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World Institute for Development Economics Research

Discussion Paper No. 2002/71

The Market Place for Ideas

An Analysis of Knowledge Diffusion in Academic Journals

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July 2002

Abstract

The thought that the academy might function like a 'market place for ideas' has been influential in the economics of science and is increasingly so in the philosophy of science/economic methodology literature. This paper contributes to this literature by examining one respect in which the academy may or may not resemble a market for ideas: it provides an empirical study of the diffusion of ideas within the academic community. In particular, it is concerned with the following questions:

i) Is the pattern of diffusion in the academic community similar to that found in industry studies on the diffusion of new techniques of production?

ii) Is the rate of diffusion faster in the academy or in industry?

iii) Has the pattern of diffusion in the academy changed over time?

Keywords: econometrics, experimental techniques, economics of science

JEL classification: B23, C30, C90, D80, I20, O30

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Professor Parikh participated in the UNU/WIDER Sabbatical Programme and the research on Globalization, Finance and Growth.

Acknowledgements

The authors would like to thank Barbara Eberth and Amy Shore for their helpful and thorough statistical assistance in the preparation of this study.

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UNU World Institute for Development Economics Research (UNU/WIDER)
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Camera-ready typescript prepared by Adam Swallow at UNU/WIDER
Printed at UNU/WIDER, Helsinki

ISSN 1609-5774
ISBN 92-9190-266-7 (printed publication)
ISBN 92-9190-267-5 (internet publication)

1 Introduction

The dynamism of any economy depends on the development and spread of new ideas, and this is possibly increasingly so in what are sometimes called the ‘knowledge economies’ of the OECD. As a result it is important to understand how new ideas are generated and disseminated. The economics of science literature distinguishes two broad communities where new ideas are produced and diffused: industry and the academy. Industry operates under the influence of the patent system while the academy is governed by a ‘priority of discovery’ norm; and much of the recent literature in this field has been concerned with the extent to which the ‘priority of discovery’ norm helps to create a ‘market place for ideas’ within the academy (e.g. see Mirowski and Sent 2002, Stephan 1996, Dasgupta and David 1994). This paper contributes to that literature by considering one respect in which the academy may or may not resemble a market: it provides an empirical study of the diffusion of ideas within the academic community.

In particular, we address the following questions:

i) Is the pattern of diffusion in the academic community similar to that found in industry studies on the diffusion of new techniques of production?

ii) Is the rate of diffusion faster in the academy or in industry?

iii) Has the pattern of diffusion in the academy changed over time?

While the spread of new ideas within industry has been extensively studied econometrically (e.g. Mansfield 1968, 1989), typically there are only historical discussions of the dissemination of ideas within the academy (e.g. Morgan 1994). There are no quantitative analyses of diffusion within the academy similar to those found for new techniques in industry, which could offer answers to these questions. Thus one contribution of the paper is that it helps, through a comparable quantitative analysis of diffusion within the academy, to fill a gap in the economics of science literature.

The paper also contributes to the literature on the philosophy of science and to the methodology of economics. Recently, there has been a turn in this literature away from prescribing methods for doing science (like ‘falsificationism’) to a consideration of the institutions that enable academic communities to function ‘efficiently’ (e.g. see Hands 2001, and Hodgson and Rothman 1999). As economics has a well-developed notion of efficiency, this literature has drawn increasingly on economics in its analysis of scientific communities (e.g. see Kitcher 1993). For the most part, however, this approach to the philosophy of science uses economic theory to examine the likely properties of academic communities. This is because there is comparatively little empirical evidence on how actual academic communities behave, particularly of the kind which might be used to assess efficiency. Thus the evidence on diffusion presented in this paper again helps in this discussion by supplying a point of comparison between the performance of the academic ‘markets in ideas’ and the more familiar markets for commodities found in economics.

The questions posed here may be important for these reasons, but they are also hard to answer because it is difficult to find good measures to assess the spread of an idea. Suppose, for instance, one picks an idea that can be associated with a particular published paper and plots its spread through citation over time. This may seem like an obvious approach but one immediate difficulty arises because, once the idea is in some degree well accepted, it becomes part of the other, so to speak, and the original paper is cited much less frequently. For example, consider how the rational expectations hypothesis has been increasingly used without citing Muth (1961) or how the 'lemon's model' is referred to without necessarily citing Akerlof (1970). Another difficulty with this approach occurs whenever an idea cannot be uniquely associated with a single article or piece of work. Thus although Muth (1961) is usually taken as the key original article for the rational expectations hypothesis, there is some controversy in the history of thought on this (see Keuzenkamp 1991) and there is significant overlap between the content of this idea and the efficient markets hypothesis in the finance literature where a more common reference is Fama (1970). Finally there is the problem that citation need not reflect acceptance of the idea since a paper may be cited as a point of disagreement as much as one of agreement.

The last of these problems is fundamental because it affects any measure that is based on citation or an indexical count of keywords. The only way around it would be to check each citation or keyword to see whether it reflects acceptance of the idea or its negation; and this threatens to become excessively onerous the moment the set of journals is sufficiently large to be reasonably representative and there are more than a few volumes.

We overcome these difficulties here by using a different method to measure the spread of two ideas in the economic part of the academy. This alternative measure is made possible by the choice of the ideas to be studied: they are ideas with respect to techniques of empirical testing in economics. One is the idea associated with the technique of econometrics and the other is the idea of using laboratory experiments in economics. This choice has the advantage that the spread of these techniques in a representative sample of journals can be monitored relatively easy. It only requires each article to be scanned for the use of the technique since it would be difficult to construe use as anything other than acceptance of the idea behind the technique. Of course, it might be complained that while this avoids the problems above, it merely creates new ones because both techniques have evolved over time. This, however, is also the case with respect to analogous industry studies on the spread of new techniques of production (e.g. see Karshenas and Stoneman 1995). What both this and the industry studies do, in effect, is focus on the spread of what is the underlying or 'generic' new idea, to use Karshenas and Stoneman's (1995) term.

The fact that we study only two ideas is, of course, a main weakness. However, some evidence is better than none and since the one technique spread about 30 years after the other, the comparison between the two provides some indication of how diffusion may have changed over time in the academic community of economists.

Section 2 describes our measurement of the spread of these techniques in a set of journals in more detail. Section 3 sets out the theoretical expectations that can be drawn from the economics of science literature on the particular questions and contrasts them with the quantitative estimates of how these two techniques actually spread in the academy. In addition to offering tentative answers to the questions above regarding the overall spread, the evidence here reveals some interesting differences between journals, which we consider in more detail in section 4 by testing a particular model of diffusion by journal.

2 The data

We chose a group of ten general journals on the basis of their status and their geographic spread. General journals avoid the bias that would come from including specialist econometric or experimental journals or specialist journals of other kinds, which might in turn be biased towards one kind of empirical testing. We looked at what are now regarded as 'high status' journals because we are interested in how these ideas have spread in the mainstream of the discipline. However, 'high status' journals are disproportionately located in the US and so to be able to test for any differences between countries we included some non-US journals, which probably lie outside the top rank. Our full list (and abbreviations) is:

American Economic Review	AER
Australian Economic Papers	JEP
Canadian Journal of Economics	CJE
Econometrica	
Economic Journal	EJ
Economica	
Journal of Political Economy	JPE
Oxford Economic Papers	OEP
Quarterly Journal of Economics	QJE
Scottish Journal of Political Economy	SJPE

Data was collected on the number of pages devoted to articles that employ econometric techniques to test hypotheses for each year from 1950 to 1990 and these were then expressed as percentages of the total number of pages in each year. This is our preferred measure of diffusion of the econometric technique. We also have data on the number of articles using econometrics and their proportion of the total number of articles.[1] Likewise, data was collected on the number of pages devoted to articles using the experimental technique for each year from 1979 to 1999 and the same measure of diffusion was calculated. In both cases the start year is dictated by the data as there was little use of econometrics and experiments before 1950 and 1979, respectively, in these journals. Our choice of an end date for the spread of econometrics was dictated again by the data as the technique had fully diffused by 1990. This was not the case for the experimental method where 1999 was the last possible observation. The full run of

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1 Most journals since the 1980s published articles of standard length and excepting *Econometrica* that published very long articles sometimes, the time series on proportion of articles to total number of articles in a journal closely resembles the time series on the proportion of pages to total number of pages in each journal. Hence we have used the proportion of pages to total pages on a chosen methodology as the diffusion variable.

years is not available for the CJE (which was established in 1968), the AEP (which started in 1962) and the SJPE, which was established in 1954.

Table 1 summarises and Figure 1 gives a plot of the data on diffusion levels.

Table 1

Means and standard deviations of variables (% of pages)

Econometric Methodology			Experimental Economics Methodology		
Name of the Variable	Mean	sd	Name of the Variable	Mean	sd
% of total pages to total of all journals	19.1000	9.6630	% of total pages to total of all journals	1.4962	0.8757
Economic Journal	11.1703	8.4434	*Economic Journal*	1.7809	1.6723
Economica	16.6000	12.7597	*Economica*	0.7948	1.5433
Oxford Economic Papers	17.4000	12.0507	*Oxford Economic Papers*	0.1552	0.7114
Scottish Journal of Political Economy	16.8919	14.8207	*Scottish Journal of Political Economy*	0.0	0.0
American Economic Review	19.2750	12.3910	*American Economic Review*	2.3109.	2.3396
Journal of Political Economy	28.3000	16.8648	*Journal of Political Economy*	1.7262	1.7679
Econometrica	23.5250	8.8549	*Econometrica*	2.5681	2.3396
*Canadian Journal of Economics**	27.0434	5.9580	*Canadian Journal of Economics**	0.1028	0.3896
*Australian Economic Papers***	25.0689	11.8017	*Australian Economic Papers***	0.0	0.0
Quarterly Journal of Economics	15.8250	10.1397	*Quarterly Journal of Economics*	1.7586	2.2291

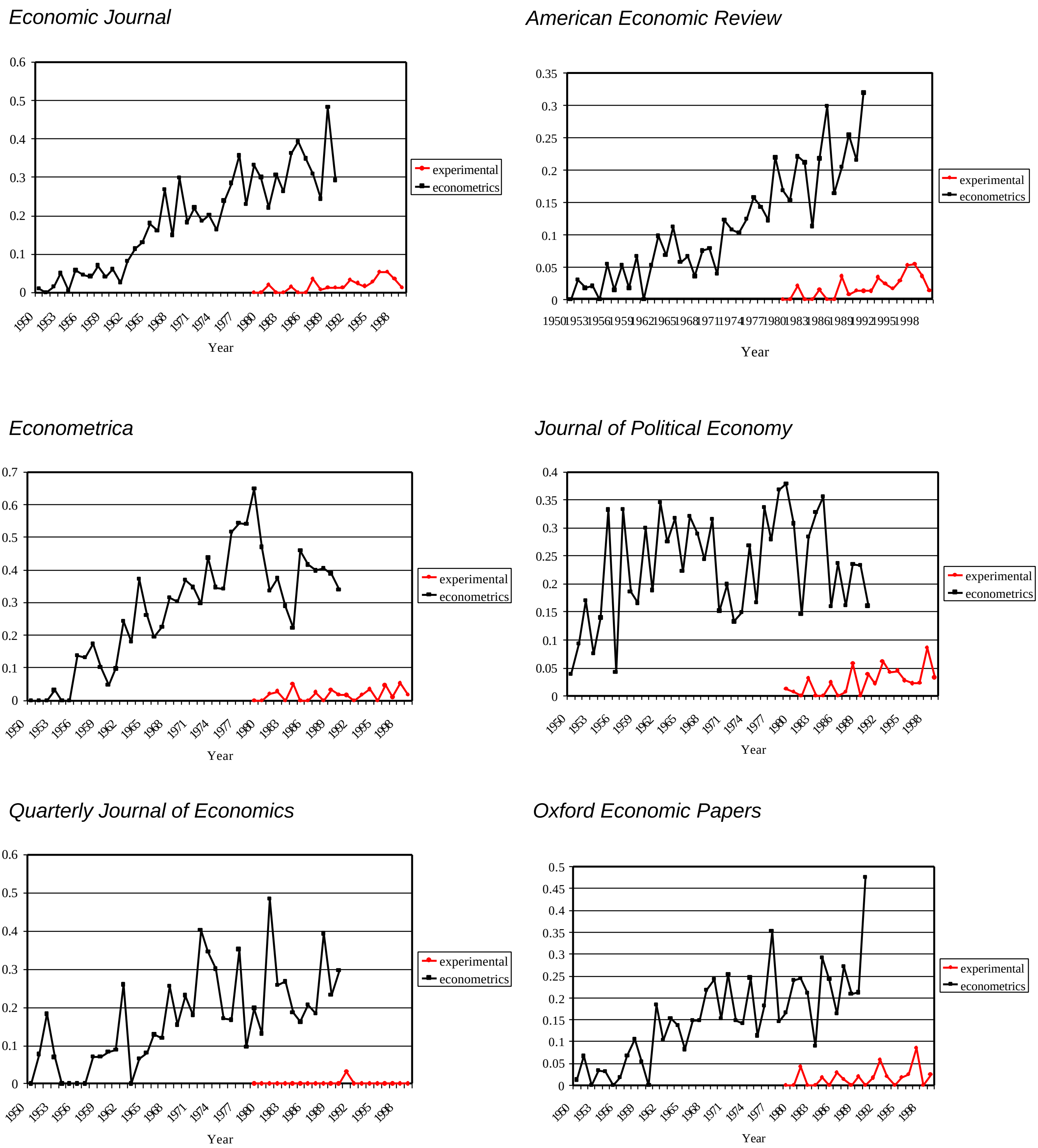
Notes: * 1968–90, **1962–90

For each journal, total number of pages on each methodology is divided by the total number of pages in each journal and is converted to percentage.

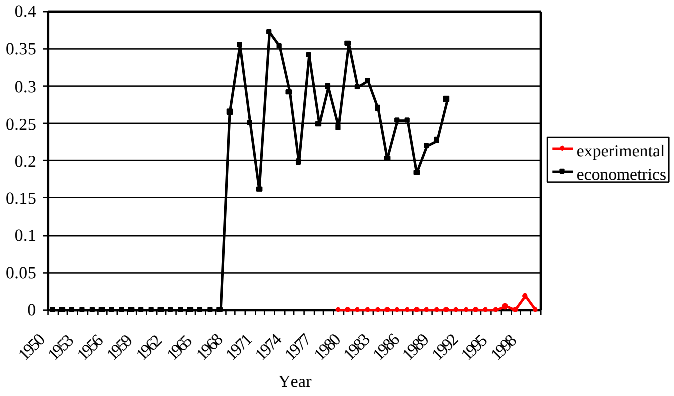
For all journals the time period is 1950–90 excepting the two.

Figure 1

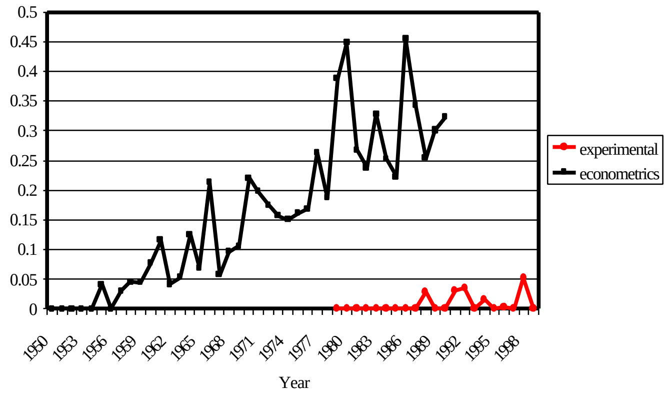
Levels of diffusion of econometric and experimental technique



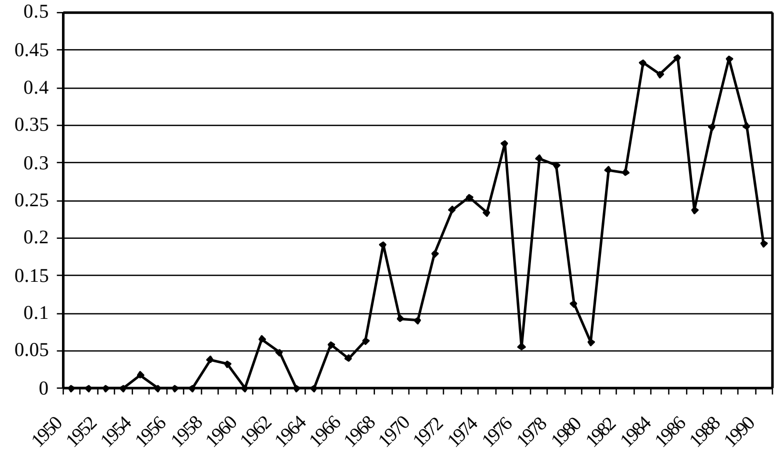
Canadian Journal of Economics



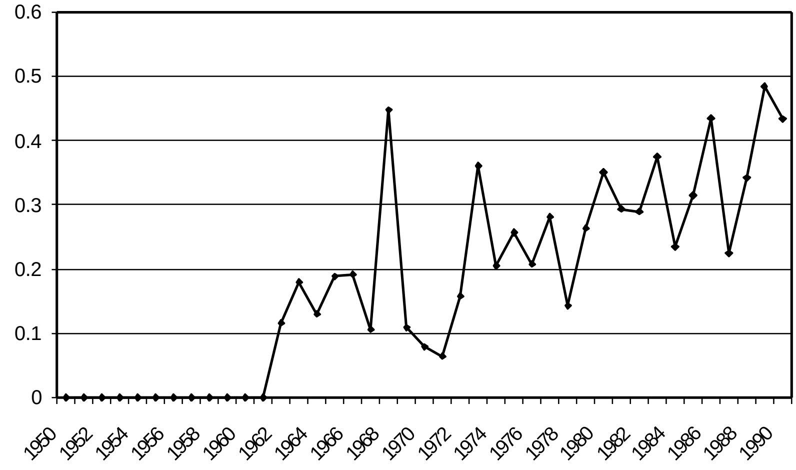
Economica

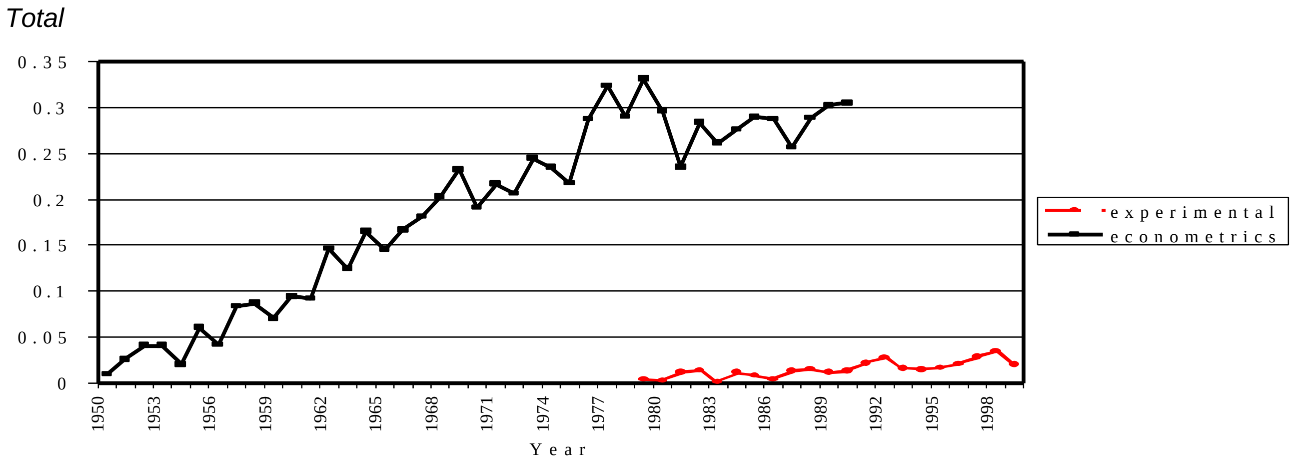


Scottish Journal of Political Economy (Econometric method only)



Australian Economic Papers (Econometric method only)





3 The pattern of diffusion of academic ideas

The pattern of diffusion for new techniques of production within the economy has been extensively studied (see Geroski 2000, for a recent survey) and, although a variety of alternative models and distributions have been used, almost invariably the logistic S-shaped function is a starting point. It captures the spread tolerably well and has the advantage for our purpose of identifying the speed of diffusion with a single parameter. Thus, by using the logistic function here, we are able to make comparisons on speed with a large number of industry studies by focussing on a single parameter estimate.

With $y(t)$ equal to the proportion of adopters in time t, the logistic function is given by

$$y(t) = \frac{A}{1 + \exp(-b - dt)} \tag{1}$$

where A equals the final saturation level.

Since $y_0 = A/[1+\exp(-b)]$, the parameter 'b' determines how far the percentage of adoption is below the saturation level at time zero and the parameter 'd' controls the speed at which the saturation level is reached. The point of inflexion occurs at $t = -b/d$ when the proportion of adopters equals $A/2$ (i.e. half the final level).

For the purposes of the comparison with industry, Table 2 gives Mansfield's (1968, 1989) estimates of 'd', the pace of diffusion, for several new technologies in the US. His measure of diffusion, as in many industrial studies, is the proportion of firms adopting the new technique and his estimates are similar to those found in other country studies (e.g. Davies 1979). However, the measure is not exactly the same as the proportion of pages given to articles using a particular technique. In some cases when a firm adopts a new technique that means all its output is produced using that technique, and so ignoring differences in the size of firms, this measure will closely match the proportion of output produced using the new technique, but this is not always the case. Studies that directly plot diffusion in terms of the proportion of output accounted for using a new technique are, unfortunately, much rarer as the data is typically not available. Mansfield (1968) does provide estimates of intra firm diffusion for one of these innovations, the diesel locomotive. In this case, diffusion at the firm level is measured by the proportion of diesel engines. The estimates of '*d*' by firm range across his sample of 30 railroad companies from 1.35 to 0.28, and so is always higher than the inter firm pace of diffusion given in Table 2 (where '*d*' = 0.2). Von Tunzelmann (1978) is another study that looks at the aggregate diffusion, of steam engines in the nineteenth century, and estimates that '*d*' is 0.25 which, again, is similar to the range found in Table 2 for inter firm diffusion.

There are also some studies that have a few discrete observations on output proportions and so report on the number of years it takes for a particular change in the percentage of output of an industry or firm using a new technique to occur. For example it took Ford and General Motors 20 years to move from zero to half the level of their current use of industrial robots (see Mansfield 1989). In the UK, from first introduction, it took three years for special presses in paper making to diffuse to 10 per cent of output, five years for the basic oxygen process to diffuse to 20 per cent, four years for gibberalic acid in brewing to reach 50 per cent, six years for continuous casting to account for 1 per cent, six years for shuttleless looms to make 1 per cent and ten years for automatic transfer lines in vehicle production to disseminate to 30 per cent (see Nasbeth and Ray 1974).

Before we compare these patterns with those that come from estimating the logistic curves for our two new techniques in the academy, it is worth rehearsing what sort of answers one might expect on theoretical grounds to the earlier questions.

Table 2

Diffusion of new techniques in industry

Innovation	Estimate of '*d*'
Industrial robots	0.28
Diesel locomotives	0.20
Centralised traffic control	0.19
Car retarders	0.11
Continuous wide strip mill	0.34
By-product coke oven	0.17
Continuous annealing	0.17
Shuttle car	0.32
Trackless mobile loader	0.32
Continuous mining machine	0.49
Tin container	2.40
High-speed bottle filler	0.36
Pallet loading machine	0.55

Source: Mansfield (1989).

One. With respect to the overall pattern of diffusion, we expect that ideas are slow to spread at first and slow again as saturation level is reached. This is the typical pattern in industry studies and we test for this broad similarity in the academy by fitting a logistic function to the spread of these two ideas in the academy. Of course, there are a variety of functions that have these attributes but for the reasons sketched earlier we shall stick with the logistic function and simply compare it to the fit with a simple exponential function.

Two. With respect to the relative speed of diffusion in the two communities, it is frequently argued that information is likely to disperse more quickly in academic communities than in commercial ones. This is because the ‘priority of discovery’ reward system requires scientists to reveal their discoveries whereas early disclosure potentially compromises a patent claim in the commercial world (see Stephan 1996, and Dasgupta and David 1994). In addition, the later use of a new idea in academic communities does not require the payment of a license or other fee associated with patented knowledge. The pace of diffusion in industry is only partially influenced, however, by the extent of early disclosure and the cost of using patented knowledge. It also depends broadly on how the perceived benefits of adoption change as compared with the costs (e.g. see Karshenas and Stoneman 1995) and one might assume some similar calculation lies behind the spread of a new technique for empirical testing in the academic community. If this is so, then it is not quite clear what to expect as it might be argued that the receptivity of each community to a ‘good’ idea depends in part on the clarity of what is ‘good’ and the extent of competition in the community (that is, the extent to which a failure to adopt is punished); and here it is possible that the pressures within commercial communities are rather keener. In part this is because ‘good’ in commercial life is more closely related to a single indicator (i.e. profit) than is the case in academic life. In part, it is because there is no parallel in the commercial world to the institution of tenure, which can insulate academics from failing to adopt new ideas.

Three. With respect how the pattern of diffusion might have changed over time, it is commonly observed that academic life has become more competitive and that the traditional norms of openness referred to above are in retreat (see Mirowski and Sent 2001, Stephan 1996, and Hirschman 1995). Since it is unclear on balance whether we should expect the spread of new techniques to be faster in the academy or industry, it is uncertain what effect such greater ‘commercialization’ of research in the academy will have on the speed of diffusion. However, we might reasonably expect that whatever the gap is between spread of knowledge in the two communities, it should have narrowed if the two communities are becoming more alike.

Table 3 gives the logistic and exponential function estimates for the spread of the two techniques for empirical testing. The graphs on each methodology for each journal showed a great deal of fluctuation and this is also reflected in the aggregate proportions, so we considered two versions of the logistic function, one with and one without ARCH (autoregressive conditioned heteroscedasticity). ARCH models account for volatility through the conditional variances, which are related to either previous similar variances or the variables that could explain the conditional variances. In neither model was there any evidence of unit root in residuals. The null hypothesis of unit-root non-stationarity was decisively rejected by the augmented Dickey–Fuller test. We find only slight improvement in goodness of fit measured by likelihood value with ARCH; and so in the remainder of the paper we did not continue with ARCH.

For both methodologies, the logistic is more appropriate than a simple exponential function. The coefficients in the econometric equation have the right signs and all are significant. However, although the logistic function is better than an exponential one for the experimental method, the diffusion speed parameter '*d*' is not significantly different from zero and so even this function does not capture well the diffusion of this methodology.

Thus in answer to the question regarding the overall pattern of diffusion, it seems that the pattern of diffusion of the econometric technique is reasonably captured by the logistic function and so is similar to that found in industry studies. However, the logistic function does not fit the spread of the experimental technique and so the overall pattern of diffusion seems rather different to that commonly found in industry.

Table 3

Logistic and other models using total of econometric methodology and experimental economics methodology

Dependent variable	Model used	Coefficient *a*	Coefficient *b*	Coefficient *d*	R^2/unit root test	Log L
Y_1: 5.7% growth p.a.	Exponential	50.3026* (5.7893)	0.0244* (3.9976)	—	0.9230	
Y_2	Exponential	8.2941* (0.5526)	0.0181 (0.9779)		0.6233	
Y_1	Logistic	29.5601* (35.5084)	-2.6929* (11.8191)	0.1764* (10.4625)	0.9543 (-4.80)	-88.63
Y_2	Logistic	4.1302 (1.1107)	-2.0623* (2.9348)	0.1286 (1.5014)	0.6392 (-4.099)	-15.7960
Y_1	Logistic with first order ARCH	28.7324* (44.7740)	-2.5951* (15.4768)	0.1725* (12.9979)	— -5.36[a] (t-value on lagged residual)	-83.83 ARCH: a_0=1.76(1.43) b_1=1.54(3.52)

Notes: * Significant at 5% level

Y_1 = econometric methodology (% of pages), Y_2 = experimental economics methodology (% of pages)

[a] First differences of residuals are regressed on the last period's residuals and the obtained t-ratio is tested against the critical value obtained from response surface estimates for T=50. The used critical value is –3.5005.

The results of logistic approach on experimental economics methodology are not significant on the speed of diffusion implying that the diffusion is not significantly different from zero. Subsequent results do not make any further use of experimental economics methodology**.**

Exponential Model: $Y_{it} = a[1 - \exp(-bt)]$

Logistic Model: $Y_{it} = \dfrac{a}{1 + \exp(-b - dt)}$

On the basis of the parameter estimates of '*d*', the answer to the question regarding relative speed seems to be that academia is rather slow compared with industry. This is obviously the case when the comparison is with the experimental technique since its '*d*' is not significantly different from zero. But equally a value of '*d*' = 0.18 for econometrics is low compared with the range of estimates in Table 2 for industry diffusion and for intra firm studies quoted in the text. It is a little difficult to make a clear cut comparison with the discrete observations on the changes in the proportion of output accounted for by various new technologies that are also reported in the text because we do not know what the saturation level is for these technologies and it is not clear what the appropriate date is for the first use of econometrics. Nevertheless, suppose we assume the saturation level is 100 per cent for each of these technologies and that to take account of the intervention of the Second World War, it is sensible to say that econometrics was first introduced ten years before 1950. Then the estimates for '*b*' and '*d*' suggest that half the saturation rate is achieved 15 years after the first observation in 1950. Hence it took 25 years, on this basis, for econometrics to diffuse from its first use to half its saturation level and this is slow compared with four of the six technologies reported in the text.

Finally in answer to the question about how the pace may have changed in academia, it seems to have slowed down as the point estimate of '*d*' for the experimental technique is both less than the econometric technique and it is not significantly different from zero.

The answer to the second question, the relative speeds of academia and industry, is perhaps surprising given the common assumption that ideas circulate more freely under the openness norm in academic communities. But it could be understood in terms of the relative lack of competition in the academy. If this is the explanation, then the answer to the third question, regarding how diffusion speeds may have changed over time in academia, seems rather puzzling. Since it is commonly observed that competition in academia is increasing, this should have increased the pace of diffusion in academia and so narrowed the gap with industry.

One way around this last conundrum is to doubt the common observation and posit the reverse instead. Whatever the merits of this explanation for the slowdown in academia, it is clear that there is another important difference in the pattern of diffusion of the two techniques. The earlier graphs in Figure 1 make plain that while econometrics has diffused in all journals, this is not the case with the experimental method. Furthermore, the precise pattern of diffusion for econometrics is itself not the same for all journals (e.g. compare *Econometrica* with the EJ and the JPE). Thus it seems that there are journal-specific influences at work in the aggregate diffusion of these ideas; and it is possible that they could help explain why the experimental technique has not diffused as rapidly as the econometric technique.

To test more rigorously for the presence of these possible journal specific effects, we have estimated a logistic function for the spread of the econometric method in each journal. The results are summarized in Table 4.

Table 4

Panel data analysis with logistic

	Model with common *a*, *b* and *d*	Model with common *a* but different *b* and *d*	Model with all *a*, *b* and *d* different	
a	29.5933 (21.85)	39.8840 (22.64)		
b	-2.5756 (7.96)			
d	0.1619 (6.89)			
b_1		-3.0926 (5.99)	-3.04949 (5.40)	A1 40.25 (1.22)
b_2		-2.9602 (5.44)	-3.2387 (3.96)	A2 35.40 (5.87)
b_3		-1.9043 (5.61)	-3.4185 (3.04)	A3 25.77 (12.02)
b_4		-4.0252 (5.65)	-4.5696 (4.00)	A4 34.99 (8.25)
b_5		-2.6138 (5.94)	-2.9318 (4.43)	A5 34.36 (9.19)
b_6		-3.6080 (4.44)	-3.4738 (4.83)	A6 41.75 (20.89)
b_7		-0.1880 (0.76)	-1.5777 (1.47)	A7 25.22 (19.31)
b_8		1.7268 (1.96)	7.0739 (0.55)	A8 29.55 (5.44)
b_{10}		-2.0141 (5.66)	-2.4263 (3.01)	A10 24.40 (8.51)
d_1		0.0911 (4.91)	0.9059 (1.93)	
d_2		0.1187 (5.41)	0.1433 (2.88)	
d_3		0.0758 (5.49)	0.2288 (2.87)	
d_4		0.1565 (5.53)	0.1942 (3.37)	
d_5		0.1195 (5.90)	0.1567 (3.56)	
d_6		0.2641 (4.36)	0.2448 (4.63)	
d_7		0.0246 (2.38)	0.4490 (1.83)	
d_8		-0.0324 (1.20)	-0.1446 (0.46)	
d_{10}		0.0718 (5.25)	0.1629 (2.61)	
R^2 / SEE	0.4946 (9.2976)	0.7083 (7.2367)	0.7294 (7.0530)	
Log L / χ^2	-1264.59	-1169.38(190.42)	-1156.17 (26.42)	
Mean/sd	18.87 (13.04)	18.87 (13.04)	18.87 (13.04)	

Notes: For CJE, the *a* coefficient is of opposite sign to what is expected. For CJE and AEP when individual logistic curves were fitted the convergence was not achieved. The best model in the above table is the unrestricted one where each journal has different *a*'s, *b*'s and *d*'s.

Journals: 1= EJ; 2= *Economica*; 3 = OEP; 4 = SJPE; 5 = AER; 6 = JPE; 7 = *Econometrica*; 8 = CJE; 9 = AEP; 10 = QJE.

Three models were estimated. The first in column 2 constrains each journal to have identical final saturation levels (‘*a*’), identical diffusion speeds (‘*d*’) and identical levels of adoption at the time zero, (‘*b*’) to provide a reference point. Estimates for AEP have been excluded because they did not converge. The second model reported in the third column relaxes some of these restrictions and allows both the base level diffusion parameter[2] and the speed of diffusion to vary while keeping the common saturation level. The third model in column 4 is the most general model and allows each journal to have a separate saturation level, diffusion speed and base level diffusion parameter[3]. Of the three models, the restricted models of columns 2 and 3 are rejected by the Likelihood ratio χ^2-test ($\chi^2 = 190.42$ for 16 degrees of freedom and $\chi^2 = 26.42$ for 8 degrees of freedom and both these exceed the critical level). Thus we prefer the model with different parameters for each journal.

We tried to fit journal specific logistic curves to the diffusion of the experimental technique within each journal but, like the aggregate data, without success.[4] Nevertheless, as remarked earlier, it is apparent from the plots of diffusion in Figure 1 that only four journals have played any role in the diffusion of this technique (*Econometrica*, AER, EJ and QJE); and we now find a similar diversity across journals with respect to the parameter values for ‘*a*’, ‘*b*’ and ‘*d*’. Whether the operation of such journal specific effects on diffusion can account for the slow take-up of the experimental technique or not, the differences in the diffusion pattern across journals is an important part of the diffusion process and needs explaining.

To see how such differences might be understood, it is worth reflecting on the process that governs article publication. In broad terms, articles are published by a journal in a particular field because they are (a) submitted in that field, (b) well received by referees and (c) accord with any editorial preference over content. (a) and (b) essentially depend on the views of worth held by the journal’s academic community while (c) depends on the particular views of an editor or editorial team. Thus there are two possible, broad sources for differences in the rate of diffusion across journals (and across time): the journals’ academic communities may differ in relevant ways (e.g. their beliefs or the extent of competition) and/or the editorial preferences may differ. Since these are all mainstream, high status journals, it would be surprising if they had significantly different academic communities in this sense, so it seems more likely that differences in diffusion arise from the distinct editorial preferences of particular journals. We investigate this possibility in more depth in the next section through a model of diffusion within a journal that contains these two broad influences.

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2 The parameter *b* determines by how much the adoption level is below the saturation level. At time zero, this parameter determines the level of diffusion in the logistic function and hence we have named it as base level diffusion parameter.

3 In columns 3 and 4, the CJE has an incorrectly signed parameters *b* and *d* and when the logistic was attempted on its own for CJE, the convergence was not achieved with nonlinear least squares routine.

4 We found that for EJ the parameter b was significant but not d while with respect to AER, QJE and *Econometrica*, neither *b* nor *d* were significant. The saturation level for *Econometrica*, EJ and AER was 4.62, 3.94 and 6.34 per cent respectively. Our conclusion is that logistic form imposes S-curve and is less flexible and another approach based on duration models might be more appropriate to study the diffusion paths of experimental economics methodology in these journals.

4 A model of diffusion by journal

In this section we focus on the cross journal differences with respect to the spread of the econometric method. We develop a model of diffusion by journal that allows for differences between journals in the relevant respects found in Table 4 (i.e. different '*a*'s, '*b*'s and '*d*'s). We then use the model to attempt to disentangle for each journal the possible influence of journal specific editorial biases from those, which may arise because the journals belong to different academic communities in the diffusion.

4.1 Journal selection

Journals select articles for publication from a set of submissions. We group the submissions into articles of various types and assume that there is no difference in quality (or in the distribution of quality) between the various types of submission. Thus, in the absence of an editorial bias, we expect the proportion of articles/pages published in j of type i (s_{ij}) to equal the proportion of articles/pages submitted to journal j of type i (z_{ij}). Editorial bias (v_{ij}), however, may force a wedge between these two proportions. Editors may have views about the importance of a particular type of article that are independent of the proportion of articles/pages submitted of this type. In turn, these can influence their choice of referees and their interpretation of referees' reports and so affect the chances of type i articles being published. Thus, assuming there is a lag of one time period between submissions and publication/rejection, the following describes the determinants of journal selection.

$$s_{ijt+1} = z_{ijt} \cdot v_{ij} \qquad (2)$$

4.2 Article submission

Suppose that individual researchers are identical in all relevant respects and decide on how to allocate their time between writing and submitting articles/pages of different types for the various journals through maximising an expected reputation function (R) that depends on the expected publications of each type-journal combination as follows. For simplicity, we assume there are two types of article i and non-i (ni) and several journals indexed by j, k, etc. The reputation function is

$$R = a_{ij} \cdot r_{ij} \cdot x_{ij} + a_{nij} \cdot r_{nij} \cdot x_{nij} + a_{ik} \cdot r_{ik} \cdot x_{ik} + a_{nik} \cdot r_{nik} \cdot x_{nik} + \ldots \qquad (3)$$

Where x_{ij} is the number of articles/pages submitted to journal j of type i, a_{ij} is the acceptance rate at journal j of type i articles/pages (= p_{ij} / x_{ij} where p_{ij} = number of pages published in j of type i), and r_{ij} is the reputation of publications of type i in journal j (which we assume can be decomposed into the reputation of journal j and the reputation of field i = $r_i \cdot r_j$).

The first order conditions for maximization yield the natural result that an individual will alter the proportion of submissions between different fields (x_{ij} / x_{nij}, x_{ik} / x_{nik}, etc.) and between journals (x_{ij} / x_{ik}, x_{nij} / x_{nik}) until the relative acceptance rates for a type of article match the relative reputation of these fields, as in (3), and until the relative acceptance rates for the journals matches their relative reputations, as in (4).[5]

$$\frac{r_{ij}}{r_{nij}} = \frac{a_{nij}}{a_{ij}}$$

$$\frac{r_{ik}}{r_{nik}} = \frac{a_{nik}}{a_{ik}} \qquad \text{etc} \tag{4}$$

$$\frac{r_{ij}}{r_{ik}} = \frac{a_{ij}}{a_{ik}}$$

$$\frac{r_{nij}}{r_{nik}} = \frac{a_{nij}}{a_{nik}} \qquad \text{etc} \tag{5}$$

We assume that the relative reputation of the two types of article in a journal depends positively on the beliefs of the academic community regarding the relative importance of the field and the journal and negatively on the proportion of pages published in each field in that journal (e.g. $= p_{ij} / p_{nij}$). In other words, for any given level of belief about the relative importance of type i articles in journal j, the reputation associated with publishing in that field falls as the number of pages in that field increases in the journal (because so as to speak the reputation is spread more or less thinly across the pages that are devoted to that field). Figure 2 illustrates this relation for journal j under two different levels of belief and it can be used to explore the behaviour of this model.

To simplify we focus on one journal and consider first the steady state where the proportion of pages devoted to articles of type i is constant (i.e. $s_{ijt+1} = z_{ijt} = s_{ijt}$) and there is no editorial bias. From (1), this means that the acceptance rates for each type of article are identical. Equal acceptance rates, however, are consistent with any ratio of publications (p_{ij} / p_{nij}) since the ratio (x_{ij} / x_{nij}) can adjust to achieve the equality between acceptance rates. What fixes the publications ratio (or the proportion devoted to a field) are the reputational beliefs within the journal's academic community. With equal acceptance rates, it follows that (r_{ij} / r_{nij}) must equal 1. Thus if the reputational beliefs are represented by B_1 in Figure 2, this fixes the proportion of articles devoted to i as s_{ij1}. Now suppose that the relative reputation of field i grows, so that reputational beliefs are now represented by B_2. The proportion devoted to field i in the new steady state rises to s_{ij2}.

The dynamics of the change are easy to follow as the change in beliefs disturbs the equality in (4) and individuals increase the proportion of articles submitted in field i. This in turn feeds through to increase the proportion published in this area, in turn restoring the relative reputations to the steady state value of 1.

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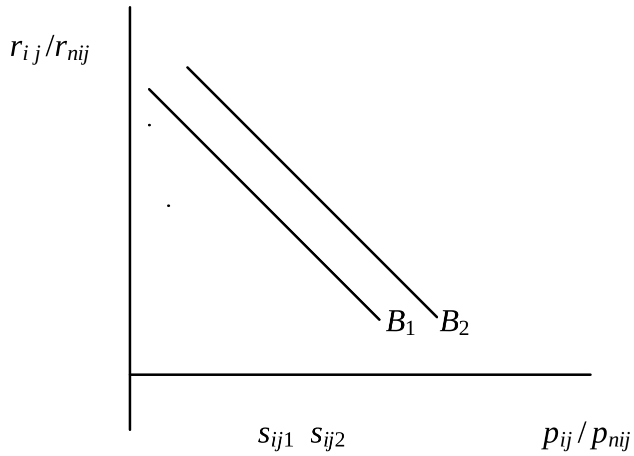
5 It will be evident that the same condition would apply to a model where there are two types of academics, the *i*'ers and *ni*'ers and where the pages submitted to journals in each category depend on the numbers of each type of academic. With this interpretation, the marginal adjustment of pages is now achieved through changes in the relative numbers of the two types of academics as academics respond to the different opportunities for gaining reputation as an *i*'er compared with an *ni*'er.

Figure 2



Now suppose there is an editorial bias influencing the acceptance rate. This alters the steady state ratio of acceptance rates coming out of the editorial process. It is now given by

$$\frac{a_{nij}}{a_{ij}} = 1 + \left(\frac{x_{ij}}{x_{nij}}\right)\left(\frac{1-v}{v}\right) \tag{6}$$

When v is greater than 1 (i.e. there is an editorial bias towards area i such that the journal starts to publish more in the field i), we can see from (3) that this will only be achieved in equilibrium if the relative reputation of i in j falls; and it will as the proportion of pages devoted to i increases. In short, editorial bias shifts the steady state equilibrium up or down the belief curve.

The model is simple, but it does allow for the following key features.

i) Different proportions can be devoted to the new technique of econometrics across journals at any moment in time.

   This may occur either because of editorial bias or because at any moment in time the relative reputation belief function does not occupy the same position for all journals.

ii) The general diffusion of a new technique through all journals.

   This occurs as the academic community comes to value increasingly the new technique and the relative reputation functions of all journals progressively shift out.

iii) The different speeds of diffusion across journals

   This can occur either because of the impact of *changes* in editorial bias or because relative reputation belief function changes at different rates for different journals.

We have no direct observations on editorial bias or beliefs regarding relative reputations. But we can test some simple joint hypotheses regarding their possible influence. Suppose we take a linear approximation of the model and choose suitable units for measuring beliefs and editorial bias so that

$$s_{ij} = B_{ij} + v_{ij} \tag{7}$$

Assume that beliefs can be decomposed into a general and a journal specific element.

$$B_{ijt} = B_{it} + e_{ijt} \quad \text{for all } j, \tag{8}$$

where e_{ijt} is the journal specific element.

Further assume that editorial bias is given by the following function

$$v_{ijt} = v_{ij} + m_{ijt} \tag{9}$$

In other words, it deviates from a constant depending on the behaviour of the variable m_{ij}.

It follows that

$$s_{ijt} = B_{it} + v_{ij} + e_{ijt} + m_{ijt} \tag{10}$$

and

$$s_{jt} = \frac{1}{n}\sum_{j} s_{ijt} = B_{it} + \frac{1}{n}\sum_{j} e_{ijt} + v_i + \frac{1}{n}\sum_{j} m_{ijt} \tag{11}$$

Now consider the following joint hypothesis regarding the evolution of beliefs and editorial bias: that e_{ijt} reflects a random perturbation from the general change for all journals which sums to zero across all journals and which is independently distributed across time periods and m_{ijt} is another independently distributed random white noise variable with $E[m_{ijt}] = 0$. So beliefs change for all journals in the same way but for random white noise and journal bias only varies from the underlying 'tradition' of that journal (v_{ij}) due to white noise. It follows that the expected difference between journal j's diffusion and aggregate diffusion is given by

$$\begin{aligned} E\{s_{ijt} - s_{jt}\} &= E\{(v_{ij} - v_i) + [e_{ijt} - (1/n)\textstyle\sum e_{ijt}] + [m_{ijt} - (1/n)\textstyle\sum m_{ijt}]\} \\ &= (v_{ij} - v_i) \end{aligned} \tag{12}$$

In other words the expected difference between diffusion in any journal and aggregate diffusion would under these conditions simply reflect the difference between that journal's underlying bias or tradition (v_{ij}) and the average bias of all journals (v_i). As a result, we can test this joint hypothesis regarding how beliefs and editorial bias evolve by running a linear regression of individual journal diffusion levels on aggregate diffusion levels. If the coefficient on aggregate diffusion is not significantly different from 1, then we cannot reject the hypothesis that belief and editorial biases evolve in this way. The regression results are reported in Table 5.

Table 5
Proportion in journal *i* regressed on total proportion

Journal	Constant	Coefficient on total proportion
EJ	-1.9 (-1.17)	0.7* (9.14)
Economica	-4.5* (-2.06)	1.11* (10.6)
OEP	1.7 (0.57)	0.81* (5.5)
AER	-2.9 (-1.8)	1.16*(15.1)
JPE	-2.08 (-0.9)	1.59* (14.6)
Ecconometrica	15.4* (5.46)	0.4* (3.05)
QJE	0.51 (0.23)	0.8* (7.67)

Notes: *Significant at 5% level, 't' statistics in parenthesis

For four journals we cannot reject the hypothesis that beliefs and biases evolve in this fashion: they are *Economica*, OEP, AER and QJE. The hypothesis is rejected in the remaining three journals. In two of these journals, there is prior information pointing to the existence of systematic editorial bias. Thus *Econometrica* is well known as the journal that played an early leading role with respect to econometrics (e.g. see Morgan 1994) and the equation in Table 5 points precisely to an early increasing and then decreasing bias with respect to econometrics. Likewise, it is frequently suggested that Keynes's editorship of the EJ left a bias against econometrics (e.g. Stigler *et al.* 1995) and again the equation in Table 5 points to precisely this in the early part of the period.

Of course, the varied patterns of diffusion in these three journals might still be partially explained by a different evolution in the beliefs of the academic community formed around these three journals. But, as suggested before, it seems difficult to argue that general journals have significantly different academic communities in a way that might contribute to systematically different changes in belief. There is, however, one respect in which the communities might have differed, at least in the early part of the period, which could have influenced the diffusion of the econometric technique. It is possible that the journals located in different countries initially had distinct academic communities both because there was less international travel and because the operation of the tenure system produced greater competition in the US than in the UK in the early part of the period.[6]

We considered this possibility by grouping the journals according to their country, estimating the logistic curve for diffusion in both countries and testing the hypotheses that $b_{uk} = b_{us}$ and $d_{uk} = d_{us}$. The results are given in Table 6.

Models 1, 2 and 3 test the hypothesis that US and UK journals have the same value for '*b*' and '*d*' and since model 1 is rejected by model 2 while model 3 is not rejected by model 2. Hence we prefer the model where we have the same saturation parameter for UK and US journals but the '*b*'s and '*d*'s differ. On the basis of the model 3, we find that the diffusion speed is notably faster in the US, but even so the pace in the US with '*d*'= 0.18 is still low compared to industrial standards. The initial degree of diffusion is also more advanced in the US with 2.95 per cent as compared with 1.75 per cent for the

6 Unfortunately, although we introduced other country journals to enable further possible cross country comparisons, as the results in Table 4 show, the logistic function could not be fitted sensibly to either the CJE nor AEP.

UK journals at time zero. The inflexion point where half of the saturation level is achieved is 21.5 years for UK journals while it is 12.3 years for US journals.

Although it is possible to interpret this as evidence in favour of the existence of two academic communities, the result could equally have arisen solely from the conjectured editorial biases in the EJ, *Econometrica* and the JPE as these would have produced faster diffusion in the two US journals than in the one British journal. Furthermore, if there were differences between academic national communities, then it would be difficult to explain why the remaining four journals appeared to have no systematic form of editorial or belief bias. One would have to conjecture that the two British journals in this group had an editorial bias which offset the belief one; and unlike the alternative conjecture at the EJ, JPE and *Econometrica*, there is no obvious piece of supporting evidence for these biases in the OEP and *Economica*.

As a further test of the influence of editorial/journal belief bias as compared with country specific effects, we have computed a measure of the joint influence of editorial/journal specific belief biases by taking the difference between the individual and the aggregate proportions ($s_{ijt} - s_{jt}$). We call this the journal *Bias* variable below and allow for its influence in the estimation of the two-country logistic diffusion model. Models 4, 5 and 6 in Table 6 repeat the test for the common values of '*a*', '*b*', '*d*' and '*e*' (the parameter on this new *Bias* variable). Model 4 is restricted with common values for of '*a*', '*b*', '*d*' and '*e*' and this model not rejected by the unrestricted model (5). The likelihood test value is 8.848 with 4 degrees of freedom while critical value with four degrees of freedom is 9.488. In short, the inclusion of editorial bias removes the country specific difference with respect to '*b*', '*d*', and '*a*'; and had there been no editorial biases, US and UK journals would have achieved the same diffusion speed, the same saturation level and same inflexion point.

Table 7 introduces the *Bias* variable into the individual journal logistic function estimates. On the basis of the likelihood ratio in model 4 or 5 in Table 6 as compared with those in Table 7, it seems that journal specific parameter model (i.e. journal specific '*a*', '*b*' and '*d*') performs better than country specific one. This supplies general support for the hypothesis that it is specific journal editorial/belief biases, which explain the different patterns of diffusion rather than differences between the UK and US academic communities. Nevertheless, although we cannot reject in the journal specific model the hypothesis that all journals are affected in the same way by the *Bias* variable (i.e. common values for '*e*'),[7] the fact that the journals still have different values for '*a*', '*b*' and '*d*' also suggests that our journal *Bias* variable is imperfect. So while we incline, on the evidence so far, to the interpretation that it is journal specific differences in editorial/belief bias that account for the observed differences in the diffusion pattern of the econometric technique across journals, there is more work to be done here.

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[7] When SJPE was introduced as the eighth journal, the results on the restricted model (i.e. identical '*a*', '*b*', '*d*' and '*e*') did not change. In the journal specific model, the model with common *e* as before was not rejected.

Table 6

Logistic diffusion relationships for US and UK journals

a_1 and t-statistic	a_2 and t-statistic	Common *a* and t-statistic	b_1 and t-statistic	b_2 and t-statistic	Common *d* and t-statistic	d_1 and t-statistic	d_2 and t-statistic	Common *d* and t-statistic	e_1 and t-statistic	e_2 and t-statistic	Common *e* and t-statistic	Log L and SB	Model
		29.5070* (18.8403)			-2.3553* (-7.33)			0.1540* (6.17)				-1047.7 1056.20	(1) Most restricted
28.721* (8.56)	30.638* (21.00)		-2.92* (-5.29)	-2.21* (-5.72)		0.14* (3.93)	0.178* (5.33)					-1026.2 1043.23	(2) Less restricted
		30.4232* (22.50)	-2.80* (-6.45)	-2.23* (-5.70)		0.13* (6.28)	0.181* (5.43)					-1026.4 1040.51	(3) More restricted
		50.8544* (28.77)			-2.1902* (-34.25)			0.0739* (21.46)			0.0947* (19.83)	-787.03 798.35	(4) Most restricted
44.007* (16.15)	53.031* (23.62)		-2.17* (-18.6)	-2.20* (-27.5)		0.084* (12.98)	0.077* (16.31)		0.098* (10.028)	0.093* (15.64)		-782.49 805.13	(5) Less restricted
44.938* (21.000)	52.575* (26.561)				-2.195* (-34.2)	0.083* (17.14)	0.072* (19.67)				0.0943* (19.15)	-782.61 799.58	(6) More restricted

Notes: * Significant at 1% level

Model 1: $Y_{it} = \dfrac{a}{1+\exp(-b-dt)}$; Model 2: $Y_{it} = \dfrac{a_{1*}UK + a_2 *US}{1+\exp(-b_1 *UK - b_2 *US - d_1 *UK *t - d_2 *US *t)}$; Model 3:

$$Y_{it} = \frac{a}{1+\exp(-b_1 *UK - b_2 *US - d_1 *UK *t - d_2 *US *t)};$$

Model 4: $Y_{it} = \dfrac{a}{1+\exp(-b - e * Bias - dt)}$; Model 5 $Y_{it} = \dfrac{a_1 *UK - a_2 *US}{1+\exp(-b_1 *UK - b_2 *US - -e_1 *UK * Bias - e_2 *US * Bias - d_1 *UK *t - d_2 *US *t)}$

Model 6: $Y_{it} = \dfrac{a_1 *UK + a_2 *US}{1+\exp(-b - e * Bias - d_1 *UK *t - d_2 *US *t)}$

Table 7

Models with editorial *Bias* or belief variables for seven journals related to econometric methodology

Name of variable	Coefficient	t-statistic	Coefficient	t-statistic
EJ: a_1	30.1302*	6.234	27.892*	12.365
Economica: a_2	40.749*	13.173	40.479*	17.871
OEP: a_3	46.692*	12.164	46.594*	15.935
AER: a_4	38.987*	17.184	41.143*	17.139
JPE: a_5	65.299*	12.577	62.310*	19.277
Econometrica: a_6	41.282*	7.995	46.084*	12.473
QJE: a_7	45.903*	10.029	44.665*	12.653
EJ: b_1	-2.394*	-7.665	-2.364*	-7.577
Economica: b_2	-2.329*	-10.219	-2.330*	-10.267
OEP: b_3	-2.127*	-12.803	-2.127*	-12.925
AER: b_4	-2.255*	-10.178	-2.226*	-11.120
JPE: b_5	-2.296*	-17.995	-2.315*	-17.981
Econometrica: b_6	-2.208*	-9.068	-2.111*	-11.489
QJE: b_7	-2.099*	-12.166	-2.097*	-12.037
EJ: d_1	0.114*	4.544	0.129*	7.979
Economica: d_2	0.101*	7.765	0.102*	9.035
OEP: d_3	0.079*	8.705	0.079*	11.448
AER: d_4	0.107*	8.338	0.098*	8.839
JPE: d_5	0.050*	9.012	0.052*	9.625
Econometrica: d_6	0.092*	5.076	0.079*	11.952
QJE: d_7	0.080*	8.293	0.083*	10.946
EJ: e_1	0.081*	2.350		
Economica: e_2	0.100*	4.769		
OEP: e_3	0.102*	7.832		
AER: e_4	0.135*	5.220		
JPE: e_5	0.095*	8.330		
Econometrica: e_6	0.122*	4.805		
QJE: e_7	0.097*	6.552		
Common *e*			0.102	15.847
Log L	-755.532		-757.573	
SB	834.765		819.827	
χ^2 (6)			4.082	

Notes: Restricted model is accepted as the critical value of $\chi^2_{.05}$ (6) = 12.592. *Significant at 1% level

5 Conclusion

This paper provides estimates of the speed of diffusion of two ideas in economics. On the basis of these estimates, it seems that (a) the speed of diffusion of ideas is typically slower in academia than is the diffusion of new techniques in industry, (b) the speed of diffusion has fallen over time, and (c) editorial biases have played an important role in the pace of diffusion in individual journals. As these conclusions are based on only two ideas, they are necessarily tentative. Nevertheless, while the last probably comes as no surprise, the first two are potentially important because they contradict parts of what seem to be the conventional wisdom in the economics of science literature.

First, while this literature has not focussed explicitly on diffusion, it has argued that new ideas are more freely available under the 'priority of discovery' norm of academic life than under the patent regime of the commercial world. Furthermore since there are no costs analogous to patent payments, which come from using a new idea in academia, one might plausibly expect on the basis of this literature that rate of diffusion is faster in the academy. Our empirical results cast doubt on this.

Second, it is a commonly assumed that academic communities have become more competitive and typically that, from a public policy point of view, this is a good thing. Again result (b) casts doubt on some aspects of this conventional wisdom: the speed of diffusion seems to have actually not increased.

Of course, the slow spread of the experimental technique is only worrying if it is, indeed, a 'good' technique. If it is not, then its slow and patchy diffusion is actually a testament to the health of the academic community. While such an assessment of the experimental technique would save conventional wisdom on this point, it would not get rid of the worry altogether. Instead it would be transferred to the state of health of some of our 'top' journals because it is these journals that have been in the vanguard disseminating the experimental technique.

Assuming that experiments are a 'good' thing, it is tempting to link result (c) with an argument that has been made over the oligopolisation of journal editorships (see Hodgson and Rothman 1999). In other words, it is the fact that editors are important and that they have come increasingly from a restricted group within the academic community that explains why diffusion of new ideas is slower now than in the past. The difficulty with this argument is that diffusion is actually very varied across journals and so editors scarcely seem to share, at least in respect of the merit of the experimental technique, such a *germeinshaft*.

Nevertheless, there is a worrying puzzle over the slow spread of the experimental technique. Either it arises from the negative editorial bias in those journals where scarcely any experimental papers have been published or it reflects the relatively poor assessment of the technique by the academic community (which is only overcome by the positive bias of those editors for the EJ, *Econometrica*, AER and QJE where experimental articles have been regularly published). A natural topic for future work would be to unravel which is the case.

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