UNIONS, INNOVATION, AND TECHNOLOGY ADOPTION: NEW INSIGHTS FROM THE CROSS-COUNTRY EVIDENCE

Hristos (Chris) DOUCOULIAGOS
Professor in Economics
School of Accounting, Economics and Finance
Deakin University, Melbourne
AUSTRALIA

Chris.Doucouliagos@deakin.edu

Patrice LAROCHE
Professor in HR Studies and Labor Relations
ISAM-IAE Nancy, Université de Lorraine
13, rue Michel Ney – CO N°75, 54 000 Nancy
FRANCE

Patrice.Laroche@univ-lorraine.fr

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Chris Doucouliagos and Patrice Laroche

1. Introduction

Intangible forms of capital, such as knowledge and R&D, are widely deemed to be significant drivers of economic growth and cross-country differences in incomes (Mankiw, Romer and Weil, 1992; Lederman and Maloney, 2003; OECD, 2008). Technology also shapes labor market outcomes, such as unemployment and the returns to skill. Consequently, much research has been directed to identifying the determinants of innovation and the adoption of new technology. One important line of research is the effects of industrial relations and unions on inter-firm and inter-industry differences in innovation (Freeman and Medoff, 1984; Addison and Hirsch, 1989; and Hirsch 1991).[1] This literature currently consists of 38 econometric studies and a very large number of case studies. There is much ambiguity about the effects of unions on innovation and relatively little is known about their effects outside the US and the UK. Menezes-Filho, Ulph and Van Reenen (1998a, p. 929) note that there is: "*still relatively little empirical work on the important issue of the effect of labor market institutions on growth and R&D.*" Unfortunately, the comparatively poor availability of unionization, R&D, and innovation data, means that the supply of new studies will be rather limited, making it imperative to draw as much information as possible from the extant evidence.

This paper offers the first quantitative research synthesis of the literature through a systematic review, or meta-regression analysis (MRA), of the evidence (Stanley, 2001; Hunter and Schmidt, 2004).

2. Theoretical Considerations

Excellent reviews of the theoretical arguments can be found in Booth (1995), Menezes-Filho and Van Reenen (2003), and Hirsch (2007). Here we present only a summary of the main arguments. There are several dimensions to the effects of unions on innovation and technology. Unions can affect the *level of investment* in R&D, which in turn can affect the rate of innovation. Unions can affect the *adoption* of technological change in the workplace and, hence, productivity growth. Unions can affect the firm's ability to *gain* fully from the benefits of new technology, and where projects vary in the degree to which they are vulnerable to rent appropriation, unions might affect the *type* of investment project undertaken (Schnabel and Wagner, 1992b). Our focus in this paper is on the first two dimensions, as they have drawn most of the attention in the empirical literature. As in many areas of labor economics and industrial relations, there are competing and contrasting views on the effect of unions on technology. Several perspectives can be identified.

[1] In this paper we abstract from macroeconomic performance issues. See Flanagan (1999) and Storm and Naastepad (2009) for reviews of this parallel literature.

A tax on capital and labor monopoly: Union wage demands can serve as a tax on labor, with an uncertain impact on investment (Denny and Nickell, 1991, 1992; Hirsch, 1991). On the one hand, they raise production costs reducing the optimal level of output and, hence, reducing capital requirements. Lower profits also make it more difficult to finance new investment. On the other hand, higher wages are an incentive to substitute labor with the relatively cheaper capital. There are also non-wage effects. For example, restrictive work practices and resistance to the introduction of new technology increase the cost of investing in both tangible and intangible assets. Unions can devote their monopoly power to rent-seeking, capturing some of the firm's quasi-rents from long lived investments. This discourages investment and decreases dynamic efficiency (see Grout, 1984; Hirsch and Link, 1984; Fitzroy and Kraft, 1990).

Collective Voices: Freeman and Medoff (1984) argued that unions have two faces – the labor monopoly and the collective voices aspect. Unions might be receptive to organizational change, creating a climate conducive to investment, and they may help to retain highly trained staff who can contribute to innovation. Unions may also enable firms to increase the speed of diffusion of technology and, hence, increase the firm's incentive to invest (see Menezes-Filho *et al*, 1998b). Higher levels of productivity (static efficiency) resulting from unionization might increase the attractiveness of investment. Hence, the *net* effect on investment in intangible assets might be positive.

Bargaining: The disincentive effects on investment may disappear with 'efficient' bargains, where unions bargain over wages and other aspects of the employment relationship, (see Menezes-Filho *et al*, 1998b). In a series of papers, Ulph and Ulph (1989, 1994 and 1998) focus on the strategic aspects of R&D rivalry between firms and argue that technology outcomes depend on the form of bargains (e.g. right-to-manage versus efficient bargaining) and union preferences for employment and wages. Depending on the competitive setting, it is possible that stronger unions cause firms to increase innovation. Tauman and Weiss (1987) show that unionized firms might adopt labor-saving technologies, especially if wages and technology are simultaneously determined and product demand is high.

In practice, firms usually have the prerogative to decide what technology to adopt, when to adopt it, the purpose to which it is to be used and who shall use it. Negotiations with unions often occur after these decisions have already been made.[2] Unions might be involved in negotiations prior to key technology decisions being made, but this in itself does not mean that technology choices will be affected: Union preferences need not prevail. In this case, the effect on technology is likely to be neutral. Unions might embrace technological change purely because they realize that they have no choice – resistance might be useless. On the other hand, even if there is no formal negotiation, it is possible that union preferences might shape management preferences. This would make it difficult to econometrically identify the effects of unions.

Are unions necessarily hostile to new technology? Union attitudes to technology are shaped by many factors, especially the structure and organization of unions, their bargaining strength, the form that bargaining takes, the nature of product market competition, and the nature of the technological change itself. Two major issues for unions are the effect of technology on employment (and, hence, union membership) and the pace of work. Unions

[2] For example, firms in the US are not required to bargain over the introduction of new technology, but they are required to bargain over the effects of technological change (Abraham and Finzel, 1997).

often seek to prevent or limit employment displacement. Technology's effect on employment depends, in part, on the elasticity of the demand for labor. Events that reduce this elasticity might trigger union opposition, e.g. trade liberalization (Lommerud *et al.*, 2006).

All these varying model predictions indicate that the net impact of unions is theoretically unclear. Hence, empirical investigations are essential. Unfortunately, econometric studies have produced a wide variation of results (reviewed below) and this variation is rather difficult to digest using the framework of a traditional review.

3. Data[3]

3.1 Search criteria

The first step in the meta-analysis was to identify the relevant studies. We conducted a comprehensive search for comparable empirical studies using numerous search engines, including EconLit and Google Scholar. We also pursued references cited in the empirical studies themselves, as well as the existing literature reviews. We restricted our search to the published literature (book chapters and journals) in the areas of economics, industrial organization, industrial relations, and management. We excluded unpublished dissertations, manuscripts and working papers. The search focused on studies published in English or French. This extensive literature search identified more than 60 articles and book chapters. However, many of these studies were not appropriate for the MRA. We eliminated literature reviews and studies that did not provide original empirical analysis. We also eliminated several studies where unions were included as a control variable but where key results, such as a t-statistic or a coefficient and its standard error, or marginal effects were not reported (e.g. Chennels and Van Reenen, 1997).

The main group consists of 29 studies that estimate the U-I effect and a second group consisting of nine studies that estimate the U-A effect. Some studies include a single estimate while others report several estimates. For the first group of studies, we have 208 comparable estimates of the effect of unions on innovation, while the second group reports 51 estimates. These are the population of estimates that meet our search criteria and they are the data we use for the MRA. The second step in the MRA is the computation of an effect size for each study. As recommended by Djankov and Murrell (2002) and Doucouliagos and Laroche (2009), we use the partial correlation for those estimates using continuous measures of innovation. Partial correlations measure the strength of the association between unions and innovation, holding all other factors constant. They are directly comparable between and within studies. We use the marginal effect for those estimates that use a binary measure of technology adoption: This was either reported in studies or we calculated it directly from information provided in the study.

The studies included in the MRA are listed in Appendix A, together with the country investigated, the measure of innovation, the average sample size, and the average partial correlation (or marginal effect).

[3] All the data used in this paper can be downloaded from (web address suppressed for the purposes of refereeing).

3.2 Comparability of estimates

We calculate three sets of averages for the pooled data. First, we calculate un-weighted averages for each country (see Table 1). Second, we apply MRA by regressing the partial correlations (or the marginal effects from the probit group of studies) upon a set of country dummy variables (see Table 1). These averages are unconditional because they abstract from data, measurement and specification differences between studies and estimates. Third, we use MRA to estimate conditional averages that control for country, time period, data, specification and measurement differences (see Table 2). We rely on these conditional MRA estimates for inference.

4.1 Unions and innovation

Table 1 reports the un-weighted and MRA weighted averages for the USA, the UK, Germany, and Canada. Column 1 reports un-weighted averages for each country separately. This is the raw average of reported results that does not take into account the fact that the precision of the estimates varies. Column 2 reports the MRA weighted results pooling all estimates together and using country dummies to identify country differences. Precision is used to assign weights to individual estimates. In case there are any country specific selection biases, we include also the standard error as an explanatory variable in the MRA, as recommended by Stanley (2008). Column 2 shows that abstracting from measurement and specification differences, the average U-I effect is negative in the US and Canada, but is positive in the UK and Germany. In section 5 below, we analyze the U-I effect within a multivariate framework controlling for various study differences.

**Table 1: Average Union Effects,
Innovation and Technology Adoption**

	Innovation (U-I)			Technology Adoption (U-A)	
Country	Un-weighted Average Partial Correlations (1)	MRA, Precision Weighted Average Partial Correlations (2)	Country	Un-weighted Average Marginal Effects (3)	MRA, Precision Weighted Average Marginal Effects (4)
US (N=120, K=15)	-0.120 (-8.88)***	-0.140 (-5.45)***	US (K=16, N=2)	-0.039 (-1.52)	-0.030 (-3.44)***
UK (N=54, K=5)	-0.021 (0.66)	0.160 (5.44)***	UK (K=24, N=5)	0.067 (1.22)	0.095 (1.85)
Germany (N=19, K=5)	-0.057 (0.70)	0.201 (11.28)***	Germany	na	na
Canada (N=15, K=2)	-0.207 (-3.12)***	-0.054 (-1.12)	Canada	na	na
Australia	na	na	Australia (K=11, N=2)	-0.026 (-1.51)	0.004 (0.25)

Notes: N denotes the number of estimates and K denotes the number of studies. Columns 1 and 3 report averages using data for each country separately. Columns 2 and 4 combine all data and use country dummy variables, so that the total effect is calculated relatively to the base (the US). The MRA in columns 2 and 4 includes also the partial correlations' standard error and the marginal effects' inverse of square root of the sample size, respectively. Figures in brackets are t-statistics using clustered data analysis to correct for any data dependence arising from the inclusion of several estimates per study. **, *** indicates statistical significance at the 5% and 1% levels, respectively. na denotes insufficient estimates.

4.2 Technology Adoption Studies

Columns 3 and 4 of Table 1 report the average marginal effect from the nine probit studies for which we were able to calculate marginal effects. As we were unable to derive standard errors for many of the marginal effects, we used the square root of the sample size as a proxy for precision. When all 51 estimates are pooled together, the simple un-weighted average marginal effect is +0.014 (t-statistic = 0.82) and the equivalent weighted average marginal effect is -0.004 (t-statistic = -0.67). In columns 3 and 4 we split the data into countries. The average marginal effect is small and negative for the US. There is a small positive effect for the UK, but the level of statistical significance is weak. The insignificant dummy for Australia means that the average marginal effect in Australia does not differ from the average marginal effect in the US.

5. Explaining heterogeneity

The averages reported in Table 1 ignore the obvious heterogeneity displayed in figures 1 to 3. The aim of this section is to identify the factors that cause heterogeneity in estimates reported within and between studies. Estimates will differ because of differences in samples (different industries, countries and time periods), differences in the measurement of key variables, differences in econometric specification, and they will also differ because of sampling error. To model these features, we use a standard MRA model:

$$r_{ij} = \beta_0 + \sum \gamma_k X_{ijk} + \sum \delta_n K_{ijn} + u_{ij} \qquad (1)$$

where r_{ij} is the i^{th} comparable partial correlation (or, alternatively, the marginal effect) derived from the j^{th} study, β_0 is the constant, the Xs are dummy variables representing characteristics associated with the j^{th} study, the Ks are continuous variables associated with the j^{th} study, γ_k and δ_n are the unknown regression coefficients, and u_i is the disturbance term (Stanley and Jarrell 1989). The X and K variables quantify the effect of key study differences on reported union effects. While the X and K variables will in the main come from information drawn from *within* the econometric studies included in the MRA, they can also include information that is *exogenous* to the studies. For example, below we consider the degree to which labor markets were regulated at the time that the samples were taken. This enables us to model potential sources of between-study variation that were not available to the authors of the primary studies.

5.1 Explanatory variables

We included 26 potential explanatory variables in the MRA. First, we considered eight variables that capture key data differences. Three of these relate to country differences: *UK, Germany*, and *Canada* are binary variables taking the value of 1 if the estimates relate respectively to the UK, Germany, and Canada, with the US used as the base. These dummies provide a test for cross-country differences in the U-I effect.[4] *Industry Level* is a binary variable taking the value of 1 if the estimates relate to industry-level innovation data and 0 if they relate to firm/establishment-level data. The use of industry as the unit of analysis can lead to problems of aggregation bias and it is arguably preferable to use firm-level data. *Services* is another binary variable taking the value of 1 if the estimates relate purely to services industries (with manufacturing as the base). *Various* is a binary variable taking the value of 1 if the estimates relate to data for several industries (again with manufacturing as the base). These variables are included to test whether the effect of unions on innovations varies across industry sectors as suggested by some studies (Hirsch, 1990; 1991; 1992). *Panel* is a binary variable taking the value of 1 if panel data are used (with cross-sectional data as the base). *Average Year* is a continuous variable representing the average year of the data sample used in studies. This variable is included to capture any time patterns in the partial correlations. Second, we consider six variables for measurement differences. *Industry Union* is a binary variable taking the value of 1 if industry-level union density is used (with firm level unionization as the base). *Union Dummy* is a binary variable taking the value of 1 if a union dummy is used (with a firm level union density as the base). *RD Level* and *Innovations* are binary variables taking the value of 1 if the dependent variable is measured as the dollar value of R&D and the number of innovations, respectively, with R&D/sales as the base. These variables capture different dimensions of innovation. The most widely used measure is the R&D ratio. Third, we consider twelve variables that reflect differences in control variables: *Firm Size*, *Profitability*, *Concentration*, *Market Share*, *Firm's Age*, *Wages*, *Advertising*, *Skills*, *Industry Dummies*, *Growth*, *High-Tech Firm*, and *Time Trend*. These are all binary variables taking the value of 1 if these variables were included as part of the econometric specification. Finally, *Non-OLS* is included to capture the effect of different estimators, with OLS as the base.

The effect of unions on innovation can depend on the institutional structure of collective bargaining, as well as the nature of the industrial relations system. In countries such as Germany, unions and employers regard each other as partners. Such cooperative industrial relations may facilitate technological progress and innovation. That is, the outcome of union rent seeking need not always be inefficient for both unions and firms. We use two variables to capture differences in bargaining and industrial relations.

First, we used data on the degree to which collective bargaining is centralized, *Central Wage*. These data are reported by the Fraser Institute as a component of their measure of economic freedom.[5] Second, we use a measure of overall labor market regulation, *Labor Regulation*, again reported by the Fraser Institute. This index is constructed by taking into account the existence and size of the minimum wage, the degree of hiring and firing regulation, the degree of centralization of collective bargaining, and mandated cost of hiring and firing. *Labor Regulation* serves as a proxy to which labor markets deviate from the competitive labor market model. Both series range from 1 to 10, with 10 being the most liberal (economically free).[6] By pooling the estimates from different studies and collecting data on labor market regulation, we can explore the links between these two series. Data on labor

[4] Table 1 reported the MRA with just country dummies. Table 2 extends this to include several control variables.

[5] http://www.freetheworld.com/index.html.

[6] The *Labor Regulation* series varies both within and between countries over time. The average value of *Labor Regulation* is 7.22, 6.90, 7.24, and 3.36 for the US, the UK, Canada, and Germany, respectively, while the standard deviation is 0.53, 0.12, 0.04, and 0.06, respectively.

market regulation, collective bargaining and the time trends in U-I can be regarded as information that is exogenous to the individual studies.

The multivariate MRA results are presented in Table 2. We use clustered data analysis to adjust standard errors for data dependence arising from multiple estimates reporting within studies. Since all observations are weighted by precision, estimation is by weighted least squares.

Table 2: Determinants of Heterogeneity in U-I effects (Dependent variable is partial correlations)

Explanatory Variable	Mean [SD]	All data, WLS (1)	Without Hirsch studies, WLS (2)	R&D studies only, WLS (3)	Without top and bottom 5%, WLS (4)	Robust regression (5)
A. General to Specific Models						
Constant (USA)	0.58 [0.50]	**-0.17** (5.45)	**-0.22** (5.24)	**-0.15** (5.80)	**-0.16** (5.34)	**-0.14** (4.21)
Data differences						
Industry Level	0.25 [0.43]	**-0.19** (7.14)	**-0.16** (7.80)	**-0.20** (6.56)	**-0.19** (6.76)	**-0.21** (9.06)
Industry Union	0.26 [0.44]	**0.06** (2.89)	**0.05** (2.82)	**0.05** (2.15)	**0.05** (2.76)	**0.04** (2.28)
Union Dummy	0.44 [0.50]	**0.05** (5.14)	**0.04** (2.75)	**0.05** (4.28)	**0.05** (5.03)	**0.04** (2.08)
Innovation	0.13 [0.34]	**0.14** (6.99)	**0.16** (6.76)	-	**0.13** (5.41)	**0.13** (5.32)
Specification differences						
Profitability	0.32 [0.47]	**0.01** (2.51)	0.01 (0.67)	**0.01** (2.99)	**0.01** (2.53)	0.02 (1.73)
Human capital	0.15 [0.36]	**0.07** (2.69)	-0.05 (1.39)	**0.10** (6.65)	**0.08** (3.33)	**0.11** (5.31)
Advertising	0.06 [0.23]	**-0.11** (3.99)	-0.05 (1.03)	**-0.16** (5.57)	**-0.09** (3.05)	**-0.08** (2.31)
Market share	0.08 [0.27]	0.04 (1.91)	**0.06** (4.03)	**0.07** (3.51)	0.04 (1.50)	0.02 (0.72)
Wages	0.40 [0.49]	-0.04 (1.74)	**0.08** (2.22)	**-0.07** (3.90)	-0.03 (1.28)	0.01 (0.32)
Firm's Age	0.40 [0.49]	**-0.06** (3.09)	-0.01 (0.65)	**-0.04** (2.12)	**-0.06** (2.39)	**-0.10** (4.22)
Industry Dummies	0.24 [0.43]	**0.01** (2.55)	**0.03** (2.74)	0.02 (1.97)	0.01 (0.86)	-0.01 (0.72)
Time Trend	0.35 [0.48]	**0.02** (2.87)	0.01 (0.23)	**0.03** (4.46)	**0.02** (2.85)	0.02 (1.18)
Exogenous Data						
Average Year	19.80 [4.63]	**0.01** (5.44)	**0.01** (5.24)	**0.01** (5.79)	**0.01** (5.34)	**0.01** (4.25)
Labor Regulation	6.79 [1.17]	**-0.01** (2.38)	0.01 (0.75)	0.01 (0.19)	**-0.01** (3.45)	**-0.03** (4.55)
SE	0.07 [0.06]	**0.80** (2.41)	**0.75** (2.48)	**0.98** (2.78)	**0.83** (3.08)	**0.51** (4.21)
N		208	129	181	188	208
K		25	21	18	25	25
Adjusted R^2		0.68	0.71	0.38	0.80	-
B. Specific MRA Models With Country Dummies						
Canada	0.07 [0.26]	-0.02 (0.84)	-0.03 (1.85)	-0.03 (1.76)	-0.02 (0.92)	0.03 (1.14)
Germany	0.09 [0.29]	-0.09 (1.30)	-0.09 (0.62)	-0.35 (5.31)	-0.03 (0.40)	-0.21 (2.13)
UK	0.26 [0.44]	-0.01 (0.63)	-0.01 (0.12)	0.01 (0.13)	-0.01 (0.08)	-0.07 (2.09)

Columns 1 to 4 estimated by weighted least squares, using precision as weights. Column 5 uses robust regression. Figures in round brackets are *absolute* values of t-statistics, using clustered data analysis to adjust standard errors. Bold indicates statistically significant at least at the 5% level. *SE* is the standard error of the individual U-I effects. N and K denote the total number of estimates and studies, respectively. Results in shaded cells are robust to alternative sub-samples. Panel B repeats the MRA models after adding back the country dummies.

Column 1 presents the results of applying a general-to-specific modeling strategy, whereby we commenced with all 26 potential moderating variables and then sequentially eliminated any that were not statistically significant at least at the 10% level of significance. Of the 26 variables, 15 were found to be statistically significant in explaining heterogeneity in the reported U-I effects.

For sensitivity analysis only, in column 2 we remove any study to which Hirsch was an author or co-author. One reason for checking the sensitivity of the results with respect to the Hirsch studies is that they use a relatively larger sample than most of the other studies, and this might affect the results. Most of the results are not affected by the inclusion of the Hirsch group of studies. Moreover, there is no valid theoretical reason to exclude them from the dataset. In column 3 we use only those estimates that use R&D as a measure of innovation, removing any estimates using measures such as the number of innovations and patents data. In column 4 we rerun the MRA after removing the largest 5% and smallest 5% correlations. Finally, in column 5 we use robust regression to estimate the MRA. While this offers MRA coefficient estimates robust to outliers, this comes at the cost of having standard errors that are not corrected for data clustering, and individual data points (estimates from individual studies included in the MRA) assigned equal weights, instead of using precision. As can be seen from Table 2, most of the results are robust, expect for the variables that capture specification differences.

The preferred results are presented in column 1, and the discussion below revolves around these results. In these estimates, the constant is an estimate of the effects of unions on innovation in the US, using cross-sectional data, with firm level innovation and unionization data, with investments measured as R&D as a ratio of sales, estimated using OLS.

5.2 Time effects

The coefficient for *Average Year* is positive indicating that the size of the adverse union effect is *declining* over time. The MRA reported in Table 2 controls for all the main differences between estimates and between studies. Hence, the time series pattern in the partial correlations is unlikely to be an outcome of the way that partial correlations are calculated.[7] The time trend exists for all countries, though it is much more pronounced for non-US estimates: Regressing the partial correlations on *Average Year* for just the US estimates gives a coefficient of +0.010 (t-statistic = 2.79), whilst for non-US estimates it gives a coefficient of +0.028 (t-statistic = 3.53).

One explanation for this trend is that it reflects structural change, with the adverse U-I effect getting smaller over time, perhaps because of the changing nature of bargaining. The trend could, for example, be driven by the weakening of union strength over time: Weaker unions could have smaller adverse effects on innovation. Further, union preferences might have changed over time, and/or the nature of contracts might have changed over time, with unions and employers negotiating not just over wages, but also bargaining over employment and, possibly, over innovation, so that these are all determined simultaneously. This might be related to declining union strength and increased competitive pressure from other (non-unionized) domestic firms and foreign competitors. If there has been a progressive shift away from non-cooperative bargaining, towards a more cooperative one, then this will lead to the observed time series pattern.

[7] If *Average Year* is replaced by the actual year of *publication*, we get a similar positive trend: +0.008, with a t-statistic of 3.30.

5.3 Country Effects and Labor Regulation

None of the three non-US dummies, (Canada, Germany, and the UK) are statistically significant in the general-to-specific model (column 1, Table 2). This means that the U-I effect in these countries does not differ from the US, once all other aspects of the research process are considered. The base in the MRA is the US, so that the constant in the MRA measures the U-I effect for the US. Since the non-US country dummies are not different to the US effect, the MRA suggests that *unions have an adverse effect on innovation in all countries included in the dataset*. Note the contrast with the results presented in Table 1, where other aspects of research design were not modeled. Simply taking an average of reported estimates gives the appearance of a positive U-I effect for Germany and a near zero effect for the UK. However, once data, measurement and specification differences are modeled, we find that U-I is negative in all countries.

Panel B of Table 2 adds the three country dummies back into the general-to-specific version of the MRA (the variables initially drop out as part of the general-to-specific modeling strategy). All three country dummies have a negative coefficient, but they are not statistically significantly.[8] Hence, the MRA (column 1 of Table 2) suggests that after controlling for the various differences in the way studies were constructed and holding time and country-specific regulatory differences constant, unions have an adverse effect in all countries studied - the US, the UK, Canada, Germany.

While the country dummies are not statistically significant, the MRA indicates that regulatory differences modify the size of the U-I effect. The negative coefficient on *Labor Regulation* in column 1 indicates that the more liberal are labor markets, the more adverse is the effect of unions.[9] This is an interesting finding to emerge from the MRA. Flexible labor markets improve the allocation of labor. However, the results presented here indicate that labor market flexibility comes at a cost in terms of increasing union resistance to innovation. To see this, consider that the average value of *Labor Regulation* was 7.22 for the US, compared to 3.36 for Germany. This means that, *ceteris paribus,* labor market flexibility adds -0.07 to the negative U-I partial correlation for the US (7.22*-0.01) compared to only -0.03 for Germany (3.36*-0.01). Hence, ignoring all other factors, the MRA estimates that U-I in the US is -0.24 (-0.17-0.07) compared to -0.20 in Germany (-0.17-0.03). These results stand in sharp contrast to what many expect regarding the effects of labor market regulations.

Schnabel and Wagner (1994, p. 493) note that: "Efficient bargaining and the cooperative behavior it entails depend on the legal framework, the institutional structure of collective bargaining, the design of negotiated contracts, and the style of industrial relations." They argue that adversarial industrial relations (such as those found in the US and UK) are more likely to result in adverse effects on innovation, than cooperative ones (countries such as Germany). The variable *Labor Regulation*, however, reflects more than just collective bargaining differences: It includes the minimum wage and regulations over hiring and firing. We replaced *Labor Regulation* with a variable that focuses purely on collective bargaining (*Central Wage*), but this was not statistically significant. We also used a series on the degree of bargaining coordination (see Flanagan, 1999). This variable is also not statistically significant.

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[8] The two exceptions are Germany in columns 3 and 5, where it has a *larger negative* effect than the US.

[9] If country and *Labor Regulation* interactions are added, they are not statistically significant.

Labor Regulation is actually very highly correlated with Germany (first order correlation of -0.93).[10] Unfortunately, we are unable to find a suitable instrument to redress this correlation. Table 3 explores the sensitivity of the MRA results by comparing the results from Tables 1 and 2, to some additional meta-regressions.[11] Each row reports two sets of results. The first set of entries reports the key regression coefficients from the MRA. The second set of entries reports the average effect on R&D, evaluated by considering the degree of labor regulation and the average year of the data used for the individual country samples. The *Labor Regulation* variable is omitted in row 3 and *Average Year* is also omitted in the results reported in row 4. Rows 5 and 6 repeat the MRA reported in rows 3 and 4, but this time with country dummies added as explanatory variables.[12] Row 6 effectively repeats the results from Table 1 but with the addition of the MRA control variables listed in Table 2 (*Industry Level*, etc.) In row 7 we report the MRA after removing all observations relating to Germany. The results from Table 3 confirm that regardless of the specification, the effect of unions on R&D is negative, in all countries. This table also indicates that the results for *Labor Regulation* are not driven by the inclusion of German data (see column 7 Table 3).

The possibility that labor market regulation might moderate the effect of unions has received little attention in the literature. The effect of labor market regulation on innovation is itself theoretically ambiguous.[13] The effect of labor market regulation on the U-I effect is likewise ambiguous: Several opposing effects might operate, so that the net effect remains an empirical issue. On the one hand, labor market *de*regulation can be expected to stimulate innovate. Deregulation benefits firms by increasing flexibility and reducing labor and production cost. Labor market deregulation is also likely to decrease unemployment thereby benefiting 'outsiders'.[14] Greater labor market deregulation should increase incentives to innovate, especially where technological change requires labor adjustment. Technological change that creates opposition from insiders might be easier to implement when labor markets are flexible. Also, flexible labor markets might limit the extent to which unions can capture rents arising from technology. On the other hand, labor market regulation might stimulate innovation through several channels:

(a) *Higher labor cost*: Tighter labor market regulations are likely to strengthen the position and bargaining power of insiders, increasing their wages. Higher labor costs increase the incentives to increase capital intensity, replacing labor with capital.

(b) *Firm's bargaining power*: Innovation improves productivity, increases profits and make new capital more attractive. It might also increase a firm's bargaining power, enabling it to capture a greater share of available rents. Labor market regulations

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[10] Of the four countries in the dataset, Germany has the highest degree of labor market regulation. *Labor Regulation* is not correlated with UK (correlation = 0.06) nor Canada (correlation = 0.11), but it does have a moderate degree of correlation with USA (correlation = 0.43).

[11] Recall that Table 1 reports the unconditional averages predicted by MRA, while tables 2 and 3 report the conditional averages.

[12] Recall that these variables drop out of the MRA when a general-to-specific strategy is pursued, meaning that there is no statistical difference between the U-I effect in the US and the other countries.

[13] Labor market deregulation does not actually mean that industrial relations become completely unregulated. Rather, the idea behind 'deregulation' is that regulations emphasize internal sources, e.g. managers are given either unilateral say within a workplace over key decisions affecting employees, or in consultation with employees. In contrast, 'regulation' means that at least some key decisions are made externally to the organization.

[14] Technological shocks might create unemployment when generous welfare state provisions (that often co-exist with labor market regulation) make displaced workers prefer unemployment.

might 'shock' firms into investing in technological change that actually shifts bargaining power in their favour.

Table 3: Country Differences in U-I Effects

	USA	UK	Germany	Canada	Labor Regulation	Average Year
Unconditional averages						
Univariate model (Table 1) (1)	-0.14 (-5.45)	0.16 (5.44)	0.20 (11.28)	-0.05 (1.12)	-	-
Average effect	*-0.14*	*+0.02*	*+0.06*	*-0.14*		
Conditional averages						
General-to-specific model (Column 2, Table 2) (2)	-0.17 (5.45)	-	-	-	-0.01 (2.38)	0.01 (5.44)
Average R&D effect	*-0.17*	*-0.10*	*-0.07*	*-0.16*		
(3)	-0.18 (5.27)	-	-	-	-	0.01 (5.23)
Average R&D effect	*-0.17*	*-0.10*	*-0.10*	*-0.16*		
(4)	-0.09 (6.42)	-	-	-	-	-
Average R&D effect	*-0.09*	*-0.09*	*-0.09*	*-0.09*		
(5)	-0.20 (3.62)	-0.01 (0.63)	-0.09 (1.30)	-0.02 (0.84)	-	0.01 (3.59)
Average R&D effect	*-0.16*	*-0.10*	*-0.06*	*-0.14*		
(6)	-0.13 (6.63)	0.06 (5.99)	0.12 (5.15)	-0.02 (0.60)	-	-
Average R&D effect	*-0.13*	*-0.07*	*-0.01*	*-0.13*		
(7)	-0.18 (6.67)	-	-	-	-0.02 (3.77)	0.01 (6.62)
Average R&D effect	*-0.19*	*-0.12*	-	*-0.18*		

Estimation is by weighted least squares, using precision as weights. Figures in brackets are *absolute* values of t-statistics, using clustered data analysis. Except for row 1, all rows include the same set of control variables as in Table 2. Row 1 reproduces the results from Table 1, column 2. Row 2 reproduces the results from Table 2, column 2. All German data are excluded from the results reported in row 7. Average R&D effects are evaluated using country specific sample means for average year and labor market regulation.

(c) *Motivation effect:* Storm and Naastepad (2009) argue that regulations might increase innovation if they increase worker motivation and commitment to the firm, making it easier to introduce labor-saving technical change. That is, regulations might increase the likelihood that labor will cooperate with management. Labor deregulation might even worsen industrial conflict, especially if it lowers wages. Consistent with this argument, Storm and Naastepad (2009) find that for OECD countries, labor market regulation increased productivity growth. Francois and Roberts (2003) argue that the more regulated European labor markets might enable firms to extract work effort at a lower cost, compared to US type labor markets.[15]

(d) *Rent seeking:* By creating frictions that restrict firing (and hiring), unions might have greater opportunities to extract rents from firms. They may thus encourage firms to innovate, so that they can subsequently extract rents from the investments. This effect would, at best, occur only in the short term.

5.4 Measurement, Data, and Econometric Specification Differences

The MRA results indicate that data differences are a robust determinant of heterogeneity in reported U-I effects. The use of industry level innovation data (*Industry Level*) produces larger adverse effects, compared to firm level data (increases the negative partial correlation by 0.19, on average). That is, the adverse effects of unions are magnified at the industry level. This result might be an outcome of aggregation bias. However, it could also reflect negative externalities, as the adverse effects spillover from one firm unto another. In contrast, the use of industry level unionization data (*Industry Union*) results in smaller adverse effects compared to firm level union data. This appears to be inconsistent with the idea of a non-monotonic relationship between unions and technology discussed in section 2 above (Dowrick and Spencer, 1994), although there is not a strong association between the use of industry level union data and industry unions. Measuring unionization as a binary variable (*Union Dummy*), instead of a more informative continuous variable (typically union density) also results in smaller adverse U-I effects.

The measurement of innovation is important. Compared to R&D based measures, studies that use innovations data (e.g number of patents and number of innovations) find much smaller adverse effects (*Innovation*). That is, using R&D data (investment flows) results in larger adverse U-I effects, compared to measures of actual innovation. This indicates that while unions depress investment in R&D (an indicator of innovation), actual innovation is not as adversely affected.[16]

The MRA shows that econometric specification differences are important, though the results are not always robust (compare columns 1 through to 5). Controlling for the firm's age, advertising, and wages all result in larger negative U-I effects. For example, studies that include the firm's age in the primary regression find, on average, a 0.06 larger negative U-I effect than those that do not. In contrast, the inclusion of industry dummies, a time trend,

[15] Francois and Roberts (2003) argue that while firms operating in highly regulated labor markets face higher hiring and firing costs, they also enjoy lower costs of extracting effort. Thus, the net effect on incentives to innovate is unclear.

[16] We rerun the MRA using country dummies interacted with *Innovation*, to test whether there are country differences with respect to innovation counts. None of the interactions were statistically significant, either individually or jointly (Wald test = 0.49, p-value = 0.62).

market share, human capital (skills), and profitability in the econometric specification are also important, resulting in smaller adverse effects.[17] For example, studies that include human capital in the primary regression find, on average, a 0.07 *smaller* negative U-I effect than those that do not.

5.5 Technology adoption (the U-A effect)

With only nine studies and 51 estimates with marginal effects, we are unable to estimate an MRA with the same number of variables as the MRA for the U-I effect. Instead, we considered an MRA with the effects of regulations, time, and country differences.[18] Only two variables emerge to be statistically significant. We find that *Labor Regulation* has a negative coefficient (-0.05, t=-1.90), confirming the results for U-I effects: Unions operating in countries with more flexible labor markets are more likely to resist the adoption of new technology. We also found a larger negative marginal effect in Australia, compared to the US (-0.11, t=-1.87). No difference was detected between the UK and the US in terms of technology adoption (0.04, t=0.84).[19] Finally, in contrast to the U-I effect, there was no noticeable pattern in union resistance to technology adoption over time (-0.011, t=-0.30).

6. Conclusion

This paper provides a systematic review of the econometric evidence on the effects of unions on innovation and technology adoption. We apply meta-regression analysis to 208 estimates reported in 29 technology impact studies and 51 estimates from nine technology adoption studies. We draw five robust conclusions from these data. First, when the existing estimates are scrutinized using meta-regression analysis, we find that there is in fact little disagreement between studies. All the available evidence indicates that unions depress the level of innovation and they also depress the adoption of technology. This finding is consistent with both the tax on capital and labor monopoly theories of union behavior (outlined in section 2), which appear to dominate any collective voice effects. Unions have a more depressing effect on R&D then they do on actual innovations. Second, country differences in the degree to which unions impact upon technology are driven largely by the degree of labor market regulation. Holding labor market regulation constant, unions have an adverse effect on investment in all countries of a similar magnitude. However, industrial relations and regulatory regimes differ between countries, and these differences matter for technology outcomes. More regulated labor markets experience less union resistance to technology. Consequently, unions have a larger negative effect on innovation in the US and Canada, then they do in Germany. Third, the U-I effect has been declining over time in all countries, though this trend is less pronounced in the case of the US. This could reflect change in the nature of bargaining processes. Fourth, the size of the direct effect of unions on technology in the US is much larger than the effect of unions on profits and the effect on physical capital: Unions have a more noticeable adverse effect on innovation. Further, by depressing profits and physical capital, unions have a small second round, or indirect, effect on innovation.

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[17] Note that the time trend referred to here is a time trend in the primary regression model capturing trends in intangible capital formation. It is *not* a measure of a time trend in the union effect: This is captured by *Average Year* in the MRA. The only other variable that is statistically significant is *Book Chapters*. Studies published as book chapters tend to report much smaller adverse effects.

[18] This is not as limiting as it might seem. All the U-A estimates are derived from firm level innovation and unionization data, so that there is no issue here regarding firm versus industry level data.

[19] We had no observations for Germany for which we could calculate marginal effects and their standard errors.

Fifth, MRA shows that most of the variation in reported estimates can be explained by differences in the data used (firm versus industry), the measurement of technology (R&D versus patents) and the econometric specification. MRA quantifies the effect of these differences.

The meta-regression analysis indicates that unions affect both infra-marginal and marginal decisions: They affect the decision to adopt technology and how much innovation is undertaken. Many econometric studies have been carried out ignoring the effects of industrial relations on technology. Such studies might very well be mis-specified, as the evidence indicates that industrial relations do matter.

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Appendix A: Econometric Studies Included in the Meta-Analysis (K=38)

Author(s) (Year)	Main Country Analyzed	Measure of Innovation[1]	Average Sample Size[2]	Weighted Average partial correlation[3]
Innovation studies				
Acs & Audretsch (1987 &1988)	US	Number of innovations	247	-0.191***
Addison & Wagner (1994a & 1994b)	UK	R&D ratio	15	0.036
Allen (1988)	US	R&D ratio	74	-0.376***
Audrecht & Schulenburg (1990)	US	Number of innovations	246	-0.185***
Betcherman (1991)	Canada	Expenditures on innovation	294	-0.047
Betts, Odgers & Wilson (2001)	Canada	R&D ratio	247	-0.241***
Blumenfeld (2002)	US	R&D ratio	1,011	-0.070
Blundell, Griffith and Van Reenen (1999)	UK	Number of innovations	4,125	0.050**
Bronars & Deere (1993)	US	R&D ratio	660	-0.153***
Bronars, Deere & Tracy (1994)	US	R&D ratio	209	-0.069
Connolly, Hirsch & Hirschey (1986)	US	R&D ratio	367	-0.137***
Fitzroy & Kraft (1990)	Germany	Innovation rate	57	-0.335**
Geroski (1990)	UK	Number of innovations	73	-0.134
Hirsch (1990)	US	R&D expenditure	2,692	-0.067***
Hirsch (1991)	US	R&D expenditure	4,327	-0.133***
Hirsch (1992)	US	R&D expenditure	4,176	-0.165***
Koeller (1996)	US	Number of innovations	246	-0.050
Kraft, Stank and Dewenter (2009)	Germany	Number of innovations	2,062	0.064***
Menezes-Filho, Ulph & Van Reenen (1998a & 1998b)	UK	R&D ratio	469	-0.037
Nair-Reichert & Pomery (1999)	US	R&D ratio	419	-0.126***
Schnabel & Wagner (1992a & 1992b)	Germany	R&D ratio	27	0.023
Schnabel & Wagner (1994)	Germany	R&D ratio	29	-0.060
Schulenburg & Wagner (1990)	Germany and US	Number of innovations	138	-0.070
Taymaz (1991)	US	Innovation rate	42	-0.116
Ulph & Ulph (1989)	UK	R&D/sales	33	-0.482**
Technology adoption studies				
Drago and Wooden (1994)	Australia	Introduction of technical change	802	-0.07**
Hirsch and Link (1987)	USA	Advantage in product-related technological innovation / Leader in developing innovative new product	315	-0.14**
Keefe (1991)	USA	Adoption of CADCAM, Numerically machine tool (NMT), Computer Numerically controlled (CNC), etc.	821	-0.02
Latreille (1992)	UK	Using new technology	418	+0.17**
Lintner, Pokorny, Woods & Blinkhorn (1987)	UK	Adoption of CADCAM, CNC, NMT, etc.	123	+0.02
Machin and Wadhwani (1991)	UK	Introduction of conventional and advanced technical change		+0.07
Michie and Sheehan (1999)	UK	Introduction of advanced technological change	374	-0.07
Michie and Sheehan (2003)	UK	Adoption of any product and process innovation	242	+0.19
Rogers (2004)	Australia	Innovator	920	-0.02

Notes: [1] Broad type of measure used. See studies for exact measures used. Some studies use several measures. **, *** indicates statistical significance at the 5% and 1% levels, respectively. [2] Average sample size and weighted average partial correlation are the averages of all estimates used, with precision used to weigh the individual correlations. [3] The average marginal effect is reported for the technology adoption studies. The MRA uses the individual partial correlations and individual marginal effects. Bibliographic references are available from the authors.