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The Last Word on the Wage Curve? A Meta-Analytic Assessment

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THE LAST WORD ON THE WAGE CURVE? A META-ANALYTIC ASSESSMENT[#]

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Abstract

During the last decade there has been extensive international research on the responsiveness of wages of individuals to changing local labour market conditions. For many countries, an inverse relationship between wages and local unemployment rates has been found. In their 1994 book, *The Wage Curve*, Blanchflower and Oswald argued that the unemployment elasticity of pay is around -0.1 in most countries. In a 1995 literature survey, Card referred to this striking empirical regularity as being close to an 'empirical law of economics'. Nonetheless, reported elasticities do vary, even excluding outliers, between about -0.5 and +0.1. There is also considerable heterogeneity among wage curve studies in terms of data and model specification. This paper carries out meta-analytic techniques on a sample of 208 elasticities derived from the literature to uncover the reasons for the differences in empirical results across studies. Several causes of variation are identified. There is also clear evidence of downward publication bias. In addition, many reported *t* statistics are biased upwards due to the use of aggregate unemployment rates. A maximum likelihood method and a trimming procedure are used to correct for these biases. Both methods give similar results for our sample. An unbiased estimate of the wage curve elasticity at the means of study characteristics is about -0.07.

Key words: wage curve, meta-analysis, publication bias

JEL classification: C12, C13, J31, R23

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THE LAST WORD ON THE WAGE CURVE? A META-ANALYTIC ASSESSMENT

1. Introduction

A promising development in economic research is the growing potential for a comparative assessment of a set of empirical case studies on a particular research issue. Seminal and path-breaking empirical contributions have usually instigated many additional research articles on the same issue. In order to assess if some general conclusions can be drawn from a large body of empirical findings, some type of research synthesis is needed. Conventionally such a synthesis takes the form of a narrative literature survey, but increasingly such surveys are complemented by quantitative methods that are used to investigate differences in results across studies. Following Glass (1976), such quantitative methods are now commonly referred to as meta-analysis.¹

Meta-analysis has become well established in the experimental sciences (see, for example, Cooper and Hedges' 1994 handbook), but has recently been growing in popularity in economics.² Stanley (2001) provides an overview and concludes that this form of research synthesis can enhance conventional narrative literature surveys considerably.

In this paper we adopt a meta-analytic approach to an empirical issue that has attracted much attention during the last decade, namely the responsiveness of the wages of individuals to local labour market conditions. The impetus for this research was a 1990 article by David Blanchflower and Andrew Oswald in which these authors reported an inverse relationship, derived from micro level British and U.S. data, between the real wage paid to individuals and the unemployment rate in local labour markets. There had been earlier studies that investigated such a relationship with micro-data,³ but Blanchflower and Oswald's 1990 article and their subsequent 1994 book achieved prominence by careful and extensive replication of this research with

¹ Glass referred to innovative and path-breaking studies, in terms of the theoretical model or estimation techniques, as *primary* analysis. *Secondary* analysis consists of the replication of a specific model with data from other time periods or cross-sectional units. The increasingly common practice to make data electronically available to other researchers has also encouraged re-analysis of existing studies to assess the robustness of primary results to the choice of assumptions and specifications. Such re-analysis may also be referred to as secondary analysis. Arulampalam et al. (1997) and others emphasized the importance of such replication and re-analysis in labour market research. Research synthesis in the form of meta-analysis can be referred to as *tertiary* analysis in Glass' classification.

² Using an *EconLit* search and other sources, we estimate that the total number of published applications of meta-analysis in economics is now around one hundred.

different data sets and by their discovery that the unemployment elasticity of pay turned out to be very similar across a wide range of countries and time periods, namely about -0.1.

Thus, their research suggests that a worker may, on average, expect to earn 1 percent less in real terms when the unemployment rate in the local labour market during a recession increases by 10 percent, *ceteris paribus*. Blanchflower and Oswald (1990) called this inverse relationship between the wage of an individual and the local unemployment rate ‘the wage curve’.

Research of this type provides a bridge between empirical macroeconomics and microeconomics in that it derives a stylised fact regarding the ‘representative’ worker by means of microeconomic data. Their research on the wage curve led several others to investigate the wage curve in different countries or for different time periods. On the whole, these studies tended to confirm the existence of this relationship, even to the extent that Card (1995, p.798) concluded in his review of the literature that the wage curve “may be close to an ‘empirical law of economics’”. Following Card’s narrative literature survey, further wage curve investigations were undertaken and perhaps close to one thousand estimates of the relationship exist at present. Thus, the wage curve would appear an obvious subject for meta-analysis, although it is not the first topic in labour economics that has been studied by means of this form of research synthesis.⁴

The main reason for the interest in the wage curve is not the magnitude of the relationship: the observed elasticity implies rather small changes in real wages in response to fairly large fluctuations in slackness of the local labour market as measured by the unemployment rate. Instead, the wage curve has drawn attention primarily due to the fact that it suggests evidence of imperfectly competitive wage determination. At the micro-level, firms do not appear to be wage takers, but adjust the wages paid downward when the local unemployment rate increases. There may be of course various reasons why individual firms could face upward sloping supply curves. The causes and implications of firms acting as local monopsonists, or being engaged in monopsonistic competition in the case of costless entry, have attracted

³ Blanchflower and Oswald (1990) reported 16 other studies of this issue between 1985 and 1990.

⁴ Other examples in labour economics include Card and Krueger (1995) and Neumark and Wascher (1998) on minimum wage effects, Jarrell and Stanley (1990) on the union-nonunion wage gap, Doucouliagos (1995) on the effects of union participation on productivity, Doucouliagos (1997) on the aggregate demand for labour, Fuller and Hester (1998) on union participation, Stanley and Jarrell (1998) on the gender wage gap, and Ashenfelter et al. (1999) and Groot and Maassen van den Brink (2000) on education issues.

considerable interest in recent years; see e.g. Abraham (1996), Boal and Ransom (1997) and Bhaskar and To (1999).

Since much of the empirical wage curve research uses pooled cross-section time-series data, another interesting aspect of this research is the variation in wage curve elasticities between different groups of workers, for different time periods and at different locations.⁵ As Card (1995, p.794) suggested, the systematic variation in the slope of the wage curve across groups of workers and sectors might be a very useful way of choosing between various theories. However, few have as yet responded to this call for explicit wage curve theory testing.⁶ The next section provides a brief review of theoretical explanations for the wage curve and some of the common findings in disaggregated analyses.

Meta-analysis provides a means of explaining the diversity in study results in relation to the heterogeneity of study features. It may also help to choose between the various theoretical explanations. In addition, it provides summary facts on the basis of statistical criteria. Section 3 reviews the variation across empirical studies of the wage curve in terms of observed study characteristics and the estimated elasticities. We provide descriptive statistics, and compute means and confidence intervals of the unemployment elasticity of pay under fixed and random effect models. However, a simple test of homogeneity of sample observations is rejected.

In Section 4 we identify the main causes of heterogeneity by means of meta-regression models. A problem with estimating this type of regression model is that it can only take account of reported results, either in the published literature or unpublished working papers. Samples of such results are usually subject to a selection bias: the studies that are reported in the literature are more likely to demonstrate a significant effect than would be the case if all studies on the key parameter would have been published. Journals are more likely to accept manuscripts that reject the null hypothesis of ‘no effect’ than manuscripts that do not have a ‘strong’ conclusion. Thus, the mean parameter estimate derived from a sample of studies is likely to be a biased estimate of the underlying population mean. This bias is referred to as ‘publication’, ‘reporting’ or ‘file drawer’ bias (see Ashenfelter et al. 1999).

We assess to what extent insignificant estimates of the wage curve elasticity are likely to have been underrepresented in our sample and in the available literature. We find that there is clear evidence of publication bias and calculate a bias-corrected

⁵ However, repeated observations on the same individuals are in this context rarely used.

average of the unemployment elasticity of pay by means of maximum likelihood estimation of a probabilistic model and by means of a sample trimming procedure. Both methods give almost identical results. At the means of study characteristics, the bias-corrected unemployment elasticity of pay is about -0.07. For macro simulation models in need of a stylised fact on the wage curve, this would be a more accurate number to insert than the previous consensus estimate of -0.1. The final section sums up.

2. What can explain the wage curve?

As noted in the introduction, Blanchflower and Oswald (1990), using U.S. and British micro data, were among the first to find evidence for an inverse relationship between the level of pay of individuals and the local unemployment rate. Subsequently, they reported on additional evidence for the wage curve in their 1994 book using data on individuals from a wide range of countries.⁷ The robustness of their finding has been confirmed by other investigators using similar data (for example, Blackaby and Hunt 1992; Groot et al. 1992; Winter-Ebmer 1996; Bratsberg and Turunen 1996; Janssens and Konings 1998; Baltagi and Blien 1998; Kennedy and Borland 2000; and Baltagi et al. 2000). Several time-series studies (Johansen 1997; Chiarini and Piselli 1997) also suggested a long-run inverse relationship between the wage level and unemployment.

Particularly striking in this research is the finding, already alluded to in the introduction, that the elasticity of the responsiveness of pay to the local unemployment rate appears to be robust and very similar across countries and time periods, namely about -0.1. Of course there is some variation. Table 4 in Card's (1995) review includes estimates ranging between -0.216 and -0.014, while Table 1 in the next section of this paper reports estimates between -1.43 and +0.09. The estimates are nonetheless bunched around the 'consensus' of -0.1. It is evidence of this nature that led Blanchflower and Oswald to conclude that "Every country seems to have a 'wage curve'" (1994, p. 12).

Some empirical studies reject this conclusion, but they form a small minority. For example, Albaek et al. (1999) found no stable negative relation between wages and unemployment across regions in the Nordic labour markets once regional fixed

⁶ Morrison et al. (2002), who formulate a labour turnover cost model, provide a recent exception.

⁷ Specifically, they estimated wage curves with data from 12 countries: USA, Britain, Canada, South Korea, Austria, Italy, Holland, Switzerland, Norway, Ireland, Australia and Germany.

effects are accounted for. Partridge and Rickman (1997) found evidence of an upward sloping wage curve.

An important result in the literature is that the unemployment elasticity of pay varies across different groups. Card (1995, Table 4) finds that the elasticity is greater for males than for females, for the lower rather than the higher educated, among the young rather than old, for non-union members rather than union members, and in the private rather than the public sector. Subsequent research has more or less confirmed these observations. For example, Baltagi and Blien (1998) found with German data that the wage curve is more elastic for unskilled workers, for younger workers and for males. Janssens and Konings (1998) find a wage curve for males but none for females in Belgium. However, there are exceptions: for example, Kennedy and Borland (2000) reported that in Australia female earnings were more responsive to the unemployment rate than male earnings.

Blanchflower and Oswald (1994) offer three possible explanations for the wage curve. A negative relationship between unemployment and wages could, they argue, be supported by a labour contract model, an efficiency wage model or a bargaining model. A summary and assessment of these contenders is given by Card (1995).

The labour contract model makes the crucial assumption that regions differ in amenity values but that the 'outside option' which laid-off workers face (the unemployment benefit or the reservation wage) is equal across regions. Firms and workers agree on a state-contingent wage level and a state-contingent employment level along the lines of the standard Azariadis (1975) and Baily (1974) implicit contracts model. Higher wages will then coincide with a higher level of contractual employment to compensate for the higher income risk. Attractive regions will be bunched at outcomes characterized by low long-run wages with high long-run unemployment. However, as noted by Card (1995) and by Blanchflower and Oswald (1995), the empirical evidence is not consistent with some of the predictions of this theory. There is some evidence that long-run wages and the long-run unemployment rates are positively related (see e.g. Hall 1970, 1972; Reza 1978; and more recently Papps 2001 and Bell et al. 2002). The wage curve, in contrast, is a short-run phenomenon.

A more promising alternative is a union bargaining model. This model, which originated with a contribution by De Menil (1971), generates a wage equation of the

form $w = a + s \pi/n$. Here, w is the negotiated wage available to union workers, a is the expected 'alternative' wage in the non-union sector, π/n is the level of profits per worker and s is a relative bargaining power parameter. Because a will decrease with increasing rates of unemployment, a wage curve results. Blanchflower and Oswald (1994) provide some supporting micro-level evidence for this theory. Nonetheless, the wage curve appears less elastic for union workers than for non-union workers and the curve is also less elastic in highly unionised countries (Card 1995; Albaek et al. 1999). Both facts contradict the union bargaining model. However, since the wage curve is a model of the local labour market, we would expect that its slope depends on the geographic coverage of collective bargaining: less elastic in the case where wages are determined nationally, economy-wide or by industry, and more elastic with enterprise-based bargaining. Buettner and Fitzenberger (2001) provide recent support for this conjecture by means of (West) German data.

The third wage curve theory builds on the efficiency wage model of Shapiro and Stiglitz (1984). Employers, who can imperfectly monitor workers' productivity, will offer a wage that will discourage workers from shirking. Because the expected penalty for shirking, when detected, is greater when it becomes harder to find a job, firms can offer a lower wage premium during times of high unemployment.

This shirking model has, as noted by Card (1995), various advantages over the two other models. Firstly, it suggests that a short-run inverse correlation between wages and unemployment rates is not inconsistent with a long-run positive cross-sectional association between expected regional wages and unemployment rates that was argued on the grounds of an equilibrium 'compensating differential' by Harris and Todaro (1970). An additional advantage of this theory is that it leads to the testable hypothesis that a group-specific unemployment rate should be a better predictor of group-specific wages than the average regional unemployment rate. This hypothesis can be tested to the extent that group-specific regional unemployment rates can be observed. Thirdly, since the shirking model is likely to be more relevant in relatively non-unionised economies, the model predicts that a decline in unionisation (at least to the extent that collective bargaining occurs at the national or industry level) should lead to a more elastic wage curve. As noted above, this is consistent with evidence reported in the literature.

In contrast to the models of Shapiro and Stiglitz (1984) and Blanchflower and Oswald (1994), wherein firms attempt to minimize the costs attributable to shirking

workers, Campbell and Orszag (1998) formulated an explanation for the wage curve by means of a model of lump-sum labour turnover costs that is based on Salop (1979) and Phelps (1994). In this model, firms in low unemployment regions economize on the costs associated with hiring new workers by paying higher wages in order to discourage existing workers from quitting. An extension of this model, that also incorporates the impact of interregional migration on the incidence of monopsony in local labour markets, was recently formulated and empirically confirmed by Morrison et al. (2002).⁸

Yet another alternative theory is that of a simple search model proposed by Sato (2000), who shows that as long as there are productivity differentials across local labour markets, those with the higher productivity have higher equilibrium wages and lower unemployment rates. Spatial real wage differentials persist because higher productivity regions have larger populations that result in offsetting congestion costs (commuting costs and land rent).

Finally, it has been argued that the wage curve may be the result of misspecification in regression analysis: it could be a misspecified Phillips curve (with wage levels rather than wage changes on the left hand side) or a misspecified labour supply curve (with unemployment acting as a proxy for labour force participation). Blanchflower and Oswald (1994) consider and reject both these conjectures. Despite Card's (1995) call for further tests of these possibilities, little has been published on this issue, possibly because of the common use of pooled cross sections rather than true panels in this literature.⁹

3. A meta-analytic comparison

Given the variety of results that was alluded to in the previous section, we will now systematically investigate any potential causes of observed variations in wage curve elasticities across studies. Figure 1 shows the 'life cycle' of this literature in terms of the number of documents recorded in *EconLit*. The first recorded working paper became available in 1989. The literature peaked in the mid 1990s, following the

⁸ Local labour markets are defined as markets which can only be entered or exited by incurring migration costs, i.e. there is no commuting between them. This assumption is unlikely to have been satisfied in all wage curve studies, but holds quite well in New Zealand, where the distances between the 30 urban areas that were defined as local labour markets are generally too large to permit commuting between these.

⁹ Using two sources of U.S. data, Card and Hyslop (1997) find support for the local labour market variant of the Phillips curve rather than the wage curve. In contrast, Bell et al. (2002) recently rejected the Phillips curve in favour of the wage curve, using U.K. New Earnings Survey data for 1976-1997.

publication of Blanchflower and Oswald's book on the topic in 1994. Many of the recorded documents are working papers that appeared in more than one working paper series or papers that do refer to the wage curve but do not carry out any new empirical analyses.

FIGURE 1 ABOUT HERE

For the present synthesis of this literature, seventeen wage curve studies that appeared between 1990 and 2001 were selected. All the *EconLit* articles, published in refereed journals during these years, that calculated new wage curve estimates by means of cross-section or panel data, are included. These studies are: Blanchflower and Oswald (1990), Groot et al. (1992), Wagner (1994), Bratsberg and Turunen (1996), Winter-Ebmer (1996), Partridge and Rickman (1997), Baltagi and Blien (1998), Janssens and Konings (1998), Pannenberg and Schwartz (1998), Buettner (1999), Morrison and Poot (1999), Kennedy and Borland (2000), Papps (2001) and Blanchflower (2001). A large number of wage curve estimates was also collected from Blanchflower and Oswald's 1994 book. With respect to as yet unpublished papers, we included Albaek et al. (1999) and Blanchflower (2001) to increase even further the range of countries for which estimates were obtained. However, the emphasis on articles in refereed journals is deliberate: peer review is the only directly measurable form of quality control.

Nonetheless, our sample covers the majority of countries and data sets by means of which wage curve analysis has been undertaken. The seventeen studies generated several hundred wage curve estimates. Selection of meta-analytic observations among these depends on the availability of a range of pre-determined study characteristics that relate to interesting issues with respect to the wage curve (such as the use of grouped versus micro data, gender effects, the role of unions, etc.). In addition, observations were selected for being 'interesting' in that they provided sufficient variation in the levels of each of the study characteristics that are potential covariates in a meta-regression model. Using these criteria, 208 meta-observations were obtained.¹⁰ As many as 97 of these were derived from Blanchflower and Oswald's 1994 book, as these authors themselves put much emphasis on replication and re-analysis. Adding also some estimates reported in Blanchflower and Oswald

¹⁰ A copy of the spreadsheet that contains the data can be requested by e-mail.

(1990) and by Blanchflower (2001), 62.5 percent of the meta-observations in our set came from the studies by one or both of these authors. This can be seen from Table 1, which provides descriptive statistics on the characteristics of the studies in the sample.

TABLE 1 ABOUT HERE

The number of observations used in the wage curve equations varied enormously. The smallest number was 36 (a regression by Albaek et al. 1999 for Finland using grouped data for 12 regions and three time periods), while the largest number was 1,534,093. The latter meta-observation came from a CPS micro data set for the USA (1963-87) used by Blanchflower and Oswald (1994). The number of regions used in the studies varied between 4 and 1395. A number of studies used only cross-sectional data, but where cross sections were pooled, a maximum of 25 time periods (between 1963 and 1998) was available. The micro-level data needed for this type of research have generally only become available with the advent of faster computers and abundant electronic storage.

Nonetheless, 27.4 percent of the studies used grouped variables (for example, the average wage of female workers in region i at time t), as individual records are not always accessible to the researcher, for confidentiality or cost reasons. Wage curves estimated with grouped data have in fact the advantage that they do not exaggerate the precision of the estimates of the elasticity (Moulton, 1990).

As estimation of the wage curve builds on the tradition of the earnings function, as first developed by Mincer (1974), it is not surprising that much attention has been paid to human capital characteristics of the workers. All but 9.1 percent of the studies used some measure of education or skill, while 88.9 percent included an age or experience variable. Industry information was somewhat more common than occupation (67.9 percent versus 47.6 percent).

Because many studies adopted a pooled cross-section time-series approach, it is natural to investigate a role for location and time fixed effects (51.0 percent and 62.5 percent respectively). While such dummy variables are often significant, their interpretation is usually problematic as there may be a number of independent influences leading to such fixed effects.

Although the wage curve is a relationship between the real wage and local unemployment, only 8 out of the 208 studies (3.8 percent) take spatial variation in the

cost of living into account. This may be due to the difficulty in obtaining regional cost of living indexes.

As was noted earlier, wage curves may not be present if countries are highly unionised and bargaining takes place at the national level. On the other hand, a prevalence of union influence at the local level may be indicative of a non-competitive local labour market where the bargaining relationship between the firms and unions does lead to an inverse relationship between wages and unemployment. 36.1 percent of the meta-observations in our sample contain a dummy variable to test whether union membership has an explicit effect on the wage level. A smaller subset of meta observations (17.8 percent) reports wage curve elasticities for males only.

Card (1995) suggested that where the actual relationship that was tested by means of regression is one between annual earnings and the unemployment rate, the observed elasticity might be due to the decline in hours worked as unemployment increases in recessions, rather than a response of the hourly wage. Only just under a quarter of studies control for this by estimating hourly earnings equations.

In assessing the relationship between wages and unemployment rates, one needs to consider the issue of simultaneity. The wage curve estimates the effect of unemployment rates on individual earnings, but pay levels could also affect labour demand and supply, and therefore unemployment. However, in micro level data sets it can be argued that the wage negotiated between a specific worker and an individual firm may be influenced by the local unemployment rate, but the micro outcome is unlikely to have a feedback effect on the unemployment rate itself (a macro variable). This may explain that less than 10 percent of the studies use instrumental variables to control for endogeneity of the unemployment rate and used OLS as the estimation technique instead.

One issue that is often ignored by researchers is the functional form of the relationship, for which theory may provide little guidance. Blanchflower and Oswald (1994) come to the conclusion that empirically the most supported relationship is one of constant elasticity: $\ln w = a + b \ln U + \text{other variables}$. The validity of this has been tested in 14.9 percent of the sampled studies by means of adding additional $\ln U$ powers.

If the wage curve provides evidence of non-competitive behaviour in local labour markets, one would expect the wage curve elasticity to be smaller in labour markets that are considered to be relatively competitive and where workers exhibit a relatively high degree of labour mobility. As the U.S. labour market may be

considered to be one of the most competitive among OECD countries, we will investigate whether there is an effect of the country on which the study is based (USA versus non-USA observations). Of our 208 wage curve estimates, 18.3 percent originated from the USA.

It can be seen from Table 1 that the observed unemployment elasticity of pay varies in our sample between -1.43 and 0.09. The mean estimate is -0.1184, which is quite close to the reported economic ‘law’ of an elasticity of -0.1. Figure 2 shows the histogram of the distribution. It is clear from Figure 2 that the distribution is quite skewed to the left. The mode is -0.06 and the median is -0.086.

FIGURE 2 ABOUT HERE

Among the elasticities, there are three outliers clearly visible in Figure 2. All three refer to wage curve regressions carried out by Blanchflower and Oswald. The rather extreme elasticities of -1.43, -1.02 and -0.79 resulted from wage curves estimated with Irish, U.K. and U.S. data respectively. They have in common that the estimates were obtained with micro data sets with a relatively small number of observations.

Compared with other meta-analyses in economics, the wage curve research has the advantage that the effect sizes across different studies are all elasticities, as the wage curves have all been estimated in loglinear form. In empirical economics there is often an emphasis on innovation and studies can vary considerably in terms of the definitions of variables and the functional form of the model. In contrast, the effect sizes and their standard errors are in our case directly comparable. As a starting point we can therefore combine the effect sizes along the lines proposed by e.g. Shadish and Haddock (1994). Such combinations take into account that a weighted average of the observed effect sizes, with weights inversely proportional to the estimated variances in each study, has a smaller variance than the unweighted mean.

When combining effect sizes, a distinction between a fixed effect (FE) and a random effects (RE) model can be made. Some notation is helpful here. Consider $k = 1, 2, \dots, K$ wage curve studies. Each study involves estimating a regression equation by means of $i = 1, 2, \dots, I_k$ individuals (or groups), located in one of $j = 1, 2, \dots, J_k$ local labour markets, and observed at times $t = 1, 2, \dots, T_k$. All wage curve studies can be described by the following regression model

$$\ln w_{ijt}^k = \gamma_0^k + (\mathbf{x}_{ijt}^k)' \gamma_1^k + (\mathbf{y}_{jt}^k)' \gamma_2^k + \beta_k \ln u_{ijt}^k + \delta_j^k + \tau_t^k + \varepsilon_{ijt}^k \quad (1)$$

where $\ln w_{ijt}^k$ is the natural logarithm of the observed wage of individual (or group) i in local labour market j at time t , used in study k , \mathbf{x}_{ijt}^k is a vector of characteristics of the individual or group, \mathbf{y}_{jt}^k is a vector of characteristics of local labour market and u_{ijt}^k is the unemployment rate in j relevant to individual i (aggregate or group-specific). The general model also allows for location or time fixed effects.

We observe the estimates b_1, b_2, \dots, b_K of the wage curve elasticities $\beta_1, \beta_2, \dots, \beta_K$, with estimated variances v_1, v_2, \dots, v_K . Under the FE model we assume $\beta_1 = \beta_2 = \dots = \beta_K = \beta$, a common effect size. Then the weighted average effect size of the K studies is calculated as

$$\bar{b} = \frac{\sum_{i=1}^K b_i / v_i}{\sum_{i=1}^K 1 / v_i} \quad (2)$$

The weighted average effect size \bar{b} has estimated variance \bar{v} , with

$$\bar{v} = \frac{1}{\sum_{i=1}^K 1 / v_i} \quad (3)$$

The latter can be used to construct a 95 percent confidence interval for the wage curve elasticity in the usual way. A test of the hypothesis that studies do in fact share a common population effect size, uses the following homogeneity statistic (Shadish and Haddock 1994, p.266):

$$Q = \sum_{i=1}^K \left[(b_i - \bar{b})^2 / (v_i) \right] \quad (4)$$

If Q exceeds the upper-tail critical value of the chi-square distribution with $K-1$ degrees of freedom, the observed variance in estimated wage curve elasticities is considerably greater than what we would expect by chance if all studies shared the same ‘true’ wage curve elasticity. When within-study sample sizes are very large, as they are in most of the wage curve studies, Q is likely to be rejected even when the individual effect sizes do not differ much, particularly when we have a large sample of studies (208 observations in our case). The best way then to account for heterogeneity is to use regression techniques, as we will do in the next section.

Alternatively, we can account for heterogeneity to some extent by the use of the RE model. In this case, the ‘true’ elasticity β_i of study i is assumed to be distributed with mean β and variance $v_i^* = \sigma_\beta^2 + v_i$, where σ_β^2 represents the between-studies variance and v_i represents the within-study variance. It can be shown (e.g. Shadish and Haddock 1994, p.274) that an unbiased estimate of σ_β^2 is given by

$$\hat{\sigma}_\beta^2 = \left[\sum_{i=1}^K b_i^2 - \left(\sum_{i=1}^K b_i \right)^2 / K \right] / (K-1) - \left(1/K \right) \sum_{i=1}^K v_i \quad (5)$$

The weighted mean elasticity and its estimated variance can then be computed by replacing v_i by v_i^* in equations (2) and (3).

Table 2 reports the results of estimating the FE and RE models under the homogeneity assumption. The three outlier observations have been excluded. This makes the mean elasticity somewhat smaller. Table 2 shows that the simple mean is now indeed strikingly close to the -0.1 consensus estimate. The weighted mean elasticity of -0.0571 for the FE model and -0.0855 for the RE model are smaller than the unweighted one. Large elasticities tend to coincide with large variances (and therefore large standard deviations). We shall see in the next section that this is partly due to an ‘unusually’ large number of cases in which t statistics are bunched around 2, i.e. due to publication bias. In the RE model, the weighted elasticity is closer to the unweighted one than in the FE model. However, the 95 percent confidence interval is, by design, much wider in the RE model (but the weighted means of the FE model lies outside the confidence intervals of the RE model).

TABLE 2 ABOUT HERE

As expected, given the large meta-analytic sample and the heterogeneity between studies in terms of the specification of Equation (1), the Q statistics are very large. Even with the RE model, the statistic is significant at the 1 percent level.

One cause of heterogeneity is the distinction between studies that use data on individuals and studies that use grouped data. The mean elasticity among the latter is much smaller than among the former. This is the case for both the unweighted and weighted means. The estimate of the between-studies variance in the RE model, $\hat{\sigma}_\beta^2$, is a little smaller among the studies using grouped data.

Using micro data permits estimation of the wage curve with greater precision, although the concurrent use of grouped labour market characteristics on the right hand side of the equation leads to the standard error on the unemployment rate being significantly underestimated (Moulton 1990, Card 1995) and, hence, the precision being exaggerated.¹¹

Thus, wage curve studies using micro data may show large t statistics due to two types of bias: discarding estimates with small t statistics because these are unlikely to be publishable (the file-drawer bias) and the statistical problem of estimating equations with earnings data on individuals, but explained by local labour market characteristics related to groups. In the next section, we will suggest a method to trim observations with ‘unusually’ large t statistics from the sample.

Table 3 provides additional information on average wage curve elasticities for sub-groups. The outliers are now included. Here, we simply report the unweighted means, but the differences would also carry across to weighted means. As the three outliers were all studies with data on individuals, the mean for studies with grouped data remains -0.0498, as compared with the now greater elasticity of -0.1443 for the studies with data on individuals.

TABLE 3 ABOUT HERE

An interesting question is the extent to which there is an advocacy effect in Blanchflower and Oswald’s results. Since these authors were the first to systematically investigate this phenomenon, one might expect that their reported research would be more supportive than other papers on the subject. Table 3 shows

that there appears to be indeed an advocacy effect: Blanchflower and Oswald's own mean estimate across a wide range of countries is about -0.15 (and thus greater than the 'stylised' value of -0.1), while the average of estimates made by others is a more modest value of -0.07. The difference is statistically significant.

Table 3 also shows that the introduction of location-fixed effects appears to take away some of the effect of unemployment in the determination of local wages, although the difference is not statistically significant at the 5 percent level. Card (1995) noted that in the U.S. the opposite is true: wage curve elasticities there tend to be larger in magnitude when locational dummies are included.

The inclusion of time fixed effects does not appear to influence the elasticity. Interestingly, studies that do not calculate gender-specific elasticities find a greater elasticity than regression equations that concern the elasticity for males only. This contradicts with evidence reported in the previous section that the wage curve appears more elastic for males than for females, but may be due to other study characteristics that are not simultaneously controlled for here. The difference is significant at the 5 percent level.

Table 3 confirms the effect predicted by Card (1995) that the wage curve is partly a phenomenon of working hours varying with the business cycle: the curve is indeed less elastic (-0.0628 on average) in hourly earnings equations than in annual earnings equations (-0.1365).

Wage curves appear more elastic when differences in local price levels are ignored (-0.1203 compared with -0.0711). It is possible that the wage curve simply picks up business cycle variation in local prices, to which nominal wages respond, with local prices of non-traded goods being high at times when the local economy is buoyant. The effect is not statistically significant, but note the small number of observations (eight) derived from studies that took cost of living differentials into account.

Interestingly, wage curve studies that incorporated a variable for the presence or membership of unions did find a more elastic wage curve (and the difference is statistically significant). If wage curves are a measure of local rents due to monopsony power among employers, such rents may generate a stronger union presence. Perhaps the union variable is an indicator of the labour market being less competitive and wage curves are more elastic in such labour markets.

¹¹ Card (1995, footnote 7) suggests a two-step procedure to compute correct standard errors for the

Studies that control for potential endogeneity of unemployment do find, as can be expected, a lower wage curve elasticity than OLS studies (-0.0641 and -0.1233 respectively) and the difference is statistically significant at the 5 percent level. Considering a nonlinear relationship between the natural logarithm of earnings and the logarithm of the unemployment rate U has a huge impact on the elasticity (the row for $\ln U$ powers in Table 3), and the difference is also statistically significant. Thus, there is some support for Blanchflower and Oswald's expectation that the elasticity may be lower at high rates of unemployment. However, goodness of fit tests have tended to support the more parsimonious constant elasticity relationship.

As noted above, if the wage curve reflects evidence of non-competitiveness in local labour markets, it could be argued that the wage curve elasticities should be less (in absolute value) for studies on the USA, which has a very competitive labour market, than for studies in other countries. However, Table 3 shows that there is no such effect on average.

The bottom half of Table 3 shows that the estimated wage curve elasticities do vary considerably between countries. Small elasticities are found for South Korea and for most continental western European countries. Among the latter, exceptions are The Netherlands, Italy, East Germany and Switzerland. Blanchflower (2001) estimated recently wage curves for ex-Communist countries of Eastern Europe and found those curves to be generally more elastic than for western economies, thus reconfirming earlier evidence on the difference between the former East Germany (see Pannenberg and Schwartze 1998, Baltagi et al. 2000) and West Germany (Blanchflower and Oswald 1994, Wagner 1994, Baltagi and Blien 1998, Buettner 1999). The Anglo-Saxon countries have also relatively greater wage curve elasticities. Ireland (as noted before), and to a lesser extent Latvia, appear clear outliers.

To what extent are our findings on the wage curve elasticity sensitive to publication bias? We first apply two simple tests for publication bias proposed by Card and Krueger (1995). Figure 3 displays the relationship between the t statistics of the studies and the square root of the number of observations. Standard statistical theory suggests that these two statistics should be proportional. This implies that a regression of $\ln t$ on $\ln \sqrt{n}$ should have a slope of one. The regression line displayed in Figure 3 has in fact a slope coefficient of only 0.535 ($\ln t = -1.099 + 0.535 \ln \sqrt{n}$, with $R^2 = 0.23$). This indicates that the studies with small numbers of observations

unemployment elasticity of pay.

have been reporting wage curve equations with unusually high t statistics. This suggests that there is some publication bias in this literature in that specification searches appear to have led to the reporting of too many equations with significant unemployment effects in wage determination.

FIGURE 3 ABOUT HERE

Another test of publication bias is inspection of a scatter plot of the wage curve elasticities and their standard errors. This scatter plot is given in Figure 4. A regression line has also been estimated. Here the line is given by elasticity = $-0.07 + 1.28 \times$ standard error of elasticity, with $R^2=0.43$). In the absence of any selective reporting this line should be horizontal, as the estimated wage curve elasticity should not vary in proportion to its standard error. However, if there is a tendency only to report results where the t -ratio is around 2 or greater, the estimated elasticity will increase as the standard error increases in order to maintain a t ratio at or above 2. Over all estimates in our meta-analysis, we find a significantly positive slope of 1.28. Interestingly, the intercept of this relationship (-0.07) turns out to be the unbiased overall estimate of the wage curve, as will be shown in the next section.

FIGURE 4 ABOUT HERE

A final way of identifying publication bias is to do a so-called funnel plot (see also Duval and Tweedie 2000). This plot is a scatter diagram of the log of the square root of the number of observations in each study against the wage curve elasticity. Figure 5 provides this plot for the wage curve studies. If all studies were drawn from the same population, a funnel shape should emerge, as the smaller samples yield wider confidence intervals for the wage curve elasticity. Figure 5 shows that the range of estimates becomes wider for smaller n , but the estimates come closer again for very small samples. These sub samples are actually based on grouped data and generate one type of heterogeneity in our overall sample. Once the studies based on grouped data are removed, the funnel shape does show up, as can be seen from Figure 6.

FIGURE 5 ABOUT HERE

Note, however, the asymmetry within the funnel plot. Figure 6 is the basis for making a correction for publication bias in the meta-regression model of the next section. Without publication bias, a symmetric funnel shape would emerge with a vertical line of symmetry at the location of the true parameter. Publication bias shows up in the asymmetry in Figure 6. Methods to ‘fill in the missing studies’ in Figure 6 are still being developed. In the next section we consider two such methods.

FIGURE 6 ABOUT HERE

4. Correcting publication and aggregation bias

Hedges (1992) proposed a formal model of publication bias that attempts to estimate the probability that a study is observed. The key variable is the p -value that is associated with each parameter estimate, whereby studies with a lower p -value are more likely to be observed. Using the notation of the previous section, consider again the estimates b_1, b_2, \dots, b_K of the wage curve elasticities $\beta_1, \beta_2, \dots, \beta_K$.

We assume now that the observed data are such that $b_i \sim N(\delta, \sigma_i^2)$, where σ_i^2 is assumed known (estimated by the regression standard error) and δ is an unknown parameter distributed as $\delta \sim N(\mathbf{z}\Delta, \sigma^2)$ where \mathbf{z} is a vector of study characteristics and σ^2 reflects unsystematic heterogeneity. Hence $b_i \sim N(\mathbf{z}\Delta, \eta_i)$ where $\sigma_i^2 + \sigma^2 = \eta_i$. This model is clearly an extension of the RE model of the previous section, in which the ‘true’ elasticity can now also vary with study characteristics.

Following Ashenfelter et al. (1999), we assume that there is a weight function $w(b_i)$ (based on observed p -values) that determines the probability that a study is observed. The weight attached to the probability that the study is observed when $0 < p < 0.01$, is set equal to one. The relative probabilities that studies are observed with $0.01 < p < 0.05$, or $p > 0.05$ is given by ω_2 and ω_3 respectively. In the absence of publication bias, ω_2 and ω_3 should be unity also. The overall pooled estimate of the wage curve elasticity is denoted by the constant term in the vector Δ . The heterogeneity in wage curve estimates is indicated by the other elements of Δ that represent the coefficients of the study characteristics \mathbf{z} . It can be shown that the likelihood function to be maximized is then as follows:

$$L = c + \sum_{k=1}^K \log w_k(b_k, \omega) - \frac{1}{2} \sum_{k=1}^K \left(\frac{b_k - z_k \Delta}{\eta_k} \right)^2 - \sum_{k=1}^K \log(\eta_k) - \sum_{k=1}^K \log \left[\sum_{l=1}^3 \omega_l B_{kl}(z_k \Delta, \sigma) \right] \quad (6)$$

where $B_{kl}(z_k \Delta, \sigma)$ is the probability that a normally distributed random variable with mean $z_k \Delta$ and variance η_k will be assigned weight value ω_l .

The maximum likelihood estimates without covariates are given at the top of Table 4, those with covariates follow further below. The top left panel shows that, as expected, studies with p-values greater than 0.01 or 0.05 are less likely to be reported than studies with highly significant wage curve elasticities (the probabilities are about half and one quarter respectively, relative to the $p < 0.01$ category).¹² The consensus wage curve estimate is now -0.077. However, the unexplained heterogeneity among studies is great relative to the mean, as indicated by $\sigma = 0.07$, which is much greater than the estimate of 0.03 in the simple RE model of the previous section.

TABLE 4 ABOUT HERE

The restricted model assumes that there is no publication bias, in which case $\omega_2 = \omega_3 = 1$. Minus twice the difference in the log likelihood ratio has a Chi-square (2) distributed. The value is here 21.2, compared with a critical value of 9.21 at the 1 percent level. Hence the null hypothesis of no publication bias is clearly rejected.

It is useful to distinguish again between studies in terms of the use of grouped or individual level data. Table 4 also reports maximum likelihood estimates for the case of data on individuals. It is clear that the wage curve elasticity is greater for the latter type of study (-0.077 versus -0.089), which confirms the significant difference we already detected in Tables 2 and 3. Again, the null hypothesis of no publication bias is also rejected for the sub sample of ‘unit record’ studies.

¹² Naturally, we would expect $1 > \hat{\omega}_2 > \hat{\omega}_3$. This is indeed the case throughout Table 4. In contrast, Ashenfelter et al. (1999) found $\hat{\omega}_2 > 1$, although not significantly so.

The lower part of Table 4 shows that several study characteristics turn out to have a significant effect on the underlying ‘true’ elasticity. Six covariates are considered: the natural logarithm of the square root of the number of observations and dummy variables indication whether studies were done by Blanchflower and Oswald, used data on individuals, controlled for hours worked, included a union membership variable, or allowed for a varying wage curve elasticity (by including powers of $\ln u$).

Several study covariates are significant. Setting these at their mean level, an overall elasticity of -0.072 results. This may be interpreted as the publication-bias corrected overall estimate of the wage curve elasticity.

Taking into account that the wage curve elasticity is negative, the wage curve becomes less negative (i.e. less elastic) when studies use greater samples (due to the positive coefficient on \ln root number of observations). Smaller micro samples have tended to yield more elastic wage curves.

However, in the multivariate model there appears to be no longer a Blanchflower and Oswald advocacy effect. As noted already in the discussion of Tables 2 and 3, and above, the wage curve is a micro-level phenomenon: the elasticity is much greater for studies using data on individuals rather than grouped data. This can be seen from the significance of the negative coefficient Δ_3 in the model with covariates for all studies and the estimate of Δ_0 of -0.146 in the sub-sample of unit record studies.

Moreover, the meta-regression model also confirms the significant effect of considering hourly earnings rather than annual earnings. Estimates based on hourly wage data show a lesser effect of unemployment than studies based on annual earnings data.

A significant effect (but only at the 10 percent level) can be found for the presence of a union membership variable in wage curve regressions (which yields a more elastic wage curve), but not for non-linearity ($\ln U$ powers). Again, the hypothesis of no publication bias is rejected (the test statistic is 10.74). The union effect is greater among the sub sample of studies using individual level data. The effect of data on hourly or annual wages is no longer significant among these studies.

Another method for controlling for publication bias involved the deleting of observations which are clear outliers in terms of the estimated elasticity, or which have ‘unusually’ large t statistics. This can be assessed by a histogram of $\ln t - \ln$ root n (recall also Figure 2 on the relationship between $\ln t$ and \ln root n). Figure 7a shows

that this distribution appears bimodal: there are too many observations with high t values.

FIGURE 7 ABOUT HERE

First we control for heterogeneity by omitting the estimates based on grouped data. Next, by deleting these observations with exaggerated t statistics, as well as some outliers of the wage curve elasticity, the histogram in Figure 7b results. This is a trimmed sample of 73 observations.

Figure 8 shows that this trimming has removed much of the asymmetry in the funnel plot.¹³ The mean estimate of the elasticity for the trimmed sample was about -0.066. This may be interpreted as an alternative publication bias corrected estimate of the wage curve elasticity. The similarity with the estimate derived with the maximum likelihood method discussed above is striking.

FIGURE 8 ABOUT HERE

5. Conclusions

Having quantitatively synthesized a rapidly expanding body of literature, what then has this study contributed? Our primary aim was to investigate the role that the local unemployment rate plays in the determination of workers' wages. When considered alongside human capital variables, like education and job experience, the unemployment rate may be regarded as a comparatively minor source of variation in earnings. Nonetheless, differences in the level of responsiveness across groups of workers or time periods can potentially provide a better insight into the important determinants of local labour market outcomes.

We carried out modern meta-analytic techniques on a sample of 208 elasticities derived from the literature to uncover the reasons for the differences in empirical results across studies. Without repeating the underlying micro-economic research and by simply deploying meta-regression analysis it was found that the wage curve is a robust empirical phenomenon, but there is also clear evidence of publication bias. There is indeed an uncorrected mean estimate of about -0.1 for the elasticity. After controlling for publication bias by means of two different methods, we estimate that

the ‘true’ wage curve elasticity at the means of study characteristics is no more than -0.07. This still hides an effect on hours worked. Using the model of the previous section, it can be estimated that the relationship between local unemployment and the hourly wage has an elasticity of about -0.05. These are useful stylised facts for macro simulation models.

We also found that the wage curve phenomenon is exaggerated by micro level studies with relatively small samples. Finally, ignoring the extent to which unions play a role in local wage bargaining makes the wage curve less elastic.

It is clear that the wage curve has prompted a wave of fascinating research on local labour markets. This paper should by no means be the ‘last word’ on the wage curve. Our quantitative literature survey has revealed many weak and strong elements in that research. Ultimately meta-analysis is an effective aid for setting the direction for further research on the complex relationship between wages and unemployment rates on a given local labour market. In this respect, our findings suggest that further explicit tests of local monopsony models and institutional factors (such as local bargaining arrangements) are likely to shed further light on the heterogeneity in wage curve studies.

¹³ An alternative way to remove the asymmetry in the funnel plot is the ‘trim and fill’ procedure proposed by Duval and Tweedie (2000).

References

- Abraham, F. (1996) "Regional Adjustment and Wage Flexibility in the European Union". *Regional Science and Urban Economics*, 26, 51-75.
- Albaek, K., R. Asplund, S. Blomskog, E. Barth, B.R. Guðmundsson, V. Karlsson and E.S. Madsen (1999) "A Wage Curve in the Nordic Countries?" Paper presented at the SOLE conference, Boston, 1999.
- Arulampalam, W., J. Hartog, T. MaCurdy and J. Theewes (1997) "Replication and re-analysis", *Labour Economics* 4(2): 99-106.
- Ashenfelter O., C. Harmon and H. Oosterbeek (1999) "A Review of Estimates of the Schooling/Earnings Relationship, with Tests for Publication Bias", *Labour Economics* 6(4): 453-470.
- Azariadis, C. (1975) "Implicit Contracts and Underemployment Equilibria", *Journal of Political Economy*, 83, 1183-1202.
- Baily, M.N. (1974) "Wages and Employment under Uncertain Demand", *Review of Economic Studies*, 41, 37-50.
- Baltagi, B.H. and U. Blien (1998) "The German Wage Curve: Evidence from the IAB Employment Sample", *Economics Letters*, 61, 135-142.
- Baltagi, B.H., U. Blien and K. Wolff (2000) "The East German Wage Curve: 1993-1998". *Economics Letters*, 69: 25-31.
- Bell, B., Nickell, S. and G. Quintini (2002) "Wage Equations, Wage Curves and All That", *Labour Economics*, 9: 341-360.
- Bhaskar, V. and T. To (1999) "Minimum Wages for Ronald McDonald Monopsonies: A Theory of Monopsonistic Competition", *Economic Journal* 109(April): 190-203.
- Blackaby, D.H. and L.C. Hunt (1992) "The "Wage Curve" and Long-Term Unemployment: A Cautionary Note", *The Manchester School*, 60, 419-428.
- Blanchflower, D.G. (2001) "Unemployment, Well-being and Wage Curves in Eastern and Central Europe", Department of Economics, Dartmouth College, mimeo.
- Blanchflower, D.G. and A.J. Oswald (1990) "The Wage Curve", *Scandinavian Journal of Economics*, 215-237.
- Blanchflower, D.G. and A.J. Oswald (1994) *The Wage Curve*. Cambridge: MIT Press.
- Blanchflower, D.G. and A.J. Oswald (1995) "An Introduction to the Wage Curve", *Journal of Economic Perspectives*, 9, 153-167.
- Boal, W.M. and M.R. Ransom (1997) "Monopsony in the Labor Market", *Journal of Economic Literature* 35(1): 86-112.
- Bratsberg, B. and J. Turunen (1996) "Wage Curve Evidence from Panel Data", *Economics Letters*, 51, 345-353.
- Buettner, T. (1999) "The Effect of Unemployment, Aggregate Wages and Spatial Contiguity on Local Wages: An Investigation with German District Level Data", *Papers in Regional Science* 78: 47-67.
- Buettner, T. and B. Fitzenberger (2001) "Central Wage Bargaining and Wage Flexibility: Evidence from the Entire Wage Distribution", mimeo, Mannheim University, Germany.
- Campbell, C. and Orszag, J.M. (1998). 'A Model of the Wage Curve', *Economics Letters*, vol. 59, pp. 119-25.
- Card, D. (1995) "The Wage Curve: A Review", *Journal of Economic Literature* 33(2): 785-799.
- Card, D. and D. Hyslop (1997) "Does Inflation "Grease the Wheels of the Labor Market?". In: C.D. Romer and D.H. Romer (eds.) *Reducing Inflation: Motivation and Strategy*, University of Chicago Press.

- Card, D. and A.B. Krueger (1995) "Time-Series Minimum-Wage Studies: A Meta-analysis", *American Economic Review* 85(2): 238-243.
- Chiarini B. and P. Piselli (1997) "Wage Setting, Wage Curve and Phillips Curve, the Italian Evidence", *Scottish Journal of Political Economy*, 44, 545-565.
- Cooper H. and L.V. Hedges (1994). *The Handbook of Research Synthesis*. New York: Russell Sage Foundation.
- De Menil G. (1971). *Bargaining: Monopoly Power Versus Union Power*. Cambridge: MIT Press.
- Doucouliagos, C. (1995) "Worker Participation and Productivity in Labor-Managed and Participatory Capitalist Firms: A Meta-Analysis", *Industrial and Labor Relations Review* 49(1): 58-77.
- Doucouliagos, C. (1997). "The Aggregate Demand for Labour in Australia: A Meta-analysis", *Australian Economic Papers* 36(69): 224-242.
- Duval S. and R. Tweedie (2000) "Theory and Methods - A Nonparametric "Trim and Fill" Method of Accounting for Publication Bias in Meta-Analysis", *Journal of the American Statistical Association* 95(449): 89-98.
- Fuller, J.B. and K. Hester (1998). "The Effect of Labor Relations Climate on the Union Participation Process", *Journal of Labor Research* 19(1): 173-187.
- Glass, G.V. (1976). "Primary, Secondary and Meta-analysis of Research", *Educational Researcher* 5: 3-8.
- Groot, W., E. Mekkelholt and H. Oosterbeek (1992) "Further Evidence on the Wage Curve". *Economics Letters*, 38, 355-359.
- Groot, W. and H. Maassen van den Brink (2000) "Overeducation in the Labor Market: A Meta-Analysis", *Economics of Education Review* 19(2): 149-158.
- Hall, R.E. (1970) "Why is the Unemployment Rate So High at Full Employment?", *Brookings Papers on Economic Activity*, 3, 369-402.
- Hall, R.E. (1972) "Turnover in the Labour Force", *Brookings Papers on Economic Activity*, 3, 706-756.
- Harris, J.R. and M.P. Todaro (1970) "Migration, Unemployment and Development: A Two Sector Analysis", *American Economic Review*, 60, 126-142.
- Hedges, L.V. (1992) "Modelling Publication Selection Effects in Meta-Analysis", *Statistical Science*, 7, 246-255.
- Janssens, S. and J. Konings (1998) "One More Wage Curve: the Case of Belgium", *Economics Letters*, 60, 223-227.
- Jarrell S.B. and T.D. Stanley (1990) "A Meta-analysis of the Union-Nonunion Wage Gap", *Industrial and Labor Relations Review* 44(1): 54-67.
- Johansen, K. (1997) "The Wage Curve: Convexity, Kinks and Composition Effects". *Applied Economics*, 29, 71-78.
- Kennedy, S. and J. Borland (2000) "A Wage Curve for Australia?", *Oxford Economic Papers*, 52, 774-803.
- Mincer, J. (1974) *Schooling, Experience and Earnings*. New York: Columbia University Press.
- Morrison, P.S. (1997) "A Regional Labour Market Profile". In Morrison, P.S. (Ed.) *Labour, employment and work in New Zealand*. Proceedings of the Seventh Conference on Labour, Employment and Work in New Zealand, Wellington: Victoria University of Wellington, 77-88.
- Morrison, P.S. and J. Poot (1999) "The Wage Curve and Local Labour Markets in New Zealand". In Morrison, P.S. (Ed.) *Labour, employment and work in New Zealand*. Proceedings of the Eighth Conference on Labour, Employment and Work in New Zealand. Wellington: Victoria University of Wellington.

- Morrison PS, K.L. Papps and J. Poot (2002) “Wages, Employment, Labour Turnover and the Accessibility of Local Labour Markets”, mimeo, School of Economics and Finance, Victoria University of Wellington.
- Moulton B.R. (1990) “An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units”, *Review of Economics and Statistics* 72(2): 334-338.
- Neumark, D. and W. Wascher (1998) “Is the Time-Series Evidence on Minimum Wage Effects Contaminated by Publication Bias?”, *Economic Inquiry* 36(3): 458-470.
- Pannenberg M. and J. Schwarze (1998) “Labor Market Slack and the Wage Curve”, *Economics Letters* 58: 351-354.
- Papps, K.L. (2001) “Investigating a Wage Curve for New Zealand”, *New Zealand Economic Papers* 35(2): 218-239.
- Partridge, M.D. and D.S. Rickman (1997) “Has the Wage Curve Nullified the Harris-Todaro Model? Further US evidence”. *Economics Letters*, 54, 277-282.
- Phelps, E. (1994). *Structural slumps: The Modern Equilibrium Theory of Unemployment, Interest and Assets*. Cambridge: Harvard University Press
- Reza, A.M. (1978) “Geographic Differences in Earnings and Unemployment Rates”, *Review of Economics and Statistics*, 60, 201-208.
- Salop, S. (1979) “A Model of the Natural Rate of Unemployment”, *American Economic Review*, 69, 117-125.
- Sato, Y. (2000) ‘Search Theory and the Wage Curve’, *Economics Letters*, vol. 66, pp. 93-8.
- Shadish, W.R. and Haddock, C.K. (1994) “Combining Estimates of Effect Size”, in: Cooper H. and L.V. Hedges (eds) *The Handbook of Research Synthesis*. New York: Russell Sage Foundation, 261-281.
- Shapiro, C. and J.E. Stiglitz (1984) “Equilibrium Unemployment as a Worker Discipline Device”, *American Economic Review*, 74, 433-444.
- Stanley, T.D. and S.B. Jarrell (1998) “Gender Wage Discrimination Bias? A Meta-Regression Analysis”, *Journal of Human Resources* 33(4): 947-973.
- Stanley, T.D. (2001) “Wheat from Chaff: Meta-analysis as Quantitative Literature Review”, *Journal of Economic Perspectives*, 15, 131-150.
- Wagner J. (1994). “German Wage Curves, 1979-1990”, *Economics Letters*, 44, 307-311.
- Winter-Ebmer, R. (1996) “Wage Curve, Unemployment Duration and Compensating Differentials”, *Labour Economics*, 3, 425-434.

Table 1 Descriptive statistics of wage curve studies (n=208)

	Minimum	Maximum	Mean	Std. Deviation
Wage Curve Elasticity	-1.43	0.09	-0.1184	0.1563
t-Statistic on Elasticity	.05	73.11	6.065	8.8436
Number of Observations	36	1534093	51689.8	190373.6
Number of Regions	4	1395	93.95	265.15
Number of Time Periods	1	25	5.16	5.69
First Year of Observations	1963	1998	1983.4	6.9
Last Year of Observations	1971	1998	1989.0	5.5

*Proportion of Studies with
the Following Features:*

Blanchflower and Oswald	62.5%
Data on Individuals	72.6%
Education or Skill	90.9%
Age or Experience	88.9%
Occupation	47.6%
Industry	69.7%
Location Fixed Effects	51.0%
Time Fixed Effects	62.5%
Regional Cost of Living	3.8%
Unions	36.1%
Males only	17.8%
Hours	24.5%
OLS	91.8%
lnU powers	14.9%
Data from USA	18.3%

Table 2 Combining estimates of the wage curve elasticity

	sample size	mean	weighted mean	95% confidence interval	$\hat{\sigma}_\beta^2$	Q
Fixed Effect Model						
All observations	205	-0.1044	-0.0571	(-0.0580,-0.0563)	0	6866 ^a
Grouped data	57	-0.0498	-0.0140	(-0.0164,-0.0116)	0	569 ^a
Data on individuals	148	-0.1254	-0.0633	(-0.0642,-0.0624)	0	4919 ^a
Random Effects Model						
All observations	205	-0.1044	-0.0855	(-0.0919,-0.0791)	0.0381	547 ^a
Grouped data	57	-0.0498	-0.0408	(-0.0510,-0.0306)	0.0311	89 ^a
Data on individuals	148	-0.1254	-0.1022	(-0.1094,-0.0951)	0.0350	451 ^a

^aSignificant at the 1 percent level.

Table 3 The effects of study characteristics on wage curve elasticities

	Without feature			With feature			Difference statistically significant at 5%? ¹⁴
	n	Mean	Std.Dev.	n	Mean	Std.Dev.	
Data on Individuals	57	-0.0498	0.0542	151	-0.1443	0.1736	yes
Blanchflower & Oswald	78	-0.0695	0.0729	130	-0.1478	0.1835	yes
Location Fixed Effects	102	-0.1356	0.1364	106	-0.1019	0.1723	no
Time Fixed Effects	78	-0.1177	0.0912	130	-0.1189	0.1850	no
Males only	171	-0.1278	0.1683	37	-0.0751	0.0659	yes
Hours Worked	157	-0.1365	0.1715	51	-0.0628	0.0717	yes
Regional Cost of Living	200	-0.1203	0.1589	8	-0.0711	0.0392	no
Unions	133	-0.0960	0.0962	75	-0.1582	0.2220	yes
OLS	17	-0.0641	0.0469	191	-0.1233	0.1616	yes
lnU powers	177	-0.1041	0.1363	31	-0.2001	0.2266	yes
Data from USA	170	-0.1185	0.1586	38	-0.1184	0.1472	no

¹⁴ Equal variances were only assumed when indicated by Levene's test.

Table 3 continued

Elasticities by country of study

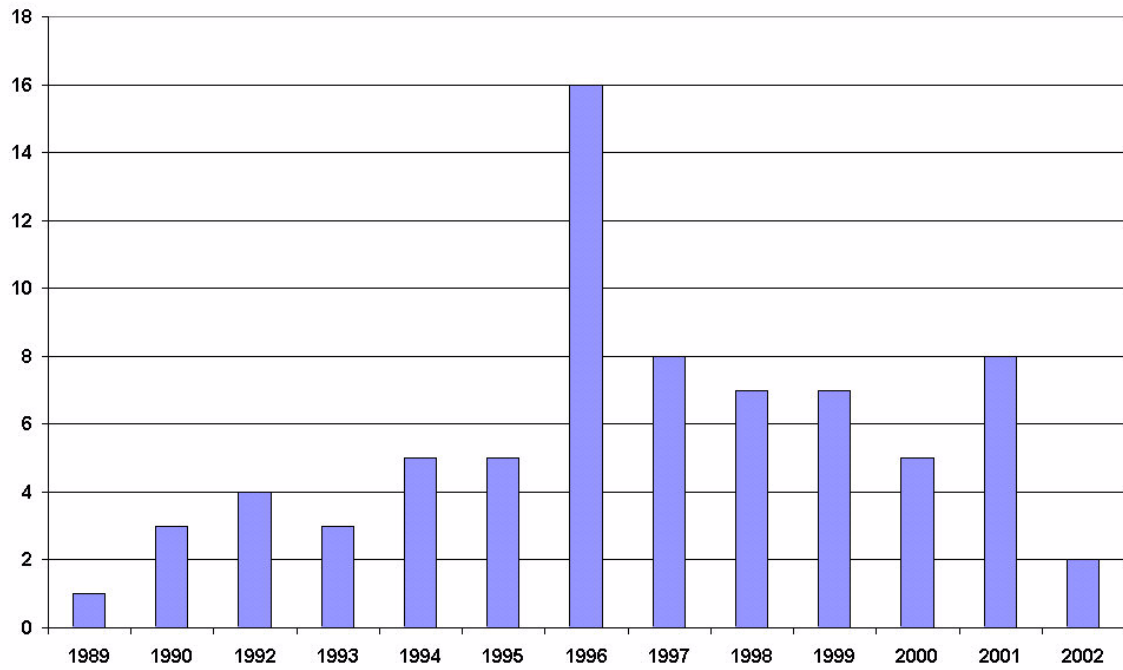
Country of Study	n	Mean
Australia	20	-0.1537
Austria	4	-0.0682
Belgium	2	-0.0645
Britain	48	-0.1140
Bulgaria	2	-0.2245
Canada	7	-0.1336
Czech Republic	2	-0.0090
Denmark	3	-0.0241
Estonia	1	-0.2910
Finland	3	-0.0336
Germany-East	9	-0.0974
Germany-West	16	-0.0488
Hungary	3	-0.1247
Iceland	3	-0.0328
Ireland	2	-0.8970
Italy	2	-0.1144
Kyrgyz	1	-0.0082
Latvia	2	-0.4910
Netherlands	8	-0.1854
New Zealand	4	-0.0925
Norway	8	-0.0519
Poland	3	-0.1560
Russia	3	-0.1767
Slovakia	1	-0.1860
Slovenia	2	-0.0285
South Korea	6	-0.0431
Sweden	3	-0.0027
Switzerland	2	-0.1642
USA	38	-0.1184
Total	208	-0.1184

Table 4 Publication-bias corrected estimates of the unemployment elasticity of pay: Ashenfelter *et al.* (1999) procedure

<i>Without covariates</i>				
All studies	Unrestricted	SE	Restricted	SE
ω_2	0.534 ***	0.171	1.000	-
ω_3	0.288 ***	0.079	1.000	-
Δ_0	-0.077 ***	0.006	-0.093 ***	0.005
σ	0.070 ***	0.004	0.073 ***	0.004
Log-likelihood	399.67		389.09	
n	208		208	
Unit record studies				
ω_2	0.263 **	0.118	1.000	-
ω_3	0.152 ***	0.052	1.000	-
Δ_0	-0.089 ***	0.008	-0.113 ***	0.007
σ	0.074 ***	0.005	0.076 ***	0.006
Log-likelihood	287.42		270.40	
n	151		151	
<i>With covariates</i>				
All studies	Unrestricted		Restricted	
ω_2	0.584 ***	0.191	1.000	-
ω_3	0.383 ***	0.109	1.000	-
Δ_0	-0.079 ***	0.022	-0.103 ***	0.022
Δ_1 (ln rt nr of obs)	0.019 ***	0.006	0.023 ***	0.006
Δ_2 (Bl & Osw)	-0.019	0.012	-0.021 *	0.012
Δ_3 (dat on indi)	-0.100 ***	0.016	-0.109 ***	0.015
Δ_4 (hours)	0.030 **	0.013	0.034 ***	0.013
Δ_5 (unions)	-0.021 *	0.011	-0.021 *	0.011
Δ_6 (ln u power)	-0.020	0.015	-0.021	0.015
σ	0.059 ***	0.004	0.060 ***	0.004
Log-likelihood	430.57		425.20	
n	208		208	
Unit record studies				
ω_2	0.290 **	0.131	1.000	-
ω_3	0.202 ***	0.072	1.000	-
Δ_0	-0.146 ***	0.041	-0.213 ***	0.038
Δ_1 (ln rt nr obs)	0.014 *	0.008	0.023 ***	0.007
Δ_2 (Bl & Osw)	-0.017	0.017	-0.018	0.016
Δ_3 (dat on indi)	-	-	-	-
Δ_4 (hours)	0.028	0.017	0.034 **	0.017
Δ_5 (unions)	-0.043 ***	0.016	-0.039 ***	0.015
Δ_6 (ln u power)	-0.008	0.019	-0.010	0.018
σ	0.068 ***	0.005	0.068 ***	0.005
Log-likelihood	298.10		286.62	
n	151		151	

* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Figure 1 The number of EconLit documents on the wage curve



Source: *EconLit* (as at 24 January 2003)

Figure 2 The distribution of wage curve elasticities

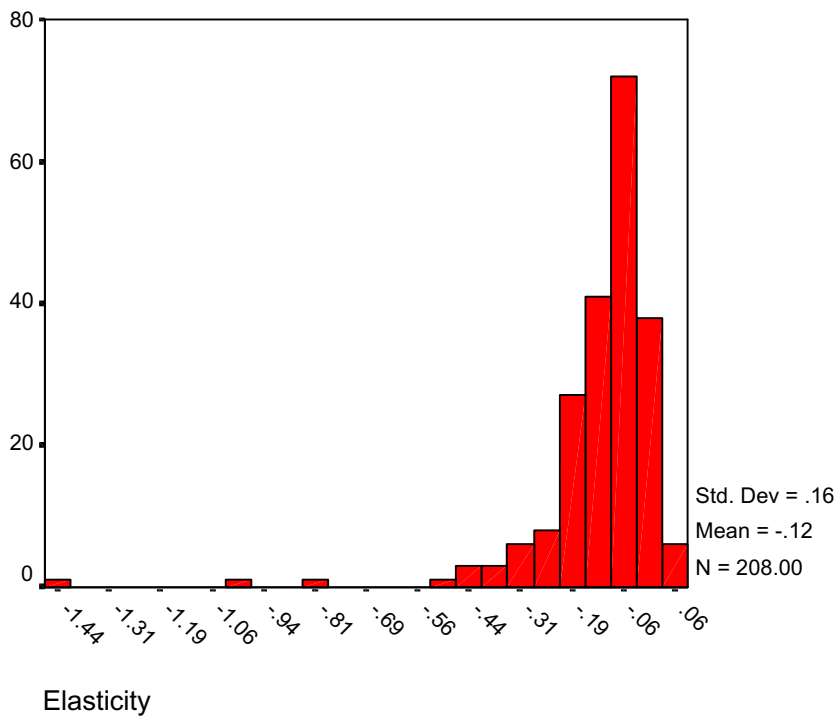


Figure 3 The relationship between the study t-statistics and the number of observations

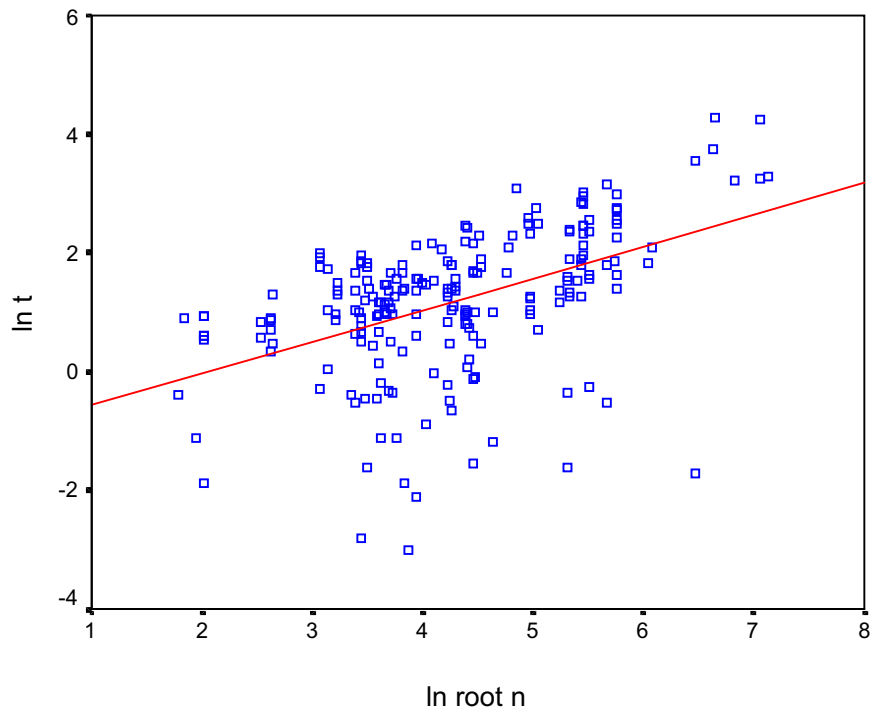
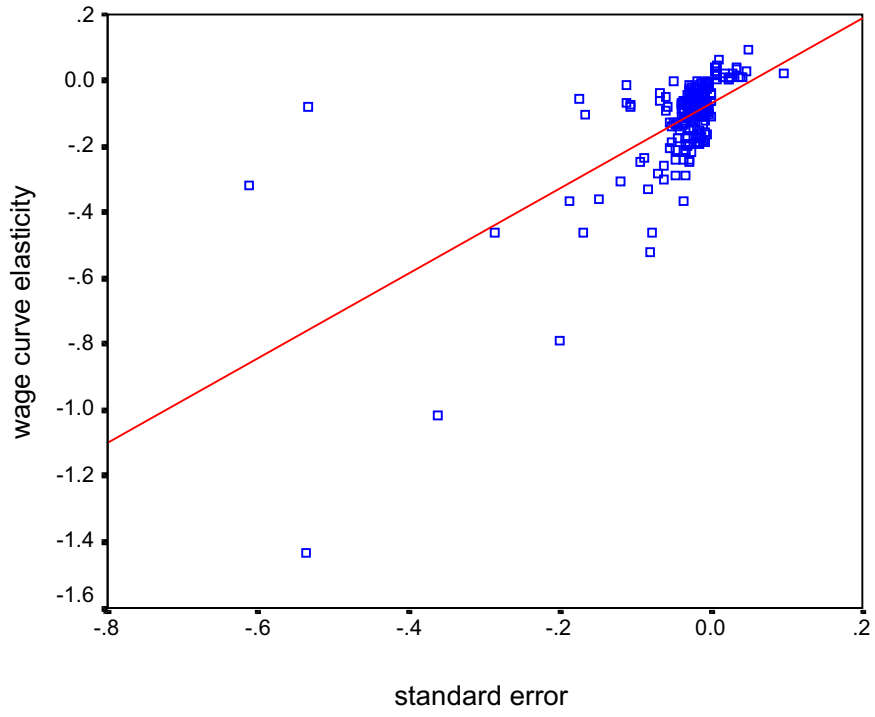


Figure 4 The relationship between the elasticities and standard errors



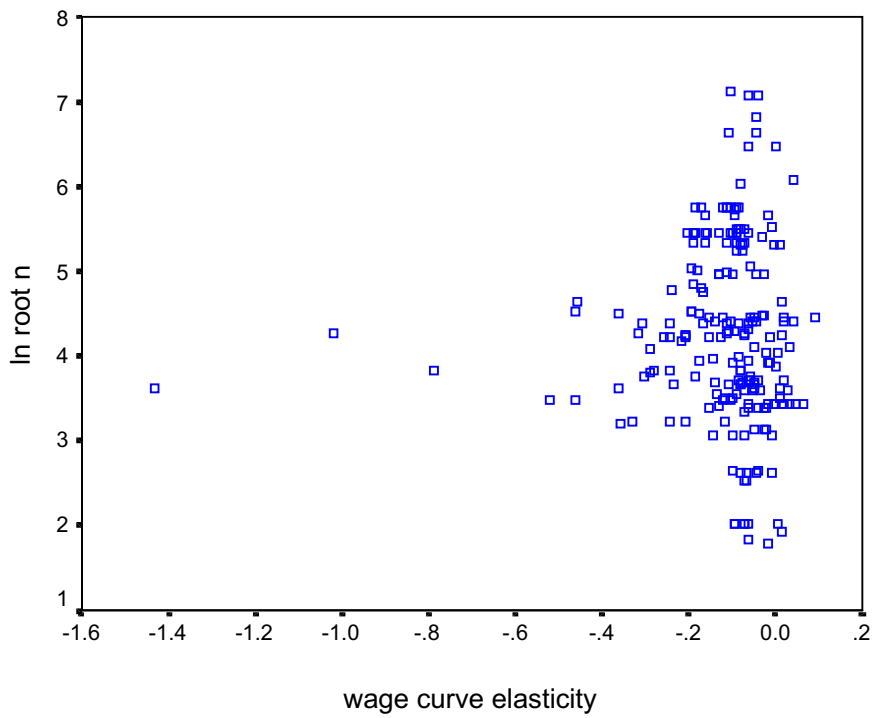


Figure 5 Funnel plot, all observations

Figure 6 Funnel plot of unit record studies, $n = 151$

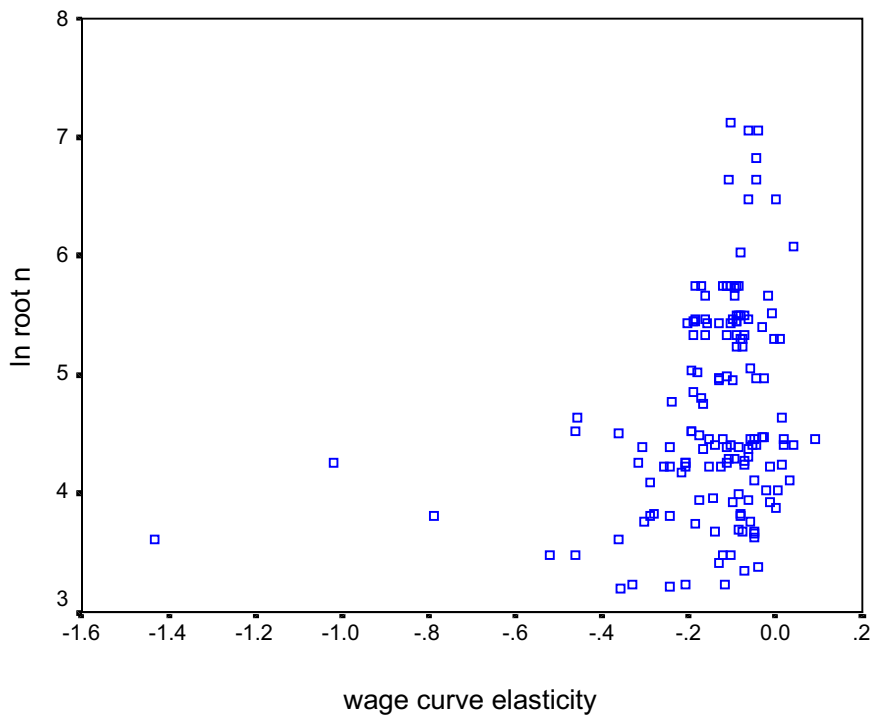
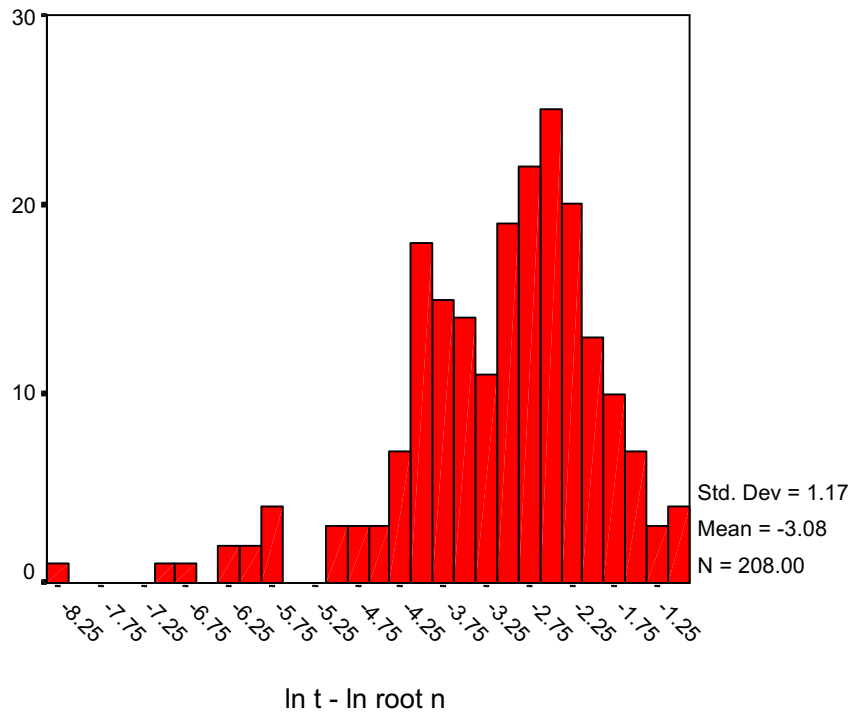


Figure 7 Histogram of $(\ln t - \ln \text{root } n)$ for total sample and trimmed sample

(a) total sample



(b) trimmed sample

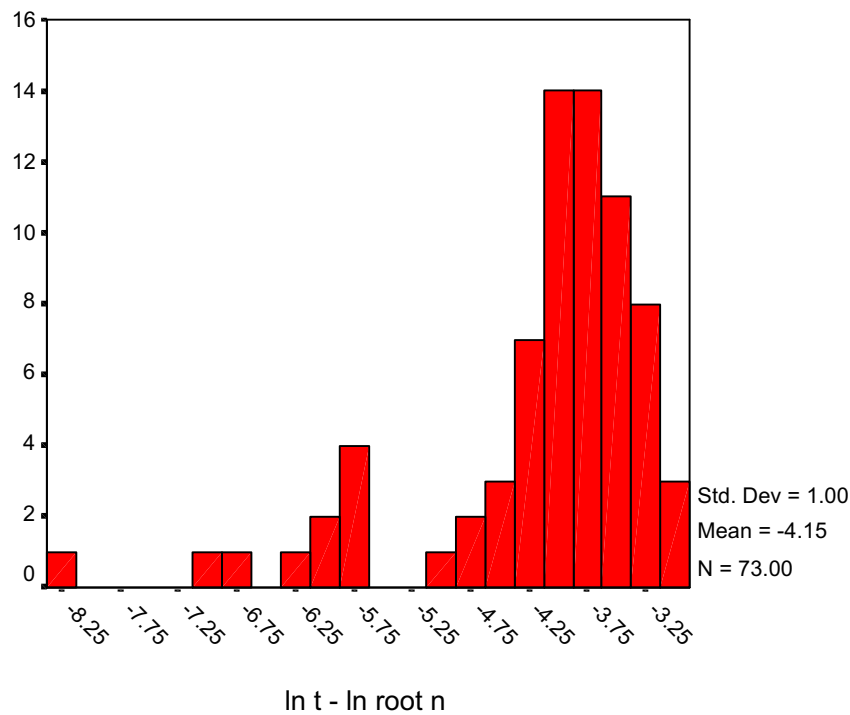


Figure 8 Funnel plot of trimmed sample, $n = 73$

