Does Employment Respond to the Minimum Wage? A meta-analysis of recent studies from the

New Minimum Wage Research

Dale Belman

School of Human Resources & Labor Relations

Michigan State University

drale@msu.edu

Paul Wolfson*

Tuck School of Business

Dartmouth College

paulw@dartmouth.edu

*Corresponding Author

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The *New Minimum Wage Research* is the name given to the stream of research into the effects of the minimum kicked off by the 1991 conference at Cornell University. The research spurred first by this conference and later by subsequent increases of existing minimum wages and establishment of new ones is considerably more heterogeneous than earlier research: heterogeneous with respect to effects studied, data sources and structures, model specification and econometric techniques. This paper presents the results of a meta-analysis of studies that have appeared since 2000 on the effect of the minimum wage on employment and on hours of employment. The conclusion is that the effects are statistically detectible but small, even when restricting attention to the effect on either youth or the food and drink sector. The largest reliable meta-estimates of employment elasticities are about -0.07. The smallest reliable estimates with respect to youth employment are about -0.04, and with respect to employment in the food and drink sector, about -0.01.

Meta-analysis is a body of techniques for combining many statistical studies to determine an overall result. T.D. Stanley has written extensively on a particularly useful and straightforward technique, metagression (Stanley and Jarell [1989], Stanley [2001], [2005], [2008]), as well as an application to the minimum wage (Doucouliagos and Stanley [2009]). This section begins with a brief description of the technique, drawing heavily on these articles, followed by a discussion of Doucouliagos and Stanley (2009), and concludes with our own metaregression analysis of the literature covered in the sections on employment and hours.

When confronted with results from many studies of the same phenomenon, summarizing them or combining them altogether into a single overall result can be a challenge. The first problem is that they must all be measuring the same thing and all must present the results in the same units, or at least in a way that the metaresearcher can put them into the same units. Once past this hurdle, an obvious way to aggregate results is to calculate their average value, and with some complications, this is what metaregression does. The complications arise from recognizing that for a variety of reasons, estimates are not all created equal, and that it is therefore not appropriate to give equal weight to all results in calculating the average.

Publication bias, an issue that Card and Krueger (1995) raise in their discussion of the earlier pre-*NMWR* literature on the minimum wage, is one reason for not treating all results as equally important. Publication bias means that the probability of a paper's being published depends on the results it reports. It can occur for reasons that are nefarious, journal editors' refusing to publish papers in which results do not toe a party line, or, as is more widely suspected, for reasons that are less so, where a scarcity of journal pages leads editors to reject papers as uninteresting papers because their results are indeterminate (i.e., not statistically

significant) or they are deemed to insufficiently novel or ingenious. For whatever reason, attempts to generalize without accounting for it give rise to biased estimates of an effect by over-counting certain results and excluding others.

Even absent publication bias, differences in standard errors are another reason for not treating all results as equally important. Imprecisely estimated values are of less value in understanding and evaluating an effect than those that are measured with greater precision (Stanley [2001]), and should not be given equal weight in any evaluation.

Finally, estimated effects may differ systematically due to differences in statistical framework, data source, data period, unknown, unrecognized actions of particular authors in analyzing the data (Stanley [2001]), and others too numerous to mention. Good meta-analysis tries to account for as many of these as are recognized and thought to be important.

We can chart the progress of this argument with a series of equations.[1] We start with a simple average:

$$Effect_k = \overline{Effect} + u_k = b_1 + u_k \qquad (1)$$

where $Effect_k$ is an estimate of the effect in question. In the case of publication bias for statistical significance, a correlation will exist between the size of the effect and its standard error, SE_k in equation (2):

$$Effect_k = b_1 + b_0 SE_k + u_k \qquad (2)$$

This equation will remove that effect from the meta-analysis estimate of the effect size. However, it still treats estimates equally regardless of their precision. The differences in

[1]This presentation draws heavily on Stanley (2001, 2005, 2008) and follows the order in which he presents the equations.

estimates' precision shows up as heteroskesdasticity. A correction for that is to weight by the inverse of the standard error, which is equivalent to dividing the variables in equation (2) by the standard error, SE_k:

$$\frac{Effect_k}{SE_k} = \frac{b_1}{SE_k} + b_0 + v_k \qquad (3)$$

Dividing the estimate by its standard error turns the variable on the left of equation 2 into the t-statistic; that is, equation 3 becomes:

$$t_k = b_0 + b_1 precision_k + v_k , \qquad (3a)$$[2]

where the precision of an estimate is defined to be the reciprocal of its standard error. Equation (3a) is the basic equation for performing a metaregression on a set of estimates to derive an overall estimate of the effect size. Because of differences in data source and type, analytic framework, idiosyncracies of individual researchers, and so forth, Stanley recommends including binary categorical variables to control for these. If these variables form a vector, X_k, equation (3a) then becomes

$$t_k = b_0 + X_k B_0 + \left(b_1 + X_k B_1\right) precision_k + v_k \ , \qquad (4)$$

where B_0 and B_1 are the metaregression vectors of coefficients for X_k. With deviation coding of the X_k variables, b_1 remains the estimate of the average effect.[3] Finally, to minimize the role of the meta-analyst's judgment in determining the results, Stanley argues for including all estimates

[2]Notice that with the heteroskedasticity correction, the constant term in equation (2) becomes the precision variable in equation (3a) and the SE variable in equation (2) becomes the constant term in equation (3a). If, for whatever reason, the metaregression does not include the correction for publication bias for statistical significance, equation (3a) will have no constant term. We return to this in section 4.
[3]A good discussion of deviation coding is to be found in Regression with Stata, "Chapter 5 - Additional coding systems for categorical variables in regression analysis", accessed on February 22, 2011 at http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter5/statareg5.htm#DEVIATION .

from each analysis, with dummy variables by study or researcher to prevent a large number of estimates from a single source from unduly influencing the results.

2. Doucouliagos and Stanley (2009)

Doucouliagos and Stanley (2009) present results of a meta-analysis of the literature that examines the response of teenage employment in the U.S. to the minimum wage.[4] They identify nearly 100 studies of U.S. employment and the minimum wage between the early 1960s and 2007, of which they exclude 31 from their analysis either because inclusion would have made the sample too heterogeneous for their purposes, or because it was not possible to gather both an elasticity and its standard error from information in the study. What remain are 64 studies with nearly 1500 point estimates of the employment elasticity. They report results from several specifications and estimation methods, and with and without moderator variables, i.e., control variables. In the simple model, without the dummy variables to control for different factors, they find strong evidence of publication bias that is large enough, by itself, to make the average reported t-statistic negative and significant at a 0.1 level. Of greater interest, they find that the (appropriately weighted) average employment elasticity is -0.01, or as they put it:

> "A 10 per cent increase in the minimum wage reduces employment by about 0.10 per cent ... But even if this adverse employment effect were true, it would be of no practical relevance. An elasticity of -0.01 has no meaningful policy implications. If correct, the minimum wage could be doubled and cause only a 1 per cent decrease in teenage employment. (pp. 415-416.)

Interpreting results from Doucouliagos and Stanley's (2009) more elaborate specifications requires some thought. Their control variables reflect the type of data used in each analysis as well as modeling choices of each analyst. When all of these variables are zero (a not very

[4]In addition to metaregression, Doucouliagos and Stanley (2009) present a graphical analysis that is useful in exploring publication bias. Because this issue is not of particular interest here, beyond purging its effect so as not to distort the results of meta-analysis, the focus is on their metaregression.

meaningful situation), the immediate employment response reflects a statistically significant positive elasticity of about 0.1. A discussion of what constitutes "best practice" follows to suggest which control variables should be taken into account in determining the "best estimate" of the elasticity. Varying definitions give estimates of the elasticity ranging between -0.003 and +0.065, none of which, they believe, are economically meaningful.

3. The Data

We began with the 75 analyses of the employment effect published from 2001 onward that are discussed in the chapter on employment, and the six additional pieces in the hours chapter that were not also in the employment chapter. From these, 23 either had estimates of elasticities and their standard errors, or it was possible to calculate them from information in the study, for a total of 439 point estimates (see Table 1).

Before turning to further quantitative results, it will be useful to consider some graphs to get a feel for the data. Suppose we have estimates and their standard errors from a collection of reasonably well designed and executed studies. Absent publication bias, if we were to use each estimate's standard error to standardize it around the true effect and plot this value against its degrees of freedom, the resulting graph should look like random draws from the family of central t-distributions (the family identified by the number of degrees of freedom). As the degrees of freedom increase, the estimates should cluster more tightly around the true value, and at each value the estimates should be (roughly) normally distributed, symmetric about more densely clustered toward the true value and thinning out away from it. Of course, this standardization presumes more knowledge than we have.

In lieu of this, a commonly used graph is the funnel plot, a scatterplot in which the

dimension of the x-axis is the estimated parameter value and the y-axis is the inverse of the estimated standard error, also known as the precision since that describes how precisely the parameter has been measured.[5] If there were no publication bias, the estimates should be distributed symmetrically about the true value of the measured effect, and the mean should be a good measure of the true effect. Because the standard error generates a loose bound on the distance an estimate falls from the true effect, more precise estimates should be more densely clustered around the mean. The plot should roughly resemblean inverted funnel resting on its top. In particular, asymmetry indicates publication bias toward a desired result, while thick tails and a thinly populated central section are indicative of a tendency toward rejection of statistically insignificant results.

Figure 1 is a simple funnel plot displaying all the data (with precision displayed on the y-axis using a log-scale). The ticks on the x-axis indicate the raw mean, -0.075, and the minimum and maximum elasticities, -1.49 and 1.44 respectively. Vertical dashed lines indicate the mean and the location of +/- 1 standard deviation around the mean.[6] The ticks on the y-axis indicate the minimum precision, 1, the median precision, 11, the values at the 90^{th} and 99^{th} percentiles, 27 and 91 respectively, and the maximum precision, 215. The raw mean is slightly negative, and

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[5]More robust but cruder measures of precision are sometimes used, including sample size or its square root, and the degrees of freedom,

[6]The terminology begins to be confusing at this point. The primary variable in this meta-analysis is a collection of point estimates of an elasticity. A very important secondary variable is the collection of standard errors, the standard error associated with each point estimate: so far so good. These two variables has a bivariate distribution, and each variable by itself has a mean and a standard deviation. Because the point estimates of the elasticities are themselves means, and the standard deviation of a set of means is a standard error, the one standard deviation lines in the graph indicate a standard error. This is obviously distinct from the collection of standard errors that make up the important secondary variable. For clarity, although the standard deviation associated with the lines is indeed a standard error, that term ("standard error") will refer only to the variable in this discussion and not to the standard deviation indicated by the lines.

with 55% of the estimates lying to the right of the mean, the median (-0.052) is slightly larger than the mean. With only one-sixth of the estimates (74) lying farther than one standard deviation from the mean (39 to the left, 35 to the right), the distribution is densely populated near its mean. The mean lies slightly to the left of the median indicating a slight asymmetry, a slight left skew that reflects not only that more points are far away from the mean to the left than to the right but also that these points to the left are on average somewhat farther from the mean than their counterparts to the right. Looking along the y-axis, the minimum precision is one, and half of the estimates have precision less than 11. Only 10% have precision greater than 27. The most precisely estimated elasticities are (with one exception) just to the right of the mean, suggesting that the precision weighted mean is likely to be closer to zero than the raw mean.

The remaining figures use modified funnel plots to display different aspects of the data.[7] Figure 2 separately identifies estimates with and without reliable standard errors, where unreliable is taken to mean that the critiques of Bertrand, Duflo and Mullainathan (2004) and Donald and Lang (2007) are likely to be pertinent.[8] Most of the estimates lacking reliable standard errors are less than the mean, and several are a standard deviation or more less than the mean. The bulk of the exceptions a group of very low precision estimates less than a standard deviation more than the mean. A handful of the unreliable estimates are apparently precisely estimated. Controlling for reliability in the metaregression is likely to increase the average elasticity.

Figure 3 compares results from studies of the restaurant industry with those of youth employment (studies belonging to neither group appear in the background). With 278

[7] In each, precision is displayed on the y-axis using a log-scale, just as in Figure 1.
[8] "Reliable" does not mean here that the standard errors are entirely or largely without problem, only that issues identified in these two analyses give no cause for concern.

observations, these two groups make up more than five-eighths of the sample: 165 (three-eighths) youth and 113 (one-quarter) eating and drinking establishments. The two distributions are somewhat shifted horizontally relative to each other, with the distribution of youth estimates to the left of that for estimates of eating and drinking establishments. One hundred of the youth estimates are less than the overall unadjusted mean and only 65 are larger than it; 13 are more than 1 standard deviation less and only two are more than 1 standard deviation more. The most precisely estimated elasticities belong to the youth group. Eighty-two of the eating and drinking estimates are larger than the mean but only two are more than one standard deviation more than the mean, and none are more than one standard deviation below the mean.

Figure 4 compares estimates from quasi-experiments, which have a clearly defined comparison group with those from regressions, which don not. At the extreme, the most precisely estimated elasticities are from regressions, and moving away from the extreme, very precise estimates are more likely to be from regressions. The most extreme negative elasticity estimates are entirely from regressions, and the most extreme positive elasticity estimates are from quasi-experiments.

Finally, there is some evidence of publication bias due not to a preferred result but to a preference for statistically significant results (what Stanley [2005] designates type II selection). Standardizing the estimates around the true value should result in a t-distribution, symmetric and with roughly 5% of values greater in absolute value than 1.96. Of course the true value is not known, but we can select some plausible values: zero, the raw mean, the raw median, the precision weighted mean and the precision weighted median. Table 2 shows the percentage of observations in each tail for each centering value and for each way of counting (unweighted and

precision weighted). When zero is the centering value, more than 20% of the observations are less than -1.96 and nearly 6% are greater than 1.96; the corresponding precision weighted counts are about 35% and nearly 5%. Of course, this may well be because the true value of the elasticity is not zero. However, the other possibilities are little better. With the raw mean, more than 25% of observations are out beyond these two borders (more than 40% for precision weighted counts) and at just under 25%, the number is little improved for the median (the precision weighted count drops to about 35%). Using the precision weighted mean or median generates similar percentages in the tails. In no case are roughly 5% of observations in any of these definitions of the tails, and with a few exceptions, symmetry is not apparent. This suggests either that many (not all) editors put the thumb on the scale for statistically significant results or at least that authors believe this to be the case.

4. Metaregressions - Part 1

Ensuring the Quality of the Metaregression Estimates

The actions required to correct the raw sample mean in order to derive a meaningful meta-estimate of the effect of the minimum wage on employment can be distinguished as either technical or substantive. The primary considerations in the technical category, corrections needed for a reliable result, include adjusting for study or author effects, for estimates' precision and for publication bias. Study (author) effects include both lack of independence across estimates from the same study (author) and variation in the number of estimates from each study (author). The main type of substantive control latter concerns whether the estimated effects for youth and for the Food and Drink Sector differ from the overall effect. It will be useful to present these separately so that the consequences of the technical factors can be understood. For

clarity of presentation, new equations will be presented below.

Equation (5a) describing the estimated effect uncorrected for anything is the same as equation (1):

$$Effect_k = \overline{Effect} + u_k = b_1 + u_k \tag{5a}$$

Correcting only for the estimates' precision gives equation (5b):

$$t_k = b_1 precision_k + v_k \qquad \text{(5b)}^9$$

Notice that neither of these two equations corrects for publication bias. Equation (5a) has only a constant term (no SE term), and when that constant term is weighted by precision to generate equation (5b), the result is an equation with only one right hand side variable, precision, and in particular, no constant term. The effect of correcting for publication bias, which will introduce the SE into equation (5a) and a corresponding constant term in equation (5b),is being deferred until after considering the effects of weighting the observations and of controlling for the imbalance resulting from the widely varying number of observations drawn from each study.

Equations (6a) and (6b) build on (5a) and (5b) by adjusting for lack of independence among estimates from the same study:[10,11]

$$Effect_k = b_1 + \sum_{s=2}^{S} c_s Study_s + u_k \tag{6a}$$

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[9]Recall footnote 4 concerning the source (or, in this case, lack thereof) of a constant term in equation (3a).
[10]Two studies, each of which contributes only one elasticity estimate to the sample, do not have a corresponding indicator variables in the list {2, 3, ... A}.
[11]Some authors were responsible for more than one study in the sample. Correcting by author-group instead of study has almost no impact on either the point estimates or their standard errors. To avoid overwhelming the reader with redundant results, those corrected for study are presented here.

$$t_k = b_1 precision_k + precision_k \sum_{s=2}^{S} c_s Study_s + v_k \tag{6b}$$

The $Study_s$ variables are indicator variables that are 1 if observation *k* comes from study *s*, -1 if from study 1, and 0 otherwise; that is, they are indicator variables for the study, coded in deviation form and where the excluded indicator corresponds to the first study. The difference between equation (5a) and (6a) is that (6a) includes fixed effects for the study. The difference between equations (5b), which includes no constant term, and (6b) is that (6b) includes interactions between precision and the study indicator variables. Finally, equations (7a) and (7b) use random effects and random coefficients, respectively, to control for study effects:[12]

$$Effect_k = b_1 + u_k, \; u_k = \mu_s + e_k \tag{7a}$$

$$t_k = b_1 precision_k + v_k, \; v_k = \rho_s precision_k + w_k \tag{7b}$$

Table 3 presents estimates of b_1 from these equations. The raw mean, the employment elasticity of the minimum wage as estimated by equation (5a), is -0.075 with a very small standard error of 0.013. When precisely estimated values are given more weight, equation (5b), the effect drops by more than half to -0.034, and the standard error drops by more than three quarters to 0.004. When we return to the unweighted mean but instead control for lack of independence within each study using fixed effects (6a) , the estimated effect rises by about one-fourth from the first value of -0.075 to -0.092 (and the standard error rises by about the proportion, to 0.016). The corresponding precision weighted value is -0.050, half again as large as the initial weighted mean and one third less than the initial unweighted value; the standard error is about twice as large as that for the original weighted value, although the estimate remains

[12]The subscript *s* on the random term indexes the study that was the source for $Effect_k$.

statistically significant by any standard (including particle physics) and is about half that of the raw mean. Using random effects (or random coefficients) in place of fixed effects leads to point estimates that are about the same size as those from the corresponding fixed effects equations, and standard errors that are about twice as large.[13] Despite the increase in the standard errors, the coefficients from the specification with random effects are strongly statistically significant.

The two main patterns are that precision weighting reduces the magnitude of the minimum wage effect in each case, relative to estimating without weighting, and controlling for lack of independence within each study raises the estimate. The first result is consistent with an editorial preference for statistically significant results. The second tells us that in this sample, studies that presented a large number of usable estimates (usable in that they included both elasticities and their standard errors) had lower average values of the estimates than those that presented fewer. It may be well be that authors of studies which presented evidence against a negative minimum wage effect provide a larger set of robustness and sensitivity tests (or their editors or referees requested them) than those with more conventional results.[14] Including study controls will prevent this issue, if it exists, from contaminating the metaregression.

The next step is to incorporate the standard error term into the equations to control for any bias toward statistically significant results in the sample. This gives the following 6 equations (the first being the same as equation 2):

[13]A Hausman test of the random effects model, equation (7b) vs. the fixed effects model, equation (6b) was attempted, but the difference of the covariance matrices was not positive definite.

[14]In this case, the characterization of the phenomenon in the previous sentence is less accurate than "studies with lower average values of the estimates presented more of them, as well as their standard errors."

OLS Models:

$$Effect_k = b_1 + b_0 SE_k + u_k \tag{5a′}$$

$$t_k = b_0 + b_1 precision_k + v_k \tag{5b′}$$

Fixed Effect Models:

$$Effect_k = b_1 + b_0 SE_k + \sum_{s=2}^{S} c_s Study_s + u_k \tag{6a′}$$

$$t_k = b_0 + b_1 precision_k + precision_k \sum_{s=2}^{S} c_s Study_s + v_k \tag{6b′}$$

Random Effect Models:

$$Effect_k = b_1 + b_0 SE_k + u_k ,\ \ u_k = \mu_s + e_k \tag{7a′}$$

$$t_k = b_0 + b_1 precision_k + v_k ,\ \ v_k = \pi_s precision_k + w_k \tag{7b′}$$

In addition, the controls for study should be interacted with SE:

$$Effect_k = b_1 + b_0 SE_k + \sum_{s=2}^{S} c_s Study_z + SE_k \sum_{s=2}^{S} d_s Study_s + u_k \tag{6a′′}$$

$$t_k = b_0 + b_1 precision_k + precision_k \left(\sum_{s=2}^{S} c_s Study_s \right) + \sum_{s=2}^{S} d_s Study_s + v_k \tag{6b′′}$$

$$Effect_k = b_1 + b_0 SE_k + u_k ,\ \ u_k = \mu_s + \gamma_s SE_k + e_k \tag{7a′′}$$

$$t_k = b_0 + b_1 precision_k + v_k ,\ \ v_k = \pi_s precision_k + \delta_s + w_k \tag{7b′′}$$

Table 4 displays estimates of b_1 and b_0 from these equations.[15] Start with the estimates of b_1. In equations (5a′)-(7b′), the patterns identified in Table 3 are present but weaker. With one slight exception in each pattern, precision weighting results in estimates of smaller magnitude than not weighting, and accounting for the study effects raises the estimate.[16] Including the standard error in the equation to control for (some types of) publication bias reduces the estimate of the effect size in each of these six equations relative to their table 3 counterparts. Third, including terms for the interaction of the study effects with the standard error, equations (6a′′)-(7b′′), has little effect on the first of the fixed effects estimates, (compare (6a′) and (6a′′)), but increases the precision weighted fixed effects estimate by a factor of three ((6b′) and (6b′′). In the random effect specifications, this change has little effect on the point estimates, although the standard errors drop. The final noteworthy point is that the only estimates in this table that are not statistically significant are three of these last four estimates for b_1, those that include the fixed effect interactions and the unweighted estimate with the random coefficients for SE.

So far, we have seen a range of meta-estimates for the minimum wage employment effect, from-0.018 to -0.099. Only four of the estimates, however, are from equations that control for dependence within study, precision and (a type of) publication bias: equations (6b′), (6b′′), (7b′)

[15]A Hausman test of the random effects model, equation (7b′) vs. the fixed effects model, equation (6b′) was attempted, but as in Table 3, the difference of the covariance matrices was not positive definite. However, for the corresponding test with the more parameterized models, equations (7b′′) and (6b′′), the test statistic is 2.34 with a p-value of 0.13. This suggests that we have no statistical reason for preferring one or the other of equation (6b′) and equation (7b′), but that equation (7b′′) is to be preferred to equation (6b′′). Both of the random parameter terms in equation (7b′′) have statistically significant standard deviations, each with a t-statistic near 4, which suggests that in the event of a substantive difference between equations (7b′) and (7b′′), the latter is to be preferred on statistical grounds.

[16]The exception for the consequence of precision weighting occurs in the equation pair (5a′) and (5b′), where the magnitude of the precision weighted estimate of the effect, (5b′), is 10% larger than the former. Note that the estimate's standard error falls by 80%; the estimate in (5a′) is not statistically significant, while that in (5b′) is, even by the standards of high-energy physics. The exception for the consequences of including study effects occurs in the transition from(5b′) to (6b′), where the point estimate falls by nearly one-fifth and the standard error more than doubles.

and (7b´´). In this group, the range is about one-third as large, from -0.022 to -0.048 (equations (7b´) and (6b´´) respectively). The mean of these four is -0.028 (and the precision weighted mean is slightly smaller in magnitude, -0.026).

There are two additional issues to consider. First, the correction for publication bias introduced in equation 2 (and present in the equations labeled with one or two primes, e.g., 6b´) is too restrictive. It posits not only a (perceived) preference for statistically significant estimates but also a (perceived) directional bias. The results in Table 2 suggest that directional bias is not an issue, certainly not the main issue, that both tails of the distribution of results are too fat. A less restrictive approach is called for. Second, the literature has focused on youth employment and the Food and Drink Sector. We have yet to obtain specific estimates for these two elasticities to determine if, as many suspect, minimum wage impacts are greater for this group and this industry than the average for all groups and industries studied, which includes, among others, various demographic groups lacking a high school diploma and other low wage sectors.

Consider next the first of these issues. Introducing a dummy variable for the sign of the estimate modifies the role of the constant to allow for a (perceived) preference for statistically significant results.[17] If this dummy variable is deviation coded then the magnitude and standard error of its coefficient is an indication of the importance of this preference, while the magnitude and standard error of the constant term captures any directional asymmetry. This reasoning gives rise to the following four equations:

[17]"Perceived" in the case that the pattern of results is a consequence not of pressure from editors and referees but rather due to what authors believe editors and referees prefer. We prefer here to sidestep the any discussion of the origins of publication bias.

$$t_k = b_0 + b_0^* Pos_k + b_1 precision_k + precision_k \sum_{s=2}^{S} c_s Study_s + v_k \tag{6b′*}$$

$$t_k = b_0 + b_0^* Pos_k + b_1 precision_k + v_k, \; v_k = \pi_s precision_k + w_k \tag{7b′*}$$

$$t_k = b_0 + b_0^* Pos_k + b_1 precision_k + precision_k \left(\sum_{s=2}^{S} c_s Study_s \right) + \sum_{s=2}^{S} d_s Study_s + v_k \tag{6b′′*}$$

$$t_k = b_0 + b_0^* Pos_k + b_1 precision_k + v_k, \; v_k = \pi_s precision_k + \delta_s + w_k \tag{7b′′*}$$

Pos$_k$ is a deviation coded dummy variable that is 1 for positive values of the dependent variable and -1 for negative values.[18]

The estimates of the employment elasticities are not greatly changed by the more flexible approach to publication bias (Table 5).[19] The range of meta-estimates has shrunk from [-0.048,

[18]Stanley (2005) suggests another approach that involves adjusting the estimates to purge them of "type II publication bias", which is an equal preference for statistically significant results regardless of sign. However he no longer recommends this technique (personal communication dated June 10, 2013).

[19]We focus our discussion on equations 6b'*, 7b'* and 7b''* but not 6b''* because, as in Table 4, the equation with the most regressors, both fixed effects for studies and interactions between them and precision, here equation (6b′′*), is a consistent outlier relative to the other three equations. The constant term in this equation, with a point estimate of 0.310 and a standard error of 0.255, is positive, imprecisely estimated and larger in magnitude than the other three constants which are negative, reasonably precisely estimated and all about the same size, with point estimates in the range [-0.244, -0.229] and standard errors between 0.093 and 0.126. The estimates of the coefficient of the sign dummy in the other three equations are tightly clustered within 0.011 of 1.245, while the estimate in (6b′′*) is one standard error away, at 1.18: all have t-statistics of about 20. In three of the equations, the magnitude of the sign coefficient is more than five times as large as the constant term and it is just less than four times as large in equation (6b′′*). Because of the switch in the sign of constant term between equation (6b′′*) and the other three, the relative size of the intensity of the publication bias for positive results and for negative results also switches. Equation (6b′′*) indicates that it is stronger for positive point estimates (i.e., the

-0.018], with most meta-estimates quite near the higher end (i.e., toward zero) of the range, to [-0.027, -0.014], with most estimates near -0.015. That the constant term is negative (and statistically significant) in the three specifications in which we have more confidence indicates that selection for statistically significant results (i.e. publication bias) is greater when the point estimates negative than when they are positive, but the much greater magnitude of the coefficient on the sign dummy (and its statistical significance) indicates that this is an issue for results of both sets of estimates.

5. Metaregressions - Part 2

Youth Employment and Employment in the Food and Drink Sector

Finally, consider the responses to the minimum wage specifically of youth employment and employment in the Food and Drink Sector. To examine them, the precision weighted equations are augmented to include dummy variables to indicate whether the observation was based on youth employment or the Food and Drink Sector. The last results in the previous section indicate that publication bias occurs in both directions but with differing intensity depending on the sign of the point estimate for the employment effect, so the starting point for this section will be equations that include the dummy variable for the sign of the effect, Pos_k. Equations (6b´*) and (6b´´*) become (8b´) and (8b´´), and (7b´*) and (7b´´*) become (9b´) and (9b´´):

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demand for statistical significance is greater for positive point estimates than for negative ones), while the other three indicate the reverse. Finally, and most pertinent, the estimate of the size of the effect is quite small and precisely estimated in all the specifications, -0.027 with a standard error of 0.014 in equation (6b´´*), and between -0.014 and -0.015 (with standard errors between 0.007 and 0.010) in the other three.

Fixed Effect Models:

$$t_k = b_0 + b_0^* Pos_k + b_1 precision_k + precision_k \sum_{s=2}^{S} c_s Study_s + b_1^Y Youth_k\, precision_k + b_1^{FD} FoodDrink_k\, precision_k + v_k \tag{8b′}$$

$$t_k = b_0 + b_0^* Pos_k + b_1 precision_k + precision_k \left(\sum_{s=2}^{S} c_s Study_s \right) + \sum_{s=2}^{S} d_s Study_s + b_1^Y Youth_k\, precision_k + b_1^{FD} FoodDrink_k\, precision_k + v_k \tag{8b′′}$$

Random Effect Models:

$$t_k = b_0 + b_0^* Pos_k + b_1 precision_k + b_1^Y Youth_k\, precision_k + b_1^{FD} FoodDrink_k\, precision_k + v_k, \qquad v_k = \pi_s precision_k + w_k \tag{9b′}$$

$$t_k = b_0 + b_0^* Pos_0 + b_1 precision_k + b_1^Y Youth_k\, precision_k + b_1^{FD} FoodDrink_k\, precision_k + v_k, \qquad v_k = \pi_s precision_k + \delta_s + w_k \tag{9b′′}$$

.*Youth*$_k$ is a dummy variable which indicates that the estimate in question is based on data for youth employment, and *FoodDrink*$_k$ indicates is the corresponding variable for the food and drink sector. The corresponding effects of interest, $b_1 + b_1^Y$ and $b_1 + b_1^{FD}$, are displayed in Tables 6 and 7 for the entire sample and several sub-samples. The second column from the right in each table shows the mean estimate of the four equations for that sub-sample and its standard

error.[20] The specification with both fixed study effects and interactions between precision and these effects is often (though not always) an outlier. More important its standard errors are typically at least four times as large as those of the other three specifications. For these reasons, the last column in each table displays the row means (and standard errors) excluding the results of 8b´´.[21]

Turning to the youth effect in Table 6, none of the individual estimates provide any evidence of an employment effect when estimated across employment and hours studies (i.e., the whole sample). This remains the case when the sample is restricted to exclude estimates for which the problems that either Donald and Lang (2007) or Bertrand, Duflo and Mullainathan (2004) identified, labeled "Reliable SEs", and when it is restricted to include only estimates based on data for the USA. However, when estimates based on hours of employment are excluded, the elasticities rise substantially and become statistically significant, although they are still well below the low end the consensus range for this response in the older time-series literature that pre-dates the *NMWR*. When the sample is defined according to all three of these restrictions (i.e., reliable SEs, USA only and Employment only - N=369), the estimates decline except for that of the most heavily parameterized (and most problematic), equation (8b´´). The mean of all the meta-estimates in this row is -0.060 (s.e.: 0.024) and the mean excluding the problematic estimate is slightly smaller at -0.053 (s.e.: 0.011).[22]

[20]This is calculated from the individual standard errors using the delta method, assuming independence of the individual means. This is almost certainly not a good assumption since all the means are based on different estimates using the same data, with the result that the estimated standard error is likely too small.
[21]See the previous footnote.
[22]The estimates from equation (8b´´) are much more problematic in Table 7. In Table 6, the standard errors of (8b´´) are considerably larger than those from the other specifications, but the point estimates do not differ much. In Table 7, the (8b´´) standard errors are up to an order of magnitude larger than those of the others, and the point estimates are between two and fifteen times as large. The rest of the discussion

A statistically significant response of employment in the Food and Drink Sector is detectible both in the sample of employment and hours effects (again, the whole sample) and in each of the sub-samples presented. In the whole sample regression, the three estimates range from -0.032 to -0.068 and each is statistically significant; their mean is -0.045.: with a standard error of 0.010. Restricting the regression to estimates with reliable standard errors reduces it by between nearly one-quarter to nearly one-half. The estimates based only on data from the USA are about one-third of the way from those of the whole toward those from the sample lacking the observations with questionable standard errors. Restricting the sample to estimates based only employment sends it back to or slightly past the value in the whole sample. Imposing all three restrictions on the sample returns the estimate of the "well behaved" fixed effects model, equation (8b′), back to the same value as in the whole sample, but the two random effects estimates are between one-third and three-fifths their values in the whole sample. The mean in this sample, a very precisely estimated -0.033, is about two-thirds of the corresponding value in the whole sample.

Conclusion

In what must be the most cited review of research into the employment effect of the minimum wage, Brown, Gilroy and Kohen (1982) concluded that "Time series studies typically find that a 10 percent increase in the minimum wage reduces teenage employment by one to three percent... We believe that the lower half of that range is to be preferred;" (p. 524). Nearly two decades later, Brown (1999) wrote in another review that "My reading of the new and old evidence suggests that the short term effect of the minimum wage on teenage employment is small. Time-series estimates that centered on an elasticity of -0.10 moved closer to zero in

of Table 7 will ignore the results from (8b′′).

samples that included the 1980s." (p.2154). Based on this meta-analysis of results from the most recent work from the *NMWR*, Brown's judgment concerning the minimum wage elasticity of employment remains valid, not just for youth but more broadly.

We have provided a very large number of meta-estimates of the employment elasticity. The range of the simplest estimates, found in table 3, is [-0.099, -0.034] with the precision weighted estimates falling in the interval [-0.050, -0.034]. Allowing for heteroskedasticity in estimates, Table 4, expands the range in both directions to [-0.106, -0.018], but generally reduces the estimated elasticity toward zero, with the magnitude of the mean dropping by about one-third and the magnitude of the median by a bit more. Movement toward more flexible estimation of publication bias moves the top end of the range down considerably. In Table 5, the range is [-0.014, -0.027] with three of the estimates clustering below -0.020. Estimates of elasticities for youth and for Eating and Drinking places are also small. In the U.S, the employment elasticity for youth appears to be between about -0.035 and -0.065. For the Food and Drink sector, the range is broader, between -0.012 and -0.068, with more weight toward the zero end of the range than the other. If one were to summarize these results in a single sentence we would be conclude that there is a negative and generally statistically significant employment effect which is between small and vanishingly small. This result is in agreement with both Brown's (1999) qualitative assessment of the old and (then) new work and Doucouliago and Stanley's (2009) meta-analysis.

We must hedge our conclusion because a number of articles could not be incorporated into the analysis. Doucouliagos and Stanley (2009) excluded about one-third of the 100 studies that they identified because they would either make the sample too heterogeneous to be meaningful or for lack of an important piece of data to enable comparison with other studies, i.e., an

employment elasticity or its standard error. In this analysis, more than two-thirds of the 81 studies could not be used. Heterogeneity is the hallmark of the *NMWR*, and if a common measure can be calculated, it would be preferable to control for heterogeneity in the metaregression. The problem is that in the minimum wage literature, the elasticity couplet, (point estimate, standard error) is too much a rare bird. One reason for this is that for some measures of the minimum wage, the fraction affected and the wage gap which may well be better measures in this context than the real minimum wage itself, it is necessary to jump through more hoops in order to derive a minimum wage elasticity of employment. However, without some common measure, and an elasticity is surely the most common measure in economics, it is not possible to compare or aggregate research results. Without presenting both some common measure as well as an estimate of its precision, the contribution to empirical knowledge of a particular piece of research is self limiting.

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TABLE 1
Studies Included in the Metaregression

	Author(s)	Year	Title	Nobs
1)	Addison and Ozturk	2012	Minimum Wages, Labor Market Institutions, and Female Employment: A Cross-Country Analysis	4
2)	Addison, Blackburn and Cotti	2013	Minimum Wage Increases in a Recessionary Environment	24
3)	Addison, Blackburn and Cotti	2009	Do MWs raise employment? Evidence from the U.S. retail-trade sector	28
4)	Addison, Blackburn and Cotti	2010	The Effect of MWs on Wages and Employment - County-Level Estimates from the Restaurant and Bar Sector	6
5)	Allegretto, Dube and Reich	2009	Spatial Heterogeneity and MWs: Employment Estimates for Teens Using Cross-State Commuting Zones	14
6)	Allegretto, Dube and Reich	2011	Do Minimum Wages Really Reduce Teenage Employment - Accounting for Heterogeneity and Selectivity in State Panel Data	64
7)	Bazen and Marimoutou	2002	Looking for a Needle in a Haystack?	4
8)	Belman and Wolfson	2009	The Effect of Legislated Minimum Wage Increases on Employment and Hours: A Dynamic Analysis	68
9)	Campolieti, Gunderson and Riddell	2006	Minimum Wage Impacts from a Prespecified Research Design: Canada 1981–1997	30
10)	Dodson	2002	The Impact of the Minimum Wage in West Virginia: A Test of the Low-Wage-Area Theory	6
11)	Dube, Naidu and Reich	2007	The economic effects of a citywide MW	30
12)	Dube, Lester and Reich	2010	MW Effects Across State Borders - Estimates Using Contiguous Counties WP	27
13)	Even and Macpherson	2012	The Effect of Tip Credits on Earnings and Employment in the U.S. Restaurant Industry	30
14)	Hyslop and Stillman	2007	Youth MW reform and the labour market in New Zealand	4
15)	Keil, Robertson and Symons	2009	Univariate Regressions of Employment on Minimum Wages in the Panel of U.S. States	13
16)	Neumark, Schweitzer and Wascher	2004	Minimum Wage Effects Throughout the Wage Distribution	1
17)	Orazem and Mattila	2002	MW effects on hours, employment, and number of firms: The Iowa case	21
18)	Orrenius and Zavodny	2008	The Effect of MWs on Immigrants' Employment and Earnings (Pub 2008 in ILRR)	36
19)	Pereira	2003	The impact of MWs on youth employment in Portugal	1
20)	Potter	2006	Measuring the Employment Impacts of the Living Wage Ordinance in Santa Fe, New Mexico	5
21)	Sabia	2009	The Effects of Minimum Wage Increases on Retail Employment and Hours: New Evidence from Monthly CPS Data	15
22)	Singell and Terborg	2007	'Employment effects of two northwest MW initiatives	4
23)	Zavodny	2000	The effect of the minimum wage on employment and hours	4

TABLE 2
Percentage of Observations in the Left and Right Tails

Value used to center the elasticticies		%age less than -1.96	%age greater than 1.96	Precision wtd %age less than -1.96	Precision wtd %age greater than 1.96
zero	0.000	22.8%	5.9%	34.8%	4.8%
raw mean	-0.075	10.0%	16.2%	8.6%	32.5%
raw median	-0.054	12.3%	12.1%	10.8%	24.8%
precision wtd mean	-0.053	12.3%	11.4%	10.8%	23.7%
precision wtd median	-0.031	15.7%	9.3%	15.4%	18.4%

Note: Elasticities have been standardized by centering around the values in the second column and dividing by the estimated standard errors. Absent publication selection for statistically significant results, we should expect to see roughly 2.5% in at least 2 adjacent cells on one side or the other of the vertical lines.

TABLE 3
Preliminary Estimates of the Effect Size, b_1

Equation Estimated	b_1	SE(b_1)	t
Equation (5a): raw mean	-0.075	0.013	-5.77
Equation (5b): precision weighted mean	-0.034	0.004	-9.57
Equation (6a): (5a) + Study Fixed Effects	-0.092	0.016	-5.76
Equation (6b): precision weighted (6a)	-0.050	0.007	-7.04
Equation (7a): (5a) + Study Random Effects	-0.099	0.037	-2.67
Equation (7b): precision weighted (7a)	-0.050	0.015	-3.30

TABLE 4
Estimates of the Average Effect Size, b_1, including SE in the equation

	b1			b0		
	Estimate	SE	t	Estimate	SE	t
Equation (5a′)	-0.020	0.019	-1.05	-0.426	0.106	-4.02
Equation (5b′): precision weighted (5a′)	-0.022	0.004	-5.12	-0.487	0.111	-4.39
Equation (6a′): (5a′) + Study FEs	-0.072	0.020	-3.61	-0.300	0.109	-2.76
Equation (6b′): precision weighted (6a′)	-0.018	0.010	-1.86	-0.599	0.128	-4.67
Equation (7a′): (5a′) + Study REs	-0.060	0.037	-1.62	-0.341	0.108	-3.16
Equation (7b′): precision weighted (7a′)	-0.022	0.017	-1.32	-0.568	0.128	-4.45
Equation (6a′′): (6a′) + FEs interacted w/SE	-0.106	0.043	-2.45	-0.292	0.925	-0.32
Equation (6b′′): precision weighted (6a′′)	-0.048	0.019	-2.59	0.193	0.339	0.57
Equation (7a′′): (7a′) + random coefs for SE	-0.059	0.020	-2.91	-0.276	0.277	-1.00
Equation (7b′′): precision weighted (7a′′)	-0.025	0.012	-2.03	-0.603	0.252	-2.39

TABLE 5

Estimates of the Effect Size, b_1, allowing for asymmetric publication bias in both directions

Effect Estimated from		precision	b_0	b_0^*	positive: $b_0 + b_0^*$	negative: $b_0 - b_0^*$
	Estimate	-0.014	-0.235	1.236	1.001	-1.472
Equation (6b´*)	SE	0.007	0.095	0.063	0.124	0.103
	t	-1.98	-2.47	19.73	8.09	-14.25
	Estimate	-0.015	-0.229	1.256	1.027	-1.485
Equation (7b´*)	SE	0.010	0.093	0.062	0.121	0.103
	t	-1.51	-2.46	20.26	8.52	-14.46
	Estimate	-0.027	0.310	1.185	1.494	-0.875
Equation (6b´´*)	SE	0.014	0.255	0.064	0.264	0.261
	t	-1.93	1.22	18.38	5.66	-3.35
	Estimate	-0.015	-0.244	1.243	1.000	-1.487
Equation (7b´´*)	SE	0.010	0.126	0.064	0.150	0.132
	t	-1.54	-1.94	19.38	6.68	-11.28

TABLE 6

Estimates of the Youth Effect Size, $b_1 + b_1^Y$

Effect Estimated on		8b′	8b′′	9b′	9b′′	Mean	Mean Excl. 8b"
Whole Sample	Estimate	-0.004	0.042	-0.020	-0.020	-0.001	-0.015
	SE	0.012	0.062	0.012	0.012	0.016	0.007
	t	-0.338	0.670	-1.688	-1.646	-0.034	-2.130
Reliable SEs	Estimate	0.011	0.073	-0.004	-0.002	0.020	0.002
	SE	0.011	0.063	0.007	0.003	0.016	0.004
	t	1.031	1.166	-0.498	-0.643	1.236	0.459
USA only	Estimate	0.005	0.009	-0.014	-0.015	-0.004	-0.008
	SE	0.013	0.080	0.011	0.012	0.021	0.007
	t	0.392	0.117	-1.288	-1.265	-0.178	-1.149
Employment Only	Estimate	-0.077	-0.069	-0.059	-0.074	-0.070	-0.070
	SE	0.024	0.103	0.015	0.019	0.027	0.012
	t	-3.142	-0.675	-3.807	-3.909	-2.572	-6.068
All of the above	Estimate	-0.065	-0.084	-0.035	-0.058	-0.060	-0.053
	SE	0.022	0.090	0.013	0.020	0.024	0.011
	t	-3.040	-0.924	-2.633	-2.940	-2.518	-4.939

TABLE 7

Estimates of the Food and Drink Sector Effect Size, $b_1 + b_1^{FD}$

		8b´	8b´´	9b´	9b´´	Mean	Mean Excl. 8b"
Whole Sample	Estimate	-0.068	-0.191	-0.032	-0.036	-0.082	-0.045
	SE	0.020	0.125	0.015	0.016	0.032	0.010
	t	-3.450	-1.533	-2.142	-2.248	-2.555	-4.615
Reliable SEs	Estimate	-0.052	-0.183	-0.013	-0.016	-0.066	-0.027
	SE	0.015	0.084	0.008	0.007	0.021	0.006
	t	-3.555	-2.186	-1.748	-2.345	-3.086	-4.549
USA only	Estimate	-0.061	-0.104	-0.025	-0.030	-0.055	-0.039
	SE	0.019	0.126	0.013	0.015	0.032	0.009
	t	-3.190	-0.829	-1.965	-2.012	-1.708	-4.237
Employment Only	Estimate	-0.077	-0.279	-0.032	-0.028	-0.104	-0.045
	SE	0.021	0.143	0.015	0.017	0.037	0.010
	t	-3.629	-1.944	-2.146	-1.595	-2.826	-4.379
All of the above	Estimate	-0.068	-0.184	-0.019	-0.012	-0.071	-0.033
	SE	0.015	0.100	0.009	0.009	0.026	0.006
	t	-4.722	-1.839	-2.076	-1.324	-2.783	-5.127

FIGURE 1

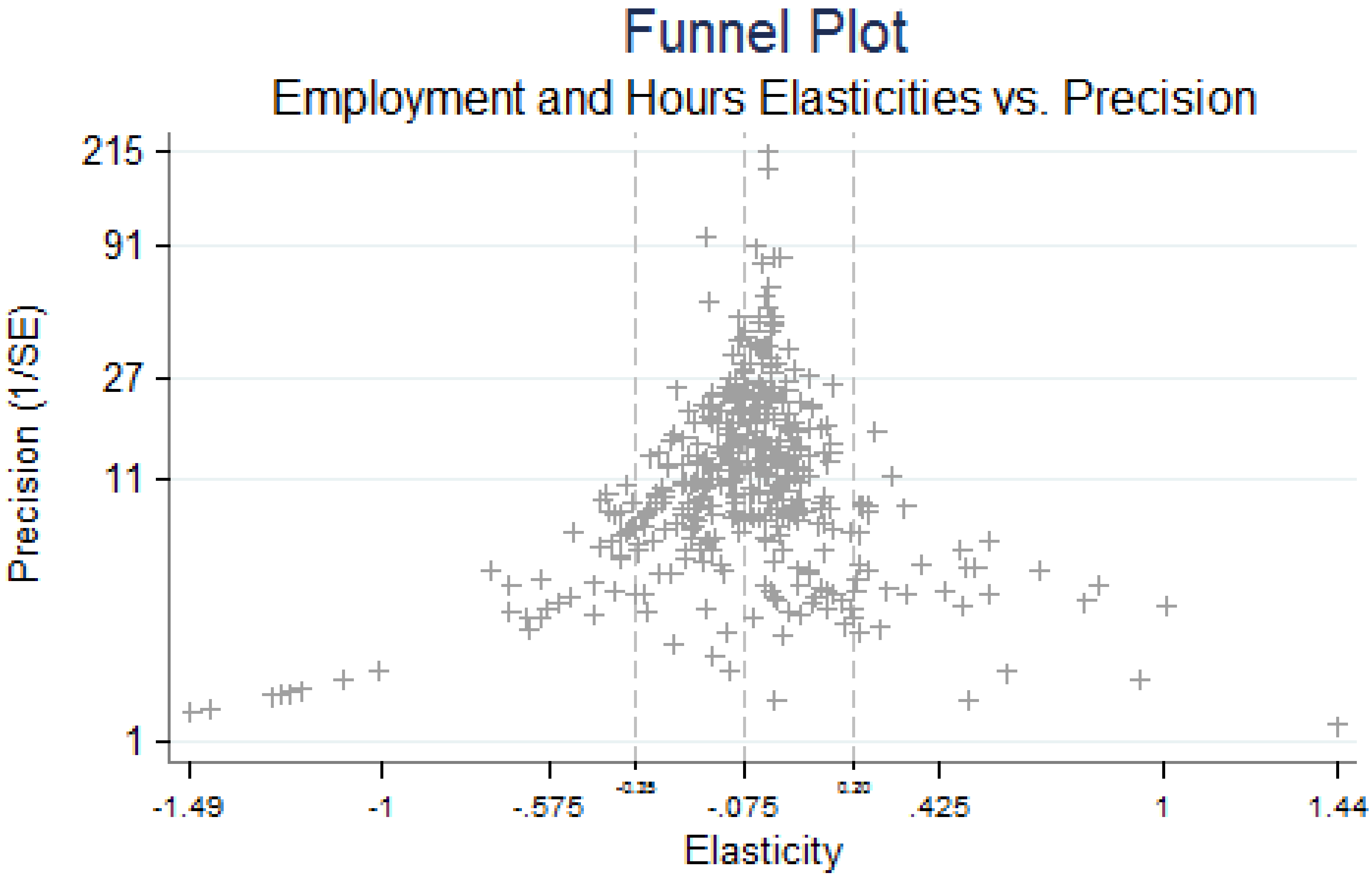

Funnel Plot
Employment and Hours Elasticities vs. Precision
Precision (1/SE)
215
91
27
11
1
-1.49
-1
-.575
-.075
.425
1
1.44
Elasticity

FIGURE 2

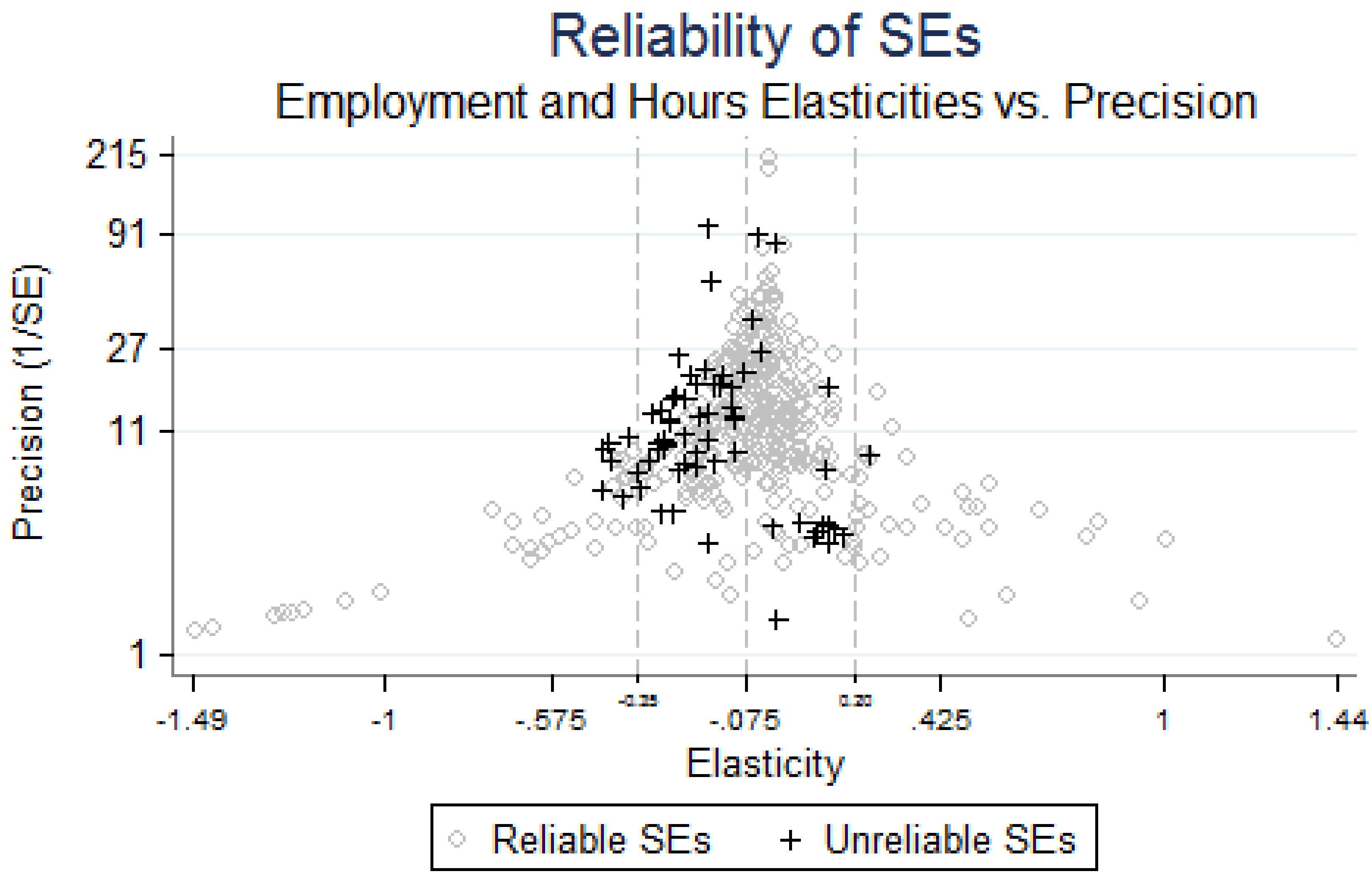

Reliability of SEs
Employment and Hours Elasticities vs. Precision
Precision (1/SE)
215
91
27
11
1
-1.49
-1
-.575
-.075
.425
1
1.44
Elasticity
Reliable SEs
Unreliable SEs

FIGURE 3

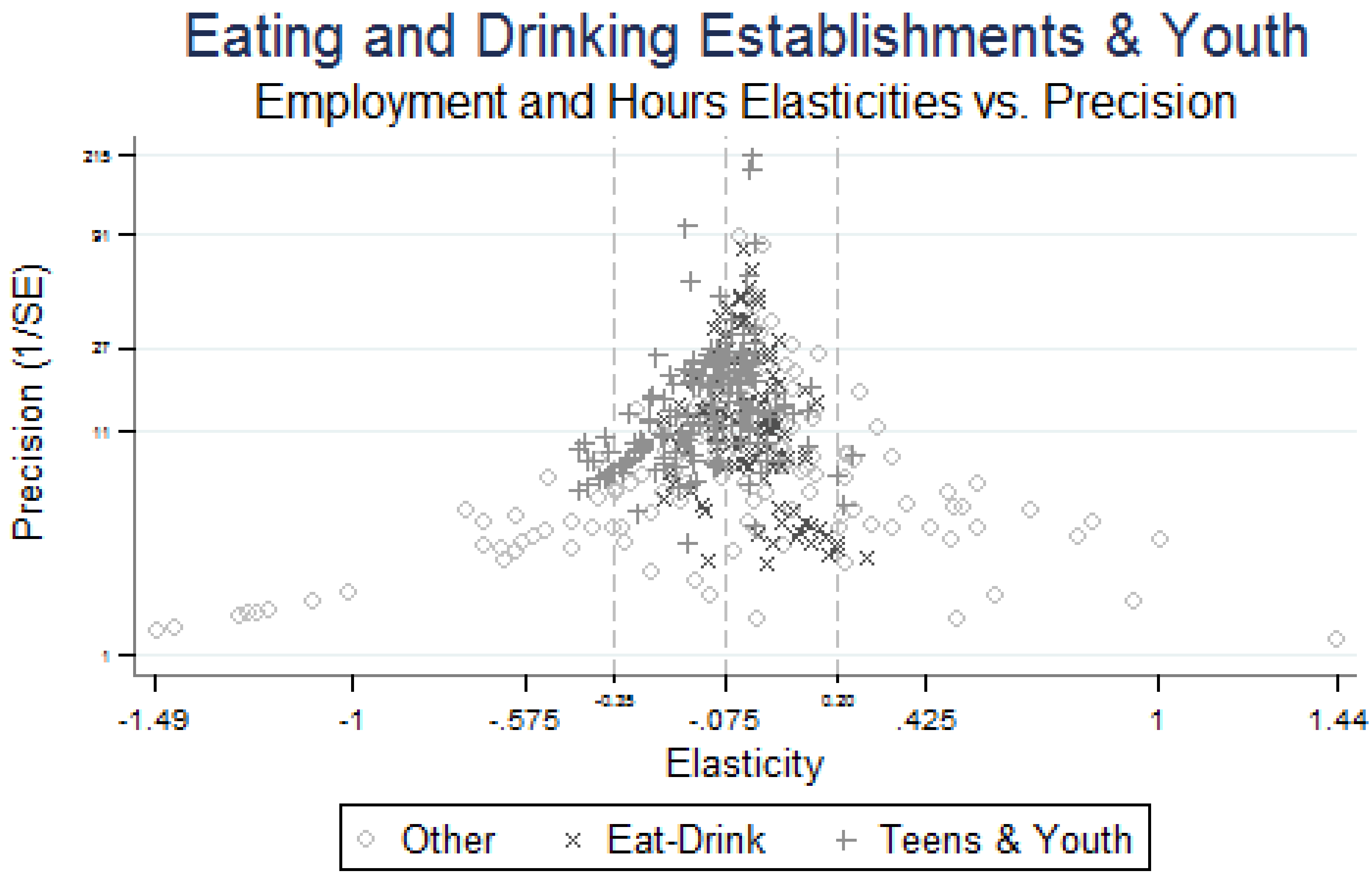
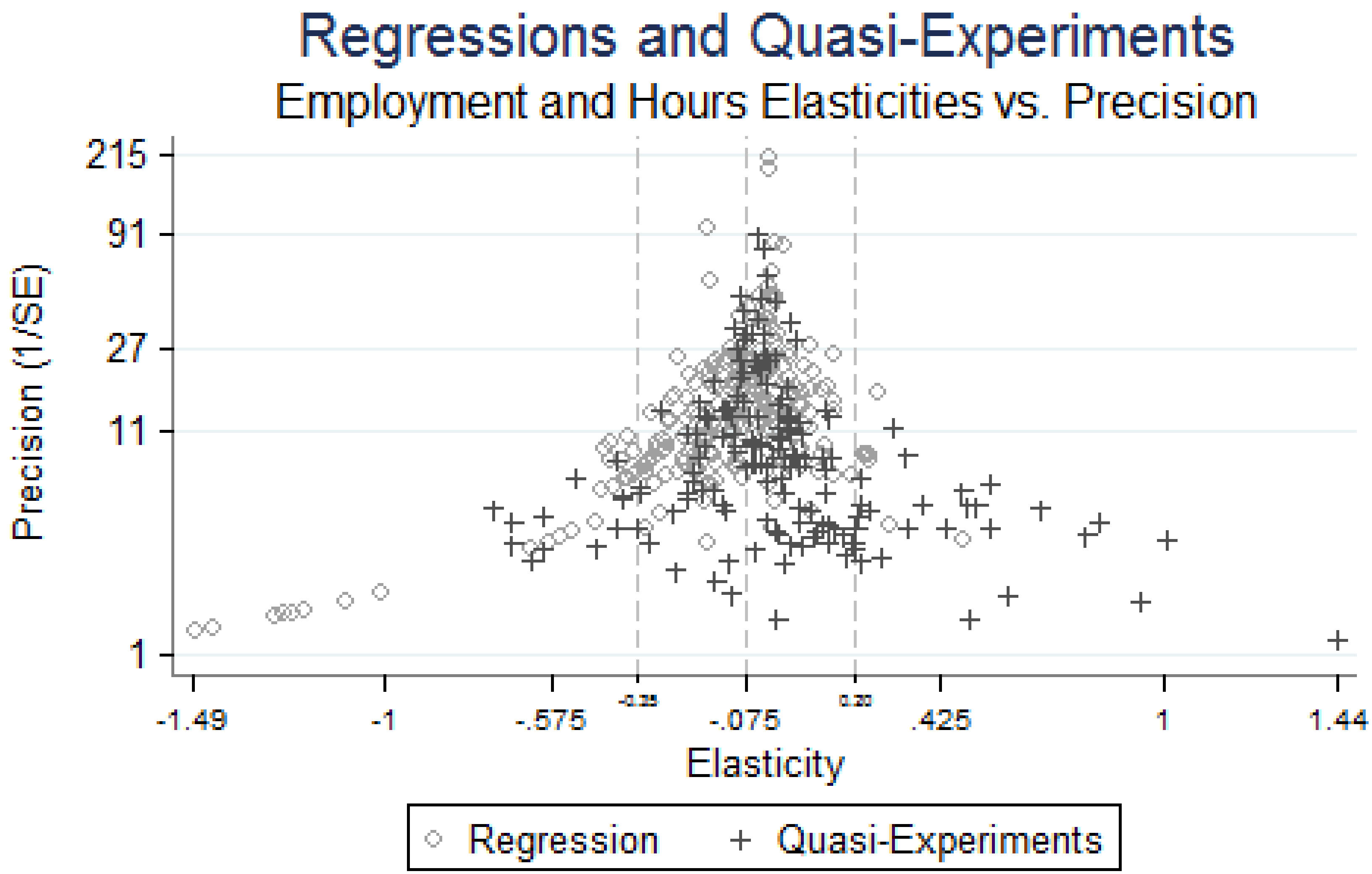

Eating and Drinking Establishments & Youth
Employment and Hours Elasticities vs. Precision
Precision (1/SE)
-1.49
-1
-.575
-.075
.425
1
1.44
Elasticity
Other
Eat-Drink
Teens & Youth

FIGURE 4


Regressions and Quasi-Experiments
Employment and Hours Elasticities vs. Precision
Precision (1/SE)
215
91
27
11
1
-1.49
-1
-.575
-.075
.425
1
1.44
Elasticity
Regression
Quasi-Experiments