



FACULTY OF BUSINESS AND LAW

School of

ACCOUNTING, ECONOMICS AND FINANCE

School Working Papers – Series 2004

SWP 2004/17

PUBLICATION BIAS IN UNION-PRODUCTIVITY RESEARCH?

H. Doucouliagos:

Email: douc@deakin.edu.au.

P. Laroche:

Email: patrice.laroche@univ-nancy2.fr

T.D. Stanley

Email: Stanley@hendrix.edu

The working papers are a series of manuscripts in their draft form. Please do not quote without obtaining the author's consent as these works are in their draft form. The views expressed in this paper are those of the author and not necessarily endorsed by the School.

URL: http://www.deakin.edu.au/fac_buslaw/sch_aef/publications/default.htm

Title: **PUBLICATION BIAS IN UNION-PRODUCTIVITY RESEARCH?**

Authors: **HRISTOS DOUCOULIAGOS, PATRICE LAROCHE, AND T.D. STANLEY**

Contact Details: Doucouliagos: School of Accounting, Economics and Finance, Deakin University, 221 Burwood Highway, Burwood, 3125, Victoria, Australia.

Email: douc@deakin.edu.au.

Phone: 61 03 9244 6531

Laroche: Institut d'Administration des Entreprises, University of Nancy 2, 13, rue Michel Ney, Case Officielle, no. 75, 54037 Nancy, France.

Email: patrice.laroc@univ-nancy2.fr

Stanley: Department of Economics, Hendrix College, 1600 Washington St., Conway, AR, 72032, USA

Email: Stanley@hendrix.edu

ABSTRACT

This paper develops and applies several meta-analytic techniques to investigate the presence and consequence of publication bias in industrial relations research, specifically in the union-productivity effects literature. Publication bias arises when statistically insignificant results are suppressed or when results satisfying prior expectations are given preference. Like most fields, research in industrial relations is vulnerable to publication bias. Unlike other fields of economics, there is no evidence of publication bias in the union-productivity literature, as a whole. However, there are pockets of publication selection and the hint of negative autoregression, confirming the controversial nature of this area of research. Meta-regression analysis reveals evidence of publication bias (or selection) among US studies.

PUBLICATION BIAS IN UNION-PRODUCTIVITY RESEARCH?

“We know that publication bias exists and that it is a serious problem.”

Begg and Berlin (1988: 440)

What determines which research manuscripts are published? Is it the quality of the research, alone? If the statistical significance of the submitted results is given preference, then the distribution of published studies will be affected by publication bias. Publication bias is a subtle, often covert, form of bias in empirical research arising when the selection of studies for publication is made on the basis of the statistical significance of results, and/or on whether the results satisfy preconceived theoretical expectations.¹ The ultimate aim of empirical explorations is to weed out invalid theories and to strengthen our confidence in supported ones. Unfortunately, if publication bias exists, then this task is greatly hindered. Publication bias can distort both scientific inferences and policy decisions.

The issue of publication bias has received considerable attention in a number of fields, especially in psychology and medicine (see Begg and Berlin 1988). Recently, economists have started to address the issue (Card and Krueger 1995, Ashenfelter *et al.* 1999, Gorg and Strobl 2001). So far, all existing investigations in economics have found evidence of publication bias. The aim of this paper is to investigate the existence and extent of publication bias in the union-productivity effects literature and to develop the tools used to investigate publication bias. These meta-analytic tools might then be used to detect and correct publication bias in other areas of applied economics.

To our knowledge, the issue of publication bias in industrial relations research has not received any formal attention. This is surprising since industrial relations is one of the most controversial research areas. Most aspects of work and employment receive considerable attention from varying theoretical and empirical perspectives. In particular, the nature of the production and labour processes, the role of incentives, ownership and

¹ Publication bias is also known as positive-outcome bias or the ‘file drawer’ problem. Studies that report statistically insignificant results tend to remain in the researchers’ file drawers never to be published or, if published, delayed (‘pipeline’ bias).

management structures, and bargaining regimes, have all received intense debate. This is especially so in the case of the economic impact of unions.

The ‘Two-Faces’ View of Unionism

There are conflicting predictions regarding the impact of unions on productivity. For example, the conceptual framework known as the ‘two-faces’ view of unionism highlights both the monopoly face and the collective voice/institutional response face of unions (Freeman 1976 and Freeman and Medoff 1984). Unions can reduce productivity by: (a) constraining management through restrictive work rules and practices, such as overtime restrictions, job protection and seniority rules; (b) striking or taking other industrial actions; (c) encouraging an adversarial industrial relations climate with low trust and a lack of cooperation; and (d) increasing wages above competitive levels and capturing part of the quasi-rents, so that unionized firms end up with lower levels of tangible and intangible assets.

Union presence can also have a positive effect on productivity. This can arise through: (a) improving communication between workers and management; (b) providing a mechanism for expressing discontent at the workplace, reducing quit rates and absenteeism; (c) establishing explicit grievance procedures which help resolve disputes between management and workers; (d) improving worker morale and cooperation between workers and management; (e) ‘shocking’ managers to improve methods of production and adopt more efficient personnel policies; and (f) encouraging increased capital intensity and higher quality labour through higher wages for unionized workers.

The net effect of these positive and negative influences on productivity is largely indeterminate and would likely vary across firms, industries, regions and over time. The net impact of unions on productivity is thus an empirical issue. Policy makers, in particular, need to draw clear inferences from the available empirical studies. These inferences will be valid only if publication bias is not a problem.

Publication Bias

Publication bias is a collective label for a set of distortions in the process of reporting of results (Sutton *et al.* 2000b). Several categories of publication bias can be identified. First, authors may submit only research with statistically significant results. Second, journals may publish only, or give preference to, statistically significant results. That is, journal editors may use statistical significance to screen findings and this may lead to potential bias if studies with non-significant results are not published. Moreover, editors may be biased against studies with small samples, and they may be biased against so-called “soft” methodologies, such as qualitative case studies. Third, authors may report only findings that are consistent with prior expectations, prior beliefs, and ideological positions. Fourth, journals may have a publication preference for findings that are consistent with the prior expectations or theoretical prejudices of the editors and referees. Fifth, interesting or surprising findings (perhaps even those in conflict with established views) may be given preference from time to time (Goldfarb 1995).

Bias need not arise because of the deliberate suppression of insignificant results, motivated by some urge to deceive. Authors may, for example, refrain from submitting statistically insignificant results on the expectation (unquestionably true in some fields) that they will have a lower probability of publication (Gilbody *et al.* 2000). Insignificant results may not be as interesting to readers and, given that journal space is a scarce resource, journals may prefer that insignificant results not be published, choosing instead to devote space to what are regarded as more informative results.²

Literature reviews play an important role in disseminating research information, drawing conclusions, and in forming consensus. Whether a review is conducted on a sample of studies or on the entire pool of studies, it is important to consider the existence and degree of publication bias in a literature. If a group of studies is under-represented in the literature, it will impact on the conclusions drawn from the truncated pool of available studies. Although publication bias is a very difficult area to explore, it does leave a number of traces. We explore the available studies in the union-productivity literature for several of these traces. In particular,

² The financial press in general prefers statistically significant results and rarely reports non-significant results.

- Is there statistical evidence of publication bias?
- Is there evidence of a positive (or negative) union-productivity effect, beyond the potential contamination of publication bias?
- Are both positive and negative findings reported?
- What is the proportion of negative findings versus positive findings?
- What is the proportion of statistically significant results?
- Is there a bias against small sample studies?
- Are smaller studies more likely to report larger effects?
- Do publication patterns differ across journals or over time?

Many other questions regarding the selection of research during the peer-review process and the evolution of that research are innately interesting to researchers. However, data limitations do not permit us to address all of the potentially interesting questions.³

In the union-productivity literature, we expect to find both positive and negative findings because conventional theory supports both. A literature contaminated by publication bias will have a dearth of published studies with statistically insignificant results. However in this area of research, we expect to find statistically insignificant results to be published. The ‘two-faces’ theory makes it clear that positive effects can cancel out the negative effects. In many cases this may mean a near zero effect, and in this application we expect such null results to be published. Publication bias is often manifested by small-sample studies reporting larger effects to overcome their larger standard errors. We explore the union-productivity literature for such patterns, explicitly, using graphs (funnel plots) and statistical analysis (meta-regression analysis).

Data

The union-productivity effects literature has been reviewed extensively by several authors. For example, expert narrative literature reviews have been conducted by Booth (1995), Kuhn (1998) and Addison and Hirsch (1989). More recently, Doucouliagos and

³ For example, we are unable to explore differences in results between submitted manuscripts and published papers, as we do not have access to original manuscripts and would be unable to locate all

Laroche (2003) provide a meta-analysis of this literature. None of these reviews, however, have explored the existence of publication bias; thus, their findings may be tainted.

In this paper we use the data published in Doucouliagos and Laroche (2003) to explore publication bias in the union-productivity literature.⁴ Doucouliagos and Laroche compiled information on 73 published studies, including partial correlations between unionization and productivity, total union-productivity effects and statistical significance status of the reported results.

The criteria for inclusion of a study in the analysis is that a study had to be published, or accepted for publication and forthcoming, and the study had to use regression analysis to explore the links between unions and productivity. Hence, case studies were excluded, as were studies that did not report the relevant regression estimates. This selection process means that a few studies are excluded from our analysis, but this criterion is necessary to ensure a consistent set of union-productivity effect measures that can be investigated analytically.⁵

Basic regression information was collected from each study, such as estimated coefficients, t-statistics, sample sizes, and standard errors. Partial correlation coefficients were also calculated and serve as our central measure of effect size, measuring the direction and magnitude of correlation between unions and productivity. The total union-productivity effect is available for a smaller group of studies; thus, we use the partial correlations coefficients. Because the focus of this paper is publication selection, we are as inclusive as possible.

Publication bias can be explored formally through both qualitative and quantitative tools. The standard approach is to use some graphical display, such as funnel plots, and to supplement this with quantitative analysis.

working papers. However, such an undertaking would be useful, and it might provide deeper insight into publication bias and selection.

⁴ For details on the construction of the database, see Doucouliagos and Laroche (2003). The data used in this paper can be found in their article, Table 1, pp. 660-662.

⁵ To anticipate a potential criticism, our 'selection bias' is entirely dictated by the possibility of making meaningful comparisons and is not influenced by the source or the outcome of the research. If a study's results can be converted to a regression measure of effect size, it is included.

Graphical Inspection

Of the 73 studies offering a quantitative assessment of the impact of unions on productivity, 45 report a positive association and 28 report a negative one. More importantly, 29 of the 73 studies reported statistically insignificant results. That is, positive, negative, as well as statistically insignificant results are well-represented in this literature. Hence, our immediate assessment of this literature is that publication bias, if it exists at all, is not a major problem. This casual observation is supported below in graphical displays and by meta-regression analysis.

Funnel Plots

The funnel plot is probably the most popular graphical technique for assessing publication bias. This scatter plot derives its name from the funnel-like pattern that emerges when there is no publication bias (see Figure 1). The funnel plot compares the effect size against some measure of precision, such as sample size or the inverse of the standard error (Sutton *et al.* 2000c). The logic behind funnel plots is that those studies with a smaller sample size or precision will have larger random error; thus a larger spread when graphed. Hence, in the absence of publication bias, the union-productivity effects from smaller studies will have a larger, but symmetric, spread around the mean effect. This, of course, is based on the assumption that there is one universal mean union-productivity effect. Authors are divided about this issue. Some authors argue that the union-productivity effect will vary from industry to industry and country to country, while others believe that there is a universal relationship. Even if the size the union-productivity effect were to vary randomly across studies due to variations in industry and country choices, the funnel graph would retain its basic symmetric shape in the absence of publication bias.

If there is no publication bias, the funnel plot should be symmetric and hence look like an inverted funnel. Figure 1 presents the funnel plot for these 73 published studies. The partial correlations are measured on the horizontal axis and the inverse of the standard error ($1/Se$) on the vertical. As can be seen from Figure 1, the graph clearly resembles a symmetric inverted funnel. As expected, smaller studies (those at the bottom

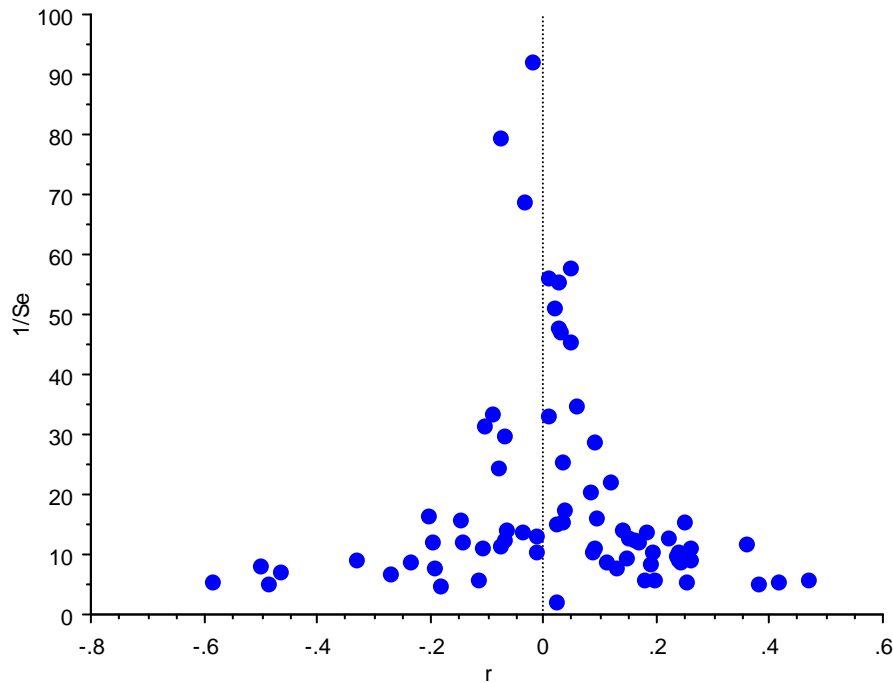
of the graph) display greater variation in productivity effects. The distinct funnel shape of this distribution gives clear visual evidence of the absence of publication bias. This result is actually quite heartening given the rather controversial nature of this literature. If there are publication biases they do not strongly favour one side or the other.

The idea behind funnel plots is that if small studies with insignificant results are not published, then the funnel shape will become asymmetric.⁶ If smaller studies with insignificant results are known to be difficult to publish, then authors may endeavour to select larger estimated effect sizes through specification searching. Thus, the reported/published effect sizes will overestimate the underlying empirical finding. This selection leads to publication bias because the authors are responding to journal preferences and skewing what they report rather than reporting unfiltered empirical results.⁷ Thus, only those small studies with large effects will be published, causing a correlation between effect size and sample size. Some authors argue that smaller studies are likely to be poorly designed studies (e.g. Sigelman 1999). However, Gerber *et al.* (2001: 386) note correctly that: “published studies based on small samples should be well-executed studies, but there should be no tendency for studies based on small samples to show unusually large effects”. The reality in many economic applications is that only small samples are available to researchers. If insignificant results are established from small samples, this fact should still be revealed to other researchers.

⁶ Actually, the funnel graph will only become asymmetric when there is a preference for significant results of a given direction. When there is an equal preference for both significant positive and significant negative results, the funnel graph remains symmetric, but hollow.

⁷ It should be noted that publication bias does not require any unethical or unscientific action by the researchers. If editors and referees are more likely to select significant findings for publication, then the same biases will be found in the literature without additional searching or selection by the authors or theoretical biases of editors and referees.

Figure 1: Funnel Plot, Union-Productivity Partial Correlations, All Studies



In meta-analysis, the potential distortion of small-samples and the resulting potential for publication bias is routinely mitigated by using weighted averages. In economics, weighted averages have been constructed using sample sizes, the number of specification tests passed, citations, and journal rankings (Stanley 2001 and Doucouliagos and Laroche 2003). A lower weight is preferable to the zero weight that would arise if smaller studies are suppressed altogether. The inverse of the effect's variance is usually considered optimal because it minimizes the variance of the weighted average (Sutton *et al.* 2000c: 58).

Meta-Regression Analysis and Meta-Significance Testing

The main problem with funnel plots is that they are graphical devices, hence prone to subjective interpretation. However, meta-regression analysis (MRA) can be used to provide a more objective test of a funnel graph's asymmetry and also to test for the existence of a genuine underlying empirical effect beyond publication bias. See Stanley and Jarrell (1989), Stanley (2001), and Stanley, Florax and de Groot (2003) for an introduction and discussion of these tools of meta-analysis. Egger *et al.* (1997) offers

a funnel asymmetry test (FAT) that looks for a significant intercept in the regression of the standardized effect (e.g., the t-value) on the inverse of the standard error (1/Se). This MRA is the weighted-least squares version of a meta-regression of a study's effect on its standard error. In the absence of publication bias, so the reasoning goes, there should be no relationship between the magnitude of the reported effect and its standard error. However, with publication bias, smaller studies will tend to select *larger* effects (in magnitude) to overcome their inherently *larger* standard errors. When we divide this simple meta-regression model by the standard error to correct for obvious heteroskedasticity, the slope coefficient becomes the intercept, and *visa versa*.

Table 1 column 1 presents the meta-regression analysis (MRA) corresponding to FAT. The intercept is not statistically significant ($t=1.72$; $p>.05$); hence, Egger's asymmetry test confirms our visual inspection of the funnel plot.

However, there is a problem with Egger's asymmetry test. Because the standard error is estimated from the sample data of each study, it contains estimation error (Macaskill et al., 2001). As widely recognized, whenever the independent variable is measured with error, the regression estimates will be biased and inconsistent—*i.e.*, errors-in-variables bias.

In this application, two strategies are readily available to remedy this errors-in-variables bias. First, the square root of the sample size, which does not contain sampling error, could be used as a proxy for the inverse of the estimate's standard error. Table 1 column 2 reports this approach and again finds no evidence of publication bias (accept $H_0: \beta_0=0$; $t=1.60$; $p>.05$). Secondly, instrumental variables estimators are known to correct for errors-in-variable bias, and, in this case, the square root of the sample size is the obvious instrument.

Table 1: Meta-Regression Tests

<i>Moderator Variables:</i>	<i>Dependent Variables</i>			
	<i>Column 1: t FAT</i>	<i>2: t FAT</i>	<i>3: t FAIVE</i>	<i>4: ln t MST</i>
<i>Intercept</i>	.65 (1.72)*	.62 (1.60)	.61 (1.47)	.39 (1.27)
<i>ln(n)</i>	----	----	----	-.0003 (-.006)
<i>1/Se</i>	-.0179(-1.06)	----	-.0158 (-.85)	----
<i>sqrt(n)</i>	----	-.015 (-1.09)	----	----
<i>n</i>	73	73	73	73
<i>R²</i>	.024	.016	.024	3.6x10 ⁻⁷
<i>Standard Error</i>	2.13	2.14	2.13	.83

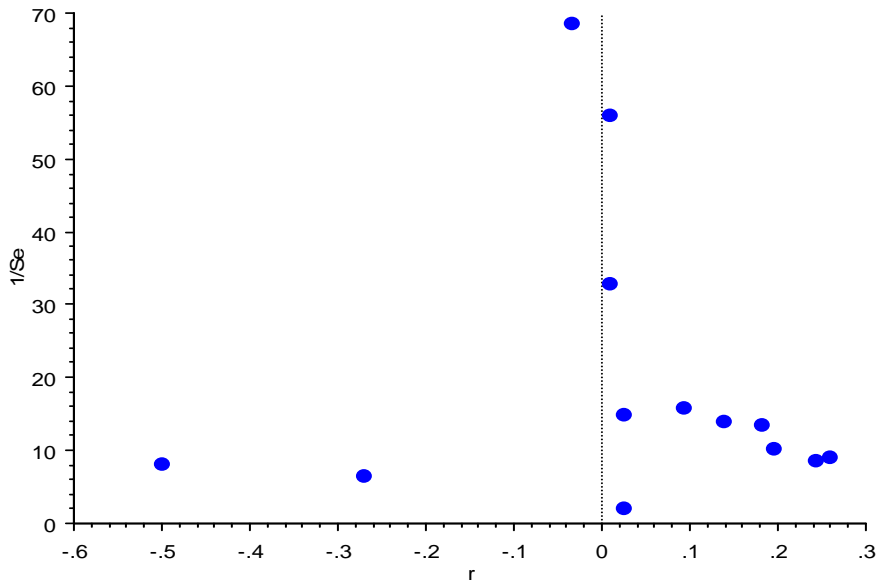
*t-values are reported in parenthesis and are calculated from heteroskedasticity-consistent standard errors.

For theoretical statistical reasons, we know that the square root of the sample size should be highly correlated with the inverse of the standard error; here, this correlation is 0.93. Yet, the sample size will be independent of the standard error’s random sampling errors. The funnel asymmetry instrumental variables estimator (FAIVE) is reported in column 3 of Table 1. Again, FAIVE accepts the null hypothesis that there is no publication bias (accept $H_0: \beta_0=0; t=1.47; p>.05$). Regardless of the estimation approach taken, we accept the symmetry of the funnel plot and find no significant statistical evidence of publication bias in the union-productivity literature. This finding of no significant publication bias in the union-productivity literature should be seen against the backdrop of other investigations for publication bias. In all other applications in economics conducted thus far, evidence of publication bias has been claimed (Card and Krueger 1995, Ashenfelter *et al.* 1999, Gorg and Strobl 2001). Hence, our finding of no publication bias in this area of industrial relations research is rather exceptional.

The only potential exception to this null finding is that FAT could be construed as providing weak evidence of publication bias. Egger *et al.* (1997) advocate using a less stringent significance level (*i.e.*, $\alpha=.10$) to compensate for the low power of their test. By this criterion, there is weak evidence of publication bias in the direction of a positive

union-productivity effect, Table 1 column 1 ($t=1.72$; one-tail $p<.05$). This positive publication bias is clearly seen among the earliest studies (Figure 2) and among US studies (Figure 3, discussed below), if not in the literature as a whole (Figure 1). However, when this asymmetry test is corrected for its known bias using FAIVE, no evidence of publication bias remains, even at this weakened significance level ($t=1.47$; $p>.10$).

Figure 2: Funnel Plot, Studies Published prior to 1985



Thus far, we have concentrated on the issue of whether publication bias exists in a given literature and how we might identify it if it does. However, the more fundamental question concerns whether there is an underlying genuine empirical effect (union-productivity effect), irrespective of potential publication bias. Stanley (2001) argues that the meta-regression of a study's standardized effect on its sample size can serve as a robust test of empirical effect. The idea for this test is simple and is based on well-known properties of statistical power. If there were a genuine union-productivity effect, then the absolute value of the associated t-statistic would tend to increase with larger samples. However, were there no genuine empirical effect, the sample size would have no systematic relationship to a study's t-statistic. It thus follows from well-known properties of regression estimators that:

$$\ln E|t_i| = \alpha_0 + \alpha_1 \ln(n) \quad (1)$$

(Green, 1990). α_I can, in theory, take on only two possible values. $\alpha_I=1/2$ when there is a nonzero effect, and $\alpha_I=0$ when there is no empirical effect (Stanley, Florax, and de Groot, 2003). This meta-significance test (MST) produces evidence of an underlying empirical effect whenever we can reject $H_0: \alpha_I \leq 0$.

However, publication bias complicates this sharp meta-significance test. By definition, publication bias is the distortion of the reported effects through selection for statistical significance. Small-sample studies will find it more difficult to report significant effects because they will tend to have larger standard errors. Hence, small-sample studies will tend to select and report larger absolute effects to increase their chances of publication acceptance. In contrast, large-sample studies will not need to search as intensively for a specification that produces statistical significance. Publication bias, therefore, may be seen as an attempt to circumvent statistical power. As a result, publication selection will attenuate the MRA estimate of α_I . Because publication bias works in the opposite direction (smaller samples, larger effects) as does statistical power (larger samples, larger t), MST provides a conservative test for genuine empirical effect in the presence of publication bias. When we reject $H_0: \alpha_I \leq 0$, we have evidence that there is a genuine empirical effect despite the potential contamination of publication bias.

Table 1 column 4 reports the MRA that forms the basis of this meta-significance test. Clearly, there is no evidence of a statistical relationship between $\ln|t|$ and $\ln(n)$ ($t=-.006$; $p \gg .05$) and thus no support for a genuine union-productivity effect. However, it is not the lack of power of MST itself that gives us this null result. In other applications, meta-significance testing has no difficulty in uncovering evidence of an authentic empirical effect. Specifically, twenty-eight tests of Ricardian equivalence, one-hundred and ten price elasticities, ninety income elasticities, and nineteen non-US union-productivity correlations (see below) all contain significant power traces (Stanley 2001, Stanley, Florax and de Groot 2003). Furthermore, FAT and FAIVE corroborate MST's inability to find an underlying empirical union-productivity effect.

The slope coefficient of Egger's asymmetry test may also be used to provide a corrected estimate of the true effect; hence, it is an additional test of significance (Macaskill *et al.* 2001: 644). Regardless of which estimation strategy we use, including

FAIVE, the estimated slope of the funnel relation is statistically insignificant—see Table 1 columns 1, 2 and 3. It may be interesting to note that the corrected estimate of the partial correlation for the union-productivity effect is negative (-.016, column 3 Table 1); whereas, the unadjusted average is positive (.026), consistent with some positive (but insignificant) publication bias. In sum, we have two separate meta-regression testing strategies that confirm the absence of a genuine union-productivity effect and several others that fail to find significant publication bias.^{8,9}

Other Patterns of Publication Selection

Autoregression: Timing is Everything

Are there patterns across time among the reported union-productivity effects? Goldfarb (1995) has suggested that there is a predictable pattern to empirical economic research. First, there is a tendency to report evidence confirming a new theory or hypothesis. Then, after a sufficient passage of time for confirmations to accumulate (typically years), further confirmation is thought to contain little new information. Thus, contradictions become more likely to be published. Again, after sufficient time elapses, such empirical criticisms will become passé, engendering another reversal of publication preferences. Such a view of empirical economic research leads to cycles of fashion much like those found in the economy. To render Goldfarb's conjecture testable, waves of publication fashion should produce positively autocorrelated findings. That is, if several years of positive reported findings are followed by years of primarily negative ones, positive autocorrelation will result.

Clearly, existing research acts as a catalyst to future research, but this does not necessarily mean that similar results will be published in the future. To test for the

⁸ This is consistent with Doucouliagos and Laroche (2003, p. 666) who conclude that: "... taking all the available evidence, the conclusion is that the central tendency of the published results falls around *zero* ..." (italics in original).

⁹ There are additional nonparametric approaches and graphical techniques (such as normal quantile plots) that are also used to identify publication bias. However, these alternative approaches only confirm our reported results. In particular, some meta-analysts investigate the rank correlation between of sample size and effect size (Sutton *et al.*, 2000c, pp. 116-117). In this application, Kendall's Tau is .018 (p=.82), which corroborates our meta-regression findings of no publication bias. However, because these non-parametric methods are known to have especially low power, this corroboration adds little weight.

existence of autoregressive effects we estimated a number of autoregressive (or AR) models, where the dependent variable was an effect size, regressed against its past values. A yearly average is constructed by averaging all the studies published in 1980, 1981, and so on. The most striking finding is the nearly significant negative autocorrelation (-.26; $t=-1.68$; one-tail $p=.054$) for a one-year lag—AR(1). This means that a positive finding tends to be followed by a negative finding, and vice versa. Such negative autocorrelations seem to refute Goldfarb's conjecture, unless of course economic fashions are very fickle.

Perhaps this negative autocorrelation can be interpreted as a form of publication bias, but one that is not entirely undesirable. A vigorous critical empirical environment may be a socially useful process. This negative autocorrelation among reported union-productivity effects may be a reflection of the controversial nature of the union-productivity effects literature. Whenever a finding in one direction or the other seems to be in the ascendancy, there is increased motivation of members of the opposing camp to quickly publish a counterbalancing finding. Such contentiousness is not unknown in other areas of labour economics. For example, there is the notorious controversy over the employment effects of the minimum wage (*The Economist*, February 3, 2001:80). Although union-productivity research may not be quite as contentious as minimum wage research, the observed negative autocorrelation may be a reflection of its controversial nature. In any case, the fact that autocorrelations are not strictly significant is another confirmation of the lack of evidence of publication bias in this area of research.

National Differences: 'US vs. Them'

Geography is the last dimension across which we search for publication selection. Do effects, or their selection, differ across countries? Obviously, there are important cultural and historical differences among nations that might well affect union productivity and/or the research climate. Here, we investigate only the broadest of such distinctions, US vs. all other nations, because a large majority of studies (74%) in this literature use US data.

In a previous study of this literature, Doucouliagos and Laroche (2003) find a positive union-productivity effect among US studies and speculate that this result

“derives from real economic forces” (p. 680). Although they recognize that this effect is quite close to zero, a 95% confidence interval remains entirely positive (0.01, 0.03). Furthermore, Doucouliagos and Laroche (2003) realize that some of their findings may be influenced by publication bias and call for further investigation. Unfortunately, meta-analysis, like all other forms of literature reviews, is vulnerable to publication bias if it is not explicitly addressed. In this case, it seems that the apparent real differences found among US studies are little more than the artifact of selection for positive union-productivity effects.

To see this, note the meta-regression results reported in Table 4, which test for publication bias (FAIVE, column 1) and an underlying real effect (MST, column 2) after adding a dummy variable for studies that use US data (US=1, 0 for other countries) along with the implied interaction term. The findings are quite interesting and robust. US studies appear to be selected for their positive union-productivity effects, and this bias is confirmed by two tests in Table 4. The FAIVE intercept reported in column 3 for the US studies alone is clearly significantly positive ($t=2.46$; $p<.05$). Likewise, the sum of the intercept and the FAIVE coefficient for US in column 1, where all studies are included, is statistically significant (Wald restriction test $\chi^2_{(1)} = 4.47$; $p<.05$). This selection is also evident in the funnel graph where only US studies are displayed (see Figure 3). Note the scarcity of values on the lower half of the left side. Yet interestingly, the three largest studies (*i.e.*, those at the top of the funnel graph) are all negative. It is this asymmetry that FAIVE detects.

Figure 3: Funnel Plot, Union-Productivity Partial Correlations, US Studies

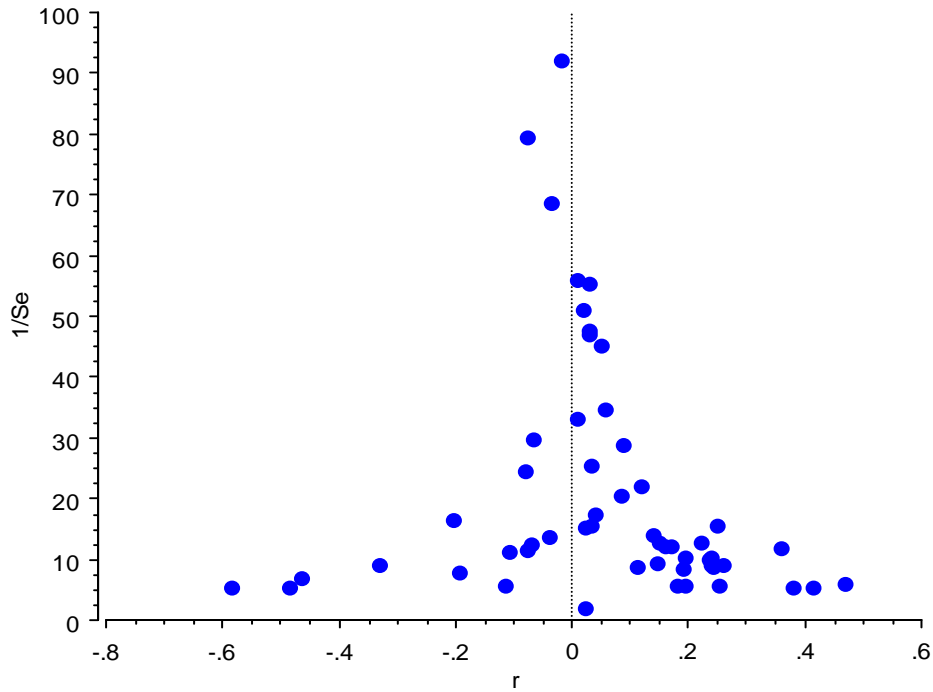


Table 4: Meta-Regression Tests for US Publication Bias and Effect
Dependent Variables

Moderator Variables:	Column 1: <i>t</i> FAIVE	2: <i>ln t </i> MST	3: <i>t</i> FAIVE	4: <i>ln t </i> MST
Intercept	-.21 (-.40)*	-.74 (-1.26)	1.15 (2.46)	.73 (2.22)
<i>ln(n)</i>	----	.20 (2.38)	----	-.05 (-.90)
<i>1/Se</i>	-.020 (-1.01)	----	-.027 (-1.43)	----
US	1.22 (2.08)	1.46 (2.18)	----	----
<i>US × ln(n)</i>	----	-.26 (-2.45)	----	----
<i>n</i>	73	73	54	54
<i>R</i> ²	.061	.035	.069	.011
Standard Error	2.08	.82	2.04	.78

*t-values are reported in parenthesis and are calculated from heteroskedasticity-consistent standard errors.

Is there evidence of a real union-productivity effect after allowing for national differences and publication bias? If there were a genuine effect among US studies the FAIVE slope coefficients for (*1/Se*) would be significant. But they are not (columns 1

and 3, Table 4). Genuine effect would also be evidenced by a significantly positive MST coefficient on $\ln(n)$. Although this is exactly what we find in Table 4 column 2 ($t=2.38$; $p=.01$), this effect is not associated with US studies, but rather with non-US studies. Recall that $US=1$ for US studies; thus, the coefficient on $\ln(n)$ in Table 4 column 2 refers to non-US studies ($US=0$). This genuine union-productivity effect for non-US studies is confirmed when only these non-US studies are included in the MRA ($t=2.32$; $p<.05$)—Table 5 column 1.¹⁰ However, in this case, FAIVE does not confirm this MST positive test result—column 2 Table 5 ($t=.39$; $p>.05$). With only nineteen observations, this lack of confirmation should not be surprising. Rather, with such a small sample, it is surprising that either test is sufficiently powerful to produce a significant result

Table 5: Meta-Regression Tests for Non-US Publication Bias and Effect
Dependent Variables

<i>Moderator Variables:</i>	<i>Column 1: $\ln t$ MST</i>	<i>2: t FAIVE</i>
<i>Intercept</i>	-.74 (-1.23)*	-.83 (-1.01)
<i>$\ln(n)$</i>	.20 (2.32)	----
<i>1/Se</i>	----	.020 (.39)
<i>n</i>	19	19
<i>R²</i>	.073	.018
<i>Standard Error</i>	.95	2.15

* t -values are reported in parenthesis and are calculated from heteroskedasticity-consistent standard errors.

Returning to the US studies and Table 4, the MST and FAIVE findings are entirely consistent. If US studies were to contain a genuine union-productivity effect beyond their publication bias, then the sum of the MST coefficients on $\ln(n)$ and the interaction term, $US \times \ln(n)$, would be positive—column 2 Table 4. However, restriction testing gives no indication of such an effect (Wald $\chi^2_{(1)} = .79$; $p >.05$), and the net effect of $\ln(n)$ is not positive as required by MST. The absence of a genuine union-

¹⁰ Note that the MST coefficients in column 1, Table 5 estimated on the non-US studies are exactly the same as the first two coefficients in column 2 Table 4, where all studies are used. Although statistical significant, the magnitude of this union-productivity effect is not large enough to be deemed practically meaningful.

productivity effect in the US is further confirmed when only US studies are used to estimate $\ln(n)$'s coefficient —column 4 Table 4 ($t=-.90$; $p>.05$).

In sum, allowing for national differences reveals significant publication selection among US studies, and evidence of some genuine empirical effect among non-US studies. Incidentally, no publication bias is indicated for these non-US studies—Table 5 column 2. It appears that there are areas of publication selection in the union-productivity literature even though the overall literature appears to be free from any trace of publication bias. Fortunately, the ‘two-faces’ view and its attendant controversy are sufficient to balance out these pockets of bias.

Conclusion

Publication is the most efficient way of disseminating research and communicating empirical results. However, the publication process is plagued by a number of problems, including publication bias. Identifying and correcting publication selection for its pernicious effects is essential if economic research is to be trusted. Otherwise, the validity of economic theory cannot be evaluated, and policy advice would remain of dubious value.

In this paper, a number of qualitative and quantitative techniques were applied to the union-productivity literature in order to explore the existence of publication bias. From the results presented, we can conclude that there is no evidence of systematic publication bias across the entire literature even though this area of research may be regarded as controversial. Nor is there any sign of a net union-productivity effect, either positive or negative. When the overall union-productivity empirical literature is investigated, there is a complete absence of a power trace that characterizes a genuine empirical effect. Importantly, it is unlikely that future research on the union-productivity will change our evaluation unless we would enter an extended period (years) of one-sided reporting of empirical findings.

Although insignificant findings may not be highly regarded by the profession, they are especially interesting in this context. All other investigations of publications bias in economics have revealed its existence. Card and Krueger (1995) find publication bias in minimum wage research, Ashenfelter *et al.* (1999) among estimates of returns to

education, Gorg and Strobl (2001) among the productivity effects of multinationals, and Stanley, Florax and deGroot (2003) uncover these same signs of publication bias among estimates to the price elasticity of water.

This investigation of potential publication bias in the union-productivity literature leads to a tentative hypothesis. Areas of research where mainstream economic theory supports a specific effect (e.g., negative price elasticity) are likely to contain publication bias. While other research areas where there is widely accepted theoretical support for both positive and negative effects are likely to be free of significant publication bias because all empirical outcomes are consistent with theory. Publication bias should be most pronounced where there is overwhelming professional consensus, for example that education has a positive return. Because union-productivity research has long been ‘two-faced’ (although this may not have always been the case, recall Figure 2), it has largely escaped one-sided distortion from systematic publication selection. In more one-sided areas of research it is unlikely that all research findings will be treated equally.

Nonetheless, pockets of publication selection may still be identified against this backdrop of seemingly balanced and objective reporting. Positive findings are likely to be followed and counter by negative reported results. Such signs of negative autocorrelation may simply reflect the fact that union-productivity research is contested and controversial. And, there is clear evidence of publication selection among US studies for positive union-productivity effects. These tantalizing hints and patterns merit further analysis.

One positive implication of our study is that literature reviews and meta-analyses can provide a fair assessment of the overall union-productivity literature. There are a number of existing reviews that do not consider the dangers of publication bias. Nevertheless, it is encouraging to note that the results presented in this paper indicate that the conclusions drawn by the existing reviews are unlikely to have been seriously affected by publication bias.

References

- Addison J. and Hirsch B. 1989. "Union Effects on Productivity, Profits, and Growth: Has the long run arrived?" *Journal of Labor Economics*, Vol. 7, pp. 72-105.
- Ashenfelter, O., Harmon C. and H. Oosterbeek. 1999. A review of estimates of the schooling/earnings relationship, with tests for publication bias, *Labour Economics*, Vol. 6, pp 453-470.
- Bauchau, V., 1997, "Is there a file drawer problem" in biological research?" *Oikos*, Vol. 79, pp. 407-409.
- Begg, C. B. and J. A. Berlin, 1988, "Publication Bias: a problem in interpreting medical data", *Journal of Royal Statistical Society, Series A*, Vol. 151, pp. 419-463.
- Booth, A. 1995. *The Economics of Trade Unions*, Cambridge University Press, Melbourne and New York.
- Card, D. and Krueger A.B. 1995. "Time-Series Minimum-Wage Studies: A Meta-Analysis." *American Economic Review*, Vol. 85, pp. 238-43.
- Doucouliafos, C. 1995. "Worker Participation and Productivity in Labor-Managed and Participatory Capitalist Firms: A Meta-Analysis." *Industrial and Labor Relations Review*, Vol. 49, pp. 58-77.
- Doucouliafos, C. and Laroche, P. (2003), "What do Unions do to Productivity: A Meta-Analysis", *Industrial Relations*, Vol. 42, pp. 650-691.
- Egger, M., Smith, G.D., Scheider, M., and Minder, C. 1997. "Bias in meta-analysis detected by a simple, graphical test." *British Medical Journal*, Vol. 316, pp. 629-34.
- Fernie, S. and D. Metcalf. 1995. "Participation, Contingent Pay, Representation and Workplace Performance: Evidence from Great Britain", *British Journal of Industrial Relations*, Vol. 33, pp. 379-415.
- Freeman R. 1976. "Individual Mobility and Union Voice in the Labor Market." *American Economic Review*, Vol. 66, pp. 361 –368.
- Freeman R. and Medoff J. 1984. *What do unions do?*, New York, Basic Books.
- Gerber, A.S., Green, D.P. and Nickerson, D. 2001. "Testing for Publication Bias in Political Science", *Political Analysis*, Vol. 9, pp. 385-392.

- Goldfarb, R.S. 1995. "The Economist-as-audience needs a methodology of plausible inference", *Journal of Economic Methodology*, Vol. 2, pp. 201-22.
- Gorg, H. and E. Strobl, 2001, "Multinational Companies and Productivity: A Meta-analysis", *The Economic Journal*, Vol. 111, No. 475, pp. 723-39.
- Green, W.H. 1990. *Econometric Analysis*. MacMillan, New York.
- Hirsch B. 1991. *Labor Unions and the Economic Performance of Firms*, W.E. Upjohn Institute for Employment Research, Kalamazoo, Michigan.
- Hunter J.E. and Schmidt F.L. 1990. *Methods of Meta-Analysis: correcting error and bias in research findings*, Sage publications.
- Jarrell, S. B. and T.D. Stanley, 1990. "A Meta-Analysis of the Union-Nonunion Wage Gap", *Industrial and Labor Relations Review*, Vol. 44, pp. 54-67.
- Kochan, T.A., H.C. Katz and R.B. MacKersie. 1986. *The Transformation of American Industrial Relations*, New York, Basic Books.
- Kuhn, P. 1998. "Unions and the Economy: what we know; what we should know." *Canadian Journal of Economics*, Vol. 31, pp. 1033-56.
- Macaskill, P., Walter, S.D., and Irwig, L., 2001. "A comparison of methods to detect publication bias in meta-analysis," *Statistics in Medicine*, Vol. 20, pp. 641-654.
- Neumark, D. and W. Wascher. 2002. "Meta-Analysis" *Journal of Economic Perspectives*, Vol. 16, pp. 226-7.
- Perotin, Virginie and Andrew Robinson, 2000, "Employee Participation and Equal Opportunities Practices: Productivity Effect and Potential Complementarities", *British Journal of Industrial Relations*, Vol. 38, pp. 557-583.
- Rosenberg, M.S., D.C. Adams, and J. Gurevitch. 2000. *MetaWin: Statistical Software for Meta-Analysis*. Version 2.0. Sinauer Associates, Sunderland, Massachusetts.
- Rosenthal, R, 1979, "The "file drawer problem" and tolerance for null results", *Psychological Bulletin*, Vol. 86, pp. 638-41.
- Rust, R.T., D.R. Lehmann and J.U. Farley. 1990. "Estimating Publication Bias in Meta-Analysis", *Journal of Marketing Research*, Vol. 27:220-226.
- Scargle, J.D. 2000. "Publication Bias: the "file-drawer" problem in scientific inference", *Journal of Scientific Exploration*, Vol. 14, pp. 91-106.
- Sigelman, L. 1999. "Publication Bias Reconsidered", *Political Analysis*, 8:201-210.

- Stanley, T.D. 2001. "Wheat from chaff: Meta-Analysis as quantitative literature review." *The Journal of Economic Perspectives*, Vol. 15, pp. 131-150.
- Stanley, T.D. 2002. Response by T.D. Stanley. *Journal of Economic Perspectives*, Vol. 16, pp. 227-229.
- Stanley, T.D. and Jarrell, S.B. 1989. "A meta-regression analysis: A quantitative method of literature surveys," *Journal of Economic Surveys*, Vol. 3, pp. 54-67.
- Stanley, T.D, Florax, R.J.G.M., and deGroot, H.L.F. 2003. "It's all about power: Differentiating genuine empirical significance from the artifact of publication bias." Discussion Paper 3, Center for Entrepreneurial Studies, Hendrix College.
- Sutton, A.J., Duval, S.J., Tweedie, R.L., Abrams, K.R. and Jones, D.R. 2000a. "Empirical assessment of effect of publication bias on meta-analyses", *British Medical Journal*, Vol. 320, pp. 1574-1577.
- Sutton, A.J., F. Song, S. M. Gilbody and K. R. Abrams, 2000b, "Modelling Publication Bias in Meta-Analysis: a review", *Statistical Methods in Medical Research*, Vol. 9, pp. 421-45.
- Sutton, A.J. et al., 2000c. *Methods for Meta-analysis in Medical Research*. Chichester: John Wiley and Sons.