Empirical Economics (2002) 27:403–425

EMPIRICAL
ECONOMICS

On the herding instinct of interest rate forecasters*

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First version received: June 1999/Final version received: February 2001

Abstract. It is not uncommon to observe the published forecasts of economic commentators closely bunched together over long periods of time. In our case, the phenomenon is observed for eight national panels of economists who report monthly forecasts. A framework is developed that conveniently nests within it several simple, yet plausible forecasting rules, and allows us to explore the extent of the clustering phenomenon.

Key words: Clustering of forecasts; forecast accuracy; panel data

JEL classification: C33, C53

1. Introduction

It is not uncommon to observe the published forecasts of economic commentators closely bunched together over long periods of time. For example, Zarnowitz (1979), and MacFarlane and Hawkins (1983), both found a strong tendency for individual forecasts to be more highly correlated with the mean forecast than with the actual outcome of the variable of interest. In our case, the phenomenon is observed for national panels of economists who report three-month-ahead forecasts of three month interest rates each month. This empirical regularity is the context within which we seek to analyse the behaviour of forecasters.

Data on panels of forecasts have previously been used to test theories of how expectations are formed. For example, Keane and Runkle (1990) and

* We acknowledge the financial assistance of the Australian Research Council. We would like to thank Graham Elliott, Brett Inder, and the editor and referee of this journal for their comments and suggestions. Sean Gleason provided excellent research assistance on this project. This project was conducted while Fiebig was affiliated to the University of Sydney

MacDonald and Macmillan (1994) investigate the rationality of expectations. The procedure they use is indirect in that there is no need to isolate the actual process by which the expectations (or forecasts) are actually generated. Rather, they test whether forecasts and subsequent realisations satisfy various theoretical properties such as unbiasedness and efficiency. By comparison, this literature also includes examples where the testing proceeds through direct modelling of an hypothesised mechanism generating forecasts. One example is testing adaptive expectations such as in Figlewski and Wachtel (1981). Our contention is that there are insights to be gained by this direct approach. As such we concentrate on modelling the forecast mechanism and do not test the rationality of our panel of forecasters; this has been considered by Kelly (1998) using a related data set.

Another potential source of data is that obtained in an experimental setting. Hey (1994) recently used experimental methods to test alternative theories of expectations formation. Participants in the experiment were shown time series data and provided incentives to accurately predict the future values. In analysing the predictions of his experimental forecasters he found that he could provide a good explanation of the predictions being made by a simple model involving past values of the variable being predicted. This part of his work is similar in spirit to ours. The important distinctions are that the data sources are different and that his forecasters acted independently without knowledge of the forecasts of the other participants. Given our results, the issue of interdependence of forecasters in an experimental setting is one worth pursuing.

While forecasters may act independently, clustering of forecasts can still occur. As Zarnowitz and Lambros (1987) observe, forecasters "use in part the same public information and the same established techniques and relationships. The common elements induce some positive correlation across the resulting forecasts." While the actual forecasting methods used by individuals are unknown to us, we have been able to successfully specify and estimate a regression model that adequately fits the observed time series of individual interest rate forecasts within and between countries. The chosen specification conveniently nests within it several simple, yet plausible forecasting rules, and allows us to explore the extent of the clustering phenomenon.

In our analysis, forecasters who are found to act independently, like Hey's experimental forecasters, are referred to as 'time series modellers'. They take little or no direct notice of the actions of other forecasters. In our modelling context, this situation occurs when the consensus mean is not an important determinant of an individual's forecasts. But as has been emphasised by Banerjee (1992), the actions of others potentially convey useful information that a rational forecaster would use. Such individuals or 'followers' (since they follow the herd) are using the information contained in the consensus mean as part of their information set.

Herding can also occur when forecasters act strategically. It is reasonable to assume that forecasters (sometimes called managers) have objective functions that depend on factors other than forecast accuracy. For example, there is the safety in numbers argument presented by Palley (1995). There are incentives to report forecasts not too far from the expected range of the remainder of the panel. There is a fear of being alone, or more precisely, alone and wrong. Using ideas similar to the safety in numbers argument, Ehrbeck and Waldmann (1996) formalised what they termed "rational cheating"; that is, reporting biased predictions because forecasters are not only trying to predict the outcome but are willing to compromise accuracy in order to "look good before the outcome is observed".

Similarly, Scharfstein and Stein (1990) suggested that under certain circumstances, forecasters would simply follow the herd fearing that doing otherwise would adversely impact on their reputations. While rational from an individual perspective, they emphasise the inefficiency of this behaviour from a social standpoint. By following the herd, forecasters are ignoring substantive private information. In terms of our results, we identify 'strong followers'. These are forecasters who ignore their own past forecast in preference to the previous consensus mean as a determinant in updating their own forecasts. We also classify those forecasters who are influenced by the previous consensus mean, but retain a dependence on their previous forecast, as 'weak followers'.

The problem with only having access to the published forecasts is that it is not possible to distinguish between those forecasters who herd because they are prepared to alter their forecasts in order to follow the pack, and those who herd because they acknowledge that there is important information contained in the previous consensus mean that was not available to the individual forecaster at the time. Thus, throughout this paper, the term herding is used to denote the tendency to produce a range of forecasts which is narrower than that which would likely be observed if the forecasts were produced on a strictly independent basis because a forecaster takes the previous consensus mean into account. Clustering, on the other hand, is a term which implies that the range of forecasts is narrower than that which might be expected from independent forecasters only because they are exposed to similar information and forecasting techniques and not because they refer to the past consensus mean.

Scharfstein and Stein also suggest the possibility of breaking from the herd and scattering. Here the incentive is to make a name for oneself, which is difficult as part of the herd. This behaviour is difficult to justify for any reason other than that defined in Scharfstein and Stein. Thus, scattering is assumed to imply that individual forecasters deliberately attempt to produce forecasts that are different from the pack.

What is the mix between followers or herders, on the one hand and time series modellers on the other? What is the prevalence of strong followers and weak followers, and is there any evidence of scattering? These are some of the questions we seek to answer using forecasts for eight different interest rates, one for each of the G-7 countries and Australia. This framework allows us to link our findings back to the difficulty of the series being predicted. Furthermore, by estimating a separate equation for each of the 104 forecasters in the data set, we allow for systematic differences in the behaviour of forecasters within and between countries. Finally, rather than the bivariate specifications of say Ehrbeck and Waldmann (1996), we analyse the data in a more general framework with a richer dynamic structure.

Our empirical results indicate that over 40% of the individual forecasters can be characterised as time series modellers using our definition. For this large group, clustering of forecasts has occurred, but the evidence is not consistent with it being a result of herding tendencies. We find no significant evidence of scattering, leaving more than half of the individual forecasters where there appears to be a significant tendency to herd. Amongst these, a substantial proportion put little or no weight on their own past forecasts. Interestingly, the degree of herding varies markedly across countries and it is argued that this behaviour might depend on interest rate volatility or predictability. That is the

Table 1. Data definitions

Country	Definition
United States	3 month Treasury Bill Rate (%)
Japan	3 month Yen Certificate of Deposit (%)
Germany	3 month Euro – DM Rate (%)
France	3 month Euro – FFr Rate (%)
United Kingdom	3 month Interbank Rate (%)
Italy	3 month Treasury Bill Rate (%)
Canada	3 month Treasury Bill Rate (%)
Australia	90 day Bank Bill Rate (%)

incentives to follow the consensus mean appears to increase with the difficulty of the forecasting problem.

2. Approximating the forecasting process

Since February 1990, Consensus Economics Inc. of London has collected and published forecasts on a number of economic variables for a number of countries including the USA, Japan, Germany, France, the UK, Italy, Canada and Australia, although in the case of Australia, the panel was not formed until November 1990. In this paper we focus on the monthly publication of three-months-ahead forecasts of a three month interest rate, the definition of which is country specific and given in Table 1.

The outcome, the consensus mean, the high and low for each panel are presented in Figure 1. A degree of clustering is self-evident and typical correlations between each consensus mean and the individual forecasts is above 0.98. The lowest such correlation is 0.966 for a forecaster in the Italian panel. However, these particularly large correlations are attributable in part to the time series properties of the series being predicted; cross-correlations are biased in the presence of autocorrelation in the component series.

In hindsight, the difficulty of forecasting each rate varies across countries. The three continental European rates were greatly affected by the Maastricht decision in 1992 while Canada experienced additional volatility during a similar time period. By comparison, the time series for the USA, Germany and Japan are relatively smooth. Importantly, the Australian series is similar to that for the USA in appearance but the conduct of monetary policy was quite different. Just prior to the period in question, the Reserve Bank of Australia announced that it would make fewer but larger changes in target rates than had previously been considered and this announcement had a possible impact on the degree of herding behaviour to follow.

Each time series is clearly persistent in the sense that the actual rates can be characterised by an autoregressive process with a dominant root near unity, and this property has the potential to impact on the distribution of regression estimates reported in the following section. However, it is unlikely that an interest rate can have a unit root as this would imply infinite variance and so cointegration methods are not appropriate.

It is known from Elliott, Rothenberg and Stock (1996) and Stock (1995) that hypothesis testing is particularly difficult in this local-to-unity case since

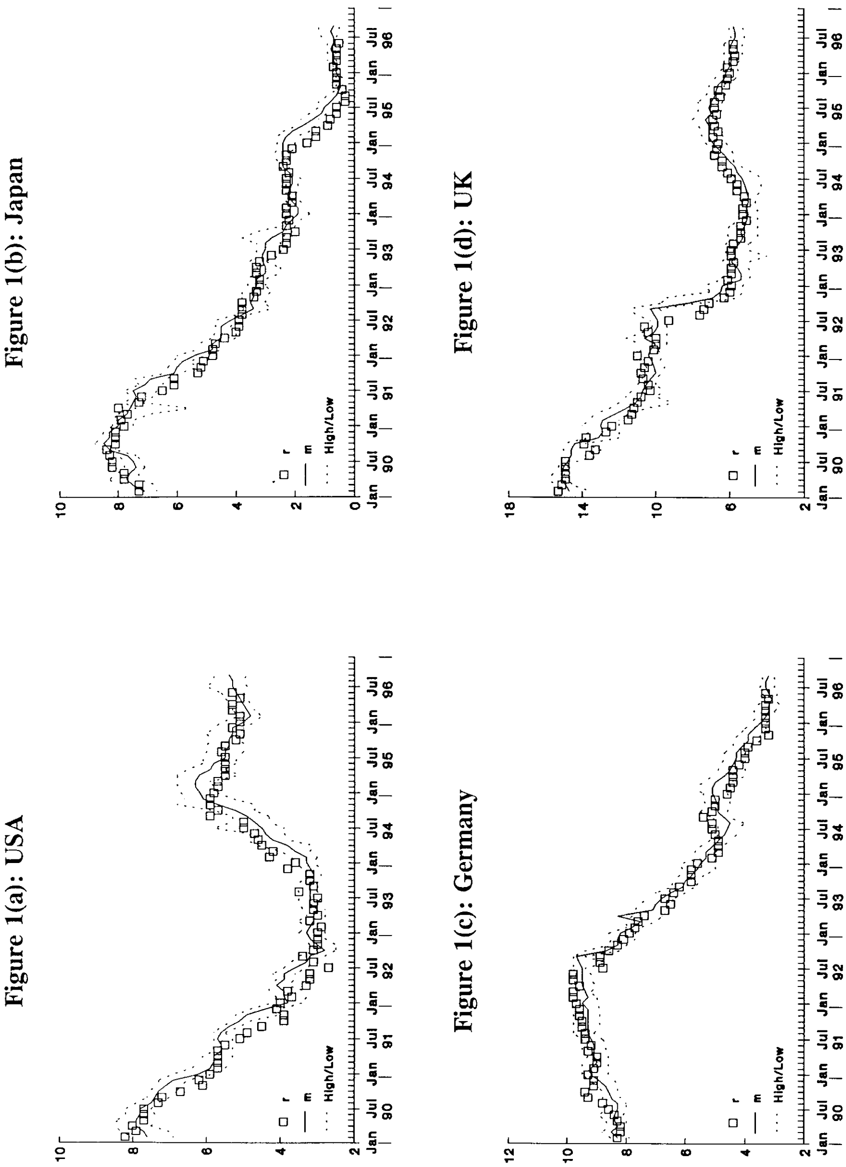

Fig. 1. Consensus Mean, High, Low and Realisations

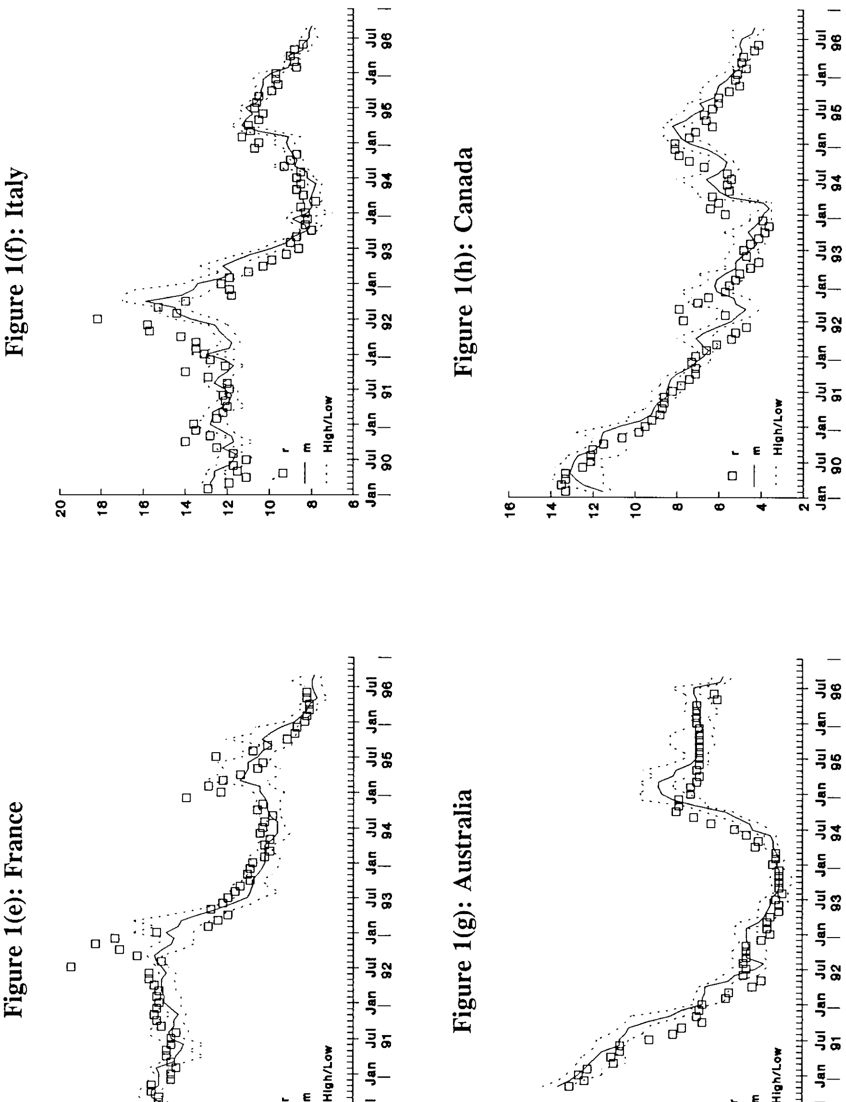

Fig. 1. Continued

neither the standard asymptotic theory for stationary time series or that for cointegrated I(1) series applies.[1] Since the appropriate theory has not yet been developed for the case of more than one regressor in the local-to-unity case, it is somewhat fortunate that certain parametric restrictions can be imposed on our model that effectively reduce each series in the estimated model to stationary processes so that asymptotic normality can reasonably be assumed.

A number of forecasters either left or joined the panels during the sample period April 1990–September 1996, or January 1991–September 1996 in the case of Australia. Moreover, not all individuals reported a forecast for every month. Given that the use of very different sample periods for each individual could cause problems of interpretation and comparison owing to the varying degree of difficulty in predicting rates over time, we chose to include only those individuals who reported more than 50 monthly forecasts. However, the reported consensus mean (using all individuals) was used in modelling behaviour since this is the consensus forecast that is readily available to the individuals in the preparation of their forecasts and the estimate of the mean did not appear to be sensitive to these variations in panel size.

In the process of generating interest rate forecasts, economic agents are assumed to draw on various sources of available information. The information set includes current and past interest rates, previous forecasts made by the individual forecaster and those made by other members of the panel. The latter will represent the previous consensus views of future interest rates which are summarised here by the published mean of forecasters.

In order to address the herding question, a model needs to be specified which enables the various types of behaviour to be tested: strong followers, weak followers and time series modellers. Our contention is that such a model for three month rates is an equation which nests within it a number of interesting alternative models which are useful for classifying the type of herding behaviour:

$$f_i = \alpha + \beta_{1i} r + \beta_{2i} r_{-1} + \beta_{3i} m_{-1} + \beta_{4i} f_{i,-1} + u_i \tag{1}$$

$$u_i = \rho_i u_{i,-1} + \varepsilon_i$$

where

f_i = 3-month ahead forecast by individual i
m = consensus mean
r = 3-month interest rate
ε_i = an i.i.d. disturbance term.

Since the means of each of the series in equation (1) are of the same order of magnitude, the β_{ji} coefficients can be interpreted as approximations to the mean elasticities of the effect of each component on the individual's forecast. Thus, β_{1i} measures the impact of new information contained in the current interest rate that was not present in the previous rate or forecasts. Similarly, β_{3i} measures the impact on the new forecast of the previous consensus mean holding the previous individual's forecast constant. A zero value for this parameter

[1] Kelly (1998) has investigated the impact of assuming stationary, nearly nonstationary, and I(1) asymptotics on hypothesis testing for any bias in consensus mean forecasts using a similar sample period and a related data set. Her results supported the more general conclusions of Stock (1995).

implies that the old consensus mean is ignored when updating the individual's forecast. Using a similar argument, a zero value for β_{4i} implies that the individual ignores his or her previous forecast in the updating process. It was found that an autoregressive error process is necessary in some cases to model the dynamics of updating forecasts and is included in all equations in the spirit of having one general model that encompasses the behaviour of all forecasters.

It is not possible for a forecaster to consistently set his or her forecasts exactly equal to the consensus mean as it is not known until after all of the forecasts have been collected and averaged. Thus, even in the most extreme case of strong herding, one would expect variations between m_{-1} and $f_{i,-1}$; it is the manner in which a forecaster reacts to a difference between those outcomes that defines the existence or otherwise of herding.

Although one could estimate equation (1) as it stands, it is useful to argue that certain reasonable restrictions can be placed on the coefficients which reduce the obvious problem of multicollinearity that would otherwise exist. These are achieved by investigating the long-run properties of equation (1).

Equation (1) implies an equivalent Bewley (1979) transformation of the form

$$f_i = \alpha/(1-\beta_{4i}) + [(\beta_{1i}+\beta_{2i})/(1-\beta_{4i})]r + [\beta_{3i}/(1-\beta_{4i})]m_{-1} - [\beta_{2i}/(1-\beta_{4i})]\Delta r - [\beta_{4i}/(1-\beta_{4i})]\Delta f_i + u_i/(1-\beta_{4i}). \tag{2}$$

Equivalently,

$$f_i = a + \lambda_{1i}r + \lambda_{2i}m_{-1} + \lambda_{3i}\Delta r + \lambda_{4i}\Delta f_i + v_i \tag{3}$$

using obvious notation.

In equilibrium, equation (3) becomes

$$f_i = a + \lambda_{1i}r + \lambda_{2i}m. \tag{4}$$

If $\Sigma_j\beta_{ji} = 1$ then $\lambda_{1i} = 1 - \lambda_{2i}$ so that, when $a = 0$ and equation (4) is averaged over all n individuals, we obtain

$$n^{-1}\Sigma[f_i = \lambda_{1i}r + (1-\lambda_{1i})m] \tag{5}$$

or

$$m = \bar{\lambda}_1 r + (1-\bar{\lambda}_1)m \tag{6}$$

where $\bar{\lambda}_1$ is the mean of the λ_{1i} and $m = r$ in equilibrium (providing that $\bar{\lambda}_1 \neq 0$). Thus, long-run rationality of the consensus is assumed, which has support from Kelly, but temporary short-run disequilibria are permitted which are consistent with such phenomena as rational cheating. Moreover, $\Sigma_j\beta_{ji} = 1$ and $a = 0$ implies $f_i = m$ in equilibrium.

The stability of the i^{th} equation (1) depends on all n equations in the country since m_{-1} is the mean of the $f_{i,-1}$. Thus, the stability of the system is more complicated than the simple requirement that $|\beta_{4i}| < 1$ in each equation.

While the basic equation (1), subject to $\Sigma_j\beta_{ji} = 1$, $a = 0$ is relatively simple, there are a number of interesting cases nested within it. For example, the following eventual forecasting functions are special cases:

(i) Random walk	$f_i = r$	$\rho_i = 0$
(ii) AR(1) in differences:	$f_i = \delta_i r + (1 - \delta_i) r_{-1}$	$\rho_i = 0$
(iii) AR(2) in differences:	$f_i = \delta_i r + (1 - \delta_i) r_{-1}$	$\rho_i \neq 0$
(iv) Exponential Smoothing:	$f_i = \delta_i r + (1 - \delta_i) f_{i,-1}$	$\rho_i = 0$
(v) ARIMA(1,1,1)	$f_i = \delta_i r + (1 - \delta_i) f_{i,-1}$	$\rho_i \neq 0$

In terms of herding, the presence of the consensus mean in equation (1) is the key. If $\beta_3 = 0$, then the corresponding forecaster can be thought of as acting independently using conventional time series models; otherwise the forecaster exhibits herding characteristics.

Herders are classified as strong followers if $\beta_{4i} = 0$ as they take no account of their own past forecasts. The remaining herders are weak followers in that they take into account both the past consensus mean and their own track records.

The subcategory of time series modellers (i.e. $\beta_{3i} = 0$) corresponding to $\beta_4 = 0$ is referred to as 'autoregressive modellers' since the forecast generating process (1) is consistent with an autoregressive model in the rates and no other variable as in models (i)–(iii). The remainder are termed 'adaptive expectations forecasters' as in models (iv) and (v). Of course, individuals may be using a variety of other techniques in making their predictions and this classification only serves to give the closest approximation to the actual processes being used from the set under consideration.

If $\beta_3 < 0$ there is an indication of scattering. Forecasters are attempting to differentiate themselves by systematically moving away from the herd.

There are two ways of classifying herding (i.e. $\beta_{3i} > 0$) in an empirical setting. On the one hand, herding characteristics can be attributed solely on the basis of the rejection of a hypothesis test that $\beta_{3i} = 0$. Naturally such a classification depends upon the chosen level of significance. On the other hand one can use the numerical values of the $\hat{\beta}_{3i}$ since poorly determined coefficients might result in large values of $\hat{\beta}_{3i}$ being insignificantly different from zero. In our situation there does not appear to be any major difference between the two approaches. This is due to the standard errors of the $\hat{\beta}_{3i}$ being reasonably similar across individuals within a given country.[2] Both approaches are considered in the following section.

3. Results

The persistence of each time series in equation (1) would cause a multicollinearity problem if extraneous information were not available or assumed, causing tests of herding to have low power. However, substituting the restriction, $\Sigma_j \beta_{ji} = 1$, which is a necessary condition for $f_i = m = r$ in equilibrium, produces alternative parameterisations, one of which is

[2] Since three of the four variables, r, r_{-1} and m_{-1} are the same over individuals, reasonably similar sets of forecasts for each individual would produce similar standard errors of the estimate and, hence, standard errors of $\hat{\beta}_{3i}$.

$$\Delta f_i = \alpha + \beta_{1i}(r - f_{i,-1}) + \beta_{2i}(r_{-1} - f_{i,-1}) + \beta_{3i}(m_{-1} - f_{i,-1}) + u_i \tag{7}$$

$$u_i = \rho_i u_{i,-1} + \varepsilon_i$$

It can be noted that the time series properties of the regressor actually used in estimation are quite different from those in (1). The degree of persistence in Δf_i is much less than in f_i itself and the differences between each of r, r_{-1} and m_{-1}, and $f_{i,-1}$ reveal much more randomness than the directly observed series. Importantly for the hypothesis testing, the degree of multicollinearity between the regressors in (7) is much less than in (1).

Each of the 104 equations (7), one for each individual forecaster, was separately estimated by maximum likelihood while allowing for autocorrelated disturbances and missing observations, due to the changes in the panels and failures to report, using SHAZAM (White, 1993): see Savin and White (1978) and Richardson and White (1979) for details.

While there is the potential for exploiting correlation among the disturbances across equations within a panel, the dual problems of autocorrelated disturbances and missing observations rendered the problem unreasonably complicated. The possibility of pooling the data across individuals was also considered but, as the main purpose of this paper is distinguish between forecasters, such an approach of assigning a common behaviour across forecasters would not be appropriate. Moreover, we have both a large number of individuals in each panel and time series observations making the need for pooling less than in the typical pooling context when typically there are insufficient data in one dimension to enable an equation to be estimated independently.

The estimation was repeated under another parameterisation to produce an estimate of β_{4i} and its standard error. The regression results are presented in Tables A1–A8 in the appendix along with LM tests for first-order serial correlation and $\bar{R}^2$, which is defined using equation (7) with Δf_i as the dependent variable.[3]

In only one of the 104 equations is the null of no serial correlation in the residuals $\hat{\varepsilon}_i$ rejected at the 1% level, two at the 2.5% level and eight at the 5% level which is reasonably consistent with the sizes of the tests under the null of no serial correlation. Moreover, the magnitudes of the $\bar{R}^2$ statistics are surprisingly large given the dependent variable is in first-difference form; 58 of the 104 $\bar{R}^2$ are greater than 0.5. That much of the variation in the changes in the forecasts is 'explained' by a five-parameter model (7) suggests that the updating method used by most individuals in the panels is relatively orderly and mechanistic. Accordingly, this model is taken to be a reasonable representation of the data.

A plot of the 104 estimates of $\hat{\beta}_{3i}$ against $\hat{\beta}_{4i}$ is displayed in Figure 2 for a numerical representation of herding characteristics from where the preponderance of $\hat{\beta}_{3i} > 0$ can be noted. Table 2 summarises the salient features of these estimates using an the asymptotic t-ratio cut-off of 1.96 to classify forecasters by the hypotheses discussed in the previous section.

In total, over 40% of the individual forecasters can be characterised as time series modellers using the statistical significance approach, or a cut-off of about

[3] For each parameterisation, the standard error of the estimate is the same but the variance of the dependent variable, and hence $\bar{R}^2$, is different. This version was chosen since it measures the degree of explanation of the forecast updating process.

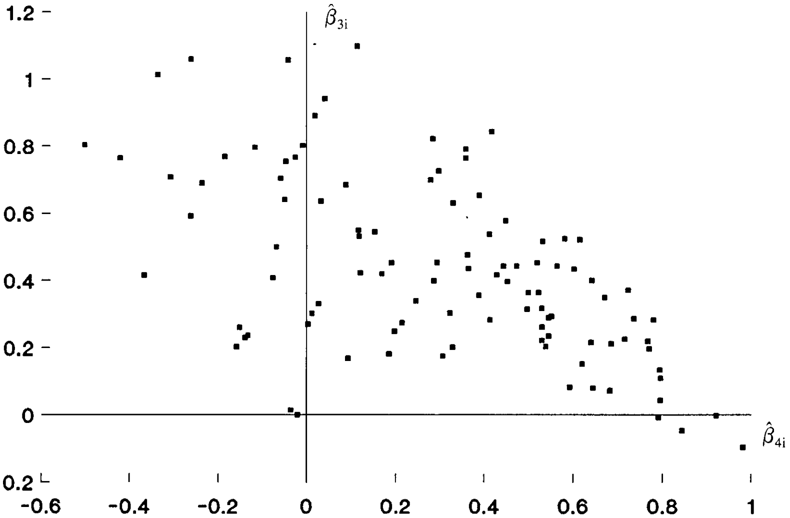

Fig. 2. Coefficient Estimates for Each Forecaster – $\hat{\beta}_{3i} v \hat{\beta}_{4i}$

Table 2. Categorisation of forecasters using a criterion of statistical significance at the 5% level

Country	Strong followers	Weak followers	Autoregressive expectations	Adaptive expectations	Total
U.S.A.	5	1	4	3	13
Japan	0	4	3	7	14
Germany	1	5	2	9	17
U.K.	4	9	0	5	18
France	6	7	0	0	13
Italy	1	2	1	3	7
Australia	1	7	0	4	12
Canada	5	1	4	0	10
Total	23	36	14	31	104

$\hat{\beta}_{3i} < 0.4$ in the numerical version of the classification from Figure 2. For this large group, clustering of forecasts has occurred, but the evidence is consistent with it not being a result of herding tendencies.

We find no statistically significant evidence of scattering, or at least no systematic tendency for any forecaster to consistently move away from the consensus mean. There are only four negative estimates of β_{3i} with the smallest being −0.097 with a *t*-ratio of −0.98. It may be that some forecasters in some periods have acted to differentiate themselves from the herd but this intermittent behaviour would not be identified by our analysis which assumes a constant behaviour over time.

This leaves more than half of the individual forecasters where there appears to be a tendency to herd. Amongst these, a proportion is classified as strong followers; 22% of all forecasters follow the herd but put little or no weight on their own past forecasts.

The proportion of forecasters who are followers varies from country to country. For example, using the results of Table 2, all of the 13 French panellists are followers but little more than a quarter of the Japanese panellists are significantly influenced by the mean. It can be recalled from Figure 1 that the French interest rate underwent a period of extreme volatility in 1992 and this may have contributed to the herding instinct in that panel. On the other hand, the Japanese rate was not as volatile and, arguably, greater (ex post) predictability reduced the need to herd.

In order to gain further insight into the herding phenomenon, the proportion of strong followers from Table 2 are plotted against the volatility of the interest rate being predicted, defined as the mean absolute deviation of the observed interest rate changes, in Figure 3(a). The averages of the $\hat{\beta}_{3i}$ for each country are plotted against the same measure of interest rate volatility in Figure 3(b). Whilst these relationships are far from perfect, Figure 3 lends some support to the belief that forecasters are more likely to herd, the more difficult is the task of prediction. It would be interesting, but extremely difficult, to build a model in which β_{3i} and β_{4i}, in particular, depended on not only country-specific features of predictability but also enabled that parameter to evolve over time based on, say, an ARCH process for the process ε_i as a measure of time-dependent predictability.

The dynamics for each national panel are more easily shown via a deterministic simulation. In each case, the impulse response functions in Figure 4 indicate how the models of the extreme individuals and the consensus mean (solid line) responded to a permanent 1% shock in time period 0.

In each case, the equilibrium is stable but it can be noted that there are variations in the speed of adjustment to a shock. Even though the French, Italian and Canadian panels experienced a similar degree of interest rate volatility, they reacted quite differently with the French panel the slowest to react and the Canadian the quickest. Only in the case of the UK and Australia does any panellist over-react to a qualitatively significant extent.

4. Conclusions

In the business economist world, it is commonly acknowledged that forecasts tend to be clustered and frequently 'wrong' together. Factor '*X*', the unknown but common forecast error pervades the real time forecasting experience. While the true forecast generation process is difficult, if not impossible, to describe, it is possible to approximate forecast behaviour in terms of a number of key drivers.

We have characterised individual forecasters of interest rates in eight countries by the estimated impact of the lags of their own forecasts and those of the consensus mean of the country's panel on the forecast updating process. In more than half of the 104 cases was the consensus mean found to be a significant determinant of the change in an individual's forecast. In approximately one quarter of all cases, the individual was not significantly affected by his/her own past forecast but was so by the consensus mean. Why forecasters should disregard their own track records is somewhat alarming but this behaviour is consistent with the notion that some individuals do not have any significant private information.

We find that the behaviour of forecasters differs markedly across countries. Not surprisingly, forecasters tend to herd, the greater is the unpredictability of

Figure 3(a): Statistical Criterion

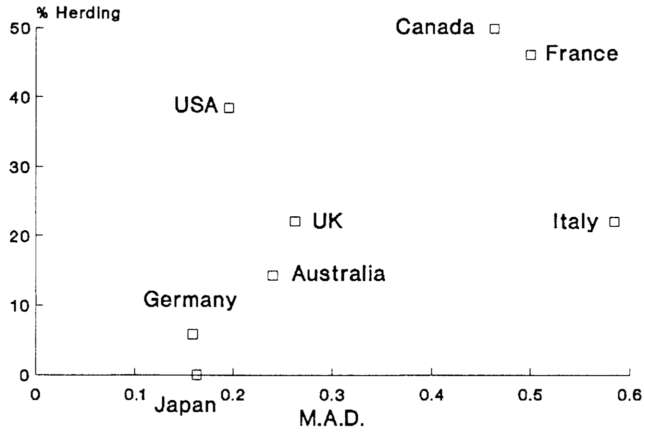

Figure 3(b): Numerical Criterion

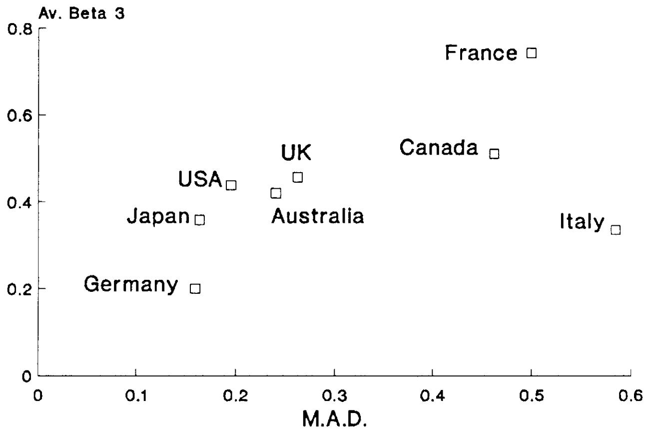

Fig. 3. Herding and Unpredictability

the series being forecast. In the case of France, which underwent extreme volatility during the middle of the sample, all 13 forecasters were found to be significantly affected by the consensus mean. On the other hand, German, US and Japanese forecasters experienced a lesser tendency to herd. Given the ex post similarity of the USA and Australian interest rate paths, it is of interest that Australian forecasters are much more prone to 'follow' which is consistent with the manner in which it was announced that monetary policy was to be conducted. Arguably, infrequent large changes in target interest rates forces forecasters to herd.

Two main reasons were suggested to motivate the herding phenomenon: the strategic altering of a forecast to be consistent with the view of the herd, and the acknowledgment that the other forecasters have information available

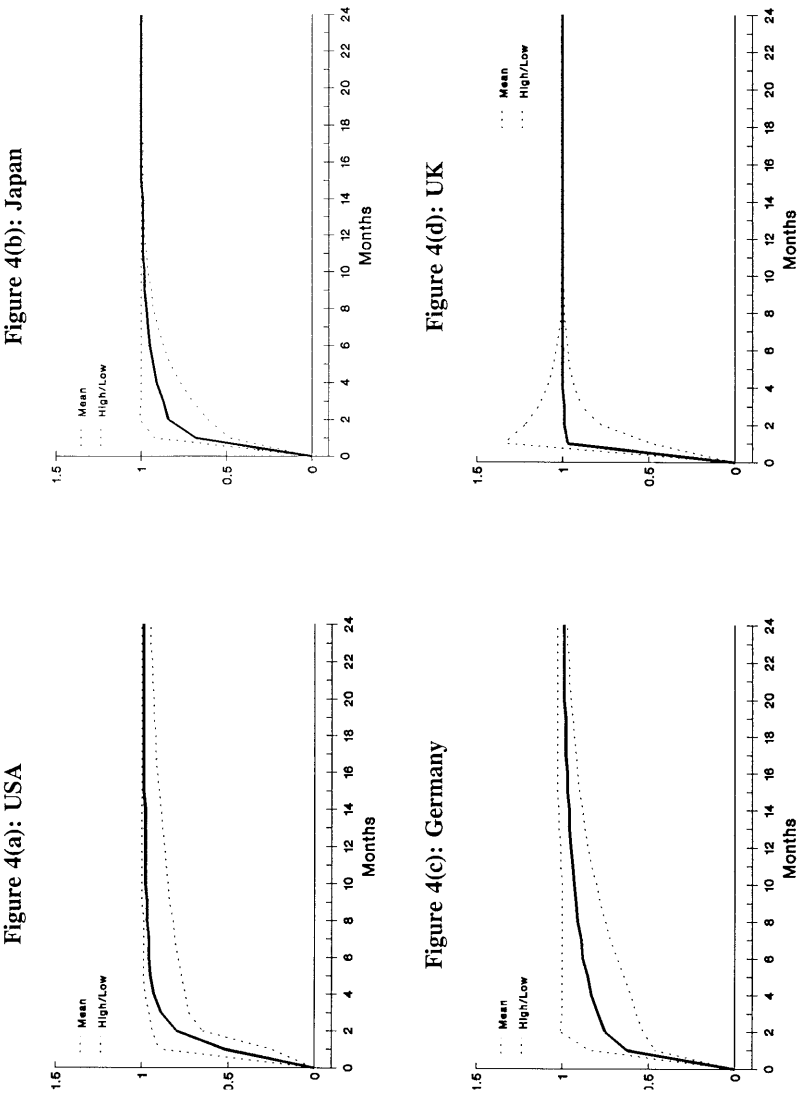

Fig. 4. Impulse Response Functions

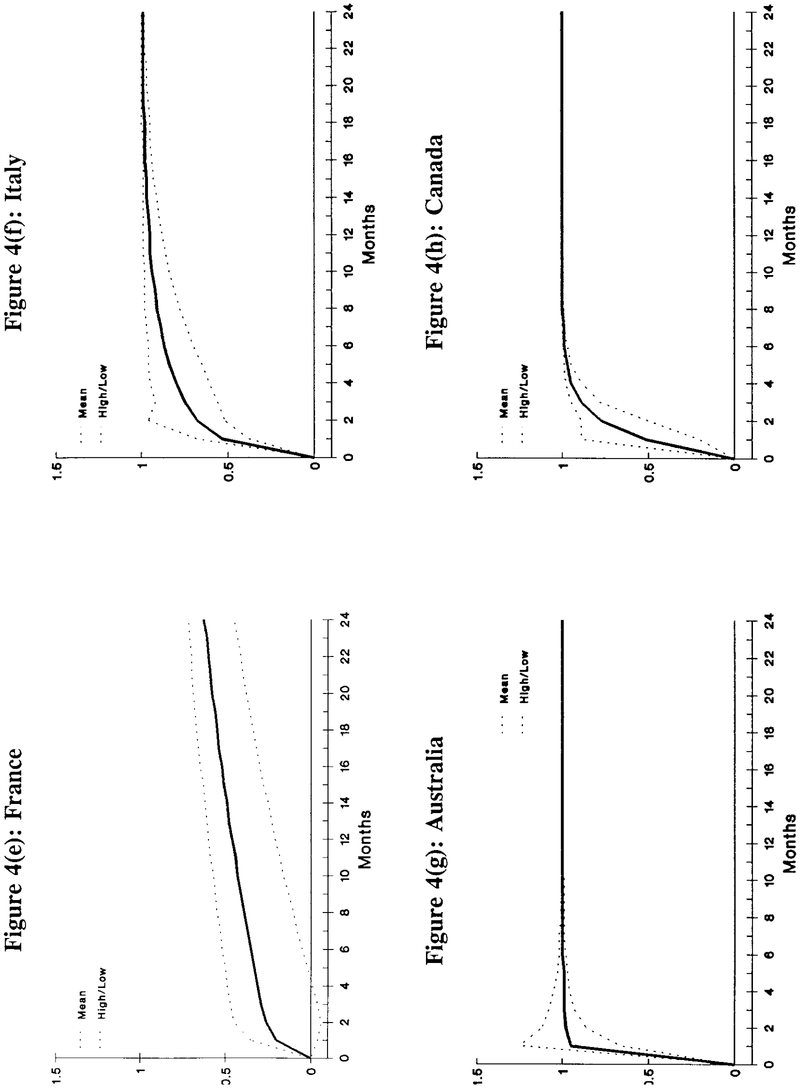

Fig. 4. Continued

to it which is not available to the individual. Unfortunately, data are not available to discriminate between these two hypotheses. It appears reasonable to conjecture that an element of both is prevalent in the real world of publishing interest rate forecasts.

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Appendix

Table A1. Regression results, USA

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
0.365	4.14	−0.107	0.84	0.768	4.07	−0.026	0.22	0.445	3.97	0.047	1.30	64	0.60	1.13
0.392	3.22	0.276	1.66	0.409	1.51	−0.077	0.50	0.551	5.07	−0.049	0.74	59	0.38	4.27
0.348	3.50	0.201	1.39	0.690	2.74	−0.239	1.59	0.722	8.55	−0.034	0.44	67	0.38	3.32
0.615	7.40	0.338	2.86	0.416	1.90	−0.369	2.19	0.575	5.62	−0.021	0.43	64	0.55	0.84
0.653	7.63	0.257	1.83	0.230	1.40	−0.140	1.09	0.446	3.67	0.006	0.16	54	0.69	0.16
0.333	3.46	0.085	0.59	0.769	3.71	−0.187	1.70	0.852	13.80	−0.069	0.47	72	0.46	1.36
0.462	4.35	−0.161	1.16	0.546	2.60	0.153	0.94	0.308	2.47	0.073	1.98	58	0.54	4.24
0.253	2.27	0.315	1.96	0.501	1.75	−0.069	0.48	0.754	9.12	−0.077	0.78	63	0.49	2.39
0.815	10.87	−0.651	8.11	0.291	2.08	0.545	4.99	−0.172	1.54	0.009	0.61	78	0.65	1.85
0.334	3.04	−0.013	0.09	0.797	3.70	−0.118	0.90	0.361	3.02	−0.089	2.08	61	0.52	0.34
0.654	4.28	−0.011	0.06	0.332	1.15	0.026	0.17	0.599	5.59	0.023	0.34	56	0.34	2.00
0.683	3.68	−0.602	3.02	−0.003	0.01	0.921	6.32	−0.091	0.67	0.032	0.85	54	0.16	0.49
0.904	7.82	−0.700	5.59	−0.047	0.23	0.844	6.80	−0.205	1.62	0.003	0.12	60	0.45	0.67

Table A2. Regression results, Japan

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
0.921	8.30	−0.714	5.80	0.263	1.38	0.530	3.56	−0.166	1.41	−0.038	1.55	70	0.54	0.17
0.827	6.88	−0.570	4.22	0.205	1.05	0.539	3.58	−0.068	0.60	−0.019	0.68	78	0.38	0.41
0.478	3.88	0.180	1.18	0.765	3.74	−0.423	3.71	0.592	6.10	−0.131	2.16	69	0.56	2.77
0.798	6.69	−0.542	3.90	0.358	1.73	0.387	2.67	0.085	0.65	−0.039	1.32	58	0.52	0.81
0.479	3.68	−0.279	1.95	0.437	2.62	0.364	2.86	−0.162	1.25	−0.032	1.09	58	0.44	0.51
0.704	4.93	−0.485	3.22	0.236	1.44	0.546	4.95	−0.035	0.28	−0.023	0.74	65	0.30	0.98
0.569	4.81	0.130	0.83	0.804	3.50	−0.503	3.27	0.486	4.48	−0.138	2.68	65	0.51	0.41
0.633	6.23	0.388	2.70	0.014	0.07	−0.036	0.24	0.725	8.75	−0.125	1.54	69	0.45	2.05
0.508	4.07	0.447	2.34	0.204	0.77	−0.159	1.00	0.761	8.61	−0.129	1.20	54	0.42	4.35
0.700	3.33	−0.961	3.62	0.844	2.34	0.416	2.75	0.058	0.42	−0.099	1.73	52	0.32	0.65
0.725	5.64	−0.508	3.35	−0.008	0.04	0.790	7.16	0.035	0.26	−0.076	2.36	56	0.34	0.32
0.840	7.81	−0.685	5.34	0.294	1.90	0.551	4.65	−0.109	0.82	−0.014	0.54	56	0.53	1.11
0.585	4.33	0.048	0.28	0.183	0.71	0.185	1.07	0.317	2.54	−0.094	2.11	58	0.50	4.09
0.824	7.08	−0.670	5.35	0.418	1.85	0.427	2.52	−0.152	1.25	−0.079	2.90	66	0.48	0.70

Table A3. Regression results, Germany

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
0.607	6.23	−0.197	1.55	0.421	2.72	0.169	1.26	0.229	2.03	−0.130	3.92	74	0.52	1.09
0.512	5.33	0.384	2.90	0.237	1.70	−0.133	1.03	0.767	10.15	−0.189	1.92	72	0.46	2.63
0.608	6.74	−0.381	3.72	0.153	1.08	0.620	4.55	−0.026	0.23	−0.050	2.17	78	0.38	0.09
0.627	5.45	−0.595	5.10	0.198	1.59	0.770	8.10	−0.257	2.28	−0.030	1.18	74	0.21	1.04
0.674	6.86	−0.698	6.76	0.288	2.38	0.736	9.01	−0.394	3.69	−0.012	0.53	74	0.43	0.99
0.507	4.57	−0.037	0.27	0.203	1.37	0.328	2.53	0.333	3.08	−0.154	3.66	76	0.28	2.04
0.458	4.93	0.054	0.46	0.275	3.41	0.214	2.16	−0.178	1.52	−0.063	3.23	70	0.56	0.39
0.805	8.06	−0.618	5.83	0.316	2.72	0.497	4.39	−0.155	1.37	−0.020	0.86	76	0.47	0.44
0.541	7.92	0.479	4.67	0.000	0.00	−0.020	0.19	0.641	7.29	−0.226	4.76	76	0.61	4.42
0.717	6.80	−0.473	3.76	0.074	0.59	0.682	5.22	−0.092	0.69	−0.094	2.89	56	0.42	0.05
0.545	4.26	−0.641	4.36	0.373	2.15	0.723	6.66	−0.096	0.85	−0.026	0.87	78	0.20	0.14
0.712	6.27	−0.618	5.42	0.111	0.91	0.795	7.88	−0.431	4.11	−0.031	1.32	74	0.39	3.34
0.527	3.69	−0.384	2.55	0.217	1.19	0.640	5.27	−0.186	1.54	−0.114	3.09	66	0.26	1.46
0.838	7.89	−0.677	6.09	0.044	0.40	0.795	8.64	−0.149	1.33	−0.034	1.41	78	0.43	0.17
0.841	8.97	−0.726	7.93	−0.097	0.98	0.982	14.19	−0.288	2.41	−0.037	2.05	64	0.47	0.76
0.546	5.00	−0.610	4.61	0.285	1.76	0.780	7.99	−0.201	1.76	−0.022	0.89	74	0.24	1.01
0.479	4.31	−0.105	0.72	0.304	2.05	0.321	2.72	0.341	3.10	−0.128	2.96	73	0.33	0.77

Table A4. Regression results, UK

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
1.099	13.07	−1.041	13.27	0.227	1.98	0.715	8.90	−0.456	4.47	0.003	0.10	76	0.70	0.07
1.008	10.77	−0.906	8.99	0.213	1.19	0.685	5.37	−0.097	0.85	−0.035	0.93	76	0.63	0.01
1.178	11.92	−0.846	8.66	0.551	3.65	0.117	0.81	−0.094	0.74	−0.075	1.88	61	0.74	0.19
1.337	16.56	−1.063	12.85	0.081	0.56	0.644	5.66	−0.456	4.13	−0.058	1.91	65	0.81	3.47
1.032	6.77	−1.154	7.19	0.766	3.05	0.357	2.47	−0.228	1.75	0.016	0.27	56	0.57	1.80
0.969	13.48	−0.856	12.30	0.366	2.94	0.522	4.34	−0.350	3.26	−0.046	1.80	76	0.74	0.07
1.041	11.41	−1.084	12.27	0.402	2.94	0.641	6.80	−0.308	2.55	−0.031	0.90	62	0.70	0.04
1.042	13.37	−0.789	9.58	0.455	3.39	0.292	2.21	−0.168	1.50	−0.059	1.96	78	0.74	0.49
1.015	8.95	−1.036	9.73	0.351	2.18	0.670	7.87	−0.322	2.78	0.014	0.34	67	0.64	0.36
1.163	11.93	−0.915	9.81	0.223	1.32	0.530	3.87	−0.325	2.62	−0.029	0.85	58	0.72	0.79
0.697	7.66	−0.658	5.01	0.632	3.52	0.329	2.67	0.318	2.68	0.012	0.19	64	0.62	0.05
1.035	8.50	−0.686	5.13	0.532	2.87	0.118	0.84	−0.050	0.40	0.028	0.51	65	0.63	0.13
1.044	8.63	−0.525	3.28	0.176	0.98	0.306	2.43	0.118	0.97	−0.168	2.58	67	0.67	0.60
0.726	6.38	−0.764	5.65	0.436	2.42	0.602	5.64	0.136	1.15	−0.042	0.74	70	0.48	0.15
0.560	6.43	−0.772	6.42	1.098	5.93	0.114	0.92	0.266	2.37	−0.070	1.42	74	0.57	0.22
1.245	10.96	−0.889	6.91	0.454	2.65	0.190	1.53	0.000	0.00	−0.053	1.01	65	0.72	0.04
0.875	7.81	−0.897	7.94	0.726	4.42	0.296	2.47	−0.222	1.98	0.079	1.80	76	0.58	0.21
0.477	4.18	−0.428	3.38	0.540	4.16	0.411	4.39	−0.277	2.48	0.105	2.40	74	0.53	0.06

Table A5. Regression results, France

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
0.224	4.37	−0.021	0.36	1.060	6.71	−0.263	1.63	0.281	2.23	−0.138	1.80	58	0.54	0.80
0.175	3.18	−0.324	5.55	0.792	4.97	0.357	2.64	−0.122	1.02	−0.094	1.78	69	0.39	0.12
−0.040	1.09	−0.098	2.31	0.523	3.95	0.614	5.85	−0.052	0.39	−0.075	1.83	58	0.16	0.04
0.239	4.21	0.086	1.34	1.013	6.79	−0.338	2.50	0.393	3.73	−0.286	3.45	76	0.44	1.93
0.315	7.18	−0.022	0.48	0.754	5.41	−0.047	0.39	0.519	4.97	−0.190	3.07	67	0.63	5.04
0.063	1.42	0.026	0.54	0.891	5.88	0.020	0.15	0.248	1.96	−0.082	1.28	59	0.46	0.83
0.166	3.34	0.060	1.11	0.686	4.94	0.088	0.67	0.309	2.66	−0.088	1.28	67	0.45	0.33
0.151	3.26	−0.134	2.63	0.942	6.63	0.042	0.32	0.279	2.43	−0.159	2.59	70	0.42	0.52
0.353	5.17	−0.396	5.58	0.655	4.02	0.388	2.68	−0.091	0.80	−0.007	0.12	76	0.42	0.39
0.223	5.78	−0.016	0.35	0.802	5.79	−0.010	0.07	0.372	3.26	−0.027	0.44	66	0.57	0.79
0.257	4.30	−0.307	5.29	0.518	2.79	0.532	3.57	−0.059	0.49	−0.063	1.30	68	0.35	0.17
0.202	3.69	−0.119	1.99	0.444	3.26	0.473	3.83	0.093	0.68	−0.053	0.77	53	0.41	1.87
0.299	4.18	−0.327	4.74	0.580	3.88	0.448	3.30	−0.279	2.36	−0.038	0.68	66	0.40	0.61

Table A6. Regression results, Italy

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
0.671	10.92	−0.356	3.82	0.400	2.12	0.285	1.52	−0.052	0.43	−0.051	0.96	69	0.67	0.08
0.383	5.03	−0.270	2.47	0.444	1.68	0.443	2.38	0.071	0.57	0.000	0.00	64	0.39	1.18
0.504	6.87	−0.492	4.22	0.221	1.15	0.768	5.76	−0.298	2.61	−0.062	1.16	70	0.37	0.24
0.678	8.01	−0.375	3.09	0.284	1.39	0.413	2.39	−0.223	1.80	−0.155	2.10	62	0.57	0.33
0.493	6.87	−0.342	3.24	0.398	3.14	0.452	5.34	−0.021	0.17	−0.095	1.76	66	0.58	3.88
0.530	11.69	−0.114	1.51	0.340	2.66	0.244	2.04	0.179	1.56	−0.123	2.39	74	0.70	0.06
0.484	6.52	0.407	2.63	0.261	1.12	−0.153	0.80	0.499	4.15	−0.294	2.13	52	0.53	3.19

Table A7. Regression results, Australia

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
1.135	12.84	−1.143	10.76	0.445	2.31	0.563	4.53	−0.357	2.93	0.032	1.26	59	0.70	0.17
0.658	5.38	−0.764	4.05	0.823	3.01	0.283	2.10	0.270	2.33	−0.098	1.78	69	0.51	0.34
1.117	14.11	−0.956	10.55	0.478	3.03	0.361	2.66	−0.348	3.09	0.016	0.70	69	0.71	1.37
0.901	16.69	−0.576	5.84	0.083	1.15	0.592	5.64	−0.299	2.40	0.050	2.35	59	0.81	0.59
0.930	11.08	−1.037	10.50	0.526	3.46	0.581	6.30	−0.279	2.34	0.042	1.47	65	0.67	0.85
1.247	13.95	−1.096	10.97	0.319	1.95	0.530	4.08	−0.333	2.66	0.011	0.44	57	0.73	0.28
0.812	10.46	−0.404	3.42	0.642	4.48	−0.050	0.35	0.102	0.80	0.088	2.97	61	0.80	0.23
0.659	6.74	−0.637	4.00	0.700	3.39	0.277	2.25	0.317	2.74	−0.044	0.95	67	0.59	1.08
0.788	8.29	−0.652	4.95	0.366	2.54	0.499	4.35	−0.104	0.82	−0.087	2.54	61	0.63	0.43
1.171	11.54	−0.925	9.06	0.072	0.46	0.682	6.26	−0.422	3.58	−0.005	0.19	59	0.68	2.17
1.015	11.04	−0.943	8.72	0.135	0.75	0.794	5.75	−0.386	3.19	−0.005	0.20	58	0.64	1.09
0.985	11.97	−0.959	9.73	0.455	2.58	0.519	3.73	−0.211	1.72	−0.013	0.50	64	0.68	0.43

Table A8. Regression results, Canada

β_1		β_2		β_3		β_4		ρ		α		T	$\bar{R}^2$	LM
est.	t	est.	t	est.	t	est.	t	est.	t	est.	t			
0.349	5.08	−0.018	0.18	0.637	3.27	0.032	0.23	0.460	4.08	−0.393	4.70	62	0.48	2.99
0.497	7.11	0.105	0.99	0.708	3.65	−0.310	2.34	0.784	11.01	−0.030	0.16	76	0.56	0.97
0.675	6.84	0.063	0.53	0.169	0.70	0.093	0.52	0.427	3.81	−0.156	1.75	65	0.56	2.98
0.574	8.58	0.112	1.10	0.302	1.82	0.012	0.09	0.610	6.79	−0.212	2.13	78	0.53	3.70
0.515	6.11	0.156	1.23	0.593	2.24	−0.264	1.57	0.687	8.35	−0.027	0.17	78	0.41	0.58
0.271	3.31	0.456	4.07	0.271	1.41	0.003	0.02	0.350	2.87	−0.029	0.36	59	0.55	3.04
0.568	4.11	−0.584	2.92	1.058	3.71	−0.042	0.28	0.452	3.79	−0.115	1.14	56	0.49	0.60
0.570	5.68	−0.115	0.71	0.424	1.47	0.121	0.66	0.281	2.27	−0.026	0.28	60	0.51	8.46
0.888	17.74	−0.334	3.06	0.249	2.84	0.198	1.46	−0.190	1.56	−0.115	3.25	65	0.85	4.48
0.200	1.86	0.154	0.90	0.705	2.32	−0.059	0.37	0.691	8.11	−0.116	0.59	72	0.24	0.80