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Working Paper

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KOF Working Papers, No. 405

Provided in Cooperation with:

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Suggested Citation: Kemper, Johanna (2016) : Resolving the ambiguity: A meta-analysis of the effect of employment protection on employment and unemployment, KOF Working Papers, No. 405, ETH Zurich, KOF Swiss Economic Institute, Zurich,
<https://doi.org/10.3929/ethz-a-010719179>

This Version is available at:

<https://hdl.handle.net/10419/148988>

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A Meta-Analysis of the Effect of Employment
Protection on Employment and Unemployment

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KOF Working Papers, No. 405, January 2016

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Resolving the Ambiguity: A Meta-Analysis of the Effect of Employment Protection on Employment and Unemployment*

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Abstract

The effect of employment protection legislation (EPL) on unemployment and employment levels is still an unresolved issue in the literature. To tackle this issue is the aim of this meta-analysis. Drawing on evidence from 72 studies, I find that EPL has no statistically significant effect on the unemployment level. Based on 42 studies, I find that EPL decreases the employment level. Analysing study heterogeneity reveals that the quality of the identification strategy matters for the results. In particular, studies that account for unobserved heterogeneity across countries or exploit variation at the country level confirm the main findings of the meta-analysis.

Keywords: Employment Protection Legislation, Unemployment, Employment, Meta-Analysis

JEL-Codes: J8, J20, J21, J65, C49

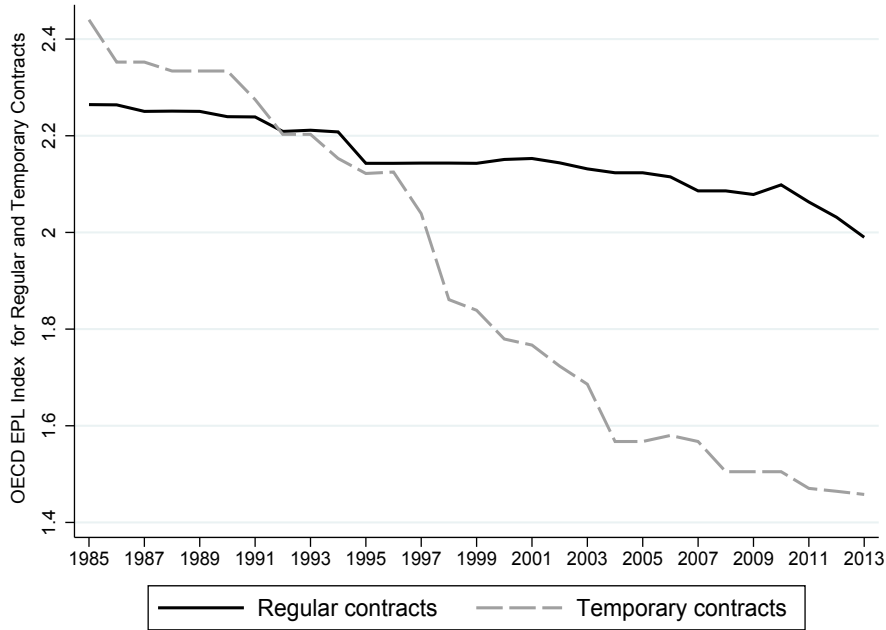
*Acknowledgments: I want to thank the participants of the Brown-Bag Seminar at the KOF Swiss Economic Institute and the Labor Lunch Seminar at UC Berkeley- in particular David Card for his helpful comments.

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1 Introduction

Strict employment protection legislation (EPL) is often blamed for high unemployment and low employment levels. The reasoning is that, through regulations on working contracts and by imposing red-tape costs in case of a dismissal, strict EPL discourages employers to hire workers and create jobs. Which leads to lower levels of employment and consequently higher unemployment over time. In particular international organizations, such as the OECD or the IMF, often recommend countries with high levels of unemployment to deregulate their employment protection regimes. Earlier examples include the OECD Jobs Study (OECD, 1994) or the IMF Staff Report (2003). More recent examples are the loan programs of the IMF, which linked its loan conditions in some European countries (e.g. Greece and Portugal) to reductions in labour market regulations, including EPL (Aleksynska, 2014). The trend to deregulate EPL is reflected in Figure 1, which shows the OECD Index of Employment Protection. In the time from 1985 to 2013, 12 out of 20 OECD countries reduced the protection of regular and 11 that of temporary contracts (OECD, 2016).

Figure 1: *OECD Index of Employment Protection Legislation, 1985-2013*



Notes: This figure shows the OECD Index of Employment Protection Legislation (EPL) for temporary and regular workers. It quantifies the strictness of EPL on a scale from 0 (low) to 6 (high). The index in this figure is based on 20 OECD countries (see appendix for list of countries). The number of countries is chosen as to maximize the length of the observation period. Between 1985 and 2013, the average index value for regular contracts dropped by 0.22 index points (from 2.27 to 2.05) and that for temporary contracts by 0.72 index points (from 2.44 to 1.72) (OECD, 2016).

However, the crucial point is that neither the theoretical nor the empirical literature comes to a definite conclusion about whether or not strict EPL lowers the employment and increases the unemployment level. From a theoretical perspective, EPL has two opposing effects on the unemployment and employment level. First, EPL can in fact discourage employers from hiring workers or creating jobs because of anticipated future dismissal costs. Through this channel, EPL could decrease the employment level and

increase unemployment over time, provided that the number of people in the labour force stays constant¹. Second, by making dismissals costly, EPL can deter employers from firing workers or destroying jobs. Thereby, it stabilizes existing employment relations and with that the employment level, leaving unemployment largely unchanged. Overall, from a theoretical perspective, the impact of EPL on the unemployment and employment level is ambiguous (e.g. Blanchard, 1998; Mortensen and Pissarides, 1999; Belot and van Ours, 2004). Also because employers may choose alternative strategies to circumvent EPL, e.g. substituting regular for temporary jobs which are less strictly regulated.

As a consequence, it is often argued that the actual impact of EPL has to be assessed empirically. But also the empirical literature is unable to clarify this link. While some studies find that EPL increases the unemployment and decreases the employment level, others cannot confirm any statistically significant connection (more details, in chapter 2).

This meta-analysis aims to resolve this ambiguity and to clarify how EPL affects the unemployment and employment levels. More specifically, I want to test if EPL increases the unemployment and decreases the employment level or if it does not affect either. I also want to analyse to what extent differences in study characteristics that are related to publication selection, study quality or effect heterogeneity across groups (e.g. the youth) can explain some of the ambiguity regarding this link.

Considering the amount of policy action taken to reduce employment protection, the effect of EPL on the unemployment and employment level is a highly policy-relevant issue. Despite its importance, it is surprising that up until now, there is no meta-analysis that analyses the effect of EPL on the unemployment level. The only meta-analysis for the employment level looks at the employment-effect of EPL in low-income countries. In their meta-analysis (Nataraj et al., 2014) analyse the employment effect of labour market regulations in low-income countries. However, of the 17 included studies, only three look at the effect of EPL. Thereof, only one focuses exclusively on EPL, while the other two focus on the composite effect of EPL and other regulations. Nataraj et al. (2014) find that labour market regulations have a negative effect on formal employment.

This meta-analysis contributes to the literature in two ways. First, based on aggregate evidence from 91 empirical studies, of which 72 analyse the effect of EPL on the unemployment and 42 that on employment level², it clarifies a previously unresolved issue in the literature. Second, it not only summarizes the existing empirical evidence in a systematic way, but also adds onto the explanatory power of all included studies by means of a meta-regression. This allows to control for factors that drive the differences in outcomes between studies, such as the identification strategy or publication selection bias, which is not possible in a narrative summary of the literature.

Building on the evidence from 72 studies, I find that EPL has no statistically significant effect on the unemployment level. Based on 42 studies, I find some evidence that EPL decreases the employment level. The results of a subset analysis for 13 comparable studies show that a one-point increase in EPL leads to about 0.62-0.64 %-points increase in the unemployment level. However, this result must be treated carefully, as all studies in this subset use different vintages of the same dataset.

¹That is, the amount of workers in- and outside the labour force stays constant, as well as the relation of the formal to informal sector employment.

²Some of the studies analyse the effect of EPL on the unemployment and employment levels at the same time.

The results of a multiple meta-regression suggest that factors related to publication selection, effect heterogeneity and in particular the quality of the identification strategy matter for the overall effect of EPL on the unemployment and employment level. The result of a sample split by identification strategy shows that studies that account for unobserved heterogeneity across countries or exploit variation at the country level further confirm the zero effect of EPL on the unemployment and the negative effect on the employment level.

The paper is structured as follows. In the second chapter, I summarize the literature that is analysed in this meta-analysis, state the hypothesis and explain how I selected the studies. In the third chapter, I explain the identification strategy employed to summarize the empirical evidence of all studies. In the fourth chapter, I show the results of the empirical analysis and conclude in the last chapter.

2 Review of the Literature, Hypotheses and Selection of Included Studies

In the first part of this chapter, I review the literature that analyses the effect of EPL on the unemployment and employment levels. Then, I describe how and according to which criteria I selected the studies for the meta-analysis.

2.1 Review of the Literature Analysing the Effect of EPL on the Unemployment and Employment Levels

Ever since the first studies were published in the beginning of the 1990s, this field of the literature has been divided into two strands. While studies belonging to one strand of the literature find that EPL increases the unemployment and lowers the employment level (e.g. Lazear, 1990; OECD, 1994; Scarpetta, 1996; Nickell, 1997; Elmeskov et al., 1998; Nunziata, 2002; Lehmann and Muravyev, 2012), studies belonging to the other strand do not find any statistically significant impact (e.g. Addison and Grosso, 1996; Jackman et al., 1996; Baker et al., 2002, 2004; Baccaro and Rei, 2007; Bassanini and Duval, 2006, 2009).

The first wave of studies in this field of the literature, which was published in the 1990s, has two major drawbacks. The first is the quality of the data on labour market institutions, including EPL. Some of these studies use simple country rankings to identify the effect of cross-country differences in EPL on the unemployment or employment level (e.g. Grubb and Wells, 1993; OECD, 1994). While others employ measures that are based on the amount of severance payments and the length of notice periods for blue- and white-collar workers (Lazear, 1990). Later, these were replaced by indices (e.g. OECD, 1999, 2004; Venn, 2009; Bank, all; Blanchard and Wolfers, 2000; Allard, 2005)³. The second drawback of these studies is their identification strategy. To assess the effect of EPL on the unemployment and employment levels, these studies use cross-section or panel data, either estimated by pooled OLS or random effects (RE) or by employing country fixed

³Often, the indices were composed of two or more older indices or country rankings or extensions of these.

effects estimation. Even if studies account for unobserved heterogeneity at the country level by including country fixed effects, most of them do not control for unobserved time-variant heterogeneity. A better solution that completely avoids problems related to unobserved heterogeneity across countries is to exploit variation at the country level.

Due to better data availability and more sophisticated estimation methods, a growing number of studies were conducted at the country level from the beginning of the 2000s onwards. In this class of studies, some use household and/or firm level data to exploit across-state and -time variation in EPL (e.g. Miles, 2000; Autor et al., 2004, 2006, 2007), while others exploit variation in the strictness of EPL by firm-size (e.g. Schivardi and Torrini, 2003; Bauer et al., 2007). Unfortunately, only one study (Miles, 2000) exploits within-country variation to quantify the effect of EPL on the unemployment level, while there are many more that analyse the effect on the employment level.

Despite the improvements of the data and identification strategy, not all studies published since the 2000s exploit within-country variation. Still, the majority of studies exploits across-country or within-country variation using country fixed effects, which did not help to resolve the ambiguity regarding the link of EPL on the unemployment level.

Some of these studies argue that controlling for other labour market institutions, and in particular their interaction, are crucial factors when analysing the employment effects of EPL (e.g. Belot and van Ours, 2004; Bassanini and Duval, 2006, 2009). Others argue that the interaction of economic shocks and labour market institutions (e.g. Blanchard and Wolfers, 2000; Nunziata, 2002; Nickell et al., 2005) as well as the interaction between EPL and product market regulation have to be accounted for (e.g. Nicoletti and Scarpetta, 2005; Griffith et al., 2007). Similar to the studies published before the 2000s, some studies find that EPL increases the unemployment and/or employment level, while others do not find any effect.

Regarding the impact of EPL on different subgroups, several conclusions stand out. For the youth unemployment and employment levels, there is a broader consensus that EPL tends to harm the young (for a more detailed review, see Noelke, 2015; Jimeno-Serrano and Rodriguez-Palenzuela, 2002). Also, the empirical evidence shows that EPL also tends to increase long-term unemployment (e.g. Elmeskov et al., 1998; Nickell, 1999). The empirical effect of EPL on low-skilled employment and unemployment is not clear. It is statistically significant negative in some studies (e.g. Feldmann, 2006, 2009; Oesch, 2010) and mixed in others (e.g. Bernal-Verdugo et al., 2012; Zhou, 2007). Finally, negative consequences of EPL seem to be stronger for women than for men (e.g. Bertola et al., 2007).

2.2 Hypotheses

Regarding the mixed empirical evidence of the literature analysing the impact of EPL on the unemployment or employment level, two hypotheses stand out.

Hypothesis 1: Stricter EPL increases unemployment and lowers employment levels.

According to this hypothesis, stricter employment protection regulations increase the cost of dismissal, which makes employers reluctant to hire workers or to create jobs. Consequently, stricter EPL decreases the hiring and job creation rate, which may lead to

lower levels of employment over time. And as more and more people struggle to find jobs, this may increase the unemployment level as well. Given that EPL discourages employers to hire or create jobs in a given country, there are several strategies how employers can react in order to circumvent substantially higher costs from stricter EPL. These include: the substitution of labour for capital, reallocation of jobs abroad or into the informal sector (in particular in developing countries) or that a firm shuts down completely.

Hypothesis 2: Stricter EPL does not affect the unemployment or employment level.

One explanation for this is that by increasing dismissal costs, EPL lowers the dismissal rate and stabilizes existing employment relations which are subject to EPL. Overall, it is unclear if the negative effect on the hiring and job creation rate or the employment-stabilizing effect of EPL dominates. Hence, the overall effect of EPL on the unemployment and employment level is ambiguous. (e.g. Blanchard, 1998; Mortensen and Pissarides, 1999; Belot and van Ours, 2004)

Alternatively, stricter EPL could lead to an increased use of temporary contracts or employment through temporary working agencies. Often, temporary contracts and employment through TWAs are relatively less strictly regulated, which implies lower costs in the case of a dismissal. If employers substitute these alternative employment forms for jobs with regular contracts as a means to circumvent the higher costs from stricter EPL, this neither affects the employment nor the unemployment levels, because workers in these alternative employment forms are still officially counted as employed. As a consequence, the effect on the employment level is zero.⁴ Rather than cutting wages of regular workers, these alternative employment forms are also an easy way to adjust the current wages in a given firm for the higher wage costs through stricter EPL.

Regarding the effect heterogeneity across groups, I hypothesize that subgroups like the youth, low-skilled workers and women are more likely to be harmed by EPL since they belong to the more vulnerable group on the labour market. The same holds for the long-term unemployed.

2.3 Selection and Description of the Included Studies

I searched for studies in three different ways. First, I looked for studies through search engines like Google, Google Scholar, but also more specific web-sites for publishing economic papers like e.g. IDEAS, MPRA, EconPapers, NBER Working Papers Series, etc. Second, I searched through literature reviews and reference lists for relevant studies. And lastly, I searched through forward-citations on Google Scholar.

The selected studies have to fulfil certain minimal criteria. They either have to analyse the effect of EPL on the unemployment or the employment level or both. I only include studies that employ an EPL measure quantifying regulations for regular contracts, not those which quantify regulations for temporary contracts or collective dismissals. In

⁴In fact, studies found that in countries where the EPL on regular contracts is relatively less strict than that on temporary contracts, an increase in the regulation of regular contracts leads to an increase the use of temporary contracts (e.g. Bentolila et al., 2008). Or an increase in EPL in general increases the amount of jobs that are outsourced to temporary working agencies (e.g. Autor et al., 2006), which also increased the job turnover rate (e.g. Blanchard and Landier, 2002).

addition, the studies have to use one of the following outcome measures as their dependent variable:

- Unemployment level: Aggregate unemployment rate, the long-term, youth, female, male or low-skilled unemployment rate.
- Employment level: Aggregate employment-to-population ratio, the employment-to-population ratio of the youth, female, male or low-skilled, as well as firm-level employment.

Regarding the construction of the dependent variable for the meta-analysis, it is crucial that the studies report the standard errors of the coefficients quantifying the effect of EPL on the unemployment or employment level or the related t-statistics. For example, in studies exploiting cross-country variation, this could be the coefficient of an EPL index. Or, in event studies, the coefficient of an interaction term from a difference-in-differences estimation.

I do not include studies that report estimates of simple bivariate correlations between the measure for EPL and that for the unemployment or employment level. Nor do I include studies in which the EPL measure is interacted with other variables, without centering the variables by their sample mean. This is important for two reasons. First, it is a crucial requirement to make the results interpretable, as the interacted variables often two different scales. For example, the interaction between an index for EPL, scaled from 0-6, and an index for the centralization of the wage bargaining process, scaled from 1-5. Since both variables have different scales, the only way to make their joint effect interpretable is to center them at their sample means. Then, results can then be interpreted as, for example, "the effect of EPL on unemployment at the average value of wage centralization". Second, in a regression model that includes an interaction term between two continuous variables, a problem of collinearity between the interaction term and the main effect can arise. Mean-centering can help to alleviate this problem (for more details, see Aiken and West (1991)).

Besides the outcome measure, I collected the coefficients and standard errors of all included covariates, as well as information about the study characteristics such as the identification strategy, the sample, the EPL measure, etc. More details about this can be found in the third section of this paper.

Table 1 shows the results of a vote counting exercise of all estimated coefficients from all included studies that quantify the effect of EPL on the unemployment or employment level. The estimates are classified as "statistically significant negative" or "positive" if the effect of EPL on unemployment or employment is significant at the 5%-level- which roughly corresponds to a t-statistic of 1.96. All remaining estimates are classified as "statistically insignificant", as these are not significant at a statistically relevant level.

Of the 666 regressions from 72 studies that analyse the effect of EPL on the unemployment level, 63% do not find any significant result, while 24% find that EPL increases the unemployment level and 13% that it decreases it. Of the 394 regressions from 42 studies which analyse the effect of EPL on the employment level, 55% do not find any statistically significant effect, while 16% find that EPL increases the employment level and 47% that it decreases it. Hence, the majority of studies does not find a statistically significant impact EPL on unemployment, while most studies find a statistically significant negative

Table 1: *Vote Counting*

	Unemployment	Employment
Result		
<i>Significant positive</i>	24%	16%
<i>Insignificant</i>	63%	37%
<i>Significant negative</i>	13%	47%
#of estimates	666	394
# of studies	72	42

effect of EPL on employment. Anticipating the results from the simple and multiple meta-regression, this finding corresponds to the final conclusion of this meta-analysis.

The critical reader may stop here and ask himself: what is the value-added of a meta-analysis beyond this point? The main arguments to convince him are the following. First, vote counting does not provide information about the statistical significance of the overall effect of EPL on the unemployment and employment levels. Second, as explained in the next chapter, this simple vote counting exercise lacks to adjust the outcome measure for differences between studies due to differences in the number of degrees of freedom. These matter when assessing the overall effect of EPL, as it will be shown in chapter 4. Fourth, as it will be proven by the results of the multiple meta-regression in chapter 4, vote counting cannot control for differences in the outcome due to differences in study characteristics. And lastly, vote counting does not allow to control for publication selection bias which is crucial in meta-analysis.

3 Methodology

In the first part of this section, I formulate two hypotheses that will be tested empirically in the course of the paper. In the second and third part, I explain the outcome measure and models I use in the empirical part.

3.1 Outcome Measure

In following, I describe the two outcome measures that are used in this meta-analysis. Namely the adjusted t-statistic, which adjusts for variation in the number of degrees of freedom between studies and the half-standardized partial regression coefficient, which, unlike the t-statistic, allows for assessment of the effect of EPL on the magnitude of the unemployment level.

3.1.1 Measure for the Sign and Direction: The Adjusted T-Statistic

One difficulty when conducting a meta-analysis is to make the result of interest comparable across all included studies, that is, to find an outcome measure for the meta-analysis that allows doing so. Two factors complicate the search for an outcome measure: if the

included studies use different empirical measures, or different transformations of the regression variables. Both factors are a problem in this meta-analysis. First, many studies use different measures for EPL, i.e. with different scales that cannot be compared. Second, many studies use different transformations of the regression variables, i.e. estimate a linear, log-linear or log-log model, or a model in first differences. As a result, I cannot compare the magnitude, that is, the economic relevance, but only the statistical significance and the direction of the effect of EPL on either the unemployment or employment level across studies (Stanley and Doucouliagos, 2012).

One outcome measure that accounts for differences in the statistical significance and direction of the effect of EPL is the simple t-statistic. It has the advantage that it is a unitless measure, i.e. it can compare results independent of their scale (ibid.).

The first outcome measure used in this meta-analysis is a transformation of a simple t-statistic. In the following, I will explain why using the simple t-statistic as an outcome measure can become a problem and why I use a transformation of the simple t-statistic instead.

One problem when using the simple t-statistic as an outcome measure in a meta-regression, is that the outcome may be distorted because of differences in the number of degrees of freedom between the included studies. As an example, consider two studies A and B. Suppose that both studies test the same null hypothesis, $H_0 : \hat{\beta}_{ij} = 0$, where $\hat{\beta}_{ij}$ is the estimate of interest from regression i of study j . Further suppose that the corresponding t-statistics are $t_A = t_B = 1.98$ and that study A has 82 and study B 230 degrees of freedom. Hence, in a two-sided t-test with a critical value that corresponds to the probability of Type I error of 5%, the t-statistic of study A has to be tested against the critical value $t_{cv_A(82,0.025)} = 1.99$ and that of study B against $t_{cv_B(230,0.025)} = 1.97$. Since $t_A = 1.98 < t_{cv_A} = 1.99$, the H_0 cannot be rejected at the 5%-significance level in study A and since $t_B = 1.98 > t_{cv_B(230,0.025)} = 1.97$, it can be rejected in study B. As long as each of both t-statistics is tested against the critical value which corresponds to the number of degrees of freedom of that study, t_{cv_A} or t_{cv_B} , there is no problem. The crucial point is that in a meta-regression with the t-statistic as outcome measure, the average number of degrees of freedom of all studies in the meta-analysis is used as the benchmark critical value to test the significance of the overall effect. Suppose that this average was 180. The respective critical value for the 5%-significance level is $t_{cv_average(180,0.025)} = 1.97$. As this is the same critical value as in study B, nothing changes here. On the contrary, when using this critical value to test $t_A = 1.98 > t_{cv_average(180,0.025)} = 1.97$, the null $H_0 : \hat{\beta}_{ij} = 0$ can now be rejected in study A, which was not the case before. Hence, variation in the number of degrees of freedom between studies can distort the actual result of the overall effect. One easy way to adjust for differences in the degrees of freedom between studies in order to make the t-statistics comparable, is to standardize the t-statistic of each study with the average number of degrees of freedom of all included studies.

The standardization is done in the following way. Define \bar{n} as the average number of degrees of freedom from all regressions of all studies in the meta-analysis and n_{ij} the number of degrees of freedom from regression i of study j . Then, $\sqrt{n_{adj}} = \sqrt{\frac{\bar{n}}{n_{ij}}}$ is the degrees of freedom correction to adjust the t-statistic t_{ij} . Hence, the degrees-of-freedom adjusted t-statistic is:

$$t_{ij}^* = t_{ij} * \sqrt{n_{adj}} \quad (1)$$

After this correction, the variation in the number of degrees of freedom between studies should not affect the result of the meta-analysis any more.

As shown later, differences in degrees of freedom between studies are only a concern for the studies that analyze the effect of EPL on the employment level⁵. Nevertheless, I will use this degrees-of-freedom- adjusted t-statistic t_{ij}^* as an outcome measure in the entire empirical part of the paper. To make a clear distinction, I will refer to this as the "adjusted t-statistic" and to the simple t-statistic as "unadjusted t-statistic" from now onwards.

3.1.2 Measure for the Magnitude: The Half-Standardized Partial Regression Coefficient

As mentioned in the previous subsection, most of the studies cannot be compared in terms of their magnitude, as they use different transformations of the regression variables or measures with different scales. However, for a small subsample of 13 studies which use the same outcome measure for unemployment and the same measure for EPL, I try to assess the magnitude of the effect of EPL on the unemployment level. To do this, I use the half-standardized partial regression coefficient.

As an outcome measure for unemployment, all studies in this subsample use the unemployment rate on a scale from 0-100 and the OECD Index of Employment Protection from the 2004 OECD Employment Outlook (OECD, 2004), which measures EPL on a scale from 0-6.

To make the estimates of the studies in the subsample comparable, I use the ratio of the estimated effect of EPL on unemployment and the standard deviation of unemployment as an effect size; also called the half-standardized partial regression coefficient (Stavig, 1977):

$$\hat{\beta}_{ij} = \frac{\beta_{ij}}{s_{u_j}} \quad (2)$$

Where $\hat{\beta}_{ij}$ is the i^{th} estimate of study j of EPL on unemployment and s_{u_j} the sample standard deviation of unemployment in study j . This outcome measure captures how much a one-index-value increase of the EPL measure (on a scale from zero to six) increases the unemployment rate by $\hat{\beta}_{ij}$ standard deviations.⁶

3.2 Meta-Regression Models

First, I shortly describe the model used for the simple meta-regression and the concept of publication bias. Second, I refer to the model for the multiple meta-regression.

⁵These differences stem from within-country studies which often have large sample sizes, as they use micro-data. However, often, the standard errors of these studies are clustered. Given that the panel structure is nested within the clusters, this lowers the number of degrees of freedom substantially (e.g. state-level variables are nested within states).

⁶It is more straightforward for the interpretation of the effect to use the standardized partial regression coefficient, which quantifies how much one standard deviation change in the EPL index increases unemployment by how many standard deviations. Unfortunately, I could not get the standard deviation of the EPL index for each study, which is necessary for the calculation of the standardized partial regression coefficient.

3.2.1 Simple Meta-Regression

To establish the simple meta-regression model, $\beta_{ij}^{EPL} = \beta_0 + \beta_1 SE_{ij} + \varepsilon_{ij}$ is taken as a starting point, where SE_{ij} , the standard error of β_{ij}^{EPL} , is inserted to control for publication selection bias. Note that if the t-statistic is used as dependent variable, not only the estimate of the outcome of interest, β_{ij}^{EPL} , is divided by the standard error, SE_{ij} . To reassure that the model identifies the true empirical effect and not only factors related to the process of publication, it is necessary to divide *all* independent variables by SE_{ij} (Stanley and Doucouliagos, 2012). As a result, I get the so-called FAT-PET meta-regression ("FAT" stands for "Funnel Asymmetry Test" and "PET" for "Precision Effect Test") (Stanley, 2005):

$$\frac{\beta_{ij}^{EPL}}{SE_{ij}} = t_{ij}^* = \beta_0 \frac{1}{SE_{ij}} + \beta_1 + \varepsilon_{ij} \quad (3)$$

Where t_{ij}^* is the adjusted t-statistic, β_0 captures the genuine empirical effect of EPL on unemployment or employment after correcting for publication bias, β_1 is a term to test for publication selection bias and, ε_{ij} is the standard error of the meta-regression.

Accounting for publication selection is important in a meta-regression. It arises if editors, referees of a journal or researchers themselves have a preference for statistically significant results or systematically select results that support their hypothesis. As higher precision or more desirable estimates are more likely to be published, the estimates of the effect of interest are positively correlated with their standard errors in the presence of publication bias. If the effect of interest is statistically significant, publication bias creates an under-or over-reporting of the true underlying empirical effect, hence a down- or upward-bias (Stanley, 2005).

One way to test for publication selection bias is to include the standard error of the effect of interest in the model. Testing for publication selection bias in model (3), results in testing the null hypothesis of the so-called "Funnel Asymmetry Test (FAT)", $H_0 : \beta_1 = 0$ (no publication selection bias) versus the alternative $H_1 : \beta_1 \neq 0$. Rejection of the null at a relevant significance level gives evidence for a publication selection bias. Note that the FAT is known to have low power (Stanley and Doucouliagos, 2012).

To test for the presence of a genuine empirical effect of EPL on unemployment or employment beyond publication selection bias, the null hypothesis of the so-called "Precision Effect Test (PET)", $H_0 : \beta_0 = 0$ (no effect) has to be tested. Rejection of the null at a relevant significance level provides evidence for a statistically significant effect of EPL on the unemployment or employment levels (Stanley, 2005).

According to Stanley and Doucouliagos (2012), the coefficient of β_0 in equation (3) provides a biased estimate of the empirical effect when there is publication selection. Based on the results of several simulation studies, Stanley and Doucouliagos (2012) suggest using the so-called "precision effect estimate with standard error (PEESE)", that is, the FAT-PET-PEESE model, rather than the FAT-PET model for estimating β_0 , *if the results of the FAT-PET model provide evidence of a non-zero statistically significant empirical effect* (i.e. $H_0 : \beta_0 = 0$ (no effect) can be rejected).

The results of these simulation studies show that if there is a non-zero empirical effect, the WLS estimates of the FAT-PET-PEESE model provide a better estimate of the underlying "true" effect than those from the FAT-PET model. On the contrary, if

there is no statistically significant empirical effect, the FAT-PET-PEESE model should not be used to estimate β_0 , as it will produce biased results. Hence, if there is a non-zero empirical effect, the FAT-PET-PEESE model should be estimated. If the effect is zero, the FAT-PET model should be preferred.

The FAT-PET-PEESE model can be formulated as (Stanley and Doucouliagos, 2012):

$$t_{ij}^* = \beta_0 \frac{1}{SE_{ij}} + \beta_1 SE_{ij} + \varepsilon_{ij} \quad (4)$$

In this model SE_{ij}^2 instead of SE_{ij} is used to correct for publication selection.

3.2.2 Multiple Meta-Regression

The FAT-PET multiple meta-regression is an extension of the simple meta-regression. The only difference is that a battery of moderator variables, which all correspond to different study characteristics, are added to the simple meta-regression model (Stanley and Doucouliagos, 2012):

$$t_{ij}^* = \beta_0 \frac{1}{SE_{ij}} + \beta_1 + \sum_{k=1}^K \beta_{ijk} \frac{Z_{ijk}}{SE_{ij}} + \varepsilon_{ij} \quad (5)$$

Where Z_{ijk} stands for the vector of k moderator variables. The remaining variables are the same as in the simple meta-regression model. As in the simple meta-regression, regression model (5) will produce less precise estimates of the underlying "true" effect if there is a non-zero effect.

Therefore, the better alternative to estimate β_0 if there is a statistically significant empirical effect, is the FAT-PET-PEESE multiple meta-regression model (Stanley and Doucouliagos, 2012):

$$t_{ij}^* = \beta_0 \frac{1}{SE_{ij}} + \beta_1 SE_{ij} + \sum_{k=1}^K \beta_{ijk} \frac{Z_{ijk}}{SE_{ij}} + \varepsilon_{ij} \quad (6)$$

As mentioned before, model (6) should be estimated by WLS. If there is no statistically significant effect, the FAT-PET multiple meta-regression model should be estimated instead.

Moderator Variables

In this meta-analysis, I include three different classes of moderator variables. The first class of variables accounts for factors that impact the likelihood of a study being selected for publication. The second accounts for factors that affect study quality and the third for heterogeneous effects of EPL on different subgroups. In the following, these will be explained in depth. Table 2 summarizes the dependent and the control variables.

Variables for Publication Selection

As mentioned before, the main way to control for publication bias is to include the standard error in the simple and multiple meta-regression. It indicates if studies with more statistically significant results have a higher likelihood to be published (Stanley, 2005).

Table 2: *Summary Statistics*

	Unemploy- ment		Employ- ment		Description
	<i>Mean</i>	<i>S.D.</i>	<i>Mean</i>	<i>S.D.</i>	
1) Dependent variables					
Unadjusted t-statistic	0.48	1.77	-1.05	2.49	see equation (1)
Adjusted t-statistic	0.6	2.67	-1.74	4.09	see equation (1)
2) Publication bias					
Journal	0.39		0.59		=1 if published in peer-reviewed journal
# of cit. Google Sch.	185	317	226	325	# of citations in Google Scholar
Author ctry strict EPL	0.5		0.22		=1 if author(≥ 2 authors) from country with strict EPL
3) Estimation quality					
Pooled OLS& RE	0.5		0.37		=1 if estimated by pooled OLS or random effects (RE)
Ctry FE & ctry time FE	0.49		0.26		=1 if estimated by country&time fixed effects (FE) or country FE
Within-ctry	0.01		0.37		=1 if estimated exploiting within-country variation
Published in the 2000s	0.88		0.89		=1 if published after 1999
4) Effect heterogeneity					
Non-OECD countries	0.08		0.56		=1 if only non-OECD ctrys
					<i>=1 if subgroup:</i>
Youth	0.12		0.06		youth
Female	0.04		0.12		female
Male	0.04		0.1		male
Low-skilled	0.02		0.05		low-skilled
Long-term	0.12		-		long-term-unemployed
# of regressions	666		394		
# of studies	72		42		
Subsample analysis					
	Unemployment				Description
	<i>Mean</i>	<i>S.D.</i>			
Half-standard. part. regression coeff.	0.042	0.36			Half-standardized partial regression coefficient
# of regressions	147				
# of studies	13				

In both the FAT-PET and FAT-PET-PEESE model, rejection of the null $H_0 : \beta_1 = 0$ at a relevant significance level gives evidence for no publication selection bias. Note that, as in the simple meta-regression, the constant in the FAT-PET multiple meta-regression, β_1 still accounts for publication selection.

Besides this, I include an author-related dummy variable that accounts for ideological publication selection bias, namely a school-of-thought-bias. The dummy is one if the author of a single-authored study was or at least two authors of a multiple-authored paper were born and raised in a country with strict EPL. It tests if authors from countries with relatively stricter EPL systematically report different results than authors who grew up in a country with less strict EPL. This way, it tests if more desirable estimates have a higher likelihood to be reported. In order to identify the home country of the authors, I searched their CVs for the country where they finished upper secondary school or their Bachelor studies. Within the set of home countries, the countries with strict EPL were selected according to the OECD Indicators of Employment Protection index. Thereby, the 10 countries with the highest average index values over the time period 1985-2013 were declared as countries with strict EPL⁷.

Variables for Study Quality

Six different moderator variables account for study quality. One is a dummy variable that is one if a paper was published in a peer-reviewed journal and zero if it was published as a working paper, policy report or the like. On the one hand, this is an indicator for the quality of a study, because papers which undergo the review process of peers are more likely to be of relatively better quality than e.g. working papers. On the other hand, it could also be classified as a variable accounting for publication selection, in that studies reporting significant results have a relatively higher probability to be published in a peer-reviewed journal. Admittedly, it is hard to say which of both dominates. This makes it difficult to disentangle one from the other. But since publication bias is controlled for by the inclusion of the standard error, I argue that this ambiguity is only a problem if there is evidence for publication selection as indicated by the statistical significance of β_1 . A closely related variable for the quality of a study accounts for the number of citations on Google Scholar. The idea is that studies that are more likely to be cited on Google Scholar are of better quality. This is a much broader measure than the journal variable.

To account for the quality of the identification strategy of a study, I define three separate dummy variables. The first dummy is for studies that exploit across-country variation (cross-section or panel data), using pooled OLS or random effects estimation. The second dummy accounts for studies that exploit within-country and over time variation (panel data), using country fixed effects estimation. The last dummy is for studies that exploit variation at the country level, using micro-data (register or survey data) and fixed effects estimation. In the following, I will refer to these as pooled OLS, RE, country-FE and within-country studies respectively.

The reason why I separated pooled OLS, RE and country-FE studies is that studies using country fixed effects control for unobserved country-specific effects that may be correlated with the error terms. While pooled OLS completely ignores unobserved heterogeneity across countries, random effects estimation assumes that any unobserved

⁷The following countries were chosen: Portugal, Czech Republic, the Netherlands, Italy, Greece, Sweden, Germany, Slovenia, Chile, Korea.

individual heterogeneity across countries is distributed independently of the regressors (Cameron and Trivedi, 2005). However, this assumption is very unlikely to hold, as it is very probable that the unobserved country-specific effects of the unemployment or employment levels are correlated across countries. Hence, in the across-country and -time setting, country FE studies seem to be the most appropriate.

In general, within-country studies produce the most convincing estimates. Mostly, because it avoids the problem of unobserved heterogeneity across countries. Unfortunately, there is only one such study that assesses the effect of EPL on the unemployment level, which is not sufficient for comparisons.

Another variable that accounts for study quality is a dummy that is one if the study was published after 1999 and zero if it was published in 1999 or before⁸. Thereby, the assumption is that the data as well as the estimation method of studies published after 1999 improved relative to those published before.

Variables for Effect Heterogeneity

One variable that accounts for heterogeneity in outcomes, is a dummy variable that is one if *only* non-OECD countries were used in the sample. Given that the laws are relatively poorly enforced in less developed countries and political reforms are not as well implemented, I expect a relatively weaker responsiveness of employers to stricter EPL in non-OECD than in OECD countries.

Lastly, I define dummy variables that control for if the dependent variable of a regression i in paper j had: youth, female, low-skilled unemployment or employment, or long-term unemployment as dependent variable. These subgroups are expected to be relatively more hurt by stricter EPL.

3.3 Estimation Method

To estimate the FAT-PET model, I use three different estimation methods: i) ordinary least squares (OLS), ii) random effects (RE), and iii) weighted least squares estimation (WLS) using two alternative weights. A fixed effects (FE) regression model is not appropriate for the class of studies analyzed in this meta-analysis, as most of the variation is between, rather than within studies.

Instead, the RE model allows for within as well as between study variation (Cameron and Trivedi, 2005). One restriction of RE estimation is that it assumes independence between the unobserved study heterogeneity and the covariates in the multiple meta-regression. In the presence of publication bias, this assumption can be violated because $\frac{1}{SE_{ij}}$ may be correlated with unobserved study effects (Stanley and Doucouliagos, 2012).

WLS is a third alternative to pooled OLS. It assumes that the unobserved study heterogeneity can be explained by an unobserved differential propensity to select for statistical significance. In a recent simulation study of 80 meta-analyses, (Stanley and Doucouliagos, 2015) show that WLS outperforms RE in the presence of publication bias and FE if there is excess between-study heterogeneity. Therefore, I include two different versions of WLS models. In the first WLS regression model (WLS1), I use the inverse of the squared standard error of the coefficient of EPL on the unemployment or employment

⁸The meta-analysis does not include any study that was published before 1990.

level as a weight ($\frac{1}{SE_{ij}^2}$). In the second WLS regression model (WLS2), I multiply $\frac{1}{SE_{ij}^2}$ by the inverse of the number of regressions per study ($\frac{1}{n_{ij}}$) and use it as a weight. This prevents studies with a relatively larger number of estimates from having a higher weight. In order to account for possible correlations among the estimates at the study level, I cluster the standard errors at the study-level in all regressions.

For the FAT-PET-PEESE model I only employ WLS1 and WLS2 estimation for two reasons. First, since there is no intercept in the FAT-PET-PEESE model, it cannot be estimated by random effects (as the intercept is assumed to account for the random effects). Second, the results of the simulation studies mentioned by Stanley and Doucouliagos (2012) in section 3.1.2, just refer to WLS estimation. Together with the result from the above mentioned simulation study, using only WLS seems appropriate.

4 Results

In the first part of this section, I present descriptive evidence of the effect of EPL on the unemployment and employment levels. In the second part, I show the results of a graphical test for publication bias. Finally, in the third and fourth part, I show the results of the simple and multiple meta-regression model.

4.1 Density of the Outcome Measures

In section 3.1.1, I introduced a simple method to adjust for differences in the t-statistics due to differences in the number of degrees of freedom between studies. In this subsection, I compare the "simple t-statistic", in the following referred to as the "unadjusted t-statistic", with the adjusted t-statistic by means of a comparison of their density distributions. Differences between the densities arise from differences in the number of degrees of freedom between the studies. If the differences are substantial, the number of degrees of freedom matter for the assessment of the overall effect of EPL on the unemployment and employment levels. Then, the t-statistic adjusted for degrees of freedom should be used in the empirical analysis.

Figure 2 shows the density of the unadjusted t-statistic (grey line) and the adjusted t-statistic (black line) of the effect of EPL on the unemployment level, as well as their weighted (dashed line) and unweighted (continuous line) means. I used the same weight as I use in the for the WLS regression⁹, which prevents the studies with more regressions from having a higher weight. There is no huge difference between both density distributions. On the contrary, the unweighted means are substantially smaller than the weighted means, as it can be seen in Table 3. Only according to the weighted unadjusted t-statistic the hypothesis that EPL has a unemployment-increasing effect cannot be rejected at the 5%-significance level (critical value: $t_{671,0.025} = 1.96$).

⁹The inverse of the standard error of the coefficient capturing the effect of EPL on the unemployment (employment) level times the inverse of the number of regressions per study, $\frac{1}{SE_{ij}^2 * n_{ij}}$.

Figure 2: *Density, Mean and Weighted Mean of the Unadjusted and Adjusted T-Statistics, Unemployment*

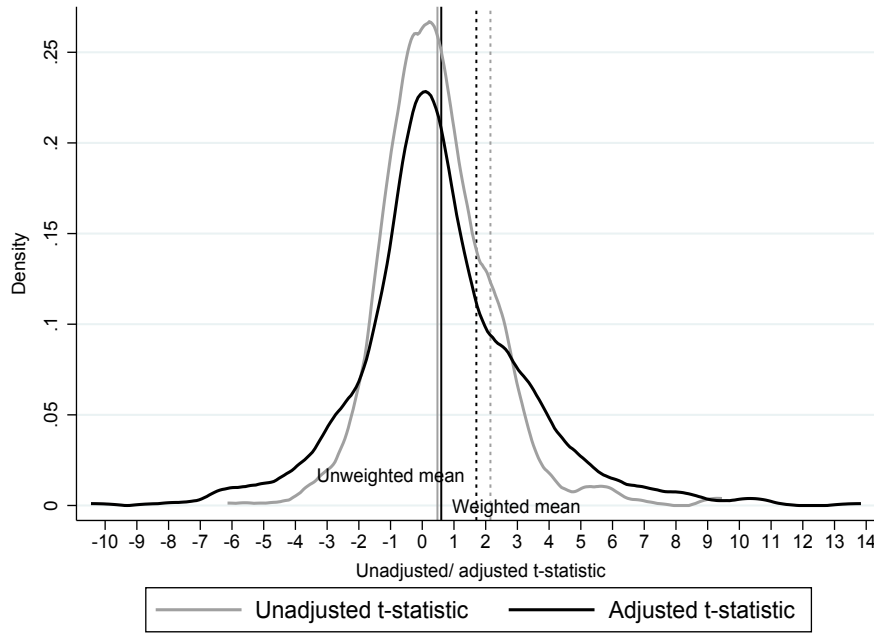
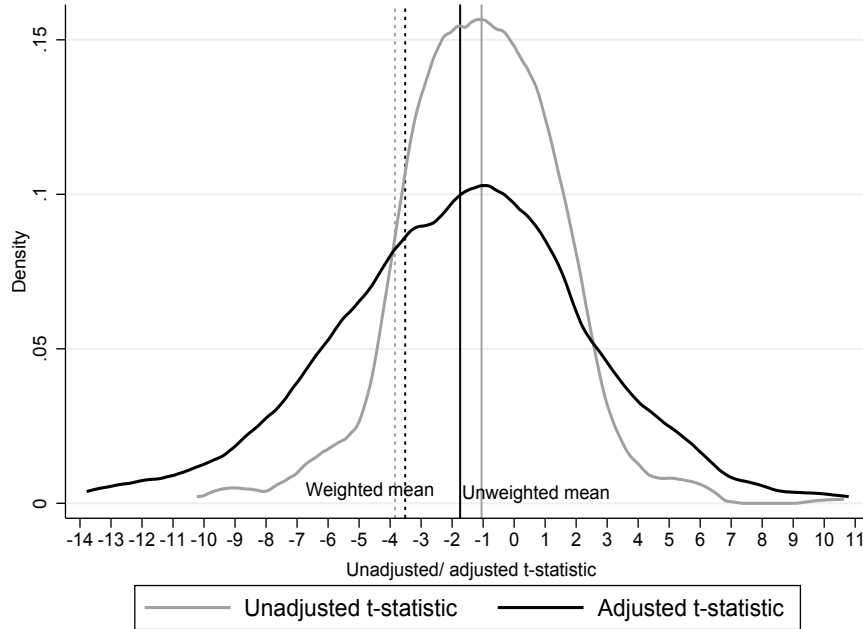


Figure 3: *Density, Mean and Weighted Mean of the Unadjusted and Adjusted T-Statistics, Employment*



Note: Figure 2&3 compare the unadjusted with the adjusted t-statistic, which is the outcome measure for the meta-analysis accounting for the effect of EPL on the unemployment (employment) level. Both densities are very similar in Figure2. Hence, differences in the number of degrees of freedom between the studies do not matter a lot in this case. The opposite is true in Figure 3 which shows large differences between both densities. Consequently, the adjusted t-statistic should be used as outcome measure. The weighted (dashed line) and unweighted means (solid lines) of the outcome measure differ quite substantially in both figures.

Figure 3 shows the density of the unadjusted t-statistic (grey line) and the adjusted t-statistic (black line) of the effect of EPL on the employment level, as well as their weighted (dashed line) and unweighted (continuous line) means. In contrast to the densities of the effect on the unemployment level, differences in the number of degrees of freedom seem to matter here. The densities and means of the unadjusted and adjusted t-statistics, especially the unweighted means, are very different. However, both weighted means suggest that EPL reduces the employment level (Table 3). This effect is statistically significant (critical value: $t_{393,0.025} = 1.96$).

Due to the difference between the densities, in particular that for employment, I will use the adjusted t-statistic as the outcome measure for the meta-analysis. Nevertheless, the results of all regressions with the unadjusted t-statistic as an outcome measure is provided in the appendix.

Table 3: *Unweighted and Weighted Means of the Unadjusted and Adjusted T-Statistics*

<i>Effect on the unemployment level</i>			
Unweighted mean		Weighted mean	
$t_{unem_{ij}}$	$t^*_{unem_{ij}}$	$t_{unem_{ij}}$	$t^*_{unem_{ij}}$
0.48	0.60	2.15	1.71
(1.77)	(2.67)	(2.09)	(1.66)
<i>Effect on the employment level</i>			
Unweighted mean		Weighted mean	
$t_{em_{ij}}$	$t^*_{em_{ij}}$	$t_{em_{ij}}$	$t^*_{em_{ij}}$
-1.05	-1.74	-3.85	-3.51
(2.49)	(4.09)	(0.95)	(0.85)

Note: Table 3 shows the weighted and the unweighted mean (see footnote 16 for more details) of the adjusted and unadjusted t-statistic (outcome measure for the meta-analysis). It shows that there are substantial differences between the weighted and the unweighted means.

4.2 Graphical Test for Publication Selection Bias

In this section, I show the graphical results of a test for publication selection bias. This graphical test is conducted by means of a funnel plot, which is a scatter plot of the estimated effect of EPL on the unemployment or employment levels against its precision, that is, the inverse of its standard error of the effect, $\frac{1}{SE_{ij}}$. In the absence of a publication selection bias, the effects would be randomly centered around the "true" effect (Stanley, 2008). Hence, an asymmetric funnel plot is an indicator of non-random selection of estimates, i.e. publication selection bias. To test for publication selection bias, I include studies that were published in a peer-reviewed journal ("published journal") and others that were only published as working papers or the like ("published otherwise")¹⁰.

¹⁰While it is sufficient to plot the estimates of studies that were published in a journal in order to test the symmetry of the funnel plot and hence publication bias, this bias can become more obvious if the estimates of the "published otherwise" studies are plotted in the same funnel plot.

Figure 4: *Funnel Plot Unemployment, Adjusted T-Statistic*

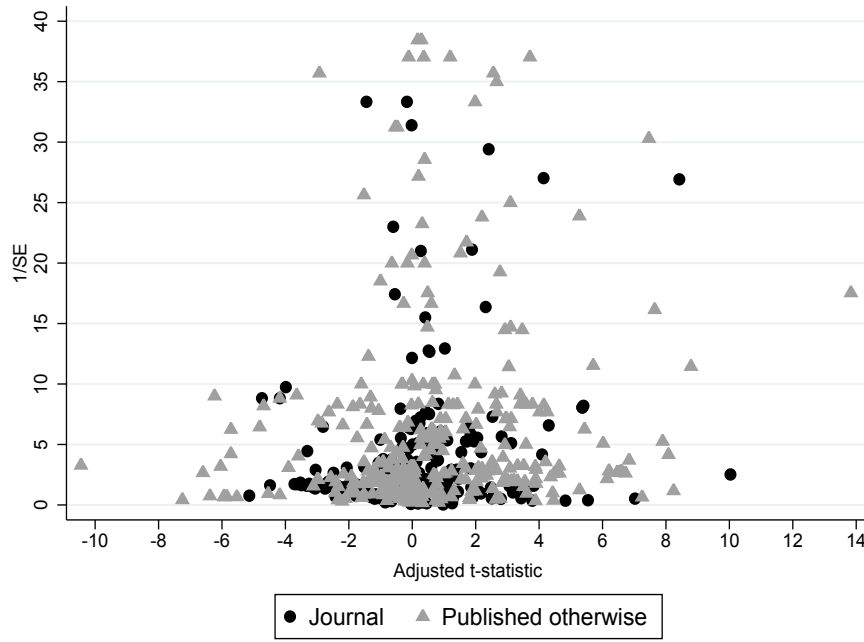
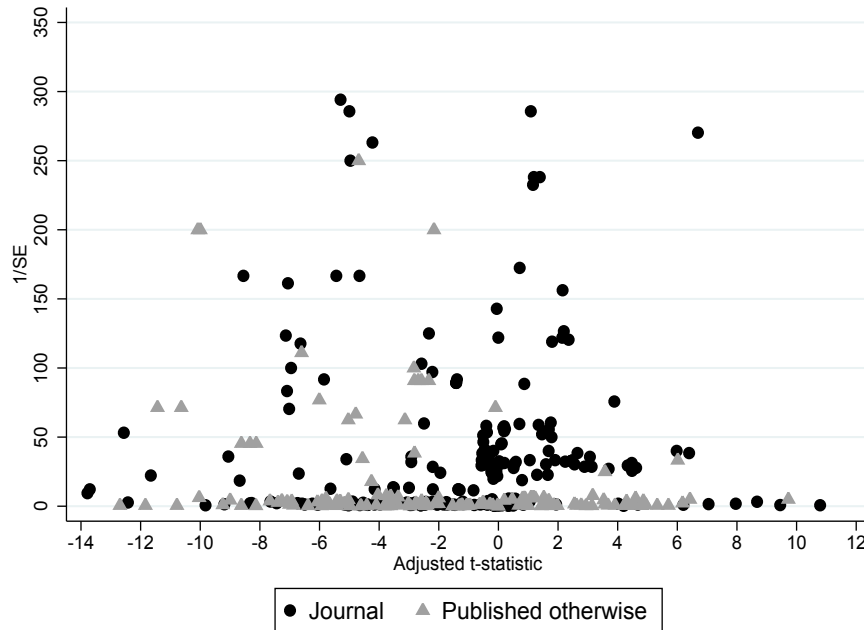


Figure 5: *Funnel Plot Employment, Adjusted T-Statistic*



Note: Figures 4 & 5 show the results of a graphical test for publication selection bias. I distinguish studies published in a peer-reviewed journal ("published journal") or elsewhere ("published otherwise"). The presence of a publication selection bias is tested in two ways: i) an asymmetric funnel plot and ii) large differences between studies published in a journal or elsewhere are both indicators of publication selection. Only the funnel plot for the effect of EPL on the employment level provides some evidence for a publication bias.

This way, the presence of a publication selection bias is tested in two ways, by the shape of the funnel plot of the estimates from studies published in a journal (is it symmetric or asymmetric?) and by the difference of the funnel plots of the estimates from journal-studies versus those of studies published otherwise (are they different?).

The funnel plot in Figure 4 scatters the adjusted t-statistic, quantifying the effect of EPL on unemployment against its precision ($\frac{1}{SE_{ij}}$). The plot does not provide indication of a publication selection bias. First, because the plots are symmetric for both, the estimates from journal-studies and otherwise published studies, and second, because there is no sizable difference between both types of studies.

This is different in the second funnel plot of the effect of EPL on employment, which is shown in Figure 5. First, compared to the previous graph, the majority of estimates is centered at the bottom of the plot and more spread out. These are studies with less precision and hence larger standard errors. It is hard to say if these are centered symmetrically around the "true" effect or not. Second, if one compares the estimates of the journal-studies with those of the otherwise published studies, it becomes clear that studies with higher precision estimates are more likely to be published in a peer-reviewed journal, as the majority of higher precision estimates from journal-studies scatters in the top part of the plot. Hence, in this case, the funnel plot provides some descriptive evidence for publication selection.

4.3 Results of the Simple Meta-Regression

In this section, I present the results of the simple meta-regression summarizing the effect of EPL on the unemployment and the employment level.

4.3.1 The Effect of EPL on the Unemployment Level

Table 4 shows the results of a FAT-PET model of the effect of EPL on the unemployment level, using the adjusted t-statistic as an outcome measure. The estimation is based on the results of 666 regressions from 72 different studies. The results for the unadjusted t-statistic can be found in the appendix.

Columns 1-4 show the results from the ordinary least squares (OLS), random effects (RE) and two weighted least squares (WLS) regressions. One of the two WLS regressions (WLS1) uses $\frac{1}{SE_{ij}^2}$, while the other (WLS2) uses $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weights. All regressions control for publication selection bias. For reasons laid down in section 3.3, WLS produces the most consistent results. Consequently, most weight will be given to the results of the WLS1 and WLS2 model. The standard errors in all regressions are clustered at the study-level.

The null hypothesis of the PET $H_0 : \beta_0 = 0$ (no effect) can be rejected at the 10%-significance level in the OLS regression, where β_0 is the coefficient of $1/SE$. That is, only the OLS regression depicts evidence for a marginally significant unemployment-increasing effect of EPL. But, provided that the RE and WLS models do not indicate the presence of a statistically significant effect of EPL, this effect is not very robust.

The null hypothesis of the FAT $H_0 : \beta_1 = 0$ (no publication bias) can be rejected at the 10% significance level in the OLS, RE and WLS2 regressions, i.e. I cannot rule out the presence of a publication selection bias, even if the statistical evidence is weak.

Table 4: *Simple Meta-Regression of the Effect of EPL on the Unemployment Level*

<i>Dependent variable: Adjusted t-statistic</i>				
<i>FAT-PET model</i>				
	OLS	RE	WLS1	WLS2
1/SE	0.001*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.554*	0.545*	1.489	1.225*
	(0.249)	(0.259)	(1.037)	(0.562)
R^2	0.007	0.0102	0.006	0.029
# of regressions	666	666	666	666
# of studies	72	72	72	72

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; OLS= ordinary least squares; RE= random effects (study RE); WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

Recall that Stanley and Doucouliagos (2012) recommend estimating the FAT-PET-PEESE by WLS only if there is evidence for a statistically significant non-zero genuine effect. Since their recommendation only concerns WLS estimation and not OLS, I do not run a FAT-PET-PEESE regression here, since the WLS estimates indicate a zero-effect of EPL.

In contrast to the t-statistic as an outcome measure, the subsample analysis in the next subsection allows drawing conclusions about the magnitude of EPL on unemployment.

The Magnitude of the Effect Size

Table 5 shows the results of a FAT-PET regression of the half-standardized partial regression coefficient of the effect of EPL on the unemployment level for a subsample of 13 studies. The same estimation methods as in Table 4 were applied. The advantage of this subset analysis is that, beyond just the statistical significance and sign, the magnitude of the effect, i.e. the economic impact of EPL on the unemployment level can also be interpret. One big drawback of this subset of 13 studies is that most of them not only use the same EPL measure, but in most cases even vintages of the same dataset of variables, such as the unemployment rate and other labour market variables. Hence, the results are highly driven by the similarity of the dataset used in the estimation.

Since a different outcome measure is used in Table 5, the results have to be read in a different way. Publication bias is now tested by a t-test of the coefficient on SE_{ij} and the existence of a genuine effect beyond publication bias is tested by a t-test of the constant.

The WLS1 and WLS2 regressions show a highly significant positive effect of EPL on the unemployment level (1%-significance level). According to the results of this subset of studies, an index point increase of the EPL measure increases the unemployment rate on average by about 0.15 to 0.155 standard deviations. Since the average standard deviation of the unemployment rate in these 13 studies is $s_u = 4.12$, this results in an increase in the

Table 5: *Magnitude of the Effect of EPL on the Unemployment Level*

<i>Dependent variable:</i>				
<i>Half-standardized regression coefficient</i>				
	OLS	RE	WLS1	WLS2
SE	0.271 (0.136)	0.282 (0.152)	-0.312* (0.127)	-0.410 (0.221)
Constant	-0.161 (0.089)	-0.173 (0.110)	0.155*** (0.009)	0.150*** (0.016)
R^2	0.190	0.0451	0.006	0.006
# of regressions	147	147	147	147
# of studies	13	13	13	13

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; SE= standard error of the semi-standardized regression coefficient; OLS= ordinary least squares; RE= random effects (study RE); WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

unemployment level of 0.62 to 0.64 percentage points. Only the WLS1 regression shows evidence for a statistically significant publication selection bias (10%-significance level). Since this test has a low power in general (Stanley and Doucouliagos, 2012), publication bias is not a big issue here.

This finding must be treated with caution due to three reasons. First, the subsample of 13 studies is rather small. Second, the similarity of the data used by the 13 studies lowers the external validity of this subsample analysis. Third, the result of the larger sample of studies does not provide evidence for a statistical link between EPL and the unemployment level, which casts further doubt on the results. Instead, this subsample analysis shows that the results of these studies finding a statistically significant link seem to be driven largely by the dataset of the OECD. In turn, this makes the results of the same class of cross-country studies that often use the same OECD dataset in general highly questionable.

4.3.2 The Effect of EPL on Employment

The results of a FAT-PET and of a FAT-PET-PEESE model of the effect of EPL on the employment level, using the adjusted t-statistic as outcome variable, are shown in Table 6. This estimation is based on the results from 394 regressions of 42 studies. The same estimation methods and order are used as in Table 4 and 5 were used.

The first half in Table 6 shows the results of the FAT-PET model. With the exception of the RE model, the results of all FAT-PET regression models suggest that EPL has a statistically significant and negative effect on the employment level, as indicated by the coefficient of $1/SE$. All four regressions show evidence for a publication selection bias (1%- level), which means that publication bias is a serious issue in these studies.

To get less biased results, Stanley and Doucouliagos (2012) recommend estimating the FAT-PET-PEESE model by WLS in case of a non-zero effect. The second half of Table 6 shows the results of the two WLS estimations of the FAT-PET-PEESE model. Again, the effect of EPL on the employment level is negative and statistically significant at the

Table 6: *Simple Meta-Regression of the Effect of EPL on the Employment Level*

<i>Dependent variable: Adjusted t-statistic</i>						
	<u>FAT-PET</u>				<u>FAT-PET-PEESE</u>	
	OLS	RE	WLS1	WLS2	WLS1	WLS2
1/SE	-0.000** (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
SE	- -	- -	- -	- -	-158.648* (67.449)	-139.267* (53.137)
Constant	-1.646** (0.498)	-1.774*** (0.475)	-2.048*** (0.391)	-2.193*** (0.384)	- -	- -
R^2	0.008	0.0102	0.108	0.081	0.9262	0.9382
# of regressions	394	394	394	394	394	394
# of studies	42	42	42	42	42	42

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; OLS= ordinary least squares; RE= random effects (study RE); WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

1%-level, suggesting that EPL decreases the employment level. In this model, publication selection is accounted for by the coefficient of SE . Publication selection is also an issue in this model, but it is less severe, i.e. the coefficient of SE is statistically significant, but only at the 10% instead of the 1%-level. According to the R^2 's, the FAT-PET-PEESE model performs much better than the FAT-PET model in assessing the empirical effect.

All in all, the result of a statistically significant employment-decreasing effect of EPL is very robust. In the next section, I will analyze to what extent differences in study characteristics drive the different outcomes between studies.

4.4 Results of the Multiple Meta-Regression

In this section, I include a battery of moderator variables for study characteristics that allow analyzing how these characteristics affect the estimated results of EPL on the unemployment and employment levels. As discussed in section 3, the moderator variables are classified into three different categories: moderator variables that quantify factors related to publication selection, estimation quality and effect heterogeneity. Table 7 shows the results of a FAT-PET and a FAT-PET-PEESE model for unemployment and employment. Stanley and Doucouliagos (2012) recommend estimating the FAT-PET-PEESE model only if there is sufficient evidence for a statistically significant genuine effect. Therefore, the FAT-PET-PEESE model was only estimated for the regressions that found a statistically significant effect in the FAT-PET model. As in the simple meta-regression, these are based on 666 regressions from 72 studies analysing the effect of EPL on the unemployment level and 394 regressions from 42 studies analysing the

effect on the employment level¹¹. Unlike the simple meta-regression, Table 7 only shows the results for the WLS1 and WLS2 regression, as these produce the most reliable results. Again, standard errors clustered at the study level are in parenthesis.

4.4.1 The Overall Effect of EPL on Unemployment and Employment

Columns 1 to 3 in Table 7 show the results of a FAT-PET and FAT-PET-PEESE model for the unemployment level. In both models, the coefficient of $1/SE$ serves as a measure to quantify the effect of EPL on the unemployment and employment levels. The WLS1 estimation result of the FAT-PET model in Table 7 indicates that EPL increases the unemployment level. However, this effect is only marginally significant (10%-level). The result of the WLS2 estimation is not statistically significant. The results of the FAT-PET-PEESE regression (WLS1 estimation) do not confirm the link between EPL and the unemployment level.

Both WLS estimations depict that EPL decreases the employment level. This effect is statistically significant in both WLS specifications (1%-level in the WLS1, 10% -level in the WLS2 estimation). The result of the FAT-PET-PEESE model underlines the results of a negative and statistically significant effect of EPL on the employment level.

4.4.2 Publication Selection

As indicated by the statistically significant constants, which reflect β_1 , publication selection is also an issue in all FAT-PET models for the unemployment and employment level. In the FAT-PET-PEESE regression, publication selection is only a problem for the unemployment level, as indicated by the marginally significant (10%-level) coefficient on SE .

Besides publication selection in the statistical sense, I also account for an "ideological publication bias" through the author(s) by means of the so-called "school-of-thought-bias variable". The results of the FAT-PET and the FAT-PET-PEESE models show that studies from authors who were socialized in countries with comparatively strict EPL find a relatively less harmful effect of EPL on the unemployment and employment levels, than studies from authors from countries with less strict EPL. Assuming that it stems from the selection of the results through the authors, this finding implies that authors from countries with stricter EPL have a relatively good opinion about EPL.

4.4.3 Estimation Quality

Both, the journal variable that is one if a study was published in a peer-reviewed journal and the variable accounting for the number of citations in Google Scholar account for the quality of a study. The assumption is that studies that are published in a journal or with more citations are of a better quality.

In the FAT-PET regression for employment, the journal dummy and the variable accounting for the number of citations on Google Scholar, are both slightly positive and statistically significant, except the journal dummy in the WLS2 estimation. It shows that studies published in a peer-reviewed journal or with a higher number of citations in

¹¹The same regressions but with the unadjusted t-statistic as dependent variable can be found in the appendix.

Table 7: *Multiple MRA, Unemployment and Employment Level**Dependent variable: Adjusted t-statistic*

Model	Unemployment			Employment			
	<i>FAT-PET</i>	<i>FAT-PET</i>	<i>FAT-PET</i>	<i>FAT-PET</i>	<i>FAT-PET</i>	<i>FAT-PET-PEESE</i>	<i>FAT-PET-PEESE</i>
Estimation	WLS1	WLS2	WLS1	WLS1	WLS2	WLS1	WLS2
1/SE	0.001* (0.000)	0.000 (0.001)	0.000 (0.000)	-0.024*** (0.004)	-0.019* (0.009)	-0.030*** (0.005)	-0.024* (0.010)
<i>Publication Selection</i>							
Constant (β_1)	1.747*** (0.419)	1.148* (0.519)	- (-)	-2.803*** (0.078)	-2.809*** (0.069)	- (-)	- (-)
SE	- (-)	- (-)	31.120* (14.983)	- (-)	- (-)	-82.163 (53.630)	-66.893 (47.644)
Auth. strict EPL	-0.005*** (0.001)	0.003*** (0.001)	-0.002** (0.001)	-0.025*** (0.005)	0.020* (0.009)	0.037*** (0.005)	0.032** (0.010)
<i>Study Quality</i>							
Journal	-0.000 (0.000)	0.000 (0.001)	0.001* (0.000)	0.023*** (0.004)	0.018 (0.009)	0.027*** (0.005)	0.021* (0.010)
# of cit. Google	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Ctry& time FE	-0.001*** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Within-ctry	-0.314*** (0.060)	-0.228** (0.074)	-0.835* (0.371)	-0.017 (0.015)	-0.025* (0.010)	-0.034 (0.017)	-0.043*** (0.011)
Published 2000s	0.001 (0.000)	0.001* (0.001)	0.002*** (0.000)	0.005*** (0.000)	0.005*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
<i>Effect Heterogeneity</i>							
Non-OECD ctrys	-0.000 (0.003)	0.004 (0.004)	0.010*** (0.002)	-0.005*** (0.001)	-0.006*** (0.001)	-0.010*** (0.002)	-0.011*** (0.001)
Youth	-0.001* (0.000)	-0.000 (0.001)	0.000 (0.000)	0.024*** (0.005)	0.046* (0.021)	0.011 (0.009)	0.027 (0.022)
Female	-0.006 (0.005)	-0.003 (0.005)	-0.003 (0.005)	-0.003 (0.008)	-0.001 (0.007)	-0.006 (0.008)	-0.004 (0.008)
Male	-0.005*** (0.001)	-0.004*** (0.001)	-0.002*** (0.001)	0.008 (0.004)	0.009** (0.003)	0.005 (0.004)	0.006* (0.003)
Low-skilled	-0.636*** (0.088)	-0.513*** (0.146)	-1.364* (0.557)	-0.025 (0.091)	-0.109* (0.051)	-0.011 (0.097)	-0.108 (0.054)
Long-term	0.031 (0.019)	0.015 (0.022)	0.040* (0.019)	- (-)	- (-)	- (-)	- (-)
R^2	0.782	0.652	0.846	0.444	0.338	0.951	0.953
# of regressions	666	666	666	394	394	394	394
# of studies	72	72	72	42	42	42	42

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; gray color: only one observation (study); clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

Google Scholar, find a relatively lower evidence for an employment-decreasing effect of EPL, than otherwise published studies. These findings are confirmed by the results of the FAT-PET-PEESE model. The only difference is that the coefficient of the journal variable becomes marginally significant (10%) and positive in the WLS1 estimation for the unemployment and the WLS2 estimation for the employment level. This underlines the previous finding of a less harmful effect of EPL on the employment level. This result also provides some evidence that studies in peer-reviewed journals tend to find relatively stronger evidence for an unemployment-increasing effect of EPL.

Also the identification strategy has a large impact on the overall result across studies. The base category consists of studies that use cross-section data or panel data estimated by pooled OLS or random effects ("pooled OLS, RE"). The remaining categories are those for studies that use panel data and country fixed-effects estimation ("country-FE studies"), or for studies exploiting within-country variation ("within-country studies"). According to the results of the FAT-PET model, country-FE studies find a relatively less harmful effect of EPL on the unemployment and employment levels than studies in the base category, i.e. pooled OLS, RE studies. This finding is statistically highly significant (1%-level) in all regressions for country-FE studies. As there is only one within-country study that analyses the effect of EPL on the unemployment level, I ignore the result. On the contrary, enough within-country studies analyse the effect of EPL on the employment level. These find a relatively more harmful effect of EPL on the employment level, than studies in the base category. However, this result is only marginally statistically significant in the WLS2 regression (10%-level). The results from the FAT-PET and the FAT-PET-PEESE model are almost the same.

The relevance of the identification strategy is further underlined by the result of the FAT-PET regression: studies that were published after 1999 find on average higher t-statistics than those published before or in 1999. This could reflect a trend of an improvement in study quality. The effect is statistically highly significant (1%-level) in most specifications, with the exception of the WLS1 regression for the unemployment level (10%-level). These results are confirmed by the FAT-PET-PEESE regression, where the statistical significance for the unemployment level is even higher.

4.4.4 Effect Heterogeneity

The results of the FAT-PET and FAT-PET-PEESE model show that studies that only include non-OECD countries in their data sample find a larger negative effect of EPL on the employment level (1%-level) than studies that only include OECD countries. In addition, there is slight evidence for a relatively more harmful effect of EPL on the unemployment level in non-OECD countries (1%-level, FAT-PET-PEESE regression). This is a surprising result, since I expected that EPL is less strictly enforced in non-OECD than in OECD countries. Consequently, I expected a relatively lower impact of EPL on the unemployment or employment level in non-OECD countries, regardless of the direction of the effect. One explanation could be that, because the informal sector in non-OECD countries is relatively larger than the formal sector, firms employing people in formal jobs are less numerous and can be better controlled by official authorities. This increases the compliance of firms with the rules of EPL, but also its potentially negative effect on employment-decisions of firms. Another explanation could be that, if the labour

costs in non-OECD countries are so low that the costs from trying to circumvent the legislation are higher than the actual benefit from doing so, then non-compliance to EPL is irrational.

Regarding the effect of EPL on the unemployment and employment levels for different subgroups, the results of the FAT-PET regression can be summarized as follows. EPL seems to have a statistically significant relatively less harmful effect on the unemployment level of the youth (10%-level), men (1%-level) and low-skilled workers (1%-level) and a relatively more beneficial effect on the employment level of the youth (10%-level) and males (5%-level). Further, EPL has a relatively more harmful effect on the employment level of low-skilled workers (10%-level). The FAT-PET-PEESE regression only partially confirms the result of a relatively less harmful effect on the outcomes of male workers and a lower negative effect on the unemployment level of low-skilled workers. In addition, it depicts marginal evidence that EPL has a more harmful effect on long-term unemployment.

The result for the youth does not confirm the hypothesis that strict EPL harms the youth relatively more. Instead, the results indicate that EPL has the same or lower effect on the youth. That strict EPL seems to hurt low-skilled workers less, is relatively surprising, given that low-skilled belong to the more vulnerable groups on the labour market. The finding that males are less hurt by strict EPL than women is not very surprising, given that men are often found to be relatively less affected by negative consequences on the labour market. Regarding the effect on the long-term unemployed, the empirical evidence is very low but points towards a more negative effect of EPL.

The multiple meta-regression reveals to what extent differences of the effect of EPL on the unemployment and employment level stem from factors related to selection, quality and heterogeneity. The main takeaways of this section are the following. The negative effect of EPL on the employment level is very robust, even when controlling for different study characteristics. The statistical association between EPL and the unemployment level is not very robust. The quality of the identification strategy matters in particular for the overall result.

In the next section, I analyse the impact of the identification strategy in detail.

4.5 Subsample Analysis by Identification Strategy

The identification strategy is an important factor for explaining differences between studies. Therefore, I run separate simple meta-regressions for each of the three different identification strategy categories: pooled OLS, RE, country FE and within-country studies. As there is only one within-country study that analyses the effect of EPL on the unemployment level, no separate regression was conducted for this category. Table 8 and 9 show the results of FAT-PET and FAT-PET-PEESE regressions for studies that analyse the effect of EPL on the unemployment end the employment levels, respectively. Both tables show the results of WLS regressions. Note that a a FAT-PET-PEESE regression was only estimated if a statistically significant effect of EPL was found in the FAT-PET regression.

Three of the four regressions in Table 8 that analyse the effect of EPL on the unemployment level find that publication selection is a problem. The results of the FAT-PET and FAT-PET-PEESE regression show that according to the pooled OLS, RE studies,

Table 8: *Subsample Analysis by Identification Strategy, Unemployment**Dependent variable: Adjusted t-statistic*

	<u>Pooled OLS, RE</u>		<u>Country (& time) FE</u>	
<u><i>FAT-PET</i></u>	WLS1	WLS2	WLS1	WLS2
1/SE	0.000 (0.000)	0.0003*** (0.000)	-0.0002*** (0.000)	-0.000 (0.000)
Constant	3.093*** (0.625)	1.947*** (0.476)	0.945*** (0.194)	0.518 (0.430)
R^2	0.003	0.175	0.091	0.012
# of regressions	370	370	290	290
# of studies	53	53	44	44
<u><i>FAT-PET-PEESE</i></u>				
	WLS1	WLS2	WLS1	WLS2
1/SE	-	0.001*** (0.000)	0.000 (0.000)	-
SE	-	97.222* (38.185)	21.912 (12.658)	-
R^2	-	0.718	0.060	-
# of regressions	-	370	290	-
# of studies	-	53	44	-

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

EPL increases the unemployment level (1%-level, WLS2 regression). On the contrary, the result of a FAT-PET regression for all country FE studies indicates at the 1%-level that EPL decreases the unemployment level (WLS1 regression). But this finding cannot be confirmed by the FAT-PET-PEESE regression. Hence, it seems that the marginally positive effect of EPL on the unemployment level in the simple and multivariate meta-regression stems from the pooled OLS, RE studies.

This subsample analysis shows that the quality of the estimation technique matters for the outcome. As argued before, country-FE studies outperform pooled OLS, RE studies in terms of identifying the effect of EPL on the unemployment level, since they account for unobserved country-specific effects. Hence, more weight should be given to their result. That is that there is no empirical association between EPL and the unemployment level.

Table 9: *Subsample Analysis by Identification Strategy, Employment*

<i>Dependent variable: Adjusted t-statistic</i>						
	<u>Pooled OLS, RE</u>		<u>Country (& time) FE</u>		<u>Within-country</u>	
<u><i>FAT-PET</i></u>						
	WLS1	WLS2	WLS1	WLS2	WLS1	WLS2
1/SE	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.0003* (0.000)	-0.032* (0.011)	-0.024 (0.013)
Constant	-3.935*** (1.038)	-3.474*** (0.799)	-2.327*** (0.305)	-2.167*** (0.182)	1.154 (1.239)	-0.638 (2.055)
R^2	0.004	0.000	0.121	0.103	0.307	0.201
# of regressions	154	154	96	96	144	144
# of studies	25	25	14	14	12	12
<u><i>FAT-PET-PEESE</i></u>						
	WLS1	WLS2	WLS1	WLS2	WLS1	WLS2
1/SE	-	-	-	-0.0005*** (0.000)	-0.024** (0.006)	-
SE	-	-	-	-123.688 (68.952)	12.577 (20.532)	-
R^2	-	-	-	0.643	0.518	-
# of regressions	-	-	-	96	144	-
# of studies	-	-	-	14	12	-

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

Table 9 shows the results for the employment level. Publication selection seems to be a problem in four out of the six regressions. According to the FAT-PET regression, the pooled OLS, RE studies do not find a statistically significant effect, while country FE studies depict a marginally significant positive effect of EPL on the employment level (10%-level). The within-country studies yield a marginally significant negative effect (10%-level). The results of a FAT-PET-PEESE regression confirm the finding of the within-country studies (5%-level), which is not the case for the country FE studies. In

the regression for the country FE studies, the sign of the effect is even reversed and statistically highly significant (1%-level). On the one hand, this underlines the result of the within-country studies. On the other hand, it casts some doubt on the unbiasedness of the estimations relying on variation across countries using country fixed effects or not. Overall, the results from the within-country studies together with the findings of the simple and multiple meta-regression lead to the same conclusion: EPL tends to lower the employment level, though the statistical association of this effect is low.

4.6 Note on the Difference Between the Unadjusted and Adjusted T-Statistic

Comparing the results for the unadjusted with that of the adjusted t-statistic of the simple meta-regression, there are no substantial differences, neither for the effect of EPL on the unemployment, nor the employment level (see Table 10, respectively Table 11 in the appendix). Only that the results of the RE estimation for the unemployment level turn statistically significant (10%-level) and publication selection is less a problem.

Instead, the results of the multiple meta-regression are very different for the overall effect of EPL on the unemployment level (Table 12 in the appendix). The results of the multiple meta-regression using the unadjusted t-statistic as dependent variable, indicate that EPL increases the unemployment level. This effect is statistically highly significant (WLS1: 1%-level, WLS2: 5%-level) in both, the FAT-PET and FAT-PET-PEESE model. Just as the results of the adjusted t-statistic, the results of the subsample analysis by identification strategy using the unadjusted t-statistic reveal that this overall result is driven by pooled OLS, RE studies. These find a statistically significant unemployment-increasing effect of EPL, while country FE studies find the opposite. On the contrary, the negative effect of EPL on the employment level cannot be confirmed by this subsample analysis. Since differences in the number degrees of freedom matter in particular for the outcome measure for employment, more weight should be given to the results of the adjusted t-statistic.

5 Summary and Conclusion

The aim of this meta-analysis is to clarify how EPL affects the unemployment and employment levels. The results of the empirical analysis can be summarized as follows. First, based on evidence from 666 regressions of 72 studies, I find that there is no statistically significant effect of EPL on the unemployment level. Second, drawing on evidence from 394 regressions of 42 studies, I find that EPL decreases the employment level.

None of these results allows for conclusions to be drawn about the magnitude, i.e. the economic significance, of the effect of EPL on the unemployment and employment levels. Therefore, I run separate meta-regressions for 13 studies that analyse the effect of EPL on the unemployment level, using the same measure to quantify EPL and the same outcome measure for unemployment. The results suggest that stricter EPL increases the unemployment level, measured by the unemployment rate, by 0.62 to 0.64 percentage points. This result is statistically significant at the 1%-level. However, it must be interpreted very carefully, as these 13 studies use almost the same dataset and identify the

causal effect by using cross-country data.

To analyse how differences in the effect of EPL on the unemployment or employment level can be associated to differences in study characteristics, I estimate multiple meta-regressions. These provide the following insights.

Publication selection in the statistical sense is a problem in all FAT-PET models and less in the FAT-PET-PEESE models. In addition, publication selection in the ideological sense, that is, the attitude of the authors of a study regarding EPL, seems to matter for the outcome. Authors who were socialized in country with strict EPL find a relatively less harmful effect of EPL on the unemployment and employment levels.

The review process of a study through editors and peers, as well as the selection of studies into a pool of the literature that is recognized by the research community, as measured by number of citations on Google Scholar, impact the quality of studies. I find that studies that were published in a peer-reviewed journal or with a higher number of citations on Google Scholar find a relatively lower employment-decreasing effect of EPL.

In particular the quality of the identification strategy is an important determinant of the overall effect of EPL. Studies that use panel data and fixed effects estimation find a statistically significant, less harmful effect of EPL on the unemployment and employment levels, than studies in the base category, which consist of studies using cross-section or panel data and pooled OLS or random effects estimation. Studies that exploit within-country variation, find a more harmful effect of EPL on the employment level, than studies in the base category.

The results of a sample-split by identification strategy suggest, that studies using cross-section or panel data and pooled OLS or random effects estimation find that EPL increases the unemployment level while they do not find a statistically significant effect on the employment level. Separate regressions for studies that use panel data and fixed effects estimation find a negative but not robust effect of EPL on the unemployment and mixed result for the employment level. Since there is only one within-country study analysing the effect on the unemployment level, there is no result for this study category. On the contrary, a rather robust and statistically significant (5-10%-level) finding of within-country studies is that EPL lowers the employment level.

Overall, these results cast doubt about the unbiasedness of the estimates from studies using cross-country data. Compared to studies that only exploit within-country variation, studies using cross-country data are less convincing. Even if these studies can control for the problem of unobserved time-invariant heterogeneity across countries by means of country fixed effects, studies relying on within-country variation completely avoid this problem. The results of the multiple meta-regression show that studies that were published after 1999 depict higher t-statistics over time. If this reflects a trend of an improvement of the study quality over time, the result suggests that these studies find a relatively more unemployment-increasing and lower employment-increasing effect of EPL.

Finally, I find that men, low-skilled workers and, to some extent, the youth are relatively less hurt by strict EPL than other subgroups.

Four factors clearly limit the scope of the analysis. First, most studies use different empirical measures for EPL or different transformations of the regression variables. Therefore, I cannot assess the magnitude of the impact of EPL on the unemployment or employment level for the majority of studies, but only the statistical significance and direction of the effect. I can analyse the magnitude of EPL on the unemployment level

only for a subset of 13 studies. Second, the quality of a meta-analysis is only as good as the quality of the included studies. This is also true for the precision of the aggregate effect of EPL on the unemployment and employment levels. As many included studies use cross-country data to identify the effect of EPL, their results may be biased due to a lack to control for unobserved heterogeneity across countries. Third, because of an insufficient number of studies, I cannot control for other causal channels that undermine the impact of EPL on the unemployment and employment levels. These include the effect of EPL informal sector and temporary employment, as well as non-employment and the rate of young people who are neither in employment nor in work. Finally, like many studies in this field, I cannot account for the endogeneity of EPL.

Which policy conclusions can be drawn from these results? Probably the most important is that the results of the literature summarized in this meta-analysis should be treated with caution. This is particularly true for studies that analyse the effect of EPL on the unemployment level, as most of these use cross-country data. Consequently, policy recommendations that are based on the results of this type of studies, are highly questionable and should be avoided. Instead, studies that exploit within-country variation should be preferred.

Still, the number of studies exploiting within-country variation is low in this field of the literature, especially those that analyse the effect on the unemployment level (one study in this meta-analysis). Hence, it is highly desirable and necessary to have more within-country studies for a broader set of countries.

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A List of Countries for Figure 1

Figure 1 is based on the following countries: Ireland, Denmark, Australia, Netherlands, Belgium, Switzerland, Norway, Spain, Greece, Portugal, Japan, USA, France, Germany, Italy, Finland, Canada, Austria, Great Britain, Sweden.

B Tables with the Unadjusted T-Statistic as Dependent Variable

Table 10: *Simple Meta-Regression of the Effect of EPL on the Unemployment Level*

<i>Dependent variable: Unadjusted t-statistic</i>				
	OLS	RE	WLS1	WLS2
1/SE	0.001** (0.000)	0.001* (0.000)	0.000 (0.000)	0.001 (0.000)
Constant	0.426* (0.192)	0.264 (0.161)	0.959 (1.313)	0.811 (0.791)
R^2	0.022	0.0381	0.075	0.143
# of regressions	666	666	666	666
# of studies	72	72	72	72

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; OLS= ordinary least squares; RE= random effects (study RE); WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

Table 11: *Simple Meta-Regression of the Effect of EPL on the Employment Level*

<i>Dependent variable: Unadjusted t-statistic</i>						
	<u>FAT-PET</u>				<u>FAT-PET-PEESE</u>	
	OLS	RE	WLS1	WLS2	WLS1	WLS2
1/SE	-0.001*** (0.000)	-0.000*** (0.000)	-0.000* (0.000)	-0.000** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Constant	-0.892** (0.289)	-0.851** (0.278)	-3.054*** (0.315)	-2.963*** (0.314)	-177.389* (86.334)	-123.071* (58.519)
R^2	0.064	0.132	0.025	0.029	0.9056	0.9265
# of regressions	394	394	394	394	394	394
# of studies	42	42	42	42	42	42

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; OLS= ordinary least squares; RE= random effects (study RE); WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

Table 12: *Multiple MRA, Unemployment and Employment Level**Dependent variable: Unadjusted t-statistic*

Model	Unemployment				Employment			
	<i>FAT-PET</i>	<i>FAT-PET-PEESE</i>	<i>FAT-PET</i>	<i>FAT-PET-PEESE</i>	<i>FAT-PET</i>	<i>FAT-PET-PEESE</i>	<i>FAT-PET</i>	<i>FAT-PET-PEESE</i>
Estimation	WLS1	WLS2	WLS1	WLS2	WLS1	WLS2	WLS1	WLS2
1/SE	0.002*** (0.000)	0.002** (0.001)	0.002*** (0.000)	0.002** (0.000)	-0.016*** (0.002)	-0.017*** (0.003)	-0.022*** (0.003)	-0.022*** (0.004)
<u>Publ. Selection</u>								
Constant	1.601** (0.469)	1.009 (0.697)	- -	- -	-3.211*** (0.240)	-3.144*** (0.163)	- -	- -
SE	- -	- -	21.798 (15.010)	6.935 (10.191)	- -	- -	-85.995 (62.448)	-70.154 (52.485)
Auth. strict EPL	-0.004*** (0.001)	-0.003* (0.001)	-0.002** (0.000)	-0.001*** (0.000)	0.015*** (0.003)	0.017*** (0.003)	0.030*** (0.004)	0.031*** (0.004)
<u>Study Quality</u>								
Journal	-0.002*** (0.000)	-0.001 (0.001)	-0.001*** (0.000)	-0.000 (0.000)	0.013*** (0.002)	0.014*** (0.003)	0.018*** (0.003)	0.018*** (0.004)
# of cit. Google	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Ctry FE & time FE	-0.001*** (0.000)	-0.001** (0.000)	-0.001* (0.000)	-0.001** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Within-country	-0.350*** (0.067)	-0.265** (0.100)	-0.661 (0.372)	-0.292 (0.253)	0.007 (0.007)	0.001 (0.004)	-0.013 (0.010)	-0.021*** (0.006)
Published 2000s	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.000)	0.001* (0.000)	0.007*** (0.001)	0.007*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
<u>Effect Heterog.</u>								
Non-OECD ctrys	-0.001 (0.003)	0.003 (0.005)	0.008*** (0.001)	0.009*** (0.001)	-0.007*** (0.001)	-0.008*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)
Youth	-0.001 (0.000)	0.000 (0.001)	0.000** (0.000)	0.001* (0.000)	0.027*** (0.007)	0.055 (0.028)	0.011 (0.011)	0.033 (0.027)
Female	-0.006 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.001 (0.003)	-0.000 (0.004)	0.002 (0.003)	-0.003 (0.005)	-0.001 (0.004)
Male	-0.004*** (0.001)	-0.003** (0.001)	-0.002*** (0.000)	-0.002*** (0.000)	0.006* (0.003)	0.007*** (0.002)	0.003 (0.002)	0.003* (0.001)
Low-skilled	-0.359*** (0.083)	-0.249 (0.145)	-0.805 (0.528)	-0.407 (0.530)	0.051 (0.032)	0.024 (0.018)	0.062 (0.051)	0.023 (0.030)
Long-term	0.003 (0.007)	0.000 (0.008)	0.012* (0.006)	0.007 (0.007)	- -	- -	- -	- -
R^2	0.817	0.777	0.886	0.880	0.506	0.403	0.952	0.955
# of regressions	666	666	666	666	394	394	394	394
# of studies	72	72	72	72	42	42	42	42

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; gray color: only one observation (study); clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

Table 13: *Subsample Analysis by Identification Strategy, Unemployment**Dependent variable: Unadjusted t-statistic*

	Pooled OLS, RE		Country (& time) FE	
<u>FAT-PET</u>				
	WLS1	WLS2	WLS1	WLS2
1/SE	0.0005*** (0.000)	0.001*** (0.000)	-0.0003*** (0.000)	-0.000 (0.000)
Constant	2.514** (0.755)	1.472** (0.429)	1.370*** (0.296)	1.021** (0.375)
R^2	0.297	0.577	0.101	0.041
# of regressions	370	370	290	290
# of studies	53	53	44	44
<u>FAT-PET-PEESE</u>				
	WLS1	WLS2	WLS1	WLS2
1/SE	0.001*** (0.000)	0.001*** (0.000)	0.000 (0.000)	- -
SE	66.066 (34.939)	55.508* (25.435)	26.516 (16.033)	- -
R^2	0.841	0.860	0.071	-
# of regressions	370	370	290	-
# of studies	53	53	44	-

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight; WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

Table 14: *Subsample Analysis by Identification Strategy, Employment*

<i>Dependent variable: Unadjusted t-statistic</i>						
	<u>Pooled OLS, RE</u>		<u>Country (& time) FE</u>		<u>Within-country</u>	
<u><i>FAT-PET</i></u>						
	WLS1	WLS2	WLS1	WLS2	WLS1	WLS2
1/SE	0.000	0.000	0.0002*	0.000	-0.008	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.005)
Constant	-5.181**	-4.376**	-2.744***	-2.656***	-0.180	-1.472
	(1.842)	(1.421)	(0.147)	(0.159)	(0.730)	(0.803)
R^2	0.037	0.005	0.061	0.053	0.060	0.003
# of regressions	154	154	96	96	144	144
# of studies	25	25	14	14	12	12
<u><i>FAT-PET-PEESE</i></u>						
	WLS1	WLS2	WLS1	WLS2	WLS1	WLS2
1/SE	-	-	-0.001***	-	-	-
	-	-	(0.000)	-	-	-
SE	-	-	252.158*	-	-	-
	-	-	(95.042)	-	-	-
R^2	-	-	0.751	-	-	-
# of regressions	-	-	96	-	-	-
# of studies	-	-	14	-	-	-

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered standard errors (study level) in parenthesis; 1/SE= inverse of the standard error of the adjusted t-statistic; WLS1=weighted least squares using $\frac{1}{SE_{ij}^2}$ as weight;

WLS2= weighted least squares using $\frac{1}{SE_{ij}^2 * n_{ij}}$ as weight.

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