

**EMPLOYMENT EFFECTS OF REDUCING LABOUR  
COSTS:**

Considering Potential Bias in Macro-estimates of the  
Elasticity of Labour Demand

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**Author: Jussi Huuskonen  
Discipline: Economics  
Supervisor: Roope Uusitalo**



JYVÄSKYLÄN YLIOPISTO



## ABSTRACT

Author Huuskonen, Jussi	
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Abstract <p>In 2016 the Finnish government decided to implement the competitiveness pact in order to increase employment. The objective is to improve cost-competitiveness by lowering labor costs in the private sector. The elasticity of labour demand plays a key role in assessing the employment effects of the competitiveness pact. The idea of this study is based on the Economic Policy Council Report (2016) which argued that the government's elasticity estimate is very high and predicts overly optimistic employment effects. The majority of studies estimate demand elasticities using aggregate data, which is likely to produce biased estimates. The problems relate in particular to the lack of exogenous variation in labour costs, the simultaneity of demand and supply, and the possibility of composition bias. This study considers potential bias in macro-estimates of the elasticity of labour demand. In the empirical part labour demand elasticities are estimated using industry-level data that cover the years 1996-2013. The key idea is to use different wage variables. Furthermore, the effects of measurement error in working hours are examined by using Monte Carlo simulation method. The calculations show that aggregate data has a tendency to produce biased and excessively large elasticity estimates. A relevant elasticity estimate should be based on research containing plausible exogenous variation in wages. Therefore, this study contains a small meta-analysis of micro-studies examining situations where labor costs have been altered exogenously. Such studies provide elasticity estimates that can be interpreted as causal effects of reducing labour costs. These micro-studies appear to produce significantly lower elasticity estimates than macro-studies based on aggregate data.</p>	
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# 1 INTRODUCTION

In 2016 the Finnish government decided to implement the competitiveness pact in order to increase employment. The objective is to improve cost-competitiveness by lowering labor costs in the private sector, and thereby increase employment. The Ministry of Finance (MoF) estimates (1.3.2016) that the competitiveness pact will reduce unit labor costs by 4.2 % compared to the baseline scenario. This general effect is a sum of several means including 1) increasing working time by 24 hours per year without increases in salaries, 2) freezing salary increases, 3) reducing employers' health insurance payments, 4) shifting 0.85 percentage points of unemployment insurance payments from employers to employees, and 5) shifting 1.2 percentage points of pension payments from employers to employees. According to the MoF, this will improve employment by approximately 35,000 persons compared to the baseline scenario by the beginning of the 2020s.

The elasticity of labour demand plays a key role in assessing the employment impacts of the competitiveness pact. Therefore, the elasticity estimate used should be as accurate and reliable as possible. The elasticity of labour demand reflects how responsive labor demand is to changes in labour costs. A point estimate for the elasticity of labour demand indicates the percentage increase in labour demand if labor costs are reduced by 1%. In order to make policy conclusions, it is useful to have such measure reflecting the relationship between exogenous wage changes and employment. Unfortunately, there is no consensus on the correct value of elasticity estimate in the literature. The MoF (29.9.2015) uses an elasticity estimate of -0.7 for the private sector.

Creating new jobs and reducing unemployment are remarkably important goals in the current situation where Finland is. But how effective it is to reduce labour costs? It may be possible that in reality labour costs will not be reduced by the total amount of 4.2 percent. In fact, many micro-studies have found that reducing payroll taxation leads to an increase in wages, with the result that labour costs remain virtually the same (Benmarker et al. 2009, Johansen & Klette 1997). However, this study concentrates on labour demand elasticities. Combined with the information about the actual reduction in the labour cost, the applicable elasticity estimate offers a convenient way to estimate employment effects of any similar policy decision.

The idea of this study is based on the Economic Policy Council Report (2016, 86-91), which argued that the government's estimate for labour demand elasticity is very high and predicts overly optimistic employment effects. The majority of studies estimate demand elasticities using aggregate data. Such studies lack exogenous variation in labour costs, which makes it impossible to measure the causal impacts of labour costs on employment in a reliable way. In this study, problems related to elasticity estimates based on aggregate data are first considered through economic theory. After that the analysis proceeds to empirical calculations that demonstrate the magnitude and direction of the bias.

Lichter et al. (2014) provide an extensive view of the empirical literature related to the own-wage elasticity of labor demand. They conduct a meta-regression analysis to re-assess empirical studies of labor demand elasticities. Their analysis is based on 924 elasticity estimates obtained from 105 studies. The sample comprises estimates from studies for 37 countries published between 1980 and 2012. The overall mean own-wage elasticity of labor demand in their sample is -0.51, with a standard deviation of 0.77. On the basis of these estimates, the elasticity of -0.7 does not seem impossibly high. However, Lichter et al. (2014) claim that many estimates of the own-wage elasticity of labor demand given in the literature are unreasonably high and upwardly inflated, and their preferred estimate of the constant output elasticity is -0.25.

The central idea in this study is to show that estimating labour demand elasticities based on aggregate-level macro-data is likely to produce biased and unreliable estimates. The problems relate in particular to i) the simultaneity of demand and supply, ii) the lack of exogenous variation in labour costs, and iii) the possibility of composition bias. Firstly, in estimating labour demand elasticities it is essential to understand the simultaneity of demand and supply. The supply of labour is generally neither perfectly elastic nor inelastic. Thus elasticity of labour demand should not be estimated without taking into account the supply of labour. Secondly, using aggregate data in estimating labour demand elasticities is problematic since such data lack exogenous variation in labour costs. Wages and employment are both endogenous variables, which constitutes a problem.

The third issue considered is the composition bias that has been previously connected mostly to the context of real wage cyclicalities. Solon et al. (1994) write that working hours of low-wage groups are more cyclically variable. This means that the aggregate wage statistics give more weight to low-wage workers during expansions than during recessions. Their key finding is that this composition effect biases the aggregate wage statistics. If aggregate wage statistics are biased due to the composition bias, there is reason to believe that elasticity estimates based on such data are also biased.

In the empirical part of my study I examine potential bias in labour demand elasticities that are estimated by using macro-data. The analysis is conducted by utilizing differently formed wage variables. Since the same model and the same period are used for every wage variable, the differences between elasticity estimates are likely to provide evidence of potential bias. The composition bias free wage growth data is based on Kauhanen & Maliranta (2012), and it reflects the average wage growth rate of people who continue in the same firm. The idea of using this data is to construct a wage statistic without cyclically shifting weights, which means that the potential composition bias is removed. Then comparing a biased elasticity estimate with an unbiased one provides information about the importance and magnitude of the bias.

A relevant elasticity estimate should be based on research containing exogenous variation in wages. Whereas elasticity estimates based on aggregate data suffer from a lack of exogenous variation in labour costs, there are some studies that avoid this problem. In order to predict what happens to employ-

ment when labour costs are reduced, one can study cases where labor costs are reduced in reality. For example wage subsidies and payroll tax cuts induce exogenous variation in labour costs, so they provide promising opportunities to estimate labour demand elasticities. This study contains a small meta-analysis of micro-studies examining situations where labor costs have been altered exogenously. These studies use the difference-in-differences (DiD) method to examine the effects of policy changes that reduce labour costs, and the resulting elasticities can be interpreted to be causal employment effects of reducing labour costs.

This study proceeds as follows. Section 2 provides a starting point for this study by introducing the theoretical framework and concept of the elasticity of labour demand. In addition, it presents the common way how the majority of studies estimate labour demand elasticities based on aggregate data. Section 3 focuses on internal validity of such studies and focuses especially on the problems that relate to the simultaneity of demand and supply, and the lack of exogenous variation in labour costs. Moreover, the effects of the potential composition bias are also considered. Section 4 starts the empirical part of this study by presenting the data and method. In section 5, labour demand elasticities are estimated by conventional means as presented in section 2. Comparing the elasticity estimates resulting from the same estimation equation but differently formed wage variables provides some interesting information of potential bias in labour demand elasticities that are estimated by using macro-data. Section 6 considers how potential measurement error in working hours affects elasticity estimates. This analysis is conducted by using Monte Carlo simulation method to generate data that is similar to the data in sections 4 and 5. Whereas previous sections focus on problems in macro-estimates, section 7 conducts a small meta-analysis of relevant micro-studies that estimate labour demand elasticities based on cases when labor costs have been altered exogenously. Finally, section 8 concludes.

## 2 THEORETICAL FRAMEWORK

### 2.1 Elasticity of labour demand

First of all, it is important to understand the concept of the elasticity of labour demand properly. The own-wage elasticity of labour demand reflects how responsive labor demand is to changes in labour costs (Lichter et al. 2014, 1), which makes it practical in drawing policy conclusions on employment effects of reducing labour costs. A point estimate for the elasticity of labour demand indicates the percentage increase in labour demand if labour costs are reduced by 1%. In other words, it is the percentage change in demand for labour divided by the percentage change in labour costs. It is useful to have this kind of measure reflecting the relations between exogenous wage changes and the determination of employment.

$$\text{Elasticity of labour demand} = \frac{\% \text{ change in demand for labour}}{\% \text{ change in labour costs}}$$

Let us start by considering theory of the elasticity of labour demand. The theory of labour demand has been greatly contributed by Daniel Hamermesh. Hamermesh (1986) focuses on the long-run static theory of labor demand and examines the long-run effects of exogenous changes in wage rates. He writes that readjustments of labour demand appear to happen rather fast, which means that the parameters describing labor demand in the long run are useful in evaluating the near-term effects of changes in labour costs (Hamermesh 1986, 430). Thus, employment effects of the competitiveness pact are more likely to be realized in the near future, rather than after decades.

Let us examine two-factor case that includes only homogenous labour and capital. Despite the simplicity of this approach, it provides us some informative outcomes. In addition, Hamermesh (1986, 431) notes that labor-demand functions are derived from production and cost functions that were initially developed for the two-factor case. Let us assume that firms maximize their profits and minimize costs, while employers are perfect competitors in both product and labor markets. Assume also that there are constant returns to scale in production. The production function is:

$$Y = F(L, K), \quad F_i > 0, F_{ii} < 0, F_{ij} > 0 \quad (1)$$

where  $Y$  is output,  $K$  is homogeneous capital and  $L$  is homogeneous labour. For a profit-maximizing firm, the marginal value product of each factor equals to its price:



$$F_L - \lambda w = 0 \quad (2a)$$

$$F_K - \lambda r = 0 \quad (2b)$$

where  $w$  is price of labour,  $r$  is price of capital and  $\lambda$  is a Lagrangean multiplier. For the firm, there is also the constraint:

$$C - wL - rK = 0 \quad (2c)$$

In linear homogeneous two-factor case, the elasticity of substitution ( $\sigma$ ) between the capital and labour is:

$$\sigma = \frac{d \ln\left(\frac{K}{L}\right)}{d \ln\left(\frac{w}{r}\right)} = \frac{d \ln\left(\frac{K}{L}\right)}{d \ln\left(\frac{F_L}{F_K}\right)} = \frac{F_L F_K}{Y F_{LK}} \quad (3)$$

$\sigma$  reflects the effect of a change in relative factor prices on relative inputs of the two factors, while holding output constant. The own-wage elasticity of labour demand at a constant output and constant  $r$  is:

$$\eta_{L,w|y} = -(1 - s) \sigma < 0 \quad (4)$$

where  $s = wL / Y$ , the share of labour in total revenue. This constant output elasticity of labour demand reflects only substitution along an isoquant. It does not include the scale effect. If labour costs decrease, the cost of producing a given output decreases too. As a result, the price of the product will decrease, which will increase the quantity of output sold. This scale effect depends on the elasticity of product demand ( $\varepsilon$ ) and on the share of labour in total costs. Adding scale effect gives:

$$\eta_{L,w} = -(1 - s) \sigma + s \varepsilon \quad (5)$$

This total elasticity of labour demand includes both substitution and scale effects. But which one of these two elasticities is more relevant to the policy analysis? A large number of studies focuses on estimating constant output elasticities. Also Hamermesh (1986, 432) recommends using constant output elasticities since the output is assumed to be constant while full employment. However, unemployment being very high in Finland, the output is likely to be below its natural level. As a result, reducing labour costs should boost the output, which suggests the existence of scale effect. Due to the scale effect, the total elasticity of labour demand should be higher in absolute terms than constant output elasticity. Thus cutting real wages should increase employment more, when also scale effect is taken into account.

## 2.2 Macro-studies

In this section I review macro-studies that estimate labour demand elasticities based on aggregate data. Knowing the common estimation method enables us to evaluate it and consider its problems more closely. It is also useful to get some idea of the magnitude of such labour demand elasticities. Lichter et al. (2014) provide an excellent starting point while they conduct an extensive review of the empirical literature related to the own-wage elasticity of labor demand. They conduct a comprehensive meta-regression analysis to re-assess the empirical studies on labor demand elasticities. Their analysis is based on 924 elasticity estimates obtained from 105 different studies, and this sample comprises estimates from studies published between 1980 and 2012 for 37 different countries. The results of this meta-study are likely to offer a useful survey of characteristics and results of macro-studies that estimate labour demand elasticities.

The overall mean own-wage elasticity of labor demand in their sample is -0.51 with a standard deviation of 0.77. An elasticity estimate of -0.7 is not impossibly high on this basis. However, Lichter et al. (2014, 19) claim that many estimates of the own-wage elasticity of labor demand given in the literature are unreasonably high and upwardly inflated, with a mean value larger than -0.5 in absolute terms. According to them, differences between elasticity estimates are due to the different methods and terms of specification. They also point out the significant effect of the publication selection bias, which means that generally researchers report only significantly negative own-wage elasticities. They find substantial evidence for publication selection bias in their sample of different studies. As a result, they conclude that estimates of the own-wage elasticity of labor demand are upwardly inflated. Their preferred estimate for the long-run, constant output elasticity is -0.25, bracketed by the interval [-0.072; -0.45]. It is obtained from a structural-form model using administrative panel data at the firm level, with control variables having mean characteristics.

There are various ways and different methods to estimate labour demand elasticities. In addition to the magnitude of elasticity estimates, Lichter et al. (2014, 7-11) offers us a review of common estimation methods with similarities and differences between them. Firstly, estimates of the constant-output elasticity of labor demand outnumber the estimates of the total demand elasticity. As previously considered, the total elasticity might be more relevant in assessing the employment effects of the competitiveness pact. Secondly, elasticities can be based on datasets collected at the industry-level or firm-level. Even if a firm-level data is likely to provide more accurate information, it may not be easily available. In the empirical part of my study elasticities are estimated based on industry-level data. Thirdly, there are two kinds of empirical models in estimating elasticities: reduced-form and structural-form models.

In structural form models, regression equations are explicitly linked to theory and own-wage elasticities are calculated from the obtained empirical

equation parameters. In turn, reduced-form models are normally based on log-linear specifications of unconditional and conditional labor demand models. These models are more flexible with respect to the variables included and coefficients are directly interpretable as elasticities (Lichter et al. 2014, 6). Also the empirical part of this study estimates elasticities using reduced-form models.

It is important to notice that there appears to be differences between the average results of reduced-form models compared to structural models. Lichter et al. (2014, 11) find that, on average, the constant-output elasticity of labor demand is significantly lower in absolute terms when being derived from a structural-form compared to elasticity estimates resulting from reduced-form models. Moreover, the total-output elasticity of labor demand appears to be significantly higher when being derived from a structural-form model. An interesting observation is that estimates of the total and constant-output elasticities do not differ in case of being obtained from a reduced-form model. Since reduced-form models are used in the empirical part of my study, this observation suggests that choosing between constant-output and total elasticity is not very crucial after all. However, what is important is that there are various possible models that can be used in estimating elasticities, and they appear to result in different results.

Before assessing potential bias in macro-estimates, it is useful to have some information on the estimation methods. Next I introduce a couple of typical studies and their estimation equations as an example. I will be using very similar methods in the empirical part of my study in sections 5 and 6. Godart et al (2009, 8) provide a good example of the most common empirical method to estimate the own-wage elasticity of labour demand. Like many other studies, they assume that labour supply is perfectly elastic. Then they take logs on both sides of the equation and have a log-log relationship that can be estimated and interpreted as elasticity of labour demand:

$$\ln(L_{it}) = \eta \ln w_{it} + \delta \ln Y_{it} + \gamma \ln r_{it} + \varepsilon_{it} \quad (6)$$

This estimation formula includes labour (L) that is explained with the wage rate (w) and cost of capital (r). In addition, the equation contains also output (Y). Since output is controlled, the resulting elasticity estimates are constant output elasticities. Hijzen and Swaim (2010) provide an example of estimating both the constant-output elasticity of labour demand and the total elasticity of labour demand. They estimate the constant-output elasticity by using conditional model, and total elasticity of labour demand by using unconditional labour demand model. Log-linear specifications of these conditional and unconditional labour demand models produce coefficients that can be interpreted as elasticities (Lichter et al. 2014, 6).

$$\ln L = \alpha_0 + \eta_c \ln w + \beta \ln k + \delta \ln y + \varepsilon \quad (7)$$

$$\ln L = \alpha_0 + \eta_u \ln w + \beta \ln k + \varepsilon \quad (8)$$

where  $L$  is industry-level labour demand,  $w$  is the price of labour,  $k$  is the capital stock and  $\varepsilon$  is a random error term. Since the output ( $y$ ) is controlled in the conditional model (7), it produces constant-output elasticities. In this model the profit-maximising level of labour demand is determined by minimizing the costs of production conditional on output. The unconditional labour demand model differs from the previous one by taking into account both substitution and scale effects. Thus, it is interpreted as the total elasticity of labour demand. Following Hamermesh (1993), it can be estimated by omitting the output from the unconditional labour demand function. In the unconditional labour-demand model, a firm maximizes its profits by adjusting hiring so that the marginal value product of labour equals the wage (Hijzen & Swaim 2010, 1020).

Lichter et al. (2014, 11-14) highlight the fact that there is considerable heterogeneity between estimates of labor demand elasticities. They identify sources of variation in the absolute value of this elasticity. They state that heterogeneity due to the theoretical and empirical specification of the labor demand model, different datasets used or sectors and countries considered explains more than 80% of the variation in the estimates. Their results suggest that there is not one unique value for the own-wage elasticity of labor demand. According to them, heterogeneity matters with respect to several dimensions:

- low-skilled vs. high-skilled labour
- differences across industries
- differences across countries
- short-run vs. long-run
- time period

The different elasticities between low-skilled and high-skilled labour suggest that the composition bias, which was briefly introduced in the introduction, might be important also in the context of labour demand. Lichter et al. (2014, 11) find that the elasticity of labor demand for unskilled labor is significantly higher than for the overall workforce. Thus demand for low-skilled labor is more responsive to changes in the wage rate than the demand for high-skilled or medium-skilled workers. They suggest a possible explanation that low-skilled tasks might be easier substituted by capital or outsourced to low-income countries. They also note that the majority of studies in their dataset do not account for heterogeneity in the workforce. In my study, the potential composition bias will be considered in section 3.3.

It is interesting to remark that there are significant differences in labour demand elasticities between industries. This suggests that when the government reduces labour costs, it might have different effects on different sectors. Sectoral differences in labor demand might also explain differences in elasticity estimates of labor demand, as some sectors are more dependent on labor than others. For example, Lichter et al. (2014, 14) find that labor demand is significantly less elastic in the food and beverages industry whereas it is significantly more elastic in the basic metals industry. More than 50% of the studies focus on

the manufacturing sector. Only few estimates refer to the service and construction sectors, whereas 35% of the estimates apply for the overall economy. However, in the context of the competitiveness pact the most important are the impacts on overall economy.

There are differences in the own-wage elasticity of labor demand across countries, too. Institutional regulations on employment protection and dismissal may crucially affect firms' demand for labor. As these regulatory rules differ across countries, it is in line with expectations to find differences in the own-wage elasticity of labor demand between different countries. Elasticities are significantly higher in absolute terms for the UK and Ireland, as well as in many Eastern European countries. In contrast, labor demand is found to be less elastic in Mexico and Peru (Lichter et al. 2014, 14). In addition, they report that labor demand is less elastic in the short-run than in the intermediate and long-run. Their meta-regression results show that labor demand has become more elastic over time. These results suggest that labour demand elasticities estimated for other countries or periods might not be directly applied to modern-day Finland.

This review on macro-studies offered us many interesting aspects of the elasticity of labour demand. However, it did not provide us a very accurate elasticity estimate that could be applied to assessing the employment effects of competitiveness pact. While Lichter et al. (2014) conducted meta-study, they reported that the average own-wage elasticity of labor demand in their sample was -0.5, with a very wide confidence interval. They also claimed that this estimate is upwardly biased. There are various possible theoretical and empirical specification of the labor demand model that appear to result in very different elasticity estimates. Furthermore, like many other studies, also Hijzen & Swaim (2010) estimate labour demand elasticities by assuming that labour supply is perfectly elastic. They admit that validity of this assumption can be questioned at the industry level, and as a result, the elasticity estimates of labour demand will be biased to the extent that this identifying assumption is violated (Hijzen & Swaim 2010, 1025). Next, my study proceeds to examine problems and potential sources of bias in macro-studies that estimate labour demand elasticities using aggregate data.

### 3 PROBLEMS IN MACRO-STUDIES

Surprisingly many macro-studies that estimate labour demand elasticities suffer from threats to internal validity. Studies based on regression analysis are internally valid if the estimated regression coefficients are unbiased and consistent. Moreover, hypothesis test should have the desired significance level, and confidence intervals should have the desired confidence level. Such studies provide statistical inferences about causal effect that are valid for the population and setting studied. (Stock & Watson 2012, 358.) However, there are various reasons why these requirements might not be fulfilled, which creates threats to internal validity. These threats might lead to failures of some of the least square assumptions in the multiple regression model (Stock & Watson 2012, 240).

1. error term  $u$  has conditional mean zero,  $E(u_i | X_{1i}, X_{2i}, \dots, X_{ki}) = 0$
2.  $(X_{1i}, X_{2i}, \dots, X_{ki}, Y_i), i = 1, \dots, n$ , are independently and identically distributed (i.i.d.) draws from their joint distribution.
3. Large outliers are unlikely:  $X_{1i}, \dots, X_{ki}$ , and  $Y_i$  have nonzero finite fourth moments.
4. There is no perfect multicollinearity.

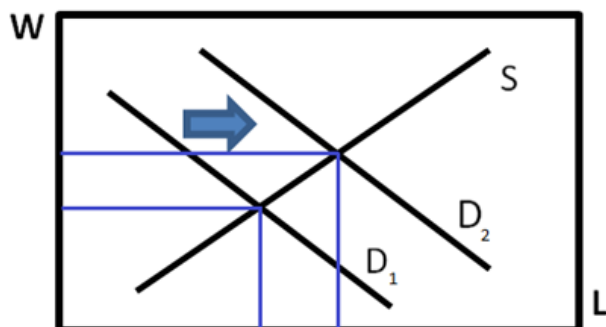
In most cases problems relate to violating the first or the second of these least squares assumptions. If the regressor is correlated with the error term in the regression, regression coefficients are likely to be biased. Stock and Watson (2012, 358) list five reasons why the OLS estimator of the multiple regression coefficients might be biased, even in large samples: 1) omitted variables, 2) misspecification of the functional form of the regression function, 3) imprecise measurement of the independent variables ("errors in variables"), 4) sample selection, and 5) simultaneous causality. Let us consider next more closely problems of simultaneous causality. Moreover, lack of exogenous variation and potential composition bias and its effects on elasticity estimates will also be considered. Errors in variables will be examined in chapter 6.

#### 3.1 Simultaneity of demand and supply

Let us consider the simultaneity of labour demand and labour supply in the framework of demand and supply curves. The idea that reducing labour costs will lead to an increase in employment is consistent with the standard neoclassical labour market theory. The demand for labor depends negatively on labor costs. The higher the labour costs are, the less profitable it is for a firm to hire more employees. This suggests that slope of labour demand curve is negative. One should note that there are also other labour costs than just wages. ( $w <$  labour costs.) Real labor costs consist of wages but there are also employers' social

insurance contributions. Reducing labour costs give a positive shift in the labour demand curve. As a result, the resulting perfect market equilibrium will be a combination of higher employment and higher wages (Stokke 2015, 9). Figure 1 demonstrates this effect of reducing labour costs.

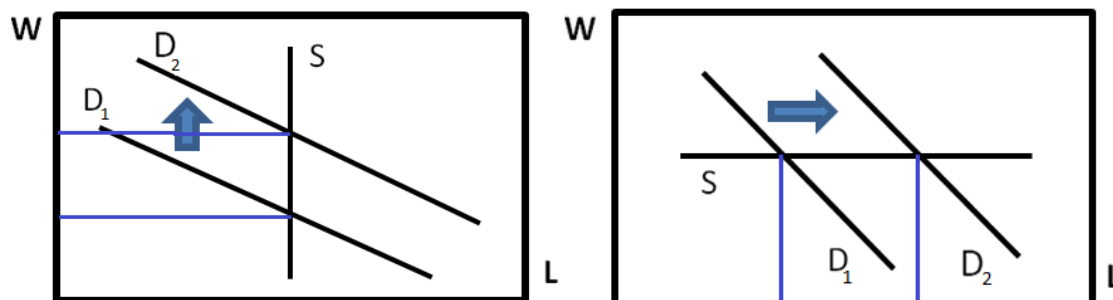
FIGURE 1 Labour demand and reducing labour costs



The magnitude of employment effects depends naturally on how much labour costs are reduced but also the elasticity of labour demand and elasticity of labour supply play a major role. Figure 2a demonstrates perfectly inelastic labour supply. For a given elasticity of labour demand, perfectly inelastic labour supply implies that a decrease in labour costs boosts labour demand but has no impact on employment while wages increase. On the other hand, as figure 2b demonstrates, if labour supply is perfectly elastic, wages remain unaffected while employment increases (Stokke 2015, 9). Presumably the reality is in most cases something between these two extreme situations. The slope of the demand curve, elasticity of labour demand, plays a key role in the size of the resulting employment effect.

FIGURE 2 2a) Inelastic labour supply

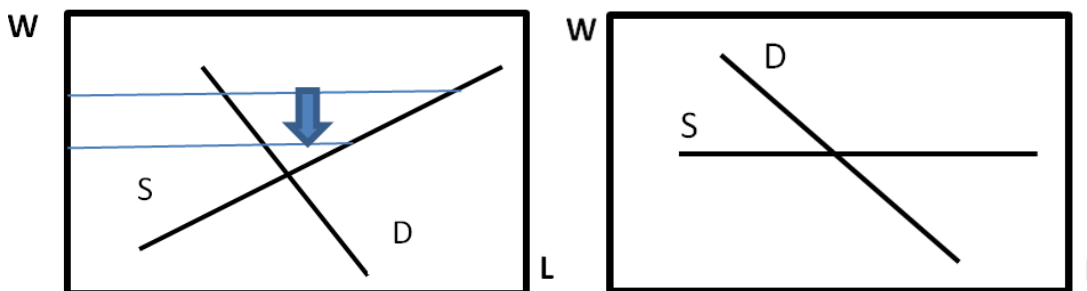
2b) Perfectly elastic labour supply



While assessing the employment effects of lowering labour costs, both labour demand and labour supply should be taken into account. According to Stock and Watson (2012, 366-368), “simultaneous equation bias arises in a regression of  $Y$  and  $X$  when, in addition to the causal link of interest from  $X$  to  $Y$ , there is a causal link from  $Y$  to  $X$ . This reverse causality makes  $X$  correlated with the error term in the population regression of interest”. On this basis excluding the labour supply from the review results in biased elasticity estimates.

FIGURE 3 3a) unionized employment

3b) perfectly elastic labour supply



However, in some cases it might be possible to argue that focusing on the labour demand is enough. Hamermesh (1986, 429) mentions two such cases: i) unionized employment presented in figure 3a and ii) perfectly elastic supply of labor to a subsector that is presented in figure 3b. Honkapohja et al (1999, 75) state that when unemployment is at a high level, the demand for labour determines employment. Then the wage can be viewed as unaffected by labor demand. This means that knowing wage elasticities of labor demand allows one to infer the effects of exogenous changes in wage rates on the amount of labor employers seek to use. Then, the employment impact of reducing labour costs can be discovered using elasticity estimates of labor-demand alone. (Hamermesh 1986, 429.) In the current situation, it may be reasonable to claim that unemployment in Finland is so high that the demand for labor is the limiting factor. At current wages, there are available much more employees than firms are willing to hire. This existence of involuntary employment refers to the situation reflected by Figure. The labour demand curve in itself tells how much employment will rise if labour costs are reduced.

While assessing employment effects of reducing labour costs, it may thereby be possible to exclude labour supply from the review, if unemployment is at a high level. But first, we must have an applicable and reasonable estimate for labour demand elasticity. However, the problem is that there is no consensus about the right value. In addition, labour demand elasticity is likely to vary between countries. In fact, it is probable that elasticity of labour demand is heterogeneous and differs greatly between e.g. low-skilled and high-skilled jobs. There is all reason to believe that labour demand elasticity is negative. Yet, it is problematic if the magnitude is not known in greater detail. Elasticity estimate of -0.3 results in 50 % smaller employment effects than using an elasticity estimate of -0.6. Since the correct value is not known, it must be estimated first. Of course, one can look at the literature in this field and find a huge amount of elasticity estimates. However, one should not just pick up any number without careful consideration. In particular, since a closer look shows that a large part of such studies are potentially prone to contain some bias. A study, which seeks to estimate the magnitude of labour demand elasticity, cannot exclude the supply side. The estimation should take into account both labour demand and labour supply. Thus, it makes sense to evaluate previous studies and their results critically.



### 3.2 Lack of exogenous variation

The lack of exogenous variation in labour costs is a fundamental problem in the macro-studies that estimate labour demand elasticities on the basis of aggregate data. At first it may appear to be a quite abstract issue but it is essential to understand its importance. Aggregate level macro-data reveals only outcomes that are combinations of employment and total labour costs, or more specifically the amount of working hours and their prices. In the context of labour demand elasticities, it is problematic that aggregate-data do not provide information on whether a decline in total wages is due to change in supply, or demand instead. In addition, reducing labour costs is likely to affect both labour demand and labour supply. Thus, when estimating elasticities of labour demand using macro-data, both demand and supply sides should be taken into account, which takes us back to the problem of simultaneous causality.

However, let us continue to another direction by considering data on labour costs. Johansen & Klette (1997, 4) write that identification of labour demand elasticities is completely dependent on good quality of price data. They diagnose two fundamental problems from which empirical research of this field is suffering from. Firstly, prices lack sufficient variation in many cases. This due to the fact that it is often difficult to obtain prices other than at aggregate levels. This tends to limit the information that can be obtained from cross sections of data. The second problem they state is that cross sectional or longitudinal variation in factor prices may reflect quality differences or other forms of heterogeneity. For example calculating hourly wage rates from plants' wage bills and hours worked is problematic. Variation in this kind of hourly wage data may reveal little information about real cost differences, if labour is not homogeneous. (Johansen & Klette 1997, 5). Actually this problem of composition bias will be considered in more detail in section 3.3.

As the Economic Policy Council report (2016, 86) notes, it is problematic to use aggregate data in estimating labour demand elasticities since such data lack exogenous variation in labour costs. Wages and employment are both endogenous variables, which constitutes a problem. If the purpose is to make policy analysis and predict the effects of reducing labour costs, it is necessary to have exogenous variation in labour costs. Thus causality interpretations made on the basis of aggregate data may be biased and even questionable. However, in estimating employment effects our intention is to make causal interpretations. The question is that how is it possible to obtain required exogenous variation in labour costs?

Studying a policy change that reduces labour costs of some worker group while labour costs of another comparable group remains the same provides some useful information on the causal employment effects of reducing labour costs. In such case one knows the source of variation in the explanatory variables. When using a quasi-experimental method, one compares the growth in employment in the treated group to that of a control group. This kind of

analysis offers more reliable results about how a reduction in labor costs affects employment, and in the best case more accurate elasticity estimates too. (Johansen & Klette 1997, 5.) This method of using policy induced variation in factor prices as quasi-experiments is a way to get exogenous variation in the explanatory variables.

Kramarz & Philippon (2001) make a very interesting finding that the employment effects of labour cost increases and cost decreases are not symmetric. They study how the changes in total labor costs affect employment. Their study focuses on low-wage workers in France, time period being from 1990 to 1998. Their difference-in-difference estimates for labour cost increase suggest that a 1% increase in costs implies roughly an increase of 1.5% in the probability of transiting from employment to non-employment. According to this result, elasticity is as high as -1.5. However, the results of labour cost reduction seem to be quite different. Similarly to the analysis of increasing costs, they examine if workers who were previously unemployed become employed after the decrease in the minimum cost. When they assess the transitions from non-employment to employment, tax subsidies seem to have an impact on entry from non-employment, but this effect is not significantly different from zero. The point estimate is as low as -0.03. (Kramarz & Philippon 2001, 21-24.) The difference in elasticities between situations of increasing costs versus decreasing costs appears to be surprisingly large. It suggests that the labour cost decreases seem to have very different employment effects than labour cost increases.

The observation that the effects of decreasing labour costs and increasing them are not symmetric is a very important finding. It suggests that elasticities based on macro-data are biased if they are used to estimate exclusively the impact of reducing labour costs. This is because wages are rising in general while wage reductions are exceptions to this trend. Thus such studies give unintentionally really high weight to the effects of wage rises at the expense of the wage reductions. When the interest is to assess employment effect of reducing labour costs, we should have such data that offers us the opportunity to concentrate on it. In order to obtain reliable estimates, wage increases must be excluded. For this reason, macro data and studies based on it appear to provide biased elasticity estimates for labour cost reductions. In fact, this observation suggests that there more than one value for own-wage elasticity of labour demand. One for rising labour costs and then another for decreasing costs. If we are interested in how reducing labour costs affects employment, we should use appropriate estimates for that.

In order to get reliable elasticity estimates that reflect effects of decreasing labour costs, one needs to survey cases when labour costs have been lowered in practice. Rather than macro-data, such studies are based on micro-data that contains exogenous variation in the price of labor. As Kramarz & Philippon (2001, 18) point out, a key feature and advantage of these micro-studies is that a decrease in labour costs affects only employers. Since the benefits that accrue to the workers remain unchanged, the experiments do not affect labor supply at all. Therefore it is possible to focus on examining the demand side only. To sum up, a relevant elasticity estimate should be based on research that contains exog-

enous variation in labour costs. There are some micro-studies that examine situations where labor costs have been changed exogenously. They will be considered more closely in section 6.

### 3.3 Composition bias

The composition bias is one more problem that is likely to cause bias in elasticity estimates based on macro-data. The literature considering the composition bias concentrates mainly exclusively on its effects on real wage cyclicality. However, data on real wages plays a key role when labor demand elasticities are estimated based on aggregate level macro-data. It is therefore plausible to think that the composition bias might be a relevant issue also in this new context. The calculations in the empirical part of this study include an attempt to analyse the magnitude and direction of the bias in elasticity estimates. In order to investigate the importance of the composition bias in estimates of labour demand elasticity, it is crucial to understand why it matters in the context of real wages first.

The pro-cyclicality of real wages means that real wages rise during expansions and fall during recessions. This means that real wages increase when output and employment increase. Aggregate time series data displays only weak cyclicality of real wages. In fact, real wages might appear to be even counter-cyclical in such data. According to Abraham and Haltiwanger (1995, 1235), it is not possible to determine whether aggregate real wages are procyclical or countercyclical based on aggregate data. Solon et al (1994, 3) state that the composition bias obscures pro-cyclicality of real wages in aggregate time series data. According to them, the apparent weakness of real wage cyclicality in the United States has been caused by this statistical illusion.

In literature, there are strong evidence of the composition bias in the context of real wages. According to Solon et al (1994, 3) evidence from longitudinal surveys that have tracked individual workers show that real wages have been highly pro-cyclical even though aggregate real wage data for the same period have not been nearly so pro-cyclical. Also Abraham and Haltiwanger (1995, 1260) conclude that in data for the 1970s and 1980s, there is a significant countercyclical composition bias in standard aggregate real wage series and in estimates of real wage cyclicality based on them. After controlling for this composition bias, real wages were strongly procyclical over the 1970s and 1980s. Thus, real wages are considerably more pro-cyclical than they appear in aggregate time series data afflicted by the composition bias.

The reason for the composition bias is that hour shares of different groups vary with the business cycles. According to Solon et al (1994, 7), the work hours of low-wage groups tend to be more cyclically variable compared to those of high-wage groups. Low-wage workers experience more cyclical non-employment compared to high-wage workers, which means that low-paid

workers are more likely to lose their jobs during an economic downturn (Abraham & Haltiwanger 1995, 1245). Since hour shares of low-wage groups tend to be pro-cyclical, aggregate wage statistics commonly used in time series studies give more weight to low-skill workers at business cycle peaks than during recessions (Solon et al 1994, 7).

The composition bias causes aggregate wage statistics to be biased in a countercyclical direction. Since the weight for low-wage workers is larger at business cycle peaks than during recessions, a conventional real wage measure falls less during a cyclical downturn compared to a composition-constant measure (Abraham & Haltiwanger 1995, 1252). The composition bias in aggregate data is therefore likely to obscure the degree of real wage pro-cyclicalities that a typical worker in any group really faces (Solon et al 1994, 7). Thus, the true procyclicality of real wages cannot be detected using aggregate time series data.

Bowlus et al (2002, 309-311) continue this discussion by considering potential bias in aggregate employment. According to them, the composition bias affects the parameters of interest unless both the price and the quantity of the labour input are adjusted appropriately. They state that if there is bias in estimating the "true" aggregate wage because of composition changes, there is likely to be bias in estimating the "true" aggregate employment. They detect that estimators that correct for the price only suffer from smaller bias than those that correct for neither. However, some composition bias will remain if only the wage measure is corrected. They report that corrected estimates of the implied labour supply elasticity are smaller compared to estimates of previous literature. (Bowlus et al 2002.) This suggests that labour demand elasticities might suffer from similar problems, and one should use corrected measures for both the input price and its quantity.

Since the composition bias causes a significant countercyclical bias in aggregate real wage measures, it is also likely to affect estimates of elasticity of labour demand that are based on aggregate data. The estimation equation of the own-wage elasticity of labour demand contains two main variables that are employment and labour costs. The close connection between labour costs and real wages means that the composition bias should be taken into account when labour demand elasticities are estimated based on aggregate time series data.

Let us consider the direction of the composition bias in elasticity estimates. During a recession employment decreases so that the proportion of low-wage workers decreases. As a result, it is possible that aggregate real wages rise during a cyclical downturn when employment decreases. At business cycle peaks the proportion of low-wage workers increases, which means that aggregate real wages might even fall. The negative elasticity of labour demand means that employment rises while labour costs reduce. Thus, the composition bias is likely to cause elasticity estimates to be too negative when aggregate time series data is used. Not surprisingly, many such studies report strongly negative elasticity estimates.

Knowing that real wages are procyclical in reality allows us to consider unbiased elasticity estimates. The procyclicality of real wages means that real

wages rise during expansions and fall during recessions. Thus real wages increase as output and employment increase. In a cyclical downturn employment falls and real wages of those who maintain their jobs decrease or at least remain unchanged. This all seems to suggest that there could be a positive relationship between real wages and employment. Also recent studies utilising policy-induced variation in labour costs tend to produce much lower elasticity estimates than studies based on aggregate data.

Knowing how it is possible to detect the actual cyclical nature of real wages might be useful also in the context of labour demand elasticities. Hamermesh (1986) states that since the problem in aggregate wage data is cyclically shifting weights, the most direct solution is to construct a wage statistic without cyclically shifting weights. Doing so is straightforward if one has access to longitudinal microdata. Then one can hold composition constant by following the exact same workers over time with fixed weights (Hamermesh 1986). According to Abraham and Haltiwanger (1995, 1246-1247), suitable data would contain average wages in the indicated periods for the sample of persons employed in both period  $t$  and period  $t-1$ . Provided that the wage changes experienced by persons in the panel for a given pair of years are comparable to the potential wage changes for persons for whom the data are missing, one can use such data to derive an unbiased estimate. However, they point out that potential importance of sample selection bias has to be recognized.

A similar method is likely to be very useful in detecting the importance of the composition bias in estimates of the elasticity of labour demand. First, estimating the labour demand elasticity based on aggregate real wage data results in an elasticity estimate that suffers from the standard sort of composition bias. Then using the same model with a preferable real wage measure should produce unbiased elasticity estimates. Comparing the elasticity estimate that is based on aggregate real wage measure to an estimate based on microdata is likely to reflect the direction and the magnitude of the composition bias.

To sum up, since aggregate wage statistics are biased due to the composition bias, there is reason to believe that elasticity estimates based on such data are also biased. In the empirical part of my study I will examine this by utilizing differently formed wage variables. The composition bias free wage growth data is based on Kauhanen & Maliranta (2012). It reflects the average wage growth rate of people who continue in the same firm. The idea of using this data is to construct a wage statistic without cyclically shifting weights, which means that the potential composition bias is removed. Then, comparing a biased elasticity estimate with an unbiased one provides information about the importance and magnitude of composition bias.

## 4 DATA AND METHOD

### 4.1 Method

In the empirical part of my study I examine potential bias in labour demand elasticities that are estimated by using macro-data. In section 5, labour demand elasticities are estimated by using common macro methods as presented in section 2. As told before, the problems are particularly related to the simultaneity of demand and supply, the lack of exogenous variation in labour costs and possibility of composition bias. Like many other macro-studies, the macro-models used in this study do not take into account the first two problems. In the background there is the assumption that the labour supply is perfectly elastic.

Labour demand elasticities are estimated by using differently formed wage variables. Comparing the elasticity estimates resulting from the same estimation equation but differently formed wage variables provides some interesting information of potential bias in labour demand elasticities that are estimated by using macro-data. The constant-output elasticity acts as a starting point but the actual comparison of different wage variables is conducted by using total elasticity of labour demand. The estimation equations are presented with the results in section 5 in order to demonstrate the large effects of small differences between those equations.

All the estimation formulas include labour ( $L$ ) that is explained with the wage rate ( $w$ ). A conditional model such as (7) includes output ( $Y$ ) as a control variable and the resulting estimates are constant-output elasticities. An unconditional labour-demand model, such as (8), represents the total elasticity of labour demand. Following Hamermesh (1993), it can be estimated by omitting the output, which means that there will be only one regressor explaining working hours. Log-linear specifications of these conditional and unconditional labour demand models produce coefficients that can be interpreted as labour demand elasticities (Hamermesh 1993).

Rather than estimating labour demand elasticities that can be used in policy analysis, the idea of these calculations is to demonstrate how commonly used methods in macro-studies are likely to produce biased elasticity estimates. However, it should be noted that keeping the estimation equations simple and without control variables may lead to omitted variable bias. This bias arises if the regression does not include a variable that determines working hours ( $L$ ) and is correlated with one or more of the included regressors. Omitted variable bias may lead to correlation between regressors and the error term, which violates the least squares assumptions (Stock & Watson 2012, 358).

These calculations should provide some interesting information about the impact of composition bias. I estimate labour demand elasticities based on wage data that suffers from the standard sort of composition bias. Then I use

the same model to estimate elasticity by using better wage data that is free from composition bias. The magnitude of bias can be detected by comparing the estimated elasticity based on aggregate real wage measure to an estimate based on microdata. Since the same model and period are used for every wage variable, the differences between estimated elasticities are likely to provide some interesting information on potential bias.

Section 6 continues the empirical analysis by examining how measurement error in working hours affects elasticity estimates. Using Monte Carlo simulation method it is possible to generate data that is similar to the data used in the previous calculations. Effects of measurement error are examined by increasing gradually the variance of the total hours worked (L) in the industry.

## 4.2 Data

When estimating the own-wage elasticity of labour demand, employment is dependent variable and labour costs the independent variable. In addition to these, an estimation equation may also include output as a control variable. The calculations in this report are based on industry-level data. Twenty-six industries are considered, based on the Standard Industrial Classification (TOL2008). Some industries are combined in order to verify the comparability of the data and results. All the data cover the years 1996–2013, while some data are available since 1975. Although similar data on the general government are also available, this study focuses on the private sector.

TABLE 1 Summary of data

Variable	Label	Obs	Mean	Std. Dev.	Min	Max
<b>W</b>	Total labour compensation by industry, 1,000,000 €	468	2310.84	2418.366	173	12 305
<b>L</b>	Total working hours by industry, 1,000,000 h	468	87.81	96.00	8.2	489.7
<b>Y</b>	Total output by industry (2010 prices), 1,000,000 €	468	8412.34	6819.10	817	31 301
<b>P</b>	Producer price index	468	0.888	0.069	0.796	1.013
<b>W/L</b>	"Real wage" by industry	468	30.190	7.091	16.815	59.462
<b>ΔL</b>	Logarithmic %-changes in working hours	442	0.0028	0.0526	-0.237	0.204
<b>ΔY</b>	Logarithmic %-changes in output	442	0.0200	0.0817	-0.324	0.332
<b>Δ(W/L)</b>	Logarithmic %-changes in "real wage"	442	0.0196	0.0448	-0.110	0.317
<b>RAGR</b>	Real aggregate wage growth	468	0.0323	0.0401	-0.189	0.387
<b>RWHR</b>	Real wage growth of job stayers	468	0.0312	0.0372	-0.199	0.343

Data on working hours represent employment. The annual data on hours worked in corporations by industry (1975-2014) are obtained from Statistics Finland's Annual national accounts. Output by industry at basic prices using year 2010 prices is obtained from the same source. The panel data on total labour compensation (W) by industry in 1975-2014 is obtained from Statistics Finland's Productivity surveys. This annual private sector data are in nominal form, and are therefore converted into real form using the Producer price index for manufactured products, the base year being 1949. The real wage variable (W/L) is formed by dividing total labour compensation (W) by the number of hours worked (L) in each industry for each year.

A special feature in this study is the idea of using several wage growth variables, which are formed in different ways. The three wage growth variables representing  $\Delta w$  are 1)  $\Delta(W/L)$ , 2) AGR 3) WHR. Since the same model is used for every wage variable, the differences between elasticities provide interesting information. While making interpretations, it is essential to understand how these wage variables differ from each other.

#### 4.2.1 Biased wage variables (W/L) and $\Delta(W/L)$

The real wage variable (W/L) is formed by dividing total labour compensation (W) by the number of hours worked (L) in each industry for each year. Since the preferred wage variables are available only as changes, W/L is converted into  $\Delta(W/L)$ , which represents wage changes. This logarithmic percentage change in real wage is calculated using natural logarithms and the following formula:

$$\Delta(W/L)_t = \ln\left(\frac{(W/L)_t}{(W/L)_{t-1}}\right) = \ln(W/L)_t - \ln(W/L)_{t-1} \quad (9)$$

When estimating the own-wage elasticity of labor demand, the dependent variable is working hours, which represents employment. The wage variable is as an independent variable in the estimation equation. Since the working hour data is also a component of the wage variable  $\Delta(W/L)$ , there will inevitably be some bias in the elasticity estimates. However, Abraham & Haltiwanger (1995) notice that the majority of studies use similar wage measure in their analysis. It is a common method to divide the total payroll during some period by the total number of hours worked during that same period, and use it as a measure of average hourly earnings.

As already told, there are many sources of bias. Hamermesh (1996, 60-71) questions studies that estimate elasticities based on such data. Firstly, the simultaneity of demand and supply should also be taken into account because labour supply is unlikely to be either perfectly elastic or inelastic. Consequently, estimating elasticities without a complete system including supply is unsatisfactory. In addition, Hamermesh highlights that there should be exogenous variation in wage data or working hours. According to him, variations in the measured price of labour may be the spurious result of shifts in the distribution of em-



ployment or hours among sub-aggregates with different labour costs. In addition, variation may also be due to the changes in the amount of hours worked at premium pay. As a result, any such study that relates working hours to real wages generates biased elasticity estimates.

According to Hamermesh (1996), studies which create their own aggregates by examining substitution among very narrowly defined groups of workers, or even among individuals, are more believable than those that take published aggregates and analyze elasticities for them. Yet, in many studies workers are just added up, and their earnings are simply summed and divided by worker-hours to yield the group's wage rate.

#### 4.2.2 AGR and WHR as preferred wage variables

In order to demonstrate the significance of the bias in labour demand elasticities, it is important to find a valid measure for the price of labour. The panel data on the wage variables AGR and WHR is obtained from Mika Maliranta, and the calculation methods are described in Kauhanen and Maliranta 2012. They study the dynamics of the standard aggregate wage growth in macro statistics using micro data, focusing on how job and worker restructuring influence aggregate wage growth and its cyclicity. Using comprehensive longitudinal employer-employee data, they measure the growth rate of average wages (the standard aggregate growth rate, AGR) and the average wage growth rate of job stayers (WHR).

These data covers the years 1996–2013, and the 26 industries are based on the Standard Industrial Classification (TOL2008). The original wage data were obtained from the Confederation of Finnish Industries (EK), being based on an annual survey of employers, which forms the basis of the private sector wage structure data maintained by Statistics Finland. The data include detailed information on wages, job titles, and unique person and firm identifiers and form a linked employer-employee panel that allows people to be followed over time. (Kauhanen & Maliranta 2012, 17.)

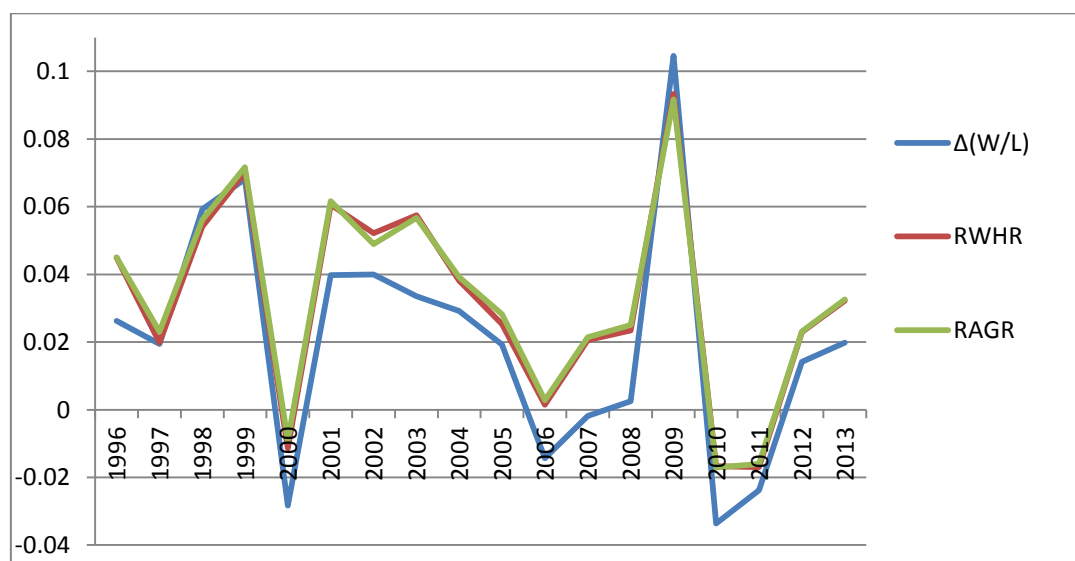
The aggregate growth rate (AGR) is based on Statistics Finland's Wage structure statistics. AGR measures the growth rate of average wages by industry, and using it instead of the original wage variable  $\Delta(W/L)$  corrects a major problem in the elasticity estimates. The cause of the problem is that working hours are simultaneously both dependent variable but also a component of the wage variable. Using the independent wage variable RAGR is a step towards more reasonable elasticity estimates. Since AGR and WHR are originally in nominal form, they are converted into real form so that the estimation results are comparable to the previous real wage data. The conversion is done by using the producer price index for manufactured products:

$$\text{RAGR} = \text{AGR} + \ln \left( \frac{P_{t-1}}{P_t} \right) \quad (10)$$

Even if using the real aggregate growth rate RAGR as a wage variable is less prone to produce biased elasticity estimates than  $\Delta(W/L)$ , there might still be composition bias. When using aggregate wage data, the hour shares of different groups vary with business cycles. The work hours of low-wage groups tend to be more cyclically variable than those of high-wage groups. Thus, aggregate wage statistics give more weight to low-wage workers during expansions than during recessions. This composition effect biases aggregate wage statistics in a countercyclical direction and is likely to obscure the real wage procyclicality that a typical worker in any group really faces (Solon et al 1994, 7).

If aggregate wage statistics are biased due to composition bias, there is reason to believe that elasticity estimates based on such data are also biased. Since the source of the problem is cyclically shifting weights, the most direct solution is to construct a wage statistic without cyclically shifting weights. By following the exact same workers over time, one can keep the composition constant, which results in a wage statistic without cyclically shifting weights (Hamermesh 1986). Comparing the elasticity estimates provides information on the importance and magnitude of the composition bias.

FIGURE 4 Real wage change measures 1996-2013  
(Average of industries, working hours as weight)



Statistics Finland, Maliranta.

The wage growth measure WHR represents the nominal change in hourly wages for people who continue in the same firm. Kauhanen and Maliranta (2012) decompose aggregate wage growth into the wage growth of job stayers and job and worker restructuring. A job stayer is an employee who stays in the same firm for two consecutive years. Such calculations of WHR allow for change of profession because the profession data were not available on an annual basis before 2004. Since the composition remains the same, this average wage growth rate of job stayers is free of composition bias. Kauhanen & Mali-

ranta (2012, 19) find that the aggregate wage growth rate is lower than the wage growth rate of job stayers, so the wages of job stayers increase more rapidly than aggregate wages. Figure 4 shows clearly that  $\Delta(W/L)$  is much lower than either of these.

Kauhanen & Maliranta (2012, 23) also find that aggregate wage growth is much less procyclical than the wage growth of job stayers. This finding that the wages of job stayers are more procyclical than the aggregate wages is similar to the findings of Solon et al. (1994). The procyclicality of real wages means that real wages rise during expansions and fall during recessions. This means that real wages increase at the same time as output and employment increase. During recessions the proportion of low-wage workers decreases, meaning that the conventional real wage measure might even rise during a cyclical downturn. On the other hand, employment falls during recessions. This particularly affects low-wage workers. Thus, in a cyclical downturn, the aggregate average real wage rises while employment decreases. On the other hand, when employment increases at business cycle peaks, the aggregate real wage can even fall as the proportion of low-wage workers increases. As a result, aggregate data are likely to produce excessively negative elasticity estimates.

## 5 RESULTS

### 5.1 Elasticities resulting from (W/L) and $\Delta(W/L)$

The AGR and WHR data cover the years 1996–2013. Therefore it makes sense to use the same period in all regressions in order to ensure the comparability of the elasticity estimates. In the literature, estimates of the constant-output elasticity of labor demand clearly outnumber estimates of total demand elasticity (Lichter et al. 2014). The difference between these two is that output is used as a control variable when estimating constant-output elasticities. When estimating the elasticity of labour demand, employment is the dependent variable and labour costs the independent variable. Let us estimate the following level model where  $L$  is log total working hours by industry,  $Y$  is log output by industry (at 2010 prices), and  $W$  is log real labour compensation by industry.

$$\ln(L_{it}) = \alpha + \eta_{L,W|Y} \ln\left(\frac{W_{it}}{L_{it}}\right) + \beta \ln(Y_{it}) + \varepsilon_{it} \quad (11)$$

Since the estimation equation (11) includes output ( $Y$ ) as a control variable, the coefficient  $\eta_{L,W|Y}$  is interpreted as the constant-output elasticity of labor demand. The resulting parameter estimate from model M1 is -0.55, with a standard error of 0.15. When fixed effects are included (M2), the elasticity estimate is -0.65. The data on  $W/L$  provides an opportunity to study whether using longer period generates divergent elasticity estimates. This is worth examining since elasticities are hardly constant over time. Extending the time interval to cover the years 1975-2013 leads to an even greater elasticity estimate, as high as -0.77, with a standard error of 0.085. These results suggest that the elasticity of labour demand may be high, and the Ministry of Finance's elasticity estimate of -0.7 for the private sector is not far from these results. However, this way of estimating labour demand elasticities suffers from some sources of bias.

In the context of the competitiveness pact, it is a little confusing to use constant-output elasticity instead of total demand elasticity, which also includes the scale effect. When the wage rate decreases, the cost of producing a given output decreases too. As a result, the price of the product will fall, which increases the quantity of output sold. Thus the scale effects must be added in order to obtain the total labour demand elasticity. According to Hamermesh (1986) a direct approach to estimate the total labour demand elasticity would be to estimate an equation like (11) but with output ( $Y$ ) deleted.

$$\ln(L_{it}) = \alpha + \eta_{L,W} \ln\left(\frac{W_{it}}{L_{it}}\right) + \varepsilon_{it} \quad (12)$$

The elasticity estimates of model M3 and M4 are lower and closer to zero than the first estimated constant-output elasticities. Both including and omitting

the fixed effects produce statistically insignificant coefficients, and the coefficients of determination ( $R^2$ ) are also extremely low. These elasticity estimates are estimated using reduced-form models. Lichter et al. (2014) found that, on average, reduced-form models tend to produce higher constant-output elasticities and lower total-output elasticities compared to structural-form models. However, adding scale-effects should result in more negative elasticity estimates. It should be noted that all the elasticity estimates in table 2 are biased, since working hours  $L$  is on both sides of the equation. To correct this problem, the variables  $RAGR$  and  $RWHR$  are used as proper independent wage measures.

TABLE 2 Elasticities resulting from the level model (1996-2013)

Variable	M1 ln L	M2 ln L	M2b (1975-) ln L	M3 ln L	M4 ln L
ln W/L	-0.546*** (0.149)	-0.649*** (0.118)	-0.774*** (0.0853)	-0.269 (0.169)	0.0247 (0.233)
ln Y	0.835*** (0.0268)	0.731*** (0.0937)	0.753*** (0.112)		
constant	-1.36** (0.47)	-0.11 (0.81)	0.12 (0.80)	4.95*** (0.58)	3.96*** (0.79)
Fixed effects	no	yes	yes	no	yes
N	468	468	1014	468	468
R <sup>2</sup>	0.666	0.653	0.659	0.004	0.000

Standard errors in parentheses, \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Since the wage variables  $RAGR$  and  $RWHR$  are available only as changes, it makes sense to compare different wage variables using the change model. Using the same estimation equation and the same time period helps to control all the other factors to keep them exactly the same. Because of this  $W/L$  is converted into  $\Delta(W/L)$ , which represents the logarithmic percentage change in real wages. The elasticity estimates using the wage variable  $\Delta(W/L)$  are directly comparable to the elasticities that are estimated based on  $RAGR$  and  $RWHR$ . The logarithmic percentage change in working hours is the dependent variable and the only explanatory variable is the logarithmic percentage change in real wages.

$$\Delta(L_{it}) = \alpha + \eta_{L,w}\Delta(W/L)_{it} + \varepsilon_{it} \quad (13)$$

During the time period 1996-2013, the resulting total labour demand elasticity  $\eta_{L,w}$  is -0.31, with a standard error of 0.087. Since the variables represent percentage changes, fixed effects do not need to be added to the equation. However, it makes sense to include year-dummies in the equation, because the remaining differences in the wage changes are dominated by the annual variation. When year-dummies are included, the total labour-demand elasticity

$\eta_{L,w}$  is -0.24 with a standard deviation of 0.12. It is again possible to examine how longer period affects results. Table 3 shows that elasticity estimates are similar when the time interval is extended to cover the years 1975-2013.

TABLE 3 Elasticities resulting from the change model

Variable	M5 (1996-) $\Delta L$	M6 (1996-) $\Delta L$	M5b (1975-) $\Delta L$	M6b (1975-) $\Delta L$
$\Delta(W/L)$	-0.312*** (0.0869)	-0.240* (0.119)	-0.265*** (0.0483)	-0.309*** (0.0857)
Year-dummies	no	yes	no	Yes
constant	0.0094*** (0.0025)	0.015 (0.0080)	0.0040 (0.0021)	0.018 (0.011)
N	468	468	988	988
R <sup>2</sup>	0.07	0.28	0.045	0.37

Standard errors in parentheses, \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## 5.2 Elasticities resulting from AGR and WHR

The problem in using the wage variable  $\Delta(W/L)$  is that working hours are simultaneously both the dependent variable but also a component of the wage variable. According to Kotakorpi et al (2016, 87) using an estimation equation, which contains  $\log(L)$  as a dependent variable  $\log(L)$  and  $\log(W/L)$  as an explanatory variable, is likely to result in elasticity estimates close to -1. Controlling output, which correlates strongly with total labour costs, only strengthens this result. However, Abraham & Haltiwanger (1995, 1244) notice that the majority of studies use similar wage measure in their analysis. It is a common method to divide the total payroll during some period by the total number of hours worked during that same period, and use it as a measure of average hourly earnings.

The real aggregate growth rate (RAGR) measures the growth rate of average wages by industry, and using it corrects this major problem in elasticity estimates. Since RAGR already represents percentage change, the estimation equation is:

$$\Delta(L_{it}) = \alpha + \eta_{L,w} RAGR_{it} + \varepsilon_{it} \quad (14)$$

When estimating equation (14) using the real aggregate wage growth (RAGR) as the wage variable, the total labour demand elasticity  $\eta_{L,w}$  is statistically insignificant with a point estimate of -0.12. Adding year-dummies result in a positive elasticity estimate of 0.22, with a standard error of 0.068. Since the independent wage variable RAGR results in lower elasticity estimates, it signals that previous models were biased.

However, the aggregate real wage growth measure RAGR is likely to suffer from the standard sort of composition bias, because aggregate wage statistics give more weight to low-wage workers during expansions than during recessions. The magnitude of composition bias can be detected by comparing the estimated elasticities based on the aggregate real wage measure RAGR to the results of a wage statistic without cyclically shifting weights. RWHR, the real average wage growth rate of job stayers, represents the change in hourly wages among persons who continue in the same firm. This composition bias-free wage growth data is utilized in models M9 and M10.

$$\Delta(L_{it}) = \alpha + \eta_{L,w}RWHR_{it} + \varepsilon_{it} \quad (15)$$

Using RWHR as the wage variable, the total labour demand elasticity  $\eta_{L,w}$  is statistically insignificant at -0.17. Adding year-dummies results in a positive elasticity estimate of 0.33. Thus these results are very similar to the elasticity estimates of the same equation where RAGR is used as the wage variable. This suggests that composition bias is not very significant after all. However, there are some factors that may blur composition bias. The concept of job stayers refers to employees who work for the same firm as they did in the previous year. These calculations, therefore, allow for change of profession. This is because the profession data were not available on an annual basis before 2004. In addition, when assessing these elasticity estimates, the wage changes experienced by persons in the panel for a given pair of years should be comparable to the potential wage changes for persons for whom the data are missing (Abraham & Haltiwanger 1995, 1246).

TABLE 4 Elasticities of different wage growth measures

Variable	M5 $\Delta L$	M6 $\Delta L$	M7 $\Delta L$	M8 $\Delta L$	M9 $\Delta L$	M10 $\Delta L$
$\Delta(W/L)$	-0.312*** (0.0869)	-0.240* (0.119)				
RAGR			-0.124 (0.0829)	0.221** (0.0679)		
RWHR					-0.168 (0.0895)	0.334** (0.121)
Year-dummies	no	yes	no	yes	no	yes
constant	0.0094*** (0.0025)	0.015 (0.0080)	0.0068* (0.0030)	0.034*** (0.0099)	0.0080* (0.0031)	0.032** (0.01)
N	468	468	442	442	442	442
R <sup>2</sup>	0.07	0.28	0.0093	0.28	0.015	0.29

Standard errors in parentheses, \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

### 5.3 Elasticities of different industries

The data allows to estimate labour demand elasticities separately for different industries. Since the data is annual, the sample size for a single industry is not very large. Thus the period is extended to cover the years 1975-2014 in order to get a slightly larger sample size. Then the only option is to use the most biased wage variable  $\Delta(W/L)$ . Labour demand elasticities for different industries are reported in the table in Appendix. They are estimated by using estimation equation (13).

The results show that there are substantial differences in elasticity estimates between different industries. In general, the elasticities of manufacture (industries 10-39) are strongly negative. For example Manufacture of machinery and equipment (28) has elasticity estimate of -0.75, and Manufacture of motor vehicles and other transport equipment (29-30) elasticity estimate of -0.63. On the other hand, labour-demand elasticities in other industries seem to be much lower and closer to zero. The estimated elasticity for Transport and postal activities (49-53) is -0.13, whereas Trade (45-47) has elasticity of -0.07 and Construction (41-44) +0.19. It should be noted that sample sizes and coefficients of determination ( $r^2$ ) are rather low. Also the wage variable is the most biased one, and standard errors are high. So, unfortunately these estimated elasticities are not very reliable. However, Also Lichter et al. (2014, 14) found differences between different industries, and reported that labor demand is significantly less elastic in the food and beverages industry whereas it is significantly more elastic in the basic metals industry.

These differences between industries and high elasticities of manufacture provide us a new potential bias in macro-estimates of labour demand. Lichter et al. (2014, 9) reported that the majority of the studies focus on the manufacturing sector, and only few estimates refer to the service and construction sectors. Focusing on manufacturing is mainly due to the lack of suitable data on other industries. If other industries have more positive elasticities, the estimates that are calculated on the basis of manufacture only produce biased and too negative elasticities.

To sum up this section 5, using aggregate data in estimating labour demand elasticities is problematic since such data lack exogenous variation in labour costs. A common method to measure average hourly earnings by dividing the total labour costs during some period by the total number of hours worked during that same period results is likely to result in excessively large negative elasticity estimates. Using an independent wage measure appears to result in considerably lower or even positive elasticity estimates. Furthermore, the results suggests that composition bias might not be very significant after all in the context of labour demand elasticities.



## 6 MEASUREMENT ERROR IN WORKING HOURS

This section continues the empirical analysis of examining potential bias in the macro-estimates of the elasticity of labour demand. The focus is now on how potential measurement error in working hours affects elasticity estimates. This analysis is conducted by using Monte Carlo simulation method that can be used to generate data that is similar to the data used in the previous calculations. Measurement error is created by increasing gradually the variance of the total hours worked ( $L$ ) in the industry.

### 6.1 Measurement error in working hours

Let us next consider how potential measurement error in working hours affects elasticity estimates. According to the previous analysis, using  $\Delta(W/L)$  as a wage variable is problematic because it means that working hours are simultaneously on both sides of the estimation equation. In many studies average hourly wages in each industry are calculated by dividing total labour costs ( $W$ ) by total hours worked ( $L$ ) in the industry. The previous calculations demonstrated also that replacing this questionable wage measure with an independent wage measure results in significantly lower elasticity estimates. Utilizing Monte Carlo Simulation method allows us to examine how measurement error in working hours affects estimates of elasticity of labour demand.

Since the two main variables are employment and labour costs, some reasoning is needed to explain why working hours are more likely to be prone to measurement error. Total working hours ( $L$ ) are based on Statistics Finland's Time Use Survey, which is a sample survey where participation in the interviews is voluntary. There are many possible sources of measurement error. For example, a respondent might give the wrong answer or he/she might not know his/her exact working hours or might misstate the amount for some other reason. In addition, certain respondents might not agree to participate in interviews, which results in deficient samples. So, the data that reflects working hours may not be entirely accurate. Data on total labour compensation ( $W$ ) may also contain some measurement error. The total labour compensation  $W$  is based on Statistics Finland's Financial statements inquiry for enterprises, which collects data on firm's income and expenditure. A majority of the data is collected from the Tax Administration's business taxation file. Thus, it can be regarded as a relatively reliable data. To sum up, the total working hours  $L$  is more likely to suffer from measurement error than  $W$ .

Previous calculations have shown that an estimation equation as (11) produces the most biased elasticity estimates. Using such estimation equation, measurement error in working hours means that there are measurement error

both in the dependent variable and in the explanatory variable. Errors-in-variables bias in the OLS estimator arises when an independent variable is measured imprecisely, and it can result in correlation between the regressor and the error term. This bias persists even in very large samples, so the OLS estimator is inconsistent if there is measurement error (Stock & Watson 2012, 361-363). In our case the source is an error in the measurement of working hours. Measured value  $\tilde{L}_{it}$  equals the actual, unmeasured value  $L_{it}$ , plus a purely random component which has mean zero and variance  $\text{VAR}(w)$ .

$$\tilde{L}_{it} = L_{it} + w_{it} \quad \text{where } \text{corr}(w_{it}, L_{it})=0 \quad \text{and } \text{corr}(w_{it}, u_{it}) = 0 \quad (16)$$

According to Stock and Watson (2012, 361-363), the effects of this classical measurement error in X are that  $\hat{\eta}$  will be biased towards 0, even in large samples. However, in our case working hours are on both sides of the estimation equation, which makes the direction of bias unclear. The major problem in our case is that the least square assumptions in the multiple regression model are not satisfied. More specifically, error term  $u$  should have conditional mean zero:  $E(u_i | X_{1i}, X_{2i}, \dots, X_{ki}) = 0$ . This assumption is violated because dependent variable  $L$  is a part of regressor  $W/L$ , making the regressor correlated with the error term (Stock & Watson 2012, 240). As a result, it is clear that elasticity estimates are biased but the direction of this bias needs to be considered further.

If working hours  $L$  is not a part of the explanatory wage variable, measurement error increases only the variance of the regression and elasticity estimate but does not induce bias in  $\hat{\eta}$  (Stock & Watson 2012, 363). Therefore, using independent wage variable (AGR or WHR) means that error in working hours does not induce bias in elasticity estimates. However, they do not solve the simultaneous causality bias, which "arises in a regression of  $Y$  and  $X$  when, in addition to the causal link of interest from  $X$  to  $Y$ , there is a causal link from  $Y$  to  $X$ . This reverse causality makes  $X$  correlated with the error term in the population regression of interest." (Stock & Watson 2012, 366-368.) This problem can be avoided by using instrumental variables regression or by implementing a randomized controlled experiment in which the reverse causality channel is nullified. Finding a proper instrumental variable has turned to be difficult but there are some quasi-experimental studies based on exogenous variation in labour costs.

## 6.2 Monte Carlo simulation

Monte Carlo simulation is a useful method that can be used in analysing effects of measurement error. Conducting a Monte Carlo simulation starts by generating data according to the desired data generating process. In this case we need to generate data that is similar to the data in sections 4 and 5, with the same averages, standard deviations and correlations as the original data. Gradually in-

creasing the variance of working hours demonstrates the effects of measurement error. Using this new data allows to estimate parameter of interest. Repeating this procedure  $N$  times produces  $N$  parameter estimates (Brooks 2008, p.547-548). Since a simulation produces random samples from a given distribution, the parameter estimate of each simulation is slightly different. Because of this, a simulation is necessary to repeat numerous times. Calculating averages on the basis of multiple simulations offers considerably more stable estimates.

The analysis begins with specifying the model to generate the data. In this study, the data is generated based on random sampling from normal distribution. Since the original data contains several variables, the simulation code must be able to generate data that satisfy the correlation restrictions of the original data. Simulating multivariate distributions produces such desired data. Examining the original data reveals that neither data on working hours  $L$ , total labour compensation  $W$  nor output  $Y$  are normally distributed. Since the logarithmic variant of original data follow rather well normal distribution, it is reasonable to generate normally distributed data based on  $\log W$ ,  $\log L$  and  $\log Y$ . Setting the number of observations to be 1000 results in generated data, which has the same averages, standard deviations and correlations as the original data.

Being determined to have the same averages, standard deviations and correlations as the original data, the simulated data is very similar and comparable to the original data. This generated data can be used in estimating labour demand elasticities. Since the generated data is similar to the original data, the resulting elasticity estimates should also be similar. Let us estimate the estimation equation (17) that contains output  $Y$  as a control variable:

$$\ln(L_{it}) = \alpha + \eta_{L,W|Y} \ln\left(\frac{W_{it}}{L_{it}}\right) + \beta \ln(Y_{it}) + \varepsilon_{it} \quad (17)$$

The central idea of Monte Carlo method is random sampling from a given distribution. Since the first elasticity estimate is based on a random number draw, it is slightly different every time. Because of this, similar data is generated 1000 times using the same data generating process, and the resulting 1000 parameter estimates are saved. As a result, we have 1000 slightly different elasticity estimates. The average of these estimates provides better information than a single estimate. Table 5 shows that the average of 1000 elasticity estimates is -0.75, with a standard deviation of 0.037. One can note that this average elasticity estimate is very similar to the one resulting from the original data. This suggests that the data generating process appears to be working properly.

Since the simulation generates desired data, this same data generating process is applicable in examining effects of measurement error in working hours. The analysis continues by examining how greater measurement error in working hours affects elasticity estimates. Let us generate data that suffer from greater measurement error. For example, the measurement error in working hours can be set so that its mean is zero and standard deviation is 0.5, while otherwise keeping the data generating process identical to the previous one. Estimating the elasticity of labour demand gives a parameter estimate, and repeat-

ing process 1000 times results in 1000 elasticity estimates that are based on less accurate data on working hours. Again, the average of these estimates provides more useful information than a single random elasticity estimate. The average elasticity is -0.89, with a standard deviation of 0.024.

Table 5 demonstrates how measurement error in working hours affects the elasticity estimates. The first column reports the standard deviation of error term in the simulated data on working hours. The errors are drawn from  $N(0, \sigma^2)$  distribution meaning that the mean of the measurement error is zero. Thus the only difference between results in each row is caused by different SD of the error term. In the first row the standard deviation is 0.1, while in the lower rows its magnitude is gradually increased. The column 'Average elasticity' shows the average of 1,000 elasticity estimates. Other statistics reported are minimum (min), maximum (max) and standard deviation of these 1000 elasticity estimates.

TABLE 5 Monte Carlo simulation: Measurement error in working hours

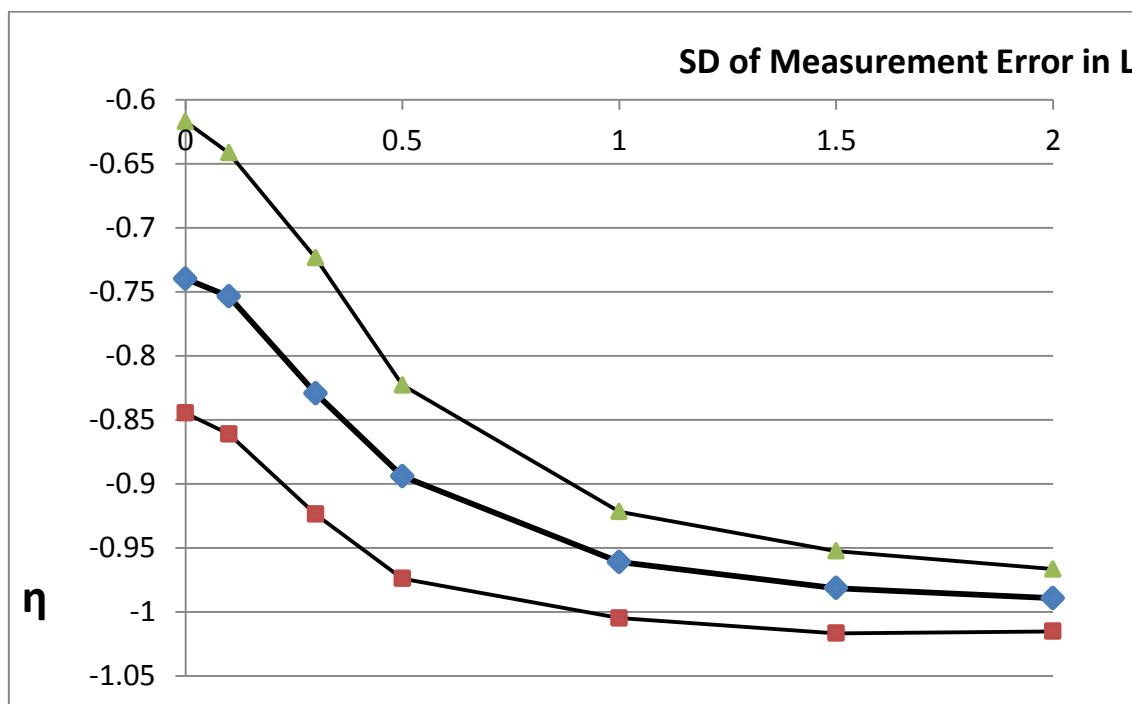
<b>SD of Measurement error</b>	<b>N</b>	<b>Average elasticity</b>	<b>SD of elasticity</b>	<b>Min</b>	<b>Max</b>
<b>0.1</b>	1,000	-0.754	0.037	-0.858	-0.613
<b>0.3</b>	1,000	-0.828	0.030	-0.917	-0.738
<b>0.5</b>	1,000	-0.894	0.024	-0.983	-0.814
<b>1.0</b>	1,000	-0.961	0.014	-1.010	-0.919
<b>1.5</b>	1,000	-0.982	0.010	-1.011	-0.952
<b>2.0</b>	1,000	-0.989	0.007	-1.014	-0.963

The results in table 5 show that larger measurement error in working hours results in more negative elasticity estimates. Actually, results of simulations based on exaggerated measurement errors suggest that the bias is towards minus one. While considering these results, it is worth noting that even the elasticity estimates resulting from the most accurate working hour data might actually be biased. Simulated data being reproduction of original data, it is already likely to suffer from measurement error in working hours. Thus, inaccurately measured working hours appear to cause severe bias in elasticity estimates based on estimation equations similar to (11) or (17).

Moreover, table 5 shows another interesting result: larger measurement error in working hours results in elasticity estimates with lower standard deviations. It is not very believable to claim that less accurate employment data could produce more accurate elasticity estimates. Figure 5 illustrates the effects of increasing measurement error in working hours. As the standard deviation of the measurement error increases from 0.1 to 2, the average of elasticity estimates approaches -1. At the same time the confidence interval of the average elasticity decreases and not a single elasticity estimate of 1000 simulations provide an estimate, the absolute value of which is lower than -0.95. All in all, comparing the case where the SD of measurement error is 0.1 to cases with SD of 1.0 or more

reveals a clear inconsistency: higher measurement error produces elasticity estimates, all of which are more negative than -0.9 while the most negative estimate resulting from SD of 0.1 is -0.86.

FIGURE 5 Monte Carlo simulation: Measurement error in working hours



To sum up, this analysis based on Monte Carlo simulation demonstrates how calculating hourly wages by dividing total labour costs  $W$  by total hours worked  $L$  in the industry is likely to cause problems in elasticity estimates. The results of this simulation show that estimating labour demand elasticities with a model, which has working hours on both side of the estimation equation, results in excessively large negative elasticities. The larger the measurement error in working hours, the closer to -1 the elasticity estimates are. Thus, using an independent real wage measure corrects a major error. Comparing the estimated elasticities based on  $\Delta(W/L)$  with those resulting from AGR supports the same conclusion. However, even elasticity estimates based on AGR and WHR are likely to be biased.

## 7 MICRO-STUDIES

This section focuses on micro-studies examining situations where labor costs have been altered exogenously. Whereas elasticity estimates based on aggregate data suffer from a lack of exogenous variation in labour costs, there are some studies that avoid this problem. For example wage subsidies and payroll tax cuts provide opportunities to study natural experiments that include policy-induced variation in labour costs. Studying a policy change reveals the source of variation in the explanatory variables, and using policy-induced variation in labour costs as quasi-experiments means that there is exogenous variation in labour costs. The resulting elasticities can be interpreted to be causal effects of reducing labour costs on employment.

### 7.1 Difference-in-differences method

In order to predict what happens to employment when labour costs are reduced, one can study cases where labor costs are reduced in reality. For example wage subsidies and payroll tax cuts provide opportunities to conduct quasi-experiments. Wage subsidies are an active labour market programme that reduces labour costs of a certain target group, which encourages employers to hire them. Payroll taxes in Finland include employer contributions to the employees' pension scheme, the national pension insurance, the unemployment insurance, the national health insurance and the employment accident insurance (Korkeamäki & Uusitalo 2009, 755). Being a rather large part of the total labour costs, reducing payroll taxes for a certain group makes that group relatively less-costly for employers to hire. Both wage subsidies and payroll tax cuts induce exogenous variation in labour costs, so they provide promising opportunities to estimate labour demand elasticities that can be used to make causality interpretations. Such elasticity estimates are useful in making policy analysis and predicting the effects of reducing labour cost.

The difference-in-differences (DiD) method exploits policy changes as natural experiments. This strategy presupposes that one can define two groups, a treatment group and a control group, which share the same trend. When using the DiD-method, one assumes that employment trends would be the same in both groups without the treatment, and that any deviation from this common trend is caused by the policy change (Angrist & Pischke 2008, 169-172). The definition of the differences-in-differences estimator is "the average change in Y for those in the treatment group, minus the average change in Y for those in the control group" (Stock & Watson 2012, 532-533):

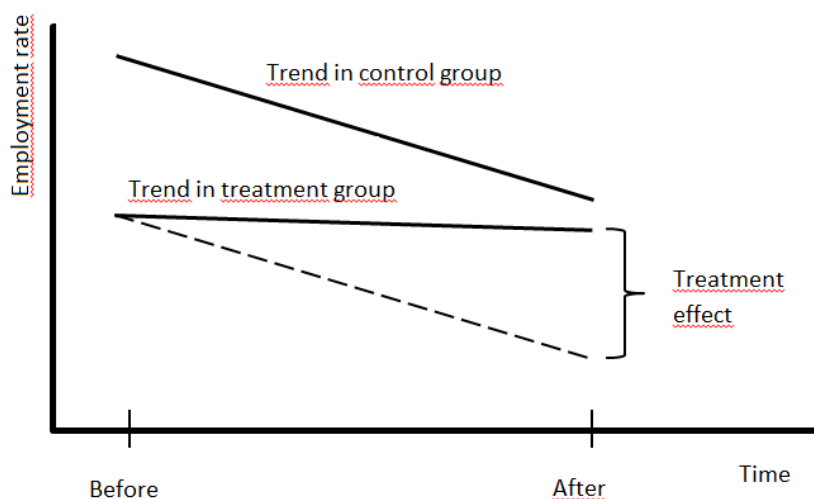
$$\begin{aligned}\hat{\beta}_1^{DiD} &= (\bar{Y}^{treatment,after} - \bar{Y}^{treatment,before}) - (\bar{Y}^{control,after} - \bar{Y}^{control,before}) \\ &= \Delta \bar{Y}^{treatment} - \Delta \bar{Y}^{control}\end{aligned}\quad (18)$$

“If the treatment is randomly assigned, then  $\hat{\beta}_1^{DiD}$  is an unbiased and consistent estimator of the causal effect” (Stock & Watson 2012, 532-533). This strategy requires that one is able to define two groups, treatment group and control group, which share the same trend. In the context of labour demand elasticities, this means that employment trends would be the same in both groups in the absence of treatment. Deviation from this common trend is caused by the treatment. As Egebark & Kaunitz (2013, 14-15) express it, DiD uses the evolution of the control group over time as a measure of how the treatment group would have evolved without policy change. This results in the following equation:

$$E[y_{i,t}^0 | Tr = 1] = E[y_{i,t}^0 | Tr = 0] + \alpha \quad (19)$$

where  $y_{i,t}^0$  is the no-treatment outcome for individual  $i$  at time  $t$ . In other words, the counterfactual outcome of the treatment group is identical to the actual outcome of the control group, except for a constant  $\alpha$ . Egebark & Kaunitz (2013, 15) admit that this is a very strong assumption. However, a common trend is an essential requirement for using difference-in-difference-method. Therefore checking whether the treatment and control group share a common trend before the policy change is a matter of considerable importance. One has to investigate data on multiple periods.

FIGURE 6 Difference-in-difference



Angrist & Pischke (2009, 231)

When using this quasi-experimental method, one compares the growth in employment in the treated group to that of a control group. Figure 6 demonstrates the average employment in a treatment group and a control group be-

fore and after a tax reduction in the treatment group. Employment in the control group reduces whereas employment in the treatment group remains the same. Since both of the groups would have shared the same trend without the tax cut, the tax cut had a positive effect on treatment group, meaning a positive difference-in-differences estimate. This kind of analysis is likely to offer results about how a reduction in labor costs affects employment.

## 7.2 Results of micro-studies

This section compiles some micro-studies examining situations where labor costs have been altered exogenously. These studies use DiD-method in order to examine the employment effects of policy changes that reduce labour costs. For example studying employment effects of wage subsidies or payroll tax cuts are likely to offer elasticity estimates that are suitable for policy analysis. Such studies provide more reliable elasticity estimates that can be interpreted as causal effects of reducing labour costs. The relevant studies, their study designs and results are reported in table 6.

Wage subsidies are an active labour market program that creates exogenous variation in labour costs. The aim of wage subsidies is to create employment that is not affordable without subsidies. Wage subsidies decrease the marginal cost of additional labour, enabling subsidized firms to employ workers who would not otherwise have been employed. In addition, the purpose is that worker's skills and human capital will develop during the subsidized period so firms will be willing to pay them according to the standard wage level (Kangasharju 2007, 53). Huttunen et al. (2013) study effects of low-wage subsidy program in Finland between the years 2006 and 2010. The treatment group in this study is workers over 54 years old who were working full-time and whose wages were between 900€ and 2000€. The control group is workers of the same age who did not receive the subsidy. Kangasharju (2007) examined wage subsidy of 430-770€ per month between the years 1995 and 2002. He compared firms who received this subsidy to companies who did not receive subsidy.

The wage subsidies seem to have stimulated employment in subsidized firms but both Kangasharju (2007) and Huttunen et al. (2013) estimate rather low labour demand elasticities. Huttunen et al. (2013, 59) discovered that low-wage subsidy experiment increased employment and the estimated elasticity was -0.13 while Kangasharju estimated labour demand elasticity of -0.09, with t-value of 11.6. These elasticity estimates are significantly lower than the elasticity estimate of -0.7 used by the Ministry of Finance.

However, one has to be careful while considering a situation where labour costs of one specific group are reduced but the costs of other workers remains the same. The very purpose is to stimulate the total employment in firms. If employees in subsidized jobs simply substitute for non-subsidized employees, the total employment will not increase, which is not a very desirable effect.



Kangasharju (2007, 64) made promising findings that subsidies did not have sizeable effects on non-subsidized firms of the industry or geographical area in question. Thus the conclusion is that the wage subsidy program stimulated the total employment.

The Swedish government released a large payroll tax cut program in 2007 and again in 2009. Due to the policy change enacted in 2007, the employer-paid payroll tax rate was lowered by 11 percentage points for employees who at the start of the year had turned 18 but not 25 years of age. The purpose was to reduce unemployment among young workers by reducing the amount of payroll taxes paid by companies. Skedinger (2014) examines the effects of this payroll tax cut program between years 2000 and 2011. In his study the treatment group is young workers aged between 21 and 25. The control group consists of workers aged between 27 and 29 who were not in the payroll tax cut program. Egebark and Kaunitz (2013) study the same payroll tax cut program. The time horizon of their study was from 2001 to 2010. Their treatment group therefore consisted of people aged 19-25, while the control group consisted mainly of 26-year-olds.

The Swedish studies report similar results of the effects of payroll tax cuts on unemployment. Skedinger (2014, 157) estimated that the elasticity is -0.19. This means that the payroll tax cut program decreased unemployment among young workforce. Egebark & Kaunitz (2013, 33) estimated a slightly larger elasticity estimate of -0.31. Korkeamäki and Uusitalo (2009, 771) study the effects of payroll tax cuts in Finland between years 2003 and 2009. The treatment group in their study consists of firms that were located in twenty target municipalities in northern Finland. The control group consists of firms located in eastern Finland. They estimate a relatively high elasticity estimate of -0.6 but report that it is not very accurate since the confidence interval is very wide.

There are many similar studies that are unable to estimate labour demand elasticities. Findings from many studies in Finland, Sweden and Norway show that a payroll tax cut is likely to push wages up. For example Korkeamäki (2011) evaluates the effects of a regional experiment that reduced payroll-taxes by 3-6 percentage points of the firm's wage sum in Northern and Eastern Finland. He finds no statistically significant effects on employment. Benmarker, Mellander and Öckert (2009, 480) evaluate the effects of regional wage subsidies in Sweden finding that changes in payroll taxes are partly shifted to wages with little effect on employment. Johansen and Klette (1997, 11) examine the effects of regional differences in payroll taxes in Norway, and find that changes in payroll taxes are for the most part shifted to wages. Even evidence from Chile suggest similar results. Gruber (1997) finds that the reduced costs of payroll taxation passed fully on workers in the form of higher wages, leaving no room for effects on employment.

These studies, therefore, share the same result that changes in payroll taxes are partly shifted to wages with little effect on employment. Such studies do not provide elasticity estimates since labour costs remained unchanged. However, the finding that payroll tax cuts and wage subsidies are likely to push wages up does not mean that elasticity of labour demand is zero. If a payroll tax

reduction leads to an increase in wages, employment effect was zero just because the actual labor costs remain unchanged, not because of zero elasticity. If wages rise in the same proportion as the payroll tax is reduced, the final impact on the labour costs is negligible. Estimating labour demand elasticities is not possible on the basis of a zero effect on total labour costs, which means that such studies do not provide elasticity estimates.

TABLE 6 Elasticity estimates of micro-studies

Study	Information	Elasticity (s.e.)
<b>Skedinger (2014)</b>	Sweden, 2000-2011. 13,000 firms with a total of 300,000 employees. Large payroll tax cuts for young workers, two reforms in 2007 and 2009. DiD. Treatment group: workers aged 21-25. Control group 27-29-year-olds.	<b>-0.19</b> (0.085)
<b>Huttunen et al (2013)</b>	Finland, a targeted low-wage subsidy experiment in 2006-2010. DiD. Eligible for the subsidy: workers over 54 years old, earning between €900 and €2,000 per month and working full-time. Control group: similar groups which were not eligible for the subsidy.	<b>-0.13</b> (0.107)
<b>Egebark &amp; Kaunitz (2013)</b>	Sweden, 2001-2010. Large payroll tax cut for young workers in 2007. DiD. Treatment group: workers aged 19-25. Control group: 26-year-olds.	<b>-0.31</b>
<b>Korkeamäki &amp; Uusitalo (2009)</b>	Finland, 2003-2009. A regional experiment that reduced payroll taxes by 3–6 percentage points for 3 years. Treatment group: firms in the 20 target municipalities in northern Finland. Control group: similar firms in a comparison region of Eastern Finland.	<b>-0.6</b>
<b>Benmarker et al (2009)</b>	Sweden, 2001-2004. 10 percentage point reduction in payroll tax in 2002 in northern Sweden. DiD. Annual firm-level data. Control group: similar firms operating in nearby regions.	<b>+0.01</b> (0.1)
<b>Benmarker et al (2009)</b>	Extending the analysis to include entry and exit of firms.	<b>-0.38</b> (0.27)
<b>Kangasharju (2007)</b>	Finland, 1995-2002. Wage subsidy of 430-770€/month. Unbalanced panel of 31,000 firms. DiD. Subsidized firms vs. non-subsidized.	<b>-0.09</b> (0.0078)
<b>Kramarz &amp; Philippon (2001)</b>	France, 1990-1998. Tax subsidies. Workers directly affected by the changes vs. control group. Transition probabilities from non-employment to employment.	<b>-0.03</b>
<b>Average elasticity</b>		<b>-0.215</b>

To sum up, the studies reported in table 6 provide the best available evidence of the effect on employment of reducing labor costs. The average labour demand elasticity of these studies is only -0.22. This is a significantly lower estimate than the result of the extensive meta-analysis of Lichter et al. (2014), which consisted of macro-studies without exogenous variation. Studies containing exogenous variation in wages provide preferable estimates for policy analysis.

TABLE 7 Meta-analysis

Study	Elasticity	s.e.	[95% Conf. Interval]		%Weight
Benmarker et al (2009)	0.01	0.1	-0.186	0.206	19.85
Benmarker et al (2009)	-0.38	0.27	-0.909	0.149	2.72
Huttunen et al (2013)	-0.13	0.11	-0.34	0.08	17.34
Skedinger (2014)	-0.19	0.085	-0.357	-0.023	27.47
Kangasharju (2007) *	-0.09	0.0078	-0.243	0.063	32.62
<b>Pooled</b>	<b>-0.112</b>		<b>-0.2</b>	<b>-0.025</b>	<b>100</b>

\* used s.e. of 0.078. The weight of this single study would be 97% if s.e. were 0.0078.

Since some of the studies in table 6 reported standard errors of their elasticity estimates, it is possible to conduct a small meta-analysis. In this meta-analysis reported in table 7, the elasticity estimates are weighted based on their standard error. While several studies do not provide standard errors of their elasticity estimates, the following table contains only those studies that report both elasticities and their standard errors. The pooled-elasticity estimate resulting from the meta-analysis is very low, being only -0.11. The difference between this and the previous average is largely due to the fact that the highest elasticity estimates are not included in the meta-analysis because their standard errors are missing. On the other hand, Korkeamäki & Uusitalo (2009, 771) reported that the confidence interval is very large, which refers to the large standard error value. In this case, the weight would be really small in meta-analysis.

FIGURE 7 Meta-analysis

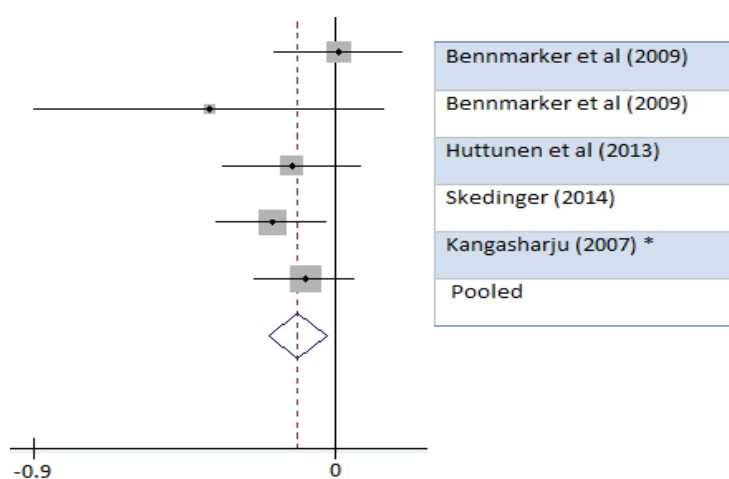


Figure 7 illustrates this meta-analysis. The black dots illustrate the elasticity estimates, while the size of the squares illustrates the weight that an elasticity estimate is getting. The horizontal lines indicate confidence intervals. The greater the confidence interval, the lower is the weight. It can be noted that most of the individual elasticities are not statistically significant. The pooled estimate, however, combines the information of several studies, and the 95-% confidence-interval of this estimate is statistically significantly negative.

### 7.3 Discussion on micro-studies

Using policy-induced variation in labour costs as quasi-experiments means that there is exogenous variation in the price of labour. Such studies provide the best available evidence of the effect on employment of reducing labour costs. This provides more reliable elasticity estimates that can be interpreted as causal effects of reducing labour costs on employment. However, it is possible to argue that these micro-studies and the effects of the policy changes that they study might not be completely comparable with the effects of the competitiveness pact. They studied experiments that were only temporary and therefore the effects on employment remained negligible.

In the context of the competitiveness pact, some questions might rise about the external validity of these micro-studies. The results of an externally valid study can be generalized to other populations and settings (Stock & Watson 2012, 356-357). Before generalizing the results of these micro-studies, one should consider potential threats to external validity. First of all, the true causal effect might not be the same in the population studied and the population of interest. Thus there is certainly reason to question whether the results of these experiments can be generalized to the entire economy and context of competitiveness pact.

The treatment studied should be representative of the treatment that would be implemented more broadly (Stock & Watson 2012, 519-520). Similar to payroll tax reductions, also the competitiveness pact will reduce employer's payments and therefore reduce labour costs. However, the micro-studies reported earlier examined policy changes that affected only a limited number of people. It might be possible that the effects of a small and temporary program do not reflect the effects of a widespread and permanent program. In this case results from the experiment cannot be generalized (Stock & Watson 2012, 519-520).

Moreover, the population studied and the population of interest should be adequately similar in order to justify generalizing the experimental results (Stock & Watson 2012, 519-520). However, the wage subsidies and tax reductions were targeted to a certain group of people, such as young workers. The results for young people offer information on how cutting costs affects youth employment. Whether elasticities calculated in this way can be generalized to apply to all age groups instead of young people only is open to question. How-

ever, a competent counter-argument is that these experiments are aimed at groups in which elasticities should, in fact, be higher than they are on average. So while these studies suggest that elasticity of labour demand seems to be rather low, the actual elasticities for the whole economy are hardly any higher but on the contrary even lower instead. Moreover, similar findings of low elasticities in all the micro-studies reported support external validity.

There are also some questions of internal validity. It might be problematic to find a treatment group and control group that are similar enough. As Egebark and Kaunitz (2013) study the payroll tax cut program, their treatment group consisted of people aged 19-25, whereas control group consisted mainly of 26-year-olds. Whether 18-year-olds and 26-year-olds are fully comparable may be a little arguable. According to Egebark & Kaunitz (2013, 15), the evolution of employment in the period before the reform differs between different age groups. Younger workers experience greater cyclical variations. This means that in 2007, during an economic expansion, a relative employment increase for 20-year-olds would have been expected even without the tax cut. Thus, comparing 20-year-olds to 26-year-olds during that period is likely to produce upward-biased elasticity estimates.

Moreover, the control group must not be affected by the policy change. For example, the 2007 tax reduction investigated by Egebark & Kaunitz (2013) increased the cost of 26-year-old labour relative to 25-year-old labour. This is likely to result in negative substitution effect for the control group. Thus the reform may have negatively affected the control group of 26-year-old individuals. One should also note that comparing only the individuals close to the cutoff is likely to underestimate the average treatment effect on the treated. This is because 25-year-old workers will have benefit from the tax cut only a short period of time compared to 20-year-old workers. As a result, the treatment effect is stronger for young workers (Egebark & Kaunitz 2013, 19-20).

To sum up, elasticity estimates of these micro-studies are useful for policy analysis because they are based on data that contain exogenous variation in labour costs. Unfortunately, the number of relevant micro-studies appears to be very limited. Another problem is that the experiments investigated were only temporary. In addition, there are grounds to doubt whether the results of these experiments can be generalized to the overall economy. However, many of these experiments are aimed at groups in which the elasticities should, in fact, be higher than on average. All in all, such studies provide the best available evidence of causal employment effects of reducing labour costs. The average elasticity estimate of the studies considered here is -0.22. It is considerably lower than the government's elasticity estimate of -0.7, which means that employment effects of the competitiveness pact are likely to be lower than the Ministry of Finance has estimated.

## 8 CONCLUSIONS

The majority of studies estimate labour demand elasticities using aggregate data, which is likely to produce biased elasticity estimates. The problems relate in particular to the lack of exogenous variation in labour costs and the simultaneity of demand and supply. Using aggregate data in estimating labour demand elasticities is problematic since such data lack exogenous variation in labour costs. This makes it impossible to measure the causal impacts of labour costs on employment. Moreover, labour supply is unlikely to be either perfectly elastic or inelastic. Thus elasticity of labour demand should not be estimated without taking into account the supply of labour. Many macro-studies that estimate labour demand elasticities suffer from threats to internal validity. Simultaneous causality may result in correlation between the regressor and the error term, which means that regression coefficients are likely to be biased.

According to Lichter et al. (2014, 4) and their meta-study, the average own-wage elasticity of labor demand in their extensive sample is -0.5, with a very wide confidence interval. They note that this estimate is upwardly biased and highlight the fact that there are considerable heterogeneity between elasticity estimates. Firstly, there are various possible models that can be used in estimating elasticities, and they appear to result in different results. Moreover, the elasticity of labor demand for unskilled labor seems to be significantly higher compared to the overall workforce. There appears to be also significant differences in labour demand elasticities between industries. This suggests that the competitiveness pact might have different effects on different sectors and worker groups.

In the empirical part labour demand elasticities are estimated by using common macro-models. The key idea is to use different wage variables. Since the same model is used for every wage variable, the differences between elasticities provide some interesting information of potential bias in labour demand elasticities that are estimated by using macro-data. Above all, the results show that a common method to measure average hourly earnings by dividing the total labour costs by the total number of hours worked results in excessively large negative elasticity estimates. Using an independent wage measure appears to result in considerably lower or even positive elasticity estimates. These calculations show that estimating labour demand elasticities based on aggregate data is likely to produce biased and unreliable estimates. Furthermore, the effects of measurement error in working hours are examined by using Monte Carlo simulation method. The calculations show that aggregate data has a tendency to produce biased and excessively large elasticity estimates.

In addition, the wage data used in this study allows to examine the importance of the composition bias. The reason for the composition bias is that hour shares of different groups vary with the business cycles. Since hour shares of low-wage groups tend to be pro-cyclical, aggregate wage statistics give more weight to low-wage workers during expansions. The composition bias free

wage growth reflects the average wage growth rate of people who continue in the same firm, which makes it a wage statistic without cyclically shifting weights. However, the results suggest that composition bias might not be very significant after all in the context of labour demand elasticities.

A policy relevant elasticity estimate should be based on research containing plausible exogenous variation in wages. Using policy-induced variation in labour costs as quasi-experiments offers elasticity estimates that can be interpreted as causal employment effects of reducing labour costs. For example wage subsidies and payroll tax cuts offer opportunities to study natural experiments that include policy-induced variation in labour costs. Unfortunately, the number of relevant micro-studies appears to be very limited. There are many studies that are unable to estimate labour demand elasticities. Findings from many studies show that a payroll tax cut is likely to push wages up with little effect on employment. Such studies do not provide elasticity estimates since labour costs remained unchanged. However, those micro-studies that do estimate elasticity estimates provide the best available evidence of the employment effects of reducing labour costs.

This study contains a brief meta-analysis of micro-studies that examine situations where labour costs have been changed exogenously. These micro-studies appear to produce significantly lower elasticity estimates than macro-studies based on aggregate data. Whereas the Ministry of Finance's estimate of 35,000 new jobs is based on an elasticity estimate of -0.7, the average labour demand elasticity of these micro-studies is only -0.22. Unfortunately, this lower elasticity estimate suggests that employment effects of the competitiveness pact are likely to be below expectations.

However, it is possible to question whether the results of these experiments can be generalized to the entire economy and to the context of the competitiveness pact. Those micro-studies and the effects of the policy changes that they study should be comparable with the effects of the competitiveness pact. As payroll tax cuts, the competitiveness pact will also reduce labour costs. However, the micro-studies did not examine the effects of extending working time. Moreover, the competitiveness pact will affect the whole private sector whereas payroll tax cuts affected only a limited number of people. It might be possible that the effects of a small and temporary program do not reflect the effects of a widespread and permanent program. In addition, the experiments investigated were only temporary. However, many of these experiments were aimed at groups in which the elasticities should be higher than on average.

For further study, it would be interesting to study the actual effects of the competitiveness pact. Since the competitiveness pact will affect labour costs from 2017 onwards, such study cannot be conducted immediately. The realized effects can be observed only after some years. However, it will offer a possibility to study the employment effects of similar policy changes. Finding a proper comparison group might be challenging since the competitiveness pact affects the whole private sector. If future studies will reveal that reducing labour costs via the competitiveness pact was an effective way to increase employment, it might be reasonable to consider similar policy measures also in the future. If

employment effects remain limited, the attractiveness of implementing such a policy measure in the future will be reduced.



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## APPENDIX

Industries, total working hours and labour demand elasticities by industry 1975-2013

Standard Industrial Classification TOL 2008		Average of annual total working hours (1 000 000 h)	Elasticities by industry (1975-2014)
05-09	Mining and quarrying	9.2	-0.50** (0.18)
10-12	Manufacture of food products, beverages, and tobacco products	64.0	-0.27 (0.14)
13-15	Manufacture of textiles, wearing apparel, and leather and related products	22.5	-0.49 (0.32)
16	Manufacture of wood and of products of wood and cork	44.5	-0.47* (0.21)
17	Manufacture of paper and paper products	50.6	-0.36 (0.21)
18	Printing and reproduction of recorded media	21.3	-0.091 (0.19)
23	Manufacture of other non-metallic mineral products	25.7	-0.45* (0.22)
24	Manufacture of basic metals	26.1	-0.039 (0.09)
25	Manufacture of fabricated metal products, except machinery and equipment	68.5	-0.64 (0.32)
26-27	Manufacture of computer, electronic and optical products; Manufacture of electrical equipment	92.6	0.078 (0.14)
28	Manufacture of machinery and equipment n.e.c.	76.3	-0.75** (0.22)
29-30	Manufacture of motor vehicles, trailers and semi-trailers Manufacture of other transport equipment	28.9	-0.63* (0.29)
31-32	Manufacture of furniture Other manufacturing	28.9	-0.27 (0.14)
33	Repair and installation of machinery and equipment	32.2	-0.37* (0.17)
35-39	Electricity, gas, steam and air conditioning supply Water supply; sewerage, waste management and remediation activities	38.9	-0.012 (0.11)
41-43	Construction	240.6	0.19 (0.37)
45-47	Wholesale and retail trade; repair of motor vehicles and motorcycles	459.6	-0.070 (0.17)
49-53	Transportation and storage	221.3	-0.13 (0.12)
55-56	Accommodation and food service activities	119.6	-0.21(0.13)
58-63	Information and communication	143.6	-0.066 (0.17)
64-66	Financial and insurance activities	70.8	-0.35 (0.18)
68	Real estate activities	35.1	0.20 (0.098)
69-75	Professional, scientific and technical activities	143.1	-0.049 (0.2)
77-82	Administrative and support service activities	124.9	-0.072 (-0.23)
84-88	Public administration and defence; compulsory social security; Education; Human health and social work activities	73.8	-0.56*** (0.12)
90-93	Arts, entertainment and recreation	20.4	-0.039 (0.12)

Standard errors in parentheses. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$