle that has been extensively tested in the laboratory. It says that decision makers:

1. overemphasize present (i.e., most recent) evidence at the expense of historical information;
2. draw unwarranted conclusions from small samples;
3. attach causal significance to extreme outcome from a distribution that is, in actuality, characterized by regression to the mean;
4. use stereotypes to reduce the cost of making a decision.

The positive feedback hypothesis is a special case of the representativeness heuristic where financial news is the present evidence. This paper argues that rates of change in asset prices are taken as the present evidence for the positive feedback hypothesis. It is the first test of the representativeness heuristic using market data.

The representativeness heuristic is tested with single-family house prices for 19 towns in the Hartford area over the 1982–88 period. There is a strong positive association between change in an index of prices for a constant-

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*Our specialization of the representativeness heuristic should hold in all asset markets. We use housing markets to test the data because transactions costs provide enough inertia to observe the diffusion of price information through the market. In financial markets, this diffusion probably occurs too fast to observe much positive feedback with daily (or longer) data.*
quality house in a given town and lagged price changes in neighboring towns. There is no such association with non-neighboring towns. A new version of the Hansen–Hodrick method was used to test the significance of these results.

Alternative theories cannot explain these results. Some price changes at the town level may be due to ‘Tiebout’ changes in taxes and public services. In this case, there should be zero (in an open economy) or negative (in a closed economy) parameters in our diffusion model. Price changes due to accessibility improvements can be investigated using the ‘new urban economics’ model, but this model predicts coefficients ranging around one, contrary to our findings. Finally, the hypothesis that neighborhood effects result from interdependent decisions (the ‘prisoners dilemma’) might explain our findings. But, the spread of blight and gentrification were localized and relatively unimportant in Hartford during our sample period.

References


